Simulating a Rapid, Minimalist BCI Keypad from Steady State Visual Evoked Potentials

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***Abstract*—As noninvasive neural recording methods such as EEG become more and more accessible, the potential for BCI systems to assist with daily tasks becomes more feasible. Here, we present simulations of a BCI keypad based on SSVEP signals recorded with a small number of visual cortex EEG electrodes. We evaluate two possible classification algorithms for a real-time system, one using power spectral density and the other using canonical correlation analysis, and demonstrate the BCI system's performance in both cases. Our results indicate that simple algorithms can be used to enable BCI systems to operate at high information transfer rates using SSVEP signals, even when very few recording electrodes are used, making these devices feasible even without a large EEG cap.**

I. Introduction

Brain-computer interface (BCI) systems offer a new way for people to interact with the world by establishing a communication link between the brain and digital interfaces [1]. With digital devices dominating human communication channels, an application where a BCI system can provide significant aid to differently-abled users is an assistive keyboard that actuates on brain signals. Typing is a nearly inescapable part of using a computer and communicating in the modern world, so a BCI that can allow people without motor abilities to operate a keyboard would be a life-changing device for someone previously unable to type.

Although systems have been developed to assist users in using computers through EEG-based BCIs, many of these are still very slow, especially relative to a healthy user [2]. There is still a great need to develop BCI systems that allow users to interact with a digital screen, such as a menu of options or a keyboard, in a way that is faster and more seamless. Although methods for recording neural signals are becoming more ubiquitous and cheaper, the ideal system should also require as few neural recording channels as possible to ensure the system is low-cost and simple to set up and deploy. BCIs based on steady state visual evoked potentials (SSVEPs) combine the advantages of obtaining higher information transfer rates with minimal computation and training times [3], [4]. SSVEPs are recorded from the visual cortex in response to a visual stimulus with a specific frequency. As long as the stimulus frequency is within a physiologically reasonable range, they are often frequency- and phase-locked to the stimulus, allowing the BCI to decode and select the stimulus the user is attending to [5]. In this paper, we demonstrate a BCI system for typing on a simple keypad based on SSVEPs that is minimalist in its hardware requirements but rapid in its information transfer.

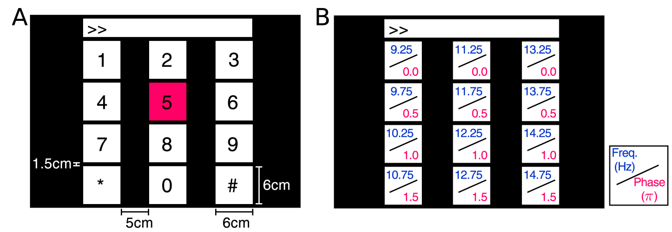

Fig. 1. Figure taken from from [6]. A) Keypad display for the SSVEP-based BCI. B) Flashing frequency and phase of each button.

II. Materials and Methods

A. SSVEP BCI Dataset

We utilize the data provided by [6], in which 10 subjects recorded 8-channel EEG data for trials with a 12-item keypad, where each of the 12 keys flashed at a different frequency and phase between 9.25 and 14.75 Hz, as illustrated in figure 1. The electrode placement can be seen in figure 2. When the subject focused on a single key, the SSVEP response in their visual cortex should match that key's frequency. The magnitude of SSVEP response is not uniform across frequencies, but prior work has indicated that it is maximized between about 12 - 18 Hz [7], though it is still high around 10 Hz as well. So, the frequencies used in this keypad are right around the optimal range. Additionally, the separation between frequencies of different buttons for best performance should be at least 0.2 Hz [8], a criteria which this dataset meets.

To put together the dataset, the authors of [6] recorded 4-second trials where the subjects focused on a single one of the keys. All 10 subjects recorded 15 trials for each key.

A typing BCI using SSVEP data like this would operate as follows. The keypad of buttons would flash for a fixed time period, such as 4 seconds, while the user focuses their attention on the single button they want to press. Once the time period of recording is complete, that window of data is given to an algorithm to decode the button by identifying the frequency of the SSVEP and matching it to one of the known button frequencies.

