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EMG INTERFACE FOR SCI PATIENTS

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***Abstract*—A significant spinal cord injury (SCI) affects between 2.5 lakhs to 5 lakhs persons annually, according to the WHO. Physical restrictions on basic movement are one of three issues that impede many persons with SCI from participating fully in society. In order to improve treatment and get around health, social, and financial obstacles, WHO advises using appropriate assistive technology to help people with SCI perform daily duties. Over the past decades, many innovations and ideas were proposed to support SCI patients to meet their daily needs. Technology advancements like electrical muscular stimulation, bionic exoskeletons, and at-home assistance devices give people with SCI hope for a much better quality of life. But not all of them gave satisfactory results as they had limitations of their own. SCI patients suffer from numbness. As a result, SCI sufferers often find it challenging to use commonplace gadgets on their own. We suggest an EMG (electromyogram)-based input interface for patients with physical impairments of the extremities using machine learning. This includes those SCI patients who are amputees. Using the dataset created from the inputs of EMG sensors, we can control various devices. In this work we are recommending an EMG based interface to control electric wheelchairs for SCI patients as a first step.**

***Index Terms*—SCI, EMG, sensors, amputees, wheelchairs**

I. INTRODUCTION

EMG is a common method for capturing muscle activity and determining the difference in electrical potential between two muscle locations using electrodes coupled to an EMG signal [1]. Muscle contraction produces electrical impulses, which is referred to as neuromuscular activity.As a result, an electrical signal is generated each time a muscle contracts.The wheelchair's forward and backward movement, as well as its left and right turns, are controlled by the EMG signal.

SCI patients suffer from numbness. The nerves that run from the neck to the hand and fingers are damaged, which results in numbness throughout the human body. As a result, SCI patients often struggle to operate wheelchairs independently. Several studies have suggested that SCI patients may benefit from various wheelchairs with various mechanics.There are many different wheelchair models available. Recent advancements in wheelchair technology. In order to make it easier and more comfortable for people who are paralysed to move around, manual wheelchairs changed from being very light, tiny, and foldable to ones that could be driven by a joystick or buttons.

However, a technological advance is necessary to enable people who have a large portion of their body paralysed, particularly their hands and feet, and who are unable to operate an electric wheelchair using joysticks or buttons. Patients with SCI are unable to make the right gestures for wheelchair movement. The system is then able to define the movement. The study's target population can move their shoulders, thus an EMG signal from the trapezius muscle is used to regulate the wheelchair's movement.

II. EASE OF USE

EMG-based wheelchair control involves the use of sensors that detect the electrical activity produced by the patient's muscles. These sensors are placed on the skin above the muscle groups that are used for wheelchair control, typically the forearm, biceps, and triceps. The EMG signals generated by these muscles are then processed by a computer or microcontroller, which interprets them and converts them into commands that control the movement of the wheelchair.

The system typically requires the patient to undergo some training in order to learn how to generate the appropriate muscle signals to move the wheelchair in the desired direction. The training process may involve tasks such as imagining movements or performing specific exercises to generate the necessary EMG signals.

Once the patient has learned how to control the wheelchair using EMG signals, they can use the system to move the wheelchair in a variety of ways, such as turning left or right, moving forward or backward, and stopping or starting. The system may also include features such as speed control and obstacle avoidance, which can help to make wheelchair movement safer and more efficient.

Overall, EMG-based wheelchair control can provide an effective way for patients with limited mobility to regain some independence and control over their movement. However, it is important to note that the system may not be suitable for all patients, and careful evaluation and training is necessary to ensure its safe and effective use.

III. RELATED WORKS

This section discusses about other related works that exists with the aim of helping people with disabilities using EMG sensor technology. The use of EMG sensor technology in the medical field has increased significantly in recent years. This is due to several factors, including advances in sensor technology, improvements in signal processing and data analysis techniques, and the increasing demand for non-invasive and personalized healthcare solutions.

EMG sensors have become an essential tool for diagnosing and treating a wide range of neuromuscular disorders. They are also used in sports medicine, physical therapy, rehabilitation, and prosthetics, among other areas. In addition, EMG sensors are increasingly being used in research to gain a better understanding of the mechanisms of muscle contraction and to develop new treatments for neuromuscular disorders.

