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RESEARCH ARTICLE

Empowering Individuals With Disabilities: A 4-DoF BCI Wheelchair Using MI and EOG Signals

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This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the Ethics Committee of University of Western Macedonia under Application No. 231/31-05-2023.

ABSTRACT The field of Brain-Computer Interface (BCI) has been rapidly expanding in the last few years and it is applicable in several fields. This study introduces a BCI-controlled wheelchair that utilizes Motor Imagery (MI) mental commands for turning left and right and Electrooculogram (EOG) signals, raising the eyebrows, for starting and stopping. The wheelchair offers 4 Degrees of Freedom (DoF), allowing users to move forward, stop, turn left, and turn right. The Emotiv Epoc headset is used to record the raw EEG data, the Common Spatial Patterns (CSP) algorithm is utilized to extract features from the data, and the Support Vector Machine (SVM) is employed to classify the mental commands. A total of 28 subjects, with half of them being individuals with motor and brain disabilities such as brain paralysis, severe brain disability, epilepsy, and spastic tetraplegia, participated in 5 experiments to assess the proposed BCI system. The results show that all participants, including those with disabilities, successfully adapted to and operated the BCI-controlled wheelchair with high accuracy and precision.

INDEX TERMS Brain-computer interface, BCI-controlled wheelchair, SVM, motor imagery, CSP, motor and mental disabilities, real-time BCI wheelchair.

I. INTRODUCTION

Brain-computer interface (BCI) technology has remarkable progress and development over the past decade, transforming the interaction of humans with computers [1], [2]. BCI systems establish a direct communication pathway between the human brain and external devices, enabling individuals to control and interact with technology using their brain signals [3]. It has the potential to impact various domains, including healthcare, assistive technologies, and gaming. It can influence various fields, including healthcare, assistive technologies, and gaming. The accuracy, speed, and reliability of BCI systems have been increased thanks to the advancements of machine learning algorithms, signal processing techniques, and better equipment [4], [5].

A widely employed method in BCI technology is Electroencephalography (EEG) [6] which includes recording the electrical activity of the brain to acquire neural signals [7]. It can be classified into two main types: invasive and non-invasive. The invasive category [8] involves placing sensors directly into the brain. This results in high spatial resolution, high accuracy, and amplitude, reduced artifacts, and noise. However, this technique is dangerous since is entails surgery and raises ethical concerns. On the other hand, non-invasive technique [9], offers safety, affordability, and ease of use. In this category, electrodes are placed on the surface of the scalp. This allows repeated measurements, long-term monitoring, and real-time feedback. This technique is sensitive to noise and artifacts, limiting signal quality.

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EEG headsets are categorized as wireless and non-wireless. Wireless headsets offer mobility but may have challenges with signal quality and latency [10]. On the other hand, non-wireless headsets provide stable, high-quality signals and are commonly used in clinical research. In recent years, real-time applications of BCI have increasingly employed commercial wireless EEG headsets since they offer the advantage of portability, flexibility, and ease of use, allowing users to engage in real-time applications without the constraints of wired connections [11].

BCI-controlled wheelchairs have emerged as a promising application, offering several benefits and advantages for individuals with severe motor disabilities [12]. They are capable of restoring mobility and independence by allowing users to navigate using only their brain signals, improving their quality of life. Real-time responsiveness enables immediate and direct control, enhancing the user experience. Also, these systems can enhance autonomy for users by reducing their reliance on physical assistance from caregivers. As a result, this increased independence offers individuals greater privacy and freedom in their daily lives [13], [14].

One of the primary applications of BCI technology is in assisting individuals with severe motor disabilities, such as brain paralysis, severe brain disability, epilepsy, and spastic tetraplegia [15], [16], [17]. These conditions significantly impair a person's ability to interact with their environment, making daily activities challenging. BCIs offer a non-invasive means to restore some degree of autonomy by translating neural signals into control commands for external devices, such as wheelchairs [12]. These systems are capable of restoring mobility and independence by allowing users to navigate using only their brain signals, improving their quality of life. Real-time responsiveness enables immediate and direct control, enhancing the user experience. Also, these systems can enhance autonomy for users by reducing their reliance on physical assistance from caregivers. As a result, this increased independence offers individuals greater privacy and freedom in their daily lives [13], [14].

However, not all disease classes benefit from BCI systems. Individuals with severe cognitive impairments or those unable to generate consistent neural patterns may find it challenging to use BCI technology effectively. BCI technology is particularly advantageous for wheelchair control due to its ability to provide precise and selective control signals, essential for maneuvering in various environments and ensuring safety and reliability. Alternative methods, such as joystick-controlled wheelchairs, require fine motor skills that many individuals with severe motor disabilities do not possess. Voice-controlled wheelchairs [18], [19] may not be suitable in noisy environments or for users with speech impairments.

Despite all these advantages, several challenges must be addressed for the development of accurate BCI-controlled wheelchairs [12]. These challenges include the variability of EEG signals among individuals, resulting in personalized calibration and training to achieve reliable control. Additionally, ensuring high-quality signals in non-invasive EEG recordings is an ongoing challenge. Users must undergo training to generate specific brain patterns, requiring the implementation of effective training protocols and user-friendly interfaces. Lastly, the developers must prioritize safety and reliability in order to prevent accidents or injuries, requiring robust system design, and fail-safe mechanisms.

The Motor Imagery (MI) paradigm is a technique in which users mentally simulate specific movements without physically performing them [20], [21]. MI generates specific neural patterns that can be detected and translated into control commands for external devices [22]. MI offers precise control signals if users train and calibrate to establish reliable mappings. Ongoing research aims to enhance MI-based BCIs through improved signal processing and personalized training approaches. The most employed MI movements are the imagination of hands and feet movement. MI paradigm can be applied for a wide range of applications, including motor rehabilitation, prosthetics control, sports training, and wheelchair navigation [23].

BCI-controlled wheelchairs can be commanded using the MI paradigm, where users imagine specific movements, like raising or moving their left or right hand, thereby indicating the desired turning direction to navigate the wheelchair [24], [25]. Machine learning algorithms can decode the MI brain patterns and translate them into commands [26]. These systems offer precise and selective control signals, allowing users to control the wheelchair.

This paper presents the development of a wheelchair controlled by a BCI system, which utilizes MI commands for left and right movements and incorporates Electrooculogram (EOG) signals. To record the brain potential, Emotiv Epoc headset is employed with 14 EEG channels. To process and classify the EEG signals Common Spatial Pattern (CSP) algorithm is employed and Support Vector Machines (SVM) classifier is utilized. The Degree of Freedom (DoF) is 4 since the wheelchair can move forward, turn left, and right, and stop. To validate the proposed system 28 subjects participated in 5 experiments, 2 simulated experiments on the computer, and 3 experiments commanding the BCI-controlled wheelchair. To our knowledge, this is the first study that half of the participants (14) have motor and brain disabilities, such as brain paralysis, severe brain disability, epilepsy, and spastic tetraplegia. A comprehensive analysis of the results, including a comparative examination between healthy subjects and patients will be presented. Lastly, the challenges encountered throughout the course of this research will be discussed in detail.

II. RELATED WORK

Xiong et al. [27] designed a BCI-controlled wheelchair utilizing MI mental commands and Electromyography (EMG) signals. To record the brain's potential 4 channels were used, C1, C2, C3, and C4. The employed mental commands were left and right MI to turn the wheelchair in the desired direction and jaw clench to stop the movement. Also, a location tracker and a heart-rate monitor were implemented to increase usability and safety. The proposed system had 2 modes; the autopilot navigation which is responsible for the forward movement of the wheelchair and the BCI control which turns the wheelchair right and left. In the first mode, an obstacle detection system was developed for avoiding walls, stairs, and other obstacles. To change the mode the user must perform an intentional jaw clench and the wheelchair stops moving. If a MI command is performed the wheelchair turns in the desired direction and in order to access the navigation mode 2 jaw clenches must be performed. To process the EEG signals a bandpass filter between 5 to 50 Hz was applied and then the power spectral density (PSD) was calculated. To classify the mental commands logistic regression algorithm was employed. 7 healthy subjects participated in the study. The mean accuracy of the classification was 60±5% and the peak subject accuracy was 82±3%. Different time windows and channels were examined to maximize the classification accuracy. Real-time experiments were not performed in this study.

