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Research Article

Control and Automation of AI Based Brain Controlled Wheelchair for Paralyzed Patients

Zaryab Basharat[1], Saqlain Abbas[1*], Ali Naqi[1], Sadaf Khan[2], Muhammad Hamza[1]

[1] Department of Mechanical Engineering, University of Engineering and Technology Lahore (Narowal Campus), Narowal, Pakistan
[2] Department of Radiology, CMH Multan, Multan, Pakistan
E-mail: saqlain.abbas@uet.edu.pk

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Abstract: Smart Wheelchairs play an important role in assisting individuals with disabilities, particularly those with motor impairments due to conditions like strokes or multiple sclerosis. This research focuses on developing a Brain Controlled Wheelchair (BCW) system using non-invasive EEG technology to empower individuals with severe mobility impairments. The study emphasizes the use of the NeuroSky EEG, which offers advantages over traditional systems by being more compact, user-friendly, cost-effective, and providing real-time signal processing with enhanced accuracy and minimal setup. The objectives include designing a robust EEG signal acquisition system, classifying EEG signals into actionable commands, exploring advancements in EEG electrode technology, and evaluating a BCW prototype for performance metrics. This system provides natural control of the wheelchair according to the user's brainwave patterns, presenting an alternate method of navigation without intricate electronics, rendering it easier and more reliable. This research introduces the BCW as a novel solution for the disabled, enhancing mobility and autonomy while solving issues related to safety and comfort.

***Keywords*:** Brain-Computer Interface (BCI), electroencephalography (EEG), wheelchair, neuroSky, micro-controller

1. Introduction

Millions of people around the world face mobility issues. Individuals with mobility issues require advanced technology to ensure comfortable mobility. Wheelchair users with mobility impairments face significant restrictions in movement and function. Hence, they require constant assistance from an assistant. Disability is becoming a serious issue as the number of cases increases annually. The World Health Organization (WHO) reported that approximately 15% of the world's population has amputees, with half of them unable to afford medical care [1].

The COVID-19 pandemic has significantly limited people's daily activities, and movement, as well as access to education, services, and healthcare. The pandemic emphasized the need for inventive devices, biomedical solutions, and assistive technologies (AT) to help individuals with severe disabilities in their daily lives [2]. During this pandemic, scientists were focusing on using the human brain for Wheelchair movement and control due to its flexibility and potential to improve independence and quality of life for elderly and paralyzed individuals. Since the initial demonstration that the "human mind can control a Wheelchair", several approaches have been suggested and 15 complex algorithms have been integrated to broaden the application of EEG-based BCIs for controlling and maneuvering Wheelchairs [3]. Robots

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are becoming more important in both industrial and everyday life. These robots can help people with disabilities with their daily activities. A Brain Controlled Wheelchair is an early step towards full robot employment in human life. The Brain-Computer Interface (BCI) is a swiftly evolving technology that seeks to enhance the lives of people with movement limitations. Brain Controlled Wheelchairs are an example of assistive technology, allowing paralyzed individuals to move around using only their thoughts. A BCI transmits messages and commands that encode the user's brain activity. The BCI system monitors and analyzes a patient's brain activity as they perform psychological tasks or generate specific neurophysiological signals. BCI has the potential to improve quality of life and aid in neurorehabilitation.

Brain activity recording is the initial process in Brain Controlled Wheelchair. While invasive neural signals offer high spatial resolution, invasive neural signals are related to significant safety threats, such as immune reactions and scar tissue creation following surgery. Nonetheless, non-invasive neural signals are safer since they do not involve surgical procedures [4]. In the first operational BCW, Tanaka et al. applied a wet electrode system to directly record and watch participants' EEG signals in real-time, making a precedent among other researchers like Millan et al. and Rebsamen et al. [5]. Other research studies have explored the various aspects of BCIs and their applications. For instance, research by Wolpaw et al. laid down the initial EEG-based BCI principles, focusing on the communication and control opportunities in individuals with severe disability [6]. Similarly, Millán et al. demonstrated the viability of using EEG signals to control robotic systems and the necessity of applying signal processing and machine learning techniques to decode brain signals [7]. Besides, research like that performed by Iturrate et al. has focused on the use of BCIs in controlling wheelchairs, conquering challenges like real-time processing of signals and accommodation of the user [8]. The shift from wet to dry electrodes, as mentioned by Chi et al., has also been a major breakthrough, enhancing the comfort and usability of EEG systems [9]. This study has the objective of advancing these core studies by formulating a comprehensive BCW system that utilizes non-invasive EEG technology. The purpose of this research is to improve the accuracy and responsiveness of wheelchair control and thus advance the field of neurorehabilitation and assistive technology. The most common physiological signal utilized in BCW is EEG, mostly because it has a very good temporal resolution, it is non-invasive, easy to use, portable and less expensive compared to other alternatives [10, 11].

