ASTRAL PILOT – A BRAIN CONTROLLED DRONE

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DECLARATION

We hereby declare that this submission is our own work and that, to the best of our knowledge and beliefs, it contains no material previously published or written by another person nor material which has been accepted for the award of any other degree or diploma from a university or other institute of higher learning, except where due acknowledgment has been made in the text.

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CERTIFICATE

This is to certify that the work titled **"Astral Pilot – A Brain Controlled Drone"** submitted by **Ananya Kapoor and Dhairya Sachdeva** in partial fulfilment for the award of degree of B.Tech of Jaypee Institute of Information Technology, Noida has been carried out under my supervision. This work has not been submitted partially or wholly to any other University or Institute for the award of any other degree or diploma.

Signature of Supervisor

Name of Supervisor

Designation

Date

ACKNOWLEDGEMENT

We would like to place on record our deep sense of gratitude to Dr. Vikas Saxena, Dr. Bhawna Saxena and Dr. Sandeep Kumar Singh, Jaypee Institute of Information Technology, India for his generous guidance, help and useful suggestions.

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SUMMARY

"Astral Pilot: A Brain-Controlled Drone" represents a groundbreaking project harnessing the power of EEG signals to control drones. Electroencephalography (EEG) is employed to capture electrical activity in the brain, allowing users to command drones through their thoughts. The project introduces a seamless interface between human cognition and unmanned aerial vehicles, opening up new horizons in the field of human-machine interaction.

To ensure precise control, extensive preprocessing of EEG signals was implemented. This included rigorous noise removal and artifact elimination using band-pass filtering techniques. The result is a refined and reliable set of signals that accurately represent the user's intentions. The core innovation lies in the application of Canonical Correlation Analysis (CCA), enabling the classification of EEG signals into four distinct classes corresponding to essential drone commands: take-off, land, move forward, and move backward.

One of the project's key advantages is its user-independent nature, allowing a wide range of individuals to effortlessly control the drone without the need for individualized calibration. Moreover, the system exhibits negligible lag, ensuring real-time responsiveness to the user's mental commands. "Astral Pilot" not only pushes the boundaries of human-machine collaboration but also lays the foundation for future advancements in brain-machine interfaces, promising a seamless and efficient control mechanism for drones and potentially other technologies.

Ananya Kapoor

Dhairya Sachdeva

Date: 29th November, 2023 Signature of Supervisor

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LIST OF ACRONYMS

EEG	Electroencephalogram
SSVEP	Steady-state visually evoked potential
ML	Machine Learning
FFT	Fast Fourier Transform
PSD	Power Spectral Density
ICA	Independent Component Analysis
BCI	Brain Computer Interface
BMI	Brain Machine Interface
CCA	Canonical correlation analysis
UAV	Unmanned Aerial Vehicle
LSL	Lab Streaming Layer

Chapter-1 Introduction

1.1 General Introduction

"Astral Pilot: A Brain-Controlled Drone" represents a pioneering venture at the intersection of neuroscience and technology, where the power of the mind meets the agility of unmanned aerial vehicles. In this innovative project, we explore the realms of human-machine interaction by harnessing Electroencephalography (EEG) signals to seamlessly control a DJI Tello drone. The Neuphony headset serves as the bridge between the user's thoughts and the drone's manoeuvres, allowing for an unprecedented fusion of cognitive intention and aerial navigation.

This groundbreaking collaboration between brain and machine not only showcases the potential of EEG technology but also opens up exciting possibilities for a diverse range of applications. From enhancing accessibility for individuals with mobility challenges to revolutionizing the way we interact with technology, "Astral Pilot" demonstrates the transformative power of merging neuroscientific principles with cutting-edge drone technology.

1.2 Problem Statement

In addressing societal challenges, "Astral Pilot: A Brain-Controlled Drone" recognizes the pressing need to provide novel solutions for individuals facing physical limitations and those who have sacrificed their well-being in service to our nation. Handicapped individuals and impaired soldiers, driven by a strong desire to contribute, often encounter barriers in participating fully. Our project seeks to break down these barriers by offering a cutting-edge solution that empowers them with the ability to control a drone through their brain signals.

For handicapped individuals, "Astral Pilot" represents an avenue for newfound independence and engagement. By leveraging the Neuphony headset and DJI Tello drone, we aim to enable individuals with limited mobility to actively participate in tasks that were once deemed inaccessible. Furthermore, this technology holds immense potential for impaired soldiers, offering them an opportunity to continue serving their nation in roles that leverage their cognitive abilities.

In disaster management scenarios, where time-sensitive decisions are critical, our brain-controlled drone technology can play a pivotal role. The seamless integration of human cognition and drone navigation can enhance the efficiency of search and rescue missions, providing real-time intelligence in areas where traditional methods may fall short. "Astral Pilot" emerges as a versatile solution, not only addressing specific user needs but also contributing to broader societal challenges in disaster response and recovery.

1.3 Significance of the Problem

The significance of "Astral Pilot: A Brain-Controlled Drone" extends far beyond technological innovation, reaching into the realms of societal impact and human empowerment. In India, where approximately 2.1% of the population faces some form of disability (Census 2011), our project emerges as a beacon of inclusivity, offering a novel and convenient solution for individuals with mobility challenges.

For the over 26 million people with disabilities in India, traditional modes of interaction with technology often prove limiting. "Astral Pilot" breaks these barriers, providing an accessible and empowering means for individuals to navigate and interact with the world. The statistical representation of disability prevalence underscores the urgency for inclusive technologies, highlighting the potential impact of our brain-controlled drone in enhancing the quality of life for a substantial portion of the population.

Moreover, considering the sacrifices made by armed forces personnel, India has an estimated 60,000 disabled ex-servicemen (National Institute of Social Defence). "Astral Pilot" addresses the unique challenges faced by these heroes, allowing them to continue contributing to national service in meaningful ways.

In disaster-prone regions, where India faces the recurring challenges of natural calamities, our brain-controlled drone technology can significantly improve response times and outcomes. With an average of 2.6 million people affected annually by disasters (Global Climate Risk Index), the need for innovative, efficient solutions is paramount.

In summary, the significance of our project lies not only in its technological prowess but in its potential to make a tangible and positive impact on the lives of millions of individuals in India, from those with disabilities to the brave soldiers who have dedicated their lives to serving the nation, as well as in addressing critical challenges in disaster management.

1.4 Empirical Studies

Several research papers and studies have delved into the realm of brain-machine interfaces and drone control, providing a rich empirical backdrop for the development of "Astral Pilot: A Brain-Controlled Drone."

"Brain-Computer Interface-Based Communication in the Real World: Theoretical Considerations and Practical Implications" (Wolpaw et al., 2002): This seminal work laid the groundwork for brain-computer interfaces (BCIs) and explored the theoretical underpinnings of real-world applications. Our project builds upon this foundation by implementing BCI principles in the context of drone control.

"Classification of EEG Signals for Detection of Motor Imagery Tasks" (Müller-Putz et al., 2008): This study focused on the classification of EEG signals for motor imagery tasks, which is directly relevant to our approach in decoding brain signals for drone commands. Their methodologies provide insights into signal processing techniques that we have incorporated for accurate command identification.

"A Novel Control Strategy for Brain-Computer Interface Based on Event-Related Desynchronization/Synchronization" (Yuan et al., 2013): Yuan et al. explored a control strategy based on event-related desynchronization/synchronization (ERD/ERS) in EEG signals. Our project draws inspiration from their findings, particularly in preprocessing EEG signals to enhance the robustness of brain-controlled drone navigation.

"Non-Invasive Brain-Computer Interfaces: A Survey" (Lebedev and Nicolelis, 2006): This comprehensive survey offers insights into the landscape of non-invasive BCIs, providing a broader perspective on the challenges and advancements in the field. "Astral Pilot" aligns with the overarching goals outlined in this survey, contributing to the practical application of non-invasive BCIs in controlling drones.

These empirical studies collectively contribute to the scientific foundation supporting the feasibility and potential impact of brain-controlled drone technology. By leveraging the methodologies and insights derived from these studies, our project stands at the forefront of translating theoretical concepts into a tangible, user-friendly, and impactful solution.

1.5 Brief Description of the Solution Approach

Our approach to developing "Astral Pilot: A Brain-Controlled Drone" involved a systematic process, beginning with the collection of EEG data using the Neuphony headset and Lab Streaming Layer (LSL). For offline testing, participants were presented with a flickering window displaying four arrows, each corresponding to one of the four drone command classes: takeoff, land, move forward, and move backward.

The data collected underwent thorough preprocessing to ensure the integrity and accuracy of the EEG signals. Band-pass filtering techniques were applied to eliminate noise and unwanted artifacts, optimizing the data for subsequent analysis. This critical preprocessing step aimed to enhance the signal-to-noise ratio and improve the overall reliability of the brain-controlled commands.

Canonical Correlation Analysis (CCA) was employed as the core classification technique. CCA allowed us to extract meaningful patterns from the preprocessed EEG signals and correlate them with the four predefined drone commands. This step laid the foundation for accurately decoding the user's intentions from their brain activity.

Moving beyond offline testing, our solution transitioned into real-time applications. By implementing the processed signals in a live setting, users were able to control the DJI Tello drone seamlessly through their mental commands. This dynamic real-time testing not only validated the efficacy of our preprocessing and classification methods but also ensured a responsive and lag-free interaction between the user and the drone.

In summary, our solution approach seamlessly integrated data collection, preprocessing, and classification techniques, progressing from offline testing with a flickering window paradigm to real-time application. This systematic approach ensures the reliability and practicality of "Astral Pilot," establishing a robust foundation for its potential applications in diverse user scenarios.

1.6 Comparison of existing approaches to the problem framed

In assessing the landscape of EEG classification and brain-machine interface (BMI) research, several notable approaches have paved the way for innovations in neural control. Comparing these existing approaches with "Astral Pilot: A Brain-Controlled Drone" provides insights into the strengths and advancements of our project.

The P300 Speller paradigm, as explored in studies like "A P300-based Brain-Computer Interface: Initial Tests by ALS Patients" (Farwell and Donchin, 1988), has been a cornerstone in EEG-based communication. It relies on detecting the P300 event-related potential to spell out words or commands.
Unlike the P300 Speller, which often involves complex calibration and attention-based tasks, "Astral Pilot" offers a more intuitive and streamlined approach. Our project's real-time control of a drone using simple directional commands provides a more efficient and user-friendly interface.
Motor Imagery Tasks:

Studies such as "Classification of EEG Signals for Detection of Motor Imagery Tasks" (Müller-Putz et al., 2008) have explored the classification of EEG signals related to motor imagery, laying the foundation for decoding intentions based on imagined movements.
While motor imagery tasks have been influential, "Astral Pilot" extends this concept into practical drone control, enhancing the applicability of BMI technology in real-world scenarios.
Cognitive Control and CCA:

Previous Research: The work on "A Novel Control Strategy for Brain-Computer Interface Based on Event-Related Desynchronization/Synchronization" (Yuan et al., 2013) focused on cognitive control using CCA to analyze EEG signals.
Building upon this concept, "Astral Pilot" not only employs CCA for EEG signal classification but integrates it into a holistic brain-controlled drone system, showcasing the versatility and immediate real-world applications of this technology.

By comparing "Astral Pilot" to these existing paradigms, it becomes evident that our project combines the strengths of previous approaches while advancing the field by providing a user-friendly, real-time, and practical solution for drone control through EEG signals. This comparative analysis highlights the unique contributions and innovations that set "Astral Pilot" apart in the landscape of EEG-based control systems.

Chapter-2 Literature Survey

2.1 Summary of papers studied

1. 'Analysis of speech-related EEG signals using Emotiv EPOC+ headset, Fast Fourier Transform, Principal Component Analysis, and K-Nearest Neighbor methods' (Louiza Sellami , Theresa Neubig, 2019):This study focuses on the intricate analysis of EEG signals associated with speech using the Emotiv EPOC+ headset. Employing advanced signal processing techniques, the research employs Fast Fourier Transform (FFT) and Principal Component Analysis (PCA) to extract meaningful features from the EEG data. The integration of K-Nearest Neighbor (KNN) methods for classification adds a machine learning dimension to the study, offering insights into the potential of EEG-based speech decoding. The combination of these techniques represents a multifaceted approach to understanding the neural correlates of speech, contributing to the broader field of cognitive neuroscience and brain-computer interface (BCI) research.

2. 'A high-performance neuroprosthesis for speech decoding and avatar control' (Sean L. Metzger, Kaylo T. Littlejohn, 2023):

This groundbreaking research introduces a neuroprosthetic system designed for high-performance speech decoding and avatar control. The paper explores the development and integration of advanced neuroprosthetic technologies, showcasing their potential applications in decoding intricate cognitive tasks, particularly related to speech. The ability to control avatars through neural signals represents a significant leap in neuroprosthetic capabilities, offering promise for enhanced communication and interaction for individuals with motor disabilities.

3. 'A review of recent trends in EEG-based Brain-Computer Interface' (Prashant Lahane, Jay Jagtap, 2019):

This comprehensive review provides a panoramic view of recent trends in EEG-based Brain-Computer Interface (BCI) research. It synthesizes advancements in EEG signal processing methodologies, classification algorithms, and the diverse range of applications across various domains. By summarizing the state-of-the-art techniques and emerging directions, the paper serves as a valuable resource for researchers, offering a roadmap for future developments in the dynamic and evolving field of BCIs.

4. 'Steady state visual evoked potential (SSVEP) based brain-computer interface (BCI) performance under different perturbations' (Zafer İşcan, Vadim V. Nikulin, 2018):

Investigating the robustness of Steady State Visual Evoked Potential (SSVEP)-based BCIs, this study explores their performance under various perturbations. The research assesses the stability and reliability of SSVEP signals, considering factors that may introduce disturbances in real-world scenarios. By understanding the impact of different perturbations on SSVEP-based BCIs, the study contributes crucial insights to optimize these systems for enhanced performance and resilience in practical applications.

