Design and Implementation of a Real-time Brain-Computer Interface for an Electric Wheelchair

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***Abstract*—The field of Brain-Computer Interface (BCI) is expanding quickly and has numerous applications in various areas including medical, gaming, and everyday living. This paper presents a BCI-controlled wheelchair with Motor Imagery (MI) mental commands for turning right and left. The Degree of Freedom is 4; going forward, stopping, turning left and right. To record the raw EEG data Muse S headband is employed and to classify the mental commands Linear Discriminant Analysis (LDA) algorithm is used. 6 subjects trained extensively and tested the proposed BCI system in 2 experiments for 100 repetitions each. The experiments are conducted in an office environment and the results demonstrated that the participants are able to successfully adapt and operate the BCI-controlled wheelchair with a high level of accuracy and precision.**

***Keywords*—Brain Computer Interface (BCI); Electroencephalography (EEG); Motor Imagery (MI); Muse S; BCI-controlled wheelchair;**

I. Introduction

Brain-computer interface (BCI) technology has emerged as a promising field of research in recent years. BCI systems allow for direct communication between the human brain and a computer or external device, providing a means for individuals to control technology using their thoughts. The potential benefits of BCI systems include improved communication, mobility, and independence for individuals with physical disabilities. However, significant challenges remain in the development of these systems, including the need for robust signal processing techniques, the limited accuracy and reliability of current BCI systems, and the ethical considerations surrounding the use of invasive techniques [1][2].

One widely used method for recording brain activity in BCI systems is electroencephalography (EEG) [3]. EEG signals can be recorded non-invasively [4] using electrodes placed on the scalp, making it a relatively safe and cost-effective option compared to invasive techniques [5] such as implanting electrodes directly into the brain. However, non-invasive EEG signals are often weaker and more susceptible to noise, making it challenging to extract meaningful information.

One trend in BCI research is developing more advanced signal processing techniques and machine learning algorithms to analyze EEG signals. This results in more accurate and reliable feature extraction from brain signals and improves the overall accuracy of the BCI systems. Another trend in the literature is implementing new applications; using BCI technology for cognitive training, rehabilitation, and mental health treatment [6][7]. These applications have the potential to greatly improve human performance and quality of life. Moreover, a trend with a lot of focus in the literature is the development of more accessible, affordable, and user-friendly BCI systems in order to increase the adoption of BCI technology for a wider range of users. As the field of BCI research continues to evolve, it is expected that new applications and trends will emerge, leading to further advancements [3][8].

One very promising BCI application is the development of BCI-controlled wheelchairs [9][10]. This can greatly help and benefit people with physical disabilities and the whole of society. BCI-controlled wheelchairs offer greater independence and autonomy for people with limited mobility; those with spinal cord injuries, cerebral palsy, or amyotrophic lateral sclerosis (ALS). In terms of autonomy for individuals with disabilities, these BCI systems can reduce the need for physical assistance from caregivers, which will result in greater privacy and higher quality of life. By allowing individuals to control their wheelchairs using their brain signals, these systems can provide a greater level of mobility and freedom that may not have been possible with traditional wheelchair control methods.

A common strategy for applications like BCI-controlled wheelchairs is Motor Imagery (MI). MI [11][12] includes imagining the movement of a body part, hands, and/or foot, without actually moving the body. Most studies in the literature, employ hand-movement imagination for manipulating BCI systems. Imagining the movement of a body part generates specific patterns in the brain which can be detected and translated into commands for controlling external devices and applications [13]. In the case of BCI-controlled wheelchairs, users can imagine specific movements, such as moving or lifting their left or right hand, in order to direct the wheelchair to turn in the desired direction. Motor imagery-based BCIs have shown great promise for individuals with physical disabilities,

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as they provide a means for controlling external devices that do not rely on physical movements or the use of assistive devices. Lastly, MI-based BCIs can be non-invasive and relatively easy to use, making them an appealing choice for a wide range of users.

