# Project 2: SSVEP Predictor

1. **Introduction:**

Steady state visual evoked potentials are a response created by stimuli that flash at specific frequencies. SSVEPs are used in brain computer interfaces to allow users to control external devices or interfaces using their brain activity. The main purpose of using SSVEPs in BCIs is to have a non-invasive method for individuals to control devices or software through brain activity. SSVEP-based BCIs have several advantages over other methods including high information transfer rates, minimal instruction for users, and strong activity in relation to artifacts and noise. SSVEP-based BCIs can also use relatively simple hardware, making them accessible for a wide range of individuals and applications.

The code we created comprises a set of functions designed for analyzing SSVEP data in multiple users. The code finds the index of the frequency closest to a given target frequency in an array of frequencies, generates predicted labels based on SSVEP data, computes accuracy and Information Transfer Rate from SSVEP data for a combination of start and end times, generates pseudo color plots for accuracy and ITR matrices, and plots a predictor histogram calculated from SSVEP data. This allows us to have insights into classification accuracy and different performance metrics for SSVEP data and SSVEP based BCIs.

1. **Methods:**

The functions in our module include find\_nearest\_frequency\_index, generate\_predicted\_labels, get\_accuracy\_ITR, loop\_epoch\_limits, generate\_pseudocolor\_plots, and plot\_predictor\_histogram. These functions do the following respectively. The first function finds the index of the frequency closest to a given target frequency in an array of frequencies. The second function extracts SSVEP features from EEG epochs, computes the Fast Fourier Transform to obtain the frequency spectrum, and determines the predicted label based on the amplitude at 12 and 15 Hz. The third calculates the accuracy of the predicted labels compared to true event and computes the rate at which information is transferred. The fourth loops through different epoch start and end times to computes accuracy and ITR. The fifth function generates pseudo color plots for accuracy and ITR matrices which provide a visual reference for the performance across different epochs. The last function plots a histogram that shows the distribution of predictor values calculated from the SSVEP data.

The code is flexible and allows the user to input different options without changing any of the code. The user can input a new dataset, a different electrode, a different set of epochs start and end times, a different number of trials, or a different set of stimulation frequencies to generate predicted labels. This will, in turn, provide unique accuracy, ITR, and plot results with the ability to input desired start and end times when looping through the computations and plotting the results.

Using the "Oz" channel in Steady-State Visually Evoked Potential (SSVEP) is favorable due to its proximity to the visual cortex and its sensitivity to visual stimuli. The Oz channel is located at the back of the head, over the occipital lobe, which is where visual processing primarily occurs. This proximity enhances the signal quality for detecting SSVEP responses, as it captures neural activity directly related to visual stimulation. Additionally, focusing on the Oz channel reduces interference from non-visual brain activity, resulting in improved accuracy and reliability in SSVEP-based BCI systems.

1. **Results:**
   1. **Accuracy and Information Transfer Rate**

A graph of different colors

Description automatically generated with medium confidence

Figure **1.**1: SSVEP predictor accuracy and ITR for subject 1.

A comparison of a graph

Description automatically generated with medium confidence

Figure **1**.2 SSVEP predictor accuracy and ITR for subject 2.

More finely sampling the epoch start and end times would theoretically give us improved resolution of SSVEP responses or temporal patterns. However, there is also the potential for overfitting and the resulting analysis lacking generalizability. Trying different electrodes could help us identify which electrode location provides the highest accuracy and information transfer rate for each subject. This in turn could show us the spatial distribution of SSVEP responses across the scalp and more information for optimization of the BCI.

The predictor accuracy ensures the reliability of our hypothetical BCI system in interpreting the user's intentions. High accuracy means that the system can correctly distinguish between different visual stimuli or commands, allowing for precise control of external devices or applications. The plots reveal that an epoch windows of approximately 10 seconds (or less) between 0 and 15 seconds results in the most accuracy for the predictor in case of subject 1. In the case of subject 2, the window of time is reduced to about 5 seconds between epoch times of 0 and 12 seconds.

A high information transfer rate (ITR) is important for the speed and efficiency of interaction with the BCI system. ITR measures the rate at which information can be transmitted from the user to the system, quantified in bits per minute. A higher ITR enables faster communication or control, enhancing user experience and productivity. The plots show that subject 2 has both a higher accuracy and information transfer rate than subject 1 for the same channel (“Oz”)

* 1. **Predictor Histograms**

A graph of a graph

Description automatically generated with medium confidence

Figure **2.**1: Histogram of the distribution of predictor variables for subject 1.

A graph of a graph

Description automatically generated

Figure **2.**2: Histogram of the distribution of predictor variables for subject 2.

The distribution of predictor values in the histogram can show where relevant features from the brain signals could be extracted for a more specific use, especially those with distinct distributions between different states or conditions of interest. Additionally, with information from the histogram we can set appropriate thresholds for classifying the brain activity of the subjects. By looking at the distribution of predictor values, we can balance sensitivity and specificity based on the requirements of the BCI application. In turn we can also use it to find insights into the performance of our classifiers by visualizing how well they discriminate between classes based on the predictor values. In this case it seems that the data varies between subjects, with one having a much cleaner distribution.

1. **Discussion:**
   1. **What epoch start and end times should we use for our BCI for each subject?**

When looking at the figures we determined that epoch windows of approximately 10 seconds (or less) between start times of 0 and 15 seconds results in the most accuracy for the predictor in case of subject one. In the case of subject two, the window of time is reduced to about 5 seconds between epoch times of 0 and 12 seconds.

* 1. **What threshold should we use for our predictions?**

Some potential BCI use cases where accuracy would be highly valued include BCI systems designed for communication, such as spelling or typing using brain signals. The most notable example is the P300 speller, which allows users to spell out words by focusing attention on specific characters presented in a matrix. Farwell and Donchin (1988) introduced this paradigm, demonstrating its accuracy in enabling users, including those with locked-in syndrome, to communicate by selecting characters with high reliability solely through brain activity. In these cases, accuracy is important to ensure that the intended message is correctly interpreted and communicated. The threshold for classifying SSVEP signals as a target, in this case letter or word, would be set relatively high.

An example of specificity driven BCIs is in the realm of neuromotor prostheses (NMP) for individuals with severe disabilities. Research by Hochberg et al. (2012) explored the use of BCIs to facilitate direct brain control of NMP devices, enabling users to o replace or restore lost motor functions in paralyzed humans by routing movement-related signals from the brain, around damaged parts of the nervous system, to external effectors. The BCI in this case values the ability of the interface to accurately and selectively interpret certain neural signals or mental processes associated with specific cognitive or motor functions.

Potential BCI use cases where sensitivity would be the paramount consideration include those used for motor activity or some type of motion. When users control virtual or robotic motion with brain signals, sensitivity is important to capture any brain activity associated with attempted movements, even if the signal is weak or has associated noise. When selecting a threshold value, it would be important to set the threshold at a lower value to capture a broader range of SSVEP signals that may be associated with attempted movements from the user, giving more control over the motion.

**References:**

Farwell, Lawrence A., and Emanuel Donchin. "Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials." Electroencephalography and clinical Neurophysiology 70.6 (1988): 510-523.

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