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# Coordination between Visualization and Execution of Movements

Rakib Hasan[1*], Rukaiya Khatun Moury[2], Nazimul Haque[3]

[1]Department of Electrical Engineering, Lamar University, Beaumont, TX 77705, USA
[2]Department of Management Information System, Lamar University, Beaumont, TX 77705, USA
[3]Department of Electrical and Electronics Engineering, United International University, Dhaka, Bangladesh

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***Corresponding author:** Rakib Hasan
Department of Electrical Engineering, Lamar University, Beaumont, TX 77705, USA

**Abstract** **Original Research Article**

Individuals living with disabilities often encounter difficulties in executing coordinated movements, particularly those with limited mobility due to conditions such as paralysis, arthritis, or spinal cord injuries. Traditional electric wheelchairs, primarily controlled through upper body strength, may be inaccessible to those with severe upper limb impairments. This study aimed to develop an innovative solution using Electromyography (EMG) technology to enable individuals with limited upper body mobility to control wheelchairs effectively. The objective was to create a user-friendly EMG-based wheelchair control system that interprets hand gestures and converts them into multi-directional commands. The research involved the development of an EMG-based wheelchair control system that recorded EMG signals from the users' hands and analyzed them for controlling forward, left, and right movements. Extensive testing was conducted with three subjects to evaluate the system's accuracy. The results were quantified regarding error percentages and compared among the subjects. The study yielded promising outcomes. Subject A exhibited a 1% error rate for right-hand movement and a 1.85% error rate for left-hand movement. Subject B achieved a 2.84% error rate for right-hand movement and a 1% error rate for left-hand movement. Subject C demonstrated a 3.84% error rate for right-hand movement and a 0% error rate for left-hand movement. The developed EMG-based wheelchair control system offers a viable solution to enhance mobility and independence for individuals with limited upper body mobility. The microprocessor-integrated design significantly improves the reliability and user-friendliness of the system. The research underscores the potential of EMG technology in bridging the gap between visualization and execution of movements for those facing mobility challenges.

**Keywords:** EMG, Wheelchair control, Mobility, Upper body impairment, Coordination.



## INTRODUCTION

Paralysis, spinal cord injuries, and various mobility-limiting conditions affect millions of people worldwide, depriving them of the freedom to move independently and engage with the world around them. In the United States alone, over 5.4 million individuals grapple with paralysis, while globally, spinal cord injuries afflict approximately 1 to 2 million people [6]. The challenges faced by these individuals are profound, as they often require assistance for even the most basic of movements, leading to a significant loss of autonomy and quality of life.

Traditionally, wheelchairs have served as the primary means of mobility for people with disabilities, providing a semblance of independence through their use. However, conventional wheelchair control mechanisms, predominantly joystick-based systems, are inherently limited. They necessitate upper body mobility, restricting access for those who are unable to manipulate a joystick due to severe paralysis or other physical constraints. Recognizing this limitation, engineers and researchers have embarked on a journey to innovate and develop alternative control methods for wheelchairs, aiming for inclusivity for all individuals, regardless of their physical capabilities.

The emergence of smart wheelchair systems represents a significant breakthrough in the quest for improved mobility solutions. These innovative systems leverage various physiological signals the human body generates, such as muscle activity, brainwaves, voice commands, head or chin movements, sip-and-puff actions, eye movements, and even tongue control. These signals open up possibilities for individuals lacking conventional means of controlling a wheelchair. Among these signals, Electromyography (EMG) signals have gained prominence as a promising avenue for achieving precise and responsive control.

EMG signals, recorded from the electrical activity of muscles, offer a unique window into the user's intent. When a muscle contracts or relaxes, it generates distinct electrical signals that can be harnessed for controlling external devices, including wheelchairs. This paper delves into developing an EMG-based wheelchair control system to empower individuals with limited upper-body mobility.

Before delving into the specifics of our project, it is essential to acknowledge the invaluable contributions of prior research in this field. The existing literature has provided critical insights and paved the way for advancements in EMG-based control systems. Several noteworthy studies have contributed to our understanding of signal processing, classification techniques, and noise mitigation in EMG-based applications.

