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Design and implementation of a non-invasive brain computer interface for prosthetic ARM

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Abstract. Brain-controlled prosthetic arms have become a significant advancement in the healthcare and assistive technology industry, bringing hope to people with limb challenges**.** This research unveils the successful development of a non-invasive brain-controlled prosthetic arm system, integrating the Emotiv EPOC X 14-channel brain sensor with 3D printing technology. This system effectively translates neural signals into precise movements, granting users a heightened level of control and functionality. The comprehensive methodology delineates the entire process, from the strategic placement of the brain sensor to data acquisition, processing, and servo control. Calibration and user training further refine system accuracy and responsiveness. Results affirm performance, boasting a remarkable 97 % accuracy rate. Response times vary depending on the complexity of the command and the amount of processing required. The user feedback praises the system's ease of use and its ability to bring about significant changes in everyday life. The following discussion examines essential factors of user comfort, long-term usage, and efficient setup, which are all critical components of the user experience. This research serves as an example of interdisciplinary collaboration, unifying neuroscience, engineering, and ethical considerations, resulting in a pioneering assistive technology. The brain-controlled prosthetic arm not only signifies technological advancement but also embodies inclusivity and ethical responsibility. In conclusion, this research illuminates the profound potential of brain-controlled prosthetic arms, empowering individuals with limb disabilities, restoring autonomy, and bridging the gap between ability and disability. As technology advances, the horizon expands, ushering in a future where limitations fade, and aspirations are realized.

Keywords: Prosthetic arm, Prosthetic Limb, EEG, Neuro-prosthetics, BCI, Assistive Technology.

Classification numbers: 5.3.9, 5.2.2, 5.6.3

1. INTRODUCTION

In a world where thoughts can shape reality, where the power of the mind breathes life into prosthetic limbs, the realm of modern healthcare and assistive technology has witnessed a remarkable transformation [1, 2]. Brain-controlled prosthetic arms, the embodiment of this transformation, bridge the chasm between the human mind and artificial limbs, offering newfound hope to those with limb disabilities [3, 4]. Brain-controlled prosthetic arms offer a myriad of strengths for individuals facing limb loss, encompassing restored functionality, heightened quality of life, and enhanced psychological well-being [1, 5]. These devices afford intuitive control, personalized customization, and seamless integration into daily routines, fostering independence and self-reliance [6]. Additionally, they facilitate naturalistic movements, bolster social interaction, and broaden vocational prospects, promoting inclusivity and empowerment. Moreover, users serve as catalysts for advocacy, inspiring advancements in assistive technology and societal acceptance. In essence, these innovations represent a paradigm shift, delivering pragmatic solutions and empowering individuals to navigate life's challenges with resilience and dignity despite the adversity of limb loss.

We commence our research expedition with an ambitious objective: to develop an advanced prosthetic arm system that can be controlled by the brain, eliminating the need for intrusive procedures. This ambitious endeavour capitalizes on the immense potential of the Emotiv EPOC X 14-channel brain sensor and the precision of 3D printing technology. Through this research, we aspire to push the boundaries of assistive technology, unlocking new possibilities for those longing to regain control over their movements.

The urgency of research is underscored by stark statistics: an estimated 1.3 billion people, constituting 16 % of the global population, grapple with significant disabilities. These individuals not only face a disproportionate risk of premature mortality, often losing up to two decades of life compared to their able-bodied counterparts but also encounter formidable challenges in accessing basic transportation [7, 8]. Confronted with these harsh realities, the need for innovative assistive technologies, exemplified by brain-controlled prosthetic arms, becomes undeniable. These technologies represent a bridge-a bridge spanning the chasm between the yearning to perform both mundane and complex tasks and the tangible ability to turn those yearnings into reality [9].

2. METHODS

The methodology section provides a detailed analysis of the sequential procedures used to develop and operate the brain-controlled prosthetic arm system. The foundation of the brain-controlled prosthetic arm system is laid by strategically positioning the Emotiv EPOC X 14-channel brain sensor on the user’s scalp as depicted in Figure 3. This sensor serves as the neural input interface, capturing intricate brain signals that reflect the user’s intentions. The prosthetic arm, with utilization of 3D printing technology, is carefully designed to cater to the user’s unique anatomical characteristics. The arm consists of an arrangement of servo motors that facilitate motion. The Arduino board takes center stage as the central processing unit, facilitating seamless communication between the neural input and mechanical output. The Emotiv EPOC X sensor, adorned with non-invasive electrodes, captures the electrical brain activity of the user. This activity delivers a continuous flow of OSC (Open Sound Control) messages that contain a large amount of unprocessed data. The methodology for the non-invasive brain-controlled prosthetic arm using the Emotiv EPOC X involves capturing a variety of mental commands and facial expressions to discern the user’s intent. The Arduino code acts as a neural translator, employing OSC message processing libraries to decode neural data. This decoding process involves parsing OSC messages to extract meaningful insights. Signal processing algorithms analyze the data, distinguishing between mental commands and facial expressions with precision. The interpreted neural commands are translated into movements of the prosthetic arm's servo motors. The Arduino board uses PWM (Pulse Width Modulation) signals to communicate with the servos, converting neural intentions into mechanical actions. Calibration ensures optimal accuracy and responsiveness by fine-tuning the system to establish a robust mapping between neural signals and prosthetic arm movements [10]. User training sessions help refine neural commands, leading to precise control and accurate movements [11].

