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An EMG signal driven Wheelchair controller for Spinal Cord Injury (SCI) Patients

By

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Declaration of Authorship

I, Shahida Afrin, declare that this thesis titled, 'An EMG signal driven Wheelchair controller for Spinal Cord Injury (SCI) Patients' and the work presented in it is my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
- Any part of this thesis has not been submitted for any other degree or qualification at this University or any other institution.
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An EMG signal driven Wheelchair controller for Spinal Cord Injury (SCI) Patients

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Abstract

In this article, the use of an EMG control based wheelchair is presented. The mechanical design is based on six gestures and eight channel EMG sensors that are controlled by six hand directions. Electric EMG-based wheelchairs are essential for SCI patients. Because cervical spinal cord injury (SCI) creates severe sensory anomalies in their bodies, SCI patients are unable to walk. Their hand nerves do not respond correctly due to their upper limb impairments. It takes a long time for their hand to react. As a result, SCI patients are unable to drive a normal joystick wheelchair manually. They must rely on others to utilize these sorts of wheelchairs. This study attempts to give a novel alternative controlling technology for people with paralysis, particularly of the feet and hands, by creating an electric wheelchair that uses the control of electromyography (EMG) signal as a consequence of muscle relaxation. EMG signals are commonly utilized to quantify torques in human muscles. We have created an electromyography (EMG)-based hand gesture dataset to control electric wheelchair for the patient with spinal cord injury (SCI). We have recorded eight-channel surface EMG (sEMG) signals from the EMG sensor placed at the forearm of the SCI patient. These signals were collected from six hand gesture-based wheelchair control movements (forward, reverse, turn left, turn right, start and stop). We collected hand gesture data containing different EMG signals from 12 healthy subjects and 7 SCI subjects. Later on, The EMG signals were segmented and the time-domain feature extraction technique was applied to generate 18000 training samples and 10500 testing samples. We then classified the hand gestural EMG signals using 5 different classical machine learning models. We analyze the classification results in two ways. The first one is, training the models using only data of healthy subjects and cross-validated using data from 7 SCI patients. And the second one is by including six SCI patient's data in the training process along with healthy subjects we performed leave one out cross-validation. From this analysis we were able to achieve the highest 95.42% accuracy using decision tree (DT) and Random Forest (RF) algorithms.

Keyword - EMG-Based wheelchair, Hand gesture define, Machine learning, EMG Signal, K-Nearest Neighbour(KNN) algorithm

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Dedicated to my parents, husband, and my two amazing kids for their tremendous support to my education…

Chapter 1

Introduction

Electromyography (EMG) is a method that uses EMG-connected electrodes to record muscle activity and measure the change in electrical potential between two muscle locations [1]. Muscle contraction generates electrical impulses, which reflects neuromuscular activity. As a result, an electrical signal is generated every time the muscle contracts. The EMG signal is used to propel the wheelchair forward and backward, as well as to turn left and right.

This study aimed to propose a gesture-controlled electric wheelchair based on learning the appropriate hand gestures from EMG signals. We propose a unique EMG-based hand gesture dataset which runs in several ML algorithms. The dataset consists of gestural EMG signals of the healthy subjects and the real SCI patients from the Centre for the Rehabilitation of the Paralyzed (CRP), Savar, Dhaka, Bangladesh. The dataset we generated includes 18 thousand samples from 12 healthy subjects and 7 SCI subjects after pre-processing. We defined the segmentation window by eliminating noises at the beginning and the end. We have extracted mean absolute value (MAV) features from the time signals of 8 electrodes placed in the armband of the subjects. We have considered both the validation set and test set separately and found convincing classification accuracy using the K-NN classification model, Support Vector Machine, Decision tree, Random forest, and Artificial Neural Network for classification.

Patients with claw hands have twisted or bent fingers as a result of their illness. This gives their hand the appearance of an animal's claw. They are unable to do anything on their own as a result of this. Because their hand takes a long time to respond. Patients may be unable to make the desired hand motion at times.

Paralysis or arm numbness in the human body can be caused by a number of factors. They are controlled by a network of nerves that goes from the neck to the hand and fingers. Any disorder affecting a nerve or a bundle of nerves anywhere from the neck to the hand might produce hand pain and numbness. The first two vertebrae at the top of the cervical spine in the human body are known as the C1 and C2 vertebrae.[2] When they come together, they produce the atlantoaxial joint, which is a pivot joint. Compression of the spinal cord at the C2 level can cause arm and leg tingling, numbness, and/or paralysis, as well as bowel and bladder control problems and other disorders. Severe paralysis of the body below the injured part of the spinal cord may occur in some cases. [3] Cervical spinal cord injury (SCI) causes severe sensory abnormalities in the human body, which is why SCI sufferers cannot walk. Because of their upper-limb problems, their hand nerves do not react properly.[4][5] Their hand reacts slowly. At times, patients may be unable to perform the necessary hand and foot actions. As a result, persons with SCI are unable to manually operate a joystick wheelchair. They have to rely on others to get around in their wheelchairs. As a result, they need a new controller to operate their electric wheelchair. We tried to develop a model by conducting an experiment in CRP with seven spinal cord injury patients to capture data from their arms in order to identify the wheelchair orientation they would want to suggest. Their arm sends a signal when they try but fail to move the wheelchair with their hand. The direction can be inferred from their hand signal. Define some wheelchair-movement hand motions, as well. Based on data collected from regular individuals and patients with spinal cord injuries, we developed a model to train with a specific hand gesture that would be delivered for a certain wheelchair orientation. On the basis of the data, we may deduce the reason for their wheelchair movement. Hand gestures in a wheelchair. We can infer the purpose of their wheelchair movement based on the data. Some wheelchair mobility hand motions need also be described. To investigate the impact of using the features for each of the patients, we have designed and implemented an experiment using the model features. Six feature sets were segmented to provide several situations, including forward, reverse, turn left, turn right, start, and stop conditions. Performance measures such as precision, recall, f-score and accuracy are used to evaluate the efficiency of the prediction. We can determine if the model provides a better answer or not based on the accuracy measurement provided by the model. This thesis makes a contribution by determining the accuracy of the model characteristics and predicting the impacts of utilizing the gadget. We constructed a model to train using distinct hand gestures that would be supplied for specific wheelchair orientations based on data obtained from normal people and those with spinal cord injuries. We can deduce the cause for their wheelchair movement from the data. To investigate the impacts, the high-fidelity prototyping approach was employed for this experiment. In terms of detail and functionality, a high-fidelity (hi-fi) prototype is a computer-based interactive product visualization that is as close to the final version as feasible. It allows for a more in-depth evaluation of usability issues and the development of user behavior conclusions. The hi-fi designs take into account the product's aesthetic and technical user interface, as well as components of the user experience such as interfaces, user flow, and behavior [6]. Appropriate hardware material was used to construct a whole wheelchair prototype. After that, the wheelchair experiment with an EMG sensor was completed.