Tsui et al. [28] developed a self-paced BCI-controlled wheelchair. To acquire the raw EEG signals 5 channels were used, C1, C2, C3, C4, and Cz. The study employed 2 mental commands, right and left MI which were utilized to command the BCI system (turn right and turn left). The logarithmic band power was calculated and 2 LDA algorithms were employed to classify the mental commands. To validate the proposed system 2 subjects participated in 2 real-time experiments. The first experiment was a simulated one, which was utilized to train the participants with safety. In the second experiment, the subjects commanded the BCI wheelchair in an indoor environment and had to perform a series of movements to reach the end of a path. To evaluate this work, a time-based metric was employed to measure the time to complete the path for a single run.

Yu et al. [29] developed a BCI-controlled wheelchair based on Sequential Motor Imagery (sMI). To acquire the raw EEG signals a 31-electrode cap was used and 3 mental commands were recorded, right and left MI and resting state. To process the raw signals a bandpass filter between 4 and 30 Hz was applied and for feature extraction, CSP algorithm was utilized. To classify the mental commands LDA algorithm was employed. Then a template-matching algorithm that calculates the Pearson correlation coefficients between a series of classification results is used. The available movements of the wheelchair were going forward, stopping, turning left, turning right, accelerating, and decelerating. To validate the proposed system, 7 healthy subjects participated in 2 experiments, a simulated and an online. In the simulated experiment, participants had to perform a series of mental commands for training. The evaluation metrics of the first experiment were the response time, the true positive rate (RT), and the false positive rate (FPR). In the second experiment, the subjects had to command the BCI wheelchair from the starting position to the end of the path position in an indoor environment. The employed evaluation metrics of this experiment were the tasks accomplished, the time taken, the missed waypoints, the commands taken, the distance traveled, the angle explored, and the collisions.

Carlson and Millan [30] designed a BCI-controlled wheelchair. The brain signals were recorded from a 16-channel EEG device with a sampling frequency of 512 Hz. To process the raw signals a Laplacian filter was applied to reduce the signal-to-noise ratio. Then PSD was calculated between 4 to 48 Hz with a 2-Hz resolution and a canonical variate analysis was employed to maximize the separability between the classes. A Gaussian classifier was utilized in this study. The mental commands that were used to command the wheelchair were right and left hand MI and the available movements of the system were turning left, turning right, and going forward. For the forward movement, autopilot navigation was implemented with an obstacle detection system using cameras and 10 close-range sonar sensors. 4 healthy subjects participated in 2 experiments. In the first experiment, participants sat in the wheelchair and performed a series of mental commands to move a cursor on a monitor. For the second experiment, the subjects had to command the wheelchair on a predefined path. A time-based metric, accuracy, path efficiency, average distance traveled, and successful completion of a navigation task were employed as the evaluation metrics of this work.

Ron-Angevin et al. [31] developed a BCI-controlled wheelchair implementing 2 mental commands; right-hand MI and idle state. To acquire the raw EEG data, a 9-channel device was used. To process the raw EEG signals the average signal power was calculated and for the 2-class problem, LDA algorithm was employed. The available movements of the BCI system were moving forward, and backward, turning left, and right. An obstacle detection system was also utilized for safety. Initially, 17 subjects participated in the recording-calibrating phase but due to poor performance 10 subjects were excluded from the virtual and the online experiments. In the virtual experiment, users had to navigate a simulated wheelchair in a predefined path in order to train. The evaluation metrics for this experiment were time-lapse, failed commands, recall, specificity, precision, NPV, and accuracy. In the online experiment, subjects had to command the wheelchair on the same predefined path as in the virtual scenario. The same evaluation metrics were employed in this experiment as well.

III. MATERIALS AND METHODS

The objective of the proposed study is to develop an affordable wheelchair that can be controlled using BCI technology for individuals with disabilities. The system consists of an Emotiv Epoc headset, a laptop, and a wheelchair. The details regarding the dataset, hardware, and software employed in this work will be presented in the subsequent sections. In figure 1 the flowchart of the proposed approach and the processing pipeline is presented.

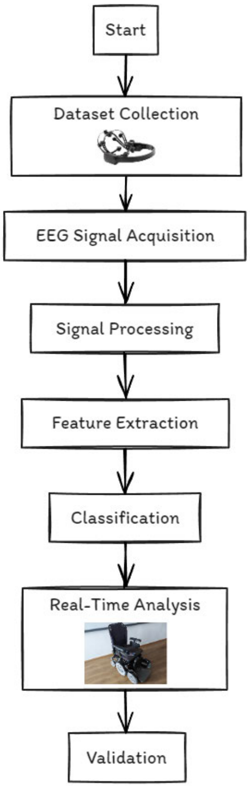

FIGURE 1. This flowchart illustrates the sequence of steps involved in the study, from adjusting the Emotiv Epoc headset, through dataset collection, EEG signal acquisition, signal processing, feature extraction, and classification, to real-time analysis and validation.

A. BRIEFING PARTICIPANTS

In this study, all participants are initially gathered in a briefing room. This meeting presents a comprehensive overview of the study protocol and objectives, emphasizing the experiments' importance and clearly presenting the goals. This ensures that everyone begins the experiment with a thorough understanding of the procedures and expectations.

During the initial briefing, the experimental equipment such as the Emotiv headset and the wheelchair is introduced. Participants are encouraged to interact with these devices physically, helping them become comfortable and familiar with the technology they use. Before the recording phase starts, the study's objectives and demonstrating the correct hand and body movements required for the study are shown again to the participants. Visually and verbally guiding participants, is crucial in maintaining the integrity and reliability of the results, ensuring that potential biases do not affect the outcomes.

B. DATASET

To validate the BCI-controlled wheelchair 28 subjects participated in the study. The participants included are both right-handed and left-handed individuals. The subjects are divided into 2 groups, patients (P1-P14) and healthy (S1-S14). The average age of all participants is 33.64 while the average age for patients is 35.92 ranging from 26 to 54 and for healthy is 31.35 varying from 23 to 62. P1, P3, and P10 are diagnosed with mild intellectual disability, P4, P5, P6, P8, and P9 have moderate intellectual disability and epilepsy. Also, P6 has a severe visual impairment and P8 has a behavioral disorder with psychotic symptoms. P2, P7, P11, and P13, have severe intellectual disability, and P12, and P14 have spastic tetraplegia, brain paralysis, and intellectual disabilities. Lastly, P9, P11, and P12 are in a wheelchair due to severe motor disability. Expect P1, P9, P10, and P13 all the other patients are on medication. The caretakers and/or parents signed a consent form to authorize their participation in the experiments. On the other hand, S1-S14 have good vision and they are mentally and physically healthy. They have also signed a consent form to be able to participate in the study. The information about the dataset utilized in this study is provided in Table 1.

TABLE 1. The table presents the subjects that participated in this study (B.D. = Brain Disability, M.D. = Motor Disability). The type of medication for each subject is not presented.

Subs	Age	Diagnosis	Medication
P1	32	Mild B.D.	no
P2	40	Severe B.D.	yes
P3	32	Moderate B.D.	yes
P4	33	Moderate B.D.	yes
P5	26	Epilepsy, Moderate B.D.	yes
P6	51	Epilepsy, Mild B.D.	yes
P7	43	Severe B.D.	yes
P8	28	Moderate B.D.	yes
P9	26	Brain Paralysis, Severe M.D.	no
P10	30	Mild B.D.	no
P11	33	Severe B.D. Severe M.D.	yes
P12	54	Brain Paralysis, Severe M.D.	yes
P13	37	Severe B.D.	no
P14	38	Brain Paralysis, Severe M.D.	yes

C. WHEELCHAIR

In this study, a commercially available electric wheelchair equipped with six wheels is utilized (Figure 2). The conventional input mechanism, the joystick, is substituted with a microcomputer that enables communication via either wifi or serial port connection (USB). For this research, the USB connection method is employed, in which a laptop connected to the EEG headset establishes a connection with the wheelchair to issue commands.

