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A Methodical Approach to Hardware Platform Design for sEMG Recording and Classification Hand Gesture Recognition using sEMG

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Hand Gesture Recognition (HGR) systems play a pivotal role in Human-Computer Interaction (HCI), offering a natural and intuitive means of communication between users and electronic devices. However, existing HGR systems encounter challenges associated with both cost-effectiveness and reliable signal capturing. This research addresses these issues by introducing a cost-effective and reliable hardware model that records the intensity of EMG signals in real-time scenarios. The main contribution of the proposed hardware prototype is to eliminate the dataset dependency of HGR systems and enhance their efficacy. To accomplish this task, a cost-effective hardware prototype has been meticulously designed and implemented on the Arduino Board. Moreover, to make the proposed module user-friendly and simpler, a Graphical user Interface (GUI) is also designed through which users can easily navigate and choose the appropriate action to be performed. In addition to this, for more efficiency and reliability, data is collected from the real world with two sensor channels, instead of one. The proposed module is designed for recognizing four gestures (Idle, fist, flexion, and extension) and their variations recorded in two channels. The analysis is performed in MATLAB software. By deploying and interconnecting the specified components on the Arduino Board, a cost-effective hardware prototype for real-time sEMG-based Hand Gesture Recognition (HGR) is achieved. This approach addresses challenges related to cost and signal reliability, providing an accessible solution for natural and intuitive human-computer interaction.

Keywords: Human Computer Interaction, Hand Gesture Recognition (HGR), Surface EMG, sensor channels etc.

1. Introduction

Many aspects of daily life, including gaming, healthcare, education, and business, rely on hand gestures. A muscle-computer interface MCI is a method for communication that transforms myoelectrical signals created from minute reflections of muscle activity into requests for human engagement that specify the intended outcome of the exercise. A muscle is made up of numerous motor units (MU), and A "motor unit action potential" (MUAP), which is the sum of the contributions from the numerous fibers that make up the MU, "discharges" or "fires" with each MU activation [1]. The creation and spread of MUAPs are reflected by surface electromyography (sEMG), which captures electrical activity from the surface of the skin in muscles. Surface EMG is useful in the domains of prosthetic control, clinical diagnosis, motion detection, and neurological rehabilitation. As it represents the status of the nerve's activity, it may be used to push back neural information [2]. Also, it has other advantages such as noninvasive acquisition and bionics [3]. A key biological signal is the sEMG signal, a weak electrical signal generated by contracting muscles [4]. Different limb movements are produced depending on whether muscles are tensed or relaxed, and the bioelectrical signals that are released differ significantly as a result too, as stated by different researchers in [5],[6],[7],[8]. The hands don't move immediately. With regard to hand motions, skeletal muscle contraction may be roughly divided into two categories: dynamic and static. While the latter requires the invariance of muscle fiber and upper limb joint, the former involves a change in the shape of the muscle fiber and movements of the joint [9][10].

Further, a convenient way to frame gesture identification based on sEMG is as a pattern classification issue, where a classifier is often learned via supervised learning. It is generally agreed that it is impracticable and wasteful to input the immediate value of myoelectric signals straight to a classifier for pattern recognition algorithms. Because the raw myoelectric signal in each channel is non-stationary, non-linear, stochastic, and unpredictable. This notion is founded on the empirical presumption that the instantaneous values of myoelectric signals are worthless for gesture recognition [11]. These characteristics of the myoelectric signal reflect both the arbitrary way in which these motor unit action potentials superimpose and the continual fluctuation of the actual set of recruited motor units within the spectrum of accessible motor units. The myoelectric signal's amplitude can quickly fluctuate between voltages above and below zero at any given time; as a result, it resembles a random process with a zero mean, with a standard deviation that depends on both the number of active motor units and the pace at which they are activated. Existing gesture recognition methods using sEMG are largely based on traditional pattern recognition algorithms (such as support vector machine [12], hidden Markov model [13]). The sequence of myoelectric signals from each channel frequently has to be translated into a collection of descriptive and discriminating characteristics retrieved using a window of EMG data, which is known as the sEMG feature space (or segment). To properly detect hand motions by processing a vast amount of data, however, is a major difficulty in the development of an active EMG-based prosthesis [14]. According to studies, the nervous system controls the joint movements of the muscles and bones in the human limbs. Due to this, each person's exercise habits are unique. Due to which even same person might move differently depending on the situation as well as their own physical and mental health. This places a heavy burden on feature extraction and EMG signal processing [15]. Furthermore, because the EMG signal is more complicated, the system's performance requirements are greater and the pattern recognition system's reaction time is longer, which negatively impacts real-time prosthesis control or other applications [16]. These are the main issues that researchers are now facing. First, whereas the hand has more than twenty degrees of freedom, only a few motions can be reliably detected. Second, fewer sensors were used to achieve the inadequate gesture recognition rate. Third, utilizing additional sensors to increase the recognition rate results in more expense and complexity. So it is crucial to investigate novel research techniques. The raw sEMG signal has been the subject of a great deal of research in the past. The raw sEMG signal is feeble because of its low frequency and amplitude (below 500 Hz). However, only a small number of research groups have focused on analyzing the sEMG envelope signal. The significant index of feature is employed to classify various hand gestures. A crucial step in the process of gathering pertinent data, removing extraneous components, and improving the effectiveness of motion detection is feature extraction. . In the practical use of surface EMG, gesture identification based on surface EMG signals is a significant study area. Reliable and efficient gesture recognition can aid in the creation of an effective human-machine interface.