In this paper, a BCI-controlled wheelchair is developed that employs left and right Motor Imagery commands and Electrooculogram (EOG) signals. The goal of this work is to evaluate a BCI wheelchair for in-office movement after a long training period. 6 subjects participated in 2 experiments, Start/Stop and Start/Stop/Turn, and had 10 sessions for each experiment with 5 trials per session in order to learn how to accurately command the wheelchair. To acquire the EEG data, the Muse S headband is used.

II. Related Work

Several studies have been published in the last decade that aim to develop BCI-controlled wheelchairs. For the selection of the papers in this section, several criteria should be satisfied. The most important one is the usage of a wireless EEG device and the real-time commanding of the wheelchair. Then the more recent works are presented. In the following papers MI, Attention-Mediation levels, and hybrid systems utilizing EEG and Electroocoulogram (EOG) are included.

Rotier *et al.* [14] developed a brain-controlled wheelchair. To acquire the raw EEG data Emotiv Epoc headset was employed with 14 EEG channels. To process the data they used the Emotiv software, EmoEngine. The BCI system comprises an EEG headset, a computer, Arduino Uno and a wheelchair. The computer connects with Emotiv Epoch to record the data then it sends the processed data to Arduino and Arduino sends commands to the wheelchair. The available commands for this work were going forward, stopping, turning left and right. Three subjects participated in the experiments to evaluate the brain-controlled wheelchair. As the evaluation metric they employed a time metric; time to finish the experiment. Overall, this work offers promising results for BCI wheelchair development.

Espiritu *et al.* [15] employed a BCI-controlled wheelchair converting the standard joystick control with EEG data. Emotiv Insight, a 5-channel EEG device, was used to record the raw EEG data and Emotiv software was used for processing and training. The Degree of Freedom (DoF) of this BCI system is five; moving forward and backward, stopping, turning left and right. The overall system used the EEG device, a computer to connect the headset via Bluetooth, Arduino Uno to send the commands to the wheelchair and the wheelchair. One subject who trained extensively participated in the experiment. The training phase included training for 4 mental commands; push, pull, left MI and right MI. The neutral mental state was the command used for stopping, push was for forward movement, pull was for backward movement and left/right MI was for turning. To send the mental commands to the Arduino Uno another Emotiv software was employed, Emotiv Xavier EmoKey, which binds the commands with keyboard keys. To evaluate this work a command response delay for action metric was employed for every movement.

Chawda *et al.* [16] designed a hybrid EEG- EOG controlled wheelchair that uses brain signals and eye blinks. The device used to acquire the data was Neurosky Mindwave Mobile 2 with a single electrode. Raspberry 3B+ was employed to connect the headset to the wheelchair and to process the data. The available movements for the BCI-controlled wheelchair were moving forward, stopping, turning left and right. For forward movement, the attention level of the user was calculated and if it was greater than a certain threshold the wheelchair moved forward. Subjects had to calm down for stopping. To turn right the users had to perform one intentional eye blink and to turn left they had to perform two consecutive eye blinks. To ensure the safety of the proposed system, an obstacle detection system was employed with ultrasonic sensors. For finding the optimum Attention threshold 8 subjects were tested by varying the threshold. Lastly, to evaluate the hybrid BCI wheelchair an experiment was conducted in an indoor environment with four subjects. The results indicate that the system had greater accuracy for forward and stopping commands than the accuracy for turning left and right while the worst accuracy obtained was for turning left.