D. EEG HEADSET

Emotiv Epoc headset [32] is employed to acquire brain signals. It is a 14-channel commercial EEG device that is utilized in various applications, including BCI research [33], [34], mental health research [35], [36], and gaming [37], [38]. Epoc is connecting with the computer via Bluetooth which enhances mobility and flexibility. The sampling frequency of the device is 128 Hz. Also, it offers a built-in Accelerometer and Magnetometer and has the potential to detect mental

FIGURE 2. The electric wheelchair employed in this study.

FIGURE 3. Emotiv Epoc headset with 14 channels.

commands, facial expressions, and several performance metrics. Emotiv provides software development tools and an SDK. It provides numerous benefits [39]. More specifically, it is lightweight and portable, making it ideal for real-time applications. It is user-friendly, and thanks to the software provided it has a quick setup time. Also, it is an affordable option compared to clinical EEG devices and it offers better coverage of brain activity compared to other commercial EEG headsets. The device is presented in Figure 3.

E. LAB STREAMING LAYER

Emotiv's software provides Lab Streaming Layer (LSL) protocol which is an open-source system for streaming, receiving, synchronizing, and recording time series data from different network acquisition devices [40]. LSL ensures secure transmission of data using the TCP protocol and simplifies cross-platform connectivity. In this study, the LSL stream is employed to record EEG signals and transmit the data to Python scripts responsible for processing and classifying the signals.

1) EEG RECORDINGS

The EEG signals are initially acquired and saved in CSV files. These files are then processed to extract features and train the classifier. Four EEG classes are recorded for each participant: right-hand MI, left-hand MI, idle state, and raising the eyebrows. The MI brain signals are recorded for 5 minutes each (5 minutes for right MI and 5 minutes for left MI), while the idle state and the raise of the eyebrows are recorded for 2 minutes each. The recording duration for each EEG class is carefully chosen to match the complexity of the tasks involved. Longer recordings are used for more complex tasks, such as hand MI movements, to ensure sufficient data for precise classification. In contrast, simpler tasks like blinking and idle state are recorded for shorter duration, as they are easier to detect in EEG signals. Participants are instructed not to execute the movements they are imagining and to remain physically still during recordings.

To ensure reliable and accurate EEG signal acquisition across all participants, several measures are taken. All recordings are carried out in a quiet room to reduce noise. The participants are required to sit on a comfortable chair, facing a white wall, to reduce potential distraction. Subjects are recorded only once, regardless of classification accuracy results, to maintain consistency. Before starting the recordings, a researcher explains the tasks and demonstrates the movements that participants need to imagine. Participants are given time to physically execute these movements before the recording phase starts. They also, have time to get familiar with the equipment which led to reduced anxiety and movement artifacts during the actual recordings. By implementing these measures, consistent EEG signal acquisition across all participants is ensured.

F. SIGNAL PROCESSING AND FEATURE EXTRACTION

After the completion of the signal capture phase, a bandpass filter between 8 to 40 Hz is applied to the signals. This filter is applied to reduce the noise and artifacts of the raw EEG data and to exclude Delta and Theta frequency bands that are associated with sleep and relaxation. Then 3 more Butterworth bandpass filters are applied to the signals to split them into 3 frequency bands:

1) Mu rhythm 8 to 13 Hz
2) Low Beta frequency 13 to 20 Hz
3) High Beta frequency 20 to 30 Hz

The mu rhythm [41], [42] is a specific pattern of brainwave activity that occurs in the sensorimotor cortex. It typically appears in the frequency range of 8-13 Hz and is associated with motor-related processes. It is observed to decrease in amplitude when a user engages in imagined movements. Beta waves [42], [43] is a type of brainwave pattern occurring in the frequency range of 13 to 30 Hz, associated with active mental states. They have fast and low-amplitude oscillations, predominantly observed in the frontal and central regions of the brain. They are involved in critical thinking, decision-making, information processing, motor coordination, and muscle movement.

Then the signals are divided into 3-second segments with a 25% overlap. The window size is selected to achieve a balance between a fast system response to the user's mental commands and accurate classification. This trade-off has been investigated through multiple trial-and-error experiments.

To extract features from the data, the CSP algorithm is employed. CSP [44], [45] uses spatial filters to maximize the discriminability of 2 or more classes. The goal of the CSP algorithm in a 3-class problem is to identify spatial patterns that differentiate 1 class from the other 2. It achieves this by maximizing the variance of EEG signals for 1 class while simultaneously minimizing the variance for the other 2 classes which enhances the separability of the 3 classes in the transformed feature space. In this study, 8 spatial filters are utilized. The features that are extracted from the signals are used to train the classifier offline.

G. CLASSIFICATION

For the classification process, the SVM algorithm is employed. SVMs [46], [47] are a powerful supervised machine learning algorithm utilized for classification tasks. The goal is to find an optimal hyperplane that separates different classes with the maximum margin, achieved by transforming the data into a higher-dimensional feature space using a kernel function. They minimize classification error while maximizing the margin, utilizing support vectors that lie closest to the hyperplane. They are also effective in high-dimensional spaces, handle non-linearly separable data, and have good generalization performance. However, they can be computationally expensive and struggle with overlapping classes or high-dimensional data. Despite these limitations, SVMs have been widely applied in various domains with success [48]. SVM [49] is one of the most effective classification algorithms for EEG analysis since it can handle complex data patterns and optimize the separation between different EEG classes.

In the specific implementation, the SVM utilizes a Radial Basis Function (RBF) kernel. The decision function for SVM with an RBF kernel is given by:

$$f(\mathbf{X}) = \sum_{i=1}^{N} \alpha_i y_i \exp\left(-\frac{\|\mathbf{X}-\mathbf{X}_i\|^2}{2\sigma^2}\right) + b \tag{1}$$

Here, α_i represents the Lagrange multipliers, y_i are the corresponding class labels, $\mathbf{X}_i$ are the support vectors, and b is the bias term. The prediction is determined by the sign of $f(\mathbf{X})$, where $f(\mathbf{X}) > 0$ implies one class, and $f(\mathbf{X}) \leq 0$ implies the other class.

SVMs are chosen instead of deep learning models because they offer robust performance while requiring significantly less computational resources. SVMS has also proven effective in EEG signal classification, as they can efficiently manage high-dimensional data and excel with non-linear kernels. This makes SVMs the best choice for the current application, allowing to establish a baseline performance for the BCI system without the complexity and computational overhead associated with deep learning models.

H. REAL-TIME ANALYSIS

Once the classifier has been trained, the BCI system is prepared for real-time utilization. During real-time analysis, identical processing techniques are applied to the signals. This involves segmenting the raw EEG data into 3-second epochs with 25% overlap and applying the 4 bandpass filters to them. Additionally, the CSP method is utilized on the filtered signals, extracting features that are then fed into the trained SVM classifier. Based on the user's generated EEE-Signals, the classifier makes predictions about the corresponding class, which are then employed to control the wheelchair and/or the in-game avatar. The predictions are integer values; 0 for right MI, 1 for left MI, and 2 for raising the eyebrows. Depending on the outcome of the classifier one of these values is translated in the corresponding command and is sent through serial port communication to the wheelchair or through an LSL stream to the game.

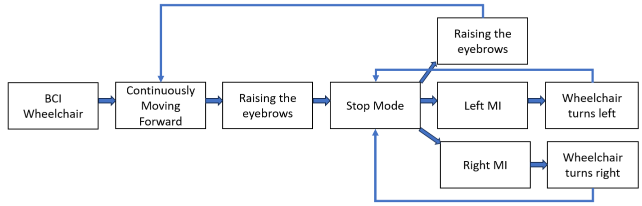

FIGURE 4. Flowchart presenting the movements of the wheelchair. There are 2 modes. In the first mode, the wheelchair moves forward by default. To change the mode the user must stop the wheelchair by raising his eyebrows. Then the stop mode is activated in which the user can turn left or right or start the movement of the system.

1) COMMANDING THE BCI-CONTROLLED WHEELCHAIR

The available movements of the proposed system are 4; going forward, stopping, turning right, and turning left. The MI mental commands are responsible for turning the wheelchair in the desired direction and the raise of the eyebrows is responsible for starting and stopping the movement of the system (Figure 4). When the system is turned on the wheelchair moves forward continuously. If the user wishes to stop the movement or turn in a different direction he has to raise his eyebrows to stop the movement of the BCI system. In the stop mode, the user can turn left or right or start moving forward. For safety reasons, turning is disabled while the wheelchair is in forward motion. A new command is sent to the wheelchair at 3-second intervals with a 25% overlap of the signals, allowing for responsive yet stable control. The speed of the system is constant at 5 km/h. Lastly, the wheelchair turns 45 degrees in a single-turn command. This specific degree of rotation allows the wheelchair to complete a 90-degree turn with just two consecutive commands, enabling precise and efficient navigation. Additionally, a safety button is integrated within the system to immediately stop the wheelchair if needed, ensuring that there are no safety risks.

