2023 IEEE IAS Global Conference on Emerging Technologies (GlobConET)
Loughborough University, London, United Kingdom. May 19-21, 2023

EEG-Assisted EMG-Controlled Wheelchair for Improved Mobility of Paresis Patients

L.K.P. Gunarathne
Department of Electronics Engineering
Sri Lanka Technological Campus
Padukka, Sri Lanka
kaveengun@sltc.edu.lk

D.V.D.S. Welihinda
Department of Electronics Engineering
Sri Lanka Technological Campus
Padukka, Sri Lanka
danulw@sltc.edu.lk

H.M.K.K.M.B. Herath
Department of Software Engineering
Sri Lanka Technological Campus
Padukka, Sri Lanka
kasunkh@sltc.ac.lk,
https://orcid.org/0000-0002-1873-768X

S.L.P. Yasakethu
Department of Software Engineering
Sri Lanka Technological Campus
Padukka, Sri Lanka
lasithy@sltc.ac.lk

2023 IEEE IAS Global Conference on Emerging Technologies (GlobConET) | 979-8-3503-3179-0/23/$31.00 ©2023 IEEE | DOI: 10.1109/GlobConET56651.2023.10149923

***Abstract*—A motorised wheelchair is a type of mobility aid that helps people with physical limitations get around independently. Historically, powered wheelchairs have been operated by joysticks, switches, or other input devices that require the user to operate physically. To promote mobility and freedom for those unable to use conventional wheelchair control methods, this research aims to develop an electroencephalogram (EEG) assisted electromyography (EMG) controlled wheelchair. The major scope of this research is divided into two sections: gesture controller (signal processing) and automated wheelchair design. The proposed system was evaluated using human test participants under approved ethical standards. The accuracy of the proposed system was achieved at 88% with a weighted average precision of 0.89.**

Keywords—Brain-computer interface (BCI), Electroencephalogram (EEG), Electromyography (EMG), Motorized wheelchair, Signal processing

I. Introduction

Paresis, also known as partial paralysis, is a condition of muscular weakness caused by nerve damage or disease. Also, the nature of muscular weakness can vary from patient to patient. Such people do not have the necessary strength or motor ability to operate a conventional manual wheelchair. Many people worldwide have paralysis, which significantly impairs their ability to move about independently. According to a survey done by the Department of Census and Statistics in 2012, 3.6% of the population had the disability of walking [1]. To solve this challenge, there has been an increasing interest in creating assistive technology, such as motorised wheelchairs, that can aid those with paralysis to restore some of their movement and independence. In the current market, automated wheelchairs are already available with joystick control. Unfortunately, these devices may be expensive, especially in developing countries with few resources. Most of these models cost over 1000 USD, which is not affordable for most of the disabled population. Also, the usage of these wheelchairs is limited to patients who can control their hands and fingers freely of their own will.

There are research and prototypes of wheelchairs based on EEG, EMG, and electrooculography (EOG) controlling. These three techniques have been used individually, such as in an utterly EMG-controlled wheelchair [2] and a completely EEG-controlled wheelchair [3]. But these techniques, when used on their own, have unique drawbacks. For example, in an EMG-based wheelchair, the wheelchair will move due to involuntary muscle contractions, and in EEG-based wheelchairs, the system's complexity and error rate is high, and the robustness is low. Also, when these techniques are used individually, higher sensitivity and complex processing are required, which drives up the cost of the components used. Also, in entirely EEG-based wheelchairs, the time taken for decision-making is higher, thus making the navigation of the wheelchair not smooth. This makes it stressful for the patient.

EEG and EMG are the two major types of bio-signals which can be utilised to obtain patient data about the functionality of the human. EEG signals can be classified into several bands like delta (δ) (0-4 Hz), theta (θ) (4-8 Hz), alpha (α) (8-15 Hz), beta (β) (15-32 Hz) and gamma (γ) (>32 Hz) [4]. These bands correspond to various states of mind, such as sleeping, meditating, relaxing, concentrating and agitated. Electromyography is defined as collecting electrical signals from muscles, which are controlled by the nervous system. These signals are generated due to the electrical potential differences generated in muscle fibers while performing some activities. The muscle fibres generate electrical activity when the muscles are active. Therefore, EMG signals can be obtained by placing the EMG electrodes closer to the muscle groups of the body. This electrical activity is generated due to the thought process occurring in the central nervous system [5].