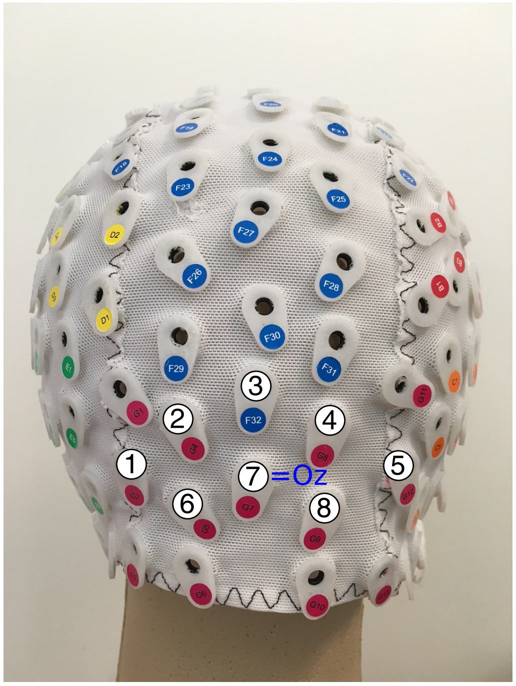

Fig. 2. Image taken by the authors of [6]. Electrode placement for the 8 EEG channels in the recordings.

B. SSVEP Classification with Power Spectral Density

Since the SSVEP is a frequency-matched response to the visual input, the most intuitive method for identifying the button from the SSVEP is to find a peak in the power spectral density (PSD) of the EEG recording and match it to the closest button frequency. For example, we could take a recording of a certain length, compute the PSD of each channel, then compute the average over all channels and find the frequency at the peak power within the range of possible button frequencies. Then, decode the button by comparing the frequency at the detected peak to the frequency of the buttons and choosing the nearest. The average PSD is often needed due to noise in some of the channels and the low sampling rate which limits the resolution of the PSD estimation, especially for shorter trial durations. This pipeline is illustrated in figure 3 using one of the cleaner samples from the dataset. This PSD algorithm was implemented in Python using Welch PSD estimation [9] from `scipy` [10].

C. SSVEP Classification with Canonical Correlation Analysis

Canonical correlation analysis (CCA) can be used to measure correlations between multivariate datasets [11]. Specifically, for matrices $\mathbf{X}$ and $\mathbf{Y}$, the algorithm finds a linear projection of each dataset, with weights $\mathbf{a}$ and $\mathbf{b}$, such that they maximize $corr\big(\mathbf{Xa}, \mathbf{Yb}\big)$. The weights are known as canonical weights and the resulting correlation is the canonical correlation. In our case, one dataset is one trial of a multi-channel EEG recording, represented by a matrix $\mathbf{X_{eeg}} \in N_c \times N_s$, where N_c is the number of channels, and N_s is the number of time samples per trial. Since SSVEPs naturally

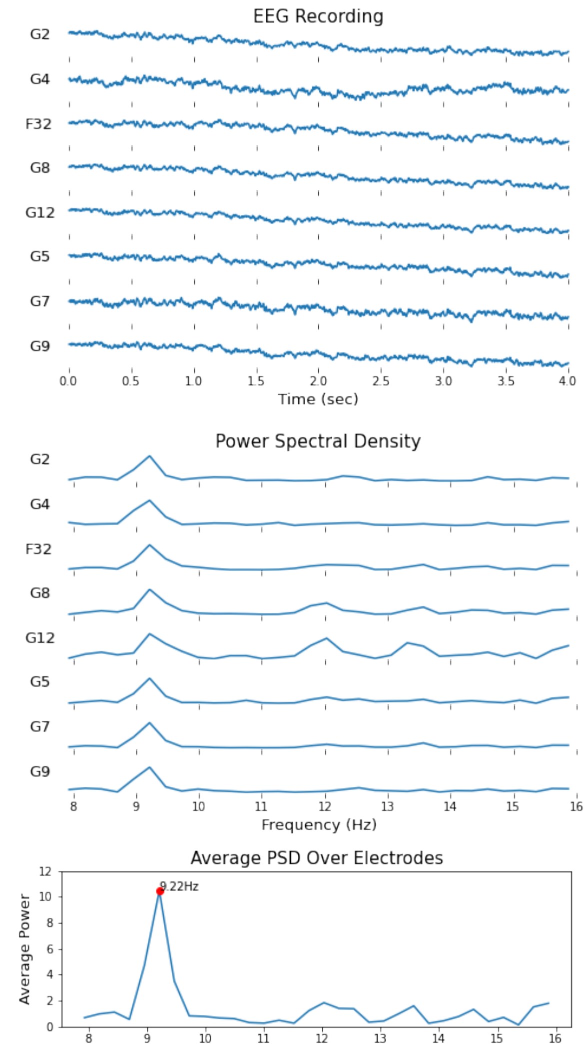

Fig. 3. Power spectral density analysis on a 4-second trial from one subject. Top) 8-channel raw EEG recordings. Middle) PSD of each electrode. Bottom) Average PSD over the electrodes and the location of the peak, which when compared to the possible button frequencies, is closest to 9.25 Hz, which is the correct decoding for this sample.