AlAbboudi *et al.* [17] developed a BCI-controlled prototype miniature wheelchair. Emotiv Epoc was employed with 14 channels to obtain the raw EEG data. The proposed concept utilized five commands/movements which were moving to the right, to the left, forward, backward, and stopping. Discrete Wavelet Transform (DWT) was used for feature extraction. Then the processed signal was fed to a classifier. To choose the best possible classifier, four different classifiers were tested; Support Vector Machines (SVM), K-Nearest Neighbors (KNN), Random Forest and Artificial Neural Network (ANN) and the best-performing was SVM. To connect the whole BCI system they used the EEG headset for data collection, a computer for connecting the headset with the software, an Arduino Uno to transmit commands to the prototype, and the miniature wheelchair. To evaluate the system, one subject trained and performed the 5 mental commands for 20 trials. The accuracy of each command was used as an evaluation metric of the experiment.

III. Methods

The proposed work aims to design a low-cost BCI-controlled electric wheelchair for people with disabilities. The system comprises a commercial EEG headset; Muse S, a computer and a wheelchair (figure 1). The hardware and software used in this work are discussed in the following subsections.

1) Muse S: The Muse S EEG headband is a wearable device that measures brain activity using EEG technology. It is designed to be user-friendly and easy to use and it is also relatively affordable compared to traditional EEG equipment or other commercial EEG headsets. The device connects to the computer via Bluetooth and transmits raw data from 4 EEG electrodes. The electrodes are located in the frontal

Fig. 1. System Overview. The Muse S connects with the computer via Bluetooth and the computer connects with the wheelchair via USB.

and temporal lobes; AF7 and AF8, TP9, and TP10. Muse S has also Pulse Oximetry, Accelerometer, and Gyroscope. The device is employed for this work because of its ability to remain securely affixed to the user's head, ensuring reliable and uninterrupted measurement of brain activity throughout the duration of the experiments, low price, compact size and wireless features. The sampling frequency of Muse S is 256Hz.

2) BlueMuse and Lab Streaming Layer: BlueMuse is a broadcasting software that connects Muse S headband with the computer via Bluetooth. It has many functions that make it simpler for the user, such as automatic detection of accessible EEG headsets within Bluetooth's range. BlueMuse streams the raw data through Lab Streaming Layer Protocol (LSL). LSL is an open-source system for streaming, receiving, synchronizing, and recording time series data feeds obtained from a variety of network acquisition devices. It offers safe data transmission; TCP protocol and it can simplify cross-platform connectivity.

3) Offline Processing: Raw EEG signals are recorded and stored in CSV files to process, extract features and train the classifier. Every subject is recorded for three separate mental states; left and right MI and raising their eyebrows for 5 minutes for each command. When the recordings are completed, the signals are pre-processed by applying a 4th-order bandpass filter between 9Hz to 40Hz. This filter reduces the artifacts of the raw EEG signals and excludes the frequency bands (Delta and Theta) that are not relevant to this work. Then the signal is split into 5 frequency bands; 1) Alpha Frequency Band 9Hz-13Hz, 2) Low Beta Frequency Band 13Hz-20Hz, 3) High Beta Frequency Band 20Hz-30Hz, 4) Low Gamma Frequency Band 30Hz-35Hz, 5) High Gamma Frequency Band 35Hz-40Hz.

The filtered signals are epoched in 3 seconds segments. The window size has been selected to be short enough for the system to quickly respond to the user's mental commands, but also long enough to include a sufficient amount of information for the classification process to be accurate. This trade-off has been studied with several trial-and-error experiments. Then the normalized energy of the signals is calculated for every frequency band and for every channel. These features are fed to the classifier for training.

4) Classification: To classify the data Linear Discriminant Analysis (LDA) algorithm is used. LDA [18][19] is a well-established and widely used classification algorithm in machine learning. It is a supervised learning technique that is used for classifying objects into two or more groups based on a set of features. The main goal of LDA is to find a linear combination of features that maximally separates the classes, while also minimizing the within-class variance. In a three-class classification problem, LDA can be used to find the best-separating hyperplane that maximizes the distance between the three classes, while also minimizing the overlap between them. This is achieved by first estimating the mean and covariance matrix of each class, and then computing a set of discriminant functions that can be used to classify new objects.