I. GAME DESIGN

To assess the proposed system, the initial two experiments involve simulating the wheelchair's movements within a gaming environment. The first game employed was presented in our previous work [50]. The goal of the game is to simulate the start and stop of the movement of the wheelchair by raising the eyebrows to jump over obstacles. For this game

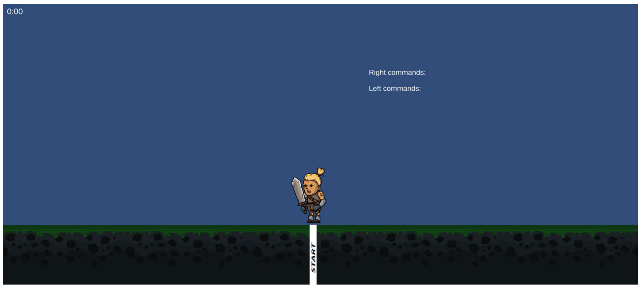

FIGURE 5. The second game is employed in the second experiment and simulates the left and right movements of the wheelchair. The time to complete the task and the number of right and left commands are recorded.

a 2-class classifier is employed; idle state vs raising the eyebrows. A score is assigned to the user based on the number of obstacles they successfully overcome, with a maximum score of 125 in this gaming scenario.

For the second experiment, a simple 2D game is developed in the Unity Engine platform [51] (Figure 5). Depending on the user's generated EEG signals, the in-game avatar can move right and left. When the classifier is predicting a class, the integer value that represents the prediction is converted to a string and sent via LSL stream to the Unity script responsible for the avatar's movement. The right MI is responsible for directing the avatar towards the right, while the left MI is responsible for guiding the avatar towards the left. By raising the eyebrows, the movement of the avatar stops. The goal of this game is to simulate the MI commands.

IV. RESULTS

A. OFFLINE RESULTS

1) CLASSIFICATION RESULTS

Table 2 presents the classification results of all subjects. EEG signals are split into 3 classes, Right MI, Left MI, and raising the eyebrows. The 10-cross-validation F1 score is calculated for each participant and the Accuracy of the Test Set is also presented. The overall average cross-validation F1 score is 84.32% ranging from 68% achieved by P10 and P11 to 98% achieved by S1. Additionally, the classification results are higher for healthy individuals, as their average result is 86.5%, in contrast to patients whose average is 82.14%. For the second metric presented in the table, the Accuracy of the Test Set, the average result of all participants is 86.90% varying from 68.69% by P10 to 98.86% by P6. The average result for patients is 85.32% while for healthy is 88.46%.

To enhance the robustness of our classification predictions, additional machine learning algorithms are evaluated. These comprise Linear Discriminant Analysis (LDA), k-Nearest Neighbors (k-NN) with 5 neighbors, Decision Tree, and Random Forest. Comparative performance analysis is conducted to identify the most effective classifier for our BCI system. The performance of these machine learning classifiers is

TABLE 2. Classification results. The mean Cross-Validation (C-V) F1 score is presented for all subjects in the second column and the Accuracy of the Test Set is presented in the third column.

Subjects	Mean C-V F1 Score	Accuracy of Test Set
P1	91%	92.78%
P2	86%	88.32%
P3	97%	97.97%
P4	70%	72.20%
P5	79%	83.90%
P6	97%	98.86%
P7	76%	79.44%
P8	84%	86.51%
P9	79%	80.77%
P10	68%	68.69%
P11	68%	74.11%
P12	86%	91.95%
P13	95%	95.66%
P14	77%	83.36%
S1	98%	98.48%
S2	83%	82.70%
S3	75%	78.75%
S4	85%	87.30%
S5	95%	93.38%
S6	87%	90.70%
S7	82%	83.42%
S8	91%	92.23%
S9	90%	92.40%
S10	75%	79.58%
S11	84%	87.10%
S12	88%	92.03%
S13	86%	87.07%
S14	92%	93.42%
Overall	84.32%	86.90%

assessed based on the Mean Cross-Validation F1 Score and the average results are 82.71% for LDA, 82.58% FOR k-NN, 79.29% for Decision Tree, and 83.98% Random Forest. As mentioned before the average Mean C-V F1 Score for the SVM classifier is 84.32% which indicates that the SVM classifier achieved the highest classification accuracy for the dataset of the study.

B. ONLINE RESULTS

The majority of participants had no prior involvement in a BCI experiment, except 4 individuals who had previously participated in an MI BCI study. An experienced researcher on our team briefed the participants on the experiments, the goal of the work, and the study protocol. To evaluate the proposed BCI system, 5 experiments are utilized, 2 on the computer (simulations of the movements) and 3 commanding the wheelchair all conducted under strict guidelines to ensure that participants only engage in brain commands without physical movement.

1) SIMULATING BCI WHEELCHAIR START-STOP DYNAMICS THROUGH A 2D GAME

The first experiment is a 2D game developed to simulate the stopping and starting of the wheelchair. More specifically, participants sit comfortably in a chair in front of the computer to play the game in which they must jump over obstacles.

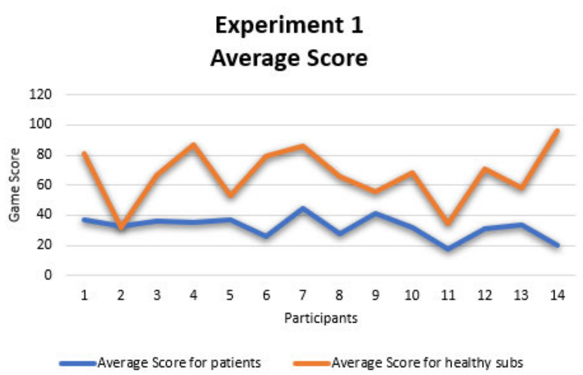

FIGURE 6. Average game score results for all subjects presented in a graph. The blue line represents the scores of the patients while the orange represent the healthy participants.

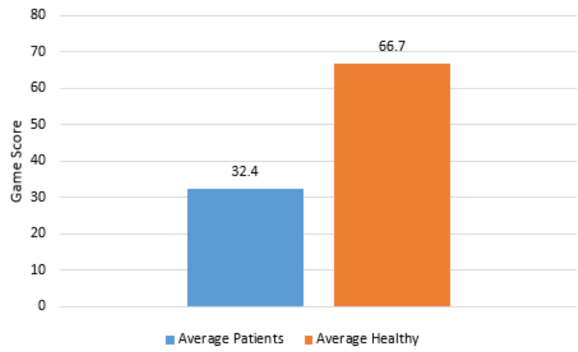

FIGURE 7. The graph compares the average results of the two groups in the first experiment. The Y-axis represents the Game Score.

To avoid the obstacle users need to raise their eyebrows. Participants go through a series of 10 trials, split into 2 sets of 5. The initial 5 trials are designed to help them get familiar with the game and the BCI. After this practice phase, users move on to the next 5 trials, where their scores for each trial are recorded see Figure 6.

The average score of all participants is 49.55 varying from 18 by P11 to 96 by S14. 5 healthy subjects, S6, S7, S8, S10, and S14 managed to successfully finish the game (score = 125) at least 1 time. 3 patients, P8, P11, and P14 have at least 1 try in which they could not overcome a single obstacle. More specifically, P11 could not jump any obstacle in 4 of his 5 trials while P14 in 3 of his 5 trials. These are the worst-performing users in the first experiment. On the other hand, the best-performing participants are S14, S7, S4, and S1 who could easily adapt and play the BCI-controlled game simulating the starting and stopping of the wheelchair. Figure 6 illustrates the average results, revealing that the patients with the highest performance are P7 and P9, achieving average scores of 44.4 and 41.2, respectively. Interestingly, the healthy subjects outperformed the patients, as 12 out of the 14 healthy participants obtained higher scores than all the patients. Among the healthy subjects, S2 and S11 had the lowest performance, with average scores of 32 and 34.4, respectively. Notably, S2 is outperformed by 8 patients, while S11 is outperformed by 6 patients.

