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Classification of Hand-Movements using MYO Armband on an Embedded Platform

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MARCH 2018

Declaration

I certify that this research work titled "*Classification of Hand-Movements using MYO Armband on an Embedded Platform"* is my own work. The work has not been presented elsewhere for assessment. The material that has been used from other sources it has been properly acknowledged / referred.

Signature of Student

Haider Ali Javaid

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Language Correctness Certificate

This thesis has been read by an English expert and is free of typing, syntax, semantic, grammatical and spelling mistakes. Thesis is also according to the format given by the university.

Signature of Student

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Copyright Statement

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Dedicated to my exceptional Parents and courteous Grandmother (Late) whose tremendous support, prayers and cooperation led me to this wonderful accomplishment

Abstract

The study proposed the classification and recognition of hand gestures using electromyography (EMG) signals with aim of controlling upper-limb prosthesis. The representation is based on measuring the EMG signals through an embedded system by using a wearable band of MYO gesture control. To observe the behavior of these change movements, we acquired the EMG data of 4 healthy male subjects performing 4-upper limb movements. After extracting EMG data from MYO, we applied the supervised classification approach to recognize the different hand movements. The classification is performed with 5-fold cross validation technique under the supervision of QDA, SVM, Random forest, Gradient Boosted, Ensemble (Bagged Tree) and Ensemble (Subspace KNN) classifier. The execution of these classifiers shows the overall accuracy of 83.9% in case of Ensemble (Bagged Tree) which is higher than other classifiers. This study also gives a comparative analysis of thirteen comprehensive and most up-to-date EMG feature signals in Time-domain and Frequency-domain. To be a successful classification of these EMG features in both domains, we prefer attribute selected classifier as it gives the better performance and higher rate of accuracy i.e. 93.8%. The experimental results prove that features with (TD) are superfluity and redundant while features in case of frequency-domain show the ultimate dominance and signal characterization. The results of this study also inferred the operations which were easy for hand recognition and can be used for developing a powerful, efficient and flexible prosthetic design in future.

Key Words: *EMG, MYO Gesture Control, Prosthesis, Ensemble classifier, MUAPs, Features, Time-domain, Frequency-domain, PSD*

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Chapter 1 INTRODUCTION

The research work involve in this dissertation is about to design and develop a system to measure and classified the hand-movements using non-invasive techniques. In past different invasive and non-invasive techniques have been establishing to design a feasible system for the assistance of amputee in the movement of prosthetic hand. The prosthetic hand movement is usually based on the Electromyography (EMG) signals produces through forearm muscle. Medical research refers that different parts of forearm muscles and EMG signals related to hand and fingers can still be measurable even after loss of hand. Detection, analysis and classification of EMG signal is a very known topic these days in biomedical industry, especially in case of prosthetic hand movement. So, it concluded that the motion of prosthetic hand can still be performable even after loss of real hand.

1.1 Electromyography (EMG)

Electromyography (EMG) is a diagnostic approach to evaluate the health of muscles and neuron cells that use to control them as motor neurons. These motor neurons are responsible to transmit electrical signals through muscles to contract them. The Electromyography (EMG) signal is the electrical illustration of neuromuscular activity linked with muscles contraction. It is extremely complex signal which is influenced by the physiological and anatomical properties of muscles, the action of peripheral nervous system and the characteristic approach of instrumentation used to detect it. A neuron acquires the wealth of coincide information from another neuron through its connection to dendritic tree. It integrates this information at summing area near the axon hillock engendering the action potentials whenever an electric gateway is reached. Action potential transmits actively through axon with minimal attenuation as shown in figure 1. The action potential can travel up to 100 m/s for myelinated axons having larger diameter. The action potential totally relies on the muscle's diameter, distance between muscle and detection site and the properties of sensors or electrodes use for detection.

In our clinical and biomedical field, the EMG testing has a variety of applications. EMG can either be used as a diagnostic tool to locate the neuromuscular diseases or to control the prosthetic hand movement.

