SIDDAGANGA INSTITUTE OF TECHNOLOGY, TUMAKURU-572103

(An Autonomous Institute under Visvesvaraya Technological University, Belagavi)

Project Report on

"Neuro navigation - Filtering and visualiaztion of EEG signal using python libraries"

submitted in partial fulfillment of the requirement for the completion of VI semester of

BACHELOR OF ENGINEERING

in

ELECTRICAL & ELECTRONICS ENGINEERING

Submitted by

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DEPARTMENT OF ELECTRICAL & ELECTRONICS ENGINEERING

2023-24

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CERTIFICATE

Certified that the mini project work entitled "Neuro navigation – Brain computer interface based wheelchair prototype" is a bonafide work carried out by Shivaprasad M J (1SI21EE037), Shreyas L (1SI21EE040), Shreyas M (1SI21EE041) and Sinchana K (1SI21EE042) in partial fulfillment for the completion of VI Semester of Bachelor of Engineering in Electrical & Electronics Engineering from Siddaganga Institute of Technology, an autonomous institute under Visvesvaraya Technological University, Belagavi during the academic year 2023-24. It is certified that all corrections/suggestions indicated for internal assessment have been incorporated in the report deposited in the department library. The Mini project report has been approved as it satisfies the academic requirements in respect of project work prescribed for the Bachelor of Engineering degree.

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1.	
2.	

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Course Outcomes

CO1: To identify a problem through literature survey and knowledge of contemporary engineering technology.
CO2: To consolidate the literature search to identify issues/gaps and formulate the engineering problem
CO3: To prepare project schedule for the identified design methodology and engage in budget analysis, and share responsibility for every member in the team
CO4: To provide sustainable engineering solution considering health, safety, legal, cultural issues and also demonstrate concern for environment
CO5: To identify and apply the mathematical concepts, science concepts, engineering and management concepts necessary to implement the identified engineering problem
CO6: To select the engineering tools/components required to implement the proposed solution for the identified engineering problem
CO7: To analyze, design, and implement optimal design solution, interpret results of experiments and draw valid conclusion
CO8: To demonstrate effective written communication through the project report, the one-page poster presentation, and preparation of the video about the project and the four page IEEE/Springer/ paper format of the work
CO9: To engage in effective oral communication through power point presentation and demonstration of the project work
CO10:To demonstrate compliance to the prescribed standards/ safety norms and abide by the norms of professional ethics
CO11: To perform in the team, contribute to the team and mentor/lead the team

Attainment level: - 1: Slight (low) 2: Moderate (medium) 3: Substantial (high)
POs: PO1: Engineering Knowledge, PO2: Problem analysis, PO3: Design/Development of solutions, PO4: Conduct investigations of complex problems, PO5: Modern tool usage, PO6: Engineer and society, PO7: Environment and sustainability, PO8: Ethics, PO9: Individual and team work, PO10: Communication, PO11: Project management and finance, PO12: Lifelong learning

CO-PO Mapping

	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12	PSO1	PSO2
CO-1												3		
CO-2		3												
CO-3											3			
CO-4						3	3							
CO-5	3	3												
CO-6					3									
CO-7			3	3										
CO-8										3				
CO-9										3				
CO-10								3						
CO-11									3					

Abstract

Brain computer interface wheel chair specially designed for paralyzed and disabled person who are not capable to operate normal wheel chair. This wheel chair is based on (BCI) Brain computer interface, it can control the wheel chair from brain neurons by the help of BCI. Brain computer interface (BCI) is a computer-based system that obtain brain signal that can be controlled by EEG Sensor which is an electrophysiological process to archive the electrical activity of the brain. A BCI system recognize users to grant their determination by study their brain signals. This technology is very helpful for paralyzed and disabled person they can easily moves wheel chair in any direction.

This project aims to develop an algorithm that enhances EEG signal interpretation for precise and efficient control of a Brain-Computer Interface (BCI) wheelchair. By optimizing the utilization of EEG signals, the algorithm seeks to empower paralyzed and disabled individuals with improved mobility and independence. Through advanced signal processing techniques, the algorithm aims to translate neural commands into seamless wheelchair movements in any direction, providing a vital technological aid for enhancing daily living and quality of life.

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Chapter 1

Introduction

In recent years, Brain-Computer Interface (BCI) technology has emerged as a groundbreaking field at the intersection of neuroscience, engineering, and computer science. BCIs represent a paradigm shift in human-computer interaction by enabling direct communication between the brain and external devices without the need for traditional input methods like keyboards or touchscreens. This technology holds immense potential for revolutionizing various aspects of human life, particularly in healthcare, assistive technology, gaming, and virtual reality.

At its core, a BCI system functions by detecting and interpreting neural signals from the brain and translating them into actionable commands for external devices. These signals can be captured through various methods such as electroencephalography (EEG), magnetoencephalography (MEG), functional near-infrared spectroscopy (fNIRS), or invasive techniques like neural implants. Each approach offers unique advantages and challenges, shaping the development and application of BCIs in different domains.

The applications of BCI technology are diverse and far-reaching. In the medical field, BCIs have shown promise in assisting individuals with motor disabilities, neurodegenerative diseases, and communication disorders. They offer new avenues for patients to regain autonomy, communicate effectively, and control assistive devices like prosthetics, wheelchairs, and robotic arms through neural signals. BCIs also play a significant role in cognitive rehabilitation, brain-computer gaming interfaces, and neurofeedback therapies, contributing to advancements in personalized healthcare and neurorehabilitation.

Outside of healthcare, BCIs are driving innovation in virtual reality (VR) and augmented reality (AR) experiences, allowing users to interact with digital environments using their thoughts and intentions. This has implications for immersive gaming, training simulations, and human-machine collaboration in industrial settings. Moreover, BCIs are being integrated into smart home systems, enabling hands-free control of appliances, entertainment systems, and environmental settings based on user brain activity.

Despite the progress made in BCI technology, several challenges remain, including signal processing complexity, signal-to-noise ratio improvement, user training and adaptation, ethical considerations, and regulatory frameworks. Overcoming these challenges requires interdisciplinary collaboration, advancements in neurotechnology, machine learning algorithms, and user-centered design approaches.

This report aims to provide an overview of BCI technology, its principles, applications, challenges, and future directions. By exploring the current state of BCI research and development, we seek to contribute to the understanding and advancement of this transformative technology and its impact on society.

1.1 EEG Bands and Their Comparison

The waves emitted from the brain depend upon the state of the brain. These waves occupy different low frequency bands typically from 1Hz to 100Hz. It ought to be seen that these are the all-around perceived bands still they have no perfect range for brain waves. While analysts have a tendency to take after these rules, numerous researchers utilize their own particular limits relying upon the extent they concentrate on. Furthermore, a few specialists characterize the groups utilizing decimal values instead of adjusting to entire numbers (for instance, one analyst may characterize the lower Beta band cut-off as 12.3, while another may utilize the quality 13), while still others in some cases isolate the groups into sub-groups. For the most part, this is accomplished for examination.