1.1 Research Motivation and Contributions

Hand Gesture Recognition (HGR) systems hold immense potential for revolutionizing human-computer interaction, offering a natural and intuitive means of communication. However, existing systems often face barriers such as high costs and limited accessibility, hindering their widespread adoption. This research is motivated by the desire to democratize HGR technology by proposing a cost-effective and user-friendly hardware-based solution. The goal is to make HGR systems accessible to a broader audience, fostering innovation in applications ranging from gaming to assistive technologies. The main contributions of the proposed study are as follow:

- Introducing a novel, cost-effective hardware module designed for the Arduino board, eliminating financial barriers to HGR adoption.
- Incorporating a user-friendly Graphical User Interface (GUI) module to enhance the overall usability of the HGR system.
- Conducting a systematic collection of real-time data to create a diverse dataset, addressing dataset dependency issues in HGR systems.
- Enhancing precision by incorporating two sensor channels, capturing intricate muscle activity for more accurate gesture detection.
- Providing insights into muscle activity variations for four distinct hand gestures, refining the HGR system's performance and understanding of gesture patterns.

The remaining section of this paper are categorized as; Section II reviews some of the recent literature related to HGR followed by the problem statement. Section III gives an overview of our hardware-based HGR model and Section IV represents the EMG signals obtained via two channels of the proposed model for different hand gestures.

2. Literature Review

In the past few years, a significant number of automated HGR models have been presented to enhance the accuracy of these models. The main aim of automating the process of Gesture recognition is to improve accuracy and speed while also reducing the complexity. In this section of the article, we will review and analyze some of the recent publications on the HGR system. Based on this review, some research gaps and findings will be observed and mentioned at the end of this section. Qi, Jinxian, et al. [17], utilized principal component analysis (PCA) approach and GRNN neural network to eliminate redundant information in EMG data, build the gesture recognition system, decrease the signal dimension, boost real-time recognition feasibility, and increase recognition effectiveness and accuracy. The precise action mode was determined using crucial information of human motion extraction. The surface EMG signal of the arm is captured by the electromyography device in this research using nine static motions as examples, and four different types of signal characteristics were extracted. The system's total identification rate was 95.1% after dimension reduction and neural network learning, and the average recognition time was 0.19 s. Similarly, Wang, Q., et al. in [18], proposed a model for online hand gesture detection based on sEMG signals and Flexible Neural Trees (FNT). Using the existing or updated tree-structure-based approaches, the PSO algorithm optimizes the FNT model's parameters. The algorithm can classify six distinct hand gestures in real-time with up to 97.46% accuracy, according to the results. Cao, Junyi, et al. [19], experimented with two hand gesture signals using the OPENBCI, which subsequently decoded for recognizing gestures. Three electrodes were placed on the subject's forearm to extract the signal, which was then delivered in one channel. They created a technique based on the Hilbert transform to create a dynamic threshold and identify the action segment. From each action, four features were extracted, creating feature vectors for categorization. Based on a modest number of samples, the authors compared K-nearest neighbors (KNN) with support vector machines (SVM) during the classification process. According to experimental findings, the SVM method has an average recognition rate that is 1.25 percent greater than the KNN algorithm but takes 2.031 seconds less time. K. Yang, et al. [20], proposed a system wherein, a sEMG signal was used on the forearm to offer a real-time hand motion identification system. By using a sliding window, the segment section of the signals was observed. Moreover, a feed-forward ANN classifier was used to extract features from the signals of each sliding window once it has been trained. Real-time systems have a classification accuracy of 96% according to experiments, and hand gestures may be identified even before they are fully formed. C Wahyu, et al. [21], utilized PCA and SVM for recognizing various gestures in this study. Principal component analysis (PCA) was used to extract 16 time-domain features from each training and testing set of data, which were then reduced to create a new set of features. The results of classifying new sets of characteristics from each subject were performed using SVM ranging from 85% to 89%. With an accuracy range of 80% to 86%, training data categorization was tested using test data from EMG signals. W Alvarado-Díaz, et al. [22], used the Myoware device and ATmega329P microcontroller, for designing and implementing a data collecting system. The authors further demonstrated the validity of the method by categorizing finger movement using the MATLAB Classification Learner code and the k-Nearest Neighbors (KNN) algorithm with an accuracy of 99.1%. Cengiz, T. et al. [23], collected data using Myo armband on their right forearms. The noise from the recorded data was first removed using a high pass filter, and the beginning and finish timings of the hand motion were then identified. The preprocessed EMG data had five-time domain characteristics that were waveform length, zero crossing, mean absolute value, RMS, and slope sign change. The most effective feature set from the retrieved features was chosen using sequential forward selection. SVM and KNN algorithms were utilized for classification. The study's findings showed that the SVM algorithm with the WL feature had the greatest performance, which was 98.75%. Liang, S, et al. [24], demonstrated that individuals have distinct optimum feature sets and redundant feature sets and extracted 76 similar characteristics from two signals. They employed a feature selection technique to obtain the best feature set and reduce complexity. The experimental findings show that the suggested strategy, while just employing two sensors, performs with the best accuracy of 95% for distinguishing up to nine movements. Finally, utilizing the suggested approach, the authors create a real-time intelligent sEMG-driven bionic hand system. S Direk, et al. [25], used MYO wristband, to propose the ideal electrode placements for surface EMG. The sEMG signal was recorded from three separate electrode sites in the extensor digitorum, flexor digitorum superficialis, and palmaris longus muscles during finger movements in the superficial forearm. In order to describe the behaviors of the EMG characteristics, scatter diagrams were used as a feature extraction approach called waveform length (WL). The findings indicated the ideal armband location for MYO armband surface EMG recording for classifying finger movement. The location is in the forearm's midway distance.

