BME 544 Final Project

Kevin Xue

20814292

Introduction

Steady-State Visual Evoked Potentials (SSVEP) based Brain-Computer Interfaces (BCIs) have gained significant attention due to their reliability, high information transfer rates, and relatively simple implementation. In an SSVEP-BCI system, visual stimuli flickering at different frequencies are presented to the user. When the user focuses their attention on one of these stimuli, neural activity in the visual cortex synchronizes with the stimulus frequency, generating SSVEPs that can be detected through electroencephalography (EEG) at specific nodes within the occipital lobe region. An application can be developed to classify which frequency the user is currently focused on, enabling the development of communication interfaces for individuals with motor disabilities. A well functioning BCI will allow these individuals to select commands or type letters by focusing on specific stimuli flickering at a certain frequency.

Feature Extraction

The features to be extracted are:

1. Filtered EEG signals: Subbands tailored to SSVEP harmonics
2. Canonical correlation coefficients: Measures similarity between EEG and reference signals
3. Weighted scores: Reflect the importance of each subband
4. Aggregated correlation vector: Final feature vector per trial

Data Collection

For one subject, 16 sessions of EEG data were collected, with 4 different stimuli frequencies (6.67 Hz, 8.57 Hz, 10.0 Hz, 12.0 Hz) per session for a duration of 1.5 seconds per stimuli frequency at a sampling rate of 125 Hz. The hardware used to conduct the data collection was the NeuroPawn Biopotential kit [1], which includes an affordable 8-channel biopotential amplifier PCB coupled with a 10-10 EEG headset with spring-loaded dry spike electrodes. The 8 electrodes are mounted at node locations O1, PO3, PO7, O2, PO4, PO8, POz, and Oz, with the ground and bias electrodes mounted on the right ear lobe.