One important aspect of this study is the participation of both patient and healthy subjects, enabling a comprehensive analysis of the experiment. By comparing these two groups, we gain valuable insights. The average score of patient subjects is 32.4, whereas the average score of healthy individuals is 66.7, as shown in Figure 7. This highlights the better adaptation of healthy individuals in the first BCI game, which simulates the wheelchair's starting and stopping. Moreover, patients encountered difficulties in performing the eyebrow raise command and in understanding the time delay of the BCI system, where users must synchronize their mental commands.

2) SIMULATING BCI WHEELCHAIR TURNING THROUGH A 2D GAME

The second experiment in this study involves a 2D game that simulates the movement of the wheelchair in the left and right directions. In this experiment, subjects have a total of 20 tries, with 10 dedicated to adapting and learning the game, and the remaining 10 employed to assess the users' ability to execute the MI commands. Each try is considered complete when the user successfully performs two same turns, either left or right, depending on the command of the researcher. To evaluate the experiment, four metrics assess the participant's performance: the time taken to complete a single try, the number of missed commands, the total number of completed tries, and Information Transfer Rate (ITR) index [52], [53]. The targets (N) of the experiment are two, and the classification accuracy (P) for each participant is calculated by dividing the number of correct commands by the total number of commands executed. To calculate the ITR index the following formula is employed:

$$B\left(\frac{\text{Bit}}{\text{Trial}}\right) = \log_2 N + P\log_2 P + (1-P)\log_2\left(\frac{1-P}{N-1}\right) \tag{2}$$

$$Q\left(\frac{\text{Trials}}{\text{Min}}\right) = \frac{S}{T} \tag{3}$$

where:

$B =$ information transferred in bits per trial,
$N =$ number of targets,
$P =$ classification accuracy,
$S =$ total number of trials,
$T =$ total time in minutes.

To obtain the ITR in bits/min, B is multiplied by the average classification time in minutes:

$$ITR\left(\frac{\text{Bit}}{\text{Min}}\right) = B \times Q \tag{4}$$

Five tries are dedicated to left MI commands, while the other five are for right MI commands. The average results for each subject are presented in Table 3.

The minimum time to complete a single try is 6 seconds, the maximum number of completed trails is 5, and the minimum missed commands possible is 0. The average duration for completing a single run among all subjects is 8.88 seconds. When considering the left MI command, the average number of missed commands (executing the right MI) is 0.96, whereas, for the right MI command, the average number of missed commands (executing the left MI) is 0.97. On average, subjects completed 4.64 trials for the left MI command and 4.93 trials for the right MI command.

For the left MI commands, only 2 individuals, P1 and S12, managed to have an average time of 6 seconds which translates into 5 perfect tries. 5 participants, S1, S2, S5, S13, and S14, managed to play the game with very high precision for the Left MI commands since they achieved an average time of 6.6 which translates into missing only 1 command in their 5 tries. The worst-performing participants that managed to complete 5 tries are P4 with an average time of 17.4 seconds and 3.8 missed commands, followed by P6 with a 14.4 average time and 2.8 miss-classified commands, and P7 with 12.6 and 2.2 respectively. P11 and P14 could not complete any of the 5 available tries since they could not issue a left MI command.

For the right MI trials 3 subjects, P3, P11, and S12, achieved an average time of 6 seconds. Also, 4 participants, P9, S6, S7, and S8, demonstrated exceptional precision in executing the right MI commands, as they achieved an average time of 6.6 seconds. Only one user, P8, was unable to complete all five tries. The lowest-performing participants in terms of average missed commands and time were P8, with 4.25 and 18.74 seconds, respectively, followed by P13 with 2.8 and 14.4 seconds, and P2 with 2.4 and 12.4 seconds, respectively.

In general, subjects have adapted well to the MI commands and achieved high precision. The best-performing participant is S12 who finished the 10 trials without any errors, The worst-performing subjects are P11 and P14 who are unable to perform the left MI command. To gain better insights from the analysis, it is important to compare the performance of healthy subjects and patients, despite the overall high accuracy of this experiment. Figure 8 displays the average results for each group. The graph clearly illustrates that healthy participants outperformed patients in the game. Specifically, patients required more time, with an average time of 10.5, to complete a single trial for the left MI, whereas healthy individuals had an average time of 7.5. Additionally, patients had an average of 1.5 missed commands for the left MI, while healthy participants had 0.5. Regarding the right MI, patients had an average time of 10.29, compared to 7.5 for the healthy group. Patients also had an average of 1.43 missed commands for the right MI, while healthy participants had 0.51.

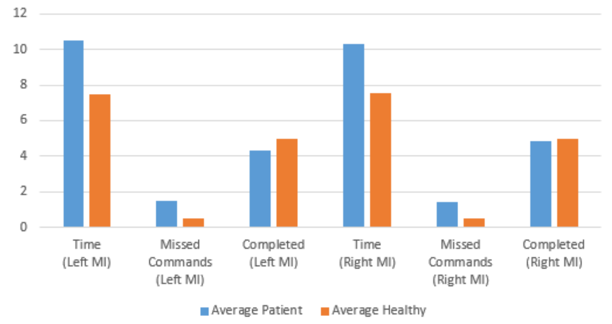

FIGURE 8. In Game 2, which simulates wheelchair movement using MI commands for left and right directions, the average results for each category (healthy vs. patients) are presented. The graph sequentially displays outcomes for left MI followed by those for right MI.

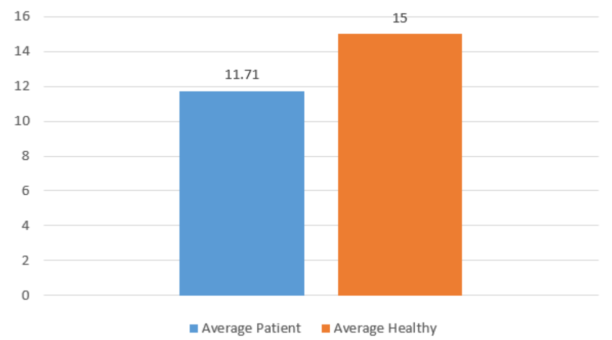

FIGURE 9. The graph compares the average results of the two groups in the third experiment.

3) REAL-WORLD ASSESSMENT OF BCI-CONTROLLED WHEELCHAIR START-STOP COMMANDS

The third experiment in this study focuses on commanding the BCI-controlled wheelchair and assesses the system's capability to start and stop the wheelchair on command. During this experiment, subjects sit in the wheelchair and start going forward. At any given time, the researcher can command the participant to stop the movement by raising their eyebrows. The experiment is completed after issuing 15 stop commands to each subject. Turning right or left was disabled in this experiment. The average results are presented in Figure 9.

The majority of subjects managed to stop the wheelchair with ease. Specifically, 21 participants successfully halted the movement in all 15 attempts. However, two subjects, P11 and P14, are unable to stop the wheelchair in any of their tries, resulting in 0 out of 15 successful stops. P10 and P7 missed 5 commands, P6 missed 3 commands, P5 missed 2 commands, and P9 missed 1 command. It is worth noting that healthy subjects exhibited better performance compared to patient subjects in this experiment. The average number of total stops for the patient subjects is 11.71 while the average number of total stops for the healthy participants is 15. The overall average number of successful stops for all users is 13.36. The success of this experiment can be attributed to

TABLE 3. Experiment 2 average results for each subject. Four metrics are employed to evaluate the performance of the users. Columns 2-4 represent the Left MI commands while columns 5-7 represent the Right MI commands.

