Multivariate FBSE-EWT based SSVEP Detection in Mobile Environment for Brain-Computer Interface Application

B .Tech. Project

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By

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Chapter 1

Introduction

1.1 Introduction

Brain-computer interfaces (BCIs) allow direct communication between the brain and external devices. Steady-state visual evoked potentials (SSVEPs) are one of the most widely used signals in BCIs due to their high signal-to-noise ratio and ease of detection. With the increasing demand for mobile and real-time applications, efficient methods for detecting SSVEPs in mobile environments are crucial. This project explores the use of the multivariate Fourier Bessel series expansion (FBSE) and empirical wavelet transform (EWT) for SSVEP detection in EEG signals, aiming for high accuracy with reduced computational complexity, which is essential for mobile BCIs.

1.2 Motivation for BTP and Problem statement

Mobile BCIs offer the potential for real-time monitoring and control applications, but detecting SSVEP signals in a dynamic, noisy mobile environment is challenging. Conventional methods such as power spectrum density (PSD) analysis or canonical correlation analysis (CCA) often struggle with noise and require long EEG recordings for accurate frequency detection. There is a need for more adaptive and robust techniques. Iterative filtering based CCA method have produced better results but lacks mathematical reasoning for the algorithm used [1]. The proposed FBSE-EWT method aims to address these issues by improving the time-frequency representation of the EEG signals, enhancing SSVEP detection in mobile settings, and facilitating real-time application.

Chapter 2

Literature Review

2.1 Introduction

Detecting SSVEP from EEG signals has been explored extensively in the literature. Various methods such as spectrum analysis, spatial filtering, and signal decomposition have been developed to improve the robustness of SSVEP detection in different environments.

2.2 Summary

Recent work by Lin et al. has focused on CCA-based methods for SSVEP detection, which offer improved performance but can still be affected by noise and require long durations of EEG recordings. Chen et al.(2023) introduced a filter bank CCA method that applies CCA to subband components, improving the accuracy of SSVEP detection but with limitations in adaptability to different noise conditions.

In contrast, empirical mode decomposition (EMD) and its variants, such as ensemble EMD and variational mode decomposition (VMD), have been used to adaptively decompose EEG signals into intrinsic mode functions [2]. These methods are well-suited for non-stationary signals like EEG but can be computationally intensive. The multivariate version of EMD, proposed by Chen [3], enhances robustness by using multiple channels but still requires significant computational resources.

Building on these techniques, Bhattacharyya et al. proposed a Fourier-Bessel series expansion (FBSE)-based empirical wavelet transform (EWT) method, which provides an improved time-frequency [4] representation with better frequency resolution, especially in cases with closely spaced frequency components. This method is particularly useful for non-stationary signals like EEG and provides a foundation for the current project.

Chapter 3

Methodology

3.1 Dataset

The dataset used for this study consists of EEG signals collected from 23 participants, recorded during two BCI paradigms: Event-Related Potentials (ERP) and Steady-State Visual Evoked Potentials (SSVEP). The data were collected in a mobile environment where participants performed tasks at varying speeds (standing, slow walking, fast walking, and slight running) [5]. EEG signals were recorded using a 32-channel EEG cap and additional sensors, including ear-EEG, electrooculography (EOG), and inertial measurement units (IMUs). For SSVEP detection, only the occipital and parietal electrodes (O1, O2, Oz, PO7, PO3, POz, PO4, PO8) were selected due to their association with visual stimuli processing in the occipital lobe.

The data were down sampled to 128 Hz to reduce computational complexity without sacrificing important information in the frequency bands relevant to SSVEP.

3.2 FBSE-EWT Method

The Empirical Wavelet Transform (EWT) is a well-established method for analyzing non-stationary signals like EEG. EWT operates by detecting boundaries in the frequency domain to define wavelet filter banks adaptively. Typically, boundary detection in EWT is performed using the Fourier transform [6]. However, Fourier Bessel Series Expansion (FBSE) offers a more accurate and efficient boundary detection method. This was demonstrated in the paper on FBSE-EWT, which showed improved frequency separation and noise resistance when compared to standard EWT boundary detection.

Moreover, the Multivariate FBSE-EWT enhances the method's robustness to noise and provides better results when applied to multichannel EEG signals, which are crucial for detecting SSVEP across multiple electrodes [7]. This advancement allows the framework to handle non-stationary signals from mobile EEG more effectively, maintaining signal integrity despite noise and artifacts.

