KLE Technological University
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Dr. M. S. Sheshgiri Campus, Belagavi

ELECTRONICS AND COMMUNICATION DEPT

Digital Signal Processing
2024-2025
V Semester

Drowsiness Detection using EEG Signals

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Department of Electronics and Communication Engineering

CERTIFICATE

This is to certify that the project entitled **"Drowsiness Detection using EEG Signals"** is a bonafide work carried out by the student team of **Basavaraj Mujagoni (02FE22BEC015), Diksha Nalawade (02FE22BEC025), Preeti Paschapuri (02FE22BEC053), Rahul Kundaragi (02FE22BEC062)**.

The project report has been approved as it satisfies the requirements with respect to the DSP project work prescribed by the university curriculum for B.E. (V Semester) in the Department of Electronics and Communication Engineering of KLE Technological University, Dr. M. S. Sheshgiri CET Belagavi campus for the academic year 2024-2025.

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Guide	Head of Department	Principal

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Contents

Chapter 1

Problem Statement

Design an EEG-based Drowsiness Detection System Using DSP Techniques, including FFT and suitable filters to remove unwanted signals and Power to classify the state of drowsiness

Chapter 2

Introduction

2.1 Background

Road Accidents are such a worse case of Human Safety, Where it directly harms Human in any of the taken scenario's ,If we closely look onto Accidents, they are caused due to some factors classified as drunk and drive etc., among these factors drowsiness is identified as one of the factors leading to serious road accidents [1] [2] [3], it is reported by police that car accidents caused due to drowsiness has been attributing 3% [4].

Drowsiness is an intermediate state of sleepy and awaken. It may be caused by many factors may be by long driving, lack of sleep, consuming alcohol, taking more medicines, early morning drive and mostly in monotonous driving environments. As per National Road Travel Protection Management analysis around 1,00,000/- crashes are directly [5] outcome of driver drowsiness each year, it has become a major concern to overcome the situation of drowsiness may be by alerting his state of drowsy.

Numerous methods for detecting drowsiness of drivers are listed in Academic Literature, documented by Stancin et al. [6] Mohammedi et al. [7], these techniques are categorized into Three main category, described by Rayan [8], first is the technique based on driver physiologic signals arising from Electroencephalogram (EEG) activities, Electrocardiogram (ECG) activities, and Electrooculogram (EOG) activities, [9]. Second one is based on measurements of vehicle parameters, Drowsiness detection is made while measuring the movements of Steering Wheel, pressure on Acceleration paddle and so on, [10]. The third and last category is based on driver's facial Movements [11]. As per the analysis [12] [13] Physiological method best fits for detecting Drowsiness effectively. The Method used is on EEG signals, in study [14] researches make significant contributions to demonstrate the originality of the authors proposed system by highlighting use of a single EEG channel, more precisely the C3-O1 channel, for analysis of Alpha and beta waves. These Results are obtained by focusing on alpha and beta waves captured by C3-O1 channel.

Chapter 3

Literature Review

3.1 Related Work

EEG needs to be preprocessed that involves many techniques. The Savitzky-Golay (SG) filter, a low-pass filter, was proposed for smoothing EEG signals, which used frame size and polynomial degree for filtering[15]. Motion artifact suppression followed methods like Discrete Wavelet Transform (DWT), Empirical Mode Decomposition (EMD), and SG filters to remove noise[16]. Studies on single-channel wireless EEG devices, such as the U-Wake, show that real-time fatigue detection through band-pass filtering (0.5–30 Hz), down-sampling (256 Hz), and FFT-based feature extraction, and the frequencies are categorised into delta, theta, alpha, and beta bands[17]. For sleep disorder detection, EEG signals are analyzed using methods like Welch's Power Spectral Density (PSD), with MATLAB employed for low-pass filtering and PSD computation to study REM and NREM stages which is also helpful in our study[18]. Driver drowsiness detection through EEG signals from BCI, using filters like notch (50 Hz) and Butterworth band-pass, with PSD computed via FFT and periodogram methods[19]. Another approach used DWT coefficients for drowsiness detection, by using entropy features from C3 and C4 electrodes with higher level Machine Learning algorithms[20]. Drowsiness detection in single-channel EEG by a portable system that used dry Ag/AgCl electrodes, AD620 amplifiers, and Butterworth filters to process signals, and to separate them into theta, alpha, and beta waves, thereby alerting through a microcontroller [21].