Subs	Time (sec) (Left MI)	# of Missed commands (Left MI)	# of tries completed (Left MI)	ITR index (bits/min)	Time (sec) (Right MI)	# of Missed commands (Right MI)	# of tries completed (Right MI)	ITR index (bits/min)
P1	6	0	5	100	11.4	1.8	5	0.20
P2	7.8	0.6	5	22.07	13.2	2.4	4	0.60
P3	9.6	1.2	5	4.56	6	0	5	100
P4	17.4	3.8	5	7.06	10.2	1.4	5	2.26
P5	9.6	1.2	5	4.56	11.4	1.8	5	0.20
P6	14.4	2.8	5	2.01	7.2	0.4	5	35.00
P7	12.6	2.2	5	0.16	7.2	0.4	5	35.00
P8	7.8	0.6	5	22.07	18.75	4.25	4	9.56
P9	15	3	5	2.90	6.6	0.2	5	56.05
P10	10.2	1.4	5	2.26	10.2	1.4	5	2.26
P11	N/A	N/A	0	N/A	6	0	5	100
P12	7.8	0.6	5	22.07	12	2	5	0.00
P13	7.8	0.6	5	22.07	14.4	2.8	5	2.01
P14	N/A	N/A	0	N/A	9.6	1.2	5	4.56
S1	6.6	0.2	5	56.05	7.2	0.4	5	35.00
S2	6.6	0.2	5	56.05	9	1	5	8.17
S3	7.2	0.4	5	35.00	7.8	0.6	5	22.07
S4	8.4	0.8	5	13.69	8.4	0.8	5	13.69
S5	6.6	0.2	5	56.05	7.2	0.4	5	35.00
S6	7.2	0.4	5	35.00	6.6	0.2	5	56.05
S7	9	1	5	8.17	6.6	0.2	5	56.05
S8	7.8	0.6	5	22.07	6.6	0.2	5	56.05
S9	9.6	1.2	5	4.56	7.2	0.4	5	35.00
S10	7.8	0.6	5	22.07	8.4	0.8	5	13.69
S11	9	1	5	8.17	7.8	0.6	5	22.07
S12	6	0	5	100	6	0	5	100
S13	6.6	0.2	5	56.05	9.6	1.2	5	4.56
S14	6.6	0.2	5	56.05	7.2	0.4	5	35.00
Average	8.88	0.96	5.00	28.49	8.89	0.97	4.93	30

the subjects' prior experience and learning from the first experiment. As a result of the initial simulated training, participants are already familiar with the process of stopping the wheelchair, which greatly contributed to their overall success. After a few initial tries, all participants appeared confident in commanding the wheelchair.

4) REAL-WORLD EVALUATION OF BCI-CONTROLLED WHEELCHAIR START-STOP AND TURNING MANEUVERS

The fourth experiment focuses on turning the wheelchair left or right. In this experiment, subjects can move forward, stop the system's movement, and turn in their desired direction. Each participant performed 10 trials, 5 for the left turns and 5 for the right turns. To complete 1 trial, users have to start the wheelchair, stop it on the researcher's command, and turn the wheelchair 2 times in the same direction. A single turn is 45 degrees so after the completion of 1 try the wheelchair will have turned 90 degrees. After every try, participants returned to the initial position and started again. The same evaluation metrics with the second experiment are employed: the time taken to complete a single try, the number of missed commands, the total number of completed tries, and ITR index. The average results of the subjects are presented in Table 4. Columns 2 to 5 represent the results for the left turns and columns 5 to 8 represent the results for the right turns. To have the same metrics as the simulated experiment, the time to complete the task in a single try starts when the movement of the wheelchair is halted so the minimum time is 6 seconds since each command is issued every 3 seconds. The calculation of missed commands is only applicable once the wheelchair has stopped. The minimum value of this metric is 0, indicating that no commands were missed. Additionally, the highest possible value for the number of completed trials is 5.

The results clearly demonstrate the high accuracy of the proposed BCI system. For the left turns, the average results for all subjects are 11.13 seconds, 1.71 missed commands, and 4.88 completed tries. The worst-performing subjects are P11 and P14 since they are not able to execute any left turn. 6 healthy participants, S1, S5, S12, and S13, managed to perform the 5 first trials perfectly resulting in 0 missed commands and an average time of 6 seconds. For the right turns, the average results are 8.98 seconds, 0.99 missed commands, and 5 completed trials. P14 encountered the most challenges during the experiment, as he is unable to complete any of his 5 trials. Furthermore, P12 and P13, despite completing all of their tries, exhibited the poorest average results with 16.2 seconds and 3.4 missed commands for P12, and 18.6 seconds and 4.2 missed commands for P13, respectively. The best-performing subjects are P11 and S8 with 5 perfect tries followed by P1, P3, S3, and S6 with average results of 6.6 seconds and 0.2 missed commands.

TABLE 4. Experiment 4 average results for each subject. Four metrics are employed to evaluate the performance of the users. Columns 2-5 represent the Left MI commands while columns 5-8 represent the Right MI commands.

Subs	Time (sec) (Left MI)	# of Missed commands (Left MI)	# of tries completed (Left MI)	ITR index (bits/min)	Time (sec) (Right MI)	# of Missed commands (Right MI)	# of tries completed (Right MI)	ITR index (bits/min)
P1	16.8	3.6	5	5.97	6.6	0.2	5	56.05
P2	10.8	1.6	5	0.89	10.2	1.4	5	2.26
P3	16.2	3.4	5	4.90	6.6	0.2	5	56.05
P4	16.2	3.4	5	4.90	7.8	0.6	5	22.07
P5	10.2	1.4	5	2.26	12	2	5	0.00
P6	23.1	5.7	4	17.36	7.2	0.4	5	35.00
P7	28.8	7.6	3	26.17	9.6	1.2	5	4.56
P8	10.8	1.6	5	0.89	10.8	1.6	5	0.89
P9	16.2	3.4	5	4.90	7.2	0.4	5	35.00
P10	12	2	5	0.00	9	1	5	8.17
P11	N/A	N/A	0	N/A	6	0	5	100
P12	8.4	0.8	5	13.69	16.2	3.4	5	4.90
P13	9.6	1.2	5	4.56	18.6	4.2	5	9.28
P14	N/A	N/A	0	N/A	N/A	N/A	0	N/A
S1	6	0	5	100	9	1	5	8.17
S2	7.8	0.6	5	22.07	12	2	5	0.00
S3	8.4	0.8	5	13.69	6.6	0.2	5	56.05
S4	7.8	0.6	5	22.07	7.2	0.4	5	35.00
S5	6	0	5	100	9	1	5	8.17
S6	10.8	1.6	5	0.89	6.6	0.2	5	56.05
S7	10.2	1.4	5	2.26	7.2	0.4	5	35.00
S8	7.2	0.4	5	35.00	6	0	5	100
S9	10.2	1.4	5	2.26	9	1	5	8.17
S10	9	1	5	8.17	9.6	1.2	5	4.56
S11	7.8	0.6	5	22.07	7.2	0.4	5	35.00
S12	6	0	5	100	7.2	0.4	5	35.00
S13	6	0	5	100	10.2	1.4	5	2.26
S14	7.2	0.4	5	35.00	7.8	0.6	5	22.07
Average	11.13	1.71	4.88	25.00	8.98	0.99	5.00	27.40

Based on the average results of the fourth experiment a comparison can be drawn between the patient and healthy subjects. Figure 10 presents the average performance for both groups in terms of precision and control. Although there are slight differences in the average performance between the two groups, both were able to effectively navigate and maneuver the wheelchair using their brain signals.

For the left MI turns, patients exhibited an average time of 14.92 seconds, compared to 7.88 seconds for healthy subjects. Patients also had an average of 2.97 missed commands, while healthy subjects had only 0.62 missed commands. In terms of completed turns, patients achieved an average of 4.75, whereas healthy subjects completed all 5 turns.

Similarly, for the right MI turns, patients had an average time of 9.83 seconds, while healthy subjects achieved an average time of 8.18 seconds. Patients had an average of 1.27 missed commands, while healthy subjects had 0.72 missed commands. In terms of completed turns, patients achieved an average of 4.64, whereas healthy subjects completed all 5 turns.

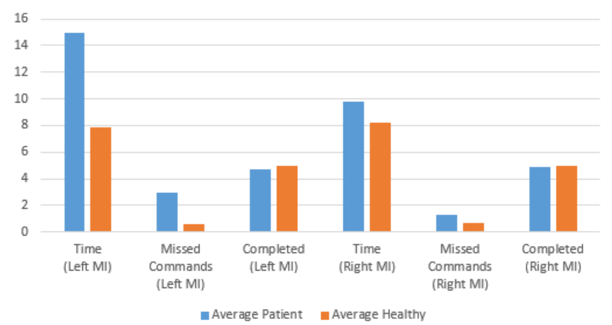

FIGURE 10. The average results for each category (healthy vs patients) are presented. The graph sequentially displays outcomes for left MI followed by those for right MI.