In a pioneering work by Biswajit *et al.*, [1], an innovative wireless wheelchair control system was introduced. This system classified three primary movement commands: forward, backward, rotation, and stop signals. It employed signal preprocessing techniques, including squaring the raw EMG signal to enhance the signal-to-noise ratio (SNR). This paper was a foundational reference for our project, inspiring our approach to signal processing and wireless communication.

Hossein Ghapanchizadeh *et al.*, [2] provided essential insights into surface electrode placement, signal acquisition techniques, and artifact removal strategies. Their work emphasized the importance of accurate electrode positioning for optimal signal strength, a key aspect of EMG-based control systems.

Furthermore, a comprehensive study by another group [3] explored diverse signal processing and classification techniques. It covered noise removal methods, signal processing approaches (e.g., Wavelet analysis, EMD, ICA), and classification algorithms (e.g., SVM, LDA, ELM). Notably, the Extreme Learning Machine (ELM) classification technique demonstrated exceptional accuracy, reaching 98%. This research was pivotal in guiding our signal analysis and classification methodologies.

In addition to these foundational studies, S. Satish *et al.*, [4] presented a basic yet insightful implementation of surface EMG in a prototype robotic toy. Their work showcased the feasibility of EMG-based control in a practical application, shedding light on the potential for real-world implementation.

Hayder A. Azeez *et al.*, [5] contributed to the field by discussing various research endeavors related to surface EMG methods. They highlighted the significance of noise removal techniques, elucidated the frequency range and EMG signal amplitudes across different muscle groups, and offered a concise review of classification algorithms such as ANN, SVM, and probabilistic approaches.

Moreover, a review paper [6] explored the pros and cons of Electroencephalography (EEG) methods and compared EEG signals with other commonly used techniques, including fMRI, ECOG, MEG, and fNIRS. While focusing primarily on EEG, this paper also touched on signal acquisition, preprocessing, and classification techniques, providing valuable insights into the broader landscape of neurophysiological signal analysis.

Building upon this foundational knowledge and inspired by these significant contributions to the field, our project endeavors to implement EMG-based control for wheelchairs. This paper will provide an in-depth overview of our project, outlining our methodology, hardware design, and results. By harnessing the power of EMG signals, we strive to enhance the mobility and independence of individuals facing mobility challenges, ultimately fostering a more inclusive society.

## METHODOLOGY

In the pursuit of developing an innovative and practical solution to address the mobility limitations faced by individuals with upper body disabilities, a well-structured methodology is essential. This section outlines the step-by-step approach employed in designing and implementing an EMG (Electromyography)--based wheelchair control system that aims to bridge the coordination between visualizing movements and their execution seamlessly.

***Data Collection:***

The foundation of this study lies in the careful selection of suitable participants. Individuals afflicted with conditions such as paralysis, arthritis, or spinal cord injuries, which severely restrict their upper body mobility, constitute the primary subjects. The acquisition of EMG signals, crucial for this research, entails the placement of EMG sensors on both hands of each participant. It is paramount to ensure the precise positioning of these sensors to capture muscle activity accurately. A diverse dataset is then created by recording EMG signals during hand movements, such as fist clenching, palm opening, and finger gestures.

***Signal Processing:***

The collected EMG signals undergo an intricate signal processing process to refine and prepare them for subsequent analysis. This involves preprocessing the signals by applying a Butterworth Bandpass filter from 10Hz to 400Hz to eliminate unwanted noise and artifacts. Feature extraction techniques are then employed to extract pertinent characteristics from the preprocessed

EMG signals. These features may include mean absolute value, root mean square, and waveform length. To facilitate analysis, the signals are further divided into windows of suitable size, typically around 1000 samples, with the potential for overlapping windows to ensure continuity.