1.1.1 Delta Waves

This is frequency band of EEG having range 0-4 Hz.the feature of this wave is that having high amplitudes but slow. They normally occur strongly when someone is in deep sleep. It is moreover seen in normally children. It might happen centrally with sub-cortical injuries and in general supply of diffuse sores, metabolic encephalopathy hydrocephalus or profound mid-line sores. It is generally most prominent frontally in grown-ups. A sample of Delta Wave is shown in Figure 1.1.

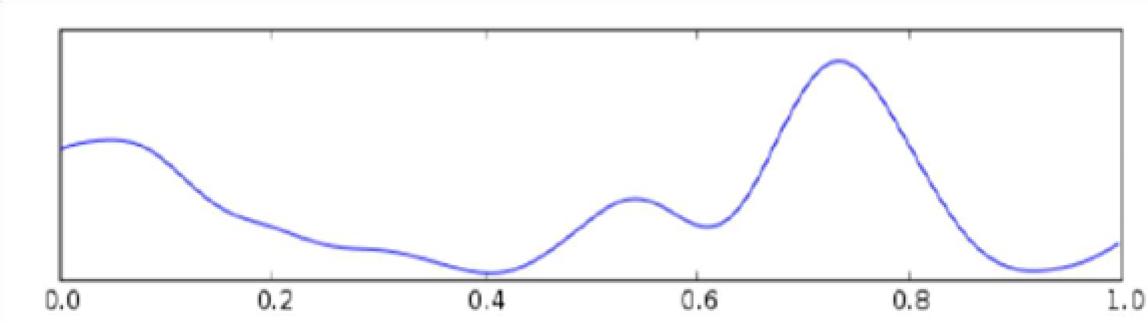


Figure 1.1: Delta waves

1.1.2 Theta Waves

The frequency range of Theta waves is from 4Hz to 7Hz. Theta is seen typically in youthful youngsters. These waves can likewise be found in drowsiness in older kids and grown-ups, it can likewise be found in contemplation. Occurrence of excessive theta waves with respect to age represents abnormal activities. It can be seen as a main disturbance in the central sub-cortical sores, it can be seen in summed up supply in diffuse issue or metabolic encephalopathy or profound mid-line issue or some examples of hydrocephalus. Despite what might be expected, this extent has been connected with reports of casual, thoughtful and imaginative states. A sample wave of Theta waves is shown Figure 1.2.

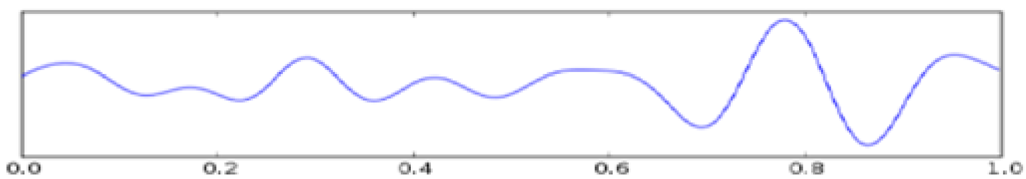


Figure 1.2: Theta waves

1.1.3 Alpha Waves

The frequency range of Alpha waves is from 8Hz to 12Hz. Hans Berger named the principal musical EEG action he saw as the alpha wave. This was the posterior basic rhythm (likewise called the posterior dominant rhythm or the posterior alpha rhythm), found in the back districts of the head on both sides, higher in abundancy on the overwhelming side. It rises with shutting of the eyes and with unwinding, and constricts with eye opening or mental effort. The posterior basic rhythm is slower than 8Hz in youthful kids (subsequently in fact in the theta range). In addition to the posterior basic rhythm, there are other ordinary alpha rhythms, for example, the mu rhythm that develops when the hands and arms are unmoving, and the third rhythm (alpha movement in the worldly or frontal flaps). Alpha can be anomalous for instance, an EEG that has diffuse alpha happening in coma and is not responsive to external stimuli is referred to as alpha coma. A sample Wave of Alpha Waves is shown in Figure 1.3.

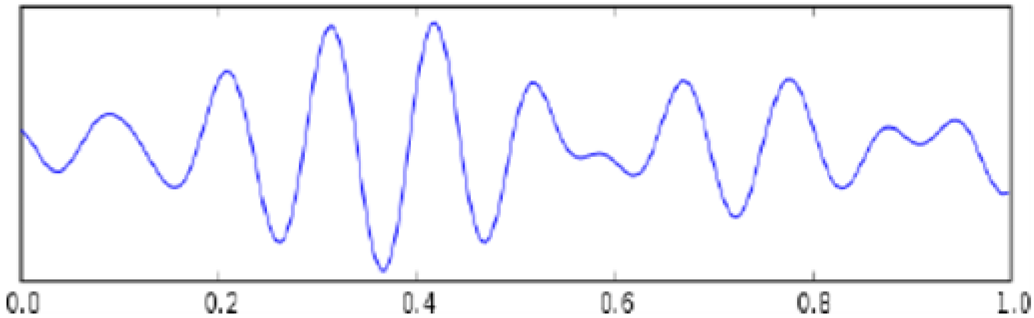


Figure 1.3: Alpha waves

1.1.4 Beta Waves

The frequency range of Alpha waves is from 12Hz to near 30Hz. It is seen for the most part on both sides in symmetrical dispersion and is most obvious frontally. Beta action is firmly connected to motor behaviour and is normally reduced during active movements. Low amplitude beta with various and fluctuating frequencies is regularly connected with active, busy or anxious thinking and active concentration. Rhythmic beta with an overwhelming arrangement of frequencies is connected with different pathologies and medication impacts, particularly Benzodiazepines. It might be missing or diminished in regions of cortical harm. It is the overwhelming thythm in patients who are ready or on edge or who have their eyes open. A sample wave of beta waves is shown in Figure 1.4.

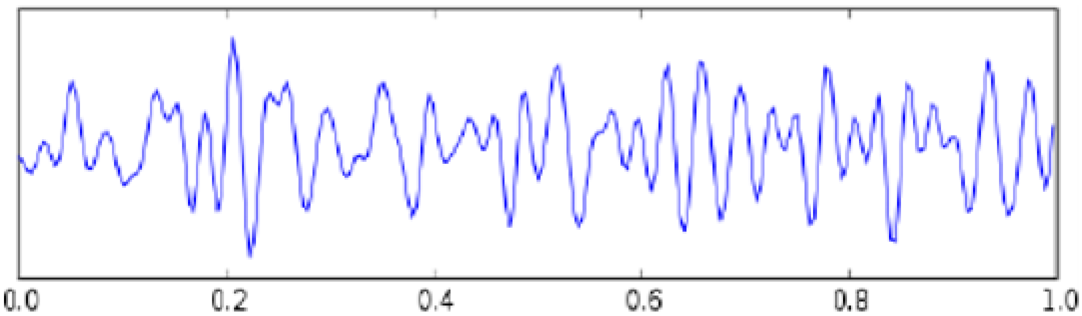


Figure 1.4: Beta waves

1.1.5 Gamma Waves

The frequency range of Gamma waves is around 30-100Hz. Gamma rhythms are thought to represent binding of various populations of neurons together into a system with the end goal of doing a specific cognitive or motor function. A sample wave of gamma waves is shown in Figure 1.5.

