Project 2

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Introduction:

For people with limited mobility, navigating the world can be extremely difficult and often they are forced to rely on caretakers to perform even the most basic of tasks. Brain-computer interfaces can give these people some agency and independence by recording brain activity like steady-state visual evoked potentials (SSVEPs) and translating those neural signals into meaningful actions. This project aimed to take a data set and calculate optimal predictor arrays for the data based on the nature of the task at hand. This kind of signal processing is necessary to move from recording brain activity to actions quickly, accurately, and safely.

Steady-State Visually Evoked Potentials (SSVEPs) are a type of brain-computer interface (BCI) that relies on the brain's response to visual stimuli flickering at specific frequencies. When a person focuses their attention on a visual stimulus oscillating at a particular frequency, their brain generates electrical activity in sync with that frequency. This electrical activity can be detected and decoded by an external device such as a computer using Electroencephalography (EEG). SSVEP as a BCI is beneficial due to its non-invasiveness and high information transfer rates, and as a result, it can assist individuals with disabilities, through neurofeedback training (Wan et. al, 2016), virtual reality control (Zhu et. al, 2023) and many other areas of neuroscience research.

For the database used in this project, two individuals observed checkerboard patterns that alternated (changing black and white positions) at consistent rates of either 12.0 Hz or 15.0 Hz. Each participant underwent 10 sessions, each lasting 20.0 seconds. A total of 32 channels of wet EEG were utilized for recording purposes.

In our project, the objective involves utilizing the FFT method on various time windows of data relative to stimulus onset to inform the decisions made by our BCI. We adjusted the start and end times of each epoch independently within a specified range to evaluate BCI performance using accuracy and Information Transfer Rate (ITR). After completing this assessment, we created two pseudocolor plots displaying accuracy and ITR across various epoch start and end times, helping us determine the most effective time window for achieving our goals.

Methods:

Our code module comprises functions designed to analyze EEG data and generate predictions for BCI control. These functions are versatile and adaptable to different datasets and experimental conditions without modification. Listed below are the functions and their applications.

1. generate_predictions

This function operates on EEG epochs data transformed using Fast Fourier Transform (FFT), referred to as 'eeg_epochs_fft,' along with an array of corresponding frequencies denoted as 'fft_frequencies.' Additionally, it takes a tuple named 'event_frequency' representing two frequencies indicative of the events of interest, and a 'Threshold' value for discerning amplitude differences between event frequencies and a 'predictor' frequency. The aim of this function is to predict outcomes based on the amplitude disparities among predictor frequencies, notably 12 Hz and 15 Hz. Subsequently, it generates 'predicted_labels' as its output.

2. calculate_accuracy_and_ITR

This function is designed to compute both accuracy and Information Transfer Rate (ITR). It requires the following inputs: 'true_labels' (in this context, 'is_trial_15Hz' represents the true labels), 'predicted_labels' generated by the 'generate_predictions' function, 'trials' denoting the number of trials in one epoch, and 'duration' representing the time per second (TPS) This function compares ‘predicted_labels’ with the true labels for the data and the length of the epochs. This determines how often it is identifying the correct frequency (accuracy) and how quickly (Information Transfer Rate, ITR) two figures of merit in determining the viability of the BCI.

3. plot_accuracy_and_ITR

This function accepts raw 'data' as input to analyze the accuracy and Information Transfer Rate (ITR) within a specified 'subject' and 'channel'. Additionally, it requires 'start_time_array' and 'end_time_array', which consist of arrays containing the start and end times of epochs, respectively. The function is designed to generate a pseudocolor plot to assess the relative accuracies and ITRs across different epoch limits.

4. plot_predictor_histogram

Once an epoch start/end time giving good ITR and accuracy is identified via the previous function, those values can be given alongside the data to generate a predictor histogram. This functions by plotting the relative amplitude for each frequency for all given epochs. Different tolerances for false negatives/positives can be satisfied by selecting different amplitude thresholds based on this histogram.