Regular EMG signals from the human body contain a voltage of 0.05-30 mV with a frequency range of 0-10 kHz. The most valuable and important frequency ranges are within the range of 50-150 Hz. When an EMG signal is being recorded from muscles, different types of noises contaminate it. Therefore, the noise should be reduced to a very low level to obtain an accurate signal.

This research proposes the development of a low-cost wheelchair that can be controlled by a combination of EEG and EMG signals for paresis patients. The patient should only have satisfactory eyesight and a sound mindset to be qualified to use the proposed wheelchair. The remainder of the paper is divided as follows; The literature evaluation is covered in Section 2, and the proposed study approach is discussed in Section 3. Results and analysis are described in section 4. Research limitations, advantages, and disadvantages are discussed in section 5. Finally, in section 6, we conclude the research.

II. Literature Review

An innovative method to aid people with paresis in regaining their movement is using an EEG-assisted, EMG-controlled autonomous wheelchair. EEG and EMG were used to drive an autonomous wheelchair that can react to the patient's brain impulses and muscle movements. In this literature overview, the relevant and vital research that has already been done will be discussed and emphasised on how crucial it is for people with paresis.

The sensor-based designs and implementations for elderly and disabled people are invading technology in today's BCI field. A wheelchair, a high-power motor controller unit, a Kinect camera, and EMG/EEG sensors comprise the developed system proposed by Kucukyildiz et al. [6]. Mistry et al. [7] offered a Steady State Visual Evoked Potential (SSVEP) based BCI system that manages the movements (forward, reverse, left, and right) of an electric wheelchair. Research on a BCI for an electric wheelchair based on EEG alpha (α) waves was performed by Banach et al. [8]. These comprised mechanical systems, the operation of the electric wheelchair motors, and real-time EEG signal processing. A hybrid BCI controller was developed by Nandikolla et al. [9] utilising an EEG headset to monitor jaw EMG signals and hand motor imagery (MI) to operate a smart wheelchair in combination with its semi-autonomous capabilities.

Some researchers have engaged with developing autonomous wheelchairs by engaging non-BCI sensors (LIDAR, vision-based approach, non-BCI wearable sensors). An autonomous wheelchair that employs LIDAR for navigation and SLAM was designed and implemented by Shamseldin et al. [10]. The connected driverless wheelchair system, developed by Baltazar et al. [11], can pick up patients from their beds, travel autonomously through multiple floors, avoid obstacles, interact with elevators, and deliver patients to the designated operating room. Using high-performance computers for real-time data processing and autonomous path planning, Hartman et al. [12] presented the design and implementation of an intelligent wheelchair prototype. Inertial measurement unit (IMU) and myoelectric units were used as wearable sensors in a hand gesture-based control system for an omnidirectional wheelchair reported by Kundu et al. [13].

Table 1 summarises related works in the field during the past five years. As seen in the table, further developments and research are required to address paresis problems by aiding EEG-assisted EMG signals using gesture command control. To address the issue, this research provides a solution by automating a traditional wheelchair using EEG, EMG, and gesture controlling for paresis patients.

TABLE I. Related Works

Author	EEG	EMG	Non-BCI sensors	Gesture command
Kucukyildiz et al. [6]	X	X	X	
Mistry et al. [7]	X			
Banach et al. [8]	X			
Nandikolla et al. [9]	X	X		
Shamseldin et al. [10]			X	
Baltazar et al. [11]			X	
Hartman et al. [12]			X	
Kundu et al. [13]		X	X	
Proposed system	X	X		X

III. Methodology

This section discusses the methodology of the proposed system.

A. EEG/EMG Signal Acquisition

Fig. 1 illustrates the overall architecture of the proposed EEG and EMG system. The acquired signals were pre-amplified to a suitable level before noise filtration, and then the final amplification was performed. Then an analogue-to-digital converter (ADC) was chosen to convert the amplified analogue signals to a digital signal and send it to the control system to be processed.