Chapter 4

EEG Signals

4.1 Signal Specification

4.1.1 Signal Type:

- Electroencephalogram(EEG) :
  Measures electrical activity in the brain by detecting fluctuations in voltage caused by neuronal activity. Recorded using electrodes placed on the scalp.

- Amplitude:
  Low amplitude, typically in the microvolt (µV) range. This low amplitude is susceptible to the noise.

- Frequency Range:
  Delta (0.5–4Hz)
  Theta (4–8Hz)
  Alpha (8–12Hz)
  Beta (12–30Hz)
  Gamma (30–45Hz)

- Sampling Range:
  A typical EEG signal is sampled at a rate of 128 to 256 Hz, enough to capture the relevant frequency bands.

- Channel Configuration:
  The number of channels used and the placement of electrodes.

4.2 Visualisation of EEG Signal

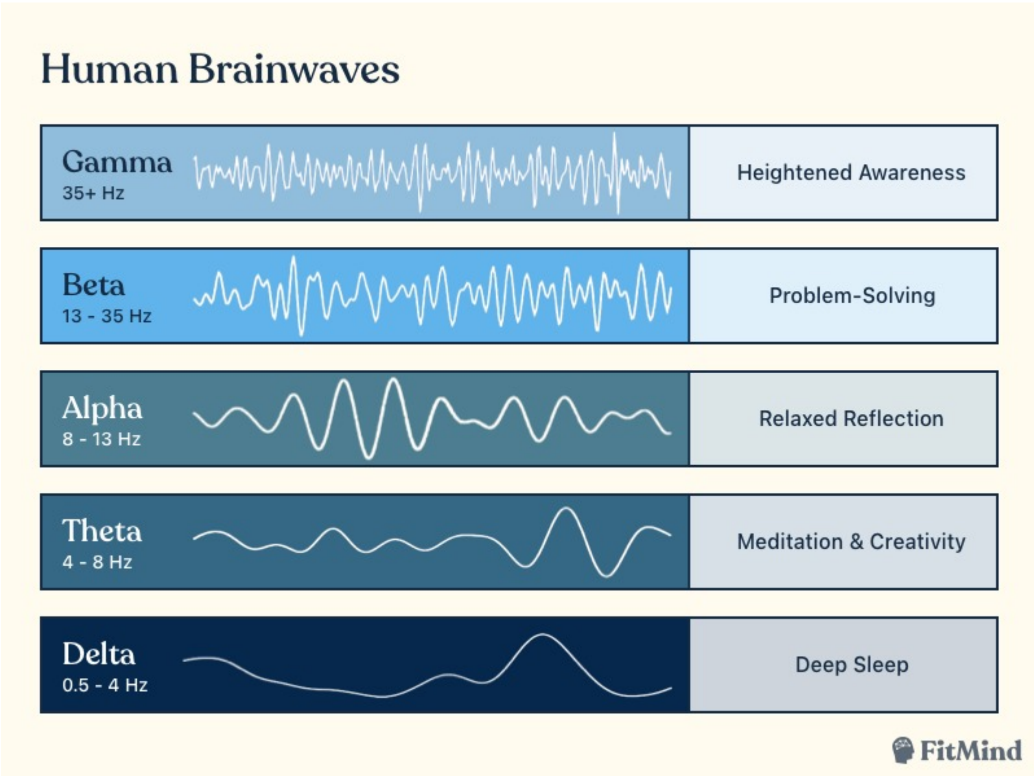


Figure 4.1: Brainwaves in EEG

Chapter 5

Data Acquisition

EEG Data was extracted using a single-channel data acquisition device and the serial plot tool.