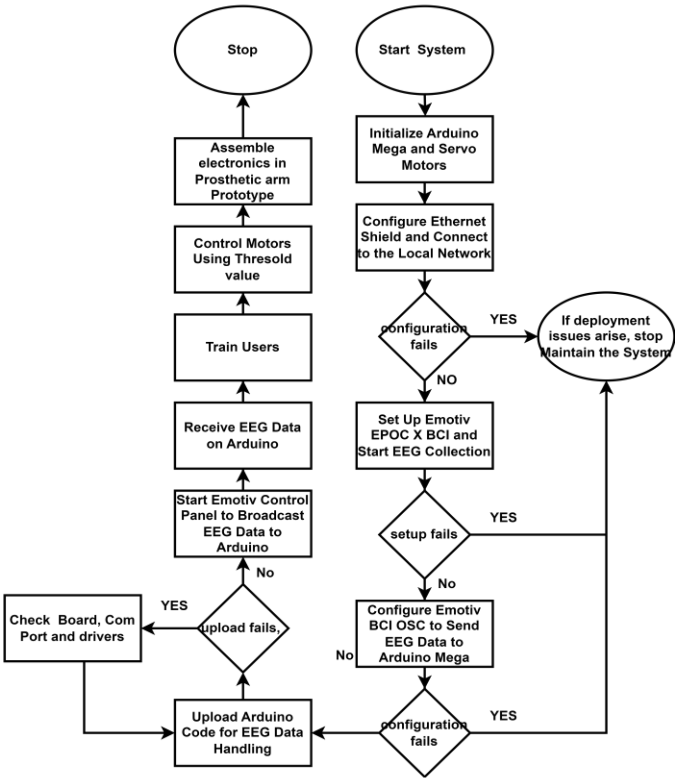

Figure 1. Development and operational sequence of the brain-controlled prosthetic arm.

The Arduino code translates decoded neural signals into physical actions of the prosthetic arm. It receives OSC messages about the user’s intent and controls the servos accordingly. Conditional statements recognize specific OSC message patterns, triggering corresponding servo movements for facial expressions like "blink" or "wink" and mental commands like "push," "pull," or "rotate." PWM signals allow smooth articulation of the prosthetic arm’s movements, with the code adjusting servo angles based on the strength and duration of neural signals for fine-grained control. The code's flexibility supports additional commands and expressions, adapting to users’ needs. Calibration and user training phases ensure accurate interpretation of individual neural signals, resulting in a personalized and responsive experience.

The operational workflow of the system (Figure 1) outlines the process of configuring and controlling the brain-controlled prosthetic arm. It begins with initializing the Arduino Mega and servo motors, followed by Ethernet shield setup, EEG signal acquisition via the Emotiv EPOC X, and OSC-based data transmission to the Arduino. The uploaded code interprets EEG data to drive servo movements. The flowchart also includes checkpoints and user training to enhance system reliability and adaptability.

3. RESULTS

In this section, the results of the brain-controlled prosthetic arm system’s performance and functionality are presented.

3.1. Experimental Setup

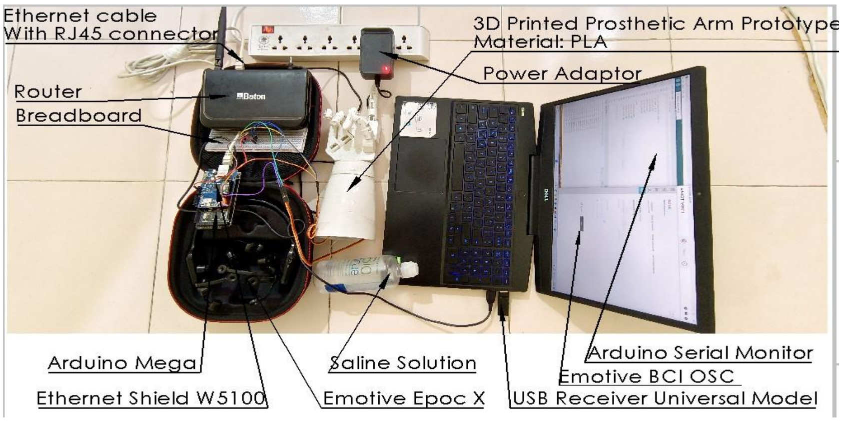

Figure 2. Experimental setup.

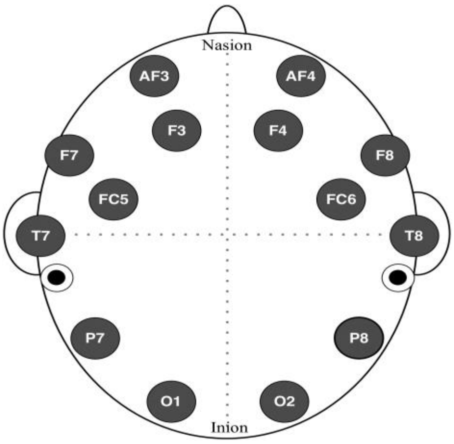

Figure 3. Electrodes position for Emotive Epoc X ([12]).

The experimental setup Figure 2 consists of a meticulously chosen combination of components, each having a unique function in the progression of brain-controlled prosthetic limbs. The Emotiv EPOC X is the main component that connects the user's brain with the prosthetic arm system, allowing for direct and instinctive control. The Arduino Mega serves as the central processing unit, analyzing neurological inputs and converting them into executable instructions for the prosthetic limb. The Ethernet W5100 module ensures strong and reliable data connectivity, while the saline solution maintains optimal electrode performance. The USB Receiver (Universal Model) enables smooth communication between the Emotiv EPOC X and the Arduino. Additionally, a prototype of a 3D-printed prosthetic arm is created to demonstrate the concept and can execute commands. By incorporating a breadboard, it becomes possible to create circuit designs that are adaptable and versatile. Additionally, the utilization of an Ethernet cable equipped with an RJ45 connector, along with a router, enhances the range of networking options available. Ultimately, a specialized power adapter guarantees continuous and uninterrupted operation. This meticulously constructed configuration represents the merging of neuroscience and engineering, showing great potential for improving the quality of life for people with limb disabilities.

Figure 3 shows the electrode arrangement of the Emotiv EPOC X headset, organized in accordance with the international 10 - 20 placement scheme. This configuration enables the device to record brain activity from the frontal, temporal, and occipital regions, which is essential for operating the prosthetic arm.

