FROM STIMULUS TO ACTION: SSVEP-POWERED BRAIN INTERFACES

Rose Pushparaj, Dua Kaurejo, Chaturya Kuppili

Abstract — Steady-State Visual Evoked Potentials (SSVEPs) offer a powerful mechanism for frequency recognition in non-invasive Brain-Computer Interfaces (BCIs). This project employed the multivariate synchronization index (MSI) algorithm to classify EEG signals elicited by three stimulus frequencies (6.2 Hz, 7.7 Hz, and 10 Hz). The model achieved 66.67% accuracy on the training file, with observed differences in accuracy across frequencies. These findings demonstrate MSI's potential for practical applications in assistive technologies and real-time frequency recognition systems.

I. INTRODUCTION

SSVEPs are frequency-dependent EEG activity evoked by an external stimulus [1]. These potentials are characterized by synchronization with the stimulus' frequency, making them ideal for frequency recognition in BCIs. SSVEPs are recorded non-invasively using EEG, with the strongest signals are typically observed in the occipital region of the brain, which processes visual information. The spatial distribution of SSVEPs is concentrated in the occipital and parietal areas, but signals may also propagate to adjacent regions depending on the individual and stimulus conditions. These unique characteristics make SSVEPs a cornerstone in developing efficient and user-friendly BCI systems.

II. METHODS

Data Description: The dataset comprised of two files with signals recorded across 7 channels (PO3, POZ, PO4, O1, OZ, O2, and Trig) sampled at 128 Hz for 15 trials. Both the training and test files had the same stimulus frequencies (6.2 Hz, 7.7 Hz, and 10 Hz); however, the target order of these frequencies was known for the training file and unknown for the test file.

Data Analysis and Classification

The classification was conducted using the Multivariate Synchronization Index (MSI) algorithm to identify the stimulation frequency of each trial.

Signal Processing Methodology

1. *Preprocessing*: DC offsets were removed by subtracting the mean value of each EEG channel from its values.
2. *MSI Algorithm*: Reference signals corresponding to each stimulation frequency were generated. For each trial, the MSI was computed to measure synchronization between EEG signals and the reference signals.
3. *Classification*: Trials were classified based on the stimulation frequency with the maximum synchronization index.

Pseudocode for Classification

```
LOAD preprocessed data file
GENERATE reference signals for 6.2, 7.7, and 10Hz
SEGMENT data into trials
FOR each trial
    APPLY MSI to compute synchronization index
    CLASSIFY trial based on maximum index
END FOR
```

Pseudocode for MSI Algorithm

Based on Saadatyar's implementation [2].

```
INPUT: EEG data (data), reference signals (data_ref), number harmonics (num_harmonic)
OUTPUT: Synchronization index (s)
1.  Transpose data if rows < columns
```

2. **Compute** covariance matrix (**c**) of **data** and **data**_ref
3. **Extract** submatrices:
    - **c1**: Autocorrelation of **data**
    - **c2**: Autocorrelation of **data_ref**
    - **c12** and **c21**: Cross-correlations between **data** and **data_ref**
4. **Construct** transformed correlation matrix (**r**) using normalized cross-correlations.
5. **Decompose** to compute eigenvalues **(λ)**
6. **Normalize** eigenvalues
7. **Compute** synchronization index (s) as:

$$s = 1 + \frac{\sum(\lambda \cdot \log(\lambda))}{\log(\text{total channels} + \text{harmonics})}$$

8. **Return s**

The synchronization index s ranges from 0 to 1, where synchronization between signals and reference increase with s.

III. RESULTS

Figure 1 shows classifier accuracy for the training file, achieving 66.67% overall.

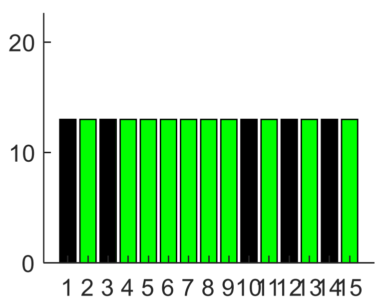

Figure 1 Accuracy results with training file.

Figure 2 presents the confusion matrix, with the highest accuracy at 10 Hz (80%) and misclassifications primarily between 6.2 Hz and 7.7 Hz.