The MATLAB code for the FBSE-EWT Method along with the subject eeg data used for results can be found here: Matlab Code

3.3 Preprocessing

Prior to applying FBSE-EWT, the EEG data undergoes several preprocessing steps to ensure the quality and relevance of the signals:

1. **Band-pass filtering:** EEG signals are filtered between 0 and 30 Hz, as SSVEP frequencies fall within this range, ensuring that irrelevant frequency components are removed.

2. **Re-referencing:** The EEG signals are re-referenced using the average of the selected occipital channels, which is crucial for reducing common noise and enhancing signal clarity in the region of interest.

3. **Epoch Extraction:** The continuous EEG is segmented into epochs of 3-second length, from [-0.1 to 2.9] seconds relative to the onset of the visual stimulus. This ensures the capture of both the pre-stimulus baseline and the post-stimulus response.

These preprocessing steps are essential to prepare the data for time-frequency analysis using FBSE-EWT, which will be applied to obtain robust representations of SSVEP signals [8].

Chapter 4

Results

4.1 Introduction

EEG signals from the occipital lobe and their time-frequency representations (via FBSE-EWT) are shown for four conditions: normal speed, slow walking, fast walking, and running.The time-frequency analysis clearly demonstrates the presence of the flickering stimuli frequency in the rest and slow walking conditions. However, higher subject speeds lead to increased signal contamination, broadening the spectral representation.

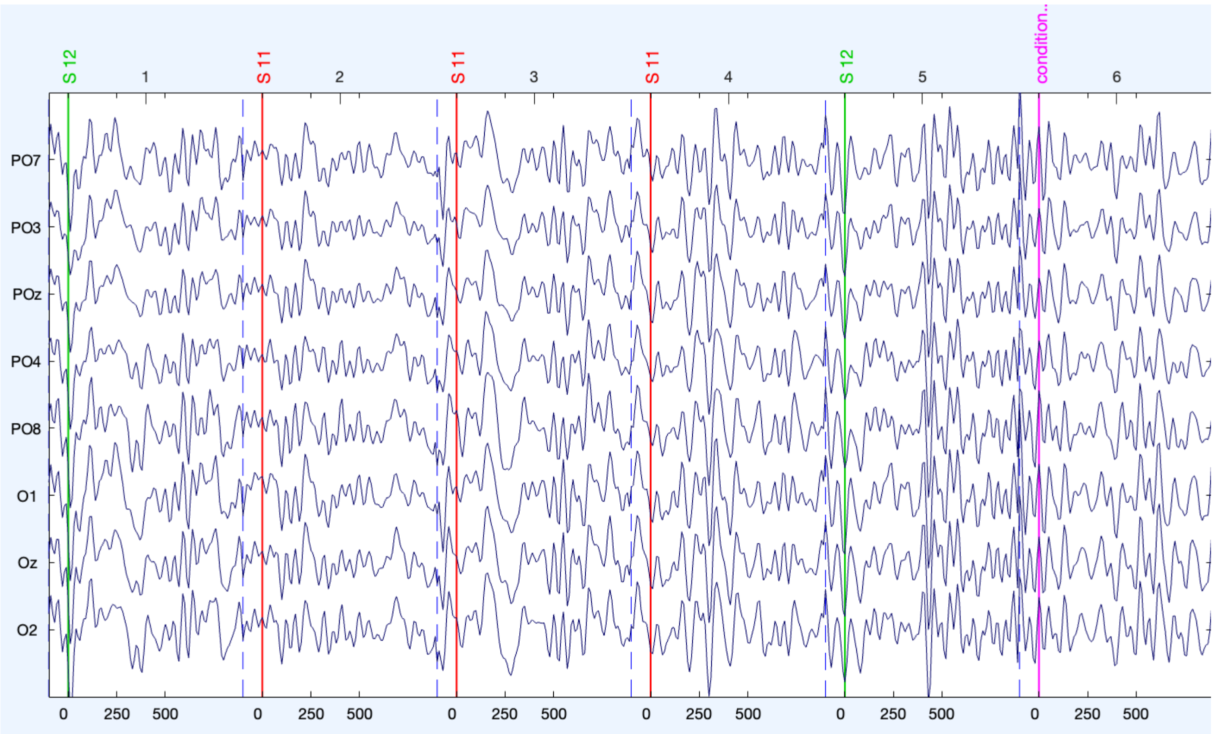

Figure 4.1: The image depicts 8-channel occipital EEG signals, epoched around 6 events, with vertical lines marking event onsets. Brain activity patterns, time-locked to events.