Noise Filtering

Experimental investigation has been initiated with the objective of comprehending voltage fluctuations across 14 electrodes in the context of 50 subjects with the help of Emotive Epoc X. These voltage values are expressed in microvolts; however, it is crucial to acknowledge that a direct current offset of 4100 microvolts exists. It should be noted that the absolute magnitude of this offset may be influenced by direct current drift, thereby manifesting as increased amplitudes in the recorded data. The data presented herein represents raw values, with no application of high-pass or low-pass filtering techniques. Consequently, the issue of accuracy has been exacerbated due to the presence of noise in the dataset. We have computed the mean values for all 14 electrodes across all 50 subjects during clenching activities, as illustrated in Figure 4.

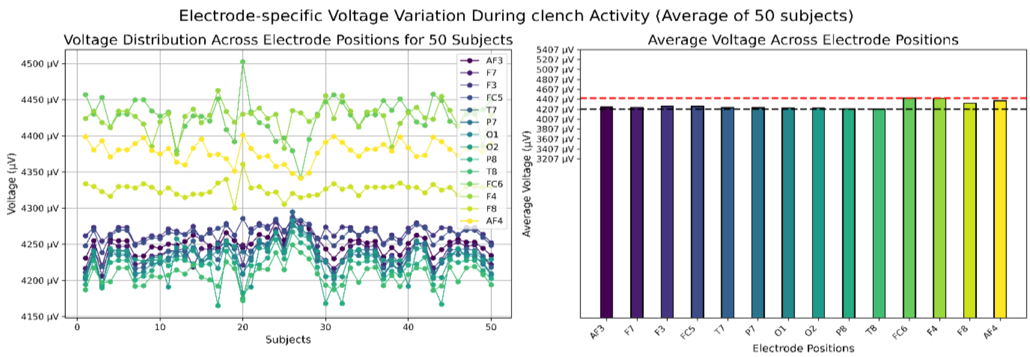

Figure 4. Electrode specific voltage distribution during clench activity (Average of 50 subjects).

Furthermore, in our quest to enhance the quality and reliability of our electroencephalogram (EEG) data, we have implemented both high-pass and low-pass filtering techniques. These filtering procedures play complementary roles in the preprocessing of EEG data, collectively contributing to the refinement of our dataset and the extraction of crucial neural information [13, 14]. By selecting a cutoff frequency of 0.16 Hz and a filter order of 4, we effectively target and remove undesirable low-frequency components inherent in EEG signals. This includes mitigating issues like baseline drift and slow oscillations, which are extraneous to our research focus on neural phenomena. The cutoff frequency defines the boundary below which signals are attenuated, and the filter order determines the sharpness of the transition between the passband and stopband. When applied appropriately, the high-pass filter eliminates baseline drift and highlights higher-frequency neural components, encompassing brainwave oscillations and event-related potentials. This not only boosts the signal-to-noise ratio but also empowers researchers to identify, isolate, and analyze neural events of profound scientific interest. In addition to the high-pass filter, we have incorporated a low-pass filter into our EEG data preprocessing pipeline. This filter serves a complementary role by addressing high-frequency noise and artifacts that can obscure the neural phenomena of interest. For our study, we selected a cutoff frequency of 30 Hz and a filter order of 4, ensuring that we retain the critical neural information while attenuating high-frequency noise. The combination of both high-pass and low-pass filters provides a comprehensive noise reduction strategy, resulting in a cleaner and more refined dataset for our research investigations.

A detailed analysis of the EEG data recorded from ‘user 2’ during the clenching task using the Emotiv EPOC Pro headset is presented here. Figure 5 offers an initial comparison between the raw EEG signals and their corresponding high-pass and low-pass filtered outputs across all 14 electrodes. Figures 6 - 19 build on this foundation by providing electrode-specific plots that contrast the unfiltered and processed signals and depict their temporal amplitude variations. Taken together, these figures clearly demonstrate the enhancement in signal quality achieved through filtering and offer a more comprehensive understanding of the neural activity patterns captured across the full electrode array.

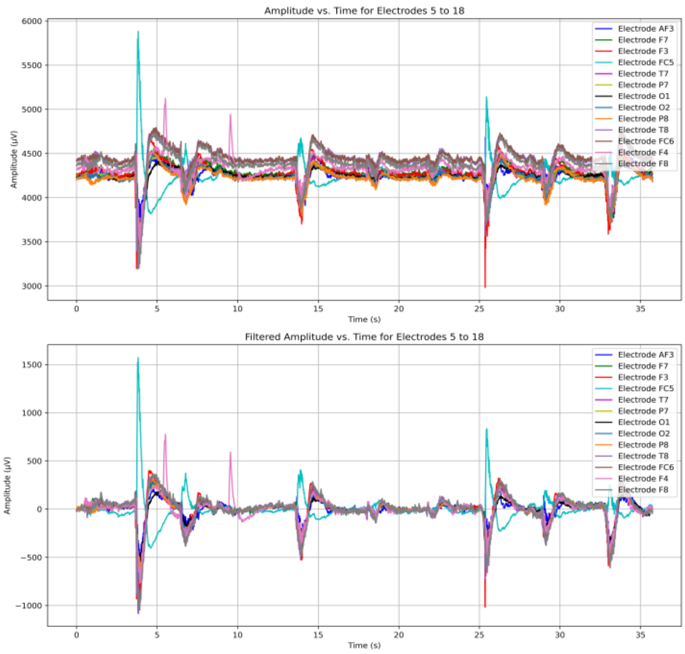

Figure 5. Electrode specific signal (raw vs filtered), Amplitude vs Time for subject 2.

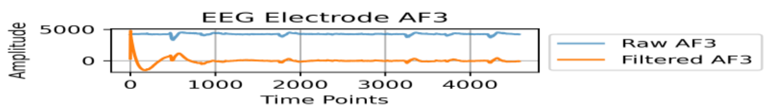

Figure 6. Raw and Filtered EEG Data (AF3).