contain frequency content from the visual stimulus that evoked them, they should contain more of the frequency from the button the subject was attending than the other frequencies. To measure which frequency a given SSVEP recording is most similar to, CCA is used to correlate the EEG data with a set of harmonics of each frequency. There are 12 buttons, and thus 12 frequencies, which might have elicited the SSVEP. For each frequency, f, construct a matrix of 6 features, $\mathbf{Y_f}$, as in equation 1.

$$\mathbf{Y_f} = \begin{pmatrix} sin(2\pi ft) \\ cos(2\pi ft) \\ sin(4\pi ft) \\ cos(4\pi ft) \\ sin(6\pi ft) \\ cos(6\pi ft) \end{pmatrix} \tag{1}$$

Then, for each trial, select the frequency f which maximizes the canonical correlation between $\mathbf{X_{eeg}}$ and $\mathbf{Y_f}$. This method can be though of as taking a weighted average of the EEG channels to see how well it can be explained by a weighted sum of several harmonics and phase shifts of a single fundamental frequency. The linear combinations allow the method to search for multiple harmonics in the EEG recording jointly. Canonical correlations were computed in Python using the `mvlearn` package [12].

D. Reduced Channel Simulation

In order to evaluate a simpler and more accessible BCI, we extracted three channels from every trial and used those for classification with the CCA method. A system requiring fewer channels would be available at a lower cost and with fewer components set up on the user, opening the market to more everyday, at-home users. The three electrodes that we selected were number 2, 4, and 7, as labeled in figure 2, which are centrally located while providing information from both hemispheres. Using three electrodes in a close triangle might enable them to be placed without a full EEG headset by some other holding cap, which would make the full system easier to wear.

E. Evaluation Metrics

To evaluate each classification model, we use two key metrics. First, for each subject, we compute the classification accuracy of the model across all recordings. While accuracy is an important metric for the strength of a model, it does not take into account the time a model takes to decode a trial, which is an important factor in the usability of a real-time BCI system. So, we also compute the information transfer rate (ITR) for each subject, according to equation 2,

$$\begin{aligned} ITR = \tfrac{1}{t_d}\Big(&p \times \log_2(p) \\ &+ (1-p) \times \log_2\left(\frac{1-p}{N-1}\right) + \log_2(N)\Big) \end{aligned} \tag{2}$$

where t_d is the average decision time for the model in seconds (duration of recording plus computation time), p is the probability of a correct decision, and N is the number of decision classes, or 12 in this case.

In order to simulate performance for multiple potential recording durations, each trial can be truncated to a specific time by using only the first portion of each trial, up to the desired duration, for classification.

F. Real-Time BCI Simulation

To simulate a BCI system that would perform real-time decoding for a keypad, we used NeuroPype (Intheon Labs, San Diego) to band-pass filter (6 Hz - 80 Hz) and stream the data over LabStreamingLayer to a Python script for online decoding. `PsychoPy` [13] was used to create a graphical user interface (GUI) with flashing buttons and real-time decoding as a user would see them. A video demo with a simulated system combining the GUI, NeuroPype, and online decoding can be found at this link. Our simulations with online decoding from a GUI demonstrate that the device could operate with only a simple EEG headset and a mobile screen, such as a tablet. The interface used in our GUI is shown in figure 4.

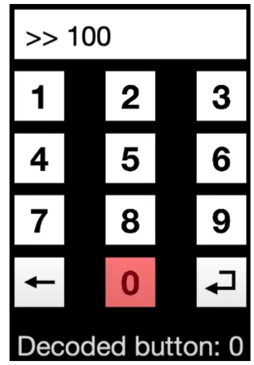

Fig. 4. Snapshot of the GUI while the simulated user is trying to type 10027. The recording data and subsequent classification just decoded a second 0.