Figure 5.1: Image of Subject captured during Data Acquisition

5.1 Tools

Serial plot tool (Software Tool)
Single-channel EEG Device (Hardware Tool)

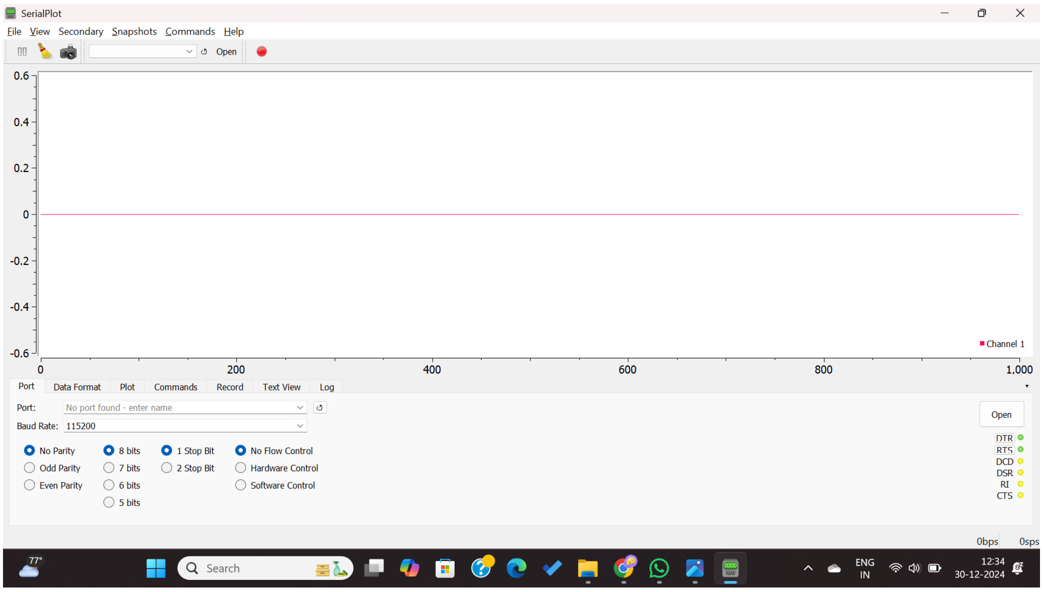


Figure 5.2: Serial Plot tool used with Data Acquisition

5.2 Dataset Link

EEG Data of Drowsy Subject

5.2.1 Description

The EEG data was recorded from the F8 region of the brain while the subject was drowsy, the frontal area is known for providing reliable information, which is found by the previous studies making it ideal for drowsiness detection studies.
The Dataset contains a single column of captured EEG Data.

Chapter 6

Methodology

The methodology used for drowsiness detection in EEG signals is as follows:

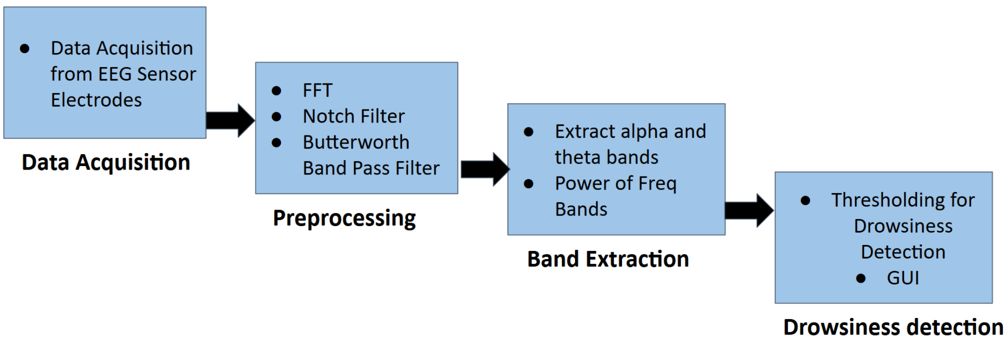


Figure 6.1: Block Diagram

1. **Load EEG Data:**
   - The EEG data is read from an Excel file ('F8-Channel-EEG-Data .xlsx') using the `xlsread` function.
2. **Preprocessing:**
   - **Sampling Parameters:**
     - Sampling frequency ($Fs = 250$)
   - **Fourier Transform (FFT):**

