Novel Characterization of the Steady-State Visual Evoked Potential Spectrum of EEG

Nicholas R. Waytowich
Old Dominion University
2117 Engineering Systems Building
Norfolk, Virginia
nwayt001@odu.edu

Dean J. Krusienski
Old Dominion University
2123H Engineering Systems Building
Norfolk, Virginia
dkrusien@odu.edu

ABSTRACT

Steady-State Visual Evoked Potentials (SSVEPs) are oscillations of the electroencephalogram (EEG) observed over the occipital area that exhibit a frequency corresponding to a repetitively flashing visual stimulus. SSVEPs have proven to be very consistent signals for rapid EEG-based brain-computer interface (BCI) control. However, due in part to perceptual and neurophysiological aspects, SSVEP signal detection biases exist for different stimulation frequencies. Furthermore, these biases tend to differ across subjects. Canonical correlation analysis (CCA) has proven to be the most robust approach for detecting SSVEPs in multiclass stimulus paradigms where each potential target flashes at a different frequency. In this work, in order to provide a better characterization of the SSVEP spectrum for BCI applications, 22 subjects were stimulated with an LED array that flashed according to a chirp signal having a frequency that varied over the typical functional range of SSVEP from 5.5-34.5 Hz. The resulting EEG was analyzed using CCA to elucidate the stimulus frequencies that produce the best discriminability for practical use. Subjects achieved an average accuracy of 72.2% using a six-class paradigm with a standardized set of stimulus frequencies. However, when using a subject-specific frequency set (i.e. frequencies optimized for each subject), the average accuracy significantly increased to 83.7% ($p = 0.03$). The results show that inherent SSVEP response differences exist between subjects, which can have a significant effect on performance. This approach also establishes a framework for a rapid optimization of subject-specific frequency profiles.

General Terms

Steady-State Visual Evoked Potentials, Brain-Computer Interfaces, Canonical Correlation Analysis

1. INTRODUCTION

Brain-computer interfaces (BCIs) are augmentative communication devices that analyze brain activity and decode user intent in order to provide a non-neuromuscular pathway of communication [7]. Some of the most promising approaches for scalp-recorded EEG-based BCIs utilize Steady-State Visual Evoked Potentials (SSVEPs). SSVEPs are oscillations in EEG that correspond to to the frequency of a flashing visual stimulus [3][6]. The fundamental frequency, as well as several harmonic frequencies, can be detected in the EEG and used to decode user intention when multiple flashing targets are presented. Recently, multichannel SSVEPs have been used on-line with Canonical Correlation Analysis (CCA) producing a robust BCI system that achieves good performance with little to no training data [1][2]. CCA is generally a preferred detection method for SSVEP BCIs because of its inherent channel harmonic analysis capabilities, relative simplicity, and robust performance. However, individuals generally have SSVEP responses in the range of 5-45 Hz, and the optimal stimulus frequencies within this range can vary greatly across individuals. This study aims to establish a novel characterization of the SSVEP using CCA, and to quantify the BCI performance differences between subject-optimized stimulation frequencies and standard, pre-selected stimulation frequencies. The results show that the brain responses over the SSVEP spectrum can vary drastically across subjects and frequencies, and that subject-specific optimization can greatly improve the performance of SSVEP BCIs.

2. METHODOLOGY

2.1 Data Collection

Subjects were 22 able-bodied adults (5 women, 17 men; age range 18-42 years). All subjects were free of neurological or psychiatric disorders or medications known to adversely affect EEG recording. All subjects had normal or corrected-to-normal vision. This study was reviewed and approved by the Old Dominion University Institutional Review Board and each user gave informed consent before participating.