Results:

Here, we present accuracy and ITR pseudocolor plots to identify key epoch ranges. The deliberate choice of the O2 channel is rooted in the visual nature of the SSVEP task, given its location in the occipital region, known for processing visual stimuli. Analysis of pseudocolor plots (heatmaps) spanning epoch start and end times from 0 to 20 seconds reveals a distinct pattern. While not reaching perfect accuracy, there is a notable peak in Information Transfer Rate (ITR) between 12 to 13 seconds. Our analysis identifies a one-second interval from 12s to 12.5s after epoch start (Fig. 1), demonstrating high accuracy and maintaining a high ITR within this timeframe. Specifically, the range between 12s and 12.5s stands out, as both the 12-13 and 11.5-12.5 intervals exhibit a significant drop in both accuracy and ITR (Fig. 2). This trend is consistent across other SSVEP-relevant electrodes for this subject (Fig. 3). Figures 4 and 5 illustrate subject 2's accuracy and ITR in channels O2 and Oz. Notably, the intervals 15.5s - 15.75s and 16.5s - 16.25s show low accuracy and high ITR, respectively, in both O2 and Oz channels. Channels further not located near the occipital lobe gave noisy, non-significant data, as expected, so the majority of testing was done on the posteriorly located channels.

Plugging this value into the histogram program demonstrates the density of correct values (fig. 4). This allows us to identify the appropriate threshold to apply to the channel to turn the brain signaling into actions.

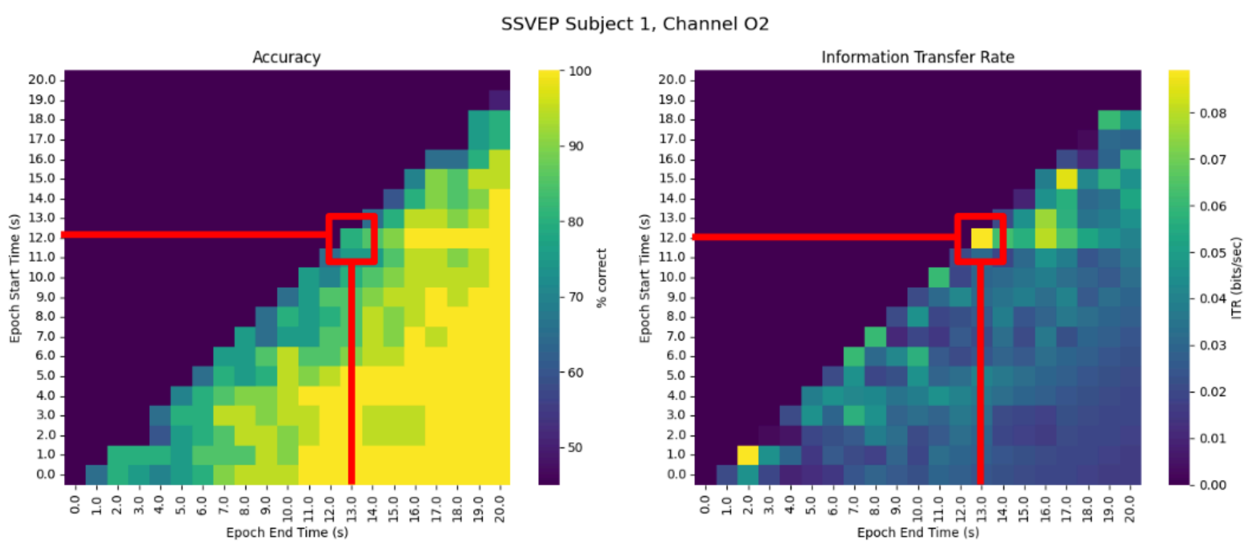


Fig. 1: Accuracy and ITR plots for channel O2 for subject 1. All epoch times presented. Highlighted is the start/end time of 12s/12.5s.