A. *Hand Gesture Classification using EMG*

- In 2019 Ulysse Côté-Allard et. al., [2] proposed that utilising deep learning algorithms' ability to acquire discriminant features from vast datasets while applying transfer learning on data that has been combined from many users.Two datasets, each with 19 and 17 able-bodied people (the first dataset is utilised for pre-training), were used to gather data for this study regarding the use of the Myo armband. The NinaPro database was used to get a third set of Myo armband data, which is made up of ten healthy people. Three distinct deep learning networks that use raw EMG, spectrograms, and continuous wavelet transform (CWT) as inputs are tested using the second and third datasets.
- Bhupender Kumar et. al., [4] introduced an EMG controlled wheel chair using SVM and kNN classifiers in 2019. Support vector machine (SVM) and k-nearest neighbor (kNN) classifiers are trained in python 3.5 software for electric wheelchairs using time domain features to classify the 5 different movement controls.A Raspberry Pi 3 processes data from a MyoWare sensor to provide control pulses for a DC motor drive, which is ultimately used by the electric wheelchair to move.
- Then in 2020 Milad Jabbari et. al., [5] proposed classification using Long-Short Term Memory (LSTM) network for EMG pattern recognition.Here, NN consists of a concatenated softmax layer and a multilayer LSTM.The fact that the procedure is tested with an unknown level of force throughout part of the trainings can be considered a drawback. In 2021 Jose Manuel Fajardo et.al. proposed a CNN model for classification. But the classification showed poor performance due to the lack of proper dataset.Same year Schabron B et. al.,[6] proposed a system that uses myo armband for data acquisition and SVM model for classification.But the classification accuracy is lesser.Only shows 90% accuracy for one person as test case.
- In 2021 Jose Manuel Fajardo et. al., [7] proposed a method for classifying signals obtained from a single channel device combines manually created features from time-spectral discrete analysis with deep features derived from a convolutional neural network (CNN). This method is known as the combined feature approach method.The suggested strategy reduces the amount of training data from each gesture to just 100 signals, which cuts down on the training period. The proposed method combines deep features with manually created features from a time-spectral analysis, including mean absolute value (MAV), slope sign changes (SSC), peak frequencies, and wavelet transform (WT) coefficients, among others, to create the feature vector. After that, the feature vector is categorised using a multi-layer perceptron classifier (MLPC).The experimental results showed an average classification accuracy of 81.54%, 88.54%, and 94.19% for the eight, six, and five gesture classes.
- Then in 2022 Albert C. Manero et. al., [9] developed a cutting-edge control technique for people unable to operate powered wheelchairs on their own. Amyotrophic lateral sclerosis patients frequently use a wheelchair, yet they have difficulty moving their hands effectively enough to operate a joystick. Because of this, they are a group that needs this type of control. They took signals from facial muscles and from that data is classified and used for the movement of a wheelchair. But in the practical model it seemed to be not feasible and less satisfying for patients.
- Shahida Afrin et. al., [1] made their dataset of hand gestures of SCI patients public in 2022. It's a well structured data with 8 channels, in which classical machine learning algorithms show greater accuracy. And among them kNN showed a better one. And it paved the way for us to develop the model over this dataset.

B. *Edge Implementation Over IoT*

- In 2020 Junxia Li et. al., [11] designed a secure architecture for SDN-based Edge computing in a healthcare IoT system.The Edge servers in the suggested framework employ a simple authentication method to confirm the IoT devices. After the patients have been verified, these devices collect data from them and send it to the Edge servers to be stored, processed, and analysed.An SDN controller is linked to the Edge servers. This controller handles load balancing, network optimization, and making the best use of resources in the healthcare system. Computer simulations are used to test the proposed framework.
- In 2022 Muhammad Usman et. al., [14] developed a novel approach to simultaneously identify and classify multiple contaminants in sEMG signals without performing feature extraction. Instead, they trained a 1D convolutional neural network (1D-CNN) to classify different contamination types in sEMG data. The network is trained to recognise five different types of pollutants using real and simulated sEMG signals. They also train and evaluate a 1D-CNN to recognise numerous pollutants simultaneously. Additionally, they provide experimental findings for safely routing the data in a planned Internet of health things (IoHT) by employing received signal strength indicators (RSSI) to create connection fingerprints in order to reliably and securely convey the data

to the doctor (LFs). The results demonstrate greater classification system accuracy at low signal-to-noise ratios (SNR) and demonstrate IoHT security that is not overly burdensome.