- Computes the frequency spectrum of the EEG signal.
- Calculates the magnitude of the FFT for spectral analysis.
-

$$X[k] = \sum_{n=0}^{N-1} x[n] \cdot e^{-j\frac{2\pi}{N}kn}, \quad k = 0, 1, 2, \ldots, N-1$$

- **Notch Filtering:**
  - Removes 50 Hz power-line noise using a notch filter.
  - Attenuates frequencies within a narrow bandwidth (± 1 Hz) around 50 Hz.
  - Reconstructs the filtered signal using the inverse FFT (IFFT).
  -

$$x[n] = \frac{1}{N} \sum_{k=0}^{N-1} X[k] \cdot e^{j\frac{2\pi}{N}kn}, \quad n = 0, 1, 2, \ldots, N-1$$

3. **Bandpass and Butterworth Filtering:**
   - Applies a 4th-order Butterworth bandpass filter to extract specific frequency bands:
     - **Theta Band (4–8 Hz):** Extracted using the bandpass filter.
     - **Alpha Band (8–13 Hz):** Extracted similarly for analysis.
4. **Power Calculation:**
   - Calculates the power in the Theta band (4–8 Hz) by adding squared FFT magnitudes in this range.
   - Similarly, computes the power in the Alpha band (8–13 Hz).

5. **Drowsiness Detection:**
   - Comparison of Theta and Alpha power was done using a threshold based logic:
     - If Theta Power > Alpha Power, drowsiness is detected or no drowsiness is detected.
6. **Visualization:**
   - Generates plots for:
     - Time-domain signals (original and filtered).
     - Frequency spectra (original and filtered).
     - Theta and Alpha band signals (time and frequency domains).
     - A bar chart comparing Theta and Alpha band powers.

Chapter 7

Results

The output of the EEG data obtained in the scenario is tested in the perspective of drowsiness, whether the person is drowsy or is alert by his EEG data.
The method is quite easier to user, making him comfortable to use it as shown in fig.7.1, where load switch at as data loader, and graphs shows the comparison of alpha and theta values on which the drowsiness detection depends. This GUI makes it easier for user to use it easily.

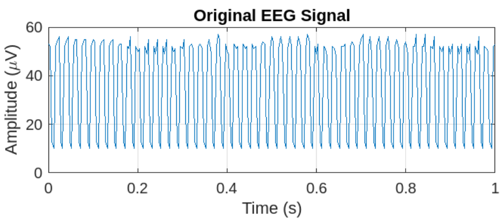


Figure 7.1:

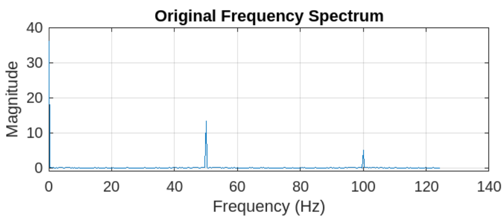


Figure 7.2:

The figures show the analysis of an EEG signal in time and frequency domains. Figure 6.1 displays the raw EEG signal over time, with amplitude (µV) on the Y-axis and time (s) on the X-axis, highlighting its oscillatory nature. Figure 6.2 shows the frequency spectrum, revealing dominant frequency components with magnitude on the Y-axis and frequency (Hz) on the X-axis. Together, they provide insights into the signal's temporal patterns and spectral content, aiding in brain activity analysis.

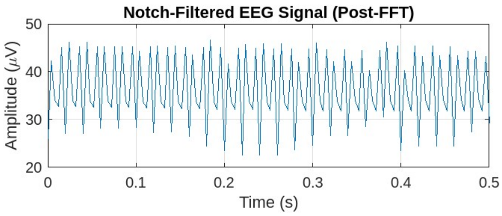


Figure 7.3:

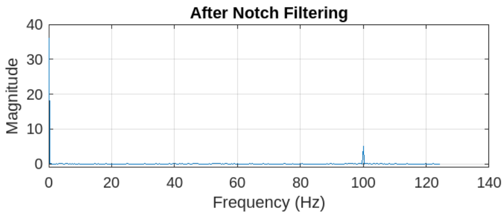


Figure 7.4:

Figures 6.3 and 6.4 illustrate the EEG signal after notch filtering. Figure 6.3 presents the time-domain representation, showcasing how the brain's electrical activity appears after the removal of noise at specific frequencies (likely 60 Hz and its harmonics) through notch filtering. Figure 6.4 depicts the frequency spectrum, revealing the distribution of power across different frequencies in the EEG signal after the notch filtering process. This analysis helps to identify the remaining frequency components in the EEG signal after the removal of the noise.