Table I presents the classification accuracy of the 3 mental commands for 6 subjects that participated in the experiments. The average accuracy for Right MI is 91.2% ranging from 85.3% to 97.5%, for Left MI is 91.1% ranging from 96.9% to 81.4% and for raising the eyebrows is 99.8% ranging from 100% to 99.3%.

TABLE I. CLASSIFICATION TRAINING ACCURACY FOR THE 3 MENTAL COMMANDS, LEFT/RIGHT MI AND RAISING THE EYEBROWS.

Subjects	Right MI	Left MI	Raising Eyebrows
1	90.2%	92.6%	100%
2	97.5%	96.9%	100%
3	85.4%	90.2%	100%
4	97.0%	81.4%	99.3%
5	85.3%	90.2%	100%
6	92.3%	95.4%	100%

5) Real-Time Processing and Classification: When the offline processing and classification are completed the BCI system is ready to be used in real-time. The same processing techniques are applied in the real-time testing and then the features are fed to the trained LDA classifier to predict among the 3 classes. Then the prediction of the classifier is sent to a second Python script that communicates with the wheelchair. Depending on the predicted mental command the script sends the corresponding command to the wheelchair via USB and the wheelchair moves. Left/Right MI is for turning and raising the eyebrows is for stopping and moving forwards. When all the components are connected and a subject starts the experiment the wheelchair moves forward by default. If the classifier predicts the raise of the eyebrows then the wheelchair stops. When the BCI system is in stop mode the user can turn left or right or move forward. Turning is disabled when the wheelchair moves forward for safety reasons. So if the user wants to turn he has to stop the movement, perform the MI mental command and then raise his eyebrows to start moving to the desired destination.

IV. RESULTS

To evaluate the proposed BCI-controlled system 6 subjects, 3 males and 3 females with 26.33 average age ranging from

24 to 35, participated in 2 experiments. All subjects had good vision and they are mentally and physically healthy. All subjects signed a consent form to be able to participate in the experiments. Firstly, they are introduced to the equipment and the concept/goal of the proposed work. Then, they sat in a quiet room with no other people in a comfortable position in order to be recorded for the 3 mental commands for 5 minutes each. The whole recording phase lasted 30 minutes for each user, 15 minutes of recording, and 15 minutes of break. After that, they are introduced to the wheelchair and had 20 minutes to learn how to command it and to get familiar with the speed of the system.

1) Start-Stop: The first experiment is about starting and stopping. Participants tested for 50 tries in order to evaluate their adaptation and asses if they could improve their performance. Basically, they had to stop the wheelchair 2 times in predetermined positions (Figure 2). 3 evaluation metrics are employed for this experiment; distance from the predetermined stop position for stop 1 and stop 2 and number of stops for each trial. The average results of the subjects are presented in Table II. The first experiment is divided into 10 sessions of 5 trials. Every session is conducted on a different day at approximately the same time as the first one for every user.

Table II shows the average results for 10 sessions for each subject. The best-performing subject is 4 with average results of 3cm for the first stop, 2.7cm for the second while he didn't make more than 2 stops in his 50 trials. The worst performing subject is 2 and 5 with average results of 7cm and 7.25cm for the first stop, 8.36cm, and 9.32cm for the second. All of the participants adapted to the BCI system and managed to perform stopping and move forward successfully. The average results for all subjects are; 5.46cm for the first stop, 5.81cm for the second and 2.23 for the number of stops. After the first 5 sessions, they all got very comfortable commanding the BCI-controlled wheelchair. After this extensive testing, all participants could start and stop the movement of the wheelchair with ease.

2) Start-Stop-Turn: The second experiment is conducted to test the ability of the BCI wheelchair to perform right turns. Subjects have to perform 4 right turns in order to reach the predefined destination (Figure 3). The evaluation metrics employed in this experiment are the number of commands to reach the destination, wrong turns and the number of stops. To reach the predefined destination from the starting position the minimum number of commands is 9; 4 turns, 3 stops and 2 forwards. Participants tested for 50 tries each. This experiment is also divided into 10 sessions of 5 trials. Table III presents the average results of the second experiment for every subject.