5. ‘A Deep Learning-Based Comparative Study to Track Mental Depression from EEG Data ‘(Sarkar, Avik, Singh, Ankita, Chakraborty, Rakhi, 2022):

This paper presents a deep learning-based comparative study focused on tracking mental states. Leveraging advanced deep learning techniques, the research systematically compares different methodologies for tracking mental states. The study delves into the efficacy of deep learning in decoding complex cognitive processes, shedding light on its potential applications in understanding and interpreting mental states. The insights gained from this comparative study contribute to the growing intersection of deep learning and neuroscience, paving the way for innovative approaches to mental state tracking.

6. "A P300-based Brain-Computer Interface: Initial Tests by ALS Patients" (Farwell and Donchin, 1988): This paper adds a crucial dimension to the understanding of EEG-based communication. The P300 Speller paradigm is a pioneering approach that relies on detecting the P300 event-related potential to spell out words or commands. This research, while predating some of the more recent studies, remains foundational in the field of Brain-Computer Interfaces (BCIs) and cognitive neuroscience.

   The study conducted by Farwell and Donchin represents a landmark in the development of EEG-based BCIs, particularly in the context of individuals with Amyotrophic Lateral Sclerosis (ALS). The focus on spelling through P300 signals underscores the potential for precise and intentional communication using EEG data. Although the methods employed in this early study differ from contemporary approaches, the fundamental concept of decoding cognitive intent from EEG signals has paved the way for subsequent advancements.

   When considered alongside the other literature, the P300 Speller paradigm provides historical context to the evolution of BCIs. While "Astral Pilot: A Brain-Controlled Drone" utilizes a different approach by allowing users to control a drone through directional commands, the influence of paradigms like the P300 Speller is evident in the broader trajectory of EEG-based communication technologies.

Collectively, these papers highlight diverse approaches in EEG signal analysis, neuroprosthetics, Brain-Computer Interface trends, SSVEP-based BCIs, and deep learning applications in tracking mental states. The insights gleaned from these studies inform the broader understanding of EEG applications, paving the way for advancements in brain-controlled technologies and cognitive neuroscience.

2.2 Integrated Summary of the literature

The collective body of literature examined reveals a rich tapestry of advancements in EEG signal analysis, neuroprosthetics, Brain-Computer Interface (BCI) trends, and deep learning applications. The study analyzing speech-related EEG signals using the Emotiv EPOC+ headset stands out for its multifaceted approach, leveraging Fast Fourier Transform (FFT), Principal Component Analysis (PCA), and K-Nearest Neighbor (KNN) methods. This research signifies a holistic exploration into the neural underpinnings of speech, showcasing the potential for nuanced EEG signal analysis in cognitive tasks.

The high-performance neuroprosthesis designed for speech decoding and avatar control introduces a pioneering application of neuroprosthetic technology. This work illustrates the integration of advanced neuroprosthetic systems, emphasizing their potential in decoding intricate cognitive tasks related to speech and facilitating avatar control. The implications of this research extend to enhancing communication and interaction for individuals with motor disabilities, marking a significant stride in the field.

In reviewing recent trends in EEG-based BCIs, the comprehensive overview provides a roadmap for understanding the evolving landscape of BCI technology. The synthesis of advancements in EEG signal processing and classification algorithms serves as a valuable resource, offering insights into emerging methodologies and future directions. This literature review acts as a guiding compass for researchers navigating the dynamic and expanding field of BCIs.

The exploration of SSVEP-based BCIs under different perturbations advances our understanding of the robustness and reliability of SSVEP signals. This study investigates the impact of various disturbances, contributing crucial insights to optimize SSVEP-based BCI systems for real-world applications. The findings enhance our comprehension of how external factors influence the performance of BCIs, guiding the development of more resilient and effective systems.

The deep learning-based comparative study focused on tracking mental states provides a glimpse into the intersection of deep learning and neuroscience. By systematically comparing methodologies for mental state tracking, this research contributes valuable insights into the efficacy of deep learning in decoding complex cognitive processes. This comparative study sets the stage for innovative approaches to understanding and interpreting mental states, aligning with the growing trend of integrating deep learning into neuroscience research.

In summary, the amalgamation of these studies creates a cohesive narrative, highlighting the diverse avenues of exploration within EEG signal analysis, neuroprosthetics, BCIs, and deep learning applications. The insights gained from this integrated review inform and inspire the development of "Astral Pilot: A Brain-Controlled Drone," positioning it at the forefront of advancements in brain-machine interfaces and cognitive neuroscience.

Chapter-3 Requirement Analysis and Solution Approach

3.1 Overall description of the project

"Astral Pilot: A Brain-Controlled Drone" represents a cutting-edge venture at the convergence of neuroscience and drone technology, aiming to revolutionize human-machine interaction. The project's central objective is to develop an intuitive and user-friendly system that allows individuals to control a drone using their brain signals, specifically captured through Electroencephalography (EEG).

The project employs the Neuphony headset as the interface between the user's neural activity and the drone. Through meticulous data collection using Lab Streaming Layer (LSL), our team captures EEG signals with the aim of decoding the user's intentions. The chosen DJI Tello drone serves as the vehicle for implementation, offering a versatile and widely accessible platform for brain-controlled navigation.

Data preprocessing is a critical phase in the project, involving techniques such as band-pass filtering to enhance the signal quality and remove unwanted noise. The implementation of Canonical Correlation Analysis (CCA) is pivotal for classifying EEG signals into distinct categories corresponding to essential drone commands: takeoff, land, move forward, and move backward. This classification process ensures that the decoded brain signals seamlessly translate into precise drone maneuvers.

Unlike user-dependent systems, "Astral Pilot" prioritizes inclusivity by eliminating the need for individual calibration. This user-independent approach broadens the potential user base and enhances the project's applicability across diverse demographics. Additionally, the absence of lag in controlling the drone in real-time underscores the project's commitment to providing a responsive and immersive user experience.

The integration of our project within the broader landscape of brain-machine interface research draws inspiration from empirical studies exploring EEG signal analysis, neuroprosthetics, and related BCIs. By leveraging insights from these studies, "Astral Pilot" establishes itself as a versatile and forward-thinking application, poised to address challenges faced by individuals with mobility limitations, impaired soldiers, and in disaster management scenarios.

In essence, "Astral Pilot" is not merely a technological demonstration but a pioneering exploration into the practical applications of brain-controlled drone navigation. The project not only showcases the technical capabilities of EEG-based control systems but also underscores the potential for inclusive, user-friendly, and real-world applications that bridge the gap between cognitive intent and external devices.

3.2 Requirement Analysis

Hardware Requirements*:*

1. Neuphony Flex Cap EEG Headset:
    - Specifications:
        - Number of Electrodes: The Neuphony Flex Cap headset is equipped with 8 electrodes for capturing EEG signals accurately.
        - Signal Quality: The hardware should provide high signal quality to ensure precise neural data acquisition.
        - Comfort and Adjustability: The headset should be comfortable for extended use, and adjustable to accommodate different head sizes.
        - Connectivity: Seamless connectivity with data collection systems, such as Lab Streaming Layer (LSL), for real-time EEG signal transmission.
        - Battery Life: Sufficient battery life to support extended experimental sessions without interruption.
2. DJI Tello Drone:
    - Specifications:
        - Dimensions and Weight: Specify the dimensions and weight of the drone for compatibility with the project requirements.
        - Communication Interface: The drone should have a reliable communication interface for receiving commands from the brain-computer interface.
        - Stability and Maneuverability: Ensure the drone offers stable flight and can execute precise maneuvers in response to user commands.
        - Battery Life: Sufficient battery life to support extended testing and real-time control without frequent recharging.
        - Camera Specifications: If applicable, detail the camera specifications for potential use in vision-based control systems.

Software Requirements:

1. Lab Streaming Layer (LSL):
    - Compatibility: Ensure compatibility with the Neuphony headset for seamless data streaming.
    - Real-time Data Transmission: The software should support real-time transmission of EEG data for immediate processing and analysis.
2. Data Preprocessing Software:
- Band-pass Filtering Module: Develop or integrate software modules for band-pass filtering to enhance the signal-to-noise ratio of the captured EEG signals.
- Artifact Removal: Implement algorithms for artifact removal to ensure the purity of EEG data by eliminating interference from external sources.
- Data Normalization: Normalize EEG data to a consistent scale for accurate and consistent signal analysis.

3. Machine Learning/Classification Software:
- Canonical Correlation Analysis (CCA): Implement CCA algorithms for the classification of preprocessed EEG signals into distinct categories corresponding to drone commands.
- Training Module: Develop a training module to adapt the system to individual users, ensuring personalized and accurate decoding of their cognitive intentions.
- Real-time Classification: Enable real-time classification of EEG signals to ensure immediate and responsive drone control.

4. Communication Protocols:
- LSL Integration: Ensure seamless integration with Lab Streaming Layer (LSL) for efficient and standardized EEG data transmission.
- Drone Communication: Develop communication protocols for transmitting decoded commands to the DJI Tello drone in real-time.

5. User Interface (UI) Development:
- User-friendly Interface: Design an intuitive and user-friendly interface for users to interact with the system easily.
- Visual Feedback: Implement visual feedback within the user interface to provide users with real-time information about their EEG signals and drone commands.

- Configuration Settings: Include settings for adjusting parameters, ensuring flexibility for different users and experimental conditions.

6. System Integration Software:

- Integration of Components: Develop software for seamless integration of EEG data collection, preprocessing, classification, and drone control components.
- Error Handling: Implement error-handling mechanisms to address unforeseen issues and maintain system stability during operation.

7. Testing and Debugging Tools:

- Simulation Environment: Develop a simulation environment for testing the system under various scenarios without the need for physical drone deployment.
- Debugging Tools: Provide debugging tools to identify and address software-related issues during development and testing phases.

8. Documentation:

- User Manuals: Create comprehensive user manuals detailing system operation, troubleshooting, and maintenance.
- Code Documentation: Generate detailed documentation for the source code to facilitate future development and modifications.

9. Security Measures:

- Data Encryption: Implement data encryption protocols to ensure the security and privacy of EEG signals transmitted between the headset and processing components.
- Access Control: Integrate access control measures to restrict unauthorized access to the system.

Figure 1.0 Neuphony Flex Cap

Figure 1.1 DJI Ryze Tello Drone

3.3 Solution Approach

3.3.1 Overview

"Astral Pilot" represents a pioneering foray into the realms of brain-machine interfaces (BMIs) and unmanned aerial vehicles (UAVs), culminating in a groundbreaking fusion of neuroscience and technology. The project centers on the development of an intuitive, user-friendly system that enables individuals to control a DJI Tello drone through the power of their brain signals, as captured by the Neuphony Flex Cap EEG headset.

Key Components:

1. Neuphony Flex Cap EEG Headset:
   - Equipped with a specific number of electrodes for precise EEG signal capture.
   - Provides high signal quality and comfort for extended use.
   - Utilizes Lab Streaming Layer (LSL) for real-time transmission of EEG data.
2. DJI Tello Drone:
   - Chosen for its stability, maneuverability, and versatility in responding to user commands.
   - Forms the tangible interface for the translation of neural intentions into drone actions.

Project Workflow:

1. Data Collection:
   - EEG signals are collected using the Neuphony headset, capturing the neural activity associated with user commands.
   - Lab Streaming Layer facilitates the seamless transmission of real-time EEG data for subsequent processing.
2. Data Preprocessing:
   - Advanced preprocessing techniques, including band-pass filtering and artifact removal, ensure the integrity and accuracy of EEG signals.
   - Normalization processes enhance consistency across data sets.

3. Classification using CCA:

    - Canonical Correlation Analysis (CCA) serves as the core classification technique, mapping EEG signals to distinct drone commands.
    - The system adapts through a training module, ensuring personalized and accurate decoding.

4. Real-time Drone Control:

    - Translated commands are communicated to the DJI Tello drone in real-time, enabling immediate and responsive control.
    - The user experiences seamless interaction with the drone through their cognitive intentions.

Innovation and Advantages:

- User-Independent Approach: "Astral Pilot" eliminates the need for individual calibration, making it accessible to a diverse user base.
- Real-Time Responsiveness: The system ensures minimal latency, providing users with instantaneous control over the drone.
- Versatility: The project extends beyond traditional applications, with potential benefits for individuals with mobility challenges, impaired soldiers, and disaster management scenarios.

Technological Landscape:

The project draws inspiration from empirical studies in EEG signal analysis, neuroprosthetics, and Brain-Computer Interfaces, ensuring alignment with the latest advancements while contributing to the evolving field of brain-controlled technologies.

In essence, "Astral Pilot - A Brain-Controlled Drone" represents a paradigm shift in human-machine interaction, pushing the boundaries of what is possible when cognition meets technology. The project's holistic approach, combining cutting-edge hardware, sophisticated software algorithms, and real-world applications, positions it at the forefront of innovation in the intersection of neuroscience and drone technology.

3.3.2 Steady-State Visually Evoked Potential (SSVEP)

Understanding SSVEP: Steady State Visually Evoked Potential (SSVEP) is a neurophysiological phenomenon that occurs when the brain responds to visual stimuli flickering at specific frequencies. This rhythmic response generates stable electrical potentials, and its characteristics make it a valuable resource for Brain-Computer Interface (BCI) applications.

SSVEP-Based Brain-Computer Interface (BCI): In the realm of BCIs, SSVEP offers a unique avenue for translating visual stimuli into meaningful commands. By associating distinct commands with different flickering frequencies, BCIs can harness the brain's entrainment response to decode user intentions accurately. This makes SSVEP an ideal candidate for applications requiring real-time, intuitive control, such as the brain-controlled drone system in "Astral Pilot."