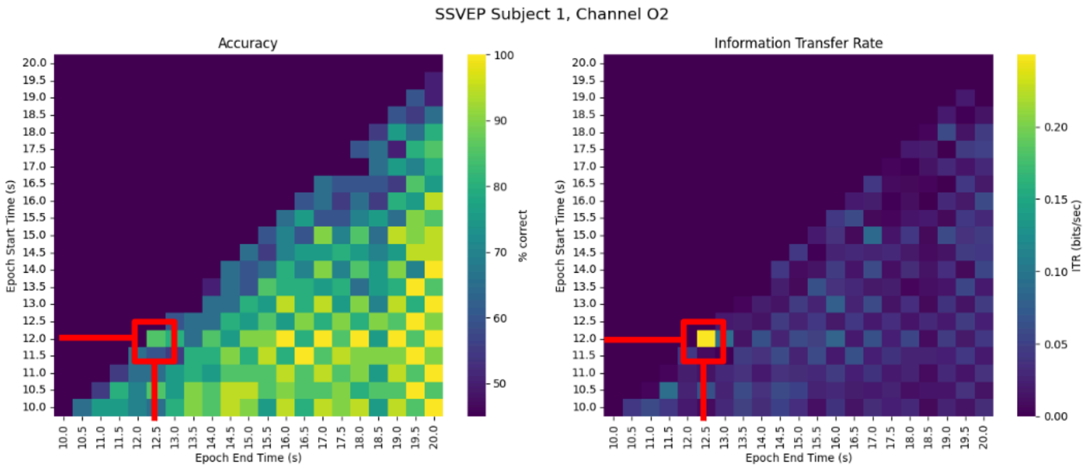


Fig. 2: Accuracy and ITR plots for channel O2 for subject 1. Epoch times 10s-20s presented. Highlighted is the start/end time of 12s/12.5s.

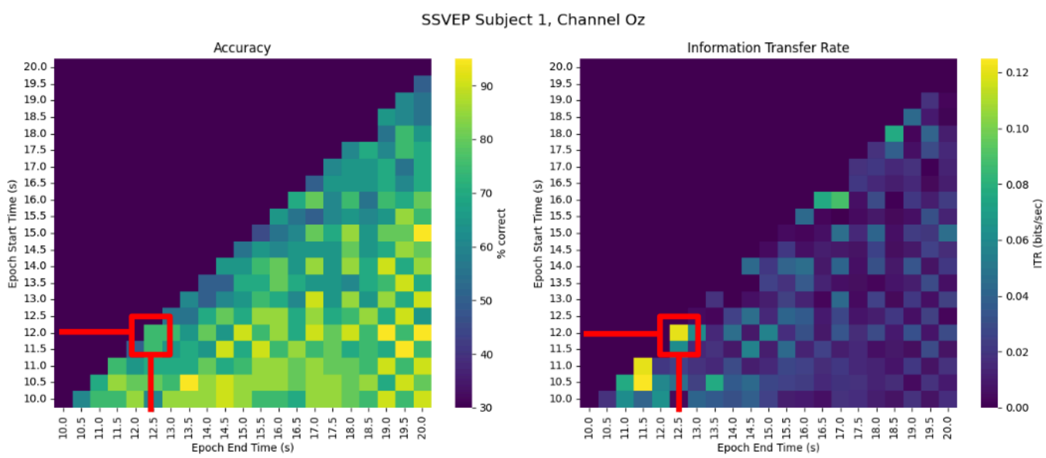


Fig. 3: Accuracy and ITR plots for channel Oz for subject 1. Epoch times 10s-20s presented. Highlighted is the start/end time of 12s/12.5s.

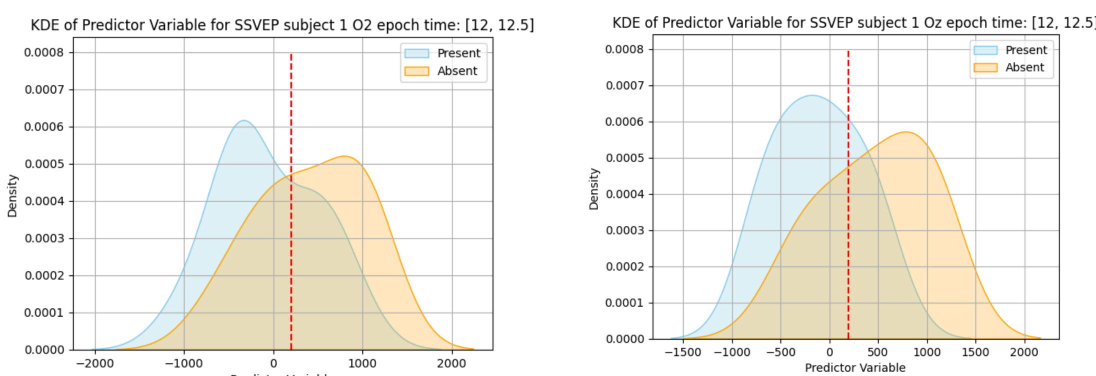


Fig. 4: Predictor histogram for channels O2 and Oz for subject 1 at duration 12s-12.5s. Dotted line shows a declared threshold of 400 for O2 and 200 for Oz.