5) BCI-CONTROLLED WHEELCHAIR NAVIGATION: REAL-WORLD ROUTE

The final experiment of this study focuses on commanding the wheelchair in a predefined path. The process involves reaching the starting point and initiating the wheelchair's movement. Upon reaching the first stop point, the subjects must stop the system to perform 2 right turns. To resume forward movement, they raise their eyebrows, aiming to reach the second stop point where they halt again to perform 2 left turns. Finally, they continue moving forward until they reach the final destination. Figure 11 displays subjects engaged in the execution of Experiment 5.

Each participant has 5 attempts in this study. The evaluation metrics used are the time taken to complete a trial, the number of successfully completed trials, and the time

TABLE 5. Experiment 5 average results. N/A represents the null value; subjects could not finish any of their 5 trials.

Subs	Average Time with BCI (sec)	# of trials Completed	Time with Joystick (sec)
P1	82	4	40
P2	139	3	43
P3	156	2	55
P4	N/A	0	45
P5	96	4	N/A
P6	105	4	N/A
P7	N/A	0	N/A
P8	126	3	52
P9	122	2	N/A
P10	62	5	N/A
P11	N/A	0	N/A
P12	102	1	N/A
P13	115	3	65
P14	N/A	0	N/A
S1	55	5	29
S2	65	4	27
S3	57	4	31
S4	42.4	5	27
S5	56.6	5	31
S6	58	5	30
S7	64	5	29
S8	49	5	30
S9	68	5	30
S10	72	5	30
S11	53	5	30
S12	54.4	5	30
S13	74	5	30
S14	52.2	5	32
Average	80.23	3.54	35.80

FIGURE 11. Subjects commanding the BCI wheelchair for Experiment 5.

taken to finish the path using the traditional joystick control. By comparing the time-based metrics between standard joystick control and BCI-control scheme, the effectiveness of the BCI system can be assessed. This is the most difficult experiment of this study since it employs every mental command and because subjects have to follow a specific path. If they get out of the path the trial is considered unsuccessful. To prepare the participants for the experiment,

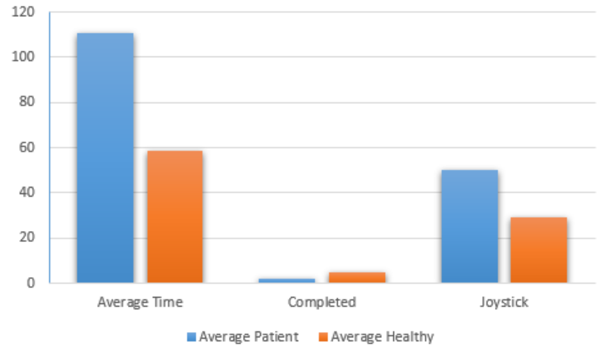

FIGURE 12. The average results for each category (healthy vs patients) are presented.

the researcher presented the desired path using the joystick control. Participants then practiced following the path using the joystick to fully understand the movement required before transitioning to controlling the wheelchair with their brain signals. The average results for experiment 5 are presented in Table 5. The second column represents the average time taken to complete the path with the BCI input (time is calculated in seconds), the second column shows the number of completed trails, and the last column shows the time taken to complete the path with the joystick (seconds).

The average time to complete the path for every subject with the BCI control scheme is 80.23 seconds (1.33 minutes) while the time to complete the path with the joystick is 35.80 seconds (0.59 minutes). The average number of completed trails is 3.54. The best-performing subject is S4 with an average time with the BCI of 42.4 seconds, a time to complete the path with the joystick of 27 seconds, and 5 completed trials. 4 participants, P4, P7, P11, and P14 could not complete any of their 5 trials. Among the subjects that completed at least 1 try, P3 has the worst performance with an average time of 156 seconds when commanding the wheelchair with the proposed BCI. In general, the results presented from the fifth experiment show the great precision of the BCI-controlled wheelchair. A crucial finding of this study is that 5 participants, P5, P6, P9, P10, and P12, successfully completed the experiment using their brain signals but could not finish the path using the joystick control.

In this experiment, healthy subjects have better adaptability and outperformed the patients (Figure 12). The average results for healthy subjects are as follows: 58.61 seconds when using BCI to control the wheelchair, 29.43 seconds when using the joystick, and completion of 4.86 trials. On the other hand, the patients' average results are 110.50 seconds with BCI control, 50 seconds with the joystick, and completion of 2.21 trials. In addition, healthy subjects have better overall control since most of them, 12 out of the 14, managed to finish all their trials. S2 and S3 lost control of the wheelchair in 1 of their tries. P10 is the best-performing patient subject and managed to complete all the trials with an average time of 62 seconds.

TABLE 6. Comparison study of this work with relevant articles from the literature.

Study	EEG Sensors	# of Subs	DoF	Reps per Sub	Real-Time Experiments	Feature Extraction	Classifier
Xiong *et al.* [27]	4	7	4	0	0	PSD	Logistic Regression
Tsui *et al.* [28]	5	2	4	8	2	Logarithmic Band Power	LDA
Yu *et al.* [29]	31	7	6	35	2	CSP	LDA
Carlson and Millan [30]	16	4	4	34	2	PSD	Gaussian
Ron-Angevin *et al.* [31]	9	7	4	82	2	Average Signal Power	LDA
This study	14	28	4	60	5	CSP	SVM

V. DISCUSSION AND CONCLUSION

In this study a BCI-controlled wheelchair is developed that employs MI mental commands and EOG signals. The available movements of the system are 4; going forward, stopping, turning left, and turning right. Emotiv Epoc is used to record the brain signals and CSP algorithm is employed for feature extraction. A 3-class SMV is utilized to classify the mental commands. To evaluate the proposed system 28 subjects participated in 5 real-time experiments. The objective of this study is to investigate the performance of BCI systems when utilized by both healthy individuals and patients. The study's findings demonstrate significant accuracy both in the simulated experiments and in controlling the wheelchair. Lastly, several evaluation metrics are utilized to gain a more comprehensive understanding of the study's findings.

BCI technology can improve the quality of life of all individuals especially people with disabilities. For many years, researchers have been trying to develop robust BCI systems to advance this technology and benefit society. The biggest drawback that has been identified in the literature is the lack of research articles involving actual participation from real patients with severe motor and brain disabilities.

This study wants to address this gap in the literature and become a reference for future articles. By involving patients with severe motor and mental disabilities in this demanding experiment, we aim to explore new insights, and trends, and identify the real challenges of these systems. Additionally, this research provides guidance on conducting such studies in the future. Even though various evaluation metrics are employed to assess the proposed system, the most significant discovery in this article is that some patients are able to control the BCI-controlled wheelchair successfully, but they cannot do so using the joystick. This remarkable outcome shows the potential of BCI technology in empowering individuals and providing them with greater freedom and independence. Also, during the recording phase and the online phase (experiments), the performance metrics that Emotiv software provides for each subject are collected. These metrics showed that all participants increased their focus, excitement, engagement, and interest when they started the experiment phase. This demonstrates how BCI systems can enhance the mental focus of individuals, and it opens up opportunities to develop various new tools that can result in greater engagement in everyday activities for people.

Literature indicates that participants can learn and adapt over time in EEG-based experiments. The experiment structure is designed, taking into consideration the order and difficulty of tasks. It is recognized that the sequencing of experiments can significantly impact participant performance due to learning effects. For that reason, simpler tasks are implemented at the beginning, with complexity increasing progressively in later experiments. The initial two tasks are virtual experiments, utilizing gamification strategies to enhance engagement and learning. Gamification in EEG experiments is particularly effective as it allows participants to play while learning the necessary skills and responses. This method ensures that participants gain experience during the early stages of the experiment. The progression and structure of these tasks are specifically designed to prepare participants for the more challenging, real-time path following experiment, which is the primary goal of this research. This careful structuring is intended to ensure that learning and adaptation throughout the experiments enhance the reliability and validity of the outcomes.