IV. PROPOSED SYSTEM

SCI sufferers often find it challenging to use commonplace gadgets on their own. We suggest an EMG (electromyogram)-based input interface for patients with physical impairments of the extremities using machine learning. This includes those SCI patients who are amputees. We can control various devices using the dataset created from the inputs of EMG sensors. This work recommends an EMG-based interface to control electric wheelchairs for SCI patients.

A. *Issues Identified in the Existing System*

In the existing system they are only considering people with SCI, there could be SCI patients with no amputees. The classification method for this case may need to be more accurate. Patient data safety is not ensured in this case as they are using the cloud for classification, so there is a need to ensure the safety of patients' data. Moreover, as the existing system are expensive, it is difficult for middle-class families to afford such equipment.

B. *Our Solution*

- Our project is an EMG-based interface for spinal cord injury (SCI) patients. We use only two EMG sensors to capture the EMG signal, which helps reduce the cost of the device. As there is no existing dataset to classify hand gestures from two EMG sensors, we first had to collect EMG data.
- Once we collected the data, we extracted 8 hand-crafted features from each channel. By extracting these features, we were able to reduce the dimensionality of the data, making it more manageable for classification purposes.
- Next, we used machine learning techniques to classify hand gestures based on the extracted features. This likely involved training a model on the collected data, testing its performance on a separate set of data, and fine-tuning the model until it achieved an acceptable level of accuracy. Once the model was trained and validated, we deployed it to an edge device, which allowed it to control the wheelchair.
- Overall, this project is an innovative and cost-effective solution for SCI patients who need a reliable and efficient way to control their wheelchairs using EMG signals. The use of only two EMG sensors and hand-crafted features is a novel approach that we believe has the potential to make this technology more accessible to a wider range of patients.

C. *Real-Time Hand Gesture Recognition Model*

The system uses two EMG sensors to capture electrical signals generated by hand muscles, which are then analyzed using an optimized ANN machine-learning model. The model incorporates eight hand-crafted features, including mean absolute value, root mean square, zero crossing, waveform length, slope sign change, mean absolute value slope, auto-regressive coefficient, and power spectral density. With an accuracy of 98.03%, the model can accurately classify five hand gestures: front, back, right, left, and stop. The system is deployed on an edge device, enabling real-time control of a wheelchair using hand gestures.

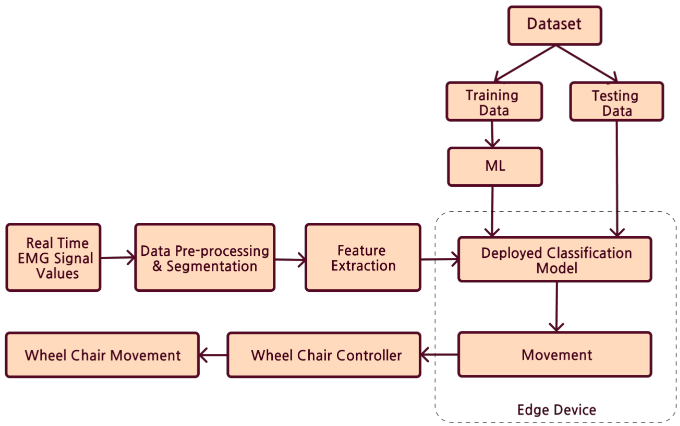

Fig. 1: Proposed EMG Based Interface Architecture

D. *Data Acquisition*

We used Muscle BioAmp Candy for data acquisition. It is a small and affordable muscle sensor designed for precise electromyography (EMG) sensing.

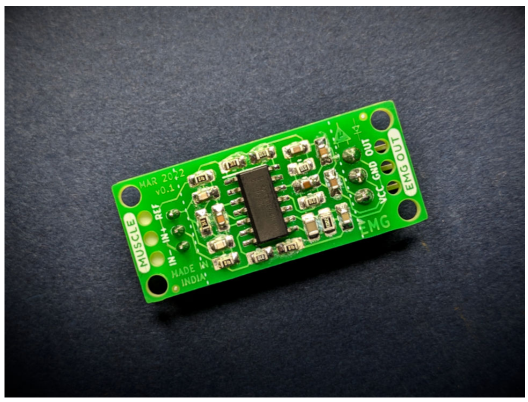

Fig. 2: Muscle Bioamp Candy

It is more affordable than other similar products available in the market. This portable device can be easily attached to the skin over a muscle to detect and amplify the electrical activity generated by the muscle. The signal is then transmitted via a cable to a computer or mobile device for further processing and analysis.