III. Results and Discussion

Evaluation metrics for the PSD model, the CCA model, and the CCA model with three electrodes are shown in figure 5. The CCA model was significantly more accurate than the PSD method, but the computation times were significantly worse (around 25 to 40 times slower). This resulted in the ITR of the two models being much closer than the accuracies. However, the CCA still easily outperformed the PSD model in ITR, and even the CCA model using just three electrodes achieved higher ITR than the PSD method, with a maximum of about 0.4 bits/second for the average subject, a rate which would still be useful in a BCI keypad for someone unable to type the traditional way. Thus, even using only three electrodes, the model can achieve an information transfer rate where the system would be worth deploying to people who cannot interact with keyboards otherwise. A device that can operate with a small number of electrodes can be increasingly mobile and require minimal head gear, improving ease-of-use by reducing the amount of time required to put the device in place and get started.

Although recent studies have proven the ability of supervised machine learning methods to achieve better results over a simple CCA decoding scheme [6], our goal was to maximize the capacity of an unsupervised algorithm for minimalist recording settings. Our focus was on building a BCI keypad for everyday people. So, the potential to quickly put on a small number of EEG electrodes and immediately start using the system without needing to record a long duration of personalized training data outweighed the accuracy or ITR gains that may be realized with a more complex, supervised system.

One area where the CCA method could be improved is in the fact that it does not utilize the phase information given by the stimuli. Each row of the keypad operates at a different phase, and if another algorithm could jointly decoding phase information, it might assist in overall classification.

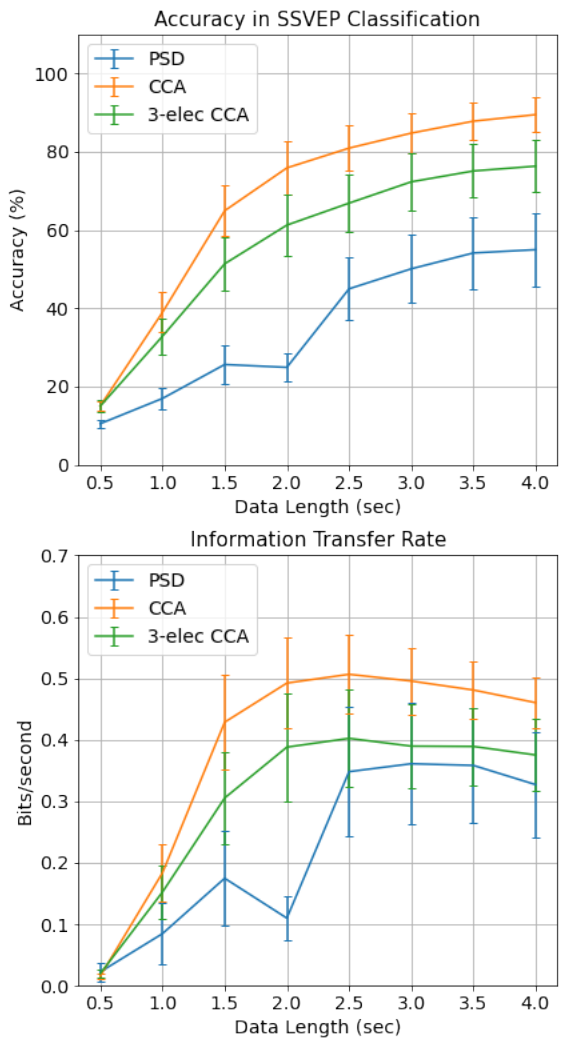

Fig. 5. Accuracy and ITR of each model over a range of recording durations for the trials used in classification. Plots depict the average over all 10 subjects with error bars for the standard error of the mean.

Although our simulations relied on data for a 12-item keypad, this type of system could be easily translated to a full keyboard (of any language). The current system uses only part of the optimal frequency range for SSVEP response, and expanding the number of items to a traditional keyboard would not necessarily reduce classification performance if the range of frequencies is kept within this range. Additionally, a simple language model could be appended to the decoding phase to disambiguate between potential character decodings by taking the recent history into account. However, this would need to be evaluated with the information transfer rate to ensure the increased computation time is worth the improved classification accuracy.

IV. Conclusion

In this paper, we have presented simulated results of a real-time BCI keypad that would be simple to design and easy to deploy for a wide range of users. With a minimal number of electrodes and no requirement for user-specific training data, a BCI system like the one described could be easily used by anyone who wants to be able to type on a keyboard. Overall, the system simulated in this paper holds a lot of potential to improve the lives of a vast array of people, from those with complete loss of motor function to people with tremors who can't type as quickly as they once could. As at-home BCIs become more and more accessible to the average person, systems like the one described here will be critical in helping people take advantage of newly available hardware to improve their quality of life.

Acknowledgment

The authors would like to Dr. Paul Sajda and Kristen Lawlor for helpful guidance and feedback on the project.

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