Implementation of signal detection for steady-state visual evoked potentials from the open source openBCI interface

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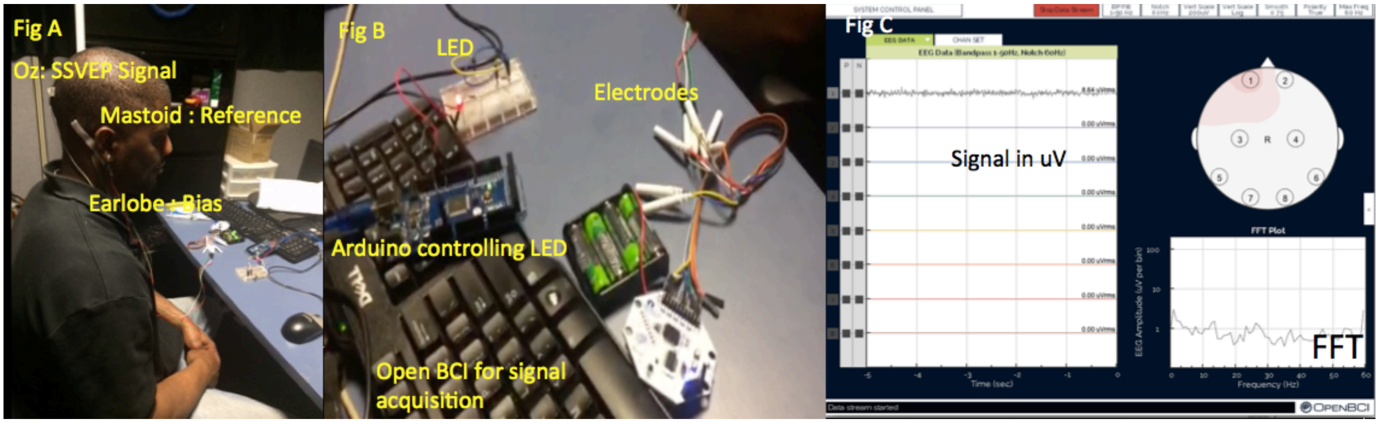

Figure 1. Experimental setup. Electrodes for recording SSVEP signal are placed over the occipital lobe (A). The electrodes are connected to the openBCI board, which sends data to USB dongle connected to computer using RFDuino; LED blinking at particular frequency acts as stimulus (B). OpenBCI GUI for visualizing. (C).

ABSTRACT
Brain computer interfaces (BCIs) connect humans to computers via the channel of electroencephalogram signals emitted from the brain. BCIs hold strong potential for improving lives of disabled individuals. However, a major limitation of them is the difficulty of extracting signals and classifying them. In this study, we extracted and classified signals from the steady state visual evoked potentials using the newly marketed openBCI interface, and developed a framework for approaching the problem of signal classification from electrode recordings.

Author Keywords
Brain-computer interface; interactive computing; wearable computing; assistive technologies.

ACM Classification Keywords
H5.2 [Information interfaces and presentation]: User Interfaces. – Interaction styles, Evaluation/methodology.

INTRODUCTION
Electroencephalograms (EEG) have been traditionally used as diagnostic aid for things such as sleep disorders or detecting seizures. However, many researchers have explored the usage of EEG signals to aid in brain computer interfaces (BCIs)[1-3]. The future holds promise for using BCIs to aid in communication or operate assistive devices for people affected by neuromuscular disorders such as amyotrophic lateral sclerosis, cerebral palsy, stroke and spinal cord injury. Another interesting possibility is to use BCI in combination with Internet of Things or as multi-modal input technique to augment daily interactions with devices like mobile, Google Glass.

The characteristics of a satisfactory BCI system are highly accurate command generation, a high speed of control, and low incidence of unintentional system suspension, i.e. continuity of control. To achieve BCI, which can be used seamlessly, it is imperative to show that signals can be acquired, processed, and classified effectively and consistently across a wide range of settings and test subjects. Some of the main factors that can determine the performance of a BCI system includes the type of the brain signal used to transfer the intentions, feature extraction methods used, classification algorithms to get the control commands etc. Our final objective is to identify a method that could consistently detect spikes in the SSVEP signal that correspond to real cortical activation events from the visual cortex

BACKGROUND AND RELATED WORK

Brain computer interfaces
Brain computer interfaces seek to pick up brain signals that represent human intents, and to translate those into control commands for other devices. The scope of our work involves BCI that use EEG signals as the main method of communication. Many

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works of the past have sought to develop augmented devices for humans. There are many motivations for doing this, including aiding disable people with neuromuscular impairments, to augmenting and accelerating people's lives.