The EEG was recorded using a 16-channel active electrode cap (g.GAMMAsys, g.tec Medical Engineering). The electrodes were positioned at locations: Fz, Pz, Poz Oz, O1, O2, Po3, Po4, Po7, Po8, Poo1, Poo2, Poo3, Poo4, Oi1h, Oi2h based on the extended International 10-20 system [5] as shown in Figure 1. All channels were referenced to the right earlobe and grounded to the left mastoid. The EEG was bandpass filtered from 0.1 Hz to 100 Hz, notch filtered at 60 Hz and digitized at a rate of 512 Hz using a g.USB amp (g.tec Medical Engineering). All aspects of the data collection and experimental procedure were controlled by

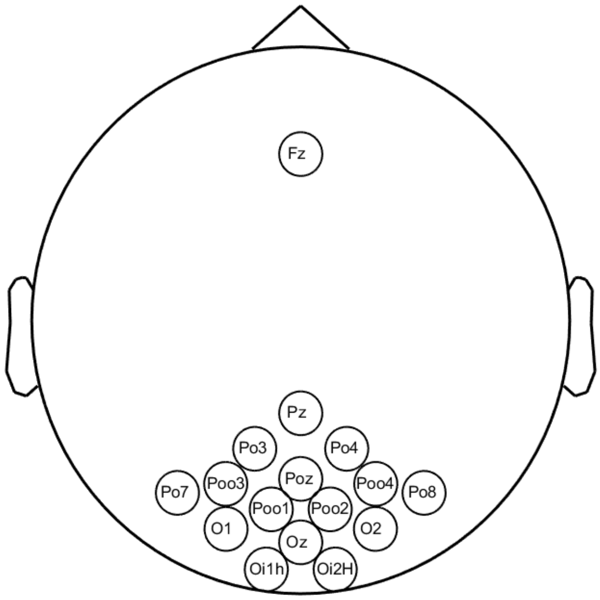

Figure 1: The EEG electrode montage used for data collection. The positions are based on the International 10-20 system. All electrodes were re-referenced to Fz.

the BCI2000 system [4].

2.2 Experimental Paradigm

Each subject sat in a dark room in front of a custom-built SSVEP stimulator composed of an 8 x 8 array of green LEDs as shown in Figure 2. Each LED in the array was connected together so that all LEDs illuminated simultaneously with the same stimulus. The stimulator is driven by a microcontroller with an output stimulation frequency of 500Hz and a 10-bit intensity resolution. The LED array was tested using a photo-diode to ensure consistent stimulation. LED luminosity was linearized over the operating range to ensure a uniform intensity distribution. All stimulation signals were generated using Matlab and loaded to the microcontroller.

The stimulator was positioned in the center of each subject's visual field and placed approximately 60 cm away from the subject so that the LED array spanned visual angles of 5.25 degrees vertically and horizontally. During the experiment, the subject's task was to attend and keep visual focus on the flashing stimulator. For each session, subjects attended to 30 seconds of continuous stimulation followed by 15 seconds of rest before the cycle repeated. The stimulation waveforms that were presented in a single experimental session were composed as follows: square waveforms with a chirp increase from 5.5-20.5 Hz, square waveforms with a chirp increase from 19.5-34.5 Hz, square waveforms with a chirp decrease from 20.5-5.5 Hz and square waveforms with a chirp decrease from 34.5-19.5 Hz. Each chirp waveform (increase and decrease) had a Δ_f of 0.5 Hz per second. This provided approximately two seconds centered on each integer frequency and is sufficiently slow enough to emulate a fixed frequency over a short time window.

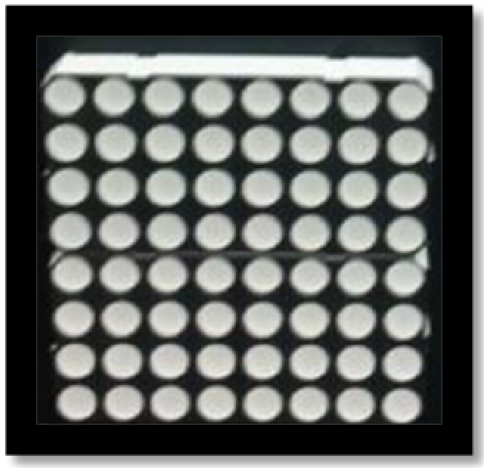

Figure 2: LED stimulator used to generate SSVEP stimulation. The stimulator consists of an 8 x 8 array of green LEDs driven by a microcontroller with a 10-bit DAC. The physical dimensions of the stimulator are 5.84 cm x 5.84 cm.

Each waveform was repeated five times, giving a total of 40 trials. The waveforms were presented in a randomized order to account for possible fatigue issues. Baseline EEG with the stimulator stimulator turned off and subject's eyes kept open was collected for approximately two minutes before and after the session. Each subject participated in a single experimental session.