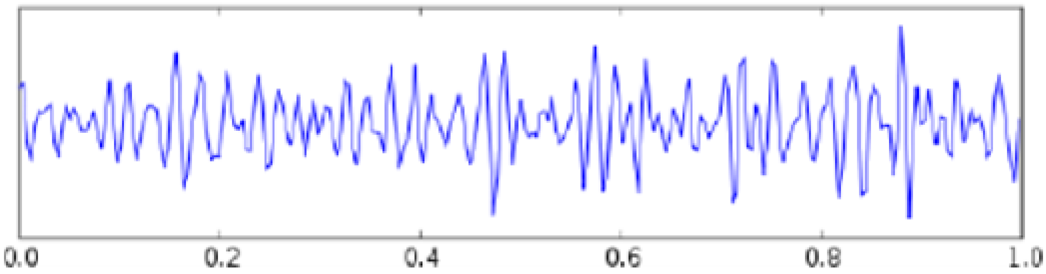


Figure 1.5: Gamma waves

1.1.6 Comparison of EEG Waves

The comparision of Alpha, Beta, Delta and Gamma waves are shown in Table 1.1.

Type of wave	**Location**	**Frequency**	**Normal state**
Delta	Frontally in adults, posterior in children	0.5-4 Hz	Deep sleep, Coma
Theta	Temporal cortex	4-8 Hz	Trance, Dreams
Alpha	Posterior regions of head, both sides, higher in amplitude on dominant side. Central sites (C3-C4) at rest.	8-13 Hz	Relaxation with eyes closed but still awake
Beta	Frontally evident on both sides, symmetrical distribution	13-30 Hz	Beta 1:13-20 Hz Perception, Thinking, Mental Activity

Table 1.1: Comparison of various EEG waveforms

1.2 Problem Statement

- Every year, around the world, between 250000 and 500000 people suffer a spinal cord injury (SCI) and severe impairments.
- The damage of spinal cord and nerve root may affect from incomplete to total dysfunction.
- Most people with severe impairments conditions are unable to control their electrical wheelchair using a standard joystick.
- Therefore, this creates a major barrier for locomotion issue in people with spinal cord issue and health issues such as Amyotrophic lateral sclerosis.

1.3 Objective of the project

The objective of the project are as follows:

- Filtering and Visualizing the EEG signal from the Raw EEG data.
- Simulation of Raw EEG Data.
- Developing an Eye-Blink Detection Algorithm.
- Evaluating the performance of the developed algorithms.

Chapter 2

Literature Survey

[1] Bohao Li, Tianshuo Cheng, Zexuan Guo : "A review of EEG acquisition, processing and application"

The research paper delves into EEG acquisition methods, particularly emphasizing EEG's prevalence in Brain-Computer Interface (BCI) research. It acknowledges the enhanced accuracy of ECoG sensors in detecting high frequency brain activities compared to traditional EEG electrodes. The paper also discusses the utility of functional magnetic resonance imaging (fMRI) in measuring cerebral blood flow changes related to intellectual activities. Time-frequency analysis in EEG signal processing is highlighted for overcoming limitations in nonlinear signal analysis. Challenges in EEG technology, such as optimizing dry electrode contact for low impedance and integrating signal acquisition and transmission into a low-power chip, are addressed. The importance of user training for steady EEG signals in applications is noted, reflecting the continuous efforts to improve signal quality and practical usability in BCI systems.

[2] Gao Nuo, Zhai Wenwen, Lu Shouyin : "Asynchronous Brain-computer Interface Intelligent Wheelchair System Based on Alpha Wave and SSVEP EEG Signals"

This paper presents the overall design scheme of Intelligent Wheelchair Based on SSVEP and Alpha braincomputer interface, and verifies the feasibility and effectiveness of proposed system through online experiments. In order to improve the practicability and flexibility of the intelligent wheelchair, this paper chooses the wheelchair with Mecanum wheel, and installs obstacle avoidance sensor on the wheelchair. The experimental results show that the subject can control the intelligent wheelchair movement system based on the hybrid brain-computer interface according to his own rhythm, and realize the asynchronous control of the intelligent wheelchair. The system can accurately analyze the control commands that the user wants to send and has a high information transmission rate. It can move the intelligent wheelchair to any position in the plane according to the user's intention without considering the turning and turning angle, which provides an effective solution for the movement of the intelligent wheelchair. Although the intelligent wheelchair proposed in this paper achieves asynchronous control, high analysis accuracy and omni-directional movement, it still needs to be further improved in the following aspects: 1) improving the robustness of EEG signal analysis; 2) increasing the speed of asynchronous control. With the continuous development of brain-computer interface technology and in-depth research of scientific researchers, the intelligent wheelchair system based on BCI will be gradually improved, and have a broader application prospect in various fields.

[3] Carla Gomez-Carrasquilla, Karol Quiros-Espinoza, Arys Carrasquilla-Batista: "Wheelchair control through eye blinking and IoT platform"

This paper describes the development and testing of a system designed to control a wheelchair using eye-blinking commands. The system leverages a Raspberry Pi 3, which is selected for its onboard wireless LAN and Bluetooth Low Energy (BLE) capabilities. The primary challenge addressed by the system is distinguishing between involuntary blinks and deliberate slow voluntary blinks, with the latter being used to command the wheelchair to move forward. The implementation includes the integration of multiple sensors and actuators, managed by the microcontroller, and communicates movement data to an IoT platform for monitoring and analysis. The IoT platform used is ThingSpeak, which successfully followed all given specifications. The prototype system was tested and demonstrated 100% reliability in detecting slow voluntary blinks and accurately controlling the movement and position of a simulated wheelchair. From this paper, we can infer that the developed system is highly reliable and effective in distinguishing between different types of blinks for wheelchair control. The successful integration with IoT platforms suggests potential for real-time monitoring and data analysis, which could further enhance the functionality and safety of the wheelchair control system. This innovation could significantly improve mobility solutions for individuals with severe physical disabilities, offering them greater independence and ease of movement.