Electroencephalography (EEG), a non-invasive method of monitoring brain activity records electrical activity on the scalp caused by neurons firing in the brain. The Wheelchairs' brain-machine interface (BMI) detects and converts brain activity into mechanical commands. Electroencephalography (EEG) recordings are conducted using both wet and dry electrodes. Using electrolyte gel to provide a pathway facilitating conductivity between the skin and the electrode, wet electrodes lessen the electrode-skin resistance. Dry electrodes provide several benefits over wet electrodes, including the fact that they take less time to perform because they don't need to undergo rigorous scalp preparation. Since dry electrodes do not require conductive gel or saline solution to maintain excellent contact with the scalp, they are more comfortable and practical than wet electrodes. They don't irritate or hurt the skin, and they are simple to attach and remove, portable, low-cost and affordable to procure. It is practical to employ EEG-based Brain Controlled Wheelchairs to operate Wheelchairs in a range of settings. Under any circumstances, there should be no compromise with the performance of the EEG recording, even for a longer time duration. There is a demand for more user-friendly and reasonably priced EEG-based Brain Controlled Wheelchairs. People with severe motor disabilities could experience a revolution in their quality of life thanks to EEG-based Brain Controlled Wheelchairs.

The primary objectives of this research are to design and develop a signal acquisition system using EEG to capture and analyze brain signals related to attention and other cognitive states, to classify EEG signals into distinct commands for controlling the wheelchair's movements (e.g., direction and speed), to implement and evaluate a Brainwave Controlled smart Wheelchair prototype, focusing on accuracy, responsiveness and user experience, to explore advancements in EEG technology, including the transition from wet to dry electrodes, to enhance user comfort and accessibility.

The novel contributions of this research are design and evaluation of an EEG-based BCW system aimed at enhancing mobility for paralyzed individuals. This includes the integration of advanced signal acquisition techniques and real-time EEG signal processing. It introduces a novel approach to acquiring and processing EEG signals using non-invasive methods (such as dry electrodes), specifically focusing on improving the reliability and efficiency of brain-to-machine communication. This research investigates innovation in assistive technology through the use of BCI systems to maneuver wheelchairs, thus providing a promising intervention for those with severe motor disabilities. The application of machine learning algorithms for EEG signal classification and interpretation is emphasized, demonstrating innovation in adaptive control strategies designed to accommodate user-specific brain activity patterns [12]. This research focuses on the possible effect on enhancing the quality of life of paralyzed patients through enhanced mobility and independence made possible by BCW technology.

Controls are electrical and electronic devices that guide and direct mechanical machines. They operate on a common program of software to regulate and guide the actions of such machines to perform what they are programmed to. Automation is putting in place systems, perhaps robots, to carry out tasks or processes automatically. Such systems follow pre-programmed rules and instructions without human input at each stage. Automation is designed to simplify processes, make them more efficient, and less susceptible to human error. AI takes it a step further by making robots or systems decision-making capable without human intervention, based on complex algorithms and data analysis. Traditional automation relies on preprogrammed decisions, whereas AI makes robots learn and adapt from the environment, making decisions that are not necessarily hard-coded. While remaining under the control of human action during the learning process, AI-based robots are able to function more independently and intelligently.

For our research project on Brain Controlled Wheelchairs, controls would involve the electronic devices and programs that recognize EEG signals and translate them to movement commands for the wheelchair. Automation would enable the wheelchair to roll in response to these commands based on predetermined rules of movement. AI would also enhance the system by enabling the wheelchair to learn from user behavior and modify its movement patterns over time, based on the principle of machine learning and cognitive computing.

The use of AI in this research is mainly dedicated to EEG signal classification and command execution in the control of a wheelchair. The system leverages the NeuroSky ThinkGear library that uses a pre-trained AI model to analyze real-time EEG signals by monitoring attention and meditation levels. These measures are derived from brainwave information, namely alpha, beta, gamma, delta and theta waves and utilized to decide on movement commands such as forward, backward, left, right and stop.

The AI-based processing guarantees that only deliberate and stable brain signals are translated into executable commands, eliminating involuntary fluctuations and noise. The NeuroSky AI model is pre-trained on a massive corpus of EEG signals with reliable and efficient classification being possible. Experimental validation was also carried out with five participants to study EEG signal differences for various movement commands.

The classification based on AI incorporated in the NeuroSky system increases the accuracy of command recognition, making the wheelchair more responsive and less prone to false activations. The classified EEG signals are further processed by an Arduino Nano, which converts the AI-based outputs into motor control signals through a relay-based mechanism, making wheelchair movement seamless and real-time.

2. Methodology

This section discusses the implementation of our BCI, with specific attention given to using an Arduino Nano microcontroller and a NeuroSky headset to collect EEG data. For a stable wireless communication link between the BCI and the Wheelchair, we have used the HC-05 Bluetooth module. Our approach to data processing is to extract various waves and apply them to control Wheelchair movement. There was a required wireless link between the NeuroSky and the Arduino nano microcontroller. Programming and setting up of the microcontroller was done through the Arduino IDE and making sure it would listen for data sent by the HC-05 Bluetooth module. Bluetooth pairing enabled interaction between the NeuroSky headset and Arduino Nano. The Arduino Nano was set up to accept EEG data from the NeuroSky headset after connecting wirelessly. The Arduino software collects and analyzes brainwave data, specifically beta waves associated with concentration levels. The Arduino nano microcontroller was programmed to use analyzed EEG data to control Wheelchair motions. These signals activated the Wheelchair's 12V DC gear motors. The Arduino IDE provided tools for creating control logic that mapped attention levels to DC gear motor operations.