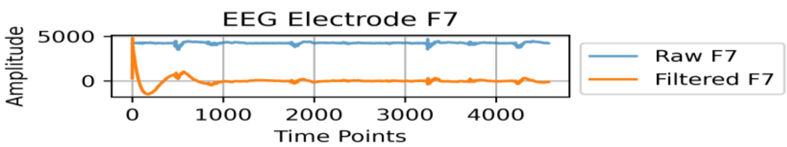

Figure 7. Raw and Filtered EEG Data (F7).

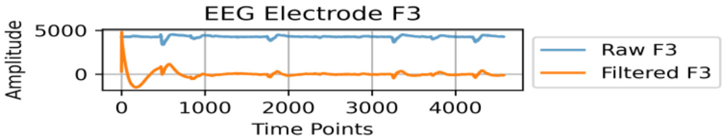

Figure 8. Raw and Filtered EEG Data (F3).

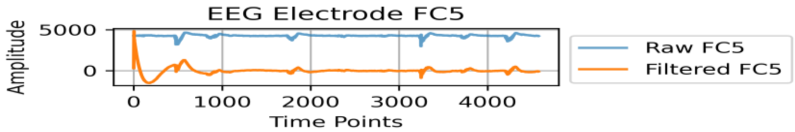

Figure 9. Raw and Filtered EEG Data (FC5).

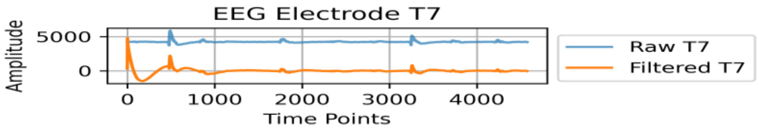

Figure 10. Raw and Filtered EEG Data (T7).

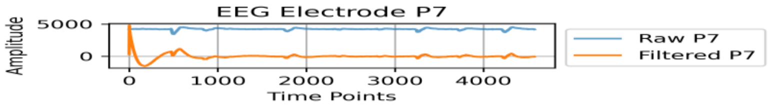

Figure 11. Raw and Filtered EEG Data (P7).

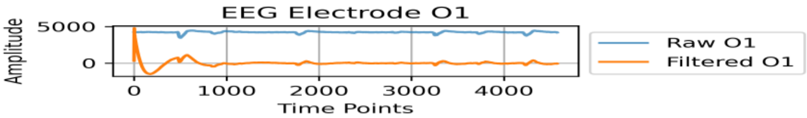

Figure 12. Raw and Filtered EEG Data (O1).

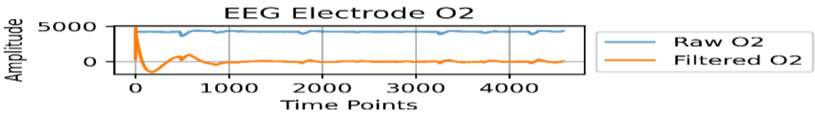

Figure 13. Raw and Filtered EEG Data (O2).

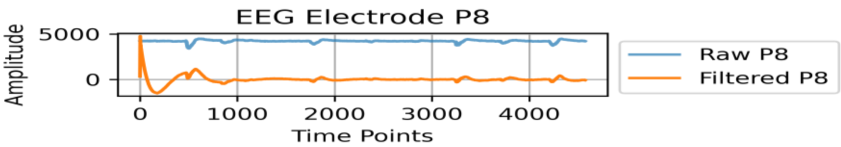

Figure 14. Raw and Filtered EEG Data (P8).

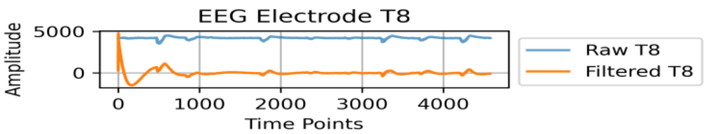

Figure 15. Raw and Filtered EEG Data (T8).

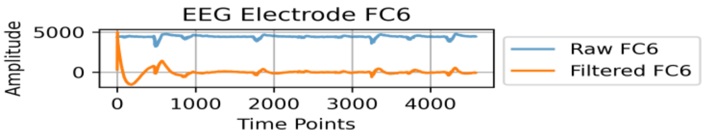

Figure 16. Raw and Filtered EEG Data (FC6).

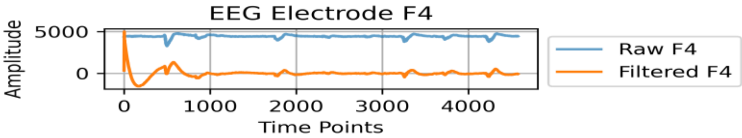

Figure 17. Raw and Filtered EEG Data (F4).

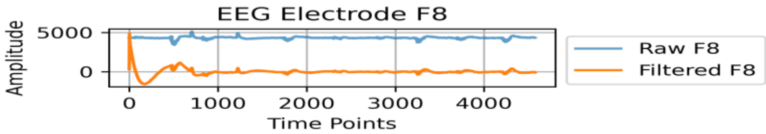

Figure 18. Raw and Filtered EEG Data (F8).

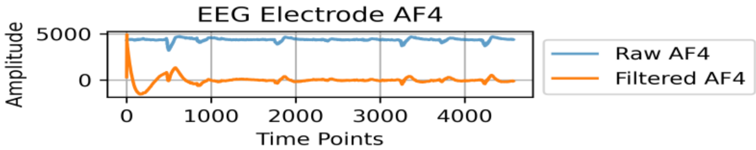

Figure 19. Raw and Filtered EEG Data (AF4).