TABLE II. AVERAGE RESULTS FOR THE FIRST EXPERIMENT

Subs	Sessions	Stop 1	Stop 2	# of stops
1	1	14cm	7.8cm	2.4
	2	3.2cm	4.8cm	2.2
	3	4.8cm	7cm	2
	4	5.4cm	7.2cm	2
	5	3.6cm	5cm	2
	6	2.8cm	0.6cm	2.2
	7	0.6cm	3.6cm	2.2
	8	2.2cm	1.6cm	2
	9	2.4cm	0.4cm	2
	10	1.8cm	1.4cm	2
2	1	14.8cm	24.8cm	2.8
	2	4.2cm	12cm	2.8
	3	10.8cm	11.4cm	2.4
	4	11cm	6.2cm	2.4
	5	2cm	5.8cm	2.6
	6	7cm	5cm	2.6
	7	4.8cm	6.2cm	2.2
	8	5.6cm	5cm	2.2
	9	6cm	5.2cm	2.2
	10	3.8cm	2cm	2
3	1	14cm	13.4cm	4.4
	2	8.4cm	14cm	2.6
	3	6.8cm	9.6cm	2.4
	4	5.4cm	4.4cm	2.2
	5	5cm	4.4cm	2
	6	5.8cm	3.8cm	2.3
	7	2.8cm	1.6cm	2
	8	3.6cm	1.2cm	2
	9	2.2cm	3.2cm	2
	10	2.6cm	2cm	2
4	1	7.4cm	6.8cm	2
	2	5.6cm	6cm	2
	3	3.6cm	1.4cm	2
	4	5.2cm	2.6cm	2
	5	0.4cm	1.6cm	2
	6	3cm	3cm	2
	7	2.8cm	2cm	2
	8	1cm	0.6cm	2
	9	0.6cm	1cm	2
	10	0.4cm	2cm	2
5	1	10.6cm	7cm	2
	2	5cm	7.6cm	2
	3	12.4cm	10.4cm	2
	4	6.2cm	14cm	2
	5	6.4cm	8.6cm	2.2
	6	10cm	7.4cm	2.2
	7	9.2cm	10.2cm	2
	8	7.6cm	8.4cm	2
	9	2.8cm	12.4cm	2
	10	2.2cm	7.2cm	2
6	1	13.8cm	5.8cm	2.4
	2	5.6cm	8.8cm	4.2
	3	8cm	6.8cm	2.6
	4	6.6cm	4.4cm	2.4
	5	7cm	5.4cm	2.4
	6	3.8cm	5.2cm	2
	7	4.6cm	1.6cm	2.2
	8	2.2cm	5cm	2.2
	9	3.4cm	2.6cm	2
	10	3.2cm	2.4cm	2

Table III shows the average results for 10 sessions performing right turns with MI mental commands. The number of commands is employed to present how many mental commands the participants performed to reach the final destination, the number of stops is used to test the ability of the user to stop the wheelchair only when they are asked to and the wrong turns are employed to test the accuracy of the right MI commands. The average results for all subjects are; 11.42 for the number of commands, 3.33 for the number of stops and 0.93 for the wrong turns. The best-performing subject is 1 with average results of; 10.64, 3.08 and 0.68. The participant who had the most difficulty in performing the predefined movements is subject 6 with average results of; 12.04, 3.44

Fig. 2. Experiment 1 set up. Subjects had to stop the wheelchair in the 2 predetermined stop positions in order to evaluate the ability of the BCI-controlled wheelchair to stop with precision. The two designated stopping points are demarcated by distinct X-shaped markings on the floor.