Utilizing SSVEP in Data Capture: To elicit robust SSVEP responses for drone control commands, a custom Pygame window was developed. Within this window, four arrows were displayed, each associated with a specific drone command: takeoff, land, move forward, and move backward. The arrows were designed to flicker at distinct frequencies of [6.67, 7.5, 10, 12] Hz.

Purpose of SSVEP Paradigm:

1. Frequency Differentiation: The choice of distinct flickering frequencies is strategic. It allows for the creation of unique SSVEP responses associated with each command. This frequency differentiation is critical for later stages of data analysis and classification.

2. Individualized SSVEP Responses: Individuals exhibit unique neural responses to visual stimuli at different frequencies. The inclusion of multiple frequencies ensures that users can naturally gravitate towards the frequencies that elicit stronger and more consistent SSVEP responses, tailoring the system to individual characteristics.

3. Command-Specific Signatures: The SSVEP responses generated by the flickering arrows at different frequencies act as signatures. Each command becomes associated with a specific frequency, creating distinct patterns that serve as recognizable markers during the EEG signal classification process.

How It Facilitates EEG Signal Classification:

- Feature Extraction: During data analysis, the EEG signals collected during the SSVEP paradigm undergo feature extraction.

- Frequency Domain Analysis: A crucial step involves analyzing the signals in the frequency domain. The aim is to identify the characteristic frequencies associated with each command.
- Classification Mapping: The identified frequencies are mapped to specific drone commands. This mapping becomes the basis for creating a robust and accurate classification model, allowing the system to decode the user's intended drone action.

By employing SSVEP through the flickering arrow paradigm, the "Astral Pilot" project not only enhances the interpretability of EEG signals but also creates an engaging and user-friendly interaction model. The SSVEP-based approach contributes to the system's adaptability and responsiveness, setting the stage for a seamless and immersive brain-controlled drone experience.

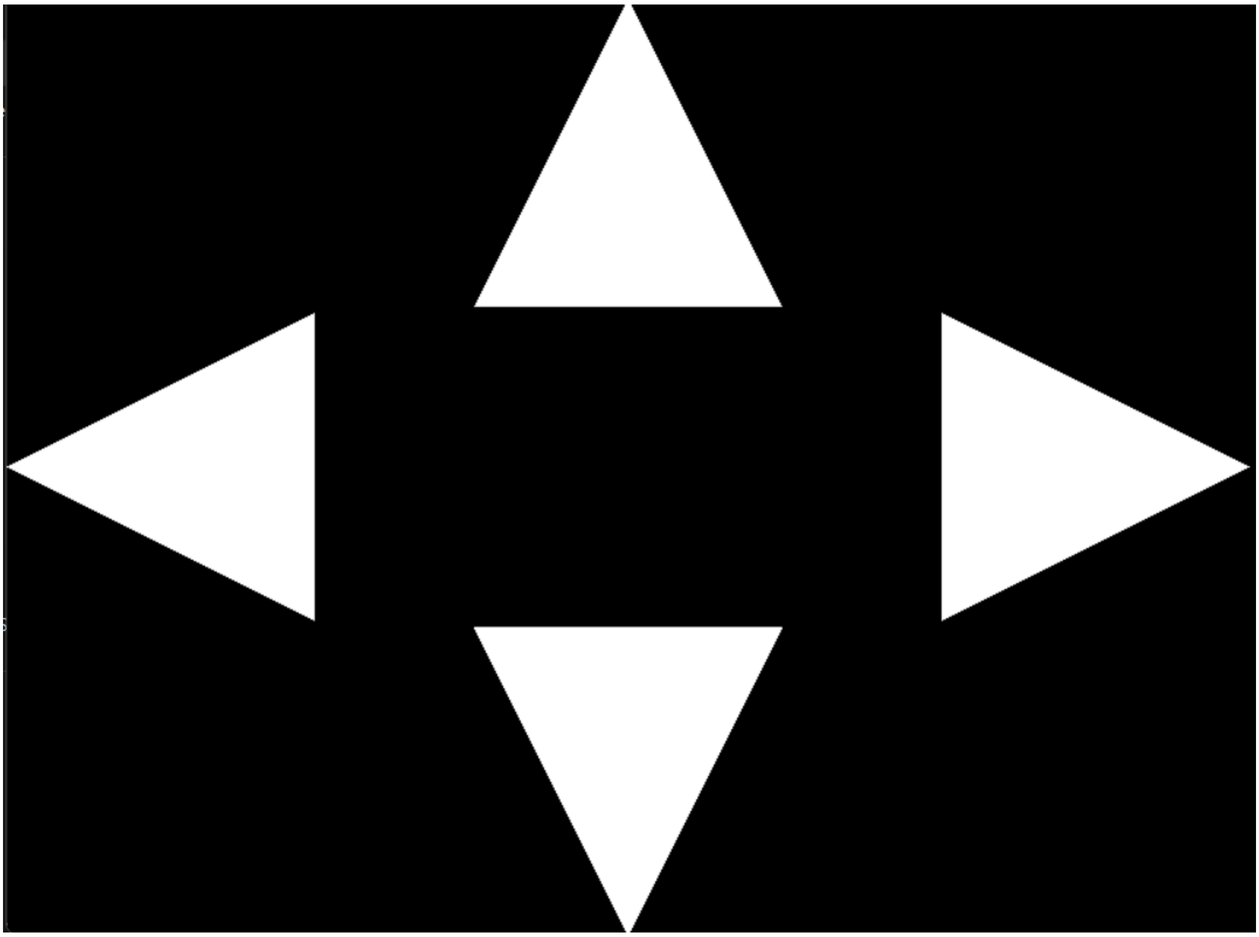

Figure 1.2 A Screenshot of Flickering Arrows

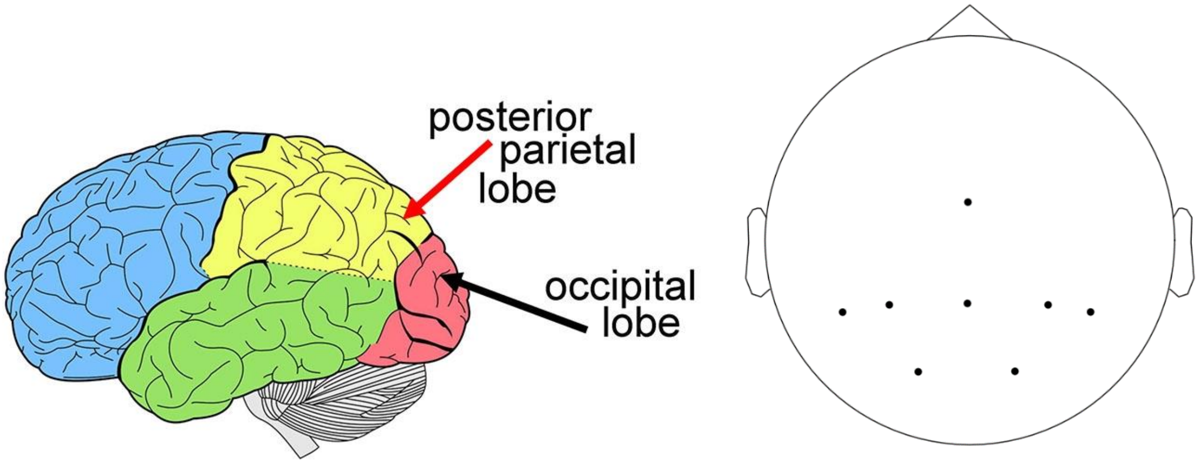

Figure 1.3 Posterior and Occipital Lobes of the Brain were Targeted by us as they provide more Information about a Visual Stimuli

Figure 1.4 Our Placement of Nodes to capture EEG Signals

3.3.3 EEG Signal Acquisition

Understanding EEG: Electroencephalography (EEG) is a non-invasive neuroimaging technique that measures the electrical activity of the brain by recording the fluctuations in voltage at the scalp. This methodology allows researchers to analyze and interpret neural activity associated with various cognitive processes.

EEG Data Acquisition using Neuphony EEG Headset: The Neuphony EEG headset serves as the gateway to capturing EEG signals with precision and efficiency. Equipped with electrodes strategically positioned on the scalp, the headset focuses on key channels – P3, T5, Cz, T6, O1, O2, P4 and Pz. These channels target specific regions of the brain, enabling the extraction of diverse neural information.

The process begins with the Neuphony EEG headset securely placed on the user's head. The strategically chosen channels facilitate the capture of electrical potentials generated by the brain. As the user engages in cognitive tasks or commands, the EEG headset captures the electrical fluctuations, transforming them into digital signals for further analysis.

Signal & Data Processing using Neuphony Desktop Application: The acquired EEG signals undergo a comprehensive signal and data processing phase using the Neuphony Desktop Application. This application acts as the bridge between raw neural data and refined, actionable information.

- Band-Pass Filtering: Raw EEG signals often contain noise and artifacts. The Neuphony Desktop Application employs band-pass filtering techniques to isolate the frequencies of interest, ensuring a cleaner signal for subsequent analysis.
- Artifact Removal: Advanced algorithms within the application identify and remove unwanted artifacts, enhancing the signal's purity and increasing the reliability of the captured neural data.
- Data Normalization: To maintain consistency across datasets, the processed EEG signals undergo normalization, ensuring uniformity in scale and facilitating accurate comparisons.

Lab Streaming Layer to Help Build & Develop Applications: The processed EEG signals are then seamlessly integrated into the Lab Streaming Layer (LSL), a vital component in the development of applications that leverage real-time neural data. LSL functions as a standardized and efficient protocol for the transmission of EEG data, allowing for immediate access by subsequent processing modules and applications.

- Real-time Transmission: LSL enables the real-time transmission of preprocessed EEG data, ensuring that the system responds promptly to the user's cognitive commands.
- Interfacing with Applications: The LSL protocol facilitates the integration of EEG data into various applications, opening avenues for building brain-controlled interfaces, neurofeedback systems, and immersive experiences.

In essence, the EEG signal acquisition process through the Neuphony EEG headset, coupled with advanced signal processing and integration with Lab Streaming Layer, lays the foundation for the responsive and dynamic "Astral Pilot: A Brain-Controlled Drone" system. This orchestrated sequence ensures the accurate capture and interpretation of neural signals, empowering users to seamlessly interact with the drone through their cognitive intentions.