1.1 Problem Statement

Cervical spinal cord injury (SCI) causes severe sensory abnormalities in the human body, which is why SCI sufferers cannot walk. Because of their upper-limb problems, their hand nerves do not react properly. They have to depend on others to move their wheelchair. For some SCI patients hands nerve does not response instantly. It takes time. The patients who has difficulties with hand movements need a system which can give them freedom to move their own wheelchair. For example, MH.In et al.[7] and P.Polygerinos et al.[8] proposed voice controlled system. this system contains a VAEDA glove uses voice recognition to determine control mode, and to execute commands using EMG signals. Sánchez-Velasco et al.[9] created an emg based dataset for their system. But they did not deploy machine learning approach. Saharia et al.[10] introduced a joystick based wheelchair control system which is not appropriate for the people who has problem in controlling by their hands. So its nesessary to overcome these drawbacks to design the wheelchair for SCI patients.

The primary objective is to develop an EMG-based hand gestural dataset to train the system. The secondary objective is to build a wheelchair prototype to evaluate the user experiences of EMG-based wheelchair interaction through the defined gestures.

1.2 Motivation & Scopes

Every year, between 250000 to 500000 people are suffering from a serious spinal cord injury (SCI), according to WHO. Physical limitations to basic movement are one of three issues that prevent many individuals with SCI from fully participating in society. WHO recommends using suitable assisting technologies to enable individuals with SCI to conduct daily tasks to improve care and overcome health, social, and economic constraints. Only 5-15 % of persons with SCI in poor and middle-income nations have access to the necessary assisting equipment[11]. SCI patient suffers from numbness. This numbness in the human body is caused by the damage of nerves that extends from the neck to the hand and fingers. Due to this fact SCI patients face difficulties in controlling wheelchairs by themselves. Many studies have indicated that various wheelchairs with different mechanics may be useful to SCI patients. There are varieties of wheelchairs available on the market. Wheelchair technology has progressed in recent years. The manual wheelchair went from a very light, compact, and foldable form combining pushing wheels utilizing hand-movement in gliding to one that could be operated using joystick or buttons to ease and give comfort in the movement to paralytics. However, a technological breakthrough is necessary to operate the electric wheelchair with an alternate controller for those who have paralysis in most of their body, particularly their hands and feet, and are unable to drive the wheelchair using joysticks or buttons.

The following points best summarize the motivation of this work-

- SCI patients have to depend on others to move their wheelchair. For some SCI patients hands nerve does not response instantly. It takes time. The patients who has difficulties with hand movements need a system which can give them freedom to move their own wheelchair.

- Researchers and practitioners are interested to design sensor-based system. But EMG based wheelchair with which machine learning approach is deployed can be an alternative and worthy solution for SCI patients.

1.3 Research Challenges

A persistent challenge for the researchers specific to the EMG sensor based system is the need to:
(a) To create a dataset consisting of EMG-based hand gesture signal to control an electronic wheelchair. Though there are existing EMG dataset in this research [9]. But A particular dataset only for SCI patients is needed for proposed system. and
(b) To develop a hand gesture-based wheelchair control for SCI patients by learning the gestures from EMG signal. There are several wheelchar control system: voice control [7][8], head motion control [12], facial expression control [10], joystick controlled[13] wheelchair. The drawback of these wheelchairs are:
Joystick controlled wheelchairs are not for the people who is unable to move their hands. Other systems also have some limitations for SCI patients user.

1.4 Research Contribution

Considering all the limitations of the existing literature, this study addresses the problems that there is not sufficient hand gesture based dataset for SCI patients. Another finding is that existing sensor based wheelchair control system does not deploy machine learning approach for controlling. The principle contributions of this thesis can be summarized as below:

- **A dataset consisting of EMG-based hand gesture signal to control an electronic wheelchair:** A dataset has been created in this research. This dataset contains hand gestural data of SCI patients. For the creation of the dataset data was collected from Centre for Rehabilitation of Paralyzed(CRP), Savar. By conducting a survey and taken data from the patients arm for particular gesture direction dataset was made.
- **High-fidelity prototype EMG based wheelchair can run in real time:** For the evaluation of research work a high fidelity emg based wheelchair is made. This wheelchair can run in real time.

1.5 Thesis Outline

In Chapter 1 the objective of the study has been discussed in a concise manner. Chapter 2 deals with the necessary background & literature review for this study. In Chapter 3, data pre-processing, feature extraction, feature selection, and classification model. In Chapter 4 the experiments are devised and the experimental apparatus necessary to conduct them is outlined. The appropriate formulae are then used to characterize the performance measures. Separately, the results analysis for the experiments are shown. Chapter 5 draws a conclusion to the current study and discusses future directions. The final segment of this study contains all the references and credits used.

Chapter 2

Literature review

In this chapter, we have presented the related works and reviews regarding our thesis. In this chapter the different types of wheelchair for SCI patients related research are described, including the effect and impact of using these model features, accuracy for using, whether these joysticks are suitable or not etc. Finally, the background limitations and challenges are presented at the end of this chapter.

Cervical SCI causes substantial sensory abnormalities in both somatic (e.g., upper and lower extremities, trunk) and vegetative functioning below the level of injury [14][15]. The innervation of the shoulder and elbow flexors is intact in a C5 SCI, whereas the innervation of the wrist extensors and elbow extensors is retained in C6 and C7 injuries. C5 to C7 injuries prevent active elbow extension against gravity [4]. As a result, their arm does not react swiftly. That is why they require an electronic system, such as a smart wheelchair, to assist them. Moreover, SCI patients frequently have hand claws that cause the fingers to twist or bend noticeably.

Claw hands can also be caused by various diseases or accidents. Depending on the severity of the condition, using one's hands to pick up and hold items might be challenging. It becomes difficult for the caregivers to provide support to allow them to move freely.

EMG is one of the most well-known unimodal hand orthosis controllers, needing truly simple algorithms and taking spontaneous action into account. In general, electrodes are linked with the damaged arm's flexor and extensor muscles, and an open-loop system opens and closes the hand when EMG arrives at an edge [16] [14].

In [17], an EMG system has been designed and verified for joint ankle motions. The technology used a multi-channel EMG data collecting device that collects EMG signals under the knee muscles and wirelessly sends them to the computer. The EMG surface system was computed from the skin using dual polar electrodes that includes the desired muscles. In other research, the sensors are placed on muscles that retain consistent EMG signals. Stroke patients, for example, can utilize the upper contralateral extremity [18] or facial expressions [19] to activate EMG-based controls. These two techniques entail learning a regulation that requires the usage of muscles unrelated to the target task.

An alternative approach is to build a multimodal regulation that not only uses EMG but also a more robust sensing modality. The VAEDA glove uses voice recognition to determine control mode, and to execute commands using EMG signals [20]. Under ideal conditions voice recognition is reliable but prone to noise. Radio frequency identification (RFID) tags on items can be used to classify desired hand positions as non-biological switches, again using EMG as a mechanism to execute these positions [21]. RFID tags predetermine which objects the subject will communicate with in real world environments, restricting their usefulness. There has been study of fusing Mechanomyography (MMG) and EMG for prosthetic control [22], [23].