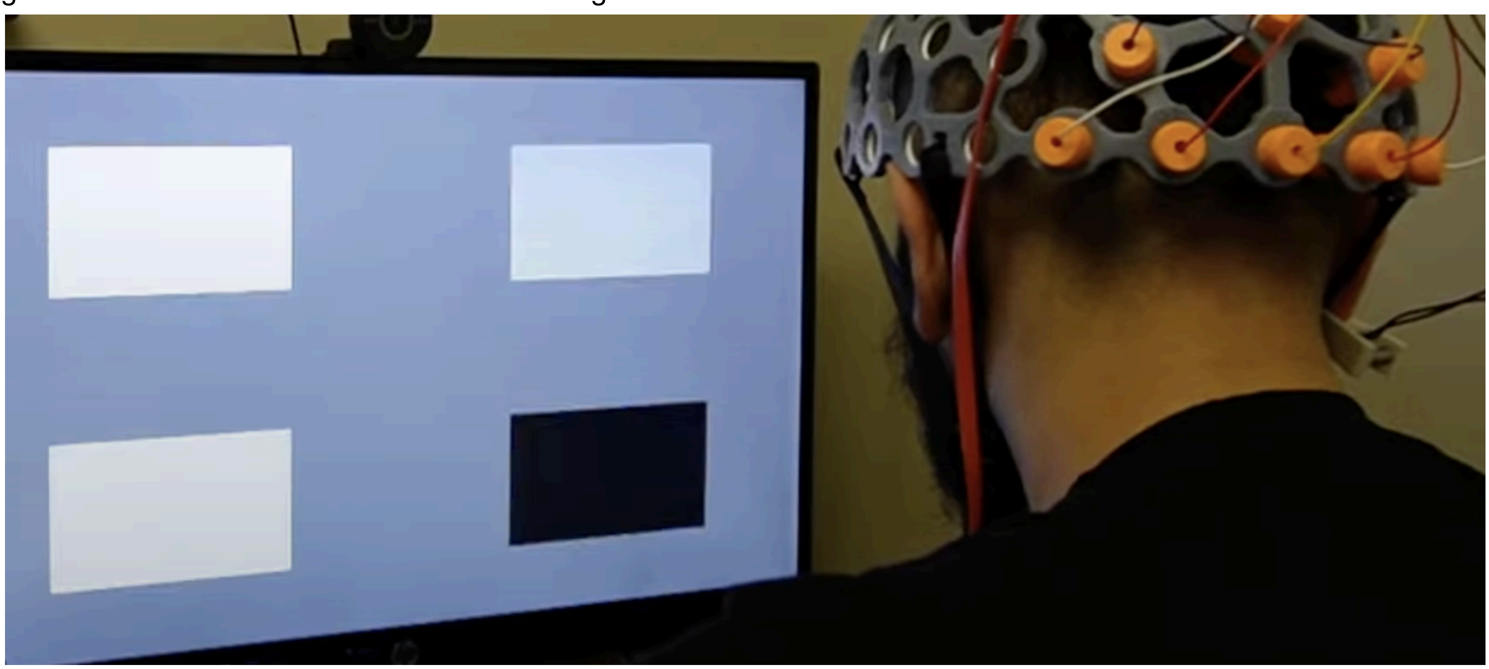


Figure 1: Subject wearing headset performing data collection task

Algorithm

The implemented algorithm is Filter Bank Canonical Correlation Analysis (FBCCA), an enhanced version of the standard CCA method that has shown superior performance in SSVEP classification tasks. CCA is a multivariate statistical method that finds linear combinations of two sets of variables such that the correlation between them is maximized. In SSVEP detection, CCA measures the correlation between: The multi-channel EEG signals and a set of predefined reference signals consisting of sine and cosine waves at the fundamental stimulus frequencies and their harmonics.

The reference signals for a frequency f are constructed as:

$$[\sin(2\pi ft), \cos(2\pi ft), \sin(4\pi ft), \cos(4\pi ft), \ldots, \sin(2\pi N_h ft), \cos(2\pi N_h ft)]$$

where Nh is the number of harmonics considered.

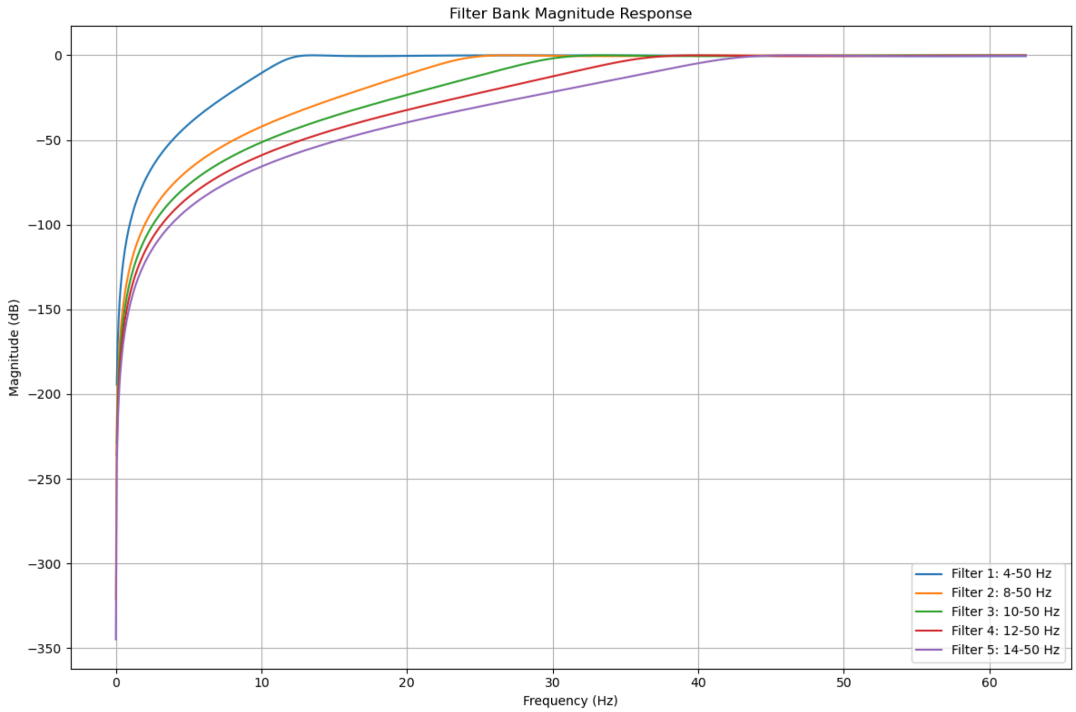
The stimulus frequency that yields the highest canonical correlation with the EEG data is selected as the classification result.