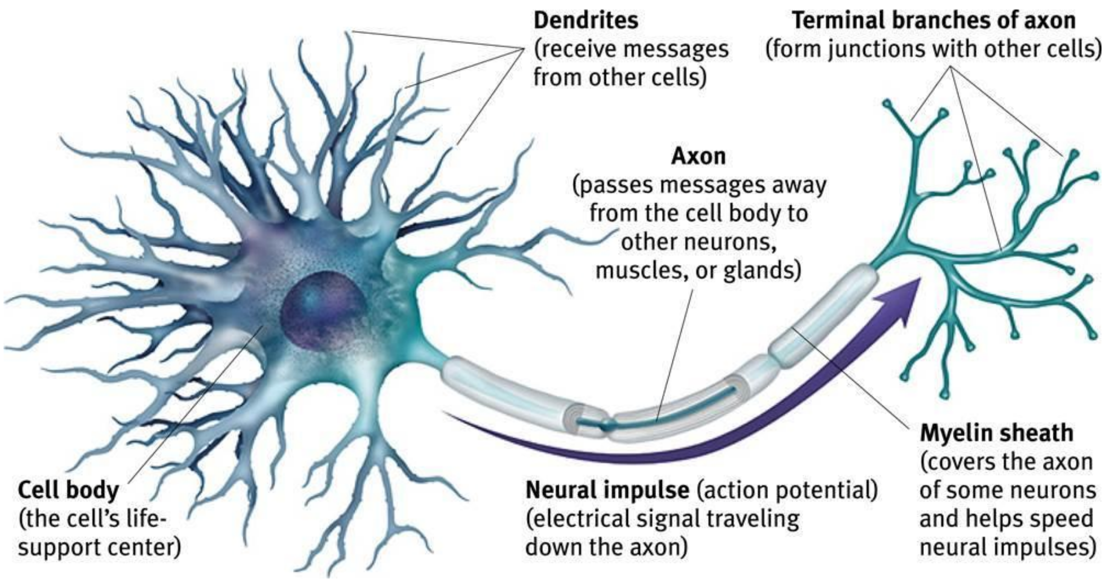


Figure 1.1 Structure of Motor Neuron [36]

In past, myoelectric control systems have been used to control any upper-limb assistive devices or prosthetic arms by steering classified EMG signals. Mostly available literature on EMG pattern focus on enhancing the classification accuracy and its usability to control assistive devices or any upper-limb prosthesis as shown in Figure 1.2

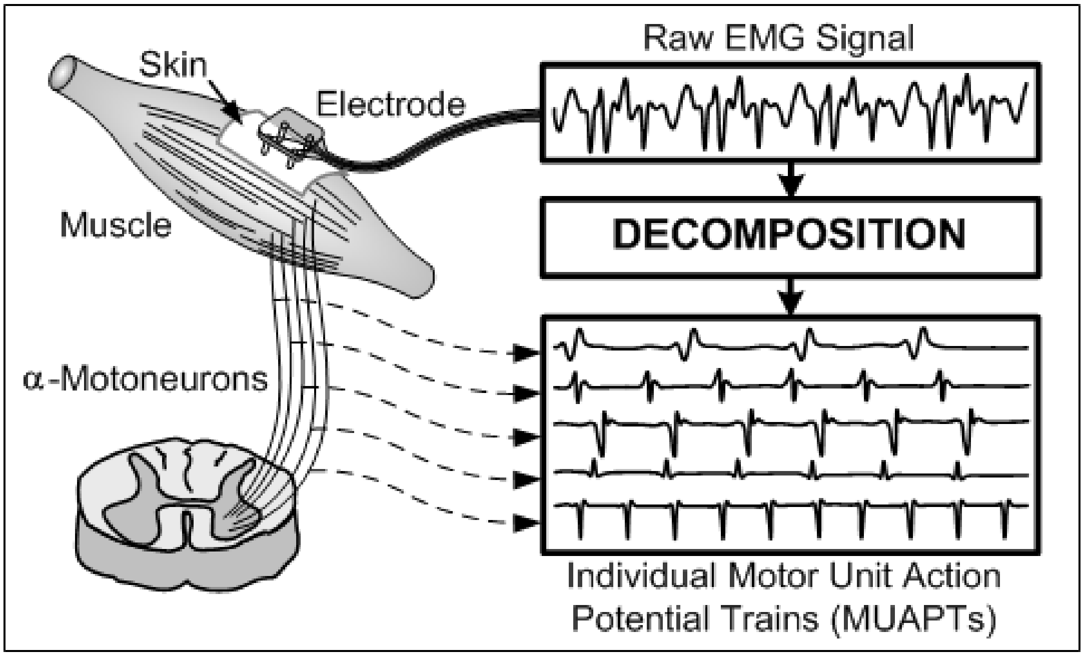


Figure 1.2 EMG Signal Decomposition [37]

1.1.1 Electrodes used for EMG signal acquisition

There are basically two types of EMG electrodes used to measure the muscle activities from forearm muscle. These electrodes are known as

1. Surface EMG Electrodes
2. Intramuscular EMG Electrodes

1.1.2 Surface EMG Electrodes

Surface EMG Electrodes are used to assess the muscle functions by measuring the action potentials of muscles from the surface above the muscle on skin. Surface electrodes can only give the limited measurement or assessment of muscle's activity. Surface EMG signal can be recorded by the pair of electrodes or multiple set of electrodes. There should always be more than two electrodes to measure the EMG activity as it required one as reference electrode to display the voltage difference between them. Limitations of this approach are inherent noise in the electronic component, ambient noise initiates from the sources of electromagnetic radiations (such as electrical power wires, radio, television transmission and electric bulbs etc.) motion artifacts and inherent instability of EMG signals. A schematic of surface electrodes to measure the EMG signal is given in Figure 1.3 below.