Since there was no existing dataset to classify hand gestures from two EMG sensors, the first step in the project was to create a new dataset. To do this, we collected continuous EMG signals from people of different categories. We recruited 10 participants for the study and collected 16 repetitions of each of the five hand gestures from each participant, resulting in a total of 800 data samples for feature extraction and classification. The data was collected by placing the sensor over flexor carpi radialis muscle and extensor carpi radialis muscle of the forearms. This likely involved attaching the EMG sensors to the skin overlying the muscles of interest, such as the forearm or hand, and recording the electrical activity produced by the muscles during different hand gestures.

E. Data Pre-processing & Segmentation

Preprocessing data is a kind of data manipulation that entails putting unstructured data into comprehensible shape. To identify the area of the sEMG that correlates to muscle activity during a gesture, segmentation is used. Removing impulses from the areas where the muscles are at rest is also required. 2000 ms windows are generated from the sEMG and the gesture detection technique is followed to retain valuable information. Preprocessing techniques include Notch Filter at 50 to 60 Hz to remove unwanted AC power line Frequencies.

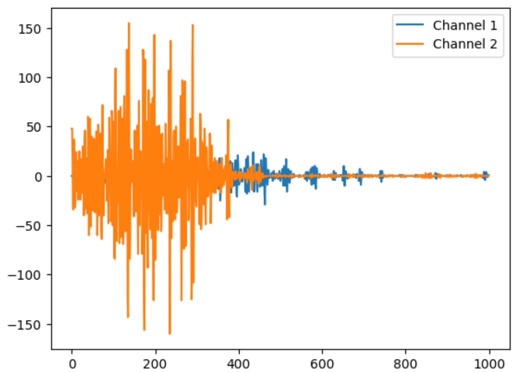

Fig. 3: Extracted Segment for 'back' Gesture

F. Feature Extraction

In order to achieve better accuracy in classifying the hand gestures, we extracted 8 hand-crafted features from each segment of the EMG signal. These features included:

1) Mean Absolute Deviation (MAD): This is the EMG signal's typical amplitude. It stands for the entire force of the muscles' contraction during a specific hand motion.

$$\mathrm{MAD} = \frac{1}{n}\sum_{i=1}^{n}|x_i - \bar{x}| \tag{1}$$

2) Root Mean Square (RMS): This is the EMG signal's root mean square amplitude. It is a measurement of the signal's overall energy and is connected to the force and length of the muscle contraction.

$$\mathrm{RMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}x_i^2} \tag{2}$$

3) Zero Crossing (ZC): This represents how many times the horizontal axis is crossed by the EMG signal. It is connected to how frequently muscles contract.

$$\mathrm{ZC} = \frac{1}{2N}\sum_{i=1}^{N-1}|sgn(x_i) - sgn(x_{i+1})| \tag{3}$$

4) Waveform Length (WL): The absolute differences between successive EMG signal levels are added up in this. It relates to the dexterity of the hand movement and serves as a gauge of the signal's overall complexity.

$$\mathrm{WL} = \sum_{i=1}^{N-1}|x_{i+1} - x_i| \tag{4}$$

5) Slope Sign Change (SSC): This is the quantity of times the EMG signal's slope shifts. It has to do with how quickly and slowly the muscles flex.

$$\mathrm{SSC} = \sum_{i=1}^{N-2}\begin{cases}1, & \text{if } (x_{i+1} - x_i)(x_{i+2} - x_{i+1}) < 0\\ 0, & \text{otherwise}\end{cases} \tag{5}$$

6) Mean Absolute Value Slope (MAVS): This is the EMG signal's typical slope. It displays the rate of variation in muscle contraction.

$$\mathrm{MAVS} = \frac{1}{N-1}\sum_{i=1}^{N-1}|x_{i+1} - x_i| \tag{6}$$

7) Auto-Regressive Coefficient (ARC): This is a measurement of the correlation between EMG signal values that follow one another. It has to do with how frequently the muscles flex.