The Filter Bank CCA (FBCCA) extends the standard CCA by:

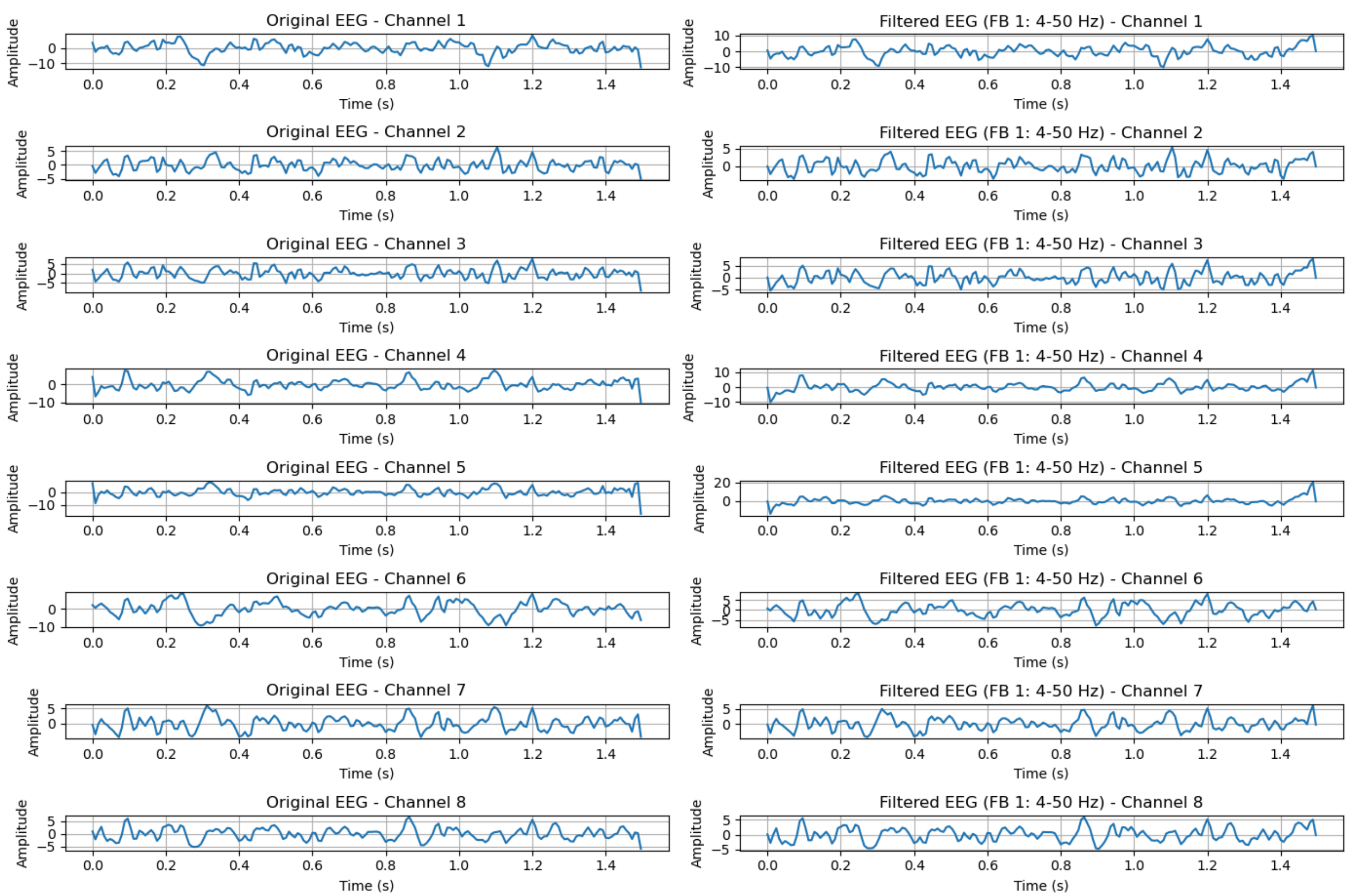
1. Decomposing the EEG signals into multiple sub-bands using bandpass filters
2. Applying CCA to each sub-band separately
3. Combining the CCA results from different sub-bands using a weighted sum