Determining the number of repetitions for each experiment involves a balance between gathering sufficient data and ensuring participant comfort. The goal is to ensure that the results are reliable and not random. The experiment's duration is approximately two hours. This includes the briefing, setup, experiments, recording phases, and breaks. According to reports from participants and their caretakers, there are no significant issues with fatigue, which suggests that the duration and intensity of the trials are well-designed. Additionally, the use of Emotiv metrics helps in assessing and maintaining high levels of engagement throughout the experiment. Also, all sessions are scheduled in the morning to ensure that participants are well-rested and not already fatigued. This scheduling, along with regular breaks and an interactive, engaging experiment design, supports optimal participant performance and data integrity.

While the proposed BCI-controlled wheelchair demonstrated great results in terms of accuracy and adaptation, it is very important to acknowledge the limitations of the system.

The system is built with a 3-second time window, which limits the users with a brief delay as they can only issue a command every 3 seconds. This can be frustrating for users when they want to turn the direction of the wheelchair 90 degrees or more because they have to wait for 12 seconds to start going in their desired direction (3 seconds to stop the movement 6 seconds for 2 turns and 3 seconds to start the movement again). Furthermore, the employed wheelchair operated through the joystick allows backward movement, which is not achievable with the proposed BCI system. Employing a third MI mental command to represent backward movement would significantly increase the system's complexity. Lastly, the system comprises an EEG headset, a wheelchair, and a laptop. In the current implementation of the system, the laptop is positioned in the user's legs leading to some discomfort and impracticality during operation.

The metrics employed in this study are focused on efficiency and accuracy. These include time-based metrics that measure the time participants take to complete a path, indicating the system's usability. The completion of a task shows the BCI system's accuracy and reliability. Additionally, the number of missed commands is used to identify areas needing improvement. In the real-time path-following experiment, performance using the BCI system is compared against using a conventional joystick, with metrics such as completion time and number of successful trials being recorded. These metrics, which are straightforward and easy to analyze, help make the findings understandable and applicable to real-world scenarios, demonstrating the practical effectiveness of the proposed BCI-controlled wheelchair.

Throughout the study, we faced several challenges. Some of the patient subjects were unable to differentiate between the left and right directions. This posed a significant challenge in the research, as the movement of the wheelchair is based on the imagination of moving the right and left hand. Also, some patients could not stand still while they were being recorded. This led to poorer signal quality and unfavorable results. In addition, patients with severe brain disabilities found it challenging to understand the study's concept and the objectives of the experiments. This led to increased stress that was observed in the obtained performance metrics. Moreover, some patient participants, despite achieving impressive results in the simulated experiments, struggled to command the wheelchair effectively in real-time due to the fear they experienced. Another major challenge in this study was the high-powered engine of the selected wheelchair. When the wheelchair came to a stop, and the user issued a command to start, an abrupt and forceful movement occurred, causing the user's body to shift and resulting in significant noise and artifacts in the EEG data. While employing the eyebrow-raising command to stop the wheelchair proved highly effective for the healthy subjects, it posed a significant challenge for the patient participants. These individuals faced difficulties in executing simple commands like blinking or raising their eyebrows. Lastly, mental fatigue can influence the accuracy of the experiments when the duration of the study is extensive. In our case, the duration of the offline and the experimental phase was approximately 2 hours.

Potential challenges related to user discomfort or inconvenience during the operation of the BCI system were addressed through several strategies. Participants were initially trained in a game environment, which made the process more enjoyable and less tiring. They had also time to familiarize themselves with the equipment and could test drive the wheelchair to understand its movement, the power of the engine, and to get comfortable with its operation. Additionally, if any participant felt uncomfortable or scared at any point, they had the option to immediately stop the experiment and leave. This approach ensured that participants were at ease and could engage with the BCI system in a stress-free manner.

Regarding the challenges faced related to the safety and well-being of the participants, several steps were taken throughout the experiments, especially when interacting with physical devices like the wheelchair. Firstly, a safety button was installed to immediately stop the wheelchair if needed. Additionally, the experiments were conducted in ELEPAP buildings, the home environment for the patient subjects, which helped them feel more secure and comfortable. Elepap's caregivers, doctors, and physical therapists were also present during the experiments to provide assistance if necessary and to help the participants feel more relaxed and supported.

A comparative analysis of this study with other works from the literature is presented in Table 6. However, a direct comparison is not feasible, since each study has employed different subjects, devices, techniques and evaluation methods, several remarks related can be drawn.

Xiong et al. [27] developed a BCI-controlled wheelchair and employed 4 EEG channels to record the brain signals from 7 subjects. The available movements of the system were 4, forward, stopping, turning left, and turning right. PSD was utilized for feature extraction and Logistic Regression was used to classify the mental commands. The proposed system was not evaluated in real-time experiments. Classification accuracy was the only evaluation metric of the system. Tsui et al. [28] designed a wheelchair that was commanded using brain signals. To acquire the raw EEG data 5 channels were employed. The Dof of the system was 4 and 2 subjects participated in the study. The Logarithmic Band Power was utilized as the feature extraction technique and the LDA algorithm was employed for the classification process. 2 real-time experiments were conducted to assess the robustness of the system and each subject performed 8 repetitions in total. Yu et al. [29] developed a BCI-controlled wheelchair and used a 31-channel EEG cap to record the brain signals. They employed CSP to extract features from the signals and LDA to classify the mental commands. The DoF of the system was 6 since the wheelchair could move forward, stop, turn left, turn right, accelerate, and decelerate. 7 subjects participated in 2 real-time experiments. Each participant had 35 repetitions manipulating the BCI system. Carlson and

Millan [30] designed a wheelchair that moves with mental commands. A 16-channel EEG device was used to record the brain signals from 4 subjects. For the feature extraction method, PSD was utilized and for the classification process, a Gaussian classifier was employed. The DoF of the system was 4. Subjects participated in 2 experiments and each of them had 34 repetitions in total. Ron-Angevin et al. [31] developed a BCI-controlled wheelchair using a 9-channel EEG device to record the raw signals. The Average Signal Power was calculated as the feature extraction technique and LDA was employed to classify the mental commands. The available movements of the system were forward, stopping, turning left, and turning right. 7 subjects participated in 2 real-time experiments. Each participant had 82 repetitions in total.

In this work, a BCI-controlled wheelchair is developed. 28 subjects, 14 healthy and 14 individuals with motor and brain disabilities participated in 5 real-time experiments. The DoF of the system is 4; moving forward, stopping, turning left, and turning right. CSP algorithm is employed to extract features from the EEG signals and SVM is utilized to classify the mental commands. Each participant has 60 repetitions in total in the 5 experiments that are conducted to assess the BCI system. To evaluate the experiments, 14 metrics are employed: Mean Cross-Validation F1 score, Accuracy of the Test Set, Average game 1 score, Time taken to complete a game 2 trial, Number of missed commands in game 2, Total number of completed tries in game 2, ITR index, Number of stops, Time to complete a trial when commanding the wheelchair, number of missed commands when commanding the wheelchair, Total number of completed trials in experiment 4, Average time taken to complete the path using BCI, Number of completed trials in experiment 5, and Time taken to complete the path using the joystick. This study is more comprehensive and extensive compared to the existing literature. While the average number of subjects in the other studies is 5.4 varying from 2 to 7, this research involved a significantly larger group of 28 participants. Furthermore, it's the only study that employs individuals with both motor and mental disabilities. The average number of repetitions per subject is 31.8 ranging from 0 to 82, while in this study subjects have 60 repetitions each. Other works involve an average of 1.6 experiments, while this study conducted 5 experiments in real-time, allowing for a more thorough and insightful analysis of the system. This research employed a greater number of metrics compared to previous works, enabling a more comprehensive analysis.

In the future, we aim to expand the capabilities of the BCI-controlled wheelchair by utilizing more movements such as accelerating, decelerating, and moving backward. Also, a speech control scheme will be employed and an obstacle detection system will be implemented in the system for more freedom and safety. More healthy and patient individuals will be involved in testing the system, aiming to achieve better and more comprehensive results. Moreover, new experimental scenarios will be employed considering the issue of mental fatigue. Finally, more extensive offline training will be implemented to familiarize the users with mental commands.

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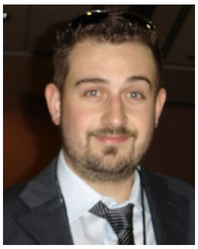

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