3.2. Response Time Analysis

The response time analysis aimed to assess the efficiency of the system in translating neural commands into physical movements. In Figure 20 and Figure 21, we observed how response times varied across different mental commands and facial expressions. In Figure 20, the analysis revealed that ”Blink” had an average delay of 0.81 milliseconds, ”Clench” exhibited an average delay of 1.21 milliseconds, ”Smirk” showed an average delay of 1.10 milliseconds, ”Smile” had an average delay of 0.92 milliseconds, and ”Wink” showed the highest average delay at 1.87 milliseconds.

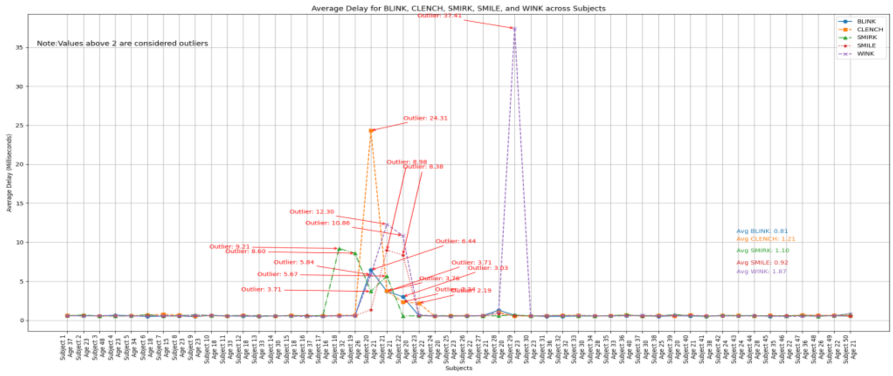

Figure 20. Average delay across subjects.

However, in Figure 21, after removing outliers, response times improved significantly. ”Blink” achieved an average delay of just 0.58 milliseconds, ”Clench” improved to an average delay of 0.61 milliseconds, ”Smirk” exhibited an average delay of 0.60 milliseconds, ”Smile” showed an average delay of 0.58 milliseconds, and ”Wink” had an average delay of 0.59 milliseconds. These findings highlight the system’s ability to respond more rapidly to commands and expressions after outlier removal, demonstrating enhanced efficiency and reliability in translating neural signals into physical movements in the Epoc X project’s brain-controlled prosthetic arm system.

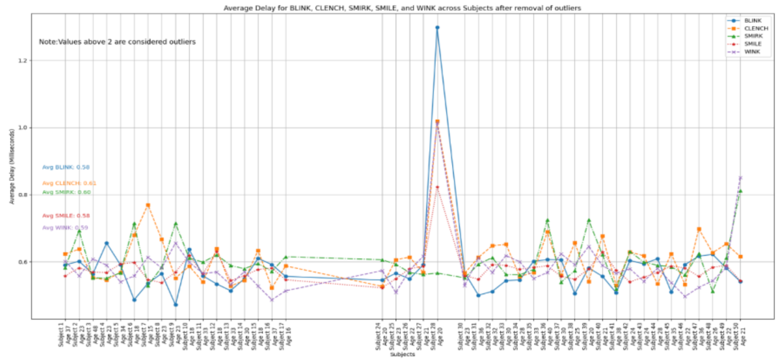

Figure 21. Typical Delay Duration (Excluding Outliers).

Additionally, the participants were also requested to operate the prosthetic arm, and response time measurements were taken from the moment the command was given to when the prosthetic arm initiated the movement. The average delay in this context was found to be 1.46 seconds, as illustrated in Figure 22. This measurement provides valuable insights into the overall system’s responsiveness and the time it takes to execute actions, complementing the earlier findings related to specific commands and expressions.

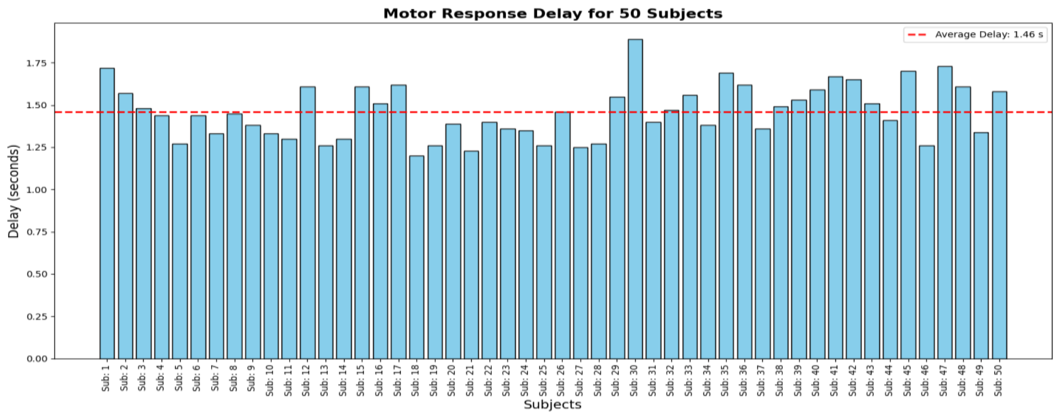

Figure 22. Brain controlled prosthetic arm latency.

The latency in brain-controlled prosthetic arm systems was examined, and three equations were formulated to quantify its different components.

Transmission Delay: The transmission delay equation calculates the time it takes for a neural command to travel from the user’s brain to the system. It is represented as:

$$\Delta t_{TD} = t_2 - t_1 \tag{9}$$

where: Δt_{TD} is the transmission delay; t_2 is the timestamp when the Arduino receives the command, and t_1 is the timestamp when the user initiates the command mentally.

Processing Delay: The processing delay equation quantifies the time taken by the prosthetic limb's control system to interpret the neural command and initiate the corresponding action. It is represented as:

$$\Delta t_{PD} = t_3 - t_1 \quad (2)$$

where:Δt_{PD} is the processing delay; t_3 is the timestamp when the prosthetic arm starts moving, and t_1 is the timestamp when the user initiates the command mentally.