$$\mathrm{ARC} = \frac{\sum_{i=k+1}^{N} x_i x_{i-k}}{\sum_{i=1}^{N} x_i^2} \tag{7}$$

8) Power Spectral Density (PSD): This is how the EMG signal's power is distributed among its many frequencies. It has to do with the muscular contraction's frequency content.

$$S_{xx}(f) = \lim_{T\to\infty}\frac{1}{T}|X(f)|^2 \tag{8}$$

By extracting these features, you reduced the dimensionality of the data and created a more manageable set of variables for the machine learning model to use in classifying hand gestures. Overall, this process involved collecting EMG data, segmenting it into useful chunks, and extracting hand-crafted features to use as inputs to a machine-learning model. This enabled you to create a new dataset and prepare it for the classification of different hand gestures, which could then be used to control the wheelchair via the deployed model.

G. Classification Methods

Once we collected our dataset of segmented EMG signals and extracted features, we developed a machine-learning model for gesture classification. In order to determine the most suitable algorithm for our specific scenario, we conducted experiments using various well-known machine learning models on our dataset. These models encompassed a range of techniques, such as Support Vector Machine (SVM), Recurrent Neural Network (RNN), k-Nearest Neighbors (kNN), Artificial Neural Network (ANN), Linear Discriminant Analysis (LDA), Decision Tree, Multi-Layer Perceptron Classifier (MLPC), and Binary Tree SVM (BTSVM).

Support Vector Machine (SVM) operates by locating the ideal hyperplane that divides the many classes of data points in a high-dimensional space. A particular kind of neural network called a recurrent neural network (RNN) is made for handling sequential data. Its distinctive architecture enables it to use the results of the previous phase as input for the following step. A non-parametric approach used for regression and classification analysis is called k-Nearest Neighbours (kNN). It classifies the data point by finding the k-nearest neighbours of a particular data point and utilising their labels.

ANN, which emulates the structure and functionality of the human brain, proves effective in solving intricate classification and regression tasks. On the other hand, LDA is a linear classification algorithm that identifies the optimal linear combination of features to distinguish various data classes. Decision Tree, on the other hand, divides the data into subsets based on feature values in a recursive manner. MLPC, another neural network architecture, comprises multiple layers of perceptrons and is capable of tackling complex classification and regression challenges. Lastly, BTSVM, a specialized SVM variant, is tailored for binary classification problems and utilizes a binary tree structure of SVMs to address intricate classification tasks.

H. *Edge Deployment & Real Time HGR Recognition*

Once the hand gesture classification model has been trained and fine-tuned to achieve optimal performance, it is implemented on an edge device, specifically the Raspberry Pi 3 model B. This deployment facilitates the real-time recognition of hand gestures, which in turn serves as a means to govern the movement of an electric wheelchair. The forward and backward motion of the wheelchair is orchestrated by DC motors, while servo motors are enlisted to effect directional changes. For the purpose of controlling the DC motors, we employ the L298 motor driver, a dual full-bridge driver renowned for its ability to drive inductive loads like relays, solenoids, DC, and stepping motors. By establishing an interface between the Raspberry Pi and the motor driver, we gain the capability to regulate the direction and velocity of the motors by leveraging the output signals generated by the hand gesture classification model. Consequently, individuals afflicted with spinal cord injuries can steer their wheelchairs by means of instinctive hand gestures, thereby bestowing upon them a heightened sense of independence and expanded mobility options.

I. *Workflow of Proposed System*

- Input: Collected EMG signals
- Output: Wheelchair movement
- Step 1: Import necessary libraries and modules
- Step 2: Preprocess the EMG data and extract hand crafted features
- Step 3: Split the pre-processed data into training and testing sets
- Step 4: Train a handcrafted feature-based classifier
- Step 5: Load the trained EMG hand gesture recognition model to the edge device
- Step 6: Set up the communication channel with the edge device
- Step 7: Initialize the connection with the edge device
- Step 8: Define a function to receive EMG data from the edge device
- Step 9: Define a function to send the predicted hand gesture class label(s) back to the edge device
- Step 10: Set up a loop to continuously receive and process EMG data from the edge device
- Step 11: Terminate the connection with the edge device (if necessary) and clean up resources

V. RESULTS AND ANALYSIS

The developed EMG interface system achieved a high classification accuracy of 98.03% for hand gesture recognition using only two EMG sensors. The handcrafted features, including mean absolute value, root mean square, zero crossing, waveform length, slope sign change, mean absolute value slope, auto-regressive coefficient, and power spectral density, proved effective in capturing the relevant information from the EMG signals. The ANN machine learning model, optimized using the grid search method, demonstrated superior performance compared to other tested models such as RNN, kNN, SVM, LDA, Decision Tree, MLPC, and BTSVM.