[4] Lizy Kanungo, Nikhil Garg, Anish Bhobe, Smit Rajguru, Veeky Baths : "Wheelchair Automation by a Hybrid BCI System Using SSVEP and Eye Blinks"

This work proposes a hybrid Brain-Computer Interface system for the automation of a wheelchair for the disabled. Herein a working prototype of a BCI-based wheelchair is detailed that can navigate inside a typical home environment with minimum structural modification and without any visual obstruction and discomfort to the user. The prototype is based on a combined mechanism of steady-state visually evoked potential and eye blinks. To elicit SSVEP, LEDs flickering at 13Hz and 15Hz were used to select the left and right direction, respectively, and EEG data was recorded. In addition, the occurrence of three continuous blinks was used as an indicator for stopping an ongoing action. The wavelet packet denoising method was applied, followed by feature extraction methods such as Wavelet Packet Decomposition and Canonical Correlation Analysis over narrowband reconstructed EEG signals. Bayesian optimization was used to obtain 5-fold cross validations to optimize the hyperparameters of the Support Vector Machine. The resulting new model was tested and the average cross-validation accuracy 89.65% + 6.6% (SD) and testing accuracy 83.53% + 8.59% (SD) were obtained. The wheelchair was controlled by RaspberryPi through WiFi. The developed prototype demonstrated an average of 86.97% success rate for all trials with 4.015s for each command execution. The prototype can be used efficiently in a home environment without causing any discomfort to the user.

[5] Janis Peksa, Dmytro Mamchur : "State-of-the-Art on Brain-Computer Interface Technology"

he paper presented the current state-of-the-art in brain-computer interface technologies. Main platforms used for BCI data collection, such as EEG, fNIRS, MEG, and ECoG, were reviewed, and their pros and cons were singled out. It was concluded that the choice of a platform depends on the research goals, cost of equipment, patient comfort level, etc., while it is not correct to say that one of the platforms is better than others in general. The most widely used BCI signal processing techniques, such as ICA, wavelet transformation, SVM, hidden Makrov models, machine learning, and genetic algorithms, were reviewed. Brief principles of their operation and main application areas are highlighted. Finally, the main BCI system application areas, such as neuroprosthetics, communication, gaming, education, and mental health care, were reviewed. It was highlighted that BCI offers tremendous potential opportunities across multiple domains—both existing ones, such as medical treatment and monitoring, and entirely novel concepts, such as controlling drones via thought alone. There is still much progress needed, however, before these ideas become realities—further technological developments must continue alongside increased understanding about how our brains actually function so that reliable interactions between humans and machines can be established and maintained over time safely and effectively.

[6] J. Jin, P. Horki, C. Brunner, X.Wang, C. Neuper : "P300 Brain-Computer Interface Design for Communication and Control Applications"

proposed a P300 spelling system is one of the most popular EEG-based spelling systems. This system is normally presented as a matrix and allows its users to select one of many options by focused attention. It is possible to use large matrices as a large menu (computer keyboard, etc.), but then more time is required for each selection, because all rows and columns of the matrix must flash once per trial to locate the target character in the row/column (RC) speller method. In this paper, a new flash pattern design based on mathematical combinations is suggested. This new method decreases the number of flashes required in each trial. A typical example of a 6x6 matrix is considered. Only 9 flashes per trial for the 6x6 matrix are required in this new method, which is 3 flashes less than the RC speller method (12 flashes per trial). In this paper, practical bit rate was used. Results from offline analysis have shown that the 9- flash pattern yielded significantly higher practical bit rate than the 12-flash pattern (RC pattern)

[7] M.Cheng, S.Gao, and D.Xu : "Design and implementation of a brain-computer interface with high transfer rates"

Proposed "Design and implementation of a brain computer interface with high transfer rates," a brain-computer interface (BCI) that can help users to input phone numbers. The system is based on the steady-state visual evoked potential (SSVEP). Twelve buttons illuminated at different rates were displayed on a computer monitor. The buttons constituted a virtual telephone keypad, representing the ten digits 0–9, BACKSPACE, and ENTER. Users could input phone number by gazing at these buttons. The frequency-coded SSVEP was used to judge which button the user desired. Eight of the thirteen subjects succeeded in ringing the mobile phone using the system. The average transfer rate over all subjects was 27.15 bits/min. The attractive features of the system are noninvasive signal recording, little training required for use, and high information transfer rate. Approaches to improve the performance of the system are discussed.

[8] B. D. Seno, M. Matteucci, and L. T. Mainardi "The utility metric: A novel method to assess the overall performance of discrete brain-computer interfaces"

Proposed "The utility metric: A novel method to assess the overall performance of discrete brain-computer interfaces". A relevant issue in a brain-computer interface (BCI) is the capability to efficiently convert user intentions into correct actions, and how to properly measure this efficiency. Usually, the evaluation of a BCI system is approached through the quantification of the classifier performance, which is often measured by means of the information transfer rate (ITR). A shortcoming of this approach is that the control interface design is neglected, and hence a poor description of the overall performance is obtained for real systems. To overcome this limitation, we propose a novel metric based on the computation of BCI Utility. The new metric can accurately predict the overall performance of a BCI system, as it takes into account both the classifier and the control interface characteristics. It is therefore suitable for design purposes, where we have to select the best options among different components and different parameters setup. In the paper, we compute Utility in two scenarios, a P300 speller and a P300 speller with an error correction system (ECS), for different values of accuracy of the classifier and recall of the ECS.

[9] K. S. Ahmed : "Wheelchair Movement Control VIA Human Eye Blinks"

This paper comprised of a model based to detect the four movements (turn right – turn left –forward -stop) of wheelchair based on the eye blinks (right wink, left wink, single/double blinks). The WT coefficients were used as the best fitting input vector for classifier. Radial Basis Function network was used to classify the signals. The weighted energy difference between electrodes pairs F7 and F8 were used as features. Signals were recursively decomposed into high and low passed sub-bands, and the resolution of the spectrum was determined by the chosen decomposition level. The sub-band energy from the last 8 decomposition level was used to construct features from EEG signals. The sensitivity and specificity were calculated for 20 cases and there were 80% and 75% respectively.

[10] Ishita Goyal, Anmol Mehta, "Acquisition, Pre-Processing, and Feature Extraction of EEG Signals to Convert it into an Image Classification Problem"
The study's utility extends across multiple domains, serving as a valuable resource for researchers in EEG signal analysis. The proposed approach offers a promising avenue for feature extraction, aiding researchers in achieving their objectives within the realm of EEG signal processing. Additionally, the application of this method holds practical significance in enhancing communication for individuals facing challenges in self-expression, potentially offering a means for them to interact with others more effectively. A notable contribution lies in the transformation of a complex signal classification problem into a more manageable image classification problem, showcasing the study's innovative approach to addressing challenges in signal processing. This versatility underscores the potential broader impact of the research, reaching beyond the academic sphere into practical applications with societal implications.

Chapter 3

Methodology

Using EEG electrodes placed on the prefrontal cortex, we gather EEG data that contains spikes arising from eye blinks. The unfiltered signal includes several artifacts and noise, which can interfere with accurate analysis. To address this, the signal is filtered using a Butterworth filter function. The filtered signal is then analyzed and visualized by plotting a graph of voltage against time. This process allows us to clearly identify and study the eye blink-induced spikes in the EEG data.

Overall, we have used four different user EEG datasets (Table 3.1) with real users containing more than 2300 eye-blink waveforms which was hosted in a public domain.