Steady-state visual evoked potentials (SSVEP)

Our work focuses on acquiring steady-state visual evoked potential (SSVEP) signals and detecting portions of the signal that correspond to increased cortical activation. SSVEP stimuli do not flash successively, but flicker continuously with different frequencies in the range of about 6–30 Hz. Paying attentions to one of the flickering stimuli elicits an SSVEP in the visual cortex that has the same frequency as the target flicker. That is, if the targeted stimulus flickers at 13 Hz, the resulting SSVEP will also flicker at 13 Hz.

OUR APPROACH

In this section we detail our BCI protocol for acquiring and processing SSVEP signals.

Experimental Setup

The system we have established includes several elements. Figure 1 shows a description of the setup. According to 10/20 electrode-positioning Ag based electrode is attached at Oz of subjects' head, in the area over the occipital lobe using electrode gel. Earlobe is taken as bias and mastoid as reference. These three electrodes are attached to OpenBCI, open source bio-sensing microcontroller recording at 250 Hz sampling rate. The RFDuino on OpenBCI board communicates with RFDuino integrated USB Dongle attached to computer. LED controlled by Arduino is used as SSVEP stimulus.

Experiment recordings

We performed openBCI SSVEP recordings on two subjects over several different testing sessions. We collected recordings in 5 different sessions for one of the test subjects, and in 1 session for the other test subject.

For each particular recording, the patient was placed in a dark room in front of a red LED light source. The LED light source flickered at a set rate. While the LED flickered, the test subject was instructed to look at and focus on the LED. The electrode potential was recorded for a period of 40 seconds. The stimulus frequencies that we used were: 7Hz, 13Hz, 16Hz, and 8Hz.

Visualization of signals

After the signal was recorded, several steps were taken to visualize the signals for exploration purposes.

The raw signal was first processed to remove DC components by passing through high pass Butterworth filter in zeroeth dimension and then notch filter to remove 60-120 Hz signal. Finally, two consecutive Fast Fourier Transform was applied to get power spectral density. The spectrogram was visualized by plotting the amplitude of the recorded signals at all possible frequencies across all possible time points of the recording. Figure 2 shows the power spectral density for a recording done in a dark room with a 13 Hz stimulus.

By taking the average of all signal amplitudes during the entire time of recording, we may obtain the root mean square of signal amplitude. Figure 2 shows a plot of the amplitude of each frequency across all frequencies picked up. Note that the first peak is noise, coming from frequencies for alpha wave. This process was performed in Python with the aid of the Matplotlib library.

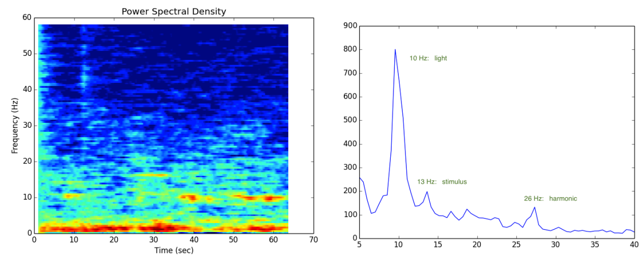

Figure 2. A) An example of the power spectral density for 13 Hz signal. The horizontal axis represents the time period in which the signal was taken, and the vertical axis represents the frequency of observation. Red represent stronger signal whereas blue represent weaker signal. B) The mean of the power for the SSVEP signal, which was obtained by calculating the average of the signal amplitude across the entire period of recording. The horizontal axis represents the frequency in Hz while the vertical axis represents the mean amplitude across the time period of analysis.

For further analysis Root Mean Square of PSD amplitude for 13 Hz was plotted as shown in Fig 3. There is clear peak at 13.75Hz and another peak at its harmonic i.e. 26Hz.