After conducting extensive testing on our dataset using various machine learning models, we identified the ANN algorithm as the most effective for gesture classification. Using the grid search method, we fine-tuned the hyperparameters of our ANN model, resulting in a classification accuracy of 98.03%. The comparison table for each of the machine-learning models tested in our study is given below:

TABLE I: Performance Comparison of Models

Models	Accuracy(%)	Precision(%)	F1 Score(%)
SVM	96.71	96.75	96.72
RNN	97.37	97.45	97.39
kNN	82.24	82.22	82.09
ANN	98.03	98.05	98.04
LDA	96.05	96.32	96.05
Decision Tree	88.82	88.94	88.83
MLPC	96.71	96.74	96.70
BTSVM	75.66	75. 69	75.59

The high accuracy of 98.03% showcases the robustness and reliability of this system in recognizing hand gestures. This accuracy level is crucial for ensuring precise control of the electric wheelchair, allowing users to rely on the system confidently. The utilization of the Raspberry Pi 3 model B as the edge device enables real-time processing and inference, ensuring immediate response and reducing any potential delays in controlling the wheelchair.

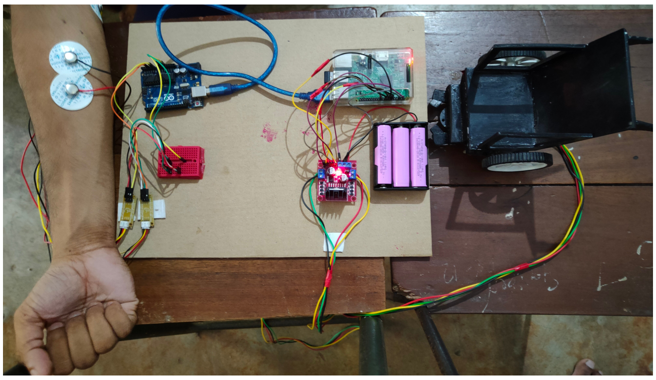

Fig. 4: Final Prototype of the Proposed System

The implementation of DC motors for forward and backward motion, along with servo motors for directional changes, offers a comprehensive control mechanism for the electric wheelchair. The integration of the L298 motor driver facilitates smooth and efficient control of the DC motors, resulting in seamless motion transitions.

The EMG interface system opens up new possibilities for individuals with spinal cord injuries by providing them with an intuitive and reliable control interface. By utilizing hand gestures, users can easily navigate and maneuver the wheelchair, enhancing their independence and quality of life.

It is worth noting that future improvements could include expanding the dataset to include more subjects and additional hand gestures, allowing for a broader range of wheelchair control commands. Additionally, exploring advanced machine learning techniques, such as deep learning algorithms, may further enhance the accuracy and robustness of the hand gesture recognition system.

VI. CONCLUSION

The EMG interface for SCI patients project successfully developed a real-time hand gesture recognition system for individuals with spinal cord injuries. By utilizing two EMG sensors and a carefully selected set of hand-crafted features, combined with an optimized ANN model, the system achieved a remarkable accuracy of 98.03% in classifying hand gestures. The deployment of the model on a Raspberry Pi 3 model B as an edge device allowed for immediate recognition and control of an electric wheelchair using the detected gestures. The integration of DC and servo motors, along with the L298 motor driver, ensured smooth and accurate wheelchair motion. This project demonstrates the potential of affordable and intuitive interfaces in empowering individuals with spinal cord injuries, enhancing their mobility and independence. Future work may involve expanding the dataset and exploring advanced machine learning techniques for further improvements in accuracy and functionality. Overall, the EMG interface system represents a significant advancement in assistive technology, providing a practical and effective solution for real-time hand gesture recognition and wheelchair control.

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