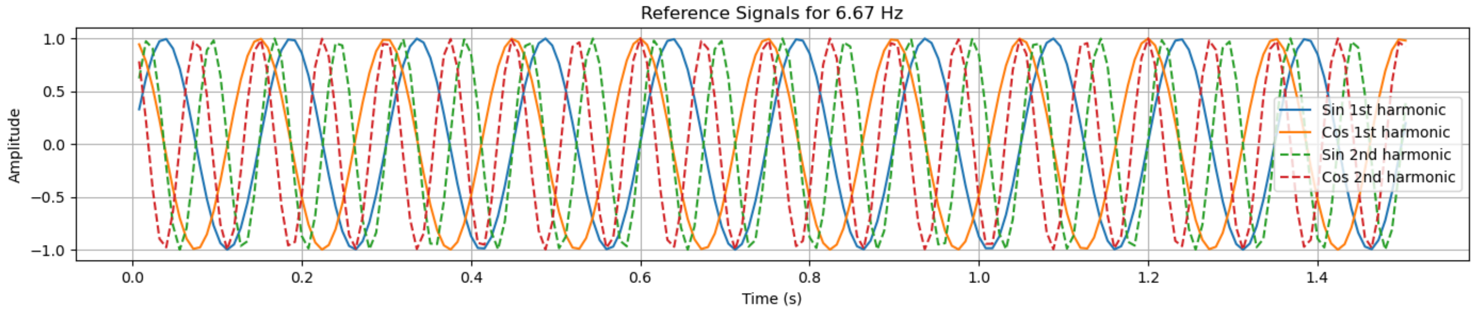
The key components of the algorithm are:

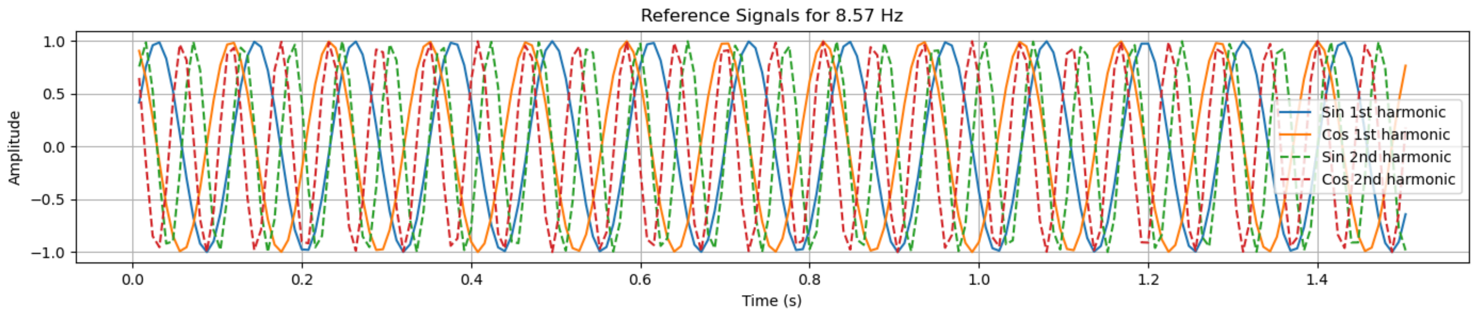
1. Filter Bank Design. The EEG signals are filtered through multiple bandpass filters, each designed to cover different frequency ranges:
    - 4 Hz - 50 Hz
    - 8 Hz - 50 Hz
    - 10 Hz - 50 Hz
    - 12 Hz - 50 Hz
    - 14 Hz - 50 Hz
2. Reference Signal Generation. For each stimulus frequency, reference signals are generated using sine-cosine pairs at the fundamental frequency and its harmonics. The number of harmonics (set to 3 in this case) is an important parameter that affects classification accuracy.
3. CCA for Each sub-band. For each trial and each candidate frequency, CCA is applied between the filtered EEG data and the reference signals to obtain correlation coefficients.
4. Weighted Fusion. The correlation coefficients from different sub-bands are combined using a weighted sum. The weight for the nth filter bank is defined as: w_n = n^(-1.25) + 0.25. This weighting scheme gives higher emphasis to lower sub-bands while still considering the contributions of higher frequency components.
5. Classification. The stimulus frequency that yields the highest weighted correlation coefficient is selected as the classification result.