Table 1.1 Summary of literature review conducted

Author Details	Work Done
Qi, Jinxian, et al. [17]	Utilized principal component analysis (PCA) approach and GRNN neural network to eliminate redundant information in EMG data
Wang, Q., et al. in [18]	Proposed a model for online hand gesture detection based on sEMG signals and Flexible Neural Trees (FNT) that Uses updated tree-structure-based approaches along with the PSO algorithm that optimizes the FNT model's parameters.
Cao, Junyi, et al. [19]	Experimented with two hand gesture signals using the OPENBCI, which subsequently decoded for recognizing gestures while comparing KNN and SVM.
K. Yang, et al. [20]	Observed the segment section of the signals by using a sliding window. Moreover, a feed-forward ANN classifier was used to extract features from the signals of each sliding window.
C Wahyu, et al. [21]	Utilized PCA and SVM for recognizing various gestures in this study
Alvarado-Díaz, et al. [22]	Used the Myoware device and ATmega329P microcontroller, for designing and implementing a data collecting system. For classification KNN and MATLAB learner code is used.
Cengiz, T. et al. [23]	Chose the features using sequential forward selection. SVM and KNN algorithms were utilized for classification
Liang, S, et al. [24]	Employed a feature selection technique to obtain the best feature set and reduce complexity.
S Direk, et al. [25]	Used MYO wristband, to propose the ideal electrode placements for surface EMG.

After analyzing the literature in the prior section, it has been observed that a significant number of scholars have proposed different techniques for recognizing hand gestures smoothly and accurately. However, the current models undergo a number of limitations that hinder their accuracy rate and hence decrease the efficiency of HGR systems. Most of the current hand gesture systems used single channels for acquiring data, however, we analyzed that by using multiple channels the performance of sEMG can be enhanced greatly. Moreover, we also analyzed it is more difficult to recognize dynamic gestures than static gestures. In addition to this, not more work has been done on real-time datasets which also plays a great role in improving the accuracy of the HGR system. Keeping these facts in mind, a new and effective hardware-based HGR will be proposed in this paper that can overcome the above-mentioned limitations.

3. Methodology

3.1 Overview of proposed HGR system

In order to overcome the shortcomings of current sEMG-based HGR systems, a new and effective prototype is proposed in this manuscript wherein, multiple channels have been used for acquiring data. The key objective of the proposed sEMG-based HGR system is to analyze the efficacy of various gestures that are collected from the real world in real-time. To combat this task, we are going to design a hardware prototype in which different modules are installed for effectively analyzing the data. Moreover, as we have mentioned it earlier, by using multiple channels the efficacy of the sEMG-based HGR systems can be improved, therefore, in the proposed model we have used two channels for analyzing different hand gestures. The proposed prototype is specifically designed for recognizing four types of hand gestures whose data is acquired from two channels. In addition to this, a Graphical User Interface (GUI) is designed that serves as the bridge for computer and hardware prototypes for making the process of communication easier and more effective. Furthermore, as we know that standard online databases are not balanced and different hand gesture images contain a lot of noise which directly impacts the accuracy of the classifier. To resolve this issue and make the proposed hand gesture recognition system more reliable and efficient, we have acquired data from various volunteers in real-time by using the designed hardware prototype. By doing so, we created our own real-time dataset that is later on used for recognizing different hand gestures. The detailed working of the proposed hardware sEMG-based HGR system is explained in the upcoming section of this paper.

3.2 Designing Hardware Prototype

This first phase of our analytical model is to design hardware module wherein different components are installed and connected via Arduino for recognizing different hand gestures. The components that are used for in proposed hardware module are mentioned below;

- USB to TTL Converter
- Buzzer
- On/Off Switch
- LED
- EMG Sensor
- 9V Batteries
- Power Adapter 12V

The USB-TTL converter is used in order to provide connectivity between USB and UART interfaces. Buzzer is a type of small speaker that can be connected to Arduino directly and can be used as alarm, timers of affirmation of a specific input device. Similarly, an on/Off switch is used for turning the circuit on or off whereas, LED is used for determining the on or off state of module. On the other hand, an EMG sensor is used for measuring the electrical activity of the muscle caused by the stimulation of nerves. While as, batteries are used for driving the circuit, and a power adapter is used for recharging it. All these components are connected via

Arduino Board. The circuit diagram of the proposed hardware prototype is designed in proteus software and is shown in figure 1.

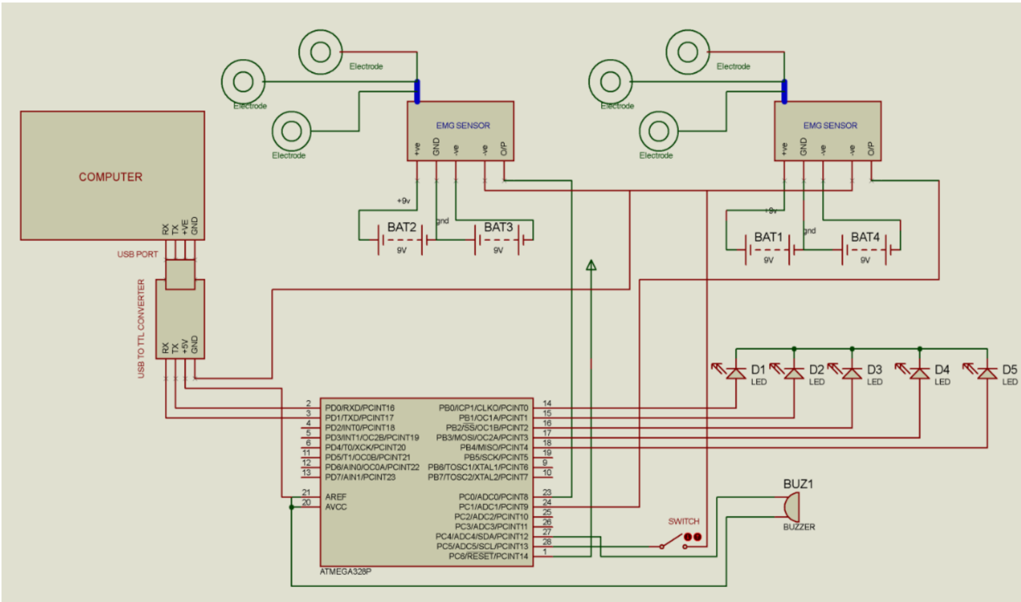
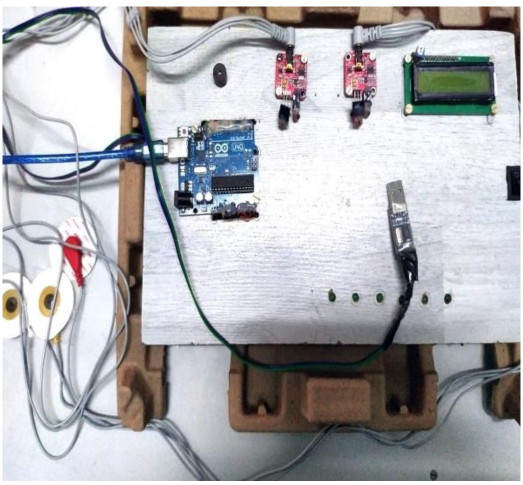
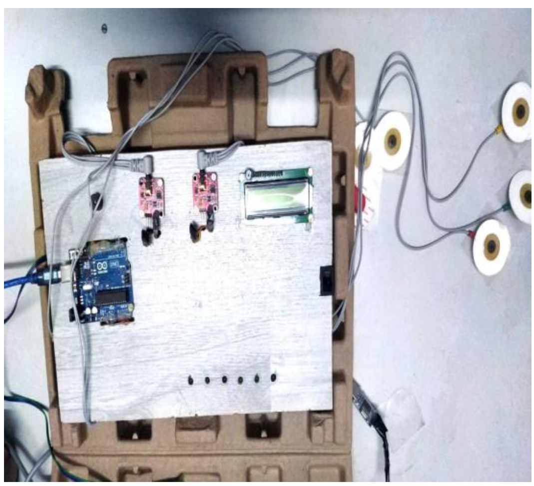