Overall Latency:
The overall latency equation represents the total time from the initiation of the mental command to the actual movement of the prosthetic arm, encompassing both the transmission and processing delays. It is represented as:

$$\Delta t_{OL} = \Delta t_{td} + \Delta t_{PD} \quad (3)$$

where: Δt_{OL} is the overall latency; Δt_{tD} is the transmission delay (as in equation 1), and Δt_{PD} is the processing delay (as in equation 2).
From the experimental setup,

- Δt_{TD} =0.00061 seconds
- $\Delta t_{OL} = 1.46$ seconds

To calculate the processing delay (Δt_{PD}):

$$\Delta t_{PD} = \Delta t_{OL} - \Delta t_{TD} \quad (4)$$

Substituting the values:

$$\Delta t_{PD} = 1.46 - 0.00061 \quad (5)$$

$$\Delta t_{PD} = 1.45939 \text{ seconds} \quad (6)$$

So, the Processing delay (Δt_{PD})is approximately 1.45939 seconds.
The Processing delay represents the time taken by the prosthetic limb's control system to interpret the neural command and initiate the corresponding action. It plays a crucial role in the responsiveness and efficiency of the brain-controlled prosthetic arm system.
In summary, by analyzing the derivatives of the overall latency (Δ_{OL}) over time, we gain valuable insights into the responsiveness of the brain-controlled prosthetic arm system.

$$\frac{d(\Delta t_{OL})}{dt} \quad (7)$$

Equation (7) measures the rate of change in overall latency over time. A positive value indicates increasing latency, possibly diminishing responsiveness, while a negative value suggests improved system performance with decreasing latency.

$$\frac{d^2(\Delta t_{OL})}{dt^2} \quad (8)$$

Equation (8) reveals the acceleration or deceleration in latency changes. A positive second derivative signals a rapid deterioration in responsiveness, while a negative second derivative indicates a slowing rate of latency increase, implying performance enhancements.

In summary, these derivatives provide a dynamic perspective on the responsiveness of one's brain controlled prosthetic arm system, helping identify trends in latency changes and make informed adjustments to maintain or improve system efficiency.

3.3. Accuracy and Consistency

In the assessment of the brain-controlled prosthetic arm system, study participants were tasked with executing specific commands and expressions while their prosthetic arm's movements were meticulously monitored. Accuracy was evaluated in two scenarios: first, based on the utilization of unprocessed raw signals to control the prosthetic arm's activity, and second, when the signals underwent filtration through a high-pass and low-pass filter, coupled with an error handling method. The results indicated an average accuracy rate of 84.58 % for raw signals and a 97 % for the filtered and error-corrected signals. The introduction of the filtering and error handling methods was instrumental in mitigating noise levels and preventing unwanted signal interruptions, thereby substantially enhancing system accuracy. Among the considered control activities, 'clench' was chosen for its reliability and ease of use. However, it's worth noting that 'blink' and 'smile' can occur involuntarily at any time, making it less suitable for precise control, and 'wink', 'smirk' can be challenging to distinguish reliably. To ensure participants' proficiency in operating the system, all users underwent a comprehensive one-hour training session aimed at acquainting them with the system's functionality. Detailed accuracy results for the various control activities across the 50 study subjects can be found in Table 1. This table provides a comprehensive summary of the accuracy achieved during the study, shedding light on the system's performance across a spectrum of controlled actions.

Table 1. Accuracy across various activities.

Subject	Gender	Age	Occupation	Marital Status	Education Level	Technology Proficiency	Accuracy %	Accuracy %
		Years		Unmarried=0 Married = 1	High-school= , Bachelor's=2, Master's = 3	Advance=3, Intermediate = 2, Basic = 1	Raw signals	Filtered signals
1	M	37	Driver	1	1	1	88	99
2	M	23	Student	0	3	2	91	98
3	M	48	Property Broker	1	2	1	90	96
4	M	23	Marketing	1	1	2	82	99
5	M	34	Marketing	0	2	2	70	98
6	M	18	Student	0	2	3	90	100
7	M	15	Student	0	1	3	92	100
8	M	23	Student	0	3	2	91	100
9	M	23	Student	0	3	3	89	98
10	M	18	Marketing	0	1	2	82	100
11	M	33	Supervisor	1	1	2	90	100
12	M	18	Student	0	1	3	86	100
13	M	33	Electrician	1	1	2	89	96
14	M	30	Electrician	1	1	3	82	100
15	M	18	Marketing	1	2	2	89	100
16	M	37	Driver	1	1	1	85	95
17	M	16	student	0	1	3	87	100
18	M	32	Clerk	1	2	2	88	100
19	M	26	Driver	1	1	2	79	100

20	M	21	Marketing	0	1	2	78	98
21	M	21	Student	0	1	3	80	100
22	M	20	Tailor	0	1	1	79	98
23	M	22	Student	1	2	2	83	97
24	M	20	Student	0	1	3	87	100
25	M	23	sales	0	1	2	85	100
26	M	22	Student	0	2	3	80	96
27	M	21	Student	0	2	3	79	100
28	M	20	Student	0	1	3	87	99
29	M	23	web developer	0	2	3	82	97
30	M	23	web developer	0	2	3	80	97
31	M	36	Trader	1	2	2	82	92
32	M	32	Civil Engineer	0	2	3	84	94
33	M	30	Accountant	1	2	3	85	95
34	M	28	Student	0	2	3	81	92
35	M	33	Developer	0	2	3	83	93
36	M	40	Sales Representative	1	1	2	82	89
37	M	30	Design Engineer	0	3	3	86	97
38	M	25	Student	0	2	2	87	98
39	M	20	Student	0	2	3	85	97
40	M	21	Student	0	2	3	84	94
41	M	38	Design Engineer	1	3	3	80	94
42	M	24	Student	0	2	3	88	96
43	M	24	Student	0	2	3	89	100
44	M	28	Student	0	2	3	86	97
45	M	35	Engineer	0	2	3	82	89
46	M	22	Student	0	2	3	83	92
47	M	36	Teacher	0	2	3	81	92
48	M	26	Student	0	2	3	84	93
49	M	22	Student	0	2	3	88	95
50	M	21	Student	0	2	3	89	100
Average		26.4	-	-	-	-	84.58	97

3.4. User Feedback

Qualitative feedback from participants highlighted the user-friendliness and intuitive nature of the brain controlled prosthetic arm system. Participants expressed a sense of empowerment and satisfaction in being able to control the arm's movements seamlessly. Comments related to the system's comfort, responsiveness, and potential impact on daily activities were also gathered.