2.1 *Setup*

Turn on the power from the Wheelchair battery (12 volts), which also powers the Bluetooth module attached to the microcontroller. The Bluetooth module on the microcontroller acts as a Slave. Another Bluetooth module, connected to the NeuroSky headset, acts as a Master. Both Bluetooth modules start blinking until they establish a connection. Once connected, the blinking stops. Turn on the NeuroSky headset. A buzzer indicates that the headset is connected to the brain. Think commands such as forward, backwards, left, and right. NeuroSky headset detects these brain signals. NeuroSky headset sends the detected brain signals via Bluetooth to the Bluetooth module connected to the Wheelchair. The Bluetooth module connected to the Wheelchair receives the signals. The microcontroller processes these signals. Four relays controlled by the microcontroller send signals to the motors. The motors execute the desired movements based on the received signals. Figure 1 shows the complete process flow chart.

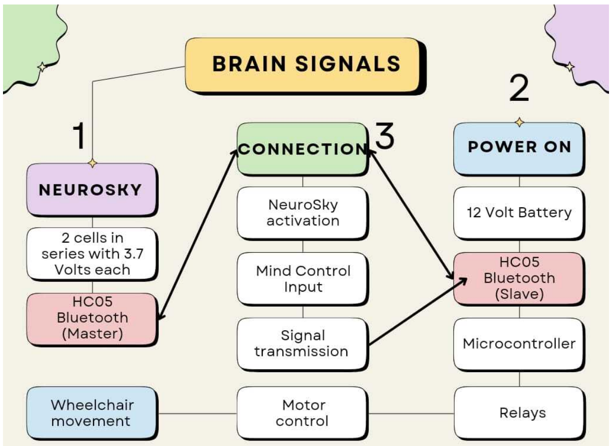


Figure 1. Process flow chart

2.2 *Components of the practical model*

The primary data collection device was the NeuroSky headset. The headset records EEG data non-invasively. The NeuroSky headset is ideal for BCI applications due to its lightweight design and ability to collect real-time EEG data. The device consists of a dry electrode and a single-channel EEG sensor that detects brainwave signals from the user's forehead (see Figure 2a). Signal processing can take place within a data processing module. NeuroSky pre-processes and transfers detected signals to a PC. Signals from the output are sent to the wheelchair. To use the NeuroSky headset, the user must follow the manufacturer's instructions and correctly place it on their forehead. The headgear was fitted with dry electrodes and a single-channel EEG sensor for recording the accurate EEG signals for analysis.

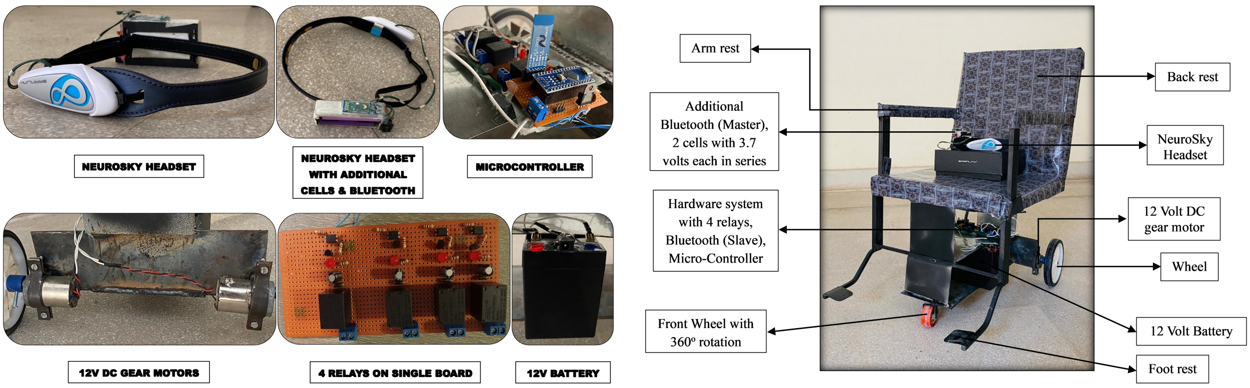
In BCW, we incorporated a NeuroSky headset alongside two additional cells, each rated at 3.7 volts, connected in series to power the system. To ensure compatibility and seamless communication, we integrated a Bluetooth module operating at 5 volts as the master device alongside the NeuroSky headset. Implementing a regulator between the cells and the Bluetooth module helped maintain stability and efficiency within the system. This setup not only facilitated the transmission of brainwave data for wheelchair control but also ensured reliable and consistent power distribution. A Bluetooth module wirelessly transferred signals from the NeuroSky headset. This component's simplicity and dependability make it a popular choice for IoT applications (see Figure 2a).

Serial communication connects the Arduino Nano microcontroller and the HC-05 Bluetooth module, enabling wireless communication. The NeuroSky Wireless headset and Arduino Nano use Bluetooth to send EEG data.