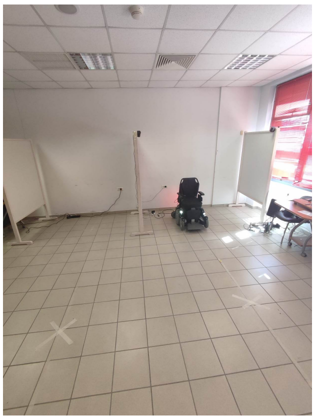

Fig. 3. Experiment 2 set up. The subjects were required to perform a series of right turns, stops, and forward movements to reach the final position, as per the experimental instructions. The X-shaped markings on the floor demarcate the designated stopping positions for executing the right turns.

and 1.42. All of the participants managed to complete a trial with the minimum number of commands (9). For both the Experiments longer time of commanding the BCI-controlled wheelchair led to greater comfort, better adaptation and results.

Table IV presents the number of forced stops subjects performed because they lost control of the wheelchair.

The average forced stops for Experiment 1 is 3, and Subject 4 made the fewest (2 stops). For the second experiment, the average number of forced stops is 3.5, and Subject 1 performed the fewest (2 stops). Forced stops are a safety measure and subjects are instructed to perform them when they feel uncomfortable or when the classifier could not identify a specific mental command and an obstacle was close to the wheelchair's path. In both Experiments, in 100 repetitions per subject, the average forced stops are 6.5. Subject 1 had to stop the wheelchair only 5 times while Subject 6 had to stop 8 times.

V. Discussion

A comparison study of other published papers from the literature and this work is presented in Table V. All of the discussed works used wireless commercial EEG devices to command BCI-controlled wheelchairs or prototypes.

Rotier *et al.* [14] designed a BCI-controlled wheelchair and tested it with 3 subjects. Emoviv Epoc was used for recording the EEG data and Emovitv software was used for processing and classifying the mental commands. The DoF of their system is 4 and the time to finish the experiment was their evaluation metric. Espiritu *et al.* [15] developed a BCI-controlled wheelchair with 5 available movements/commands. Emotiv Insight was employed to acquire the raw EEG signals and 1 subject tested the system for 30 trials. Command Response Delay for Action was employed as the evaluation metric.

TABLE III. Average Results for the second Experiment

Subs	Sessions	# of Commands	# of Stops	# of Wrong Turns
1	1	15.6	3.2	2.8
	2	11.4	3.2	1.2
	3	11.6	3	1.4
	4	10.4	3	0.4
	5	9.6	3.2	0.4
	6	9.8	3.2	0.2
	7	9.6	3	0.2
	8	9.6	3	0
	9	9.8	3	0.2
	10	9	3	0
2	1	12.8	3.8	1.8
	2	13.8	4.2	2
	3	11.2	3.8	1.2
	4	10.8	3.8	0.8
	5	10.6	3.6	0.4
	6	10.8	3.8	0.2
	7	9.2	3.2	0
	8	9.4	3.2	0.2
	9	10.2	3.4	0.2
	10	10	3.2	0.2
3	1	14.6	3.4	2.2
	2	15.4	3.4	2.8
	3	13.4	3	1.8
	4	12.2	3.4	0.6
	5	11	3	1
	6	10.6	3	0.8
	7	10.2	3	0.6
	8	10	3.2	0.4
	9	10.2	3.2	0.6
	10	9.4	3	0.2
4	1	18	3.4	3
	2	11.4	3.6	0.4
	3	12.6	3.2	1.4
	4	12.2	3.6	1.2
	5	11.2	3.2	0.4
	6	10.2	3.4	0
	7	9.6	3	0.4
	8	10	3.2	0.6
	9	9	3	0
	10	9.8	3.2	0.4
5	1	15.8	3.8	2.6
	2	16	4.2	2.8
	3	13.2	4	1.2
	4	10.8	3.6	0.2
	5	11	3	1
	6	10.4	3	0.4
	7	11	3.8	0.2
	8	10.2	3	0.2
	9	10	3	0
	10	10.2	3	0.8
6	1	16.4	3.4	3
	2	13.8	4	2.2
	3	12.8	3.4	1.4
	4	11.2	3.8	1.2
	5	11	3.2	1.6
	6	11.6	3.4	1.6
	7	10.4	3	0.4
	8	11.4	3.6	1.6
	9	10.8	3.2	0.6
	10	11	3.4	0.6