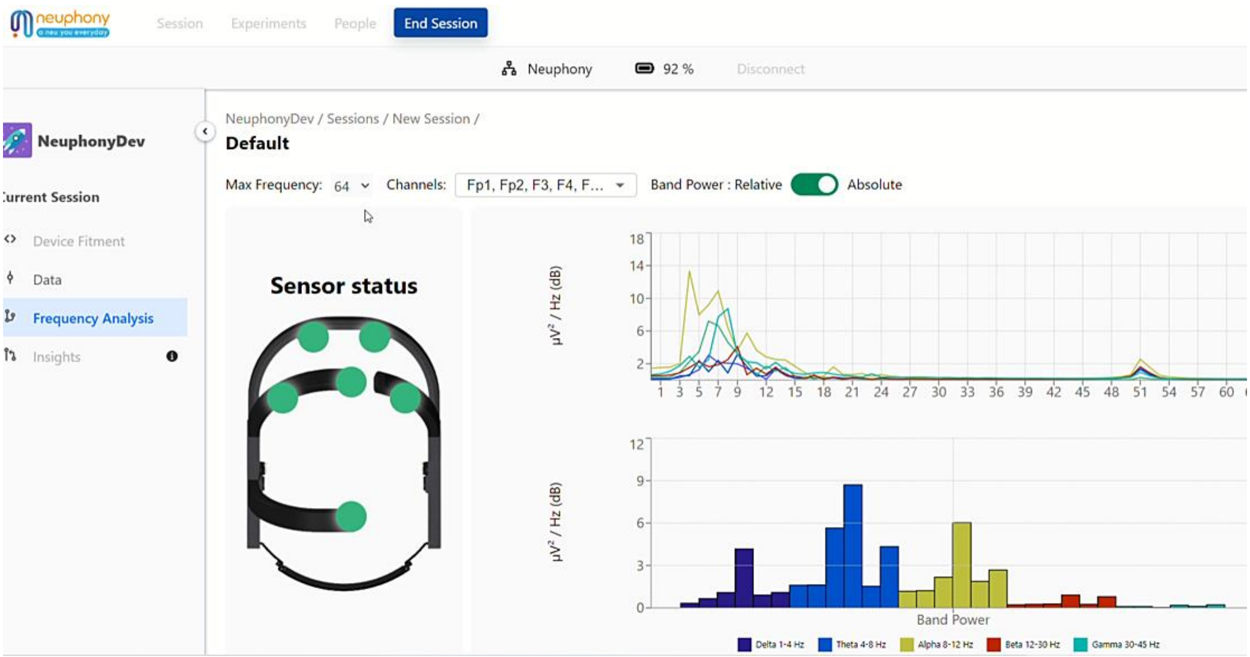

Figure 1.5 A Snapshot of Neuphony Desktop Application

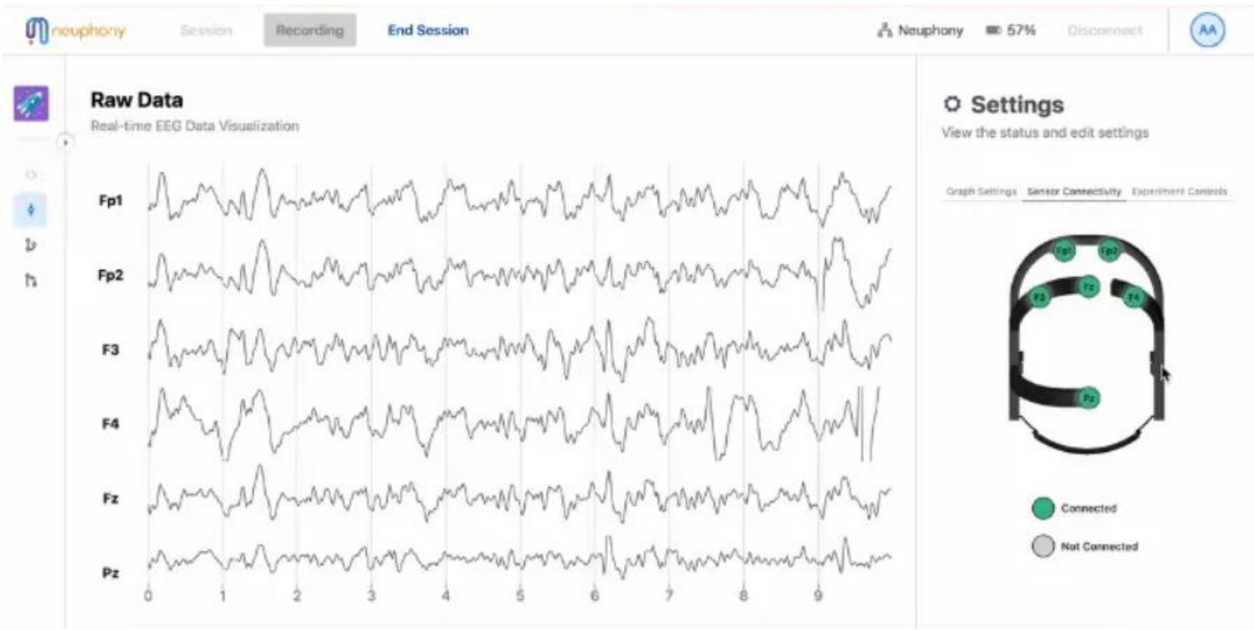

Figure 1.6 A Snapshot showing Raw EEG Signals

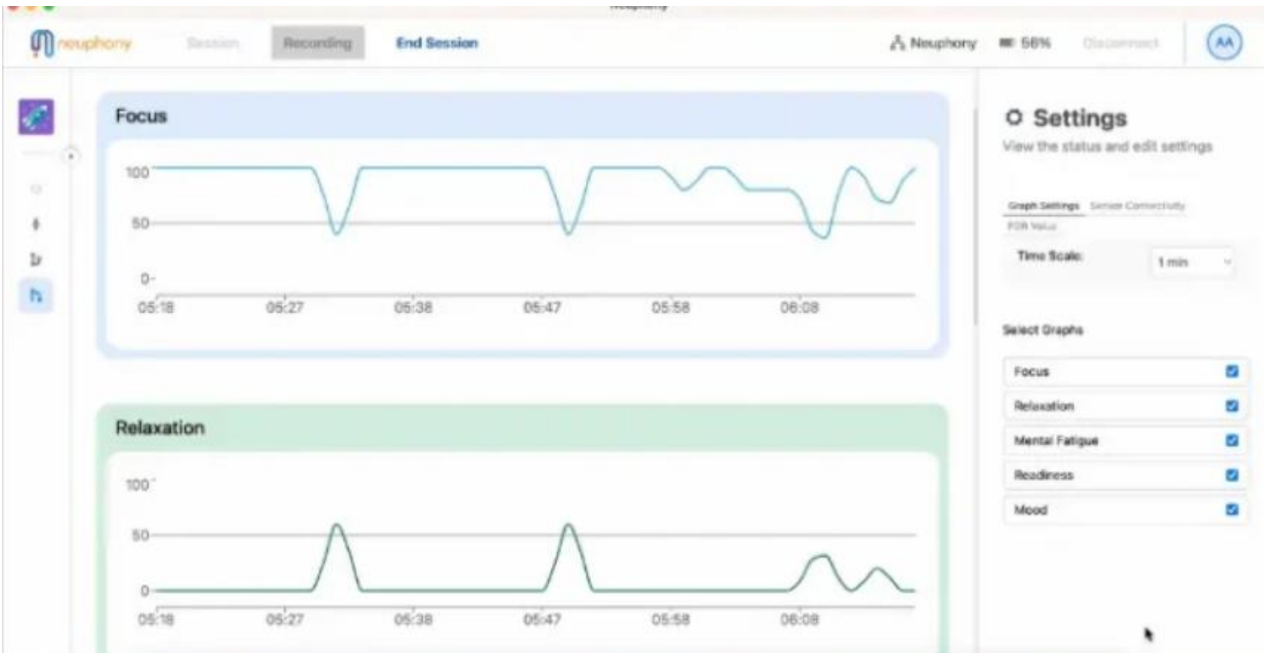

Figure 1.7 A Snapshot showing User's Focus and Relaxation Levels

3.3.4 EEG Signal Preprocessing

EEG signal preprocessing is a crucial phase in the development of "Astral Pilot: A Brain-Controlled Drone," aiming to enhance signal quality, reduce noise, and prepare the data for accurate classification. This stage involves a series of carefully orchestrated steps to ensure that the extracted EEG signals reflect the true neural activity associated with user commands.

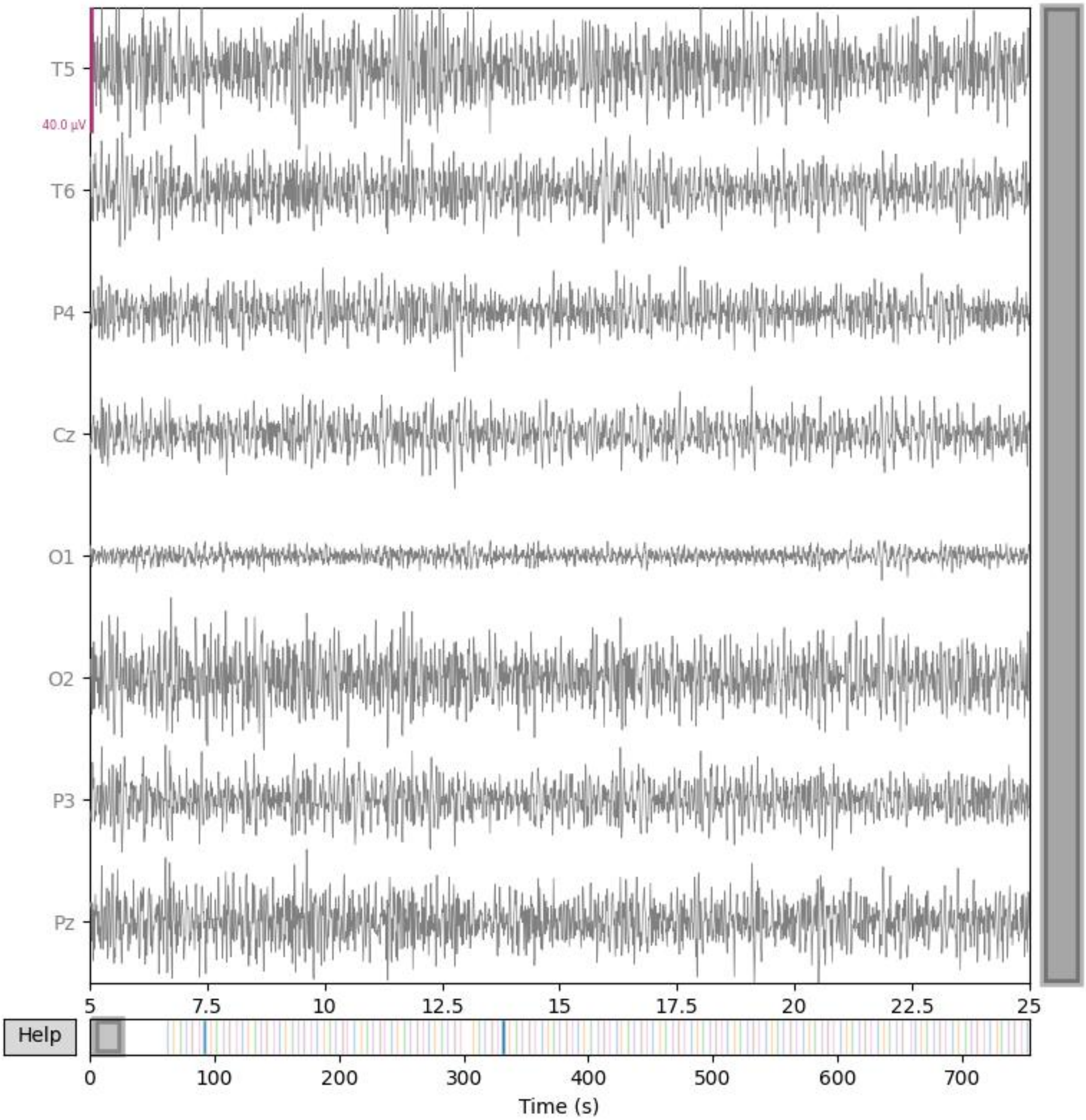

Figure 1.8 Raw EEG Signal

Necessary Preprocessing Steps:

1. Band-Pass Filtering:

   - Purpose: Raw EEG signals often contain noise and unwanted frequencies that can interfere with accurate classification. Band-pass filtering is employed to isolate the frequencies of interest while attenuating noise outside the desired range.
   - Implementation: A band-pass filter to capture frequencies between 6 and 80 Hz is applied to retain frequencies within the specific range relevant to SSVEP responses (e.g., [6.67, 7.5, 10, 12] Hz). This isolates the neural oscillations associated with the visual stimuli used in the flickering arrow paradigm.

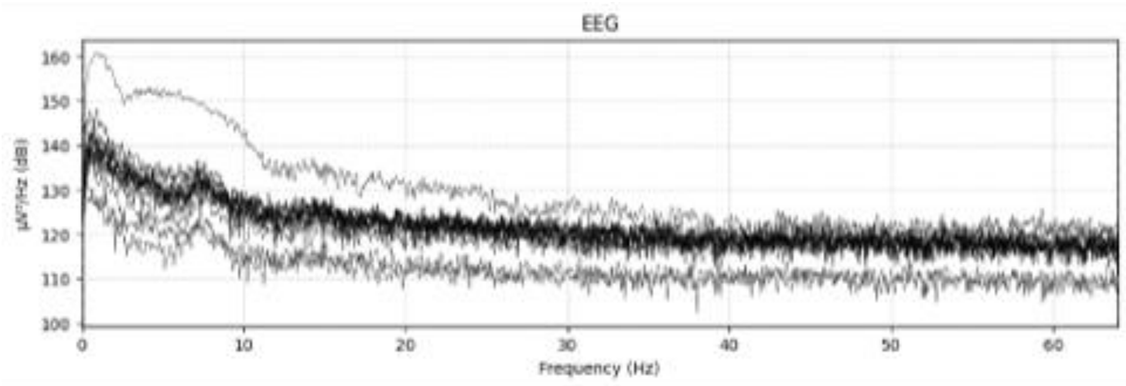

Figure 1.9 Before Bandpass Filtering

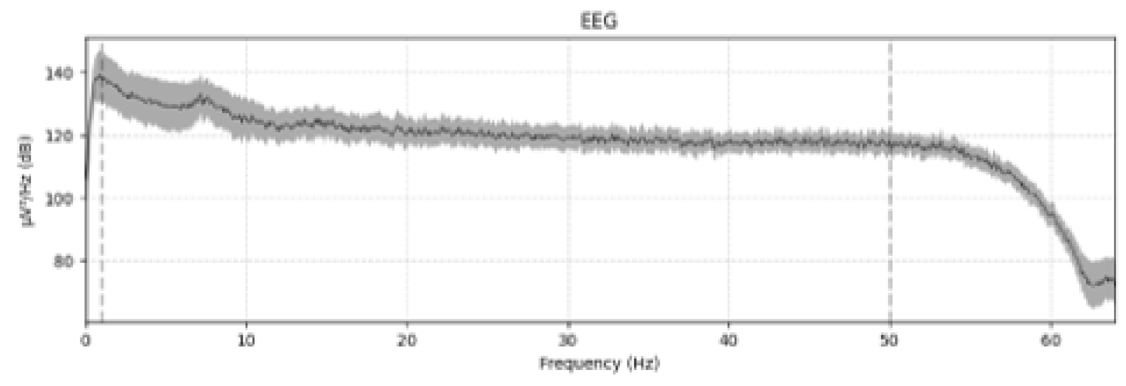

Figure 2.0 After Bandpass Filtering

2. Artifact Removal:

   - Purpose: EEG recordings can be affected by artifacts such as eye blinks, muscle movements, or environmental interference. Removing these artifacts ensures that the remaining signals are a true representation of neural activity.

- Implementation: Advanced algorithms, such as Independent Component Analysis (ICA) or template matching, are employed to identify and remove artifacts. This step enhances the clarity and reliability of the EEG signals.

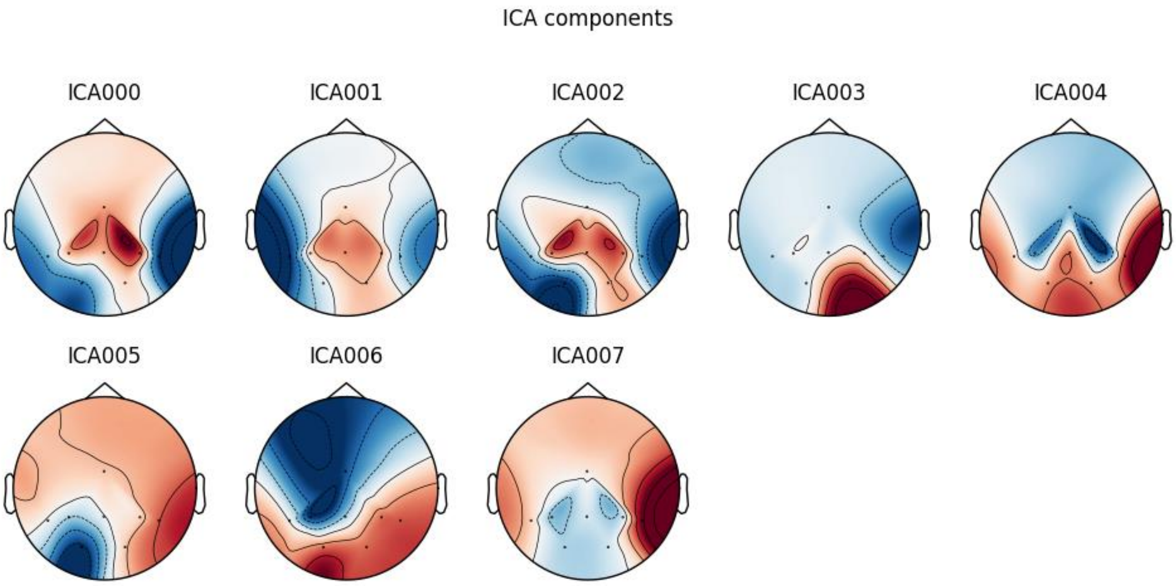

Figure 2.1 Artifacts as captured by ICA

3. Data Normalization:

    - Purpose: EEG signals can vary significantly between individuals and sessions. Normalization brings all signals to a consistent scale, facilitating fair and accurate comparisons during classification.