Figure 1. Circuitry diagram of proposed sEMG based HGR system

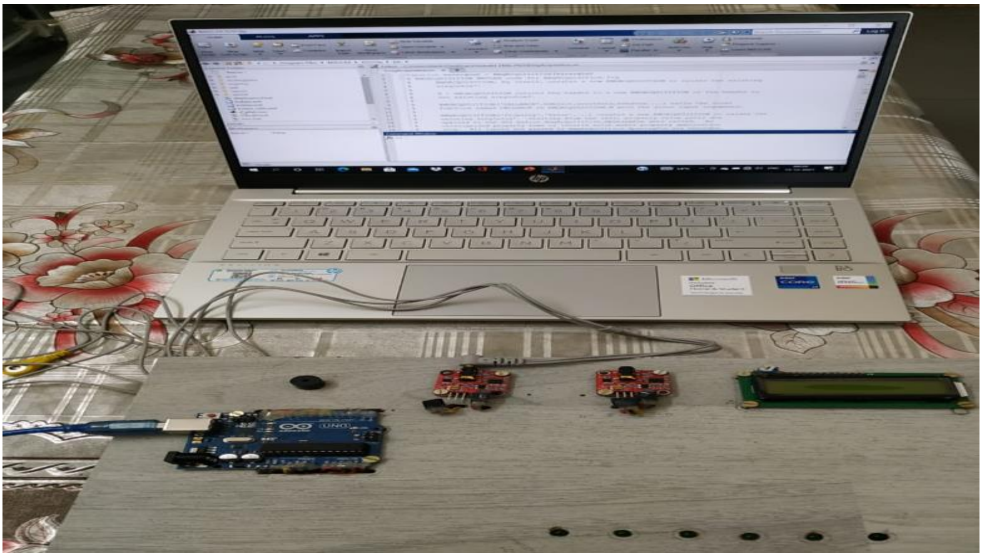
After this, the work for the next phase is initiated i.e. combining and installing all the components on the Arduino motherboard to develop a hand gesture recognition prototype. All the components i.e. EMG sensor, battery, buzzer, power adapter switch, USB to TTL converter are connected together to analyze the hand gestures by measuring the nerve stimulation of muscles. The final designed prototype of our EMG based HGR model is shown in figure 2 (a, b and c) respectively.



(a)



(b)



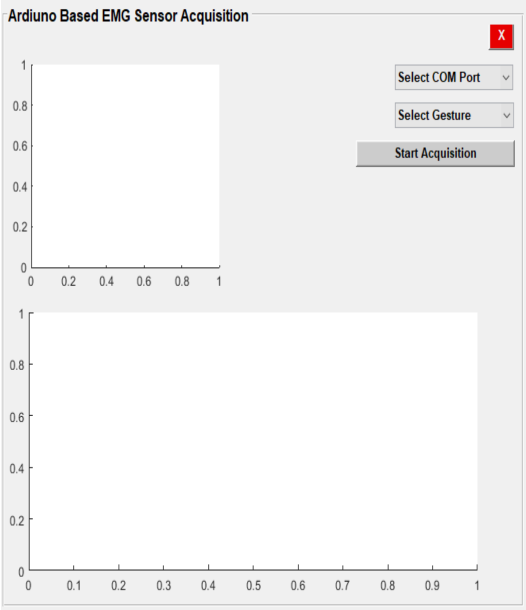
(c)

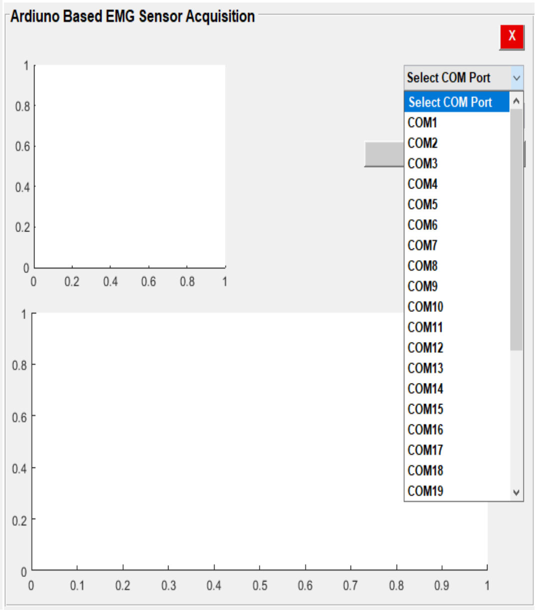
Figure 2. Hardware designed for the proposed sEMG based HGR system

Once the hardware module is designed, it’s time to connect it with the computer through a GUI interface so that the process of communication gets easier. The design of GUI is explained in the next section of this paper.