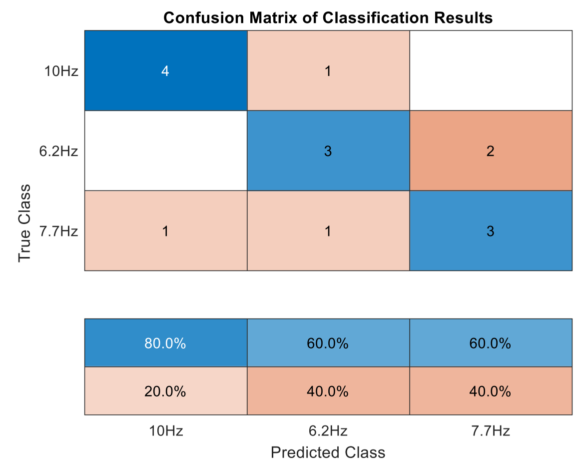

Figure 2 Classifier Confusion Matrix

Figure 3 illustrates the FFT heatmap, highlighting power differences across trials and frequencies which were critical for classification with MSI.

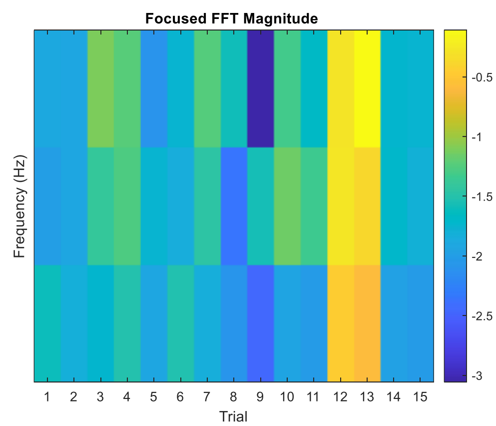

Figure 3 FFT heatmap for 6.2, 7.7, and 10 Hz (top to bottom) calculated using the test file.

Figure 4 depicts the SNR by channel for the test file, with Channel 4 showing the lowest SNR. Attempts to remove low-SNR channels or applying bandpass filtering were found to degrade classification accuracy on the training data, likely due to loss of information. However, MSI has been demonstrated to perform robustly even under conditions of reduced SNR [3], supporting the decision to retain all channels and leverage complementary information effectively.

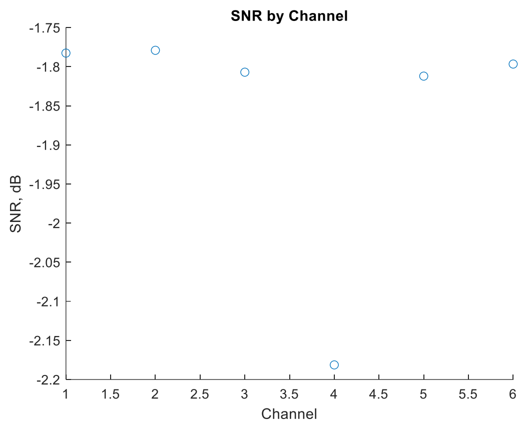

Figure 4 SNR by channel for test file.

Table 1 shows the predicted frequencies for each trial in the test file.

Trial	Predicted Frequency
1	6.2
2	6.2
3	7.7
4	6.2
5	10
6	6.2
7	7.7
8	7.7
9	10
10	6.2
11	7.7
12	6.2
13	6.2
14	6.2
15	7.7

Table 1 Predicted frequencies in test file.

IV. DISCUSSION

The experimental results highlight the potential of the MSI algorithm in SSVEP-based BCI systems for both research and practical applications. While our implementation was able to classify stimulus frequencies, the observed accuracy limitations suggest that further optimization is needed to fully leverage MSI's capabilities. Refining preprocessing techniques and parameter selection could enhance classification performance, improving its suitability for real-time assistive technologies. These systems hold promise for facilitating communication in individuals with disabilities, enabling control of external devices or robotic limbs [3].

Although prior studies suggest that MSI can perform well under low-SNR conditions, our results indicate that its effectiveness is sensitive to implementation choices. Addressing these limitations could expand its applicability to brain-controlled gaming and other interactive experiences. Additionally, incorporating advanced algorithms such as the Filter Bank Temporally Local Multivariate Synchronization Index (FBTMSI), which extends MSI by improving frequency resolution and temporal adaptability, may enhance detection accuracy [4]. These findings underscore the importance of continued development in SSVEP-based BCI systems for advancing assistive technologies, entertainment, and neurotechnology research.

REFERENCES

[1] University at Albany, Dept. of Electrical & Computer Engineering. Intro to Brain-Computer Interfaces. Lab 5 - SSVEP. Fall 2024.

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[4] Xu T, Ji Z, Xu X, Wang L. Filter bank temporally local multivariate synchronization index for SSVEP-based BCI. J Neural Eng. 2018;15(3):0