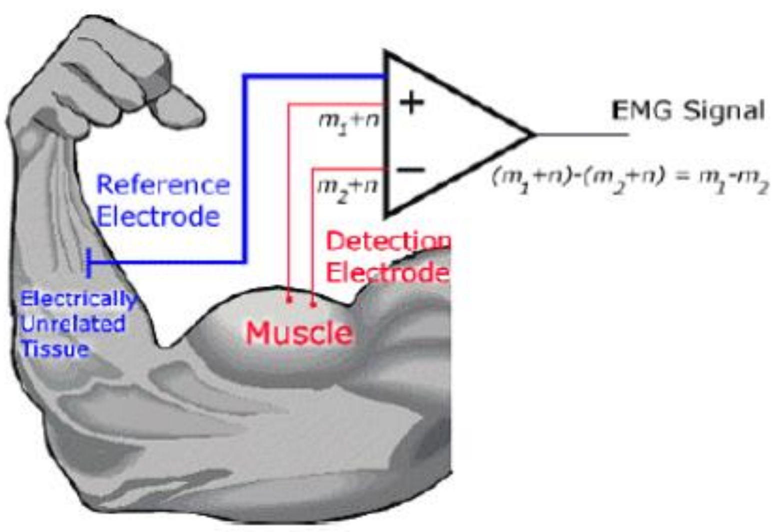


Figure 1.3 A Schematic of surface EMG electrodes with differential amplifier configuration [38]

1.1.3 Intramuscular EMG Electrodes

Intramuscular EMG electrodes also play a vital role in acquiring the EMG data through various recording techniques and usually refer as an invasive approach. Monopolar needle electrode is one of the simplest approach of intramuscular EMG electrodes consisting of a fine wire to penetrate into a muscle with a surface electrode as a reference outside. Two wire monopolar needle electrode is also used to inject in muscle for data acquisition with reference to each other. These monopolar EMG electrodes are insulated and basically stiff enough to insert in skin with the tip exposed to reference using surface electrodes. Most commonly these intramuscular electrode fine wire recordings are used for research or in studies of kinesiology. Figure 1.4 represent two different types of intramuscular electrodes to measure EMG signal.

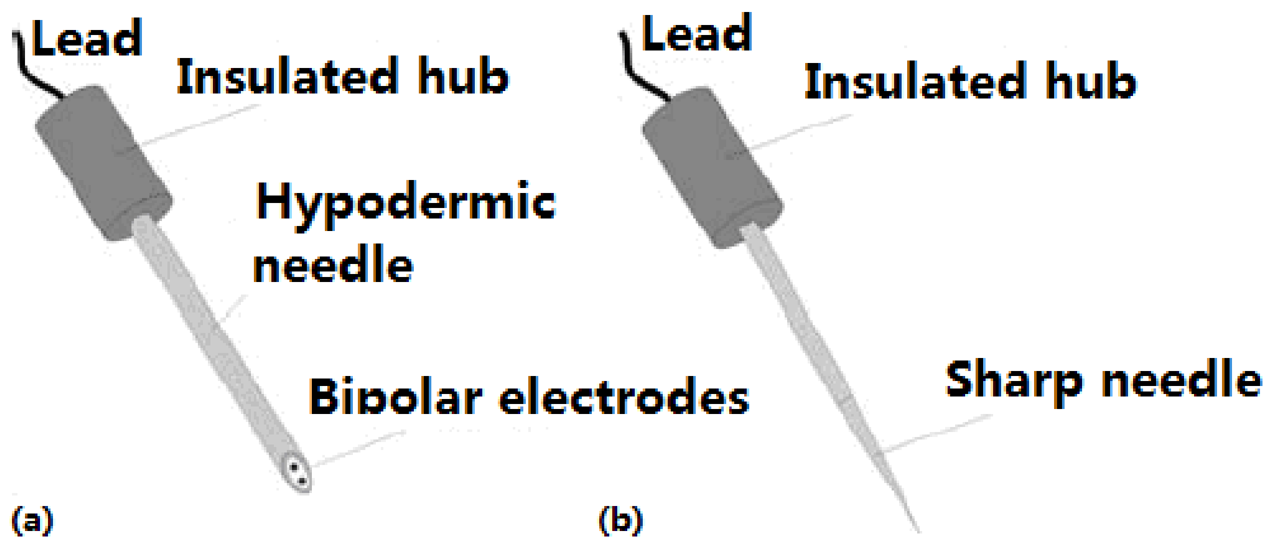


Figure 1.4 Types of Intramuscular EMG Electrodes [39]