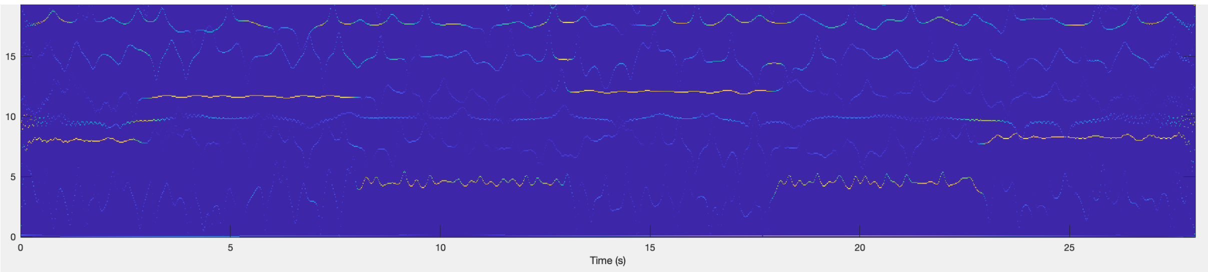

Figure 4.2: Rest Condition

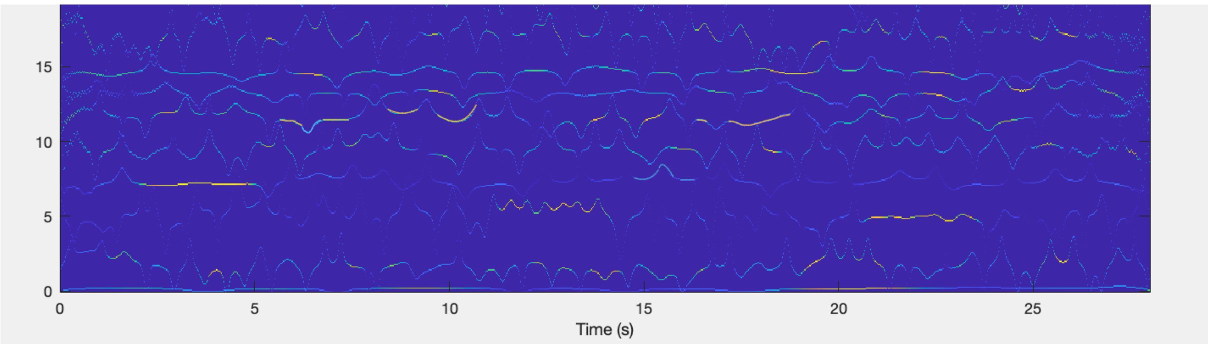

Figure 4.3: Slow Walking Condition

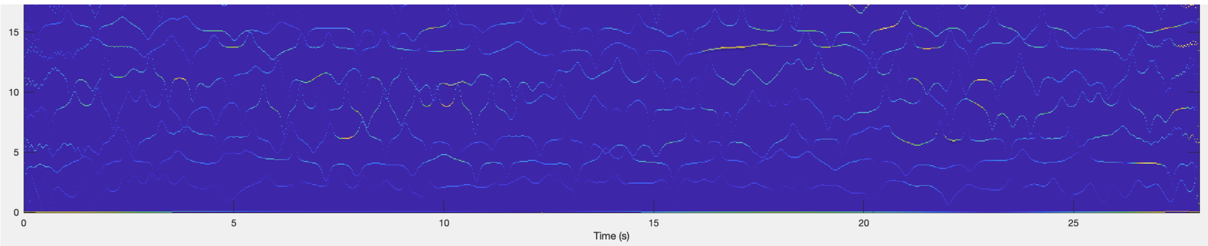

Figure 4.4: Walking Condition

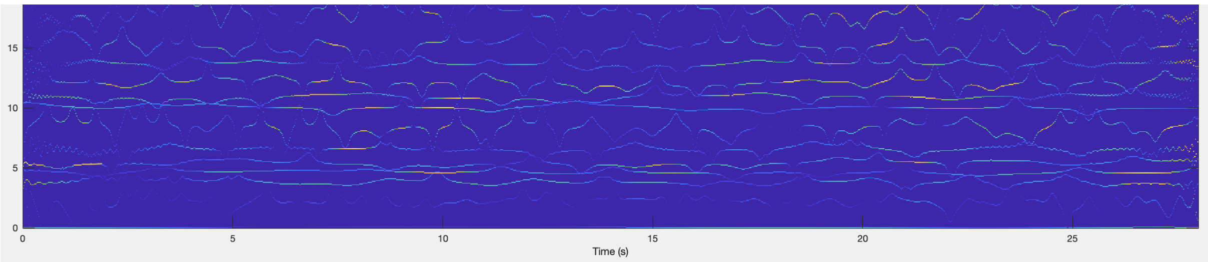

Figure 4.5: Running Condition

4.2 Summary

The time-frequency representations reveal that the EEG signals reflect the flickering stimulus frequency clearly under normal and slow walking conditions. However, as the movement speed increases, the quality of the frequency representation deteriorates due to increased noise and artifacts, especially during fast walking and running.

Chapter 5

Conclusions and Future Work

5.1 Conclusions

The FBSE-EWT method has been successfully implemented for the time-frequency analysis of SSVEP EEG signals in a mobile BCI environment. The initial results show promising improvements in frequency resolution and noise robustness compared to traditional methods and more importantly is theoritically backed unlike other processing techniques. The TF representations generated by FBSE-EWT provide a solid foundation for SSVEP detection. The frequency bands related to events are already visible for normal speeds, with increasing speed artifacts also increased making the TF representation disperse.

5.2 Future scope of work

The next phase of the project involves integrating a CNN-based classifier to identify the flickering frequency to which the participant is responding. The CNN will be trained on the TF representations generated by FBSE-EWT, and the classification accuracy will be evaluated. The major hinderance is the small data set available. This problem can be solved using techniques like data augmentation.

Month	**Proposed Work**
July	Signal Processing & Literature Review
August	Data Preprocessing & FBSEEWT Implementation
September	CNN Model Development & Data Augmentation