Several research works proposed controls that rely on different kinds of sensors other than EMG. Many of these controllers are unimodal; they activate the system by pressing a simple analog button [24], a wrist bend sensor [24], body- powered motions [25], or myographic force [21], also a hands-free EMG and EOG-based control system is suggested [26]. Authors in [27] presented a low-cost ECG and EMG device that may be utilized for a variety of biometric and medical purposes. The Soft Extra Muscle Glove employs force-sensitive resistors (FSRs) as a monitor because they give useful information when individuals connect with objects [28]. [29] [7], used optical strain sensors to provide location input for control and movement analysis in a pneumatic actuation-based rehabilitation system.[30] These are unimodal control that is yet to be demonstrated to be a reliable system for long-term service and frequently rely on external signals rather than natural hand motions.

EMG signal has been used as an alternative controller for electric wheelchairs in numerous research [2], [31], and [32]. In certain experiments, the electromyography (EMG) signal was coupled with the EOG signal to drive the electric wheelchair.

To move forward and backward, as well as turn right and left, the EMG signal was employed. Meanwhile, the EOG signal was used to regulate the speed of the motors [27], [17].

There are different machine learning-based approaches used by the researchers to recognize activities or gestures to control electric wheelchairs [33]. A KNN-based subtler hand motion classification approach was applied to control the bionic arm to control the wheelchair. An EMG signal-based electric wheelchair control system was proposed in [34]. The Artificial Neural Network (ANN) model was proposed in [35], to recognize control gestures of the electronic wheelchair from EMG signals. Researchers in [7], proposed three EMG signal-based muscle-computer interfaces to operate the electric wheelchair. They collected the EMG signals and tried to regulate angular velocity and linear acceleration of the wheelchair.

Surface electromyography (sEMG) signals have been widely employed in the control of robotic prosthetic devices in recent years, see e.g.[36], [37], [38], and references therein. Russo et al. [39] identify three different hand movements and operate the artificial hand using a commercial artificial hand (Open Bionics), a commercial muscle sensor (MyoWare), and an Arduino Nano module. They created classifiers based on Support Vector Machines (SVM) and neural networks utilizing time domain properties of EMG signals, achieving a performance of about 90%. [11] built a two-channel sEMG pattern-recognition system to distinguish four human hand poses. Handposture identification was performed using the k-nearest-neighbors (KNN) method as a classifier. This technology was used to operate a DIY robotic hand with five fingers that move using four servomotors. The data collecting was done with LabVIEW software, and the servomotors were controlled by an Arduino microprocessor. The authors suggest that research on nuanced finger postures rather than whole-hand mobility should be a future trend in myoelectric control of bionic hands. The mechanical restrictions of the bionic hand and the non-portability of the data collecting and processing system are the key drawbacks of this technology for possible implementation in prosthetic devices.

Wang et al. [40] demonstrated the design and myoelectric control of a robotic hand with five fingers and four degrees of freedom (DOF). The pattern recognition system recognizes eight prehensile hand gestures and is based on Linear Discriminant Analysis (LDA) using a collection of temporal characteristics from EMG data. The hardware consists of four CD graphite brush micromotors, encoders, and line drivers manufactured by Maxon, two DE-2.1 differential EMG sensors with the Bagnoli-4 EMG system manufactured by Delsy Inc., and an acquisition device (National Instruments, PCI-6220). The data processing is done on a PC using LabVIEW software, which limits the system's mobility. The robotic hand has only been tested for gesture detection, not gripping activities. In [13], the use of a commercial EMG armband for the motion control of a prototype hand prosthesis is proposed. The mechanical design is based on an open source six degree of freedom hand.The development of a low-cost prototype EMG-controlled hand prothesis based on an open source robotic hand was presented. The original mechanical design and the actuation system were modified in order to reduce the production cost of the prototype and improve thumb mobility. An EMG-Based dataset also made for their system.

According to study of literature review,research and development activities are necessary to create active EMG-based electric wheelchair that meet functional criteria while remaining cheap. EMG-Based wheelchair can be a solution for SCI patients to control wheelchair by their own.

Chapter 3

Proposed Approach

An EMG sensor-controlled module has been created to collect data from the arm muscle. Previously, EMG data from the neck, thigh, masseter, and buccinators muscles[30] was acquired to power wheelchairs for those with upper limb impairments. Those systems were not that efficient in terms of affordability and ease. Controlling wheelchairs using little hand movements could be trained using machine learning algorithms and accurate commands could be generated to control electric wheelchairs. Upper-limb impairments make it difficult for people to move their wheelchairs using their hands. However, we can easily determine the direction using EMG signals collected from the forearm muscles when an SCI patient performs a hand gesture to direct the wheelchair.[31][41] SCI patients cannot give the proper gesture for wheelchair movement. The classification system can define the movement. Relationship between software and hardware is given below:

3.1 System Design

For the creation of a full wheelchair prototype, appropriate hardware material was employed. The system was built according to their specifications after visiting CRP, Savar and interviewing SCI patients. SCI patients who can occasionally lift their hands can use this device. The system consists of a transmitter and receiver and they are connected via wireless components. The transmitter module is the EMG sensor embedded armband, placed in the forearm of the patient and the receiver part is the wheelchair which is motorized in the workshop.

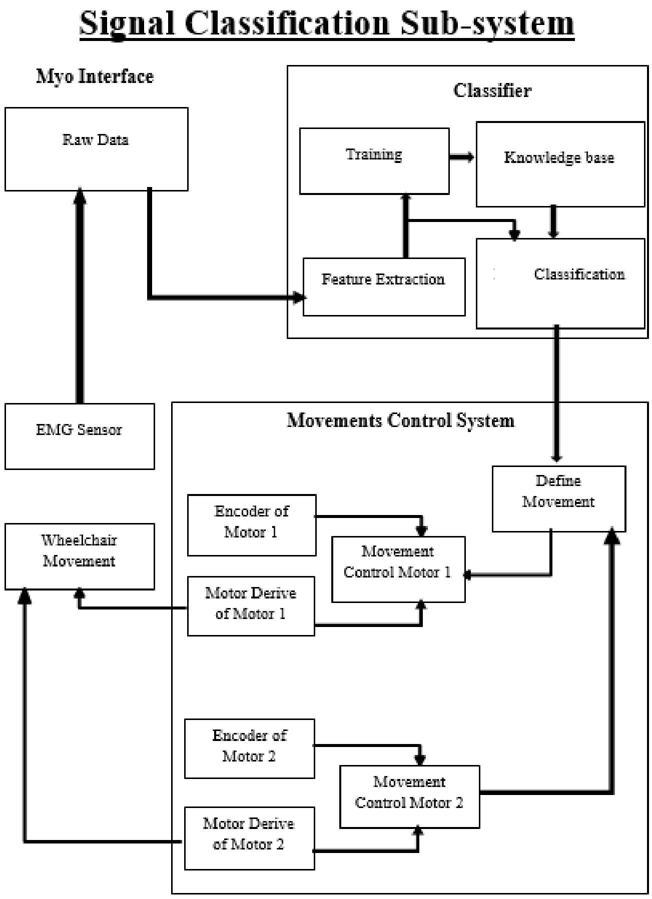


FIGURE 3.1: Relationship between software and hardware

FIGURE 3.2: EMG-based module to capture EMG signals from the patient's arm

3.2 Defining Hand Gestures

In order to carry out this study, we have obtained the information of eight SCI individuals at CRP and defined the wheelchair con- trolling movement gestures accordingly. Those are dynamic hand gestures containing six directional commands to move the wheelchair according to their intention to move. Six gestures that we define are: 'front', 'back', 'left', 'right', 'start', and 'stop'. Figure 4 shows the six hand gestures of the SCI patients. Using these gestures an SCI patient can operate the electric wheelchair. Firstly, the EMG signal is detected and collected from the muscle of the forearm. Then the feature is extracted. After classification of the signal wheelchair movement is defined for the particular hand gesture. The process of controlling the electric wheelchair through hand gesture is given below:

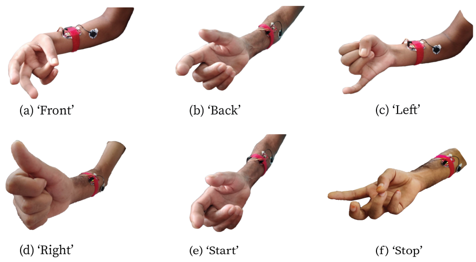


Figure 3.3: Six hand gestures (a–f) of the SCI patients to control directional movements of the EMG-based wheelchair

Both the suggested approach and the experimental method might be used interchangeably in this chapter. The processes for overall techniques include data collection or dataset utilization, data pre-processing, feature extraction, feature selection, and application of the classification model. Our proposed system consists of dataset generation, segmentation and classification.

3.3 Dataset Generation:

Following a visit to CRP, Savar, and interviews with individuals with spinal cord damage, the EMG sensor-based wheelchair system was created to their demands. This gadget can be used by patients with SCI who are unable to walk, use wheelchairs, and can only rarely lift their hands. An EMG sensor attached to the patient's arm serves as the wheelchair's systems transmitter. The motorized wheelchair serves as the receiving component. The system is a mechanism that moves the devices in a predetermined pattern. When a patient is unable to make a correct gesture due to hand clawing, the gadget assumes the EMG signal gesture. Six directions for 6 movements are determined in this system. These motions are left, right, front, back, start and stop. The device experiment was performed with 7 patients at CRP (Centre for Paralyzed Rehabilitation) in Savar, Bangladesh. Patient data were obtained for the device experiment. From the survey, 250 samples were gathered for each gesture movement performed by 7 patients. The link of generated data set is given below: https://drive.google.com/drive/folders/1MhAeyTmRSFXVVqAL8DRtFrLEybPNat5n

EMG signals from various participants, and from different sessions, varied dramatically. Normalizing the data is required to adjust for these discrepancies [42]. Normalization converts the current amplitude to a proportion of the original or smoothed sEMG amplitude [43]. The benefit of normalization is easy and precise; the outcome has no conflict with repetition, and it can increase the model's accuracy. The drawback is that all examined components must be fully peaked and separated in the same session [44]

3.3.1 Dataset Pre-Processing:

A Kalman filter is an algorithm that uses a time series of measurements. These values will contain noise, which will contribute to the measurement's inaccuracy. The Kalman filter will then attempt to estimate the system's state using the current and past states, which is more accurate than measurements alone. The Kalman filter removes noise from the EMG signal.

The problem here is that the accelerometer is often fairly noisy when used to determine gravity acceleration since the wheelchair is moving. The gyro's challenge is that it wanders with time, much like a spinning wheel does when it loses speed.

The Kalman filter creates a statistically optimal estimate of the system state based on the measurement. To do so, it must understand both the noise of the filter's input, referred to as measurement noise, and the noise of the system itself, referred to as process noise. To do this, the noise must have a Gaussian distribution and a mean of zero, which most random noise does. The Arduino library for the Kalman filter is provided below:

https://www.arduino.cc/reference/en/libraries/kalman-filter-library/

3.3.2 Segmentation:

There are two elements to the segmentation stage: gesture detection and sliding windowing. To improve prediction accuracy and training speed, it is usually necessary to determine the region of the sEMG corresponding to gesture or muscle activity and delete signals where the muscles are resting. Following the establishment of a threshold, all instants greater than or equal to the threshold should be extracted from the smoothed signal. The first of these examples depicts the beginning of the muscular activity zone, while the final shows the end of the activity zone [44]. CH1-8 are eight channel sEMG signals, and S2 is the standard deviation of eight channel sEMG signals computed using the moving average approach, as illustrated in Figure 5.

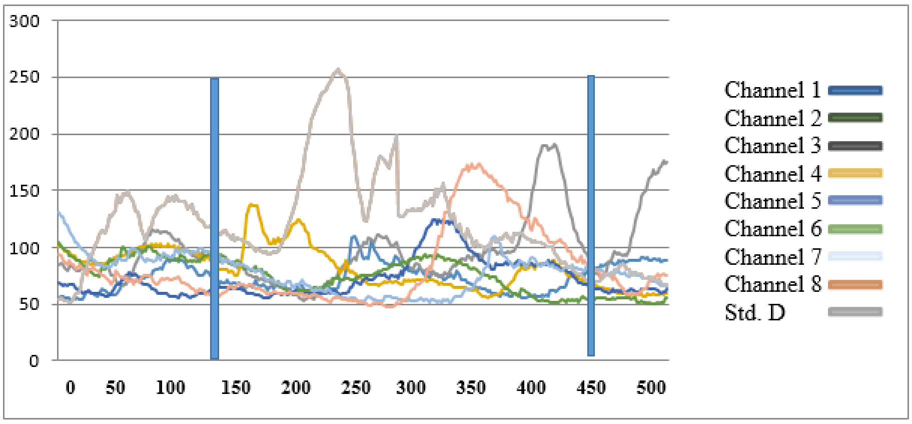


FIGURE 3.4: Segmentation

In the realm of sEMG control, the ideal sliding window length can ensure the lowest classification error with the appropriate con- troller delay [45]. A lengthy sequence may result in a considerable processing delay for the system, whereas a brief window may not include enough valuable information. For a trustworthy control system, the maximum permitted delay between signal generation and driving command creation should be no more than 300 ms [45]. [46] revealed that mechanical sensors benefit from sEMG windows of 150–250 ms. [47] proved that the system's performance declines when the sliding window length surpasses 100 ms. Windows can be separated or combined. Real-time continuous classification needs not just high classification accuracy but also rapid response [45]. The overlapping analysis window method may assist you in making a decision more quickly [47]. The system's major feature is correctly adjusting the window increments. In terms of hardware processing capability, overlapping analysis windows that provide speedy and dense decision processes are often preferred.

In this research, we employed mean absolute value (MAV), which is one of the most often used temporal feature extraction approaches, particularly for EMG data analysis. The MAV's operation is based on the segmentation of the EMG signal, after which a feature is generated for each segment (see Fig. 5). This feature is an average of the absolute value of the EMG signal amplitude in a segment of S samples, providing an estimate of the mean energy of this signal in a specific time period. Given that the EMG signal is split into w segments, each of which contains S samples, the MAV of the $w-th$ segment is defined as in 4.3.2.

$$MAV_w = \frac{1}{S}\sum_{k=1}^{5}|y_k| \tag{3.1}$$

where, y_k is the $k-th$ sample in the segment w. Finally, the feature vector of the EMG signal is defined as $[MAV_1; MAV_2, ..., MAV_w]$.