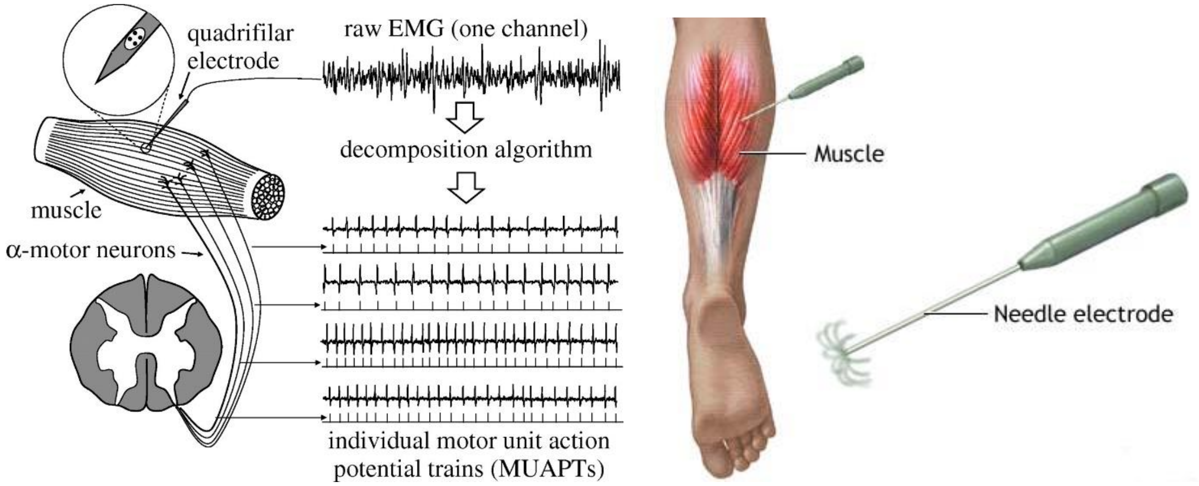


Figure 1.5 EMG Signal acquisition through intramuscular EMG electrodes [40]

1.2 Invasive and Non-invasive approaches to assess EMG signals

Different invasive and non-invasive approaches have been used by different researchers in their studies to utilize the EMG signals in better way to perform upper limb movements.

Surface electrodes were used by Nihal Fatma et al [12] to take the EMG signals from the ulnar nerve of patients with DAQ board(PCI-MIO-16XE-10) and 16-bit A/D converter which was stored in computer's hard disk. The stored EMG data was then used for feature extraction using FFT and PCA.

Yu Su et al. [1] used 11 electromagnetic sensors to capture the corresponding hand pose in real time. In this technique exterior EMG sensors were used to measure the categorization of EMG potential with the help of PC sound card and a novel 3-D electromagnetic positioning system along with a data-glove on which 11 miniature electromagnetic sensors were mounted.

Derya Karabulut et al [3] used SEMG sensors to carried out the EMG data for six healthy subjects. Two types of muscle contraction: (Isometric & isotonic) and (anisometric & anisotonic) were consider to take EMG data for applied forces. Surface electrodes show the limited asses to count the muscular activity. In case of SEMG a pair or electrodes or a complex array of multiple electrodes would be use to count the muscle data. Because EMG recording exhibit the potential difference between the two electrodes so that's why we need more than one electrode to capture data.

Zachary Abraham et al [5] used a three dimensional (3D) printed prosthesis for below-elbow amputees paired with MYO armband to provide an affordable, practical, and convenient solution for amputees.

During dynamic contraction six pairs of surface electrodes (Ag/AgCl) were used on dominant forearm muscle. The surface EMG data with amplified gain of 2000dB, filtered between 47 and 440 Hz, and sampled at 1024Hz were recorded during the bipolar derivations. T. Lorrain et al [7].

Muscle-gesture computer interface (MGCI) with wearable MYO armband is used to control the five-fingered robotic hand movement. The MGCI basically consists of three parts: (a) MYO armband with user (b) muscle- gesture interface (c) The Robotic hand. The muscle-gesture computer interface recognizes the hand or wrist motion under supervision of three steps as segmentation, feature extraction and classification by Guan-Chun Luh et al [5].