In this research, EMG electrodes were used to obtain the information from muscles, and then these data were used to process complicated signal patterns. These EMG signals depend on the internal structure of the muscle, skin formation, blood flow velocity, skin temperature, tissue structure and the measured site. So, it is essential to consider these factors to gain a proper output waveform. Haotian She et al. [14] stated that surface EMG (SEMG) signals had been widely used in upper-limb prosthesis control because they are convenient and non-invasive. Therefore, non-invasive electrodes that usually use a sticky electrode coated with a conductive gel were used to obtain SEMG signals from the muscles. Fig. 2 depicts the wearable EMG sensors used for the research. Impedance reduces as electrode size increases. The size of the electrodes should be manageable, too. On the other hand, a poor signal-to-noise ratio results from high electrode impedance, which essentially lowers the signal quality. Subsequently, these factors should be considered while constructing a suitable dry electrode for collecting EMG signals.

When measured on the scalp, the amplitude of an EEG wave is around 100 µV. The bandwidth of an EEG signal lies in the range of 1-50 Hz. Therefore, amplifying a signal with such a very low amplitude and low frequency is very challenging. To filter such a signal, a reliable processing chip had to be used since a simple operational amplifier could not process such a signal to provide accurate test data. Therefore, the Neurosky Mindwave Mobile II was used to acquire EEG signals. To drive this wheelchair, the requirement was to identify if the patient was focused on driving. The existence of beta (β) waves in the frequency range of 12–30 Hz was monitored to determine if the patient was in focus.