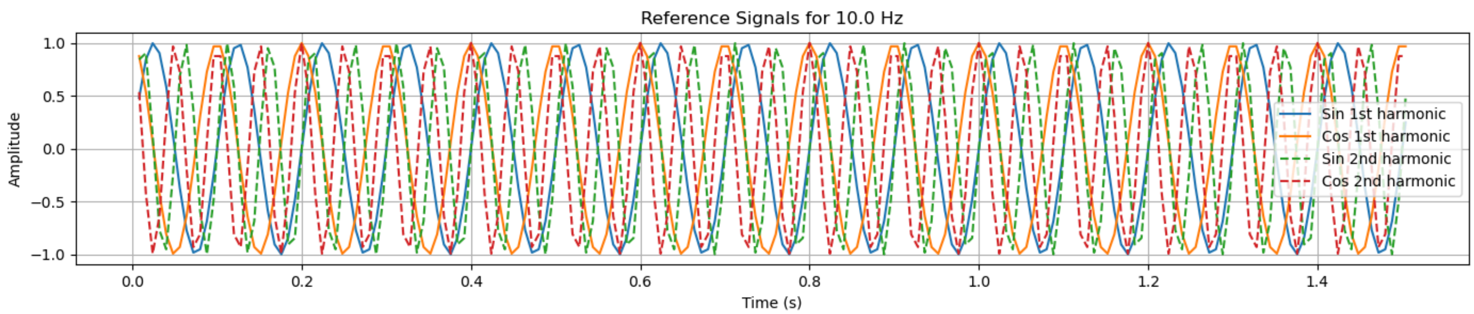


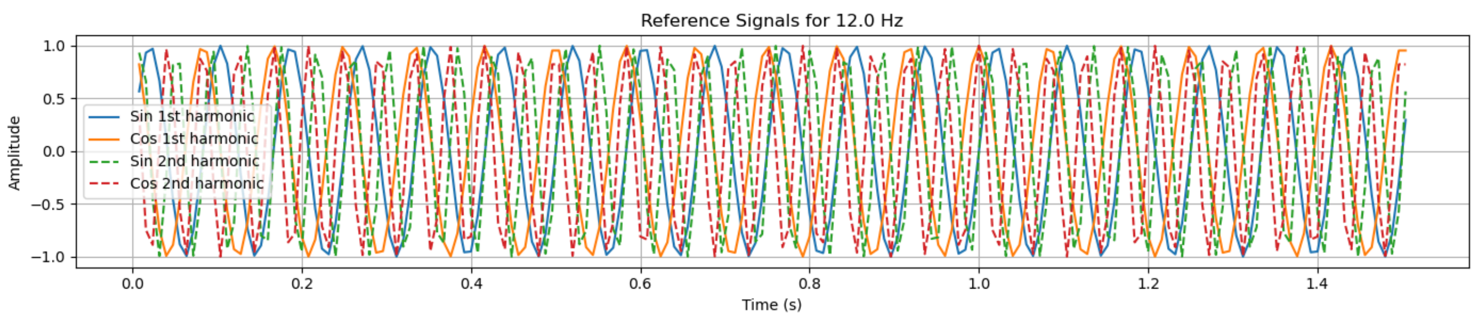
Trial 0: Original vs. Filtered EEG Signals




Reference Signals for 6.67 Hz
Amplitude
Time (s)
Sin 1st harmonic
Cos 1st harmonic
Sin 2nd harmonic
Cos 2nd harmonic

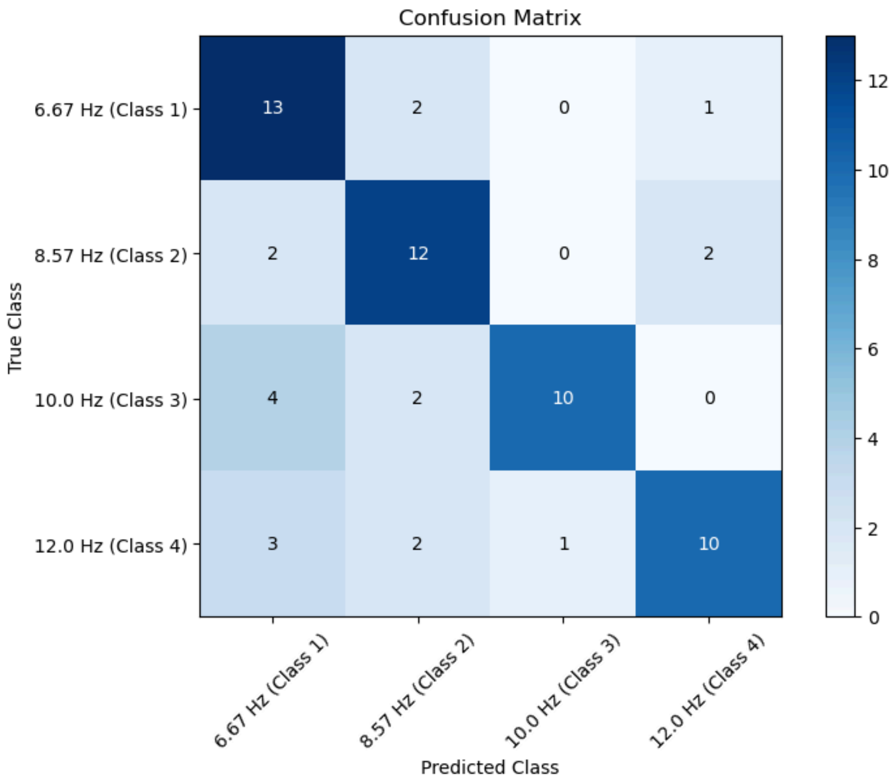

Reference Signals for 8.57 Hz
Amplitude
Time (s)
Sin 1st harmonic
Cos 1st harmonic
Sin 2nd harmonic
Cos 2nd harmonic