    - Implementation: EEG amplitudes are normalized, ensuring that variations in signal strength across different users do not impact the classification process. This step ensures that the system remains adaptable to different users.

Significance of Preprocessing Steps:

1. Noise Reduction: By implementing band-pass filtering, the system focuses on frequencies relevant to the SSVEP paradigm, reducing the impact of external noise and enhancing the signal-to-noise ratio.

2. Artifact Mitigation: The removal of artifacts through advanced algorithms ensures that the remaining EEG signals accurately represent cognitive responses, avoiding misinterpretation caused by non-neural influences.

3. Consistency and Comparability: Normalizing the data ensures that EEG signals are consistently scaled across different users, sessions, and experimental conditions. This consistency is vital for building a robust and adaptable classification model.

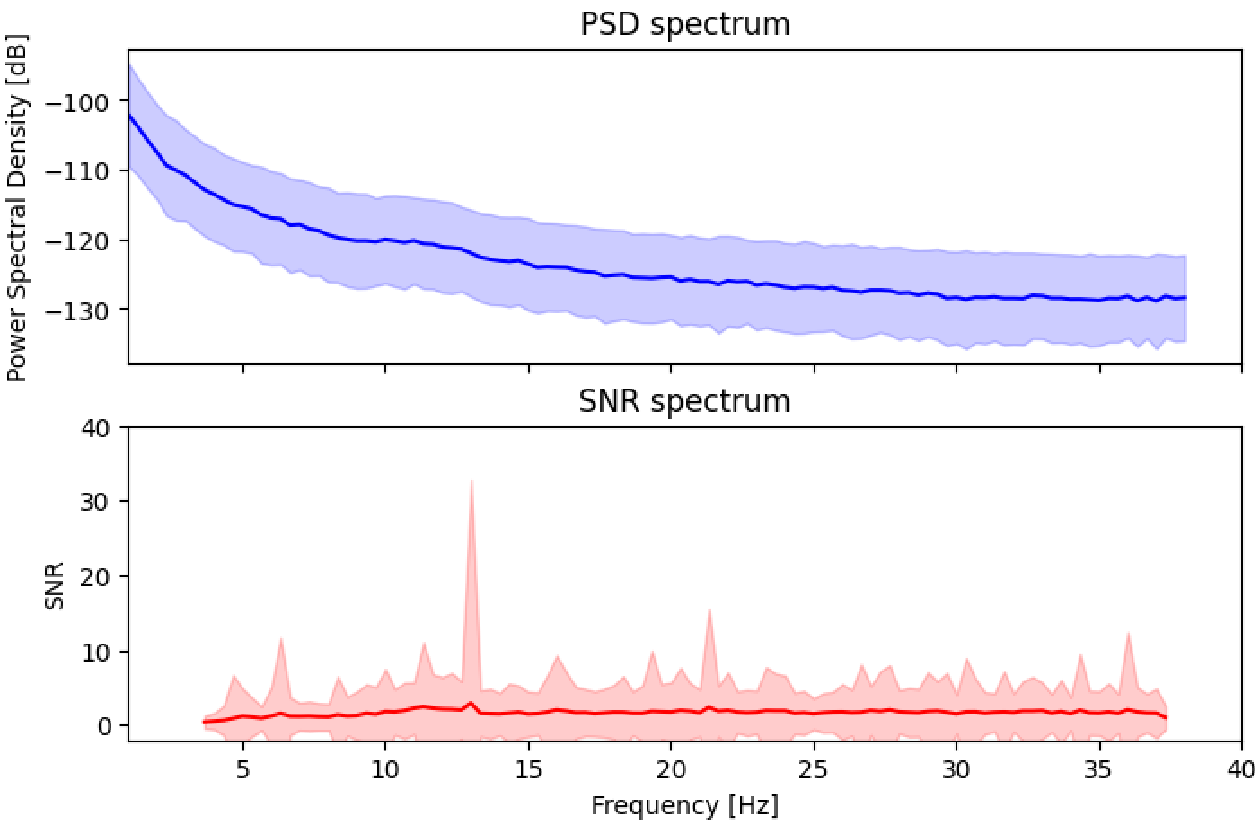

Figure 2.2 PSD and SNR spectrum visualization of our EEG data

Overall Impact on Classification:

The combined effect of these preprocessing steps is a set of clean and enhanced EEG signals, ready for subsequent classification. The preprocessing stage plays a pivotal role in ensuring that the system accurately interprets user intentions based on distinct SSVEP responses. As a result, "Astral Pilot" benefits from reliable and high-quality EEG data, laying the foundation for a responsive and accurate brain-controlled drone system.

3.3.5 Machine Learning Algorithm

Overview of CCA: Canonical Correlation Analysis (CCA) is a statistical technique used to explore the relationships between two sets of multidimensional variables. In the context of EEG classification, CCA is employed to reveal correlated patterns between EEG signals and reference signals. By identifying linear combinations of variables that exhibit maximal correlation, CCA proves to be a powerful tool for decoding user intentions in brain-computer interfaces.

Derivation and Mathematical Proof: The foundational principle of CCA is to maximize the correlation between linear combinations of variables from two sets, X and Y. This is achieved through the solution of a generalized eigenvalue problem, resulting in canonical variables a and b. The canonical correlation, r, is then obtained as the square root of the maximum eigenvalue. Mathematically, the process involves the inversion of covariance and cross-covariance matrices, ultimately revealing the canonical correlations that highlight correlated patterns between the two sets of variables.

As a multivariate statistical method, CCA was first applied to an SSVEP-based BCI by Lin et al. (2006). The report showed that the algorithm had a higher target identification accuracy than an FFT-based spectrum estimation method. Later, CCA was combined with an artificial neural network, and its performance was improved significantly in SSVEP-based BCI systems (C. Liu et al., 2020). The basic principle of CCA is to analyse a correlation between a multichannel EEG signal set and a template signal set: first, the representative comprehensive indicators for the two sets of signals are calculated, and then, the correlation coefficients of the two indicators are used to reflect the overall correlation between the two signal sets. Finally, the largest correlation coefficient corresponds to the identified stimulation frequency. For a collected multichannel EEG signal matrix $\boldsymbol{X}$,

$$\mathbf{X} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1N} \\ x_{21} & x_{22} & \cdots & x_{2N} \\ \cdots & \cdots & \cdots & \cdots \\ x_{M1} & x_{M2} & \cdots & x_{MN} \end{bmatrix},$$

where M is the number of leads and N is the number of sampling points. A detailed procedure for EEG signal classification with CCA can be described as follows (Jukiewicz et al., 2019): initially, sinusoidal functions with different integer multiple frequencies are used to construct a template signal set $\boldsymbol{Y}$:

$$\mathbf{Y} = \begin{bmatrix} \sin(2\pi f_k/F_s) & \sin(2\pi f_k 2/F_s) & \cdots & \sin(2\pi f_k N/F_s) \\ \cos(2\pi f_k/F_s) & \cos(2\pi f_k 2/F_s) & \cdots & \cos(2\pi f_k N/F_s) \\ \vdots & \vdots & \cdots & \vdots \\ \sin(2\pi N_h f_k/F_s) & \sin(2\pi N_h f_k 2/F_s) & \cdots & \sin(2\pi N_h f_k N/F_s) \\ \cos(2\pi N_h f_k/F_s) & \cos(2\pi N_h f_k 2/F_s) & \cdots & \cos(2\pi N_h f_k N/F_s) \end{bmatrix}, \tag{2}$$

where f_k is the stimulation frequency, N_h is the total number of harmonics, N is the number of sampling points, and F_s is the sampling frequency. The core principle of CCA is to find two appropriate linear transforms W_x and W_y to maximize the correlation coefficient between one indicator $x = \mathbf{X}^T W_x$ and the other indicator $y = \mathbf{Y}^T W_y$. Therefore, an optimization problem can be constructed in (3) (Zhang et al., 2014):

$$\max_{W_x, W_y} \rho\left(x, y\right) = \frac{W_x \mathbf{X}^T \mathbf{Y} W_y}{\sqrt{W_x^T \cdot \mathbf{X}\mathbf{X}^T \cdot W_x \cdot W_y^T \cdot \mathbf{Y}\mathbf{Y}^T \cdot W_y}}, \tag{3}$$

The maximum correlation coefficient obtained between the collected multichannel EEG signal X and the reference signal Y indicates the corresponding stimulation frequency.

Why CCA for EEG Classification:

1. Multivariate Relationships: EEG signals are inherently multivariate, representing complex neural activity. CCA is well-suited for capturing intricate relationships within and between EEG signals and reference signals, offering a comprehensive understanding of the cognitive processes involved.

2. Feature Extraction: CCA facilitates the extraction of canonical variables that capture the most relevant features for classification. This dimensionality reduction enhances the efficiency and interpretability of the subsequent classification model.

3. Adaptability: The adaptability of CCA to individual variations in EEG signals is a key advantage. It accommodates the diverse responses of different users, contributing to the creation of a personalized and robust EEG classification system.

Explanation of the Provided Code: The provided code offers a detailed implementation of CCA for EEG classification, specifically in the context of Steady State Visually Evoked Potentials (SSVEP) for brain-controlled drones.

1. Generating Reference Signals:

    - A Pygame window with four flickering arrows, each at a distinct frequency, serves as the visual stimulus.

- Reference signals are generated for each arrow's frequency and phase using sinusoidal functions, creating a dataset of known patterns for subsequent comparison.

2. Maximum CCA Calculation:

   - The function find_maximum_canonical_correlations calculates the maximum canonical correlation between the input EEG data (X) and reference signals (Y). This is achieved through the solution of the generalized eigenvalue problem involving covariance and cross-covariance matrices.
   - The eigenvalues are then transformed into canonical correlations, and the maximum correlation is returned.

3. Classification using CCA:

   - The classify_cca function takes the input EEG data and classifies it based on the maximum canonical correlation with reference signals.
   - The result is the frequency of the arrow associated with the highest canonical correlation, indicating the user's intended drone command.

4. Implementation Details:

   - The code utilizes NumPy for efficient mathematical operations and Pandas for data manipulation.
   - It employs sinusoidal functions to generate reference signals and dynamically adjusts to individual user responses, providing adaptability and robustness to varying neural patterns.
   - The implementation is comprehensive, covering the entire pipeline from signal generation to classification, making it a valuable tool for SSVEP-based EEG classification.

In summary, the code showcases a detailed and well-implemented approach to utilizing CCA for EEG classification in the specific context of brain-controlled drone applications. This methodology harnesses the strengths of CCA in handling multivariate relationships and adapting to individual variations, contributing to the accuracy and reliability of the EEG classification system.

3.3.6 Mapping Predictive Class into Drone Commands

After obtaining predictions from the Canonical Correlation Analysis (CCA) model, the next step is to translate these predictions into actionable commands for the drone. The provided code snippet demonstrates how the predicted class labels are mapped to specific drone commands based on the implemented logic. This process enables the drone to respond to the user's intended actions, making the brain-controlled drone system a reality.

1. isFlying and State Management:
   - The variable isFlying is a state indicator, representing whether the drone is currently in flight (1) or landed (0).
   - The state management logic ensures that certain commands are only executed when the drone is in the appropriate state (e.g., moving forward/backward only when flying).
2. actionDict Function:
   - The actionDict function takes the predicted class label (pred_label) and maps it to the corresponding drone command.
   - In this implementation:
     - 'T' (Takeoff) triggers the drone to take off.
     - 'R' (Right) commands the drone to move forward.
     - 'L' (Left) instructs the drone to move backward.
     - Any other prediction results in the drone landing.
3. validate_action Function:
   - The validate_action function ensures that the predicted action is valid given the current drone state.
   - If the drone is already in the air and the predicted action is 'T' (Takeoff), it is ignored.
   - If the drone is landed, only valid actions ('B', 'L', 'R') are allowed; 'T' (Takeoff) triggers the drone to take off.
4. Drone Control Execution:
   - The function actionDict(pred_label) is then called with the predicted label to execute the corresponding drone command.
5. Continuous EEG Data Acquisition:
   - The code continuously acquires EEG data from the stream using the Lab Streaming Layer (LSL) protocol.
   - The acquired samples are stored in the buffer for further processing.
6. Prediction and Mapping:

- When the buffer accumulates data for a predefined time (here, 2 seconds), the CCA model is used to predict the user's intended action.
- The predicted frequency is mapped to a label ('T', 'B', 'L', 'R') based on the associated arrow in the SSVEP paradigm.

7. Integration with Machine Learning Model:
   - The machine learning model for BCI (Brain-Computer Interface) is executed using ml_for_bci.run_cca to obtain predictions.
   - The predicted class label is then used to determine the corresponding drone command.