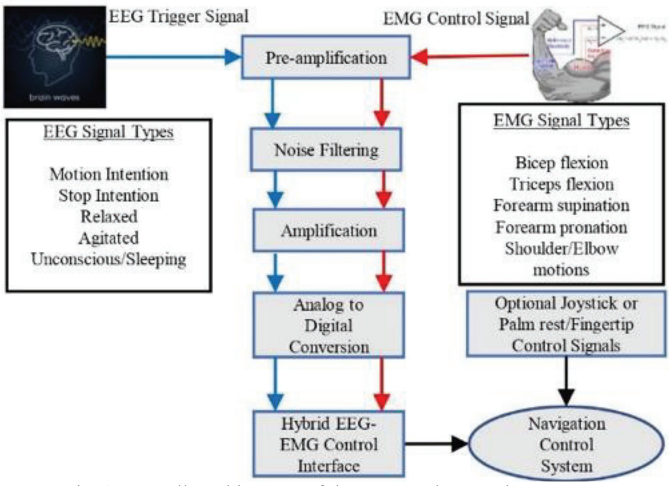

Fig. 1. Overall Architecture of the Proposed Control System

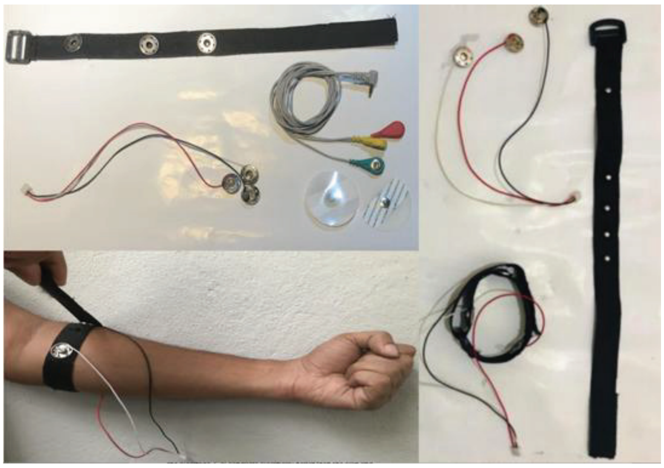

Fig. 2. Wearable EMG Armband Compared to Conventional Gelled Electrodes

B. EEG/EMG Signal Processing

The signals should be pre-amplified to a suitable level before noise filtration, and then the final amplification should occur. Fig. 3 illustrates the proposed schematic diagram of the EMG signal-filtering process. The inverting input, non-inverting input and reference input (Vref) were used as the three input signals fed into an instrumentation amplifier with a gain of 11× to amplify the bio-potential signal obtained from the motor units. To set the idle output at the midpoint (half-level) of the supply voltage, the reference input served as the amplifier's reference. After that, the output was again sent to a differential gain amplifier. A band-pass (Fig. 4) filter with a passband of 72-720 Hz was produced using a differential amplifier with a gain of 220×. The reference electrode and instrumentation amplifier provided the input to the differential gain amplifier. In addition, two filters were used to filter out extraneous noises and let only the threshold (72-720 Hz) pass.

A power circuit was used as an emitter-follower that derives a mid-point voltage for full output swing. The voltage divider gave the Vref a reading of 2.5 V. Bio-signal amplifiers were susceptible to modest amounts of outside interference since they were measured in the mV and V ranges. A voltage may build over the human body, acting as an antenna that can take up messages. The main supply was one such source of interference that produced 50–60 Hz noise. The EMG signal filter circuit had the final output, which was sent into an ADC with a 10-bit resolution to synthesise the EMG signal in a digital format that the microcontroller (ATmega328P) can process. A digital IIR filter was used to post-process the converted digital waveform. A Butterworth filter was utilised, whose flat frequency response was optimised. A bandpass frequency of 74.5 Hz to 149.5 Hz was used with a sampling rate of 500 Hz.

The development of the hybrid EMG-EEG system was handled by the microcontroller unit (MCU). Initially, the MCU observed the EEG spectrum to detect beta (β) waves and, if present, returned a condition. The MCU then checks to see whether any incoming EMG waves from the sensors are present and, if they are, returns a condition. The wheelchair driving algorithm will only operate the wheelchair if both return statements are passed. The wheelchair will be locked and would not be permitted to be driven if one of these requirements are not met. Because of this, it is essential to make sure that every electrode for the EEG and EMG sensors is appropriately in touch with the patient's body

C. Development of a Powered Wheelchair

To design a modular kit (Fig. 5) for an existing wheelchair, many parameters had to be considered. To develop a low-cost wheelchair, the selection of motors was a critical decision. Hence far cheaper and readily available windshield wiper motors were selected. They provide high torque at low speed and consist of a built-in worm gear assembly. As shown in Fig. 6, a motor coupling mechanism to couple this motor to the hub of the wheelchair was designed. A chain–sprocket system was developed along with mechanical supports to mount the motors. The system had to be designed in a way such that the portability of the wheelchair was maintained. The design should also be rugged, reliable and safe for the patient.