2.3 Canonical Correlation Analysis

CCA is a multi-dimensional correlation analysis technique that finds underlying correlations between two sets of data. It linearly filters the two data sets to produce a pair of canonical variants whose correlation is maximized. Given two multi-dimensional data sets X, and Y, the canonical variants $x = X^T W_x$ and $y = Y^T W_y$ can be found by determining the weight vectors W_x and W_y that produce the maximum correlation between x and y. This optimization problem can be achieved using the singular-value decomposition method. Lin et all [1] proposed using this method to decode and analyze SSVEP signals. In this way, the multidimensional EEG data, X, can be canonically correlated with a multivariate set of reference signals Y_f. The reference signals Y_f are a set of sine and cosine signals derived from N_h harmonics.

$$Y_f = \begin{pmatrix} \sin(2\pi ft) \\ \cos(2\pi ft) \\ \vdots \\ \sin(2\pi N_h ft) \\ \cos(2\pi N_h ft) \end{pmatrix} \tag{1}$$

There is a reference template for each target frequency. The multi-channel EEG and reference signals are used in the CCA to produce a canonical correlation for each target frequency. The output class is determined as

$$C = arg\, max_i \rho_i, \qquad i = 1, 2, ...K, \tag{2}$$

where K is the total number of classes or target frequencies used for the SSVEP BCI.

2.4 Data Analysis

2.4.1 Pre-Processing

All data were first pre-processed by applying a zero-phase IIR bandpass filter from 0.5-40Hz. Each channel was then re-referenced to Fz. All data were segmented by trial for each chirp stimulus condition. Inter-trial data (i.e. rest periods) were discarded.

2.4.2 SSVEP Characterization

The data elicited from the chirp signals were analyzed using the CCA method. SSVEP reference signals, Y_f, were created that were centered at 0.5 Hz increments across the chirp signal. Reference signals were created for each frequency using 1, 2 and 3 harmonics of the respective center frequencies. This resulted in three sets of reference signals for evaluation of the impact of the harmonics.

The chirp data from the 5.5-20.5 Hz waveform was concatenated with the chip data from the 19.5-34.5 Hz waveform to produce an SSVEP response signal from 5.5-34.5 Hz. The decreasing chirp signals (20.5-5.5 Hz and 34.5-19.5 Hz) were concatenated to produce a 34.5-5.5 Hz response and then time-reversed to match the previous 5.5-34.5 Hz.

Fixed frequencies were approximated from the chirp signal by using a sliding window with a length of two seconds and a one-second overlap. This corresponds to frequencies starting from 6 Hz to 34Hz in increments of 0.5 Hz (55 total distinct frequencies), which covers the functional range of the SSVEP spectrum with sufficient resolution.

CCA was performed on each window of the EEG response and on each frequency from the SSVEP reference signals. Each target frequency (i.e. the current time window corresponding to the frequency from the chirp stimuli) was canonically correlated with each reference signal frequency. This results in a quantitative measure of target discrimination from background EEG activity for each of the selected frequencies.

2.4.3 SSVEP Classification

For BCI applications, it is common to select a somewhat arbitrary set of stimulation frequencies based on hardware restrictions or EEG spectral characteristics (e.g., alpha-band overlap). To assess the discriminative capacity of CCA for the broad range of stimulus frequencies provided by the chirp signals, an offline BCI classification scheme was set-up using 6-classes. As a reference, 13 Hz, 14 Hz, 15 Hz, 16 Hz, 17 Hz and 18 Hz were ealuated based on Gao et al., 2009 [1], which is the landmark SSVEP CCA study. This reference frequency set represents typical, generic stimulus frequencies that are not optimized for each subject. Using the SSVEP response data due to the chirp stimuli, the time windows centered at these six frequencies were extracted to set up a simulated BCI classifier.