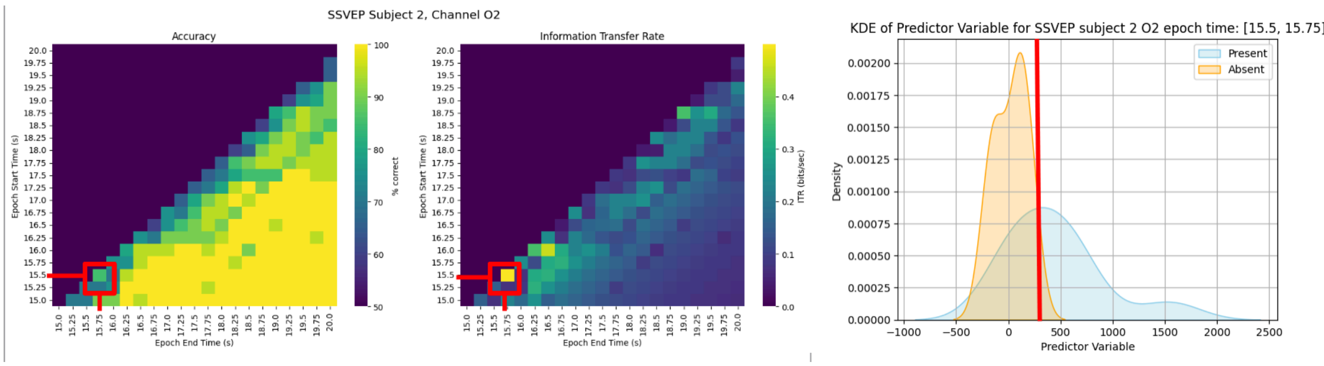


Fig. 5: Accuracy, ITR plot, and histogram for channel O2 for subject 2. Epoch times 15s-20s presented. Highlighted is the start/end time of 15.5s/15.75s. Estimated threshold is 300.

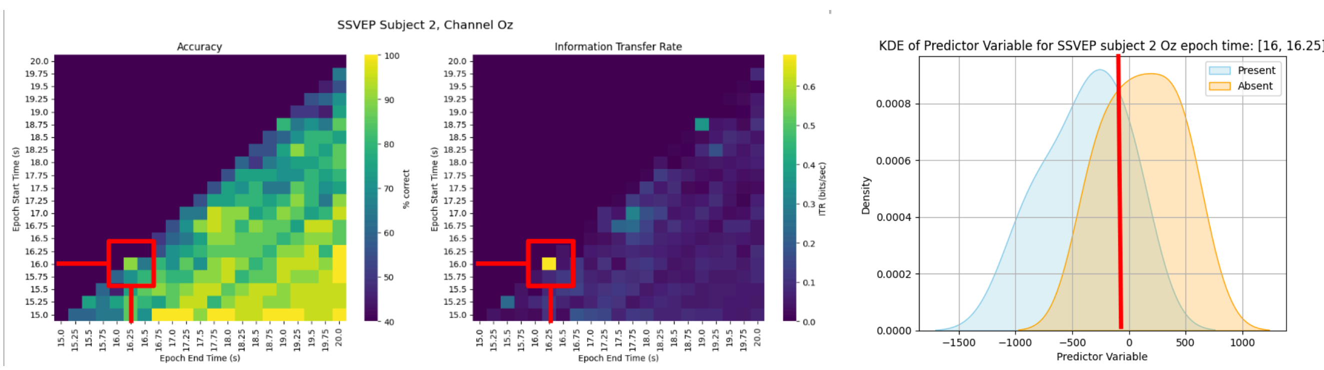


Fig. 6: Accuracy and ITR plots for channel Oz for subject 2. Epoch times 15s-20s presented. Highlighted is the start/end time of 16.5s/16.25s. Estimated threshold is at -100.