The goal of this research is to control AI based Brain Controlled Wheelchair that is affordable, dependable and has significant design improvements over the current inmove research. There is currently no specific method for connecting the motors to an Arduino microcontroller. 12V DC gear motors can be connected to the Arduino via their signal pins, as illustrated in Figure 2a. These motors are connected in parallel. The signal pins are connected to the Arduino's digital PWM pins and the motors' power and ground connections are made using an appropriate power supply. Programming the Arduino board and libraries can provide precise motor control, allowing for desired motions and grasping actions.

Relays are electromechanical switches that can be controlled by a small electrical signal, making them ideal for interfacing between low-power control signals from a microcontroller and high-power devices like motors or actuators. In our research, we're likely using relays to control the movement of the wheelchair's actuators (e.g., motors) based on signals from the microcontroller. It consists of a coil and a set of contacts. Relays may have normally open (NO), normally closed (NC) or changeover (CO) contacts. When the coil is energized, it creates a magnetic field that attracts or repels a switch (or multiple switches) causing them to open or close. We appear to be using a relay module, which contains multiple relays on a single board (see Figure 2a). Relays are commonly used in conjunction with microcontrollers. Our Brain-Controlled Wheelchair system likely has multiple functions or movements to control, as evidenced by the use of four relays. Each movement function forward, backward, turn Left, turn Right, Stop sets the appropriate relay pins to control the wheelchair's motors. For example, forward activates the relays to move the wheelchair forward by spinning both motors in the same direction.

The Battery Management System integrates the BMS module to efficiently manage and step down the voltage from the 3-cell battery pack, allowing for motor driving. This ensures the wheelchair receives maximum force enabling regulated and accurate motions. The circuit diagram has been illustrated in Figure 3.



(a) (b)

Figure 2. (**a**) Components of the practical model; (**b**) Brain controlled wheelchair

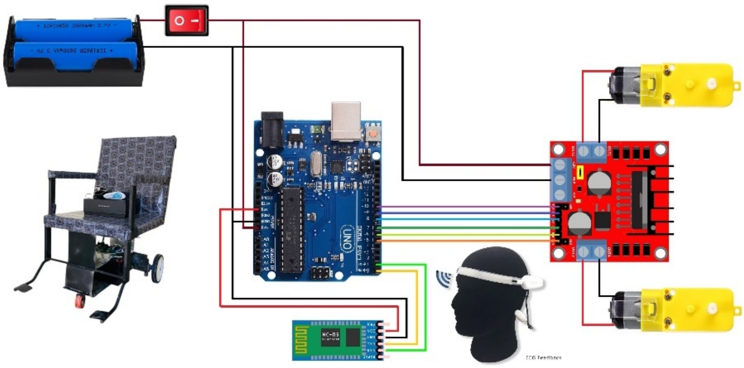


Figure 3. Circuit diagram

2.3 *Signal processing techniques*

This section describes the experimental procedures adopted in the research. The experiment aimed to evaluate the performance of an EEG-based wheelchair control system. The experiment included participants who were fitted with an EEG-based wheelchair. Participants received training sessions to familiarize with the system and establish a baseline for comparison. During the experimental sessions, participants performed brain-based tasks and movements while recording their EEG signals. The experiment aimed to collect enough data to evaluate the accuracy, reliability and usability of the system.

For EEG data processing and applying AI methods, we utilized Python as the primary programming language. The ThinkGear library was integrated to extract EEG signals, particularly the attention level, from the NeuroSky EEG headset. The system processes the signals in real time and translates them into wheelchair movement commands. The processing workflow includes signal acquisition, preprocessing, classification and command execution using an Arduino microcontroller.

2.3.1 *Data acquisition and processing*

During data collection and processing, participants' EEG signals were recorded and analyzed using the NeuroSky headset. The consumer-grade headset uses a single electrode sensor on the forehead to detect and quantify brainwave activity in a non-invasive way. The headset was properly mounted on each participant's head during data collection to ensure electrode contact with the forehead. The EEG signals were wirelessly transmitted from the headgear to the designated data processing device, an Arduino Nano microcontroller, via Bluetooth. The NeuroSky library-programmed data processing unit began with basic pre-processing after obtaining EEG signals. Throughout these steps, the methods described below were used:

- Signal Amplification: For improving signal-to-noise ratio, EEG data were amplified. The brain's weak electrical signals are amplified to improve clarity and reliability for further investigation.

- Digital Filtering: To remove noise and artifacts from EEG signals, high-pass and low-pass filters were used. Low-pass filters filtered out high-frequency noise and high-pass filters removed low-frequency noise. Filtering enhanced the quality and clarity of the EEG data, ensuring precise representation of brainwave activity.

- Baseline Correction: The EEG signals were normalized through baseline correction. To remove DC offset and data drift, the signal baseline must be brought to zero. Baseline correction gives a uniform point of reference to compare and analyze EEG signals.

- Artifact Removal: Methods were employed to eliminate unwanted interference from EEG signals. Artifacts usually come from eye movements and muscle activity. We could eliminate artifacts from EEG data and have it reflected brainwave activity.