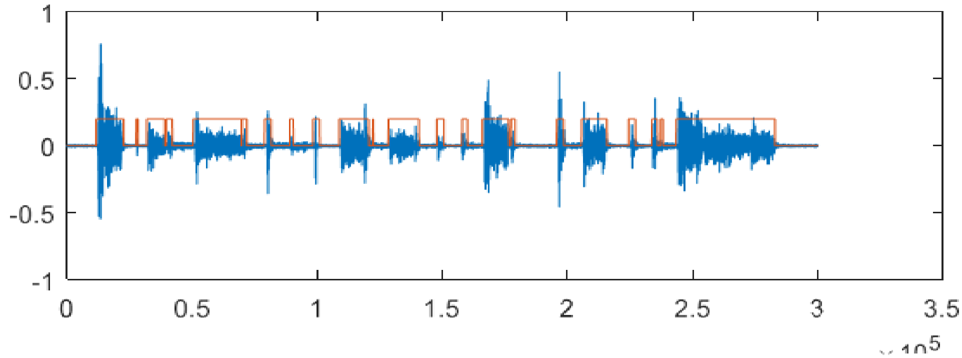


**Figure 1: Feature extraction**

From the figure above, we can see that the inactive phase is below the value of 0.04. This value changes with the target muscle and the EMG device gain. Also, we used a window of 1000 samples. Every 1000 samples is averaged and is compared with 0.04. If the average value is above 0.04, we term it as an activated phase. Windowing allows us to avoid minor artifacts. The muscle emits voltage even in the inactive stage due to small finger movements. When we keep our hands steady, we can see our fingers move automatically on a small scale. Windowing will allow us to avoid such artifacts. Even if it does, it will be less. Also, windowing allows us to make decisions after a specific interval. For example, a thousand sample windows allow us to decide after every 0.33 sec.

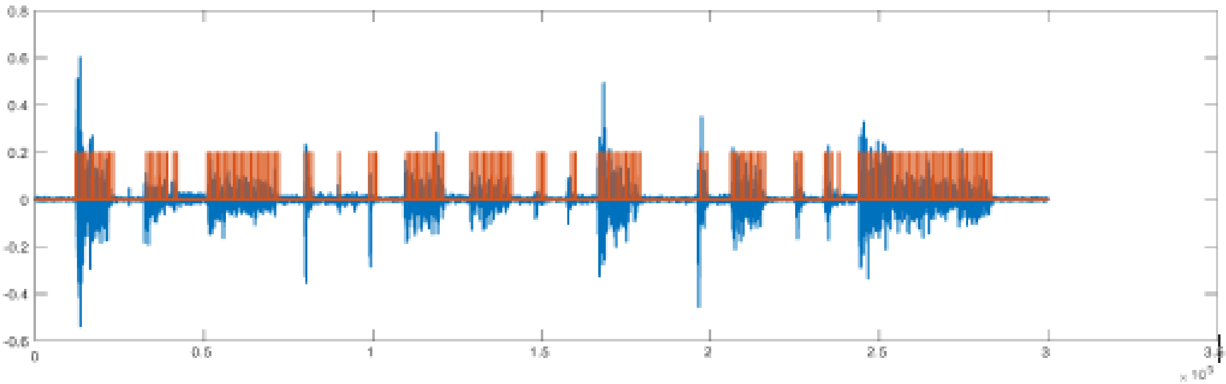

**Figure 2: Windowing, 1000 sample**

Again, a window of 500 samples allows us to decide after every 0.16 sec. But if a mistake is made, it will take a large portion of that value.

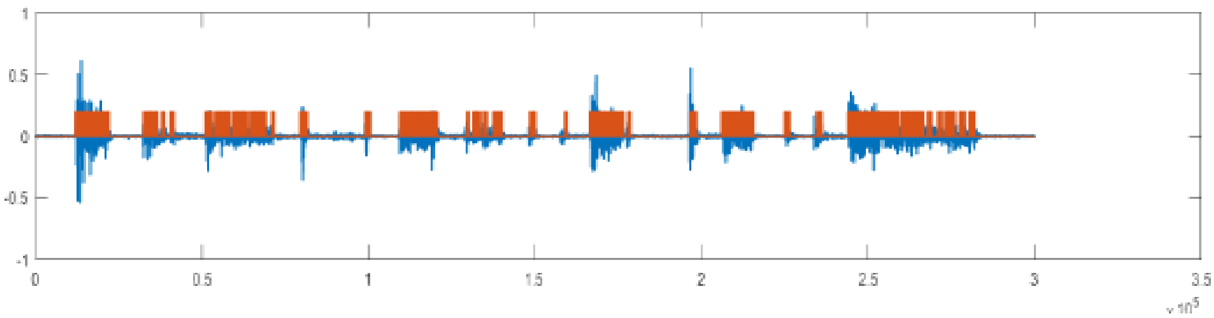

**Figure 3: Windowing, 500 sample**

A window of 1500 samples allows us to decide after every 0.5 seconds, which is a lot of time. The signal seems to have a delay in the decision. But if a mistake is made, it takes less value.