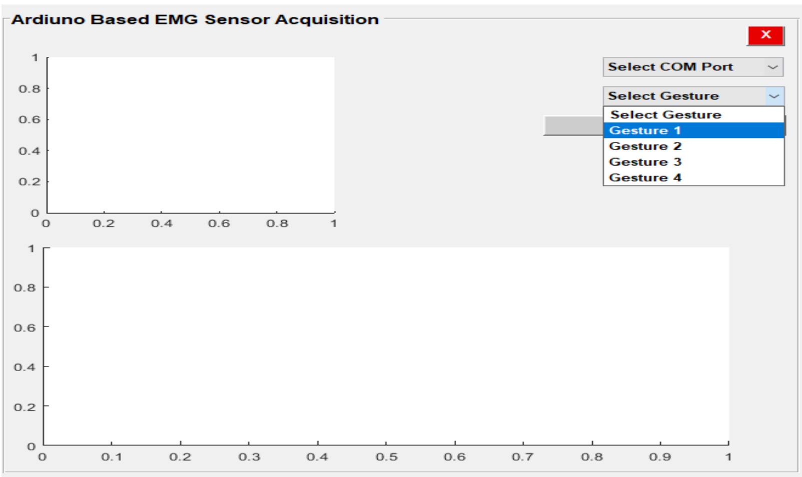
3.3 Designing of GUI

In the next phase of the proposed module, work has been done on designing the Graphical User Interface (GUI) so that interaction between computer and human gets easier and more effective. Moreover, the GUI interface makes the proposed HGR system user-friendly and simpler.





(a) (b)



(c)

Figure 3. GUI for the proposed HGR model

The GUI interface designed for the proposed HGR system is shown in figure 3 a, b, and c respectively. Figure 3 (a) represents the first screen that appears to the user wherein three buttons i.e. select Com Port, select gesture, and start acquisition are deployed. The user can easily navigate to the button and choose the desired action. The Com port is selected by clicking on the "Select Com Port" option and then data can be acquired through the given port by clicking on the "Start Acquisition" button.

As mentioned earlier, that proposed model is designed specifically for analyzing and recognizing four widely used hand gestures i.e. idle, Fist, Extension, and Flexion. Figure 4 shows the images of four gestures that are recognized and analyzed in the proposed module.

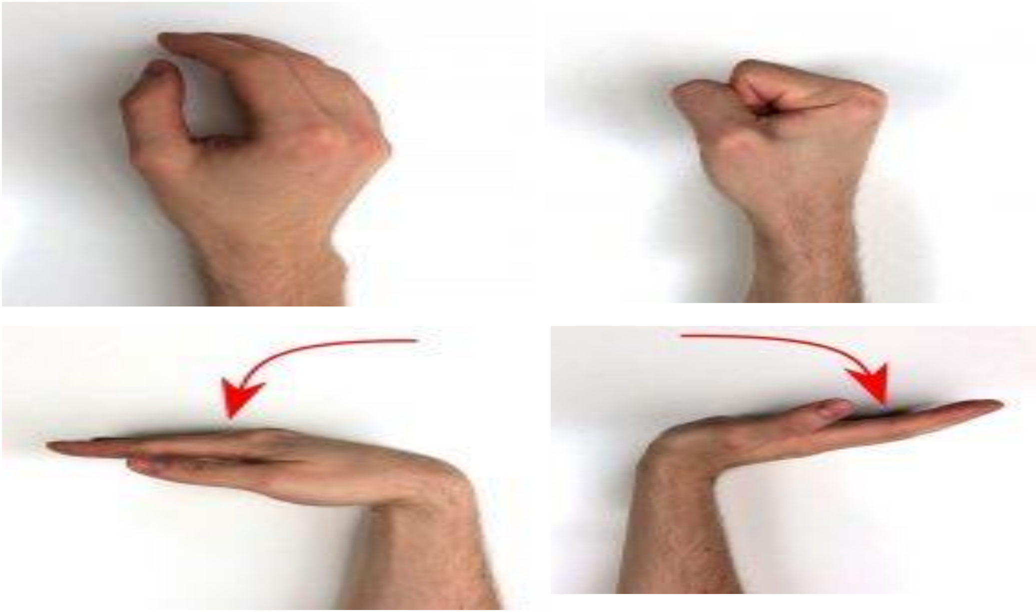


Figure 4. Four different gestures identified in the proposed HGR model

3.4 Data Acquisition

Now, once the hardware and GUI interface of the module is designed, it is time to collect data from volunteer individuals. To do so, the sEMG sensor with two channels in the proposed HGR hardware module is placed on muscles for acquiring data and analyzing it. The main motive of collecting data in a real-time basis is to create our own database that can, later on, be used for recognizing various hand gestures. A great number of individuals came forward as volunteers whose nerve activity impulses were collected by using the sEMG sensor, (see figure 5). The signals generated by the sEMG sensors are received and recorded via two channels, so that accuracy of the detection rate is enhanced. Figure 6 represents the GUI screen of our approach wherein signals received from two channels for fist hand gesture is analyzed ad depicted. The blue and red lines given in the figure demonstrate the EMG signals received for Fist from channel 1 and channel 2 respectively.