The accuracy and Information Transfer Rate (ITR) heatmaps reveal consistently high accuracy in SSVEP tasks within electrode channels in the occipital lobe, such as O2 and Oz, indicating a heavy reliance on visual stimulus processing. We observed a trade-off between accuracy at threshold 0 and ITR, where ITR tends to increase as accuracy decreases. In other words, preferring a faster transfer rate will decrease accuracy at threshold 0, indicating the necessity to seek a threshold correctly representing its predictions. Balancing this trade-off is essential when selecting optimal time combinations for threshold determination in SSVEP analysis. The predictor histogram plots go a step further, demonstrating the importance of amplitude when considering the cutoff threshold. An epoch time may have relatively high accuracy (represented by little overlap of present/absent predictions) but the distribution of the prediction must be considered and is not reflected by observing the accuracy alone. For example, subject 2 O2 15.5-15.75 (fig. 5c) would have very similar thresholds for specificity and accuracy, but distant selectivity.

Discussion:

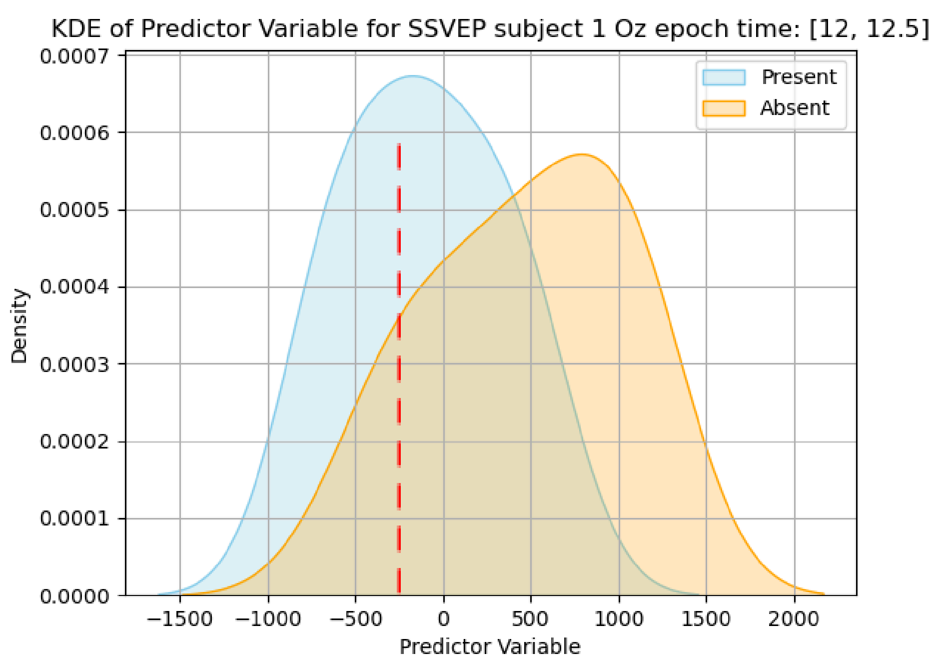
There are two main questions that we sought to answer:

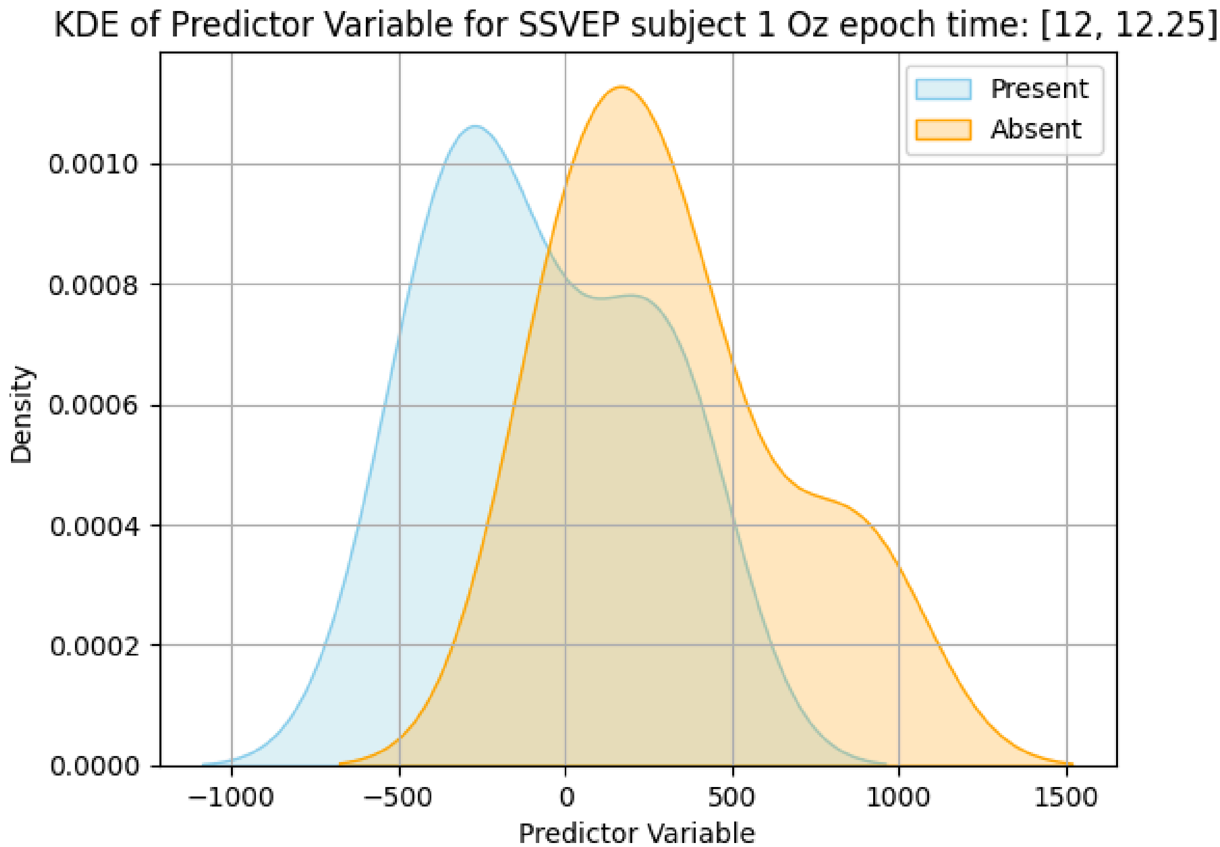
1. What epoch times should be used for each subject?
2. What threshold should we use for the predictions?

The answer to the first question depends on the channel being measured. Once an epoch has been established, different channels have different optimal response windows, and taking a composite response from several of them during a given window will give a more accurate reading than combining the signal across different channels at the same time point. For our examples, subject 1, O2 seemed to perform best at 12s-12.5s, and subject 2 O2 performed best at 15.5-15.75s. Subject 1 Oz also performed well at 12.5-12.5s, but subject 2 Oz performed optimally at 16-16.25s.

Different applications for this program value different characteristics. In the case of controlling a wheelchair, specificity is the most important as false positives have the potential to put the user into dangerous situations, like driving into traffic when the user wants to stay still. In contrast, using it to detect an imminent seizure or other emergency event would benefit from higher sensitivity since false negatives are more dangerous than false positives. Finally, manipulating a cursor would benefit from a higher accuracy to get precise placement. Because our case wants to avoid false positives, a high specificity is needed. This necessitates a higher threshold where a majority of the absent cases would not produce a response. In our subject 1, Oz 12-12.5 recording, this would be around the -250 mark. A threshold closer to 400 would be the most accurate, and a 750 threshold would be optimal to reduce false negatives.

Fig. 7: Predictor histogram for Oz for subject 1 at duration 12s-12.5s. Estimated threshold for mobilizing a wheelchair is at -250.





Citations

Wan F, da Cruz JN, Nan W, Wong CM, Vai MI, Rosa A. Alpha neurofeedback training improves SSVEP-based BCI performance. J Neural Eng. 2016 Jun;13(3):036019. doi: 10.1088/1741-2560/13/3/036019. Epub 2016 May 6. PMID: 27152666.

Zhu S, Yang J, Ding P, Wang F, Gong A, Fu Y. Optimization of SSVEP-BCI Virtual Reality Stereo Stimulation Parameters Based on Knowledge Graph. Brain Sci. 2023 Apr 24;13(5):710. doi: 10.3390/brainsci13050710. PMID: 37239182; PMCID: PMC10216479.