Crucially, the integration of end-user feedback throughout developmental stages facilitates the refinement of prosthetic arm ergonomics, control mechanisms, and overall user interface. This iterative refinement process, addressing factors encompassing durability, comfort, and adaptability to varying daily activities, ensures sustained usability and acceptance across diverse real-world environments.

4. DISCUSSION

Our previous article featured a comprehensive comparative analysis of various prosthetic arm technologies, detailing their methodologies, strengths, limitations, and implications. Leveraging these insights, we aim to enrich the current manuscript's discussion, providing contextualization for the Emotive EPOC X based brain controlled prosthetic arm [1]. The successful implementation of the non-invasive brain-controlled prosthetic arm system using the Emotiv EPOC X relies on various factors, including the preparation time required for the device [15]. This section explores the preparation process and examines its implications on the patient’s experience and usability of the system. The Emotiv EPOC X 14-channel brain sensor serves as the neural input interface for the brain-controlled prosthetic arm system [16]. The preparation process involves several key steps: Sensor Placement: Proper placement of the Emotiv EPOC X sensor on the user’s scalp is essential and typically takes a few minutes [17]. This process includes adjusting the sensor’s position and ensuring a secure fit to capture accurate neural signals [18]. The sensor is equipped with non-invasive electrodes that need to be correctly adjusted for optimal signal acquisition [19]. This may require a few minutes of electrode positioning and contact checks. To establish a robust mapping between the user’s neural signals and prosthetic arm movements, a training phase is essential. Depending on the user’s familiarity with the system, this phase may take several minutes to fine-tune the system’s understanding of the user’s intentions, enhancing accuracy and responsiveness. The preparation time for the Emotiv EPOC X sensor plays a significant role in the overall patient experience and usability of the brain-controlled prosthetic arm system [15]. The process of sensor placement, electrode adjustment, and calibration can be time-consuming, especially during the initial setup [20]. Users may need to invest a total of 15 to 30 minutes before they can begin using the prosthetic arm effectively. This time investment can impact the system’s practicality for daily use. Patient comfort is paramount during the preparation process. The snug fit of the sensor and proper electrode adjustment are crucial not only for signal quality but also for ensuring that users can wear the sensor comfortably for extended periods. Discomfort or irritation can hinder the user’s willingness to utilize the system [1]. Patients require training and adaptation sessions to become proficient in using the brain-controlled prosthetic arm [1, 20]. The calibration phase and initial usage may involve a learning curve for users. Effective training and support are essential to help patients overcome any challenges and maximize their control over the system. While the preparation time may be relatively lengthy during the initial setup, users often become more efficient with subsequent use. Long-term usability and patient satisfaction can be influenced by the effectiveness of the system and the patient’s ability to seamlessly integrate it into their daily routine. Efforts to streamline the preparation process are ongoing to minimize the time investment required for users. This includes advancements in sensor technology, improved calibration algorithms, and user-friendly interfaces. As technology evolves, the goal is to make the setup more efficient and user-friendly, reducing barriers to adoption for individuals with limb disabilities. The observed variations in response time can be attributed to a combination of factors. The complexity of the mental command or facial expression plays a role, with simpler actions such as ”blink” being executed faster than more intricate commands like ”rotate Counter Clockwise.” Additionally, the processing overhead involved in translating neural signals into mechanical movements contributes to the response time variability. Further optimization of signal processing algorithms and hardware components could potentially minimize these variations and enhance overall system responsiveness. The results underscore the potential impact of the brain-controlled prosthetic arm system in real-world scenarios. The accuracy achieved in translating neural intentions into precise mechanical actions holds promising implications for individuals with limb disabilities. By seamlessly integrating the system into their daily lives, users could regain functional autonomy and independence, enabling them to perform tasks that were previously challenging or impossible [21]. While the system demonstrates remarkable performance, several limitations warrant consideration. The sensitivity of the Emotiv EPOC X sensor to external interferences, coupled with variations in signal quality, occasionally affected response times and accuracy. Future iterations could explore advanced signal filtering techniques and sensor designs to mitigate these limitations.

The concept of long-term usability and user acceptance of brain-controlled prosthetic limbs is fundamental to their development as advanced assistive technology [1]. Highlighted in current research and clinical trials, the creation of a smooth connection between users' neurological impulses and the capabilities of prosthetic limbs is seen as extremely important [22].

Yet they confront several limitations [23 - 26]. Continuous adaptation and calibration to evolving neural patterns, alongside challenges in replicating natural feedback, hinder full immersion. External factors like electromagnetic interference and environmental conditions impact reliability, while high costs and limited accessibility pose socioeconomic barriers.

Electromagnetic interference (EMI) poses a risk of distorting sensor signals, potentially compromising data integrity [27]. Temperature fluctuations can disrupt sensor calibration, leading to inaccuracies in measurements [28]. Ambient light interference may disturb brain signals, impacting data reliability [29]. Physical obstructions obstruct sensor paths, resulting in weakened signal strength. Exposure to chemicals can also degrade sensor performance, while dust particles may cause operational malfunctions. Additionally, changes in altitude require recalibration of sensors for accurate readings. These challenges can be mitigated through strategies such as EMI shielding, temperature compensation mechanisms, robust mechanical design, and the use of protective housings. Implementing these measures enhances the reliability and performance of sensor systems in various environmental conditions.