To compare with the classification performance of this frequency set, 1600 unique frequency sets were extracted and used in the off-line classification. Each subject's SSVEP stimulus frequencies were optimized by finding the combination that maximized the individual classification performance. The value of 1600 frequency sets was selected to provide comprehensive combinations of six stimulus frequencies over the range of 6-34 Hz (55 distinct frequency choices). The theoretical number of frequency permutations for a set of 6 out of 55 is approximately 28 million combinations. Since it is impractical and unnecessary to test all of these frequency combinations in a exhaustive optimization, selected uniformly-spaced and randomly-determined frequency sets were evaluated. The 1600 different sets were generated as follows: 100 frequency sets of 6 frequencies starting from 6 Hz to 34 Hz with spacings of 0.5 Hz, 1 Hz, 2 Hz, and 2.5 Hz (i.e., Set 1: 6, 6.5, 7, 7.5, 8, 8.5; Set 2: 6.5, 7 ,7.5, 8, 8.5, 9, 9.5; etc.). The uniform sets cover the entire range of the SSVEP spectrum of frequencies. The next 1500 frequency sets were generated by selecting 500 random frequency permutations each in the low (6-15.5 Hz), medium (16-25 Hz) and high (25.5-34.5 Hz) frequency ranges.

To optimize the frequency set for each subject, the first 70% data were used for training and the remaining 30% for testing. The accuracies for the training data were evaluated and the frequency set that performed the best for each subject was recorded. In the event of ties (i.e. cases where multiple frequency sets provided the equivalent best performance) the frequency set for each tie was recorded. The testing data was then used to evaluate the performance of the frequency set optimization. For ties, each set was individually evaluated and the results were averaged. To assess the prevalence of optimal frequencies across subjects, a histogram was created showing the proportion of times a particular frequency was included in the optimal frequency set. The contributions from each subject to the histogram were normalized to adjust for subjects with ties.

3. RESULTS

3.1 SSVEP Spectrum Characterization

The SSVEP Spectrum Characterization is shown in Figure 3. This figure shows a time-frequency plot of the CCA correlation values of the reference signals and the EEG across the 60 s of concatenated chirp signal. The CCA was repeated using three different combinations of progressive harmonics: the first (fundamental) harmonic only, the first two harmonics, and the first three harmonics. Each time-frequency plot represents the average across all subjects. Since the EEG signal is in response to a linearly increasing chirp signal, the prominent diagonal lines in Figure 3 represent the expected strong correlation of the EEG signal with the target frequency.

The diagonal line representing the fundamental frequency is present in all three graphs. Likewise, the second and third harmonics are also pronounced in each plot, though not as nearly as prominent as the fundamental. What appear to be sub-harmonics in the lower two plots are actually the result of performing CCA with harmonics. For instance if the EEG is oscillating at 20 Hz due to a 20 Hz stimulus, there will be a correlation with a 10 Hz reference signal when the harmonics are included in the CCA. This is an important consideration when evaluating harmonic frequencies.

Figure 4 shows the CCA correlation values of the SSVEP response as a function of stimulation frequency averaged across all subjects. A second-order polynomial is fit to the correlation data. It is observed that the correlation values generally increase as more harmonics are added.

3.2 SSVEP Classification

The SSVEP classification results are shown in Table 1. The first column shows the performance using the reference frequency set from [1]. This frequency set resulted in an average classification accuracy of 72.2% $\pm$ 20.7% across subjects.

For the 1600 uniform/random frequency sets, the frequency set that maximized the average performance across all subjects was determined to be: 6, 7, 7.5, 8.5, 9.5, and 11 Hz. The performance of this group-wise set is given in the second column. This set produced an average classification accuracy of 77.2% $\pm$ 17.6% across subjects. Although the average accuracy of the group-wise set is greater than the reference set, a two-tailed t-test indicates that the increase is not a statistically significant ($p = 0.38$).

Lastly, individually optimized frequency sets were determined by selecting the set with the highest classification accuracy for each individual subject. These individually-optimized frequencies represent the best classification performance that a subject can obtain given the range of available frequency values. The individually-optimized frequency sets produced an average classification accuracy of 83.7% $\pm$ 15.0% across subjects. The accuracies produced using individually optimized frequencies resulted in significantly higher accuracies compared to the reference set ($p = 0.03$). Compared to the group-wise set, the individual accuracies were better on average, although the increase was not statistically significant ($p = 0.19$).