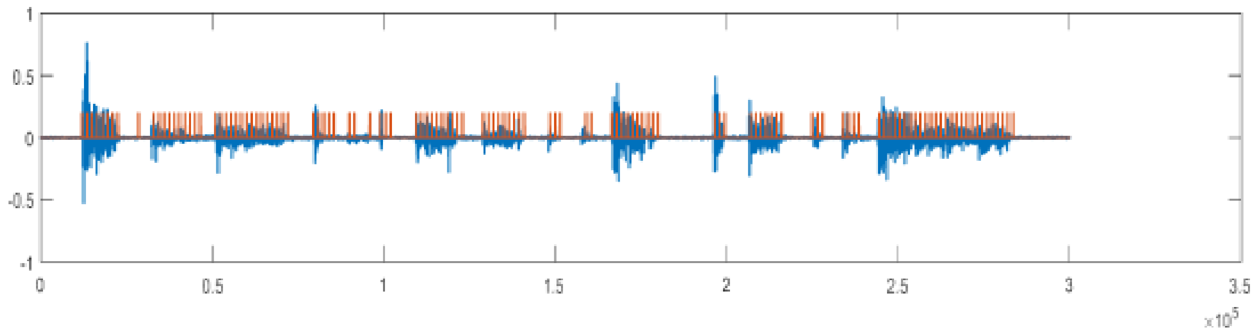


**Figure 4: Windowing, 1500 sample**

As we can see, there is a lot of delay in 1500 samples and the possibility of making more mistakes in 500 samples, so we stuck with 1000 samples.

***Classification Model:***

The next crucial step involves selecting and implementing an appropriate classification algorithm. Options may include Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), or Extreme Learning Machine (ELM). The choice of algorithm hinges on its ability to interpret EMG signals accurately. To determine the most suitable algorithm, rigorous evaluation and comparison of different options are carried out.