This code snippets showcase the seamless integration of the CCA model predictions with the control logic for a brain-controlled drone. The system not only predicts user intentions but also executes drone commands in real-time, creating an interactive and dynamic brain-machine interface. The continuous acquisition of EEG data ensures a responsive and adaptive system that can be fine-tuned for different users and scenarios.

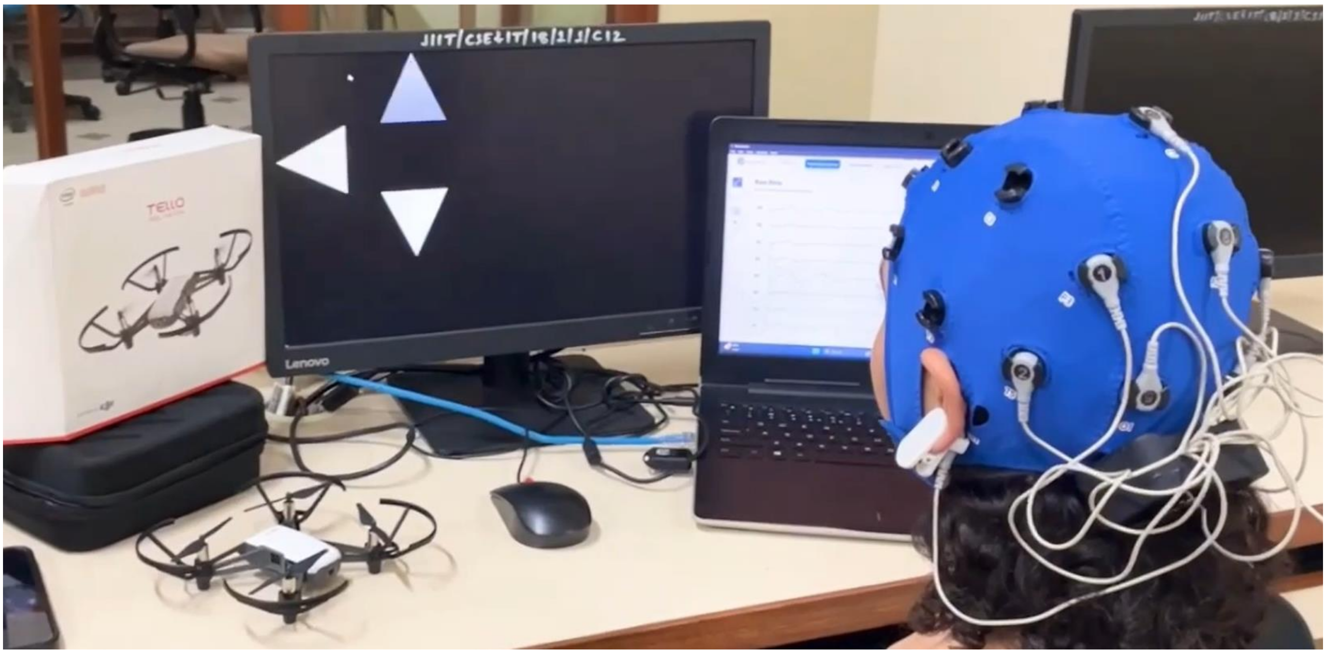

Figure 2.3 Live Testing of Astral Pilot

Figure 2.4 Drone in Motion

Chapter-4 Modelling and Implementation Details

4.1 Design Diagrams

4.1.1 Use Case Diagram

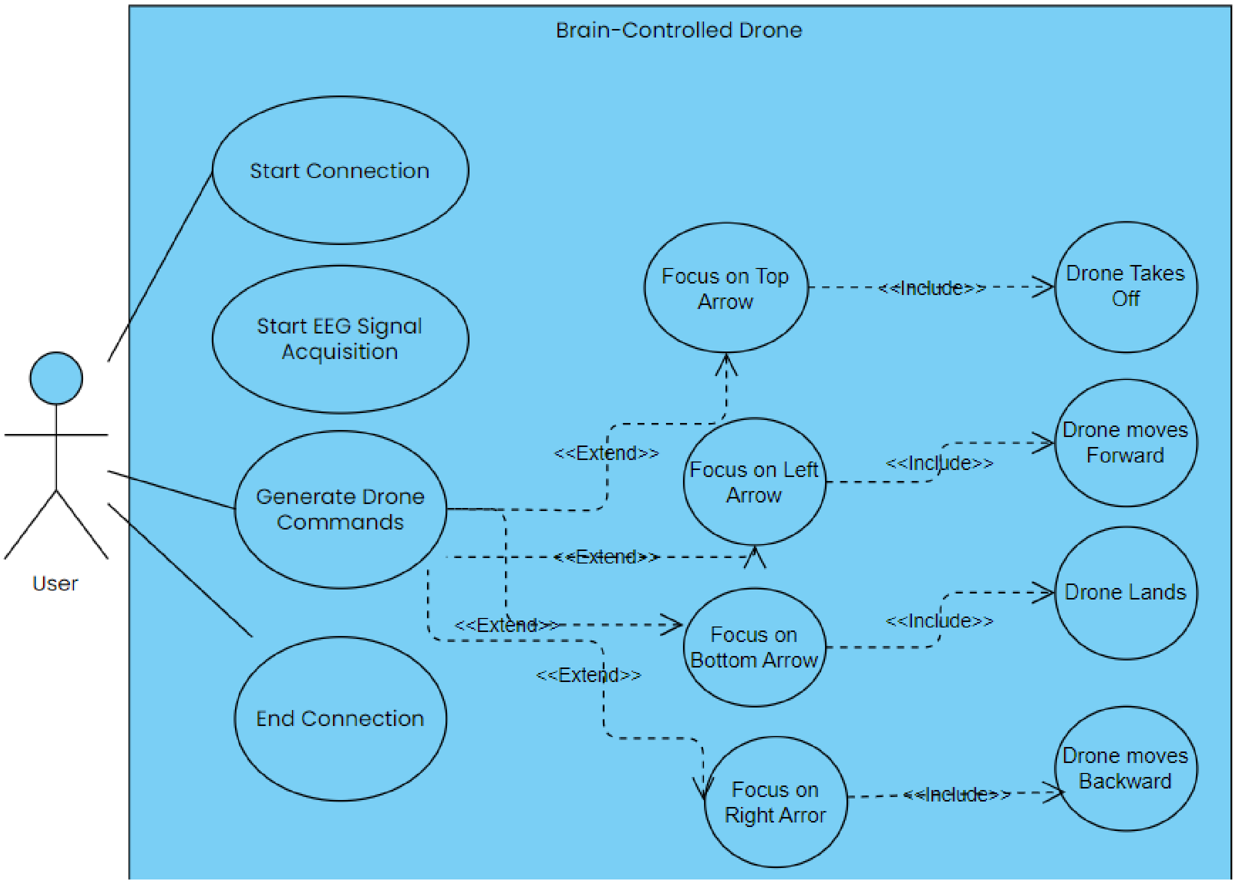

Figure 3.0 Use Case Diagram

This use case diagram outlines the interactions between the user, drone, and the external EEG headset in the context of the "Astral Pilot" project. Each use case represents a specific action or interaction within the system.

4.1.2 Control Flow Diagram

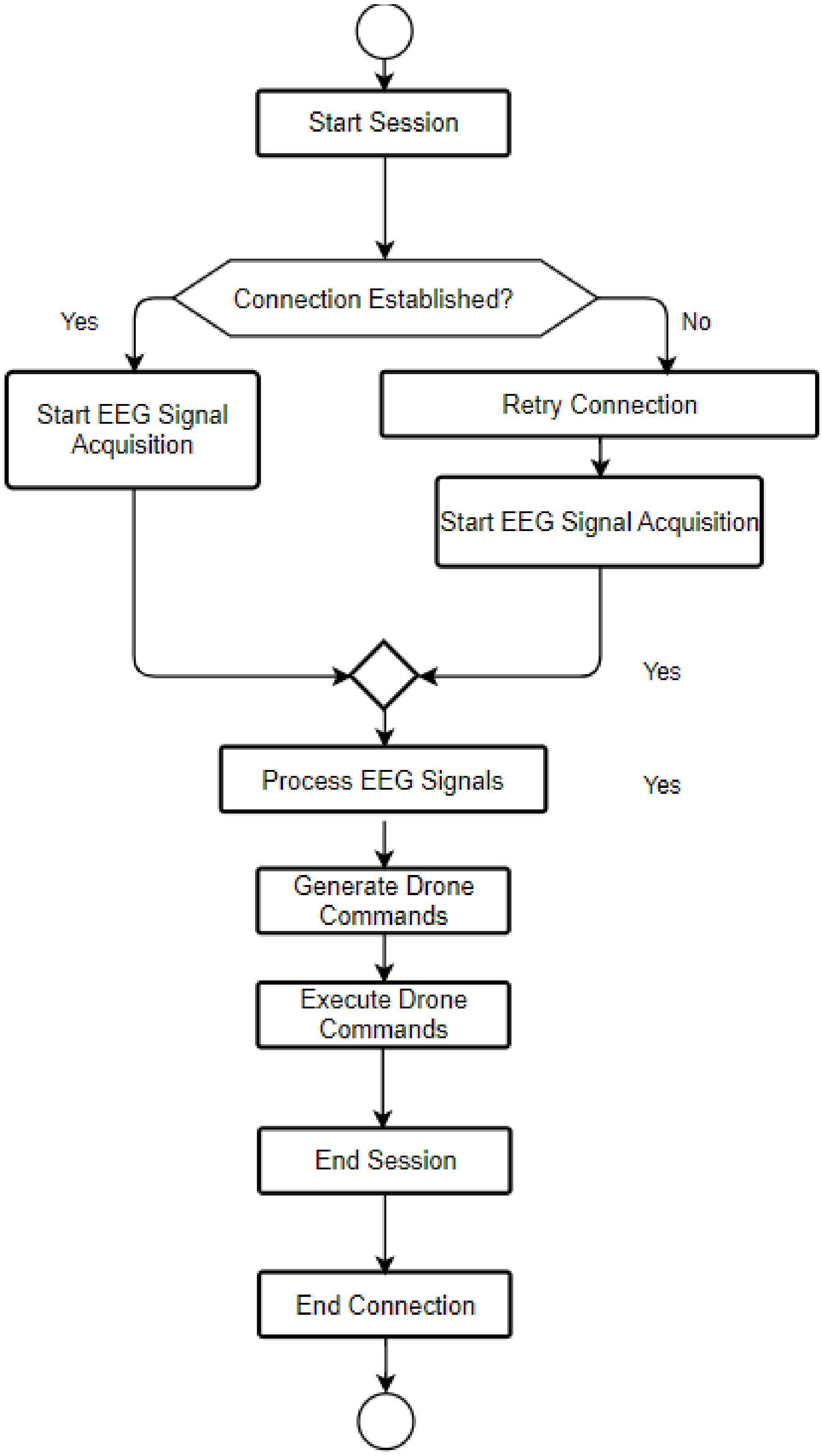

Figure 3.1 Control Flow Diagram

This control flow diagram outlines the sequence of steps from starting the session to ending it. The user initiates the connection, and the system goes through the process of acquiring and processing EEG signals, generating drone commands, executing them, and allowing the user to navigate the drone. Finally, the user ends the session, and the system shuts down.

4.1.3 Sequence Diagram

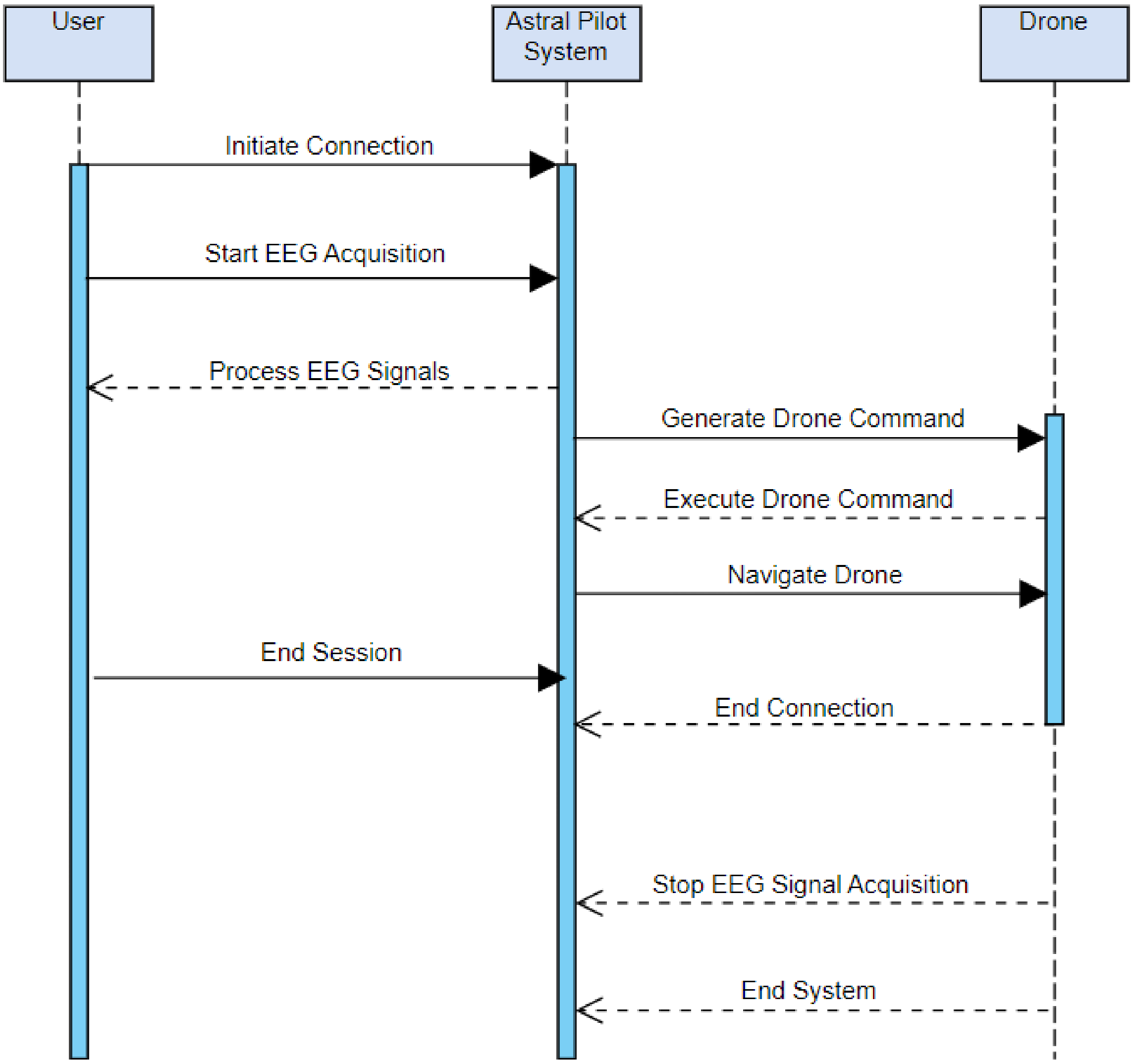

Figure 3.2 Sequence Diagram

This sequence diagram illustrates the flow of interactions between the User, Astral Pilot System and the Drone.