Figure 5. Sample collection in labs

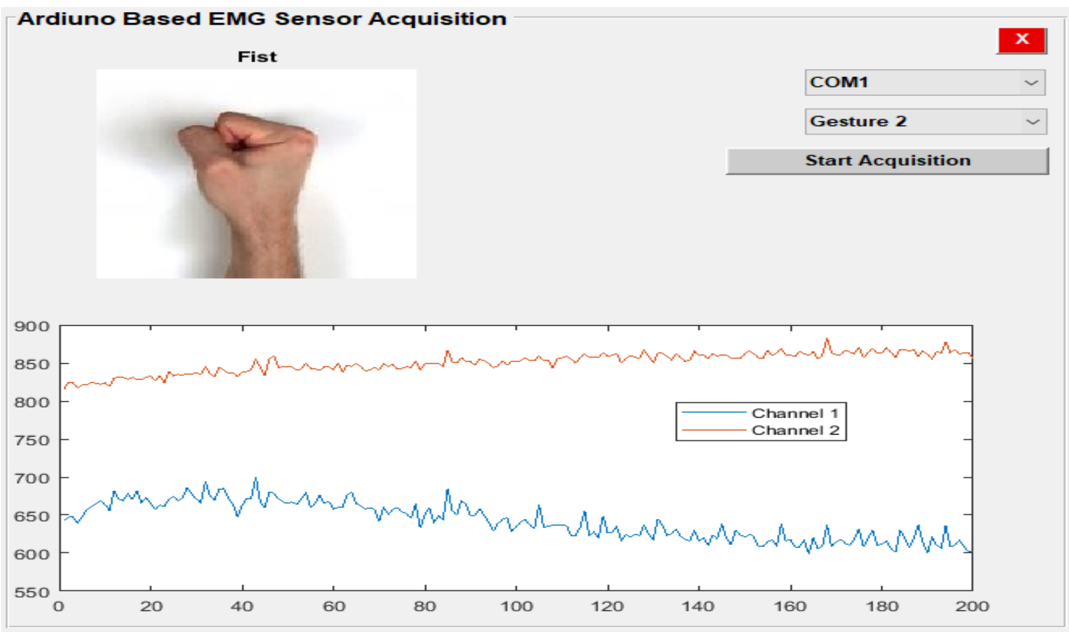
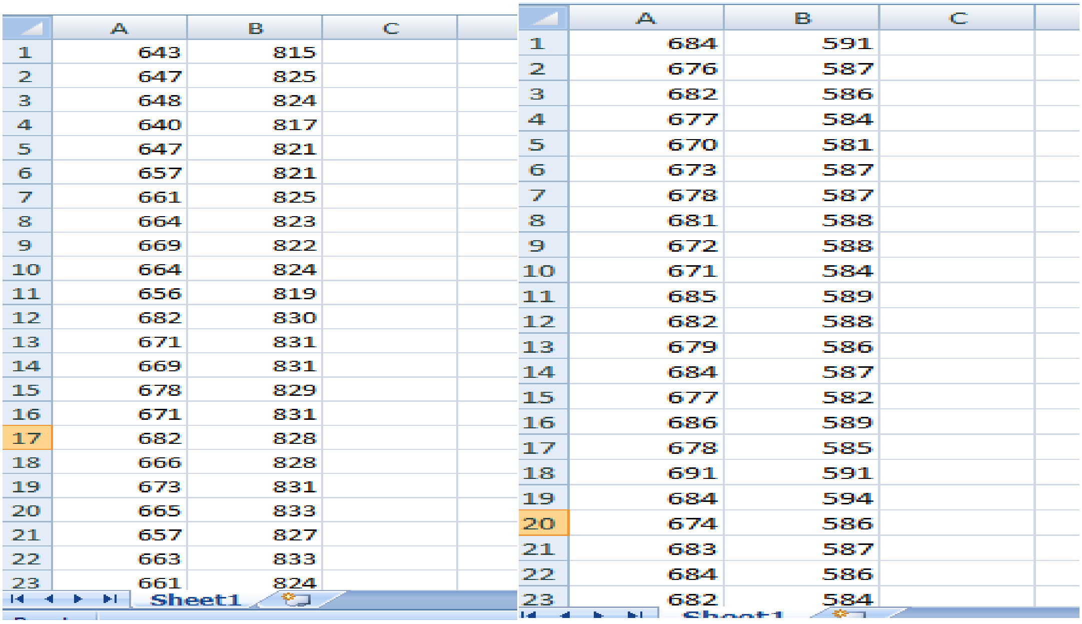


Figure 6. sEMG signals for Fist gesture



	A	B	C
1	643	815	
2	647	825	
3	648	824	
4	640	817	
5	647	821	
6	657	821	
7	661	825	
8	664	823	
9	669	822	
10	664	824	
11	656	819	
12	682	830	
13	671	831	
14	669	831	
15	678	829	
16	671	831	
17	682	828	
18	666	828	
19	673	831	
20	665	833	
21	657	827	
22	663	833	
23	661	824	

Sheet1

	A	B	C
1	684	591	
2	676	587	
3	682	586	
4	677	584	
5	670	581	
6	673	587	
7	678	587	
8	681	588	
9	672	588	
10	671	584	
11	685	589	
12	682	588	
13	679	586	
14	684	587	
15	677	582	
16	686	589	
17	678	585	
18	691	591	
19	684	594	
20	674	586	
21	683	587	
22	684	586	
23	682	584	

Figure 7. Data stored in the proposed sEMG-based HGR model

3.5 Storing Data

After collecting the data samples from individuals, this data needs to be stored and preserved for future use. For storing the EMG signals that are received via two channels, we have used an excel sheet wherein data is stored in two columns for two channels respectively (as shown in figure 7). The x-axis column and y-axis column of the data represent the total number of samples collected and EMG amplitude respectively. This data doesn't contain any null or empty value as data is collected manually, which in return improves the performance of HGR systems. By analyzing this data, the classifier of the proposed HGR model will be trained and its performance will be analyzed in the second part of our work. It must be noted here, that in this manuscript we are going to only test the performance of our hardware module by analyzing the EMG signals from two channels. The analysis for the given four gestures obtained for the proposed work is discussed in the next section of this paper.