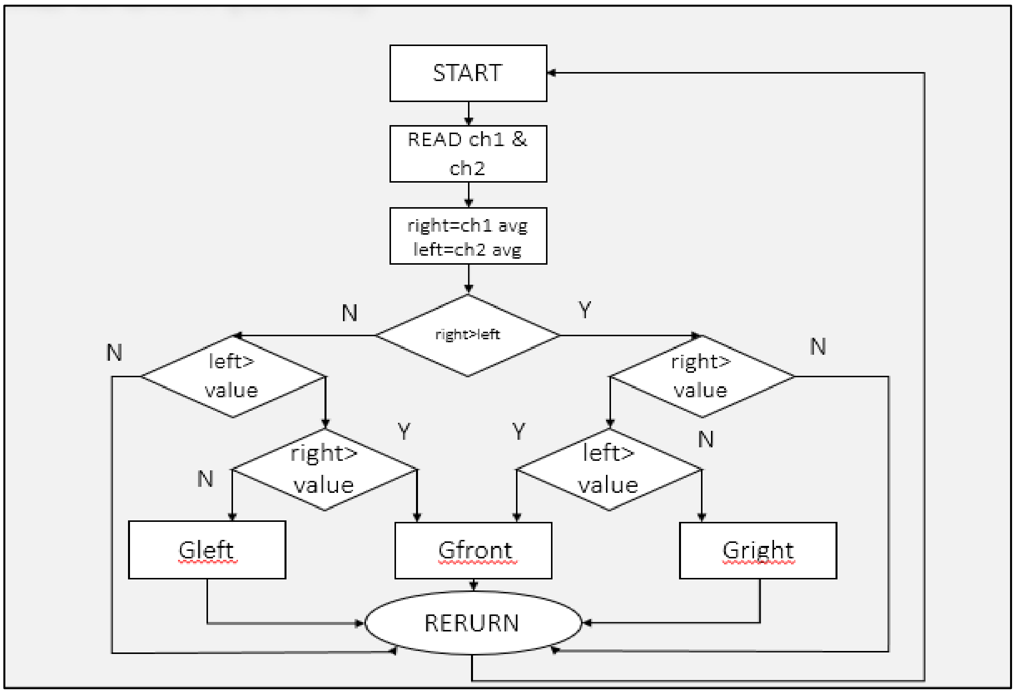


**Figure 5: Flow chart based on truth table**

In the flow chart, the Left is an average window of 1000 samples in the left channel. Right is an average window of 1000 samples in the right channel. It will go right when a proper channel is activated, and the left channel is inactive. It will go left when a left channel is activated and a right channel is inactive. Finally, when both channels are simultaneously in the active phase, they will go front—giving us three classifications: Left, right, and front.

***Training and Testing:***

The dataset is divided into distinct training and testing subsets, following a standard split ratio, typically 70-30 or 80-20. The selected classification algorithm is then trained using the training data, with hyperparameter tuning for optimization. Subsequently, the trained model is subjected to rigorous testing using the reserved testing data, particularly in calculating error rates for different hand movement classifications, such as right, left, and front.

***Hardware Implementation:***

This methodology phase focuses on translating the theoretical framework into a practical, real-world solution. A suitable microprocessor, such as Arduino, is chosen to integrate the EMG sensors and the classification model. A hardware interface is developed to establish real-time connectivity between the EMG sensors and the microprocessor. Logic is implemented to convert the classified EMG signals into multi-directional control commands, including forward, left, and right movements. Additionally, the microprocessor is interfaced with the wheelchair's motor control system to execute the desired movements based on the generated commands.