The individual frequency sets varied greatly across each of the 22 subjects, thus indicating that each subject has a rather unique frequency response profile that should be individually optimized. To illustrate the commonly selected frequencies, Figure 5 shows a histogram of the relative occurrence of frequencies in the optimized frequency sets. This figure shows two distinct frequency ranges that were most commonly selected as frequencies for the optimized sets. The majority of the optimized frequencies tend to be the lower frequency range from 6 to 15Hz, with a smaller grouping in the higher frequency range from 22 to 34 Hz and very few frequencies selected from the mid range (16-21 Hz).

4. DISCUSSION

While it is generally known that subject-specific stimulation frequencies should produce superior performance, there has been little work to quantify and evaluate optimal frequencies. This study represents a fairly comprehensive analysis and characterization of the full SSVEP spectrum and its effect on SSVEP BCI performance.

The results shown in Figures 3 and 5 indicate that lower stimulus frequencies (i.e., 6-15 Hz) generally produce the best SSVEP discrimination. This is likely the result of the higher signal-to-noise ratio (SNR) of the lower frequencies due to the 1/frequency power characteristic of the EEG, which impacts the correlations as shown in Figure 4. Additionally, the histogram plot in Figure 5 shows that frequen-

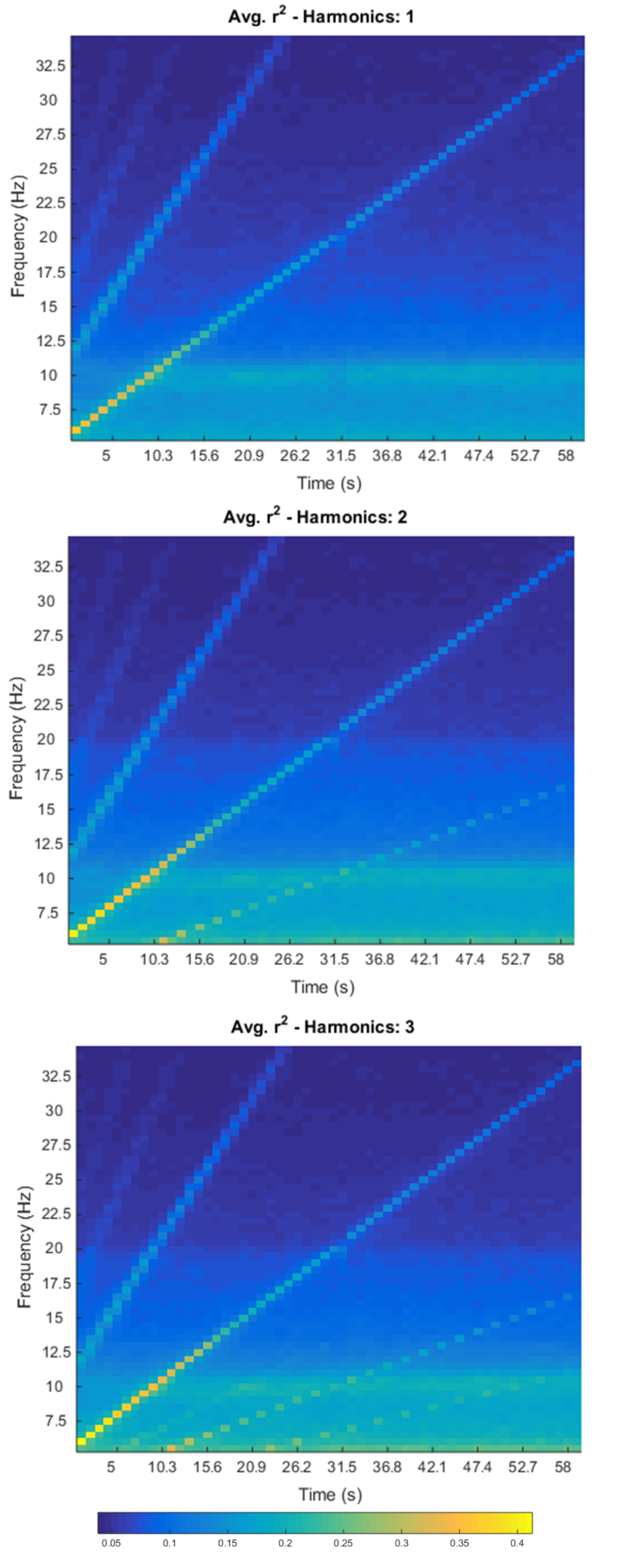

Figure 3: CCA squared correlation values using for first harmonic (top), first two harmonics (middle), and first three harmonics (bottom), averaged across all subjects.