Because the amount of samples per segment is the sole parameter that influences MAV performance, it is critical to determine the segment length. Different segment lengths are tested in our proposal to see which one gives a more efficient categorization. Because the preceding considers just the EMG signal of one sensor and for eight sensors, the total feature vector is calculated as,3.2

$$x = [MAV_1^1, ..., MAV_w^1, ..., MAV_1^2, ..., MAV_w^2, ..., MAV_1^8, ..., MAV_w^8] = [x_j]_n \tag{3.2}$$

where, $n = 8 \times w$. This vector is used as an input for a classifier.

3.4 Classification Algorithm

After feature extraction, a feature vector is created. Classical machine learning techniques K-Nearest Neighbor, Support Vector Machine, Decision Tree, Random Forest and Artificial Neural Network algorithm are used to assess the performance characteristics.

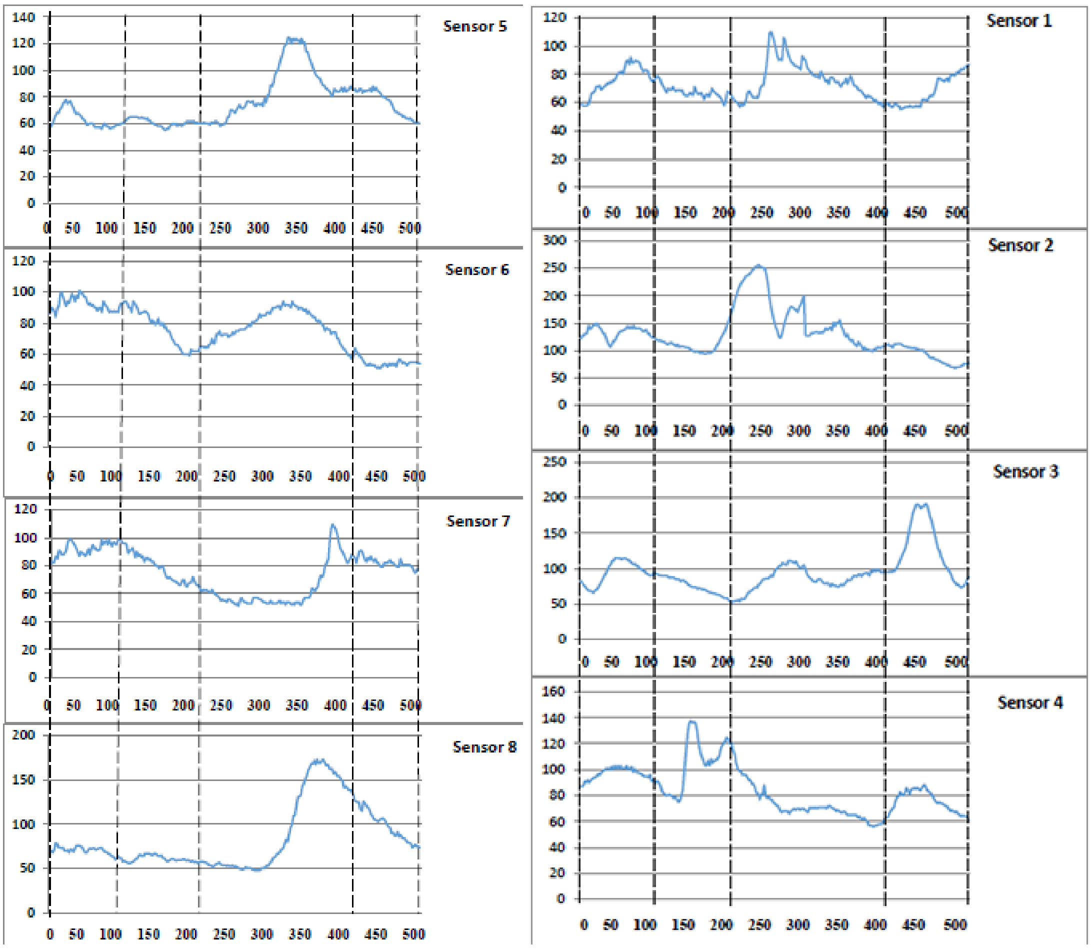


FIGURE 3.5: Segmentation

3.4.1 K-nearest Neighbor:

KNN has lately emerged as a major machine learning technique because to its processing speed and simplicity in the recognition process [48]. KNN is a straightforward notion. The KNN approach builds a collection of k data points from training data and predicts test data using the closest neighbor. The value of k, on the other hand, must be set with care because it has a considerable influence on classification performance [49]. More specifically, the data collection and model formulation have a significant impact on the k-value.

3.4.2 Support Vector Machine

In the categorization of EMG signals, the support vector machine (SVM) is known as one of the best and most accurate classifiers. Many researchers have found that

SVM has a lot of promise when it comes to identifying EMG data [50][51]. In the EMG data set, SVM tries to provide the best classification function for distinguishing members of various classes. SVM also applies the notion of hyperplane separation to data in order to identify data sets that did not separate linearly. The complexity of selecting a kernel function and the longer calculation time are two disadvantages of SVM. According to the research, the radial basis kernel function (RBF) performs best in the categorization of EMG signals [50] [52].

3.4.3 Decision Tree

Decision Tree is a supervised learning method that may be used to solve classification and regression problems, however it is most typically used to solve classification problems. In this tree-structured classifier, internal nodes hold dataset properties, branches indicate decision rules, and each leaf node offers the conclusion. The attributes of the submitted dataset are used to make the judgements or tests. It is a graphical representation of all possible solutions to a problem/decision based on specified factors. To create a tree, we use the CART method, which stands for Classification and Regression Tree algorithm. It just poses a question and splits the tree into subtrees based on the response (Yes/No).

3.4.4 Random Forest

Random forest (RF), based on the theory of decision trees, was first proposed by Breiman [53]. Since RF creates accurate classifiers and regressors given the correct input, it is a helpful technique for prediction [53]. The optimum split among all variables is used to split each node in standard trees. Each node in an RF is divided using the best predictor from a selection of predictors chosen at random. In comparison to other classifiers such as discriminant analysis, SVM, and neural networks, this seemingly paradoxical technique outperforms them all and is resistant to overfitting [54]. Furthermore, when utilized to analyze high-dimensional data, RF takes considerably less time to execute than RBF and SVM since the RF algorithm can automatically identify the key characteristics [55]. It also stands up to outliers and noise well. Because of these benefits, RF was chosen for use in this investigation to investigate the link between the sEMG and the knee joint. By building several decision trees, RF delivers greater generalization performance as an ensemble learning approach. If RF contains N decision trees, N sample sets must be generated to train each tree. Each tree is grown in the following manner [56][57]:

If the number of instances in the training set is Tr, then Tr cases are picked at random from the original data but with replacement. This sample will serve as the tree's training set.