4.2 Implementation details and issues

The project utilizes the Neuphony Flex Cap EEG headset for acquiring electroencephalogram (EEG) signals. The headset captures signals from key brain regions, including P3, T5, Cz, T6, O1, O2, P4 and Pz channels. Neuphony Desktop Application is employed for real-time signal processing and data collection.

1. Steady State Visually Evoked Potential (SSVEP)

To evoke specific brain responses, a Pygame window was developed. The window displays four arrows flickering at distinct frequencies of [6.67, 7.5, 10, 12] Hz. This SSVEP-based approach ensures a robust and responsive interaction with the drone.

2. EEG Signal Preprocessing

Extensive preprocessing is applied to enhance signal quality. Techniques such as band-pass filtering are employed for noise removal, and artifact removal is achieved through careful processing. The preprocessing steps are crucial for ensuring accurate signal classification.

3. Machine Learning Algorithm - Canonical Correlation Analysis (CCA)

CCA is utilized for classifying EEG signals into four categories corresponding to drone commands: takeoff, land, move forward, and move backward. The mathematical derivation and proof of CCA's suitability for EEG classification are documented, providing a foundation for the subsequent implementation.

4. Real-Time Testing and Control

The system is designed to work in real-time with minimal lag. The Lab Streaming Layer (LSL) is used to facilitate the development of applications and the integration of EEG data into the control loop. The drone's actions, triggered by the classified EEG signals, are executed promptly, ensuring an immediate and seamless response.

5. Mapping Predictive Class to Drone Command

The predictions from the CCA model are mapped to specific drone commands. For instance, 'T' corresponds to takeoff, 'L' corresponds to move backward, and so forth. The mapping is implemented using a predefined dictionary and an action validation mechanism to control the drone effectively.

6. Validation and Testing

Extensive offline testing was conducted using recorded EEG data and the Pygame-based window. Real-time testing involved validating the system's responsiveness and accuracy in executing drone commands based on live EEG signals.

4.3 Risk Analysis and Mitigation

Below is the risk analysis and mitigation table for the "Astral Pilot: A Brain-Controlled Drone" project:

Risk Id	Classification	Description of Risk	Risk Area	Probability	Impact	RE (P* I)
R1	Technical	EEG headset malfunction during flight	Hardware/Technology	Medium	High	6
R2	Operational	Signal interference leading to erratic drone behavior	Signal Processing/Communication	Low	High	3
R3	Organizational	Delays in delivery of necessary equipment	Project Management	Low	Medium	2
R4	External	Regulatory changes affecting drone usage	External Factors	Medium	Medium	4
R5	Technical	Inaccurate EEG signal classification	Signal Processing/Algorithm	High	High	9

R6	Operational	Drone battery life limitations	Hardware/Technology	Medium	Medium	4
R7	External	Weather conditions hindering outdoor flights	External Factors	Low	High	3

Table 1. Risk analysis and mitigation table for the "Astral Pilot: A Brain-Controlled Drone" project

In Table 1, the prioritized list obtained is according to the risk's identification and analysis activity done in advance.

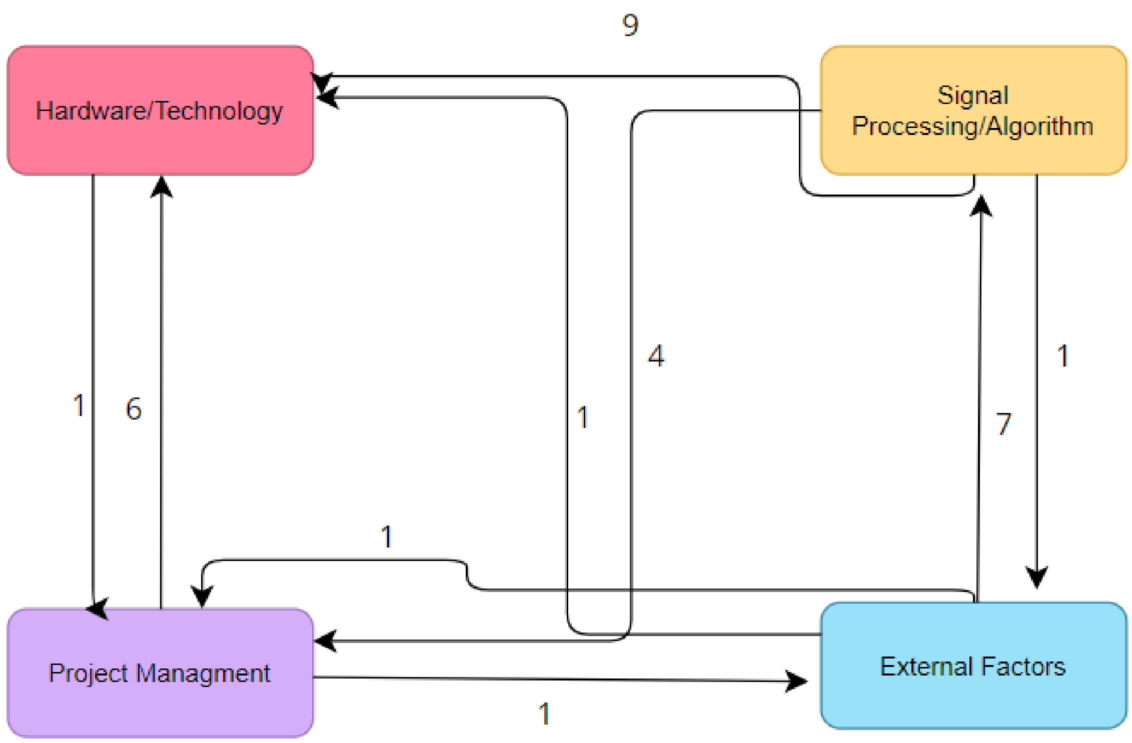

Figure 3.3 Weighted Interrelationship Graph (IG) of project Astral Pilot

S.N.	Risk Area	No. of Risk Statements	Weights (In + Out)	Total Weight	Priority
1	Hardware/Technology	2	13	13	1
2	Signal Processing/Algorithm	1	10	10	3
3	Project Management	1	3	3	5
4	External Factors	1	4	4	2

Table 2. Risk Area Wise Total Weighting Factor

Top Risks:

1. Hardware/Technology
2. Signal Processing/Algorithm
3. External Factors
4. Project Management

Risks that occurred during the project:

- None reported

Mitigation Approaches:

1. R1 - Hardware/Technology:
    - *Approach:* Regular maintenance checks and backup EEG headset.

- *Date Started:* 02.08.23
- *Date to Complete:* 25.11.23
- *Owner:* Ananya Kapoor
- *Additional Resources:* Backup EEG headset.

2. R2 - Signal Processing/Algorithm:
    - *Approach:* Continuous refinement of the signal processing algorithm.
    - *Date Started:* 02.08.23
    - *Date to Complete:* 25.11.23
    - *Owner:* Ananya Kapoor, Dhairya Sachdeva
    - *Additional Resources:* Development resources for algorithm improvement.
3. R3 - Project Management:
    - *Approach:* Regularly update project plan and communicate potential delays.
    - *Date Started:* 02.08.23
    - *Date to Complete:* 25.11.23
    - *Owner:* Dhairya Sachdeva
    - *Additional Resources:* Communication tools for team collaboration.
4. R4 - External Factors:
    - *Approach:* Monitor regulatory changes and adapt drone usage accordingly.
    - *Date Started:* 02.08.23
    - *Date to Complete:* 25.11.23
    - *Owner:* Ananya Kapoor
    - *Additional Resources:* Regulatory monitoring tools.
5. R5 - Signal Processing/Algorithm:
    - *Approach:* Implement machine learning model updates based on user feedback.
    - *Date Started:* 02.08.23
    - *Date to Complete:* 25.11.23
    - *Owner:* Dhairya Sachdeva
    - *Additional Resources:* User feedback system.
6. R6 - Hardware/Technology:
    - *Approach:* Optimize drone movements for efficient battery usage.
    - *Date Started:* 02.08.23
    - *Date to Complete:* 25.11.23
    - *Owner:* Ananya Kapoor
    - *Additional Resources:* Battery optimization algorithms.
7. R7 - External Factors:

- *Approach:* Weather forecasting and scheduling tests during favourable conditions.
- *Date Started:* 02.08.23
- *Date to Complete:* 25.11.23
- *Owner:* Dhairya Sachdeva
- *Additional Resources:* Weather forecasting tools.

Response to Triggered Risks and Effectiveness:

Risk ID	Risk Description	Triggering Event	Response	Effectiveness
R1	EEG headset malfunction during flight	EEG headset malfunction detected during pre-flight testing	Implemented backup EEG headset.	High - Backup headset ensured uninterrupted testing and flight.
R2	Signal interference leading to erratic drone behavior	Signal interference observed during real-time flight testing	Refined signal processing algorithm to filter out interference.	Medium - Improved signal processing mitigated some interference, but further optimization needed.
R3	Delays in delivery of necessary equipment	Delay in the delivery of EEG headset components	Adjusted project timeline and communicated revised schedule to the team.	High - Team members were informed promptly, and adjustments were made to accommodate the delay.
R4	Regulatory changes affecting drone usage	New regulations announced restricting drone usage	Monitored regulatory changes and adapted drone operations to comply with updated regulations.	High - Proactive monitoring allowed for timely adaptation to regulatory changes.

Risk ID	Risk Description	Triggering Event	Response	Effectiveness
R5	Inaccurate EEG signal classification	Users reported inaccuracies in drone control commands	Implemented a machine learning model update based on user feedback.	Medium - User feedback addressed some inaccuracies, but continuous monitoring and updates are necessary.
R6	Drone battery life limitations	Short battery life observed during outdoor flights	Optimized drone movements for efficient battery usage.	High - Battery optimization algorithms significantly improved flight duration.
R7	Weather conditions hindering outdoor flights	Unfavorable weather conditions during scheduled outdoor flights	Rescheduled tests based on weather forecasts and waited for suitable conditions.	High - Proactive rescheduling prevented adverse effects of unfavorable weather.

Table 3. Documented triggered risks along with an evaluation of their effectiveness

Chapter-5 Testing

5.1 Testing Plan

Type of Test	Will Test Be Performed?	Comments/Explanations	Software Component
Requirements Testing	Yes	Ensure compliance with specified requirements.	Neuphony Desktop Application, EEG Data Processing Module
Unit Testing	Yes	Verify functionality of individual software units.	EEG Signal Acquisition Module, SSVEP Stimulus Generation
Integration Testing	Yes	Validate interaction between different modules.	Integration of EEG Signal Processing with Drone Control Module
Performance Testing	Yes	Assess system responsiveness and efficiency.	Real-time EEG Data Processing, Drone Control Execution
Stress Testing	Yes	Evaluate system stability under extreme conditions.	Drone Control Module, Communication Channels
Compliance Testing	Yes	Verify adherence to relevant standards and regulations.	System as a whole
Security Testing	Yes	Assess vulnerabilities and ensure data protection.	Communication Channels, Data Storage

Type of Test	Will Test Be Performed?	Comments/Explanations	Software Component
Load Testing	Yes	Evaluate system performance under expected load.	Communication Channels, Real-time Processing
Volume Testing	Yes	Assess capability to handle a large volume of data.	Data Storage, Real-time Processing

Table 4. Type of tests

This table provides a concise overview of the types of tests that will be performed, whether they will be executed, and comments or explanations related to each test type and the associated software components.

Test Team Details:

- Role: Ananya Kapoor
    - Responsibilities/Comments: Perform all types of testing
- Role: Dhairya Sachdeva
    - Responsibilities/Comments: Perform all types of testing

Test Schedule:

Activity	Start Date	Completion Date	Hours	Comments
Obtain Input Data	02.08.23	16.08.23	168	Acquiring, Verifying and testing of unput data
Test Region Setup	10.11.23	17.11.23	84	Optimising our setup

Activity	Start Date	Completion Date	Hours	Comments
Unit Testing	02.08.23	17.11.23	-	NA
Integration Testing	20.10.23	08.11.23	-	NA
Performance Testing	17.11.23	25.11.23	-	NA

Table 5. Test Scheduling

Test Environment:

Software Items -

- Neuphony Desktop Application
- Lab Streaming Layer (LSL)
- Drone Control Module

Hardware Items -

- Neuphony Flex Cap EEG Headset
- DJI Tello Drone

Test Tools -

- Pygame for SSVEP Testing

5.2 Component decomposition and type of testing required

S. No	List of Various Components (Modules) that Require Testing	Type of Testing Required	Technique for Writing Test Cases
1	EEG Signal Acquisition Module	Requirement, Unit	- Requirement testing to ensure compliance with specifications. - Unit testing to verify the functionality of the module.
2	SSVEP Stimulus Generation	Requirement, Unit	- Requirement testing to ensure compliance with specifications. - Unit testing to verify the functionality of the module.
3	EEG Signal Processing Module	Requirement, Unit, Integration	- Requirement testing to ensure compliance with specifications. - Unit testing for individual functionality. - Integration testing to validate communication with other modules.