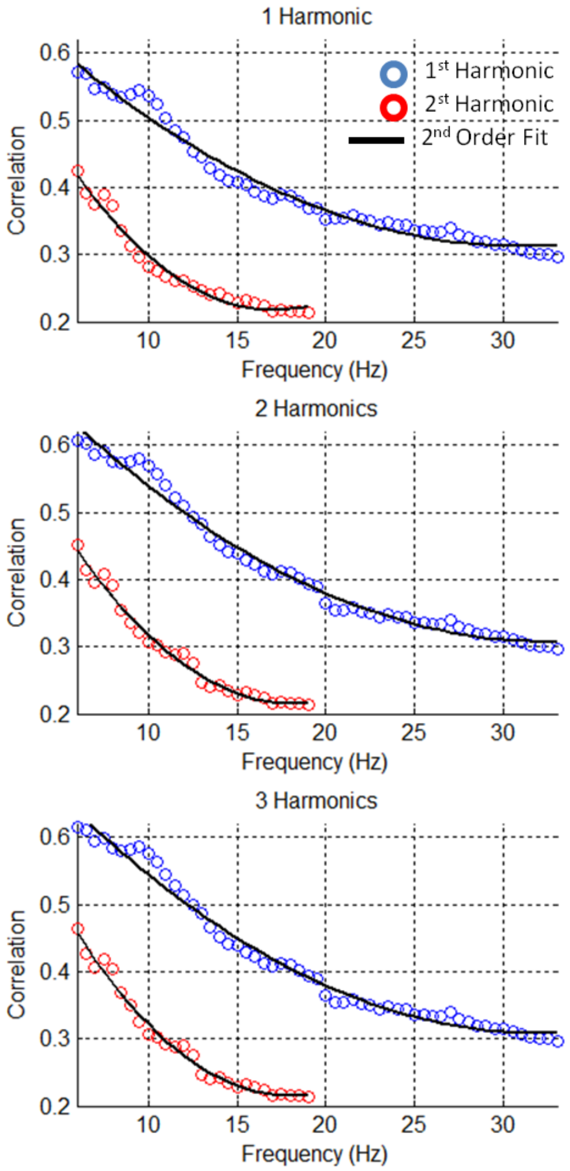

Figure 4: CCA correlation values of the SSVEP response as a function of stimulation frequency averaged across all subjects. Top: first harmonic, middle: first two harmonics, bottom: first three harmonics

cies in the high-range (22-34 Hz) more often contributed to optimal BCI performance compared to the mid-range (16-21 Hz). Since this higher range has a lower SNR compared to the key lower-range frequencies, the higher frequencies may serve as an "outlier condition" that serves to boost discrimination; although this must be validated through further analysis.

The classification results indicate that frequency selection can have substantial impact on overall BCI performance, increasing from 72.2% to 83.7%$(p = 0.03)$. To date, there is no widely accepted stimulus frequency set or standardized methodology for obtaining subject-specific stimulus frequen-

Table 1: Classification results for different frequency sets

Subject	Reference	Group-wise	Individual
1	95.8	100	98.3
2	83.3	95.8	95.8
3	54.2	66.7	64.6
4	70.8	95.8	94.4
5	66.6	83.3	80.8
6	45.8	75	78.12
7	37.5	87.5	87.5
8	91.6	54.2	94.4
9	70.8	87.5	83.3
10	37.5	45.8	61.1
11	100	87.5	95.8
12	87.5	70.8	75
13	75.0	87.5	95.8
14	73.5	37.5	41.6
15	41.7	45.8	58.3
16	87.5	83.3	87.5
17	83.3	91.7	88.6
18	91.7	75.0	95.8
19	83.3	91.7	88.4
20	75.0	70.8	87.5
21	79.2	83.3	94.4
22	91.7	83.3	95.0
Avg	**72.2**	**77.3**	**83.7**