October	Classifier Evaluation & Gap Analysis
November	Project Finalization & Documentation

References

[1] K. Das and R. B. Pachori, ”Multivariate Iterative Filtering-Based SSVEP Detection in Mobile Environment for Brain–Computer Interface Application,” in *IEEE Sensors Letters*, vol. 8, no. 4, pp. 1-4, April 2024.

[2] L. Chang, R. Wang, and Y. Zhang,, ”Decoding SSVEP patterns from EEG via multivariate variational mode decomposition-informed canonical corrrelation analysis,” Biomed. Signal Process. Control, vol.71,2022, Art. no. 103209.

[3] Y. F. Chen, K. Atal, S. Q. Xie and Q. Liu. ”A new multivariate empirical mode decomposition method for improving the performance of SSVEP-based brain-computer interface.” *J. Neural Eng.* vol 31.pp.4203-4210.2023.

[4] A. Bhattacharyya, Lokesh Singh, R. B. Pachori, ”Fourier–Bessel series expansion based empirical wavelet transform for analysis of non-stationary signals” in *Digital Signal Processing*, Volume 78, 2018, Pages 185-196, ISSN 1051-2004,

[5] Y. E. Lee, G. H. Shin, M. Lee and S. W. Lee, ”Mobile BCI dataset of scalp-and ear-EEG with ERP and SSVEP paradims while standing, walking, and running,” *Biomed. Signal Process. Control, vol.71, 2022, Art. no. 103209.*

[6] J. Gilles, ”Empirical Wavelet Transform,” in *IEEE Transactions on Signal Processing*, vol. 61, no. 16, pp. 3999-4010, Aug.15, 2013, doi: 10.1109/TSP.2013.2265222.

[7] A. Bhattacharyya, R. K. Tripathy, L. Garg and R. B. Pachori, ”A Novel Multivariate-Multiscale Approach for Computing EEG Spectral and Temporal Complexity for Human Emotion Recognition,” in *IEEE Sensors Journal*, vol. 21, no. 3, pp. 3579-3591, 1 Feb.1, 2021.

[8] Y. Zhang, S. Q. Xie, H.Wang, and Z. Zhang, ”Data analytics in steady-state visual evoked potential-based brain-computer interface: A review” *IEEE Sensors J.* vol.21, no 2.pp.1124-1138.Jan. 2021