If there are Iv input variables, a number Nf Iv is supplied, so that Nf variables are randomly picked from the Iv at each node, and the best split on these, m, is used to divide the node. During the growth of the forest, the value of Nf remains constant.

Each tree is cultivated to its full potential. Pruning is not an option.

3.4.5 Artificial Neural Network

This study's ANN is a dynamic and powerful back-propagation (BP) network. Its state changes over time until it reaches the final equilibrium point, which is achieved by good training. To build BP, the Widrow-Hoff learning rule is applied to a multi-layer network with a nonlinear differentiable transfer function. The neural network propagation learning rule governs how the weights between the layers change. The neural network is trained with input and target vectors until it can approximate a function, correlate input vectors with certain output vectors, or accurately categorize input vectors based on defined criteria. An input layer, a tansigmoid hidden layer, and a linear output layer comprise the ANN. With the exception of the input layer, each layer has a weight matrix W, a bias vector b, and an output vector a. Layer weights (LW) are weight matrices derived from hidden layer outputs, whereas input weights (IW) are weight matrices derived from inputs (LW). Superscripts are also used to identify the network's distinct weights and other components' source (second index) and destination (first index).

Chapter 4

Experimental Result and Discussion

We have offered an in-depth examination of the experiments conducted for this thesis in this chapter. In this chapter, the experiments are devised and the experimental apparatus necessary to conduct them is outlined. The appropriate formulae are then used to characterize the performance measures. Separately, the results analysis for the experiments are shown.

4.1 Experiments

The research contributions are presented in chapter 1 while describing the problem statement of the thesis. From the contribution point of view, we have designed and come up with two different experiments for this thesis. The first one is, training the models using only data of healthy subjects and cross-validated using data from 7 SCI patients. And the second one is by including six SCI patient's data in the training process along with healthy subjects we performed leave one out cross-validation.

The positive impacts are evaluated by the performance metrics such as precision, recall, f-score, accuracy.

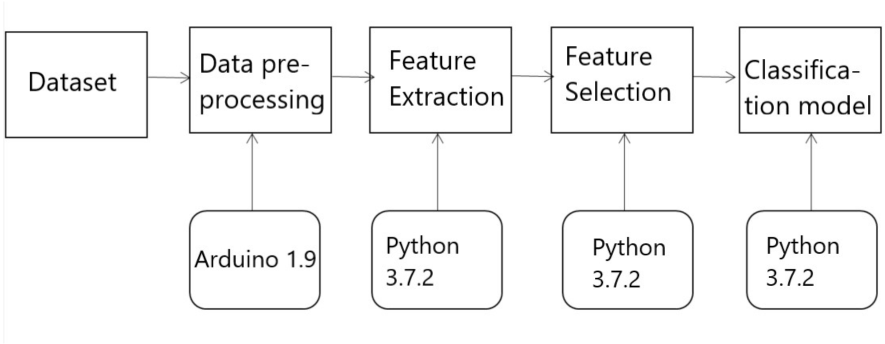


FIGURE 4.1: Experimental setup

4.1.1 Experimental Setup

The experimental setting, which includes data gathering, data pre-processing, feature extraction, data processing, and classification models, was developed according to the ideal pattern recognition procedure. Different sorts of software tools and methods are required for the setup.

As shown in fig. 8, we used a variety of software and open-source tools to assess the performance and efficacy of our experiment. The studies took place on a computer with the following settings.
Operating system: Windows 10
Processor : Core i5
Ram : 8 GB
System type: 64 bit operating system
Internet: 3G Connection of Local Operator

The above figure shows the name of the packages, descriptions and URL links used for the experiments. These open source packages are used in our experiment as they are being used widely by the machine learning researchers.

4.1.2 Performance Evaluation Metrics

For evaluating prediction systems, the widely used performance metrics is finding the accuracy. As we have applied different binary classification algorithms, the evaluation metrics are kept the same for all the algorithms. In this subsection, we are going to describe these performance metrics with the help of formulas to calculate them. In the context of our experiments, True Positive (TP) = Wheelchair

Package Name	Descriptions	URL link
Arduino 1.9	The open source arduino software (IDE) makes it easy to write code and upload it to the board. The Arduino IDE supports the languages **C and C++** using special rules of code structuring. The Arduino IDE supplies a software library from the Wiring project, which provides many common input and output procedures.	https://www.arduino.cc/en/software
Python 3.7.2	Python is a widely used high-level, general-purpose, interpreted, dynamic programming language. Its design philosophy emphasizes code readability, and its syntax allows programmers to express concepts in fewer lines of code than would be possible in languages such as C++ or Java. The language provides constructs intended to enable clear programs on both a small and large scale.	https://www.python.org/downloads/release/python372/

FIGURE 4.2: Open source software/packages used for experimental analysis

directions for hand gesture are actually positive and predicted positive; True Negative (TN) = Wheelchair directions for hand gesture are actually negative and predicted negative; False Positive (FP) =Wheelchair directions for hand gesture are actually negative but predicted positive and False Negative (FN) = Wheelchair directions for hand gesture are actually positive but predicted as negative. For each of the wheelchair directions that we are working on are considered to be examined using these same metrics.

Accuracy is considered to be the base metric for any kind of prediction system. The percentage calculated over the equation is within the range of zero to hundred percent and the more it is the better.

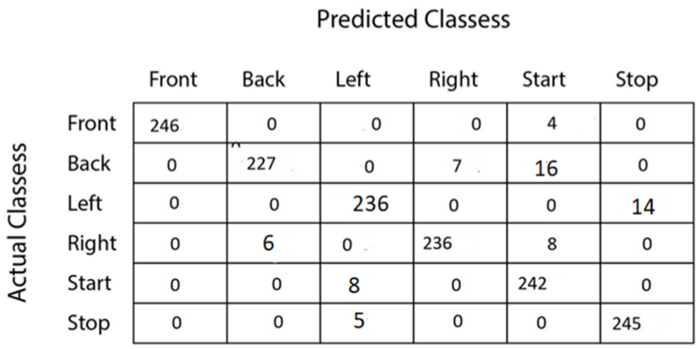
$$Accuracy(ACC) = \frac{TP + TN}{TP + TN + FP + FN} \tag{4.1}$$

SectionResult Analysis of Experiment The training dataset was created using hand gestures from 12 healthy subjects. The test dataset was created using hand gestures from seven SCI patients. Each patient dataset comprises 1500 samples. For our experiment, the outcome of the KNN accuracy test was 94%.For SVM, Decision tree, Random forest and ANN average accuracy is 81%. ,95.42% and 95.42%, 93.14%.