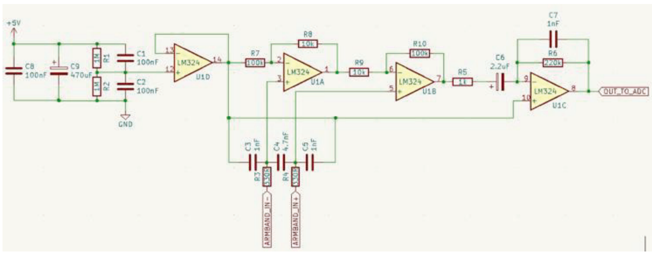

Fig. 3. Schematic of the EMG Signal Filter

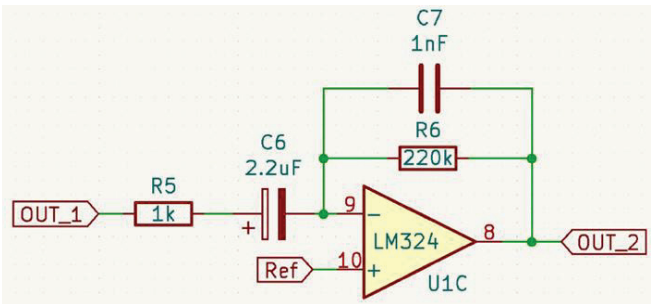

Fig. 4. Schematic of the Band-Pass Filter

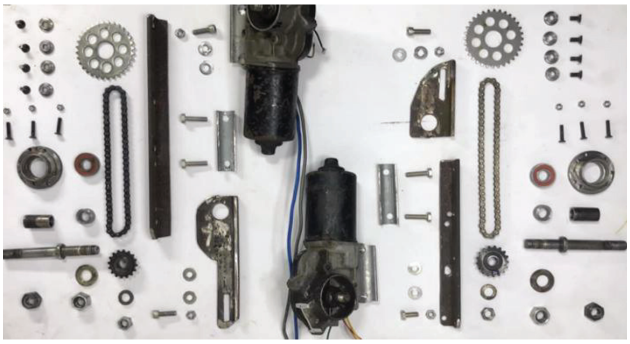

Fig. 5. Components of the Modular Wheelchair Kit

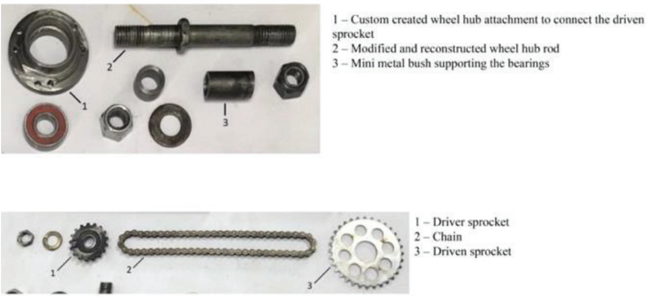

Fig. 6. Chain and Sprocket System

TABLE II. HAND GESTURE CONTROL LOGIC

Left Hand	Right Hand	Control Command
Flexed	Flexed	Move Forward
Flexed	Relaxed	Move Right
Relaxed	Flexed	Move Left
Relaxed	Relaxed	Stop

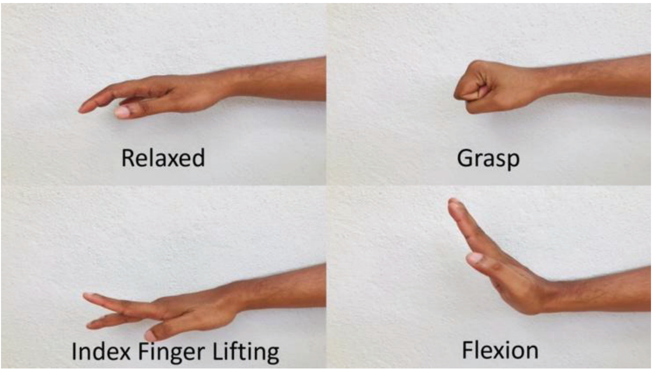

Fig. 7. Different Hand Gesture Commands

Fig. 8. Final Designed of the Proposed Wheelchair

To drive the wheelchair, a motor driver unit was required. The VNH2SP30 H-Bridge motor driver was used because it could handle up to 14A of current and was cost-effective. The motor driver receives the MCU output directly, and the user can act on the wheelchair by utilising the command that had been processed.

There are several gesture commands selected to control the wheelchair. Table 2 depicts the hand gesture control logic generated through the left and right hands. Fig. 7 shows the different hand gesture commands used in the research.

IV. RESULTS AND ANALYSIS

As the proposed model is supposed to be a universal solution, any paresis patient or a person with a movement disability/difficulty should be able to manoeuvre the powered wheelchair based on the user's movement ability. Fig. 8 shows the completed hardware design of the powered wheelchair. As shown in the image, all the hardware components were attached to a traditional wheelchair which is cost-effective.

Table 3 depicts the experimental results of 16 test trials. The experimental scenario was performed as rest, grasp, index finger lift, and flex for the same duration (7 seconds). These movements and logic generated the most acceptable threshold levels, which can be easily differentiated from the signal levels when the hand was at rest. It's also evident that some test cases showed +Ve errors while others showed -Ve errors.

Fig. 9 depicts the envelope signal, displayed in red for the EMG signal generated for wrist flexion. Immediately after the movement stops, the call returns to the reference value (0 V), while peaks are caused due to external noise factors.