The geometric characteristics of hand describe the hand posture depends upon the finger locations, center of palm location and wrist positions. To localize and extract each finger, an algorithm of weighted radial projection with its origin at wrist position was applied. The system used in this approach can not only evaluate the features of extensional fingers but also the flexional fingers with rate of high accuracy. For this approach Yimin Zhou et al [6] proposed a novel method in real time for recognition of hand gesture.

Abdulhamit Subasi et al [10] proposed different methods of feature extraction for understanding motor unit action potential (MUP) morphology. The (MUPs) in EMG signals have a significant source of information to aces the neuromuscular disorders. Needle electrode was used to record the EMG data from a contracted muscle to investigates its neuromuscular disorder. For classification of EMG signals soft computing techniques had been adopted that will automatically classify the EMG signals into normal, myopathic or neurogenic. For this purpose, three classifiers named as multilayer perceptron neural networks (MLPNN), Adaptive neuro fuzzy inference system (ANFIS) and dynamic fuzzy neural network (DFNN) were compared in order to their accuracy for EMG classification. The results show that the adaptive neuro fuzzy inference system (ANFIS) has a high degree of accuracy, recognition rate and repeatability than (MLPNN) and (DFNN) for classification of EMG signals.

Although aforementioned approaches improve the cost of amputation but it is still very expensive particularly for the patients of under developed countries. Therefore, in this study we'll try to give a non-invasive, feasible and cost-effective solution for people with amputation.

1.3 Classification

Classification is an approach of data mining that is used to assign categories to a big amount data in order to evaluate the accurate predictions and analysis. The aim of classification is to forecast the true class accurately for each class in data set. For example, a classification prototype could be used to predict the behavior of weather as cloudy or shiny on basis of data set provided or it may be used to predict the loan applications as low, medium or high credit in banking systems.

Binary classification is the modest form of classification problem. In binary classification, the target attribute has only two possible values: if we take the example of weather than either it would be shiny or cloudy. Multiclass targets have more than two values: for example, shiny, cloudy, Rainy, or unknown. Figure 1.6 shows the classification model for predicting the behavior of weather in future.

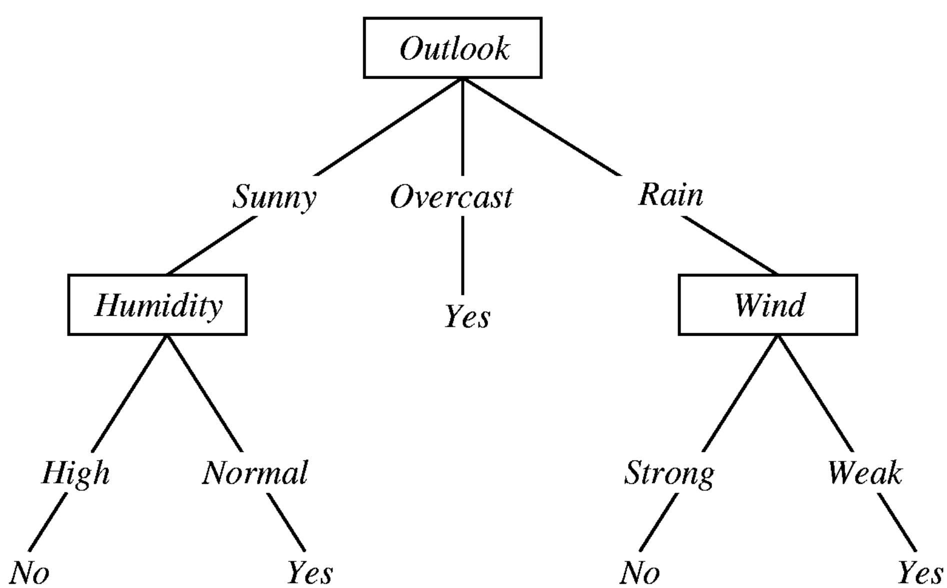


Figure 1.6 Classification model for weather prediction [41]

1.4 Classification algorithms and classifiers

Different classification tools and approaches are available that has been used to classify the big amount data for prediction and analysis. Some classifiers names are given below while their details would be discus briefly in chapter 3.