3.6 sEMG Signal Processing

In this section of the paper, we are going to analyze the EMG signals that are received for four hand gestures (idle, fist, flexion, and extension). The samples are generated from the real-world by recoding the sEMG sensor on the muscle of individuals. The amplitude of EMG signals with each moment of hand is analyzed and depicted here. Initially, we analyzed the sEMG signal through two channels when the hand is idle or static. The graph obtained for the same is shown in figure 8. The x-axis and y-axis of the given graph correspond to the total number of samples recorded and their amplitude for idle hand gestures. Moreover, the signals received via channel 1 & 2 is depicted by blue and red color solid lines. After analyzing the graph, it can be concluded that channel 1 is showing high EMG signal amplitudes than channel 1. It has been analyzed in both channels that with the increase in the sampling rate the EMG of signals also increases, however, the amplitude is recorded in the range of 420 to 450 for channel 1, while as, it lies in the range of 290 to 300 for channel 2.

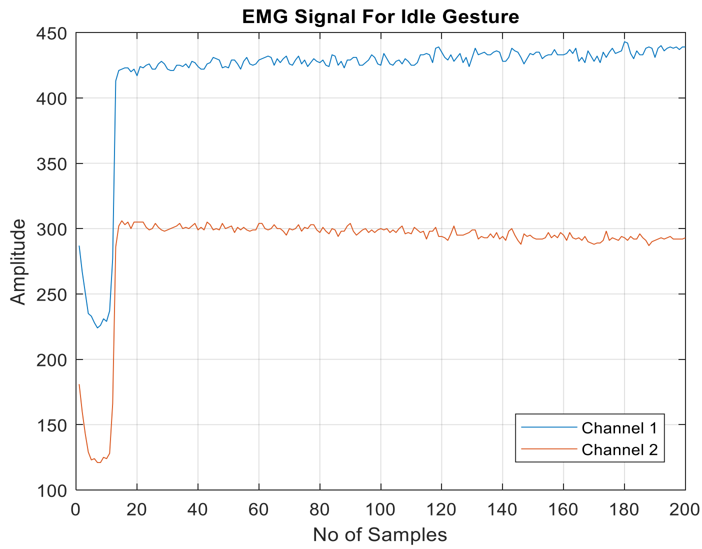


Figure 8. EMG signal for idle hand gesture

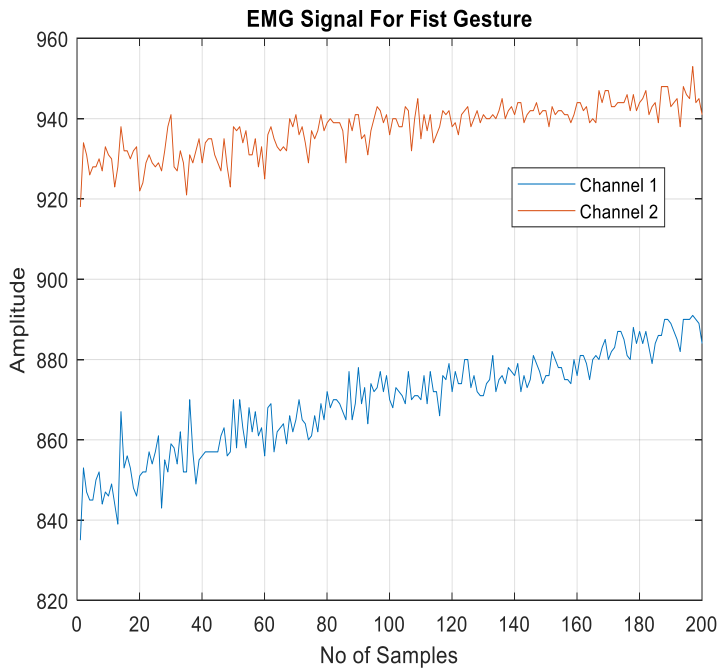


Figure 9. EMG signal for fist Hand Gesture

As mentioned earlier, that EMG signals vary continuously for same gesture in same individual under various physical, mental and psychological conditions. Therefore, we also analyzed the variation of EMG signals for Fist hand gesture through two channels. Figure 9 illustrates the graph that depicts the magnitude of EMG signal with respect to total samples for Fist hand gesture. The fluctuating red and blue lines depict the magnitude of EMG signals for channel 2 and 1 respectively. As analyzed earlier that when hand was idle, higher EMG signal amplitude was obtained by channel 1 than channel 2, however this is not the case here. The amplitude of EMG signal for fist hand gesture reaches to the maximum value of around 950 and its minimum value was 920. On the other hand, channel 1 has least amplitude for Fist hand gesture with minimum value of around 840 and maximum value of 890. It has also ben analyzed that that the amplitude of EMG signals for fist hand gesture keeps on increasing with the increase in sampling rate.