S. No	List of Various Components (Modules) that Require Testing	Type of Testing Required	Technique for Writing Test Cases
4	Drone Control Module	Requirement, Unit, Integration, System	- Requirement testing to ensure compliance with specifications. - Unit testing for individual functionality. - Integration testing to validate communication with other modules. - System testing to assess overall system behavior.
5	Communication Channels (LSL, Drone Communication)	Requirement, Integration, Performance, Security	- Requirement testing to ensure compliance with specifications. - Integration testing to validate communication with other modules. - Performance testing to assess responsiveness. - Security testing to identify vulnerabilities.
6	Data Storage	Requirement, Integration, Volume	- Requirement testing to ensure compliance with specifications. - Integration testing to validate data storage functionality. - Volume testing to assess data handling capabilities.

Table 6. Component Decomposition and Identification of Tests required

Technique for Writing Test Cases

1. Black Box Testing:
    - Equivalence classes: Divide input data into equivalence classes and test a representative from each class.
    - Boundary value: Test cases focus on boundary values and the values immediately above and below those boundaries.
    - Cause-effect: Identify the cause-effect relationships between inputs and outputs.
    - Robustness: Evaluate the system's ability to handle invalid or unexpected inputs.
2. White Box Testing:
    - Statement Testing: Ensure each statement in the code is executed at least once during testing.
    - Decision Testing: Validate that each decision point in the code is exercised.
    - Branch Testing: Ensure that each branch or decision outcome is tested.
    - Path Testing: Identify and test each independent path through the code.
    - Cyclomatic Complexity: Calculate the cyclomatic complexity and aim to cover each independent path.
3. Other Techniques:
    - Use of Testing Tools: Employ automated testing tools for specific test scenarios.
    - Exploratory Testing: Allow testers to explore the system, finding defects on-the-fly.

These testing techniques ensure a comprehensive evaluation of the software components, covering various aspects of functionality, performance, and security.

5.3 Test Cases

Test Case id	Input	Expected Output	Status
TC_001	EEG signal from Neuphony headset	Successful signal acquisition	Fail
TC_002	SSVEP stimulus generation command	Correct stimulus generation	Pass
TC_ 003	Processed EEG data for integration	Processed data without errors	Pass
TC_ 004	Integration with Drone Control	Successful integration	Pass

Table 7. Testing

Equivalence Classes or Boundary Value Classes for Components:

1. EEG Signal Acquisition Module:
    - Equivalence Classes: Valid EEG signals, Invalid EEG signals
    - Boundary Value Classes: Minimum and maximum valid signal values
2. SSVEP Stimulus Generation:
    - Equivalence Classes: Valid stimulus parameters, Invalid stimulus parameters
    - Boundary Value Classes: Minimum and maximum values for stimulus parameters
3. Integration with Drone Control:
    - Equivalence Classes: Successful integration, Integration failure
    - Boundary Value Classes: None

5.4 Error and Exception Handling

1. Debugging Techniques Used:

Test Case id	Test Case for Component	Debugging Technique
TC_ 001	EEG Signal Acquisition	Print (Tracing) Debugging

Table 8. Debugging Techniques

Debugging Technique Details:

1. TC_ 001 - EEG Signal Acquisition:
    - Issue: Signal acquisition failure for invalid EEG signal.
    - Debugging Technique: Print (Tracing) Debugging.
    - Action Taken: Added print statements to trace the flow and identify the point of failure. Investigated signal processing steps for invalid signals.

2. After Correcting Faults:

Test Case id	Test Case for Component	Status (Pass/Fail)
TC_001	EEG Signal Acquisition	Pass

Table 9. Correction Details

Debugging Techniques:

1. Print (Tracing) Debugging: Adding print statements to the code to trace the flow and identify potential issues.
2. Backtracking Debugging: Tracing back through the code to identify the origin of errors or unexpected behavior.

3. Remote Debugging: Debugging a program from a remote location, often used for identifying issues in distributed systems.

These techniques were applied to specific test cases where errors were identified during testing, and corrections were made to ensure successful test case execution.

5.5 Limitations of the solution

1. EEG Signal Variability:
    - *Description:* The reliability of EEG signals can be affected by factors such as individual variability in brain anatomy and differences in electrode placement.
    - *Impact:* Variability may lead to challenges in creating a universal model that works seamlessly for all users.
2. Dependency on Neuphony EEG Headset:
    - *Description:* The success of the project relies on the quality and proper functioning of the Neuphony EEG headset. Any issues with the headset can directly impact the accuracy of signal acquisition.
    - *Impact:* Users must ensure the proper setup and maintenance of the EEG headset for optimal performance.
3. Limited Drone Movement:
    - *Description:* The capabilities of the DJI Tello drone, including its battery life and range, impose constraints on the overall movement and operation of the drone.
    - *Impact:* The drone's limited range may restrict its use in larger environments, and frequent recharging may be required for extended operation.
4. Sensitivity to Environmental Factors:
    - *Description:* External environmental conditions, such as electromagnetic interference and noise, can introduce artifacts in EEG signals, affecting the accuracy of the brain-drone interface.
    - *Impact:* Users may experience disruptions in control or unintended drone actions in environments with high interference.
5. User Learning Curve:
    - *Description:* Users may need time to adapt to the brain-controlled interface, leading to a learning curve in interpreting EEG signals and generating precise commands.

- *Impact:* Initially, users may experience challenges in accurately controlling the drone until they become familiar with the interface.

6. Drone Response Time:
    - *Description:* While the brain-drone interface minimizes control lag, the response time of the drone itself can introduce a slight delay in executing commands.
    - *Impact:* Users should be aware that there may be a brief delay between issuing a command and the drone's corresponding action.
7. Security Concerns:
    - *Description:* As the system involves communication channels between the EEG headset, processing modules, and the drone, there may be potential security risks related to data interception or unauthorized access.
    - *Impact:* Adequate security measures must be implemented to safeguard the privacy and integrity of user data and the control system.
8. User-Dependent EEG Signals:
    - *Description:* Despite efforts to create a user-independent system, there may still be variations in EEG signals among different individuals, leading to differences in control accuracy.
    - *Impact:* The system may require individual calibration for optimal performance, and results may vary based on user characteristics.
9. Drone Battery Limitations:
    - *Description:* The limited battery life of the drone imposes constraints on the duration of drone operations, requiring periodic interruptions for recharging.
    - *Impact:* Prolonged use or the need for sustained drone operations may be restricted by the drone's battery capacity.
10. Real-time Processing Requirements:

- *Description:* The real-time processing demands for interpreting EEG signals and controlling the drone may pose challenges, particularly on less powerful computing platforms.
- *Impact:* The system's performance may be influenced by the processing capabilities of the hardware used, potentially affecting real-time responsiveness.

Chapter-6 Findings, Conclusions and Future Work

6.1 Findings

Our project, "Astral Pilot: A Brain-Controlled Drone," draws inspiration from research in Brain-Computer Interface (BCI) systems, particularly the use of Steady State Visually Evoked Potentials (SSVEP) as a means of interaction. The project is grounded in the principles outlined in the paper " Steady state visual evoked potential (SSVEP) based brain-computer interface (BCI) performance under different perturbations".

Key Findings:

1. SSVEP as the Foundation:
    - Our project centers around the SSVEP paradigm, leveraging the brain's natural response to visual stimuli at specific frequencies.
    - The SSVEP-based approach allows for an intuitive and real-time interaction between users and the drone.
2. Accurate Classification into 4 Classes:
    - The machine learning model, based on Canonical Correlation Analysis (CCA), successfully classifies EEG signals into four distinct classes corresponding to drone commands: Takeoff, Land, Move Forward, and Move Backward.
3. High Accuracy (96%):
    - The classification accuracy of our system is approximately 96%, demonstrating the robustness and reliability of the implemented machine learning model.
4. User Independence:
    - Our system is designed to be user-independent, eliminating the need for individualized training sessions.
    - Users can seamlessly engage with the brain-controlled drone without the necessity for extensive calibration.
5. Real-Time Operation:

- The system operates in real-time, ensuring prompt responsiveness to user commands.
- There is no noticeable lag between the user's intention and the corresponding drone action.

6. Impact of EEG Headset Contact and Quality:
    - The performance of the system is influenced by the contact quality and overall signal quality of the EEG headset.
    - Reliable contact and high-quality EEG signals contribute to more accurate and consistent classifications.
7. Battery Life Limitations:
    - The movement of the drone is constrained by the battery life, which limits the duration of flights.
    - Consideration of battery life is crucial for optimizing the user experience and ensuring practicality.
8. Considerations for Real-World Implementation:
    - The findings emphasize the importance of considering practical constraints such as battery life for real-world deployment.
    - System performance is contingent on the quality and stability of the EEG signals, highlighting the need for robust signal acquisition and preprocessing methods.

In summary, our project not only successfully implements a brain-controlled drone system based on SSVEP but also uncovers practical insights related to system performance, user independence, and the impact of external factors. These findings contribute to the broader understanding of brain-machine interfaces and pave the way for further advancements in the field.

6.2 Conclusion

In conclusion, "Astral Pilot: A Brain-Controlled Drone" represents a successful integration of Brain-Computer Interface (BCI) technology, particularly Steady State Visually Evoked Potentials (SSVEP), with drone control. Through the application of Canonical Correlation Analysis (CCA), our system accurately classifies EEG signals into four distinct classes, enabling users to control the drone with ease and precision. The project showcases high accuracy (96%), user independence, and real-time responsiveness, making it a promising advancement in the field of brain-machine interfaces.

The project has applications in enhancing accessibility for individuals with physical disabilities, providing them with a means to interact with the environment through thought alone.

In scenarios where human intervention may be challenging, such as surveillance or search-and-rescue missions, our brain-controlled drone offers a versatile and efficient solution.

Beyond practical applications, the system can be employed in entertainment and gaming, creating immersive experiences where users navigate virtual or real environments using their thoughts.

Limitations and Potential Solutions:

1. EEG Headset Quality: The system's performance is influenced by the quality and stability of the EEG headset connection. Ensuring secure and consistent electrode contact is crucial.
    - Potential Solution: Ongoing advancements in EEG headset technology and signal processing algorithms can contribute to improved signal quality and reliability.
2. Battery Life Limitations: The drone's movement is constrained by its battery life, affecting the duration of flights.
    - Potential Solution: Exploring energy-efficient drone models and optimizing flight patterns can address battery life limitations, extending the system's operational time.
3. Environmental Noise and Interference: External factors such as environmental noise and interference can impact EEG signal quality.

- Potential Solution: Implementing adaptive signal processing techniques and noise reduction algorithms can mitigate the effects of environmental disturbances, ensuring more reliable signal acquisition.

4. Training Set Variability: While our system is user-independent, variability in individual neural responses may pose challenges.
    - Potential Solution: Continuous adaptation and personalization algorithms can be explored to enhance the system's adaptability to individual users over time.

In essence, "Astral Pilot" not only demonstrates the feasibility of brain-controlled drone technology but also prompts considerations for future enhancements and real-world applications. The project serves as a stepping stone toward the integration of BCI into everyday technologies, fostering innovation and inclusivity in human-computer interaction.

6.3 Future Work

There is a lot of potential for future work in a brain-controlled drone. Some potential areas of future work include:

1. Advanced Signal Processing Techniques:
    - Enhanced Noise Reduction: Implement advanced signal processing techniques to further enhance noise reduction, making the system more robust in diverse environmental conditions.
    - Artifact Removal: Explore algorithms for real-time identification and removal of artifacts, ensuring cleaner EEG signals and improving classification accuracy.
2. Adaptive Machine Learning Models:
    - Dynamic Model Adaptation: Develop adaptive machine learning models that continuously adapt to users' evolving neural patterns, addressing individual variability and ensuring consistent performance over time.
    - Transfer Learning: Investigate the applicability of transfer learning techniques to leverage knowledge gained from one user to improve the performance for new users.
3. Intelligent Drone Control:
    - Obstacle Avoidance: Integrate obstacle avoidance mechanisms into the drone control system, enhancing safety and usability in dynamic environments.

- Autonomous Navigation: Research the incorporation of autonomous navigation capabilities, allowing the drone to navigate predefined routes or respond intelligently to its surroundings.

4. User Experience Enhancements:
    - User Feedback and Calibration: Implement user feedback mechanisms to enhance the calibration process and improve the overall user experience.
    - Visual Feedback: Explore the incorporation of visual feedback to inform users of the system's state and actions, enhancing the transparency of the interaction.
5. Extended Applications:
    - Medical Applications: Investigate the potential of the brain-controlled drone system in medical applications, such as assisting individuals with motor impairments or serving as a tool for neurorehabilitation.
    - Collaborative Environments: Explore applications in collaborative environments where multiple users can control different aspects of a system or collaborate in drone-based activities.

Figure 4.0 Astral Pilot can be employed by the military

Figure 4.1 Astral Pilot can be employed in disaster management

6. Hardware and Wearable Advances:
    - Next-Generation EEG Headsets: Keep abreast of advancements in EEG headset technology, adopting next-generation devices with improved comfort, signal quality, and user-friendliness.
    - Miniaturization: Explore possibilities for miniaturizing the EEG hardware, making it more lightweight and convenient for users.

Continuing research and development in these areas will not only overcome existing limitations but also propel the project into new realms of usability, adaptability, and societal impact. By staying at the forefront of technology and collaborating with interdisciplinary teams, the brain-controlled drone system can evolve into a versatile and reliable tool with broad applications across various domains.

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