Additionally, complexities in operation, substantial user training requirements, and ensuring durability and maintenance add further challenges. Ethical considerations surrounding data security and psychological impacts on users must also be addressed. Furthermore, achieving optimal physical comfort and fit, managing battery life, integrating with existing technologies, ensuring real-time feedback, and designing intuitive user interfaces present additional hurdles [30 - 32]. Overcoming these challenges demands collaborative efforts across technological and socioeconomic domains, ensuring improved functionality, accessibility, and user satisfaction.

These advancements, on-going research endeavours continue to refine and expand the capability of prosthetic arm development. Studies by Hochberg *et al.* [33], Collinger *et al.* [34], and Velliste *et al.* [35] have demonstrated the transformative potential of BCI technology in enhancing autonomy through intuitive control of prosthetic limbs. Meanwhile, research by Nisar *et al.* [36] highlights the accessibility of BCI systems, albeit with reliability challenges noted by Duvinage *et al.* [37]. Malik *et al.* [38] and Staffa *et al.* [39] further explore BCI applications, showcasing promising results in predicting movement intent and proposing novel approaches for robotic-prosthesis control, respectively. These studies collectively underscore the ongoing efforts to develop practical and effective assistive technologies for individuals with neural injuries.

Table 2 presents a structured comparison of the main types of prosthetic arms, detailing their control mechanisms along with their respective strengths and limitations. The table differentiates among passive, body-powered, myoelectric, and brain-controlled systems, providing a clear summary of their functional characteristics and practical considerations. This description offers a concise understanding of how these technologies vary in design, usability, and performance.

Table 2. Comparison of different types of Prosthetic arms.

Type	Control and Movement	Strengths	Limitations
Passive [40]	Stationary or adjustable	•Natural appearance • Lightweight, low cost • Easy to use, minimal maintenance	• Limited functionality • Poor grip and grasp • Ineffective for bimanual tasks
Body-powered [41]	Cable and linkage-based control	• Low cost and reliable •Provides proprioception • Simple setup, low training need	• Unattractive design • Muscle-dependent • Limited motion and grip force
Myoelectric [42, 43]	Motor-driven; muscle signals via sensors	• Adaptive grip force • High functional capability	• Moisture-sensitive • Requires calibration and training • Expensive and battery-dependent
Brain-controlled [29, 44, 45]	Neural activity sensed; motor control via microcontroller	• High precision and functionality • Suitable for paralyzed users • Independent of muscle strength	• High maintenance • Invasive risk or complex setup • Intensive training and focus required

Scalability is crucial for the brain-controlled prosthetic arm system. Signal reliability challenges, including noise and variability, are addressed with integrated high pass and low pass band filtering in the Arduino code. The lightweight, ergonomic design could enhance usability, while AI capabilities such as predictive modelling, adaptive control systems, and NLP, could optimize user interaction and control. Ongoing collaborations aim to refine AI algorithms for personalized user experiences and seamless integration into clinical settings, advancing assistive technology accessibility and functionality for individuals with limb disabilities.

5. CONCLUSION

The proposed research represents a substantial progress in the field of assistive technology, particularly in the development and implementation of a brain-controlled prosthetic limb. Our investigation was fundamentally underpinned by the Emotiv EPOC X device, an instrumental apparatus adept at capturing and decoding brain activity data derived from a cohort of 50 subjects. By seamlessly integrating this technology, we have introduced a new era where prosthetic limbs may be controlled with accuracy and ease. This has greatly enhanced the independence and overall quality of life for individuals facing limb loss or disability. A critical revelation within our study pertained to the judicious implementation of signal processing methodologies. Initial accuracy challenges, hovering around the threshold of 84.58 %, were attributed to unwarranted noise and disruptive elements. However, our steadfast commitment to refinement bore fruit in the form of advanced filtering techniques and meticulous error handling mechanisms.

These interventions culminated in a remarkable accuracy rate of 97 %, thereby underscoring the paramount significance of signal optimization within the ambit of brain-controlled prosthetic arms. The temporal dimension of our research yielded further salient insights. We introduced specialized equations, serving as analytical tools to quantify processing and overall delays. These equations afford invaluable insights into the time-sensitive facets inherent to brain-controlled prosthetic systems. Concurrently, our study exercised judicious discretion in the selection of control activities. While ’clench’ emerged as a dependable and user-friendly choice, alternate facial expressions such as ’blink’ and ’smile’ posed substantive challenges due to their involuntary nature. Furthermore, distinguishing between expressions like ’wink’ and ’smirk’ proved arduous, amplifying the need for precise distinctions. Moreover, our investigation illuminated the presence of a direct current offset, measuring 4100 microvolts within our collected data. This offset, hinging on the potential influence of direct current drift, offered a plausible explanation for amplified amplitudes observed in the recorded data. Recognizing and proactively addressing this offset assumes paramount importance in the context of future endeavours concerning brain-controlled prosthetic systems. The physical manifestation of our research materialized through the application of 3D printing technology, with Polylactic Acid (PLA) serving as the principal material. The orchestration of actuation was delegated to two servo motors, constituting a dynamic tandem that conferred precision and finesse upon the prosthetic arm’s motor functions. In summation, our research journey underscores the transformative potential harboured by brain-controlled prosthetic technology in elevating the lives of individuals grappling with limb loss or impairment. From the meticulous refinement of signal processing techniques to the judicious selection of control activities and the resolution of data offsets, our interdisciplinary collaborative effort epitomizes the synergy of innovative solutions. Looking ahead, these advancements move us closer to giving people the ability to regain a deep sense of control and independence in their everyday lives, through the brain-controlled prosthetic limbs.

Ethical Considerations. The development process is underpinned by a commitment to ethical principles. Informed consent from participants ensures their voluntary participation. Data privacy takes precedence, safeguarding the confidentiality and security of sensitive neural data. These considerations are woven into the fabric of the system’s design, aligning technological progress with ethical responsibility.

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Credit authorship contribution statement. All the authors have contributed equally to the development and writing of this work.

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