TABLE 4.1: Experiment 1

Algorithm	Test1	Test2	Test3	Test4	Test5	Test6	Test7	Average
KNN	95	92	99	97	95	91	89	94
SVM	76	83	82	77	88	78	81	81
DT	96	94	99	98	97	94	90	95.42
RF	96	94	99	98	97	94	90	95.42
ANN	92	92	97	95	96	90	90	93.14

Highest average accuracy achieved in experiment 1 through Decision tree. Average confusion matrix for decision tree is given below:


Predicted Classess

Actual Classess

	Front	Back	Left	Right	Start	Stop
Front	246	0	0	0	4	0
Back	0	227	0	7	16	0
Left	0	0	236	0	0	14
Right	0	6	0	236	8	0
Start	0	0	8	0	242	0
Stop	0	0	5	0	0	245

FIGURE 4.3: Confusion Matrix of Decision tree

Another experiment was done with a training dataset containing data of the healthy person and patient data mixup. In each training dataset, there is data of 12 healthy people and 6 patients data. Testing was done by one patient's dataset every time. Each testing dataset contains 1500 data of patients. In leave one class out method average accuracy of KNN, SVM, Decision tree, Random forest, ANN are 94.85%. 80.28%. 95.42%,95.42% , 93%.

In the following table accuracy of each testing is given. Testing accuracy table is given below:

TABLE 4.2: Experiment 2

Algorithm	Test1	Test2	Test3	Test4	Test5	Test6	Test7	Average
KNN	96	93	97	96	91	94	97	94.85
SVM	77	84	85	79	76	78	83	80.28
DT	96	94	99	98	97	94	90	95.42
RF	96	94	99	98	97	94	90	95.42
ANN	98	89	95	91	92	91	95	93

DT and RF algorithm shows highest accuracy for leave one class out cross validation. Average confusion matrix for is given below:

Predicted Classess

Actual Classess	Front	Back	Left	Right	Start	Stop
Front	246	0	0	0	4	0
Back	0	227	0	7	16	0
Left	0	0	236	0	0	14
Right	0	6	0	236	8	0
Start	0	0	8	0	242	0
Stop	0	0	5	0	0	245

FIGURE 4.4: Confusion Matrix of Random forest

4.1.3 High Fidelity Prototype Building

We've gone over the system of wheelchair control in depth in this chapter. The processes for overall techniques include hardware setup, dataset utilization, Signal Filtering , feature extraction, feature selection, and gesture recognition from the classification model.

4.2 Hardware setup

There are two portion in hardware. First one is transmitter side which containing the EMG sensor. Second one is receiver side which attached with wheelchair.

Transmitter:
The transmitter side of the system consists of following component:
Arduino Uno

LM2596 Voltage Regulator
EMG Sensor
Gyro Sensor
12C LCD
Radio transmitter

Receiver:
The receiver side consists of following components:
Arduino nano
BTS 7960 motor driver
LM2596 Voltage Regulato
12C LCD
Radio receiver

The equipment used in this prototype are: Wheelchair, Wripper Motor, BTS7890 Motor Driver, Lipo Battery, Arduino Mega, Gyro Sensor, Circuit, Battery Charger, Accelerometer, and EMG sensors

Figure 4.5: WheelChair

Receiver side circuit is attached with motorized wheelchair. Circuit of receiver side is given below:

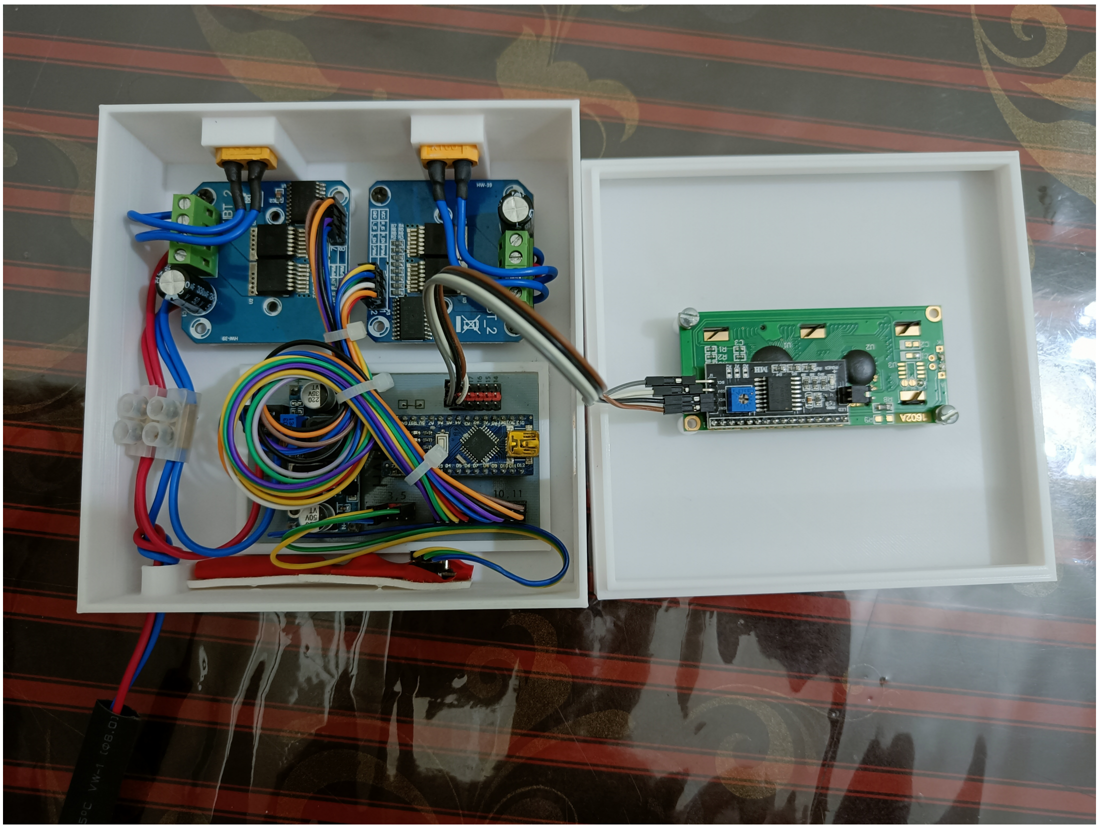


FIGURE 4.6: Receiver side circuit

When signal transmit from transmitter side receiver side responses according to it. The above figure shows the response of receiver side according to transmitter side.

4.3 Implimenting K-Nearest Neighbour in Weelchair

The prediction of motion based on supplied information in a human–computer interaction has the potential to increase the reliability of motion classification to operate a human-assisting device. After processing, the electromyography (EMG) data were employed as a control source for wheelchair movement. K-Nearest Neighbor (K-NN) is one of the most essential and straightforward approaches for recognizing hand gestures. One of the most extensively used and well-known categorization algorithms is K-Nearest Neighbour. Cover and Hart suggested it. [57] Its simplicity and utility have led to its widespread application in a wide range of categorization challenges. [58]

FIGURE 4.7: Receiver side response according to transmission side

Here are a few ways to determine your K-nearest neighbors (KNN algorithm)
1. Determine the parameter K, which is the number of nearest neighbors.
2. Determine the distance between the query-instance and all training samples.
3. Sort the distance and find the nearest neighbors using the K-th shortest distance.
4. Collect the nearest neighbors' category Y.
5. As the query instance's prediction value, use the simple majority of the category of nearest neighbors.