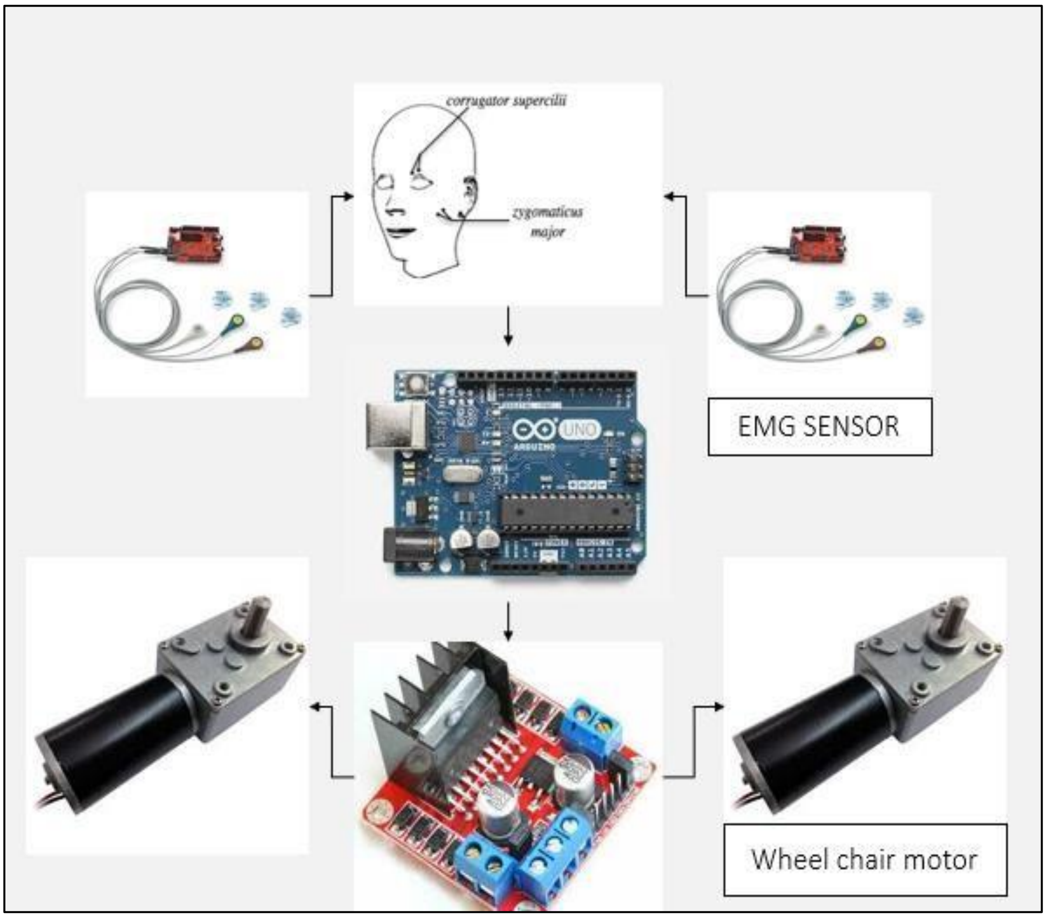


**Figure 6: Hardware design**

***Testing and Evaluation:***

The effectiveness of the EMG-based wheelchair control system is evaluated through practical testing involving the selected subjects. Their interactions with the system are meticulously recorded, and system performance is monitored throughout the testing phase. Error analysis is conducted, encompassing calculations of error percentages for different hand movement commands, enabling a comprehensive assessment of the system's accuracy, reliability, and user-friendliness.

The study encapsulates error percentages and system performance for each subject. The significance of the developed EMG-based wheelchair control system in enhancing mobility for individuals with restricted upper body mobility is discussed. The system's potential impact on improving the coordination between visualizing movement and its seamless execution is highlighted. In essence, this methodology aims to demonstrate the feasibility and effectiveness of the proposed approach in addressing the research objectives and ultimately enhancing the quality of life for individuals with mobility challenges.

## RESULTS AND DISCUSSIONS

we present the results of implementing and testing the EMG-based wheelchair control system. The results provide valuable insights into the system's performance, accuracy, and effectiveness in enabling individuals with upper body disabilities to control a wheelchair through hand movements. The chapter is structured to include data collected from three subjects, each representing a unique set of challenges and requirements.

**Table 1: Summary of Results for Subjects A, B, and C**

| **Subject A** | **Subject A** | **Subject B** | **Subject C** |
|---|---|---|---|
| **Muscle Movement Classification (Before Windowing)** | | | |
| Muscle Moved Right | 153995 cases | 149635 cases | 130802 cases |
| Muscle Stable Right | 146037 cases | 150397 cases | 169230 cases |
| Muscle Moved Left | 160028 cases | 195809 cases | 150194 cases |
| Muscle Stable Left | 140004 cases | 104223 cases | 149838 cases |
| **Muscle Movement Classification (After Windowing - Window Size: 1000)** | | | |
| Right Channel | 154 cases | 154 cases | 136 cases |
| Left Channel | 163 cases | 196 cases | 150 cases |
| **Classification Results** | | | |
| Front Movement Cases Identified | 106 | 133 | 88 |
| Left Movement Cases Identified | 57 | 63 | 62 |
| Right Movement Cases Identified | 48 | 21 | 48 |
| **Error Percentage (Right)** | 1% | 2.84% | 3.84% |
| **Error Percentage (Left)** | 1.85% | 1% | 0% |