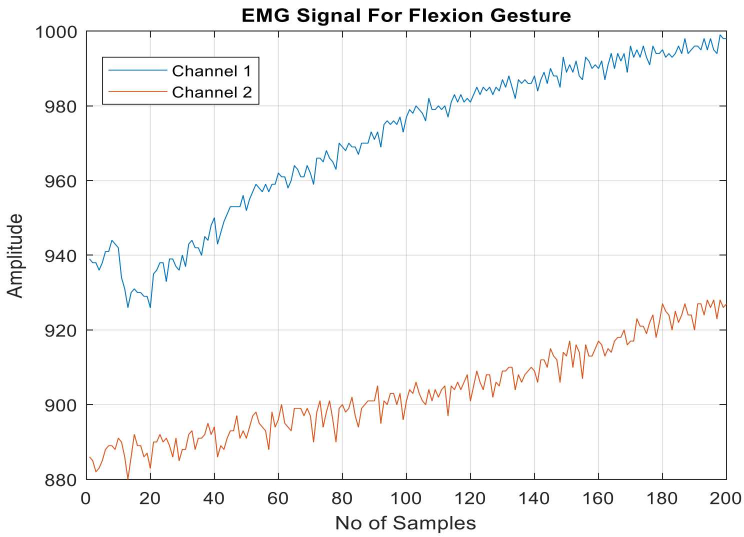


Figure 10. EMG signal for Flexion Gesture

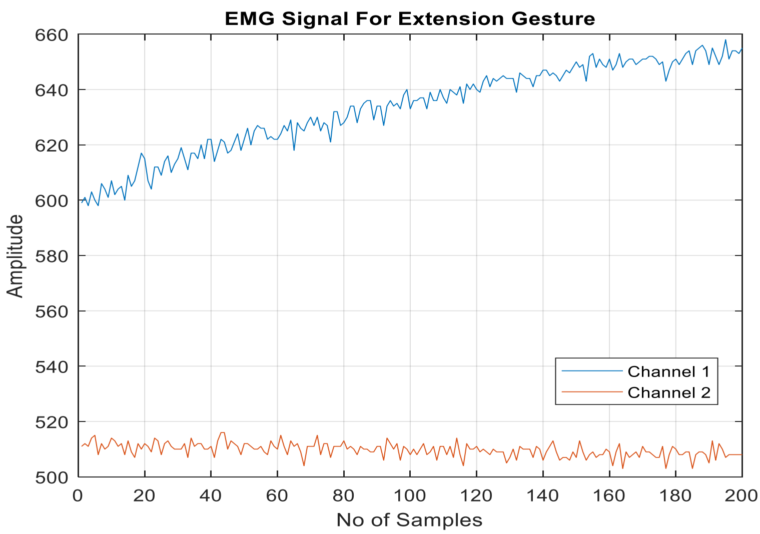


Figure 11. EMG signal Analysis for Extension hand gesture

Furthermore, the EMG signals generated through two channels are also analyzed for Flexion and Extension hand gesture, whose graph are given in figure 10 and 11 respectively. The x and y-axis of the two graphs calibrate to the number of samples and Amplitude of signal at each sample respectively. Also, the signal obtained from channel 1 and 2 are represented by using two colors of blue and red respectively. While analyzing the EMG signals for Flexion hand gesture, we observed that magnitude of channel 2 is far lower than channel 1. The range of EMG signal for flexion hand gesture via channel 2 is in the range of 880 to 920, while as, the EMG signal amplitude starts from 930 and goes up to the maximum amplitude of 1000 for flexion hand gesture via channel 1.

On the other hand, when the movement of hand is changed to extension, we observed huge fluctuation in the magnitude of EMG signals for both channels (see Figure 11). The amplitude of extension hand gesture starts from 600 which then keeps on increasing as the sampling rate is going higher and reaches a maximum value of around 660. Whereas, in case of channel 1, the amplitude of EMG signal is recorded between the range of 500 and 520. These variations observed between the two channels while recognizing various hand gestures will help in determining that whether there is the need of applying any pre-processing, feature extraction technique or not.

4. Summary

This research endeavors to revolutionize Hand Gesture Recognition (HGR) technology by addressing key challenges related to cost and accessibility. Motivated by the aspiration to democratize HGR systems, the study proposes a novel, cost-effective hardware module for the Arduino board, eliminating financial barriers to adoption. Accompanied by an intuitive Graphical User Interface (GUI) module, the research prioritizes user-friendliness. A data-driven approach involves collecting real-time data to create a diverse dataset, mitigating dataset dependency issues. Precision is enhanced through the integration of dual sensors, capturing nuanced muscle activity for accurate gesture detection. The research culminates in a detailed analysis of variations in muscle activity for four hand gestures, refining system performance and advancing the understanding of gesture patterns. In summary, this research contributes to the accessibility and usability of HGR technology through innovative hardware design, user-friendly interfaces, and data-driven insights, fostering its broader application in fields such as gaming and assistive technologies.

4.1 Challenges and future work

The proposed HGR system, while promising, faces several challenges that warrant careful consideration. One prominent concern is the susceptibility to noise and interference from external sources, which can potentially compromise the accuracy of gesture recognition. Overcoming this challenge necessitates the development of robust filtering techniques to ensure the system's reliability in real-world environments. Additionally, users may encounter a learning curve in adapting to the system's nuances and gestures. To address this, future work should focus on implementing user-friendly tutorials or training mechanisms to enhance the overall accessibility of the technology.

5. Conclusion

This paper presents a cost-effective hardware module for detecting four specific (idle, Fist, Flexion and extension) hand gestures. The analysis of the proposed hardware-based HGR module is recorded in MATLAB software. In the proposed approach, data has been collected in real time scenarios wherein, samples have been collected from a number of individuals in order to make the system dataset independent. Moreover, the aim of collecting data from various individuals via two-channel sensors is to analyze the variation of various gestures. This helps in determining the whether there is the need of implementing advanced techniques like data pre-processing and feature extraction before classification. The result analysis simulated that there is a huge difference in amplitude of EMG signals between two channels for each hand gesture. Therefore, in order to optimize these variations and enhance the accuracy of hand gesture recognition, new and advanced techniques must be employed on the dataset so that its overall accuracy is enhanced while cost and dataset dependency is lowered. Looking ahead, the Hand Gesture Recognition (HGR) system could advance by incorporating edge computing for faster processing, exploring applications in human-robot collaboration, and integrating with augmented reality (AR) environments. The development of gesture-controlled smart environments and proactive security applications presents exciting opportunities for expanding the HGR domain.

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