4.3.1 Case Study

The methods of gesture Recognition are divided into two states:

Training Sate: In this section the system is trained by EMG-based dataset. As we have generated our own dataset of 18000 samples we trained with it. For six gesture direction there are 250 samples for each person. Datset containing data of 12 subjects. EMG data has been collected from eight muscle position.

Feature extracted using Mean Absolute Value(MAV).

4.3.2 Classification state

this state has following steps:
Step one: In this step take the feature extraction of input signal to produce vector of six elements Z.

Step Two: Taking Euclidean distance between input vector Z and the data base X.

$$D(x_i, z) = D(x_i, z)i = 1, 2...48 \tag{4.2}$$

$$D(x_i, z) = [\sqrt{(x_i^1 - z_1)^2 + (x_i^2 - z_2)^2 + (x_i^3 - z_3)^2 + (x_i^4 - z_4)^2 + (x_i^5 - z_5)^2 + (x_i^6 - z_6)^2} \tag{4.3}$$

step three: Sort the distance and take first Kth element.
Step Four: Calculate which class has more elements in this group which represents this class.

4.3.3 Gesture Reognition Experiment

There are total six hand gesture direction for six movements of wheelchair(left, right, front, back, start, stop). As we know from confusion matrix there is confusion between back and right. There is also confusion between back and start. So we exclude the back movement when implementing KNN in wheelchair prototype. Firstly we trained our system with dataset. Then feature extracted and classified the dataset into six classes. We put the value of K= 5 to 30. The system gives best performance at k=6. When the system is trained its ready to use. Then the user will give hand gesture to move the wheelchair. Then the Euclidian distance of the training sample and input sample will be measured.Then Kth minimum distance was sorted out. Applying majority rule of the nearest neighbours hand gesture has been recognised for particular wheelchair direction. Time frame for the wheelchair movement was 300ms. For each gesture movement 300ms is allocated. When we have surveyed at CRP(Savar) we record the time period of the patients when they give the gesture. Average time period was 250-300 ms. So during experiment we allocate the time 300ms. So that any user can use this. When the patient gives a particular hand gesture for wheelchair movement the wheelchair move to the particular direction. Patients have to give new gesture after 300ms to continue the wheelchair. Wheelchair stopped before 300ms. It stopped before 5ms. When a patient gives a gesture sensing module get the data from muscle. Then it classifies the data and send to receiver module. Based on class receiver module take the decision of wheelchair movement. Receiver module receive the data from transmitter module through wireless communication. RF based wireless communication has been used in this system.

4.4 Discussion

Using EMG signals to control wheelchairs for SCI patients can be a revolutionary idea. SCI patients are unable to move their wheelchair on their own. So an EMG-Based wheelchair can give them freedom of movement. We can see from the experiment that EMG signals from arm muscles can move the wheelchair appropiately. Using this technology, we can monitor patients' muscle activity outside of the hospital, such as at home or at work. The EMG equipment aids in the transmission of medical information in real time. Electromyography (EMG) is a technique for recording muscle activity and measuring the change in electrical potential between two muscle sites utilizing EMG-connected electrodes. KNN is involved to train the wheelchair. So when user use give the gesture to move wheelchair the signal classified and find the nearest neighbours from trained module. Then it takes the decision of movement.

Chapter 5

Conclusion and Future Work

We attempted to create an Emg-based hand gesture controlled wheelchair for SCI patients in this thesis. EMG signals are commonly used as reference signals because they more closely represent the muscular condition of the individual receiving the signal. The major purpose of this study is to use EMG signals to monitor the movement of a smart power-assisted wheelchair in six directions utilizing data from the forearm. This implies that the method of collecting data from the muscles of the forearm is ideal for the elderly, persons with amputated hands, or people with hand claws. Furthermore, the control mechanism is relatively simple and has a high level of dependability when applied to the wheelchair. This is a low-cost gadget. The initial mechanical design and actuation mechanism were changed to minimize prototype manufacturing costs and increase thumb mobility. The EMG system was used to create a practical and inexpensive wheelchair. Finally, the experimental findings demonstrate the feasibility of obtaining both power and accuracy gripping motions using the suggested integrated system. It works well for SCI patients with hand claws. For experimental assessment, a high-fidelity system was employed. It is beneficial for people who are unable to move properly. A patient who is unable to use a wheelchair. They can use this wheelchair and can control it using their gestures. If they have trouble operating their wheelchair, the signal from the EMG sensor will assume the gesture. We have created an EMG-Based hand gesture dataset to control electric wheelchairs for the patients with Spinal Cord Injury. Classifying the EMG dataset in five machine learning techniques (KNN, SVM, RF, DT and ANN), we were able to achieve the highest 95.42% accuracy in DT and RF algorithms.

For future scopes with this area of research, there are many opportunities and challenges. In this section, we have highlighted some of them.

Applying Modified Machine Learning Algorithms: For more accuracy improvement, any modified feature selection algorithms could be applied on the dataset.

Enhance the Dataset: There is scope to enhance the dataset by collecting data from more patients.

Modify the Wheelchair Prototype: For our research work we developed an Emg-Based electric wheelchair. This chair can be more user friendly by further research.

Appendix A

Appendix

A.1 Survey

We have done a survey on SCI patients in CRP, Savar. We also took signals from their muscle contraction to create our dataset. The questionnaires form of survey is given below:

Findings from the Survey:

1. Patients average age 15-65 years
2. In most cases accidentally fall from rickshaw, cycle, bi-cycle, Slipped in bathroom, pond, or road.
3. Problem faces after having SCI: Numbness in lower part of body, Numbness in back, in several cases numbness in hands.
4. Arround 30% SCI patients of CRP have hand claws due to SCI.
5. In 70% cases patients drive their own wheelchair. Rest of them take help.
6. Patients happily want to wear EMG controllable device in their hands.
7. Gesture giving time varies patient to patient. Average time for one gesture 250-300 ms.
8. 80% patients think EMG-based wheelchair can solve his/her problem. Rest of them have no opinion.

40% patients think the system is comfortable, 25% thinks very comfortable, 5% thinks not comfortable at all, and 30% patients think somewhat comfortable.

Name: Date:

Questionnaire	Answer
1. Patients age	
2. How did the patients have Cervical Spinal Cord Injury?	
3. Problem faces due to SCI	
4. Does the patient have hands claw due to SCI?	
5. Does the SCI patient drive his/her own wheelchair?	
6. Is the patient interested to wear a control device of wheelchair in his or her arm?	
7. How much time does it take to give one gestures?	
8. Does the patient think that EMG-based wheelchair can solve his/her problem.	

If the system is used by patients in hospital or home how much comfortable will it be?

- Comfortable
- Very Comfortable
- Not Comfortable at all
- Somewhat Comfortable

FIGURE A.1: Survey form of SCI patients

A.2 Dataset Generation

EMG data captured from patients arm to create dataset.

Summery of the dataset is given below:

Number of Subject	Number of Sample Per Gesture	Training Sample	Testing Sample	Gesture based movement
12 healthy subject & 7 SCI patients	250 sample per gesture	18000	10500	forward, backward, left, right, start and stop

FIGURE A.2: Dataset Summery

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