Fig. 10 to Fig. 13 showed the signal variation during the experiment on rest, grasping, index finger lift, and flexed state. Fig. 10 shows the resultant waveform generated during the rest state. The illustration shows that the waveform is flat and relatively steady, with only slight amplitude fluctuations brought on by little muscular activity, such as little twitches or movements. The EMG waveform displayed a clear and distinct pattern of electrical activity when the hand was actively grabbing or gripping an object, as seen in Fig. 11, which correlates to the activation of the muscles used in the gripping movement. As the muscles contract to elevate the finger, the EMG waveform often exhibits an initial burst of electrical activity, followed by a persistent period of action.

TABLE III. EXPERIMENT RESULTS ON DIFFERENT TEST TRIALS

Test No	Gesture Command	CH-out / (mV)	Error
T-1	Flex	2.44	-0.042
T2		2.45	-0.031
T-3		2.51	+0.140
T-4		2.48	-0.014
T-5	Grasp	2.46	-0.061

Test No	Gesture Command	CH-out / (mV)	Error
T-6		2.43	-0.041
T-7		2.58	+0.101
T-8		2.58	+0.103
T-9	Index finger	2.33	-0.151
T-10		2.59	+0.111
T-11		2.47	-0.013
T-12		2.27	-0.224
T-13	Rest	2.76	+0.284
T-14		2.45	-0.034
T-15		2.46	-0.023
T-16		2.49	-0.015

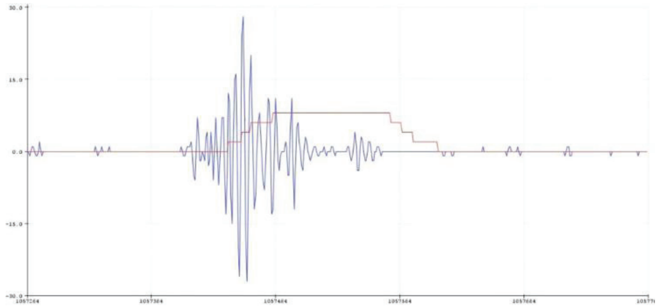

Fig. 9. Envelope Signal Generated for a Wrist Flexion

In contrast, the muscles hold the finger position. Fig. 12 shows the output waveform during the index finger lifting experiment. As shown in Fig. 13, when the hand is flexed, the EMG waveform shows a clear and distinct electrical activity pattern corresponding to the activation of the muscles involved in hand flexion. Also, we found that the precise pattern and shape of the EMG waveform during hand flexion depended on the factors such as power and speed of the movement, the particular muscles used, and the individual's level of motor coordination and control.

Fig. 14 illustrates the confusion matrix of the proposed methodology. As shown in the matrix, it produces minor errors in index finger lift and left experiments. A significant error occurred in the rest experiment due to the age variation. We have observed that the response to the system is reducing with ageing. However overall accuracy of the proposed method was 88% achieved.

V. Discussion

This research aims to develop a motorised wheelchair control system that uses EEG and EMG data to enable more precise and effective control. The study's findings demonstrated that the EEG-EMG interaction could give each participant reliable and effective control over the motorised wheelchair. Using electrical impulses from muscles regulated by the neurological system, wheelchair navigation was accomplished. These signals were generated due to the contraction and relaxation of muscles. For this research, surface EMG was used as there is no harm to the skin from surface EMG, unlike intramuscular electrodes. It was required to find the exact location of the muscle where the EMG signals are generated around the forearm muscles.

A majority of the participants expressed high levels of satisfaction with the technology, and several even said they preferred it to their conventional joystick-controlled wheelchairs.