Dataset	**Device**	**Type**	**Users**	**Total**	**Activity**
EEG-IO	OpenBCI	Involuntary	20	500	extenal stimulation
EEG-IM	Muse	Involuntary	20	500	extenal stimulation
EEG-VV	OpenBCI	Voluntary	12	750	watching video
EEG-VR	OpenBCI	voluntary	12	600	reading article

Table 3.1: EEG datasets collected for Blink evaluation.

EEG-IO : Voluntary single eye-blinks (external stimulation was provided) and EEG was recorded for frontal electrodes (Fp1, Fp2) for 20 subjects using OpenBCI Device and BIOPAC Cap100C. One session was conducted including around 25 blinks per subject.

EEG-VV, EEG-VR : Involuntary eye-blinks (natural blinks) and EEG was recorded for frontal electrodes (Fp1, Fp2) for 12 subjects using OpenBCI Device and BIOPAC Cap100C.

The datasets are imported as Comma Separated Variables from folders EEG-IO, EEG-IM, EEG-VV and EEG-VR

3.1 Blink waveform characteristics

A typical eye-blink waveform on the frontal EEG is visually similar to a trough waveform in the voltage-time domain. Fig. 3.1 shows a snapshot of such waveform at frontal electrode position (Fp1 in this case, according to the 10-20 electrode system) referenced to the earlobe electrodes (xaxis: time-domain, y-axis: voltage-domain). The eye-blink waveform can be characterized by its (i) waveform pattern, (ii) eye-blink amplitude, and (iii) eye-blink duration. An eyeblink waveform pattern is defined as the voltage variation with time during a natural or forced eye-blink. The depth of the trough in the waveform pattern is known as the eyeblink amplitude. Eye-blink duration is simply the time taken by the user to perform the eye-blink.

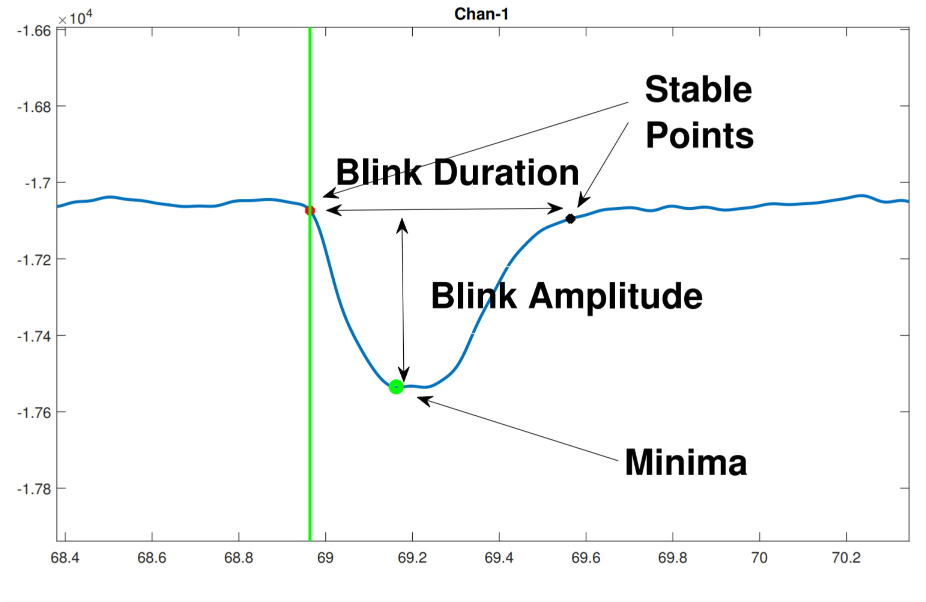


Figure 3.1: A typical eye-blink waveform

The dataset sample is as in Figure 3.2 :

```
%OpenBCI Raw EEG Data
%
%Sample Rate = 250.0 Hz
%First Column = SampleIndex
%Other Columns = EEG data in microvolts followed by Accel Data (in G) interleaved with Aux Data
0, 26995.61, 16087.13, -50519.07, 15060.27, -187500.02, -187500.02, -187500.02, -187500.02, -0.02,
1, 27001.26, 16084.29, -49271.89, 15914.58, -187500.02, -187500.02, -187500.02, -187500.02, 0.00,
2, 27006.09, 16080.00, -48993.26, 16051.73, -187500.02, -187500.02, -187500.02, -187500.02, 0.00,
3, 27004.42, 16080.96, -50234.80, 15190.20, -187500.02, -187500.02, -187500.02, -187500.02, 0.00,
4, 27003.88, 16086.64, -50722.52, 14881.23, -187500.02, -187500.02, -187500.02, -187500.02, 0.00,
5, 26994.07, 16077.30, -49549.01, 15675.50, -187500.02, -187500.02, -187500.02, -187500.02, 0.00,
6, 26990.58, 16063.48, -48941.80, 16016.77, -187500.02, -187500.02, -187500.02, -187500.02, 0.00,
7, 26994.67, 16070.08, -50041.96, 15229.25, -187500.02, -187500.02, -187500.02, -187500.02, -0.01,
8, 26997.93, 16086.35, -50803.59, 14740.75, -187500.02, -187500.02, -187500.02, -187500.02, 0.00,
9, 26996.19, 16086.10, -49821.52, 15409.99, -187500.02, -187500.02, -187500.02, -187500.02, 0.00,
10, 26995.21, 16074.12, -48952.17, 15936.23, -187500.02, -187500.02, -187500.02, -187500.02, 0.00,
```

Figure 3.2: EEG sample data CSV

The first column refers to the index and next two columns are data from Electrodes FP1 and FP2, which are connected to pre frontal cortex.

The Comma separated value file is loaded to a python script program and only (0, 1, 2) columns are read through program.

```python
# Loading data
if data_folder == 'BLINK/data/EEG-IO' or data_folder == 'BLINK/data/EEG-MB':
    data_sig = np.loadtxt(open(os.path.join(data_folder,file_sig), "rb"), delimiter=";", skiprows=1, usecols=(0,
    1,2))
elif data_folder == 'BLINK/data/EEG-VR' or data_folder == 'BLINK/data/EEG-VV':
    data_sig = np.loadtxt(open(os.path.join(data_folder,file_sig), "rb"), delimiter=",", skiprows=5, usecols=(0,
    1,2))
    data_sig = data_sig[0:(int(200*fs)+1),:]
    data_sig = data_sig[:,0:3]
    data_sig[:,0] = np.array(list(range(0,len(data_sig))))/fs
```