Reference Signals for 10.0 Hz
Amplitude
Time (s)
Sin 1st harmonic
Cos 1st harmonic
Sin 2nd harmonic
Cos 2nd harmonic


Reference Signals for 12.0 Hz
Amplitude
Time (s)
Sin 1st harmonic
Cos 1st harmonic
Sin 2nd harmonic
Cos 2nd harmonic

Results

The evaluation was conducted on the full dataset from *Data Collection*. Further metrics can be derived from the confusion matrix shown below:



The class average was 71.88%, and the per class accuracies were:

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Class 1 (6.67 Hz) accuracy: 75.00 %
Class 2 (8.57 Hz) accuracy: 81.25 %
Class 3 (10.0 Hz) accuracy: 68.75 %
Class 4 (12.0 Hz) accuracy: 62.50 %
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Justification

`filtfilt` was used to ensure the preservation of the EEG waveform shape, which is especially important during correlation.

Filter Bank

Lower cutoff frequencies: The lower bounds of the filter banks (4 Hz, 8 Hz, 10 Hz, 12 Hz, etc.) were chosen to progressively include the stimuli frequencies and their harmonics. Decreasing these values would include more low-frequency components, potentially capturing more of the SSVEP response but also incorporating more motion artifacts and baseline drift. Increasing these values would exclude lower frequency components, potentially missing fundamental frequency responses for the lower frequency stimuli (e.g., 6.67 Hz).

Upper cutoff frequency: The 50 Hz upper bound was chosen to include higher harmonics while avoiding power line interference. Decreasing this value would exclude higher harmonics, potentially reducing classification accuracy for higher frequency stimuli. Increasing this value beyond the Nyquist frequency (62.5 Hz for 125 Hz sampling rate) would lead to aliasing, and even approaching the Nyquist frequency could introduce filter instability.

Number of Filter Banks

5 filter banks were used instead of the 10 described in the original paper [2]. The sampling rate of 125 Hz limited the usable frequency range to approximately 0-60 Hz. With a Nyquist frequency of 62.5 Hz, only 5 filter banks could be reasonably implemented within this range while preserving inter-class dissimilarity.

Number of Harmonics

3 harmonics were used for reference signal generation since SSVEPs typically show strong responses not only at the fundamental frequency but also at its harmonics. Including harmonics in the reference signals improves the detection of these frequency components. Increasing the number of harmonics would capture more of the harmonic structure of SSVEPs, potentially improving classification for subjects with strong harmonic responses. However, too many harmonics might include frequencies beyond the usable range given the sampling rate constraints. Decreasing the number of harmonics would focus more on the fundamental frequency response, which might be beneficial for subjects with weak harmonic responses but would generally reduce classification accuracy.

Filter Bank Weights

The weight formula w_n = n^(-1.25) + 0.25 was used for combining filter bank results. This weighting scheme gives higher emphasis to lower frequency bands while still considering contributions from higher frequency components. SSVEPs typically have stronger power at fundamental frequencies compared to harmonics, making this a sensible approach. Increasing the exponent (more negative than -1.25) would give even more emphasis to lower frequency bands, which might improve performance for lower frequency stimuli but reduce sensitivity to higher frequency components. Decreasing the exponent (less negative than -1.25) would distribute weights more evenly across filter banks, potentially improving detection of higher harmonics but might reduce overall accuracy if fundamental responses are dominant.

References

[1] “Neuropawn,” NeuroPawn, https://www.neuropawn.tech/ (accessed Apr. 14, 2025).

[2] X. Chen, Y. Wang, S. Gao, T.-P. Jung, and X. Gao, “Filter Bank canonical correlation analysis for implementing a high-speed SSVEP-based brain–computer interface,” *Journal of Neural Engineering*, vol. 12, no. 4, p. 046008, Jun. 2015. doi:10.1088/1741-2560/12/4/046008