The pre-processing techniques effectively paved the way for EEG data for subsequent analysis, such as feature extraction and classification. Amplifying, digital filtering, baseline correction, and elimination of artifacts refined EEG signal accuracy and reliability. This facilitated the more comprehensive and meaningful examination of participants' attentiveness.

2.3.2 *Processing*

Following the recording of EEG data via the NeuroSky headset, several processing techniques were employed to increase signal quality and readability. NeuroSky EEG data was filtered and processed using algorithms based on its properties. EEG signals are amplified and filtered to remove noise in order to improve signal quality. EEG data are processed using sophisticated signal processing techniques to yield useful information.

- Bandpass Filtering: A bandpass filter was applied to filter out the desired frequency bands in EEG signals. The filter rejects unwanted frequency components while allowing frequencies within the specified range, such as the Alpha (8–13 Hz) and Beta (13–30 Hz) bands. The headset captured accurate brainwave patterns corresponding to attention levels, enabling more effective study.
- Artifact Rejection: Procedures were implemented to provide stable EEG readings. After initial preprocessing, these techniques seek to detect and eliminate any lingering artifacts or sources of noise. The artifacts were detected and eliminated with the use of threshold-based detection and adaptive filtering. This was done to ensure that the processed data truly mirrored attention-related brain activity captured by the headset.

For enabling feature extraction and analysis, EEG data were split into shorter, non-overlapping epochs. There was a specific duration of brain activity associated with each epoch. The segmentation algorithm of the headset retrieved useful information from time intervals of recordings and revealed temporal variation in attention-related brainwave activity.

2.3.3 *Feature extraction*

After segmenting and pre-processing the EEG signals, the next step was to extract useful features. EEG waves are examined for some features or patterns. These features may be indicative of various intentions or commands, i.e., moving forward, turning, stopping, or changing direction. The objective of feature extraction was to identify specific features of brainwave patterns for varying levels of attention. Standard techniques were used to extract features from segmented data, including:

- Power Spectral Density (PSD): For the estimation of Power Spectral Density (PSD), EEG data was analyzed within various frequency bands to establish levels of power. The power spectral density of EEG signals was computed through the Fast Fourier Transform (FFT) and Welch method. Levels of attention were identified based on power in certain frequency bands, i.e., Alpha, Beta or Theta.
- Statistical Parameters: Statistical parameters like mean, standard deviation and variance were calculated to analyze the EEG signals. These statistical patterns were used to differentiate between varying states of attention.
- Wavelet Transform: To decompose EEG signals' temporal and frequency information together, wavelet transform was utilized. Wavelet analysis was applied to decompose signals into scales and extract features that show the presence or strength of certain brainwave patterns.

Machine learning algorithms or pattern recognition methods were employed to classify levels of attention based on extracted features in the feature classification process following feature extraction. Machine learning, field of AI allows computers to learn automatically and improve from experience without being programmed. Machine learning algorithms examine the brain impulses of the user and classify them into different commands, for example, go left, go right, stop or begin. Computer vision algorithms help the Brain Controlled Wheelchair perceive its environment, for example, detect obstacles, recognize objects, or estimate distances.

2.3.4 *Feature classification*

Following the elimination of useful points from EEG activity recorded using the NeuroSky headset, attention levels were categorized according to these parameters. Different methods and algorithms have been employed for precise categorization of the data.

In feature extraction, significant values of EEG signals were calculated, i.e., power spectral density (PSD) in various frequency bands, statistical measures such as mean and standard deviation and coefficients of wavelet transform. All the features successfully discriminated brainwave patterns with various levels of attention. Post-restoration of features, feature selection was done to determine the best and discriminating characteristics to use for the attention classification. This technique minimized dimensionality and enhanced the accuracy of classification models. Classification of features was the step meant to develop an accurate and trustable model of classifying levels of attention according to recovered EEG features. This EEG-based BCW control system depended significantly on this classification model to give real-time control and natural wheelchair and the user interaction.

2.3.5 *Potential challenges and solutions*

One of the key advancements in assistive devices for the paralyzed is the design of Brain Controlled Wheelchairs employing EEG signals. The usability, functionality and performance of such systems can continue to be optimized in various aspects through research and development, despite recent achievements. Researchers have attempted different techniques such as Brain Computer Interface (BCI) techniques, intelligence techniques and shared control methods to provide safety and enhance performance. But much work still needs to be done, especially in increasing BCI robustness, designing hybrid BCI systems, and combining BCI with machine learning to provide better control and teaching ability. Future directions may involve combining BCI and robot intelligence, as well as optimizing the embedded control system and EEG signal processing to achieve effective performance with low error rates. Future research on Brain Controlled Wheelchairs for paralyzed people with Electroencephalograms (EEG) holds enormous potential to transform assistive technology and enhance the quality of life for those with mobility limitations. Researchers may make substantial progress towards developing more efficient and user-friendly wheelchair systems that enable paralyzed people to lead more independent and meaningful lives by tackling important issues with signal processing, control algorithms, user experience, safety and rehabilitation. Some potential direction for future work includes Improving Signal Acquisition and Processing, Enhancing Control and Navigation, Enhanced Wireless Connectivity, Refinement of Mechanical Design.