Chawda *et al.* [16] used Neurosky Mindwave Mobile 2 headset to command a BCI-controlled wheelchair with 4 available movements. 4 subjects participated in the experiments for 25 tries each and the Accuracy of the system was the evaluation metric. AlAbboudi *et al.* [17] designed a wheelchair prototype commanded by a BCI system with Emovitv Epoc headset. The

TABLE IV. THE TABLE PRESENTS HOW MANY TIMES SUBJECTS HARD-STOPPED THE WHEELCHAIR BECAUSE THEY LOST CONTROL IN EXPERIMENT 1 AND EXPERIMENT 2.

Subjects	Experiment 1	Experiment 2
1	3	2
2	3	4
3	3	3
4	2	4
5	3	4
6	4	4

TABLE V. COMPARATIVE STUDY

Authors	Device / Wheelchair	Subj	Repetition per Subj	Results
Rotier *et al.* [14]	Emotiv Epoc Real Wheelchair	3	-	Time to finish the experiments
Espiritu *et al.* [15]	Emotiv Insight Real Wheelchair	1	30	Command Response Delay for Action
Chawda *et al.* [16]	Neurosky Mindwave Mobile Real Wheelchair	4	25	BCI Wheelchair Accuracy
AlAbboudi *et al.* [17]	Emotiv Epoc Miniature Wheelchair	1	20	BCI Wheelchair Accuracy
This work	Muse S Real Wheelchair	6	100	Classification results Start-Stop results Start-Stop-Right turn results Forced Stops

DoF of this work was 5. 1 subject tested the BCI prototype 20 times and the Accuracy of the system was evaluated. In this work, a BCI-controlled wheelchair is developed with 4 available movements. Muse S headband is used to record the brain signals from 6 subjects that participated in 2 experiments. The subjects tested the proposed system 100 times each, to evaluate the safety and functionality of the system. To evaluate the experiments 4 metrics are employed; Classification results, Experiment 1 (Start-Stop) results, Experiment 2 (Start-Stop-Right turn) results, and Forced Stops. This is a more thorough work since it is tested by more subjects (6) while the average is 2.25 participants, ranging from 1 to 4 and the average repetitions per subject are 25 while for this proposed work subjects performed 100 repetitions. In addition, to ensure a more robust assessment of the BCI system, more evaluation metrics are employed in this work. These metrics serve to provide a more comprehensive evaluation of the system's performance and increase the reliability of the results.

VI. CONCLUSION AND FUTURE WORKS

In this work, a BCI-controlled wheelchair is designed. The available movements are 4; moving forward, stopping, turning left and right. In order to turn left or right users need to perform the corresponding MI mental command. To acquire the EEG data, the Muse S headband is employed that connects with a computer via Bluetooth and the computer sends the commands to the wheelchair via USB and serial port communication. To classify the brain signals LDA algorithm is utilized for a 3-class classification task. 6 subjects participated in 2 experiments; the first is stopping and starting the wheelchair and the second is combining starting and stopping with turning right.

Subjects trained extensively, commanding the BCI-controlled wheelchair for 100 trials. The results are promising and show that participants adapted to the proposed system and managed to manipulate it with great precision. After getting familiar with the BCI wheelchair subjects felt very safe and comfortable commanding it.

In the future, the goal is to extend the BCI-controlled wheelchair, with backward movement and an obstacle detection system for safety. Furthermore, more subjects will test the system in order to have more reliable results. Also, different commercial EEG headsets will be used to design the best possible BCI smart wheelchair.

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