1. Linear Discriminant Analysis (LDA)
2. Quadratic Discriminant Analysis (QDA)
3. Support Vector Machine (SVM)
4. Decision Tree Algorithm
5. K-Nearest Neighbor Algorithm (KNN)
6. Neural Networks (NN)
7. Artificial adaptive neuro fuzzy inference system (ANFIS)
8. Fuzzy Inference system (FIS)
9. Random Forest
10. Naïve Bayes classifiers
11. Artificial Neural Networks (ANN)
12. Multilayer perceptron neural network (MLPNN)
13. Ensemble classifiers
14. Linear Regression
15. Logistic Regression

1.5 Classification Tools

For extracting data to get good results and better accuracies in prediction, different platforms are available in field of machine learning to provide assistance namely known as

1. WEKA
2. Classify Learner
3. Rapid Minor
4. LIBSVM
5. SAGA GIS
6. Oracle Data Mining
7. Natural Language Toolkit

8. Opticks
9. Orange
10. Cloud compare
11. Orfeo toolbox
12. Keras
13. Apache Mahout
14. JUICE
15. llastik

Chapter 2 LITERATURE REVIEW

This chapter includes the study review on basic knowledge regarding the history and the work so far in the field of upper limb prosthetics, interfacing techniques, classification of hand-movements and the feature extraction methodology. The next chapter will be the introduction of our specified products MYO, arduino and HM-10 blue tooth module. Besides, this product (MYO) has built in Electromyography (EMG) sensor to give raw EMG data of muscles in several hand gestures, thus to understand how the sensors work to measure the muscle activity one should have a basic understanding of (EMG) study.

Different techniques used for prosthetic hand movement:

Different research papers have proposed different designing techniques for interfacing of prosthetic hand with amputee. Some used the surface (EMG) sensors to perform the gesture of upper prosthetic limb while some used the classical methods of 3-D Electromagnetic positioning system to control the prosthetic hand. But with the development of MYO arm band by Thalamic labs a new revaluation come in the field of prosthesis, robotic arms, biomedical, spy drones and other field of life.

Yu Su, Mark H. Fisher, Andrzej Wolczowski, G. Duncan Bell, David J. Burn, and Robert X. Gao [1] proposed a novel method to control the prosthetic hand through electromyography (EMG) potential generated by forearm muscle when hand and finger movement occur. In this technique superficial EMG sensors were used to measure the classification of EMG potential with the support of PC sound card and an innovative 3-D electromagnetic positioning system along with a data-glove on which 11 miniature electromagnetic sensors were mounted. These 11 electromagnetic sensors were used to attain the consistent hand pose in real time. The corresponding measurement of hand motion and the accompanying EMG signals deposited as prototypes exemplify a numerical expression of hand shape in the form of sequence of data frames, each contain of a set of posture and its allied EMG data. This permits a engendered graphical 3-D model to combine with quantified EMG signals to assess the approach of hand movement. This graphical user interface (GUI) might also empower the amputees to exercise a prosthetic hand movement using EMG signals derived from their forearm muscles. By comparing the results of EMG data mounts with stored prototypes, mostly the data frame order can be recognized and used to control a prosthetic hand according to user's desire.

Zachary Abraham, Dong Bien Kwon, Talia Solomon, Michael Xie and Karina Yeh [2] used a three dimensional (3D) printed prosthesis for below-elbow amputees paired with MYO armband to provide an affordable, practical, and convenient solution for amputees. The MYO gives EMG data of forearm muscles and the orientation data of arm as well. The data was processed to arduino that interfacing with servo motors attached with prosthetic hand to rotate. The arduino was programmed in visual studio with C++ to accept the data from MYO to execute its desired gesture.

Asilbek Ganiev, Ho-Sun Shin and Kang-Hee Lee [3] give an idea to control the virtual robotic arm which was built in Unity 3D (a very popular intuitive interface application use to create virtual space, 3D objects, animations and visualize experimental results) by EMG, accelerometer and gyroscope sensors. For this purpose, they used the MYO armband that gives all features in one band. To detect the electro activities in muscle EMG sensors are used. They used the obtain EMG data from muscle to control the virtual robotic arm and compare it with another virtual robotic arm processed by accelerometer and gyroscope to show their dynamic movement of arm.

Mahmoud Abduo and Matthias Galster [4] study the relationship between surface electromyography, hand kinematics and the accuracy of MYO armband. For this an experimental setup used a data gaining interface to gather (sEMG) to organize hand movements and the accuracy of MYO can be equated to other devices of similar benchmark. By investigating its performance results show that MYO armband can be a very suitable and viable replacement for other sensors as it is comparatively inexpensive than other sEMG electrodes such as Ottobock and Delsys electrodes. They also used the data acquisition setup to classify the hand movements of 2 classes of people, normal and amputees. The data acquisition set up consists of several integrated sensors to compute the dynamics, kinematics and muscular activity. They used a CyberGlove II dataglove, a Finger-Force Linear Sensor and either OttoBock or Delsys double differential sEMG electrodes to record the data. The data obtained was relabeled, synchronized and filtered. The data was tested for 50 gestures. For normal subjects, the highest classification accuracy was approximately 75% while for other class; the highest classification accuracy was approximately 46%.