3. Experimental setup

3.1 *Number of participants & experimental steps*

We tested 5 participants on our BCI tests to gauge the reliability and accuracy of the system. The NeuroSky EEG headset was used by all the participants and they were informed about what the experiment was about. The system took baseline EEG recordings to ascertain personalized attention thresholds for the individuals. Participants learned to concentrate attention on certain mental commands (e.g., “Forward,” “Backward,” “Left,” “Right,” “Stop”). Participants (as shown in Figure 4) gave commands to propel the wheelchair and accuracy of responses was recorded. Reaction time, accuracy and error rates of the system were quantified for each participant.

Figure 4. Participant

3.2 *Training sessions before experiments*

All the participants received a training session in which they were taught to concentrate on various mental states to produce identifiable EEG signals. The training was of 5–10 min duration per participant to allow them to operate the wheelchair effectively. The training was performed to improve familiarity with the system, to resolve issues of the learning curve, and to improve control accuracy. Figure 5 demonstrates comparison of command accuracy across participants with average performance highlighted.

The system was tested and applied to 5 participants and their performance measured in terms of the BCI-controlled wheelchair. The accuracy of each participant for different commands (forward, backward, left turn, right turn, and stop) is presented in Table 1. The overall average accuracy was between 80% and 94%, and slight deviations were observed in some directions, especially for participant 2 and 5 for the right and left turns.

Table 1. BCI experiment testing results on 5 participants

Participant	Forward command accuracy (%)	Backward command accuracy (%)	Left turn command accuracy (%)	Right turn command accuracy (%)	Stop command accuracy (%)	Average accuracy (%)	Issues/Observations
1	90%	85%	92%	88%	95%	90%	High accuracy, minimal distractions
2	80%	82%	78%	75%	88%	80.6%	Minor distraction during right turn
3	95%	94%	97%	91%	96%	94.6%	Excellent focus, slight fluctuation in left turn
4	92%	89%	91%	93%	94%	91.8%	Consistent results, stable EEG signals
5	85%	87%	80%	82%	90%	84.8%	Slight signal noise during left turn

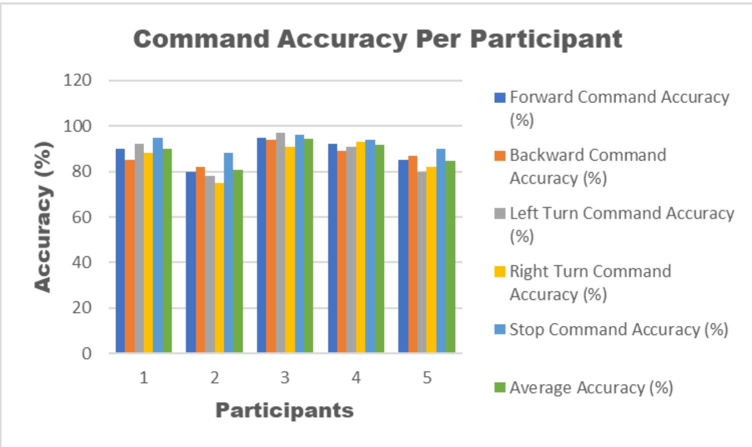


Figure 5. Comparison of command accuracy across participants with average performance highlighted

Table 2 lists in detail the experiments conducted, including signal detection, processing times, accuracy, and problems that were encountered. The results indicated that the system was able to perform in the majority of the cases, with little or no distractions or noise influencing the overall accuracy. Processing times for signal processing were well within the threshold, which allows for real-time operation. Issues of slight delays in left and right turns as well as fluctuations in the signals were experienced but will be eliminated in future modifications.

Table 2. Experiment checklist and signal detection analysis

Direction	Command sent	Signal detected	Signal processing time (s)	Accuracy level	Issues encountered	Signal quality (Poor/Good)
Forward	Yes	Yes	2.5	90%	None	Good
Backward	Yes	Yes	2.7	84%	Minor interference	Good
Left Turn	Yes	Yes	2.8	91%	Signal fluctuation	Good
Right Turn	Yes	Yes	3.1	83%	Slight delay	Good
Stop	Yes	Yes	2.4	94%	None	Good

The system accuracy was high overall for all participants, with a majority of participants having an accuracy of over 80%. The left and right turn commands were somewhat variable, particularly in participants 2 and 5. Signal processing time was consistent (2.4 to 3.1 s) and within the acceptable limit of real time. Minor issues like distractions and signal noise were noted in a few cases, particularly for left and right turns. However, these did not significantly affect the overall performance of the system. The signal quality remained good throughout the experiment, with only occasional fluctuation, which was corrected by recalibrating the headset.

3.3 *Wheelchair movement analysis*

The Brain Controlled Wheelchair (BCW) was tested for movement efficiency across a predefined route, analyzing the response time and accuracy of commands. The experiments were conducted on a straight path of 5 m, followed by a route involving 90-degree turns to evaluate the precision of directional control.

Table 3 presents the time taken by each participant to complete different movement tasks, while Table 4 summarizes the command frequency and execution accuracy.