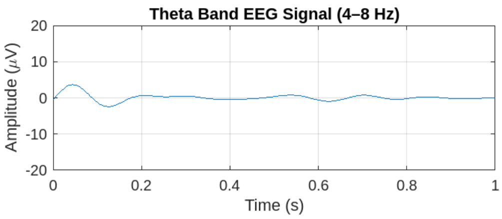


Figure 7.5:

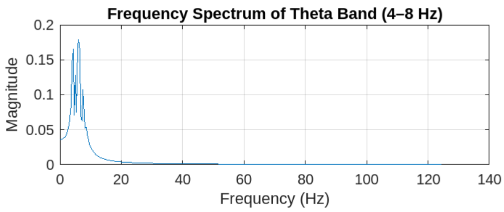


Figure 7.6:

Figures 6.5 and 6.6 illustrate the theta band EEG signal. Figure 6.5 presents the time-domain representation, showcasing how the brain's electrical activity fluctuates in the theta frequency range (4-8 Hz) over time. Figure 6.6 depicts the frequency spectrum, revealing the distribution of power across different frequencies within this band. This spectral analysis helps to identify the dominant frequencies within the theta range.

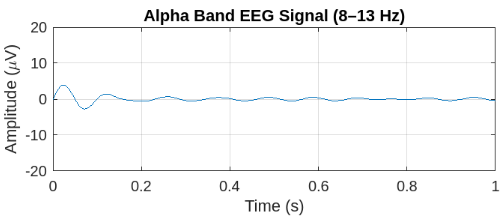


Figure 7.7:

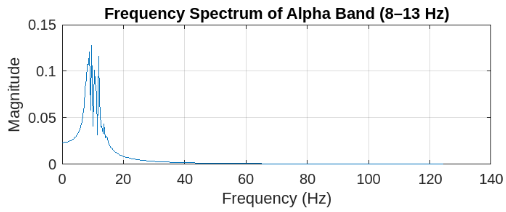


Figure 7.8:

Figures 6.7 and 6.8 focus on the alpha band EEG signal. Figure 6.57presents the time-domain representation, illustrating the fluctuations of brain activity in the alpha frequency range (8-13 Hz) over time. Figure 6.8displays the frequency spectrum, revealing the distribution of power across various frequencies within the alpha band. This analysis highlights the dominant frequencies within this band.

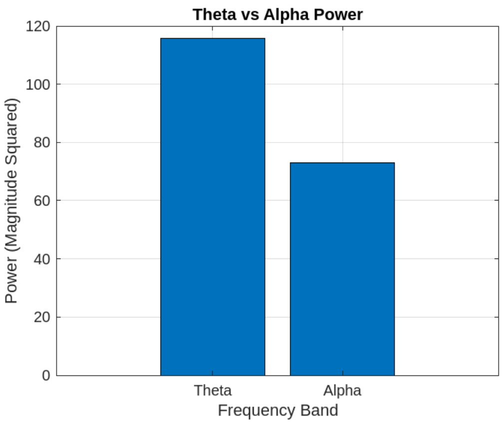


Figure 7.9:

Figure 6.9 presents a bar graph comparing the power of theta and alpha brainwaves. Power, measured in magnitude squared, represents the strength of the electrical activity in each frequency band. The graph shows that the theta band exhibits significantly higher power compared to the alpha band. This suggests that during the recording, brain activity was more prominent in the theta frequency range, which is typically associated with drowsiness states.