Paul Bernhardt [5] on MyoBlog talks about how to interface Myo armband with arduino using an app of MyoDuino (available in Myo Market) that will run on PC. It would be mostly hardware focused. Before interfacing you should have an Arduino(UNO), Myo armband, Arduino software/IDE and a window PC. Microsoft Visual C++ Runtime will also be there for MyoDuino project. In this technique of interfacing your PC perform as a bridge among Myo armband and the Arduino board. To make you Arduino eligible you should first open the Arduino SDK and add the MyoDuino/Arduino/Myo Controller folder as a library. After that import the microcontroller example and tweak your set up. It's set up use 4-8 pins, with one pin for each hand pose. The pin is set to HIGH when new pose detected otherwise all the pins are set at low with rest of motion. Now go for your sketch and make sure that your Myo is connected to your computer and synced.

Vroland share his experience in a blog on github named with Getting Started with MyoBridge Firmware [6] in which he describes that how to use the MyoBrigde Firmware with HM-11 blue tooth module directly without bridging it through a computer. For flashing the Myobridge firmware we need a blue tooth of HM-11 with CC Debugger or a CC Loader file to execute its program on arduino. Soldering equipment and breadboard is also necessary. For flashing the firmware, you have to be a Smart RF Flash programmer. If you have no such file for the chip or you want to modify your firmware, then you have to go with IAR Embedded workbench for 8051. After successfully firmware flashing, MyoBridge is ready to use with arduino. Now you have to connect your arduino with HM-11/MyoBridge Module.

Selami Keleş and Abdulhamit Subaşı [7] proposed a precise system to classify EMG signal using decision tree algorithm. They preprocessed the EMG signal for features selection using autoregressive method (AR). Different filtering methods and decision tree algorithms namely CART, C4.5, Random forest and Random tree are applied for feature reduction. EMG signals are classified in three classes as Myopathy, Neuropathy and Normal. All data are compared each other to discover the best classification and feature reduction methods. The tree algorithms classify the data with accuracy of 89%, 82% and 99% respectively. It express that it's conceivable to implement an accurate instinctive diagnostic system to classify the EMG signals as Myopathy, Neuropathy and Normal by using Decision Tree algorithms. All the Decision Tree based classification algorithms used in this study can be used as classifier for creating such automated systems.

Shuxiang Guo, Muye Pang, Baofeng Gao, Hideyuki Hirata and Hidenori Ishihara [8] observe eight blends of four feature extraction methods with two classifiers to recognize eight upper-limb motions, using features extracted from sEMG signals as inputs. Four feature extraction methods (Root Mean Square (RMS), Detrended Fluctuation Analysis (DFA), Weight Peaks (WP), Muscular Model (MM)) and two classifiers (Neural Networks (NN) and Support Vector Machine (SVM)) are used for mapping of sEMG signals to upper-limb motions. Six upper-limb muscles were nominated to measure the sEMG signals and for this purpose seven subjects participated in this experiment. Results showed that neural network NN classifier has (88.7%) of accuracy while SVM have (85.9%) accuracy in real-time. WP and MM have highest recognition accuracy while MM in real-time applications with a trade-off of about a 3% lower recognition rate than WP. For classifiers, although NN have high recognition rate than SVM in the training process but SVM is more accurate and better than NN in on-line tests. MM and NN both are recommended for strict real-time performance otherwise the MM and SVM group may be used for higher and more stable recognition accuracy rates.

Minas V. Liarokapis et al [9] describes the muscular activation pattern for reach to grasp motions and learning schemes to discriminate the different strategies depend on muscular co-activations. For this purpose, surface electromyogram (sEMG) sensors were used for both the upper arm and forearm muscles. Total sixteen muscles of the upper-limb and forearm were recorded during hand to grasp movements. Six classification techniques namely LDA (Linear Discriminant Analysis), QDA (Quadratic Discriminant Analysis), SVM (Support Vector Machine), ANN (Artificial Neural Network), KNN (k-Nearest Neighbors) and a Random Forest classifier were adopted to classify and measure the accuracy of different poses of hand to grasp movements. Boxplot zones as a novel method for statistical representation was introduced to give a visual estimation of muscular co-activation. This methodology is able to give a switching mechanism for trigger-task specific motion and for the models of force estimation to improve their EMG base robotic-arm systems.