Table 3. Movement time and distance analysis

Participant	Forward (5 m) time (s)	Left turn time (s)	Right turn time (s)	Backward (2 m) time (s)	Stop response time (s)
P1	8.5	3.2	3.1	5.4	1.2
P2	9.2	3.5	3.3	6.0	1.4
P3	8.0	3.0	3.2	5.1	1.1
P4	8.7	3.3	3.0	5.5	1.3
P5	9.0	3.6	3.4	5.8	1.2

Table 4. Command frequency and accuracy

Participant	Commands issued	Successful executions	Execution accuracy (%)
P1	12	11	91.7
P2	14	12	85.7
P3	13	12	92.3
P4	12	11	91.7
P5	13	12	92.3

The mean time of 5-m movement was recorded as 8.68 s, with slight differences among the participants. On average, turning maneuver performance required about 3.3 s, and reaction time to the stop signal was 1.24 s on average, demonstrating a rapid performance.

The rate of commands was inconsistent across participants at a mean of 12.8 commands per trial. Execution accuracy was more than 85% and consistent with steady system response.

3.4 *Route and performance analysis*

The experiment findings show that the BCW system was responsive to EEG-based commands with minimal delay. The 5-m forward movement took around 8.7 s to perform, and stop commands were executed in 1.24 s on average. Turns were achieved within an average time of 3.3 s with little deviation across users. The path was a straight line with turns at predetermined points to provide controlled navigation testing. The frequency of commands issued averaged 12.8 per trial, with the accuracy of execution in excess of 85%, validating the usability of the system in real-world applications.

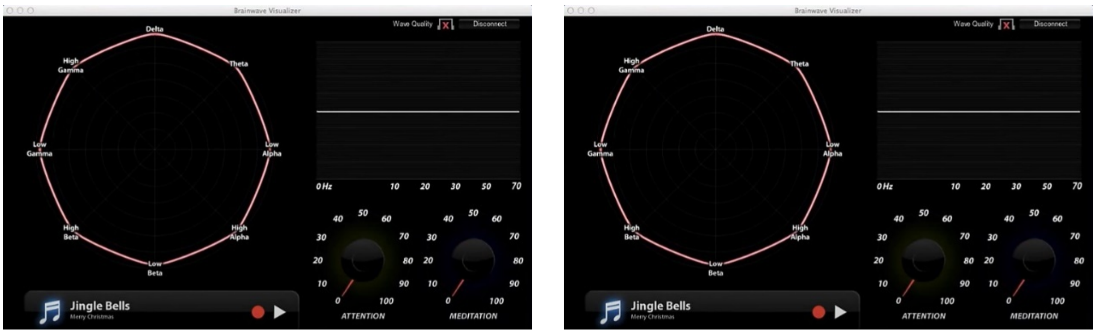
3.5 *Attention level & system stability*

We recognize the difficulty of sustaining stable levels of attention needed for accurate control. In addressing this problem, we instituted a threshold-based filtering mechanism that was designed to eliminate spurious variation from commanded intentions. The system incorporates real-time feedback, which enables participants to modulate their focus and enhance commanded execution. These features notably enhance the stability of the system, eliminating spurious action and enabling more fluid wheelchair movement.

4. Results and discussion

4.1 *Analysis of EEG signal processing*

EEG signal processing plays a key role in analyzing brain activity and cognitive processes. Utilizing EEG/Brainwave visualizer software offers real-time information on the various frequency bands (alpha, beta, theta, gamma) of the EEG signals. This analysis examines the importance of EEG signal processing and its use in unraveling the intricacies of brain function. EEG signals are recorded with an EEG/Brainwave visualizer to perform the analysis. The visualizer application, together with the relevant hardware (e.g., NeuroSky), facilitates the acquisition of EEG data. Acquisition is achieved (as shown in Figure 6) through electrode placement, recording and calibration of the data to guarantee precise and consistent measurements.



(a) (b)

Figure 6. (**a**) No attention and meditation; (**b**) With attention and meditation using brainwave visualizer

The acquired EEG signals are analyzed to investigate the distribution of different frequency bands. The visualizer generates graphs representing the power spectrum of the EEG signals, with frequency plotted on the x-axis ranging from 0 Hz to 70 Hz. The analysis identifies and characterizes the frequency bands of interest, including low alpha, high alpha, low beta, high beta, low gamma, and high gamma.

4.2 *Types of EEG signals*

Five different types of waves may be distinguished based on frequency ranges. In decreasing sequence of frequency, these are named alpha, beta, delta, theta and gamma [13]. Although it’s not always the case, one specific wave is often only accessible in one region of the brain’s cortex. As can be seen from Table 5, a person’s present location may be described in terms of the specific brain waves associated with their particular mental state.

Table 5. Waves, frequency and mental states

Waves	Frequency (Hz)	Mental states
Alpha	8–13	Tranquility, relaxation, abstraction
Beta	13–30	Extremely concentrated and alert
Delta	0–4	Deep sleep
Theta	4–8	Floating ideas, dreams, and creativity
Gamma	>30	Performing multiple tasks at once

4.3 *Analysis of EEG attention levels*

Readings of the EEG attention levels were obtained using the NeuroSky headset.