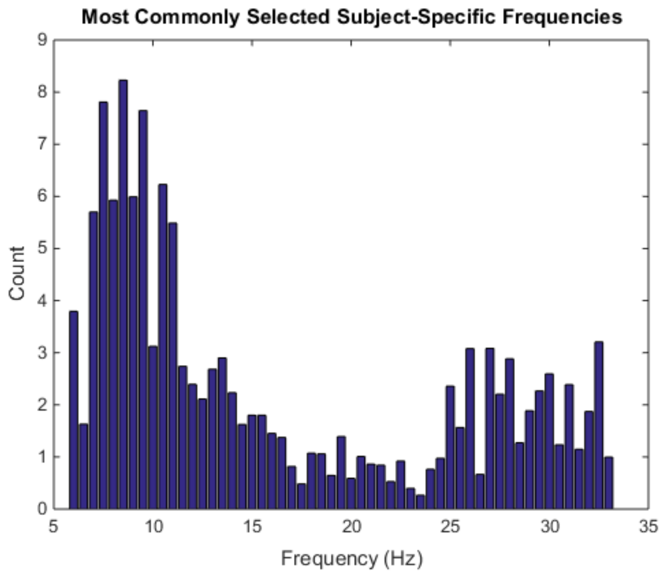

Figure 5: Histogram plot showing the relative occurrence of each frequency in the optimal frequency sets for all subjects.

cies. As a result, most studies use sub-optimal frequencies, although this can still lead to acceptable performance - particularly in individuals with strong SSVEP responses.

If a subject-specific frequency optimization is not feasible for a particular scenario, the results show that frequencies in the lower frequency range (particularly from 6-11 Hz) provide the best performance. These findings are consistent with the results from [6], indicating that the majority of subjects have an SSVEP response innately present in the EEG, while a small percentage of subjects will naturally have a weaker or even no detectable SSVEP response.

The method utilized in the study can be used as an efficient way to characterize the response of the SSVEP spectrum for an individual. The chirp stimulus displayed at a rate of 0.5 Hz/s can be achieved much more rapidly than evaluating individual frequencies independently. Additionally, only several passes of the chirp signal would be required, leading to calibration times on the order of minutes.

Because of the continuous nature of the chirp signals and the limitation of monitor refresh rates, this study was done using LED stimulation and not the more convenient LCD stimulation. An identical follow-up study using an LCD monitor is planned, although it is not expected that the results will significantly differ from the present study. Additionally, the long-term stability of the SSVEP spectrum has yet to be assessed and longitudinal online experiments need to be conducted. Nevertheless, the present offline results serve as a strong indicator of the potential impact of optimized SSVEP frequencies and efficient characterization of the SSVEP spectrum.

5. ACKNOWLEDGMENTS

This work was funded in part by the National Science Foundation (1064912).

References

[1] G. Bin, X. Gao, Y. Wang, B. Hong, and S. Gao. An online multi-channel ssvep-based brain-computer interface using a canonical correlation analysis method. 6, 2009.

[2] Z. Lin and Gao. Frequency recognition based on canonical correlation analysis for ssvep-based bcis. *IEEE trans. Biomed. Eng.*, 53:2610–4, 2006.

[3] M. Middendorf, G. McMillan, G. Calhoun, and K. Jones. Brain computer interfaces based on the steady-state visual-evoked response. *IEEE Trans. Rehab. Eng*, 8:211–4, 2000.

[4] G. Schalk. Bci2000, a general-purpose brain-computer interface (bci) system. *IEEE Trans. Biomed Eng*, 51:1034–43, 2004.

[5] F. Sharbrough, C. Chatrain, R. Lesser, H. Luders, M. Nuwer, and T. Picton. Amearican electroencephalographic society guidelines for standard electrode position nomenclature. *J. Clin Neurophysiol*, 8:200–202, 1991.

[6] I. Volosyak. Bci demographics: How many many (and what kinds of) people can use a high-frequency ssvep bci? *IEEE Trans. Neural Systems*, 19, 2000.

[7] J. R. Wolpaw, N. Birbaumer, D. J. Mcfarland, G. Pfurtscheller, and T. M. Vaughan. Brain-computer interfaces for communication and control. *Clin. Neurophysiol*, 113:767–91, 2002.