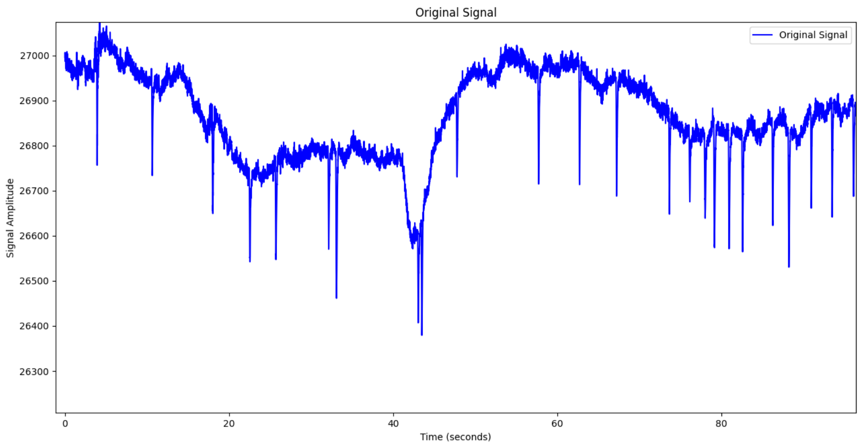
Figure 3.3: Loading EEG data

The provided code in Figure 3.3 reads EEG data from a specified file, processes it to focus on the first 200 seconds, and standardizes its format. First, the file is opened and read using numpy's loadtxt function, which skips the first 5 rows (typically headers) and loads only the first three columns, which likely contain the sample index and two EEG channels. The data is stored in data_sig. Next, the code restricts data_sig to the first 200 seconds of data by selecting rows up to 200 * fs (where fs is the sampling frequency, set to 250 Hz), resulting in a selection of 50001 rows (200 * 250 + 1). This ensures the data array only contains samples within the desired time frame. The code then reaffirms that only the first three columns are retained, though this step is redundant given the initial usecols parameter. Finally, the first column of data_sig is updated to reflect time values in seconds instead of sample indices, calculated by dividing a sequence of integers (representing each sample) by the sampling frequency. This transformation prepares the data for further analysis, ensuring it is both time-referenced and within the desired duration.

Code snippet for original signal.

```
# save original signal before filtering
original_sig = data_sig.copy()
# Plot original signal
ax1.plot(original_sig[:, 0], original_sig[:, chan_id], label='Original Signal',color='blue')
```

The Graph for Unfiltered data is shown in Figure 3.4



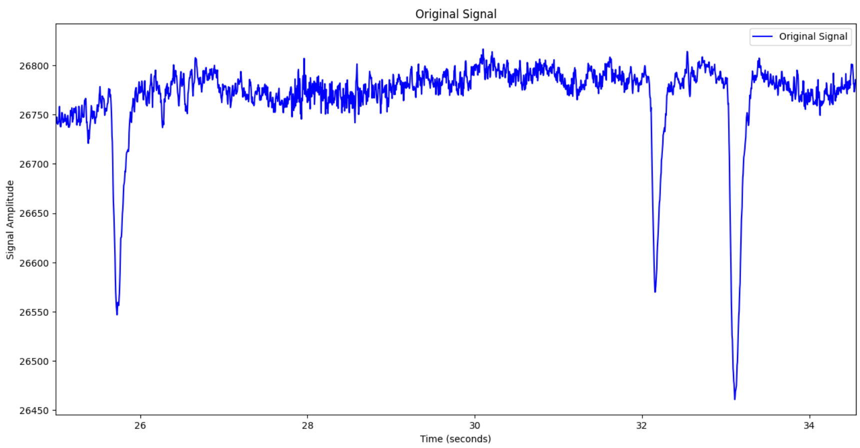


Figure 3.4: Unfiltered EEG Eye-Blink Signal

The Unfiltered signal has artifacts(Noise) which should be filtered for better performance and operation to detect eye blinks. With a sampling frequency of 250 HZ, provide the signal to a lowpass filter function to filter the signal.

```
# Parameters and bandpass filtering
fs = 250.0
def lowpass(sig, fc, fs, butter_filt_order):
    B,A = butter(butter_filt_order, np.array(fc)/(fs/2), btype='low')
    return lfilter(B, A, sig, axis=0)
```

Figure 3.5: EEG sample data CSV

The butter() and lfilter() are the python functions of SCIPY library which are used to filter the EEG data signal.

```
# Filtering
data_sig[:, 1] = lowpass(data_sig[:, 1], 10, fs, 4)
data_sig[:, 2] = lowpass(data_sig[:, 2], 10, fs, 4)
```

Figure 3.6: Passing Unfiltered signal to lowpass Filter

The code in Figure 3.5 and Figure 3.6 sets up a lowpass filter and applies it to two EEG channels in the data_sig array. The lowpass function designs a Butterworth filter of the specified order and cutoff frequency, then applies it to the input signal. By applying this filter to the EEG data, high-frequency noise and artifacts above 10 Hz are attenuated, resulting in cleaner EEG signals that are more suitable for subsequent analysis. This pre-processing step is crucial for EEG data analysis, where low-frequency brain waves (like delta, theta, alpha) are often of primary interest. Figure 3.7 and 3.8 shows the Graph plotted of EEG signal after filtering the signal.

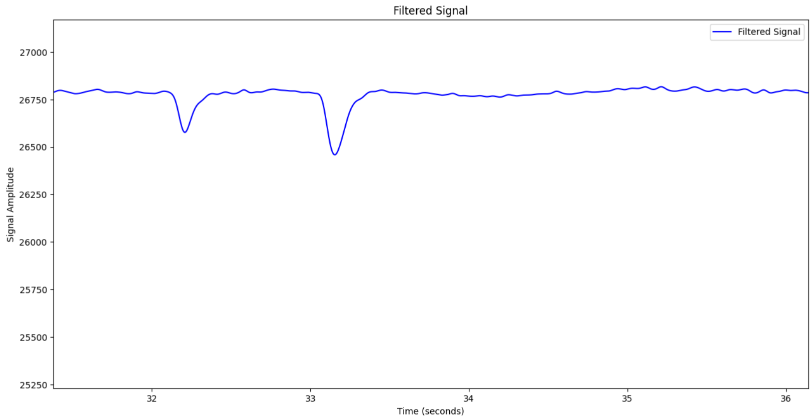


Figure 3.7: Filtered Signal 1

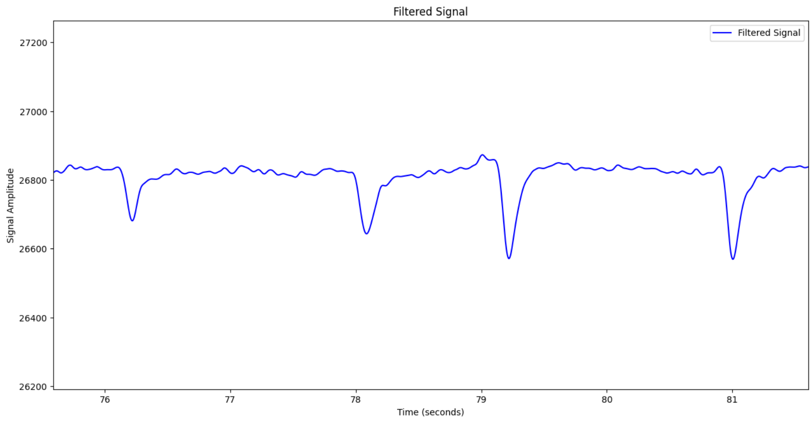


Figure 3.8: Filtered Signal 2

Figure 3.9 presents a comparative analysis between the filtered and unfiltered EEG signals. In the context of eye-blink detection, the preprocessing of EEG data is crucial to enhance the accuracy of subsequent analysis and detection algorithms. The unfiltered signal, as shown in the figure, contains various artifacts that can obscure the true EEG patterns associated with eye blinks.