The graph shows a variety of peaks that correlate to different degrees of focus, with high peaks indicating intense concentration, which in turn prompts more complicated Wheelchair motions. A fascinating pattern may be seen after carefully examining the comprehensive EEG attention level graph shown in Figure 7. The attention level curve starts at a baseline value of 0, which denotes a comparatively low or insignificant degree of focus. The graph indicates a progressive climb from this beginning position, culminating at around 60, indicating a considerable gain in attention and concentration. As the curve flattens down to around 45, there is a following reduction in the attention level. This decreasing trend suggests a loss of focus due to a change in the user's psychological state or distraction. The curve represents times of enhanced or reduced attention. Notably, there are times when the interest level curve stays essentially constant for a while, indicating a continuous degree of focus. The curve's various peaks, valleys, and plateaus reveal the user's shifting concentration levels and highlight the complex interaction between mental states and the Wheelchair movement. Table 6 demonstrate the threshold for wheel chair actions.

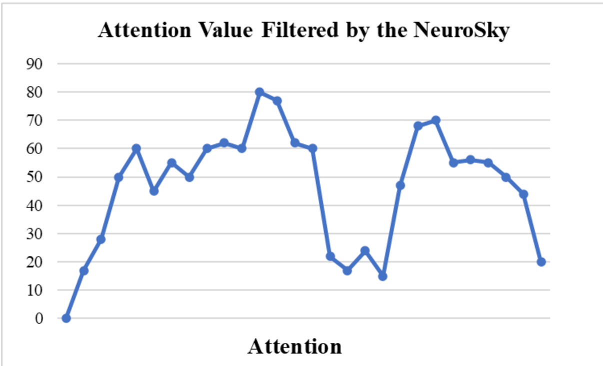


Figure 7. Attention level readings

Table 6. Threshold for wheelchair actions

Attention levels	Actions
40 to 60	Forward
60 to 70	Backward
30 to 40	Turn left
20 to 30	Turn right
0 to 20	Stop

4.4 *Collection and analysis of real-world brainwave data*

Real-world brainwave data was collected using the NeuroSky headset to verify the Brain Controlled Wheelchair (BCW) system's functionality and capability to translate brainwave signals into actionable wheelchair commands in a real-world environment. The NeuroSky headset, which captures EEG signals from the user's forehead, was used to collect brainwave data while participants engaged in controlling the wheelchair. The system was tested under various conditions where users were asked to perform specific tasks such as moving forward, backward, turning left, and turning right. Brainwave data was recorded while participants concentrated on the respective tasks, with the signals being transmitted to the wheelchair's microcontroller via Bluetooth for processing.

4.4.1 *Signal collection process*

The process of acquiring the signal started with the validation of the accurate calibration of the NeuroSky headset, along with the establishment of a strong connection between the headset and the microcontroller's Bluetooth module. Instructions were provided to the participants to focus on specific commands, and the brainwave activity associated with the commands was recorded and sent to the microcontroller. The microcontroller, after acquiring the signals, executed the data processing and then activated the relays that power the motors, employing pre-established thresholds associated with attention and meditation levels.

4.4.2 *Signal processing and analysis*

Following the collection of (EEG) data through acquisition, the data were processed by removing noise and artifacts prevalent in EEG signal acquisition using signal filtering techniques. This entailed the elimination of interference resulting from movement artifacts and external electrical disturbances. The filtered signals were next analyzed to validate the accuracy of the correlation of brainwave activity with commanded motion. EEG signals were separated into various frequency bands, including alpha, beta, and gamma, each corresponding to a specific state of cognition (e.g., relaxation, focus, multitasking). The legitimacy of the brainwave signals was confirmed by validating the commanded movement (forward, backward, left, right, stop) and the actual movement of the wheelchair. Errors and discrepancies identified were noted for further optimization.

Initial feedback from the set of real data indicated that the system was able to identify brainwave signals appropriately and translate them into appropriate movements. Both forward and reversal movements were preceded by high attention levels, and turning and braking actions were preceded by low attention levels. The system demonstrated a high level of reliability in a controlled environment, with occasional errors due to user concentration levels or external disturbances. Future improvements will include further refining the signal processing algorithms to improve the system's resilience to noise and external interference, as well as testing the system with a larger group of users to assess its scalability and adaptability.

5. Conclusions

This study aimed to create a Brain Controlled Wheelchair that users can control directly with their brains. An EEG-based Brain Controlled Wheelchair was created to assist elderly and disabled individuals with daily activities. NeuroSky technology was used to develop a prototype of an EEG-based Wheelchair. While the BCI system is still in its early stages of development, there is room for improvement in Wheelchair design to make it more accessible. To improve the Wheelchair's control accuracy and prevent collisions, artefacts and noise levels will be removed during signal processing. This study resulted in the successful realization of a Brain Controlled Wheelchair capable of operating in both normal Wheelchair and brainwave control modes. This study provides a new and effective solution for physically disabled people and patients with neuromuscular disorders to regain mobility.

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Conflicts of interest

The authors declare no conflict of interest.

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