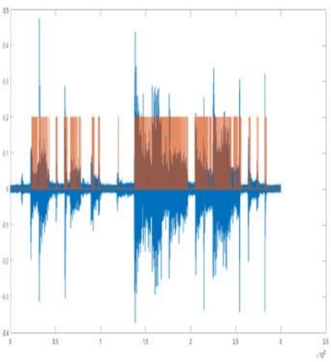

**Figure 7: Subject A left channel readings**

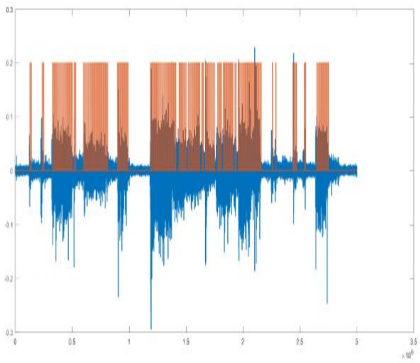

**Figure 8: Subject A right channel readings**

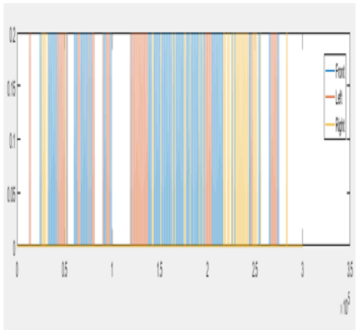

**Figure 9: Subject A movements**

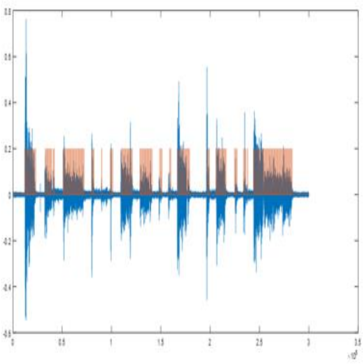

**Figure 10: Subject B left channel readings**

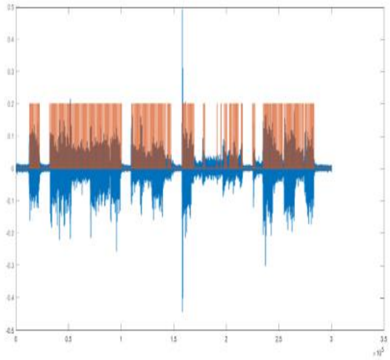

**Figure 11: Subject B right channel readings**

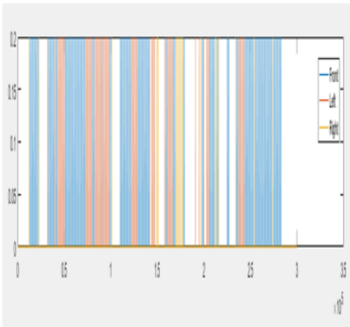

**Figure 12: Subject B movements**

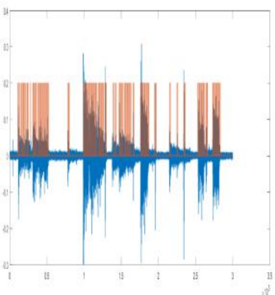

**Figure 13: Subject C right channel readings**

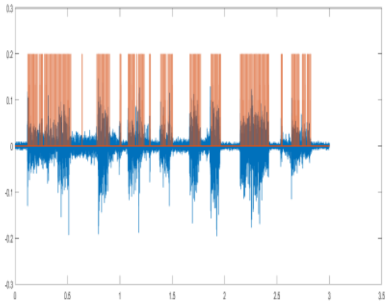

**Figure 14: Subject C left channel readings**

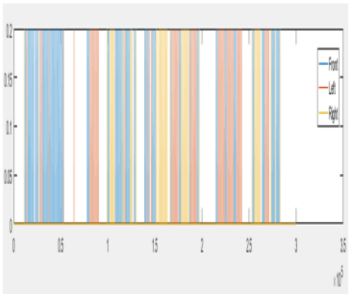

**Figure 15: Subject C movements**

**Table 2: Summarizes the key data collected from all three subjects**

| Case\Subject | Subject A | Subject B | Subject C |
|---|---|---|---|
| Muscle moved R | 153,995 | 149,635 | 130,802 |
| Muscle moved L | 160,028 | 195,809 | 150,194 |
| Window R | 154 | 154 | 136 |
| Error (Right) | 1% | 2.84% | 3.84% |
| Window L | 163 | 196 | 150 |
| Error (Left) | 1.85% | 1% | 0% |
| Front | 106 | 133 | 88 |
| Left | 57 | 63 | 62 |
| Right | 48 | 21 | 48 |

The results from the three subjects demonstrate the feasibility of using EMG signals from hand movements to control a wheelchair. Subject A exhibited a relatively low error percentage for both right and left movements, indicating high accuracy in classifying the intended movements. Subject B displayed a slightly higher error percentage for right movements but a low error percentage for left movements, highlighting some variability in system performance. On the other hand, Subject C achieved a low error percentage for right movements and a perfect accuracy rate for left movements. These results suggest that the EMG-based wheelchair control system has the potential to provide individuals with upper body disabilities a reliable means of controlling their mobility. However, further refinements and optimizations may be necessary to enhance system accuracy and consistency across users.