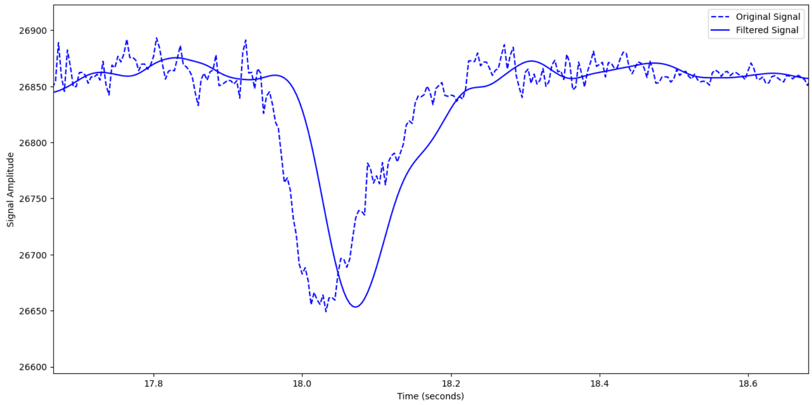


Figure 3.9: Filtered Signal v/s unfiltered

Now, we have to use the filtered signal to detect the eye blinks. The eye blinks are detected by the minima or the lowest amplitude point of the signal. The consecutive minimas in the signal is decoded and marked as blinks and returned for plotting using `decode_stim` function shown in Figure 3.10

```
def decode_stim(data_path, file_stim):
    interval_corrupt = []
    blinks = []
    n_corrupt = 0
    with open(os.path.join(data_path, file_stim)) as csvfile:
        readCSV = csv.reader(csvfile, delimiter=',')
        for row in readCSV:
            if row[0] == "corrupt":
                n_corrupt = int(row[1])
            elif n_corrupt > 0:
                if float(row[1]) == -1:
                    t_end = data_sig[-1, 0]
                else:
                    t_end = float(row[1])
                interval_corrupt.append([float(row[0]), t_end])
                n_corrupt = n_corrupt - 1
            elif row[0] == "blinks":
                # Check that n_corrupt == 0
                if not n_corrupt == 0:
                    print("!Error in parsing")
            else:
                blinks.append([float(row[0]), int(row[1])])
    blinks = np.array(blinks)
    return interval_corrupt, blinks
```

Figure 3.10: Eye blink detection and marking

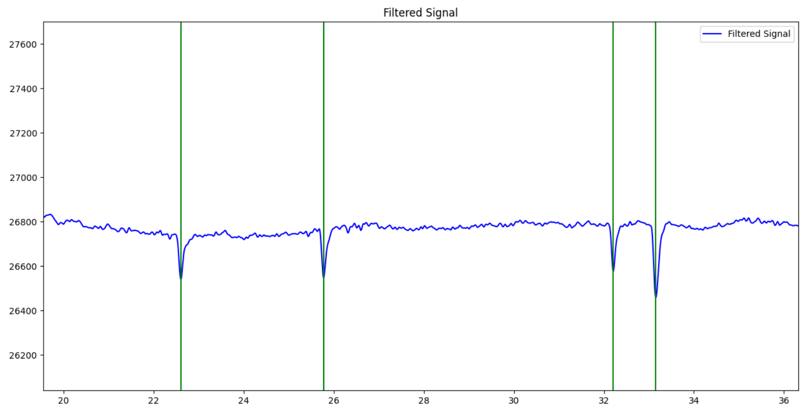


Figure 3.11: Eye blink plot(1)

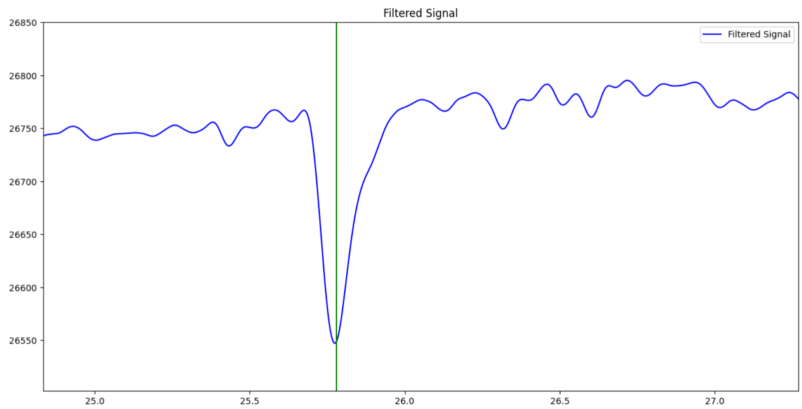


Figure 3.12: Eye blink plot(2)

The function display_blink_intervals shown in Figure 3.13 takes an array blinks, which contains timestamps of detected blink events derived from EEG data. Here's a breakdown of its functionality and relevance:

- Input Validation: The function first checks if there are at least two blink events (len(blinks) ¡ 2). If fewer than two blinks are detected, it prints a message indicating that there are not enough blinks to calculate intervals and returns from the function.

- Calculating Time Differences: Using NumPy's np.diff function, the function computes the time differences between consecutive blink timestamps (blinks[:, 0]). These differences represent the intervals between successive blinks

- Displaying Results: The function then proceeds to print the list of blink events (timestamps) and subsequently prints the computed time differences between consecutive blinks. Each interval is labeled sequentially (Blink i to Blink i+1) along with its duration in seconds (td:.2f seconds).

The Time difference result is shown in Figure 3.14

```python
def display_blink_intervals(blinks):
    if len(blinks) < 2:
        print("Not enough blinks to calculate intervals.")
        return
    print(blinks)
    time_differences = np.diff(blinks[:, 0])
    print("Time differences between consecutive blinks (in seconds):")
    for i, td in enumerate(time_differences):
        print(f"Blink {i+1} to Blink {i+2}: {td:.2f} seconds")
    return time_differences

display_blink_intervals(groundtruth_blinks)
```