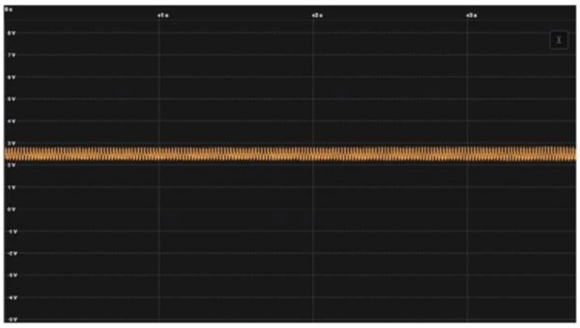

Fig. 10. Filtered Waveform When the Hand is at Rest

Fig. 11. Filtered Waveform When the Hand is Grasping

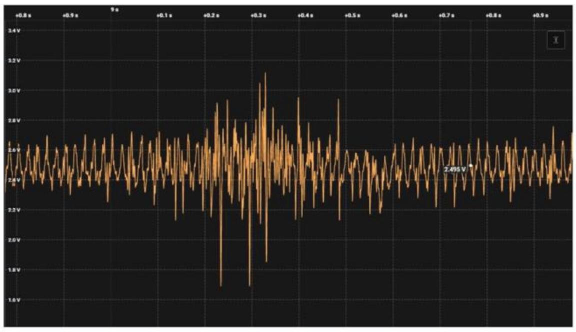

Fig. 12. Filtered Waveform When the Index Finger is Lifted

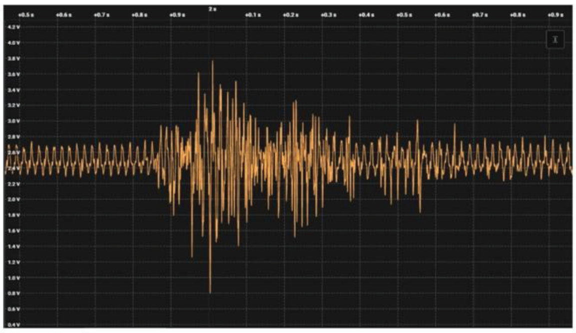

Fig 13. Filtered Waveform When the Palm is Flexed

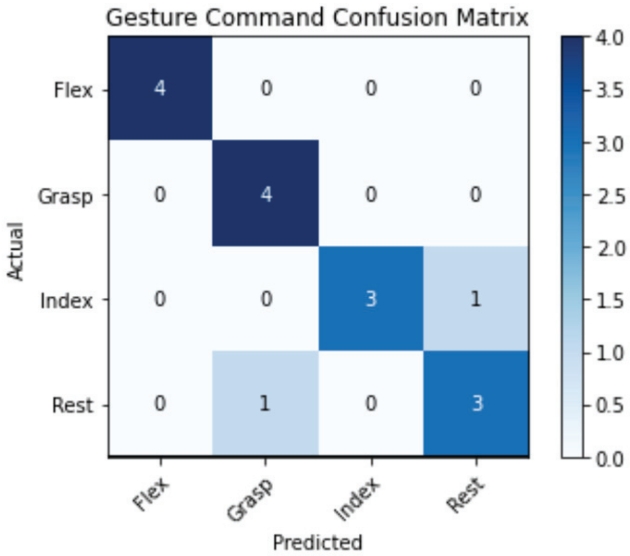

Fig. 14. Confusion Matrix of the Experiment

In comparison to conventional joystick control, the device was also able to lessen the cognitive burden needed to operate the wheelchair considerably.

The electrode size had to be large enough to acquire the signal and small enough to reduce the noise level. Shielded wires were used to minimise interference with the original signals. Required circuits were implemented, which are needed to acquire the EMG signals. A passive filter, an instrumentation amplifier, an active filter and an operational amplifier were developed to acquire the signals from the forearm muscles. Moreover, any significant or sustained changes in the muscle waveform amplitude could also indicate abnormal muscle activity or a neuromuscular disorder and should be further investigated.

Although the study has significant drawbacks, such as a small sample size and a brief testing period, the results are encouraging and point to the possibility that the EEG-EMG interface might increase mobility and quality of life for those with upper-limb paresis. Further research might look at the system's long-term usability and efficacy and its possible integration with other assistive technologies to give people with mobility problems even more functionality and independence.