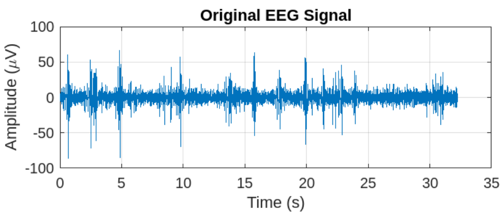


Figure 7.10:

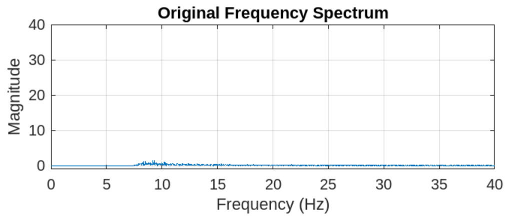
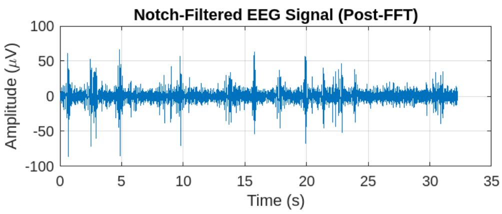


Figure 7.11:

The figures show the analysis of an EEG signal in time and frequency domains. Figure 6.10 displays the raw EEG signal over time, with amplitude (μV) on the Y-axis and time (s) on the X-axis, highlighting its oscillatory nature. Figure 6.11 shows the frequency spectrum, revealing dominant frequency components with magnitude on the Y-axis and frequency (Hz) on the X-axis. Together, they provide insights into the signal's temporal patterns and spectral content, aiding in brain activity analysis.



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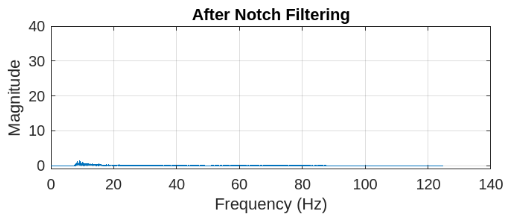


Figure 7.13:

Figures 6.12 and 6.13 illustrate the EEG signal after notch filtering. Figure 6.12 presents the time-domain representation, showcasing how the brain's electrical activity appears after the removal of noise at specific frequencies (likely 60 Hz and its harmonics) through notch filtering. Figure 6.13 depicts the frequency spectrum, revealing the distribution of power across different frequencies in the EEG signal after the notch filtering process. This analysis helps to identify the remaining frequency components in the EEG signal after the removal of the noise.

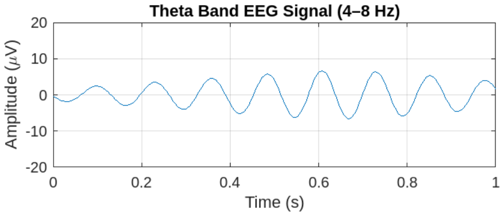


Figure 7.14:

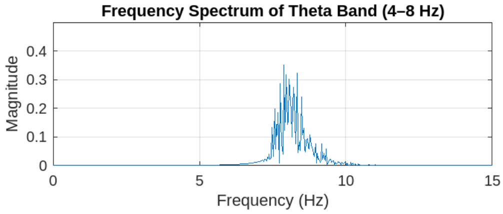
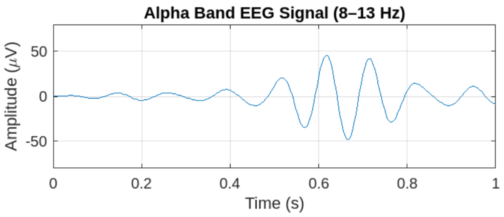


Figure 7.15:

Figures 6.14 and 6.15 illustrate the theta band EEG signal. Figure 6.14 presents the time-domain representation, showcasing how the brain's electrical activity fluctuates in the theta frequency range (4-8 Hz) over time. Figure 6.15 depicts the frequency spectrum, revealing the distribution of power across different frequencies within this band. This spectral analysis helps to identify the dominant frequencies within the theta range.



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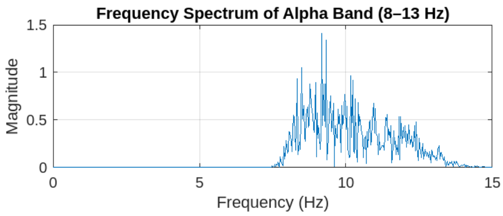

Figure 7.17:

Figures 6.16 and 6.17 focus on the alpha band EEG signal. Figure 6.16 represents the time-domain representation, illustrating the fluctuations of brain activity in the alpha frequency range (8-13 Hz) over time. Figure 6.17 displays the frequency spectrum, revealing the distribution of power across various frequencies within the alpha band. This analysis highlights the dominant frequencies within this band.