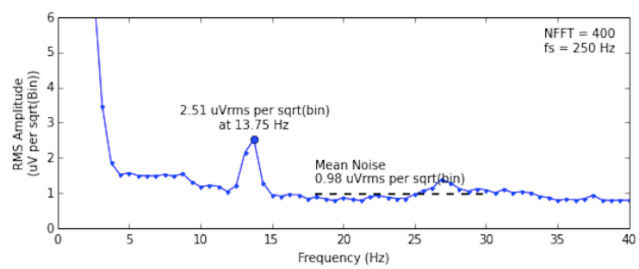

Fig 3. Root Mean Square of PSD vs. Frequency

Peak Detection

Method 1: Since we wish to determine whether or not a peak exists at the stimulus frequency, we implemented a peak detection algorithm on the power spectral density. For a set period of time, a peak detection algorithm was run on the average power spectral density, with the constraint that the peaks be located at least 2 Hz away from each other. We know that the peaks at frequencies less than 10Hz are considered noise and therefore filter them out. Next, we classify all remaining peaks as follows. A peak is classified as a valid positive SSVEP signal if both conditions are met:

1. The frequency at which the peak is located on the spectrum lies within 1Hz of a harmonic value of the stimulus frequency
2. The amplitude of the peak is greater than the mean of amplitude of the signal from 10Hz to 60Hz.

For all recordings we took, we were able to identify at least one harmonic peak. Figure 4 shows an example where we the method detected peaks at 13Hz, the stimulus frequency, as well as 26 Hz, the harmonic frequency.

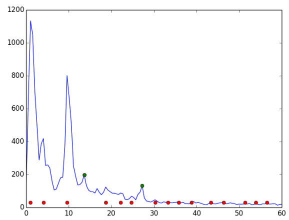

Figure 3. The mean of the power for the SSVEP signal, which was obtained by calculating the average of the signal amplitude across the entire period of recording. The horizontal axis represents the frequency in Hz while the vertical axis represents the mean amplitude across the time period of analysis

Method 2: We used a machine learning based approach to classify peaks in the RMS power spectral density vs. frequency plot (Fig 3). Since we know that 13 Hz has harmonics at 26Hz and there is always noise due to alpha waves before 10Hz, we regarded only 10Hz-30Hz. We regarded the amplitudes of the signal at each frequency from *f= 1,2, f_max* as features, where *f_max* represents the highest frequency at which we have recorded in Hz. We used a sliding window of width 2 s, 1 s and 0.5s to compute the feature values (representing amplitudes) at all possible windows in the recording period for various sessions. We performed 10-fold cross validation with the random forest (RF). The performance metrics are shown in Table 1.

Window	Training Size	Test Size	Accuracy	Recall	Precision
2 s	69	23	95.6-100	100	90.9
1 s	138	47	87.2	83.3-100	90.9
0.5 s	281	97	83	94	70.2

Table 1. Performance metrics for the classification algorithms that were used for classification of peaks in the SSVEP signal.

For 2 second window, classifier built from subject one was used to test the accuracy for second test subject for 13Hz frequency. For, 19 test sample precision was found to be 63%.

DISCUSSION

There are various challenges in SSVEP signal detection in brain computer interfaces. These include interference from noise (background 60Hz DC, alpha waves, harmonics), selection of correct stimulus frequency, actual ability of detection of signals themselves, as well as lag time. It is a challenge to design of a signal processing method that is both accurate and also computationally efficient. We observed that a simple thresholding based signal detection approach may be quick but misses some peaks when detecting target stimulus frequencies. On the other hand, we observed that a machine learning based spike detection approach may result in higher accuracy, precision and recall, but pose the challenge of training the classifier for each user.

FUTURE WORK

In the future we wish to repeat the same process but with the ear EEG electrode and Google Glass with an effort to make the system real-time. We believe the ear EEG recording would be challenging to implement but in the long term would be more amenable to use in a commercial device. We would record SSVEP from the ear EEG and perform signal processing on the signals recorded over time, in order to find an efficient strategy for detecting spikes in the signal that indicate cortical activation. We also plan to implement our code into a mobile device that can be used to register the input signal from the openBCI.

CONCLUSION

We have deployed and tested a system for recording SSVEP signals from the occipital lobe and identifying peaks of cortical activation that represent human intent via signal processing and machine learning techniques. To our knowledge, we were the first to accomplish this with the openBCI device. In the future we wish to further test the durability of our system on more test subjects, under different lighting conditions, and with different electrodes placements such as the ear EEG. Finally, our study should motivate future work on efficient detection of SSVEP signals using the openBCI interface.

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