VI. Conclusion

In conclusion, the development of an EEG-assisted EMG wheelchair represents a significant advance in the field of devices that help people with physical restrictions move about more easily. To provide users with more movement and freedom, this research proposed a system that can get beyond the drawbacks of traditional wheelchair control techniques. The proposed system focuses on the design of powered wheelchairs, signal processing model, and controller, all of which are essential system components. 88% accuracy was achieved with a weighted average precision of 0.89 when the system was evaluated using human test subjects. The findings of this study indicate the potential of cutting-edge assistive technologies to raise the standard of living for people with physical limitations.

VII. Ethical Clearance

This research granted ethical clearance approval from the ethical committee of the Sri Lanka Technological Campus (SLTC) under the ethical clearance number **DPRI/EC/MT/01/01/23**.

References

[1] ”Department of Census and Statistics Characteristics Of The Disabled Persons - Census Of Population And Housing”, Statistics.gov.lk, 2021. [Online]. Available: http://www.statistics.gov.lk/Population/PopHouStat-Disability.

[2] G. Jang, J. Kim, S. Lee and Y. Choi, ”EMG-Based Continuous Control Scheme With Simple Classifier for Electric-Powered Wheelchair”, IEEE Transactions on Industrial Electronics, vol. 63, no. 6, pp. 3695-3705, 2016.

[3] S. Swee, K. Teck Kiang and L. You, ”EEG Controlled Wheelchair”, 2021.

[4] H. M. K. K. M. B. Herath and W. R. de Mel, “Controlling an Anatomical Robot Hand Using the Brain-Computer Interface Based on Motor Imagery,” Advances in Human-Computer Interaction, vol. 2021, pp. 1–15, Aug. 2021.

[5] T. Kawana, Y. Yoshida, Y. Kudo, C. Iwatani and N. Miki, ”Design and Characterization of an EEG-Hat for Reliable EEG Measurements”, Micromachines, vol. 11, no. 7, p. 635, 2020.

[6] G. Kucukyildiz, H. Ocak, S. Karakaya, and O. Sayli, “Design and Implementation of a Based Interface for a Robotic Wheelchair,” Journal of Intelligent & Robotic Systems, vol. 87, no. 2, pp. 247–263, Jan. 2017, doi: https://doi.org/10.1007/s10846-017-0477-x.

[7] K. S. Mistry, P. Pelayo, D. G. Anil, and K. George, “An interface system to control electric wheelchairs,” 2018 IEEE International Instrumentation and Measurement Technology Conference (I2MTC), May 2018.

[8] K. Banach, M. Małecki, M. Rosół, and A. Broniec, “ interface for electric wheelchair based on alpha waves of EEG signal,” Bio-Algorithms and Med-Systems, vol. 17, no. 3, pp. 165–172, Sep. 2021.

[9] V. K. Nandikolla, T. K. van Leeuwen, and A. Hartman, “Hybrid BCI Controller for a Semi-Autonomous Wheelchair,” Volume 3: Biomedical and Biotechnology Engineering, Nov. 2019.

[10] M. A. Shamseldin et al., “A New Design Identification and Control Based on GA Optimization for An Autonomous Wheelchair,” Robotics, vol. 11, no. 5, p. 101, Sep. 2022.

[11] A. R. Baltazar, M. R. Petry, M. F. Silva, and A. P. Moreira, “Autonomous wheelchair for patient’s transportation on healthcare institutions,” SN Applied Sciences, vol. 3, no. 3, Feb. 2021.

[12] A. Hartman, R. Gillberg, C. T. Lin, and V. K. Nandikolla, “Design and development of an autonomous robotic wheelchair for medical mobility,” 2018 International Symposium on Medical Robotics (ISMR), Mar. 2018.

[13] A. S. Kundu, O. Mazumder, P. K. Lenka, and S. Bhaumik, “Hand Gesture Recognition Based Omnidirectional Wheelchair Control Using IMU and EMG Sensors,” Journal of Intelligent & Robotic Systems, vol. 91, no. 3–4, pp. 529–541, Oct. 2017.

[14] She, Zhu, Tian, Wang, Yokoi, and Huang, “SEMG Feature Extraction Based on Stockwell Transform Improves Hand Movement Recognition Accuracy,” Sensors, vol. 19, no. 20, p. 4457, Oct. 2019.