The results obtained from the testing of the EMG-based wheelchair control system indicate its potential to significantly improve the quality of life for individuals with upper body disabilities. The ability to control a wheelchair through simple hand movements offers newfound independence and mobility to these individuals, reducing their reliance on others for assistance. While the system demonstrates promise, ongoing research and development efforts should focus on refining the classification algorithms and addressing user-specific variations to ensure consistent and accurate performance. The potential impact of this technology on enhancing the coordination between visualizing movements and their execution is substantial, opening doors to greater autonomy and freedom for those with mobility challenges.

## CONCLUSION

The study presents a comparative analysis of subjects, yielding varying thresholds for potential smart wheelchair implementation. Despite COVID-19 constraints, the proposed approach offers cost-effective and accessible wheelchair design without complex machine learning algorithms. The analytical approach, based on diverse subject observations, proves time-efficient. The variable threshold voltages across subjects yield intriguing results. This paper aims to impart fundamental insights into EMG-based electric wheelchair development.

**Recommendations:**

- Conduct additional research to investigate the variability in threshold voltages among different individuals. Understanding these variations can lead to personalized wheelchair control systems, optimizing user experience and comfort.
- Explore the integration of machine learning algorithms to enhance the accuracy and efficiency of EMG-based wheelchair control. Machine learning can adapt to users' unique EMG patterns, improving responsiveness and reducing error rates.
- Focus on developing an intuitive and user-friendly interface for EMG-based wheelchair control. Prioritize ease of use and accessibility to ensure disabled individuals can operate the wheelchair independently and confidently.

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## REFERENCES

1. Champaty, B., Dubey, P., Sahoo, S., Ray, S. S., Pal, K., & Anis, A. (2014, July). Development of wireless EMG control system for rehabilitation devices. In 2014 Annual International Conference on Emerging Research Areas: Magnetics, Machines and Drives (AICERA/iCMMD) (pp. 1-4). IEEE.
2. Ghapanchizadeh, H., Ahmad, S. A., Ishak, A. J., & Al-Quraishi, M. S. (2017). Review of surface

electrode placement for recording electromyography signals. *Biomedical Research* (0970-938X), 28.

3. Chowdhury, R. H., Reaz, M. B., Ali, M. A. B. M., Bakar, A. A., Chellappan, K., & Chang, T. G. (2013). Surface electromyography signal processing and classification techniques. Sensors, 13(9), 12431-12466.
4. Sathish, S., Nithyakalyani, K., Vinurajkumar, S., Vijayalakshmi, C., & Sivaraman, J. (2016). Control of robotic wheel chair using EMG signals for paralysed persons. *Indian Journal of Science and Technology*, 9(1), 1-3.
5. Yousif, H. A., Zakaria, A., Rahim, N. A., Salleh, A. F. B., Mahmood, M., Alfarhan, K. A., ... & Hussain, M. K. (2019, November). Assessment of muscles fatigue based on surface EMG signals using machine learning and statistical approaches: A review. In IOP conference series: materials science and engineering (Vol. 705, No. 1, p. 012010). IOP Publishing.
6. Lakshmi, M. R., Prasad, T. V., & Prakash, D. V. C. (2014). Survey on EEG signal processing methods. *International journal of advanced research in computer science and software engineering*, 4(1).
7. Ahamed, N. U., Sundaraj, K., Ahmad, R. B., Nadarajah, S., Shi, P. T., & Rahman, S. M. (2011). Recent survey of automated rehabilitation systems using EMG biosensors. *Journal of Physical Therapy Science*, 23(6), 945-948.
8. Keenan, K. G., Collins, J. D., Massey, W. V., Walters, T. J., & Gruszka, H. D. (2011). Coherence between surface electromyograms is influenced by electrode placement in hand muscles. *Journal of neuroscience methods*, 195(1), 10-14.
9. Merletti, R., & Muceli, S. (2019). Tutorial. Surface EMG detection in space and time: Best practices. *Journal of Electromyography and Kinesiology*, 49, 102363.
10. Küçükyıldız, G., Ocak, H., Şayli, Ö., & Karakaya, S. (2015, October). Real time control of a wheelchair based on EMG and Kinect for the disabled people. *In 2015 Medical Technologies National Conference (TIPTEKNO)*; pp. 1-4) IEEE.