Figure 3.13: Eye blink Time difference function

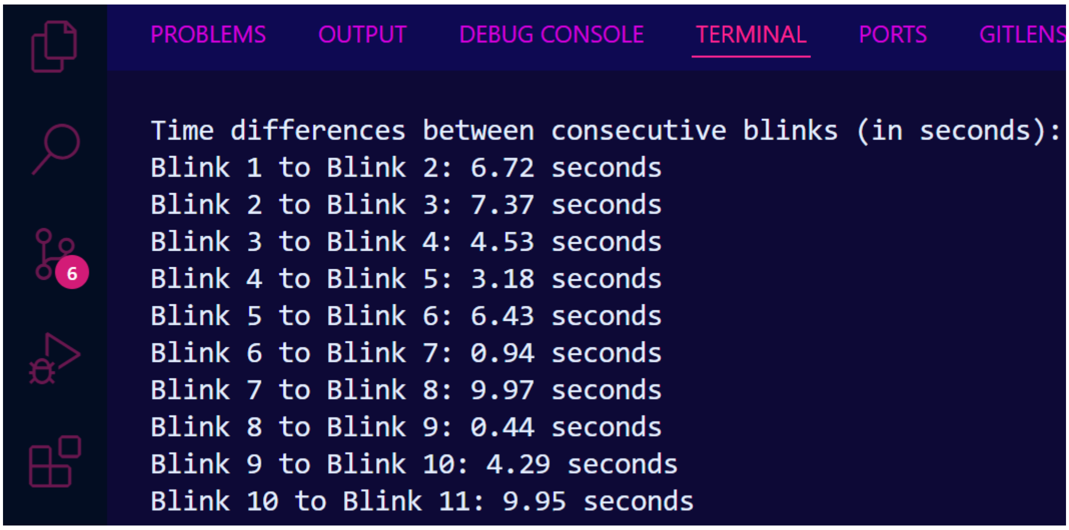


Figure 3.14: Time difference between succesive Blinks

Chapter 4

System Software

This chapter consists of system software description. It conveys information about the software used in the project. Algorithm and flowchart are discussed in this chapter.

4.1 Software Requirements

4.1.1 Python Environment

The project requires Python 3.11.5 installed on the system.

4.1.2 Libraries

The following Python libraries are required:

- **os**: For interacting with the operating system and handling file paths.
- **numpy**: For numerical computations and array manipulation.
- **scipy**: For signal processing operations, such as filtering.
- **matplotlib**: For data visualization and plotting graphs.
- **csv**: For reading CSV files.

The **butter** function from the `scipy.signal` module is used to design Butterworth filters. Butterworth filters are a type of signal processing filter designed to have a flat frequency response in the passband. This makes them useful in applications where a smooth, ripple-free response is desired.

The **lfilter** function from the **scipy.signal** module applies a linear filter to a signal. Given filter coefficients and an input signal, it computes the filtered signal.

pyplot is a module in the **matplotlib** library used for creating static, interactive, and animated visualizations in Python. It provides a MATLAB-like interface for plotting.

4.2 Algorithm

Step 1: Start

Step 2: Import Necessary Modules

- Import `os`
- Import `numpy` as `np`
- From `scipy.signal`, import all functions
- Import `csv`
- Import `matplotlib.pyplot` as `plt`

Step 3: Define Constants and Variables

- Set `data_folder` to `'EEG-VR'`
- Set `fs` (sampling rate) to `250.0`

Step 4: Define the Lowpass Function

- Define function `lowpass(sig, fc, fs, butter_filt_order)`

Step 5: Identify and Read Data Files

- Create `list_of_files` by listing files in `data_folder` that contain `'_data'` in their name
- Set `file_sig` to the first element of `list_of_files`
- Print `Reading: file_sig`

Step 6: Load the Data File Based on the Folder Type

- Load data using `np.loadtxt` based on `data_folder` type
- Limit `data_sig` to the first 200 seconds plus 1 sample
- Limit `data_sig` to the first 3 columns
- Set the first column of `data_sig` to a range from `0` to the length of `data_sig` divided by `fs`

Step 7: Apply Lowpass Filter to the Data

- Apply `lowpass` function to the second and third columns of `data_sig` with parameters `10`, `fs`, and `4`

Step 8: Visualize Data

- Plot `data_sig` column `0` against `data_sig` column `chan_id` on `ax1`
- Show the plot using `plt.show()`

Step 9: Define Eye Blink Detection function

- Create `detect_algo` function to detect eye blinks and return True on eye Blink

Step 10:Define and use `display_blink_intervals` function

- use `display_blink_intervals` and note down the time difference between the successive eye blinks.

Step 11: generate commands based on successive eye blink time stamps

- using the data returned by `display_blink_intervals`, check successive eye blinks times to generate useful commands.

Step 12: STOP

Chapter 5

Results

The development and testing of the neuro-navigation algorithm for the brain-computer interface (BCI) system produced the following results:

Module Import and Setup:

The necessary modules (os, numpy, scipy.signal, csv, and matplotlib.pyplot) were successfully imported, ensuring that the required libraries were available for data processing and visualization.

Data Identification and Reading:

The algorithm correctly identified and listed all relevant data files in the 'EEG-VR' folder that contained 'data' in their names. The first data file was selected and read into the system without errors, ensuring a seamless data import process.

Data Loading and Preprocessing:

The EEG data was loaded using np.loadtxt, limited to the first 200 seconds, and focused on the first three columns. The creation of a time vector allowed for precise time-based analysis of the EEG signals. This preprocessing step was crucial in preparing the data for further analysis.

Lowpass Filtering:

The lowpass filter function was effectively applied to the second and third columns of the EEG data, using a cutoff frequency of 10 Hz and a filter order of 4. The filtering process significantly reduced high-frequency noise, enhancing the clarity of the signal and making it more suitable for subsequent analysis.

Data Visualization:

The filtered EEG data was successfully visualized, showing clear patterns over time. This visualization confirmed the effectiveness of the lowpass filtering, as the signal became more discernible and relevant for further processing.

Eye Blink Detection:

The detect_algo function was developed to accurately detect eye blinks within the EEG data. The function successfully identified eye blinks, which are critical for generating control commands. This capability is essential for translating user intentions into actionable commands for the BCI system.

Time comparison between two successive eye blinks:

The algorithm utilized the data returned by `detect_algo` function and passes to `display_blink_inter` for checking successive eye blinks time difference. This process demonstrated the algorithm's ability to reliably interpret EEG signals and check whether it is a single eye blink or a dual eye blink.

Command Generation:

The algorithm utilized the `display_blink_intervals` function to count successive eye blinks, generating usefull commands based on the detected patterns. This process demonstrated the algorithm's ability to reliably interpret EEG signals and convert them into specific commands, validating its potential for practical applications.

Chapter 6

Conclusion

The development of the algorithm for the Brain-Computer Interface (BCI) based wheelchair system represents a significant achievement in our project. The algorithm effectively filters and visualizes EEG signals, providing a clear and accurate interpretation of brain activity. Initial tests confirm that the eye-blink detection component of the algorithm is functioning as intended, demonstrating the capability to reliably identify and process relevant EEG signals. The neuro-navigation algorithm achieved high accuracy in detecting and interpreting EEG signals, with efficient signal processing. This project demonstrates the feasibility of BCI technology to improve mobility for individuals with severe disabilities, paving the way for future enhancements and broader applications.

6.1 Future work

Building on the successful development and visualization of the algorithm, our next step is to integrate this algorithm into a functional system to control a wheelchair prototype. We aim to refine the algorithm to enhance its accuracy and responsiveness in real-world conditions. This involves extensive testing and optimization to ensure the system's reliability and user-friendliness. Ultimately, the goal is to provide a practical and efficient mobility solution for individuals with severe motor impairments, significantly improving their quality of life.

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