Figure 6.18 presents a bar graph comparing the power of theta and alpha brainwaves. Power, measured in magnitude squared, represents the strength of the electrical activity in each frequency band. The graph shows that the alpha band exhibits significantly higher power compared to the theta band.

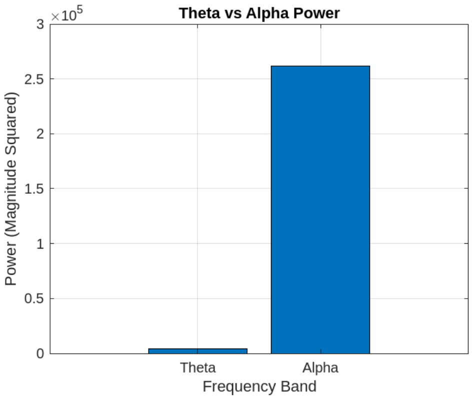

Figure 7.18:

This suggests that during the recording, brain activity was more prominent in the alpha frequency range, which is typically associated with relaxed wakefulness and mental calmness.

7.1 GUI Description

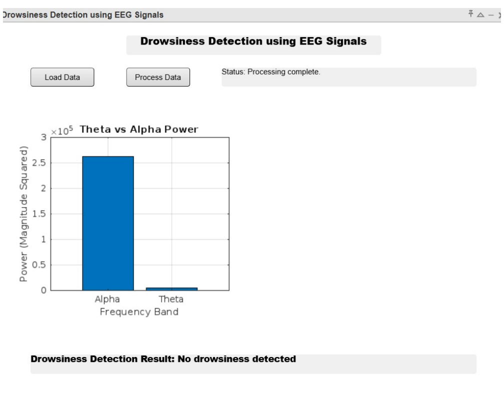

Figure 7.19:

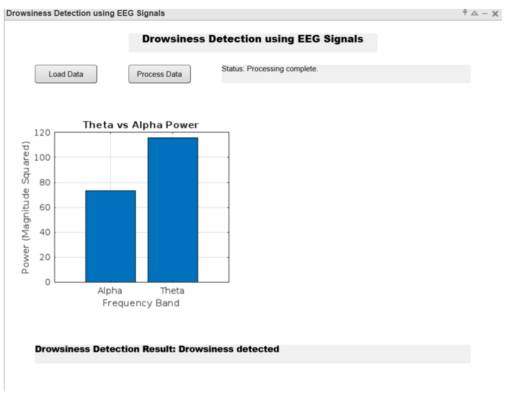

Figure 7.20:

Fig.7.1 represents the person alert as the alpha value is greater than theta. Fig.7.2 represents the person drowsy as theta value is greater than alpha.
MATLAB GUI facilitates drowsiness detection using EEG signals by analyzing the theta and alpha frequency bands. The

user-friendly interface allows users to load EEG data from an Excel file and process it with just a few clicks. The "Load Data" button imports the signal, while the "Process Data" button performs signal processing. The processing involves applying a notch filter to eliminate 50 Hz noise, followed by bandpass filtering to isolate theta (4-8 Hz) and alpha (8-13 Hz) frequency components. The power of each band is then calculated using the Fourier Transform, and these values are used for drowsiness detection.

If the theta power exceeds 1.5 times the alpha power, the program identifies drowsiness, displays the result, and plays an alert sound. A bar chart visually compares the theta and alpha power, helping users understand the data. The GUI provides real-time feedback and a simple way to monitor drowsiness effectively using EEG signals.

Chapter 8

Conclusion

This report demonstrates the feasibility of using EEG signals and DSP techniques for drowsiness detection. By analyzing the power of theta and alpha bands, the system effectively distinguishes between alert and drowsy states. The findings highlight the potential of EEG-based systems to enhance road safety by providing real-time drowsiness alerts.

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