Guan-chun luh et al [10] proposed a system of (MGCI) muscle-gesture computer interface with wearable MYO armband to control the five-fingered robotic hand movement. The MGCI basically consists of three parts: (a) MYO armband with user (b) muscle- gesture interface (c) The Robotic hand. The muscle-gesture computer interface recognizes the hand or wrist motion under supervision of three steps as segmentation, feature extraction and classification.

A processor named cortex M4 was used to execute the machine learning algorithms for classification of different hand motions. Segmentation identify the part of measured EMG signal correspond to the hand motion and feature extraction shows the transformation of raw EMG signal to a feature vector. In EMG based system there are three types of features involve namely as Time-domain, Frequency domain and Time-Frequency domain. After feature extraction from raw EMG data different classifiers were used to distinguish the behavior, hand gesture and movement of hand to use it as control command. Several classifying techniques were employed for classification using neural network, Bayesian classifier, fuzzy logic, support vector machine (SVM) and hidden Markov models. The EMG data were acquired and segmented from eight channels of MYO. Total 72 different features were extracted from the 16 different hand motions. The recognition utility of these features were very high as in case of artificial neural network (ANN). The average best classification rate was 87.8% during off-line training session and was increased to 89.3% in real-time. This shows that real-time myoelectric control for robotic hand followed feasibly and nicely with human's hand gesture.

The main goal of Yinlai Jiang et al [11] is to develop a simplified EMG based prosthetic hand to perform a limit free gestures for amputee. This simple EMG prosthetic hand basically consists of five major parts as:

1. A robotic hand, two motors and a socket are available in its mechanical design

2. Need a highly stretchable cosmic glove to wear

3. Required the soft EMG sensors of conductive material to measure the EMG signals

4. A microprocessor of 32-bit used in this novel design to process the EMG signals, pattern recognition and motion control of prosthetic hand

5. A human tablet or smart gadget require to operate the simplified EMG prosthetic hand by amputee him or herself

The surface EMG sensors were basically electrochemical transducers used in this study to detect the bio potentials by using electrodes (Ag/AgCl) on skin surface. The surface EMG signals were send to the controller where A/D conversion, FFT, feature extraction and recognition of gestures occur. After that a classifier of artificial neural network (ANN) was used to train data through a tablet and then used it to classify and pattern recognition of various hand movements. Three volunteers were selected to test this novel design of simplified prosthetic hand. The results support this lightweight, low cost and efficient prosthetic hand with durability and user friendly behavior.

The study of Tobias Mulling et al [12] reveals the characteristics of different gestures via MYO armband and a case study of MYO armband that how can we use it to recognize gestures in map navigation with help of Apple Maps Connector. In this study a questionnaire model was introduced to take different thoughts on the use of different gestures of MYO armband in map application. Three categories were introduced based on HCI design and evaluation methods, Natural language interfaces and gestural input. In this research 23 volunteers were participated to perform common tasks such as zoom, focusing and panning for navigating map using the predefined commands of MYO armband i.e. Fist, Finger spread, wave in, wave out and Double Tap. Use of arms and hand gestures to control the navigating map can be optimized from the design of application for MYO. For this purpose, a user could perform a several design processes to understand that which gesture is suitable and feasible for which task of map navigation. The study of gestural interaction with design of specified application for device shows a good potential of acceptance by users and in future it would be a challenge for designers and developers.

Nihal Fatma et al [13] compared the classification performances of multi-layer perception (MLP) and support vector machine (SVM). Surface electrodes were used to acquire the EMG signals from the ulnar nerve of the patients with DAQ board(PCI-MIO-16XE-10) and 16-bit A/D converter. The data of A/D converter was stored in hard disk of computer. The stored EMG data was then used for feature extraction using FFT and PCA. For this experiment 59 patients were selected as 19 were normal,20 were diagnosed with neuropathy and 20 with myopathy. The use of principle component analysis (PCA) had been reduced the amount of FFT coefficients. To compute the classification performance, the PCA coefficients were applied on both the SVM and MLP classifier which shows that SVM has high level of anticipation to diagnose the neuromuscular disorders. So it concludes that SVM has high classification performance as compared to MLP in this case.

T. Lorrain et al [14] investigates the influences of training data set for the various algorithms of pattern recognition during dynamic contraction. The combination of a threshold for the detection of onset contraction, used of current algorithms of pattern recognition on static condition can maintain a high classification accuracy for dynamic situations. Eight subjects with 5 males and 3 females were participated in this experiment. This experiment consists of 9-class problem with hand and wrist motions. 9-class problem involve the wrist flexion, wrist extension, thumb close, making a fist, fingers spread, 4-finger close, forearm supination, forearm pronation, open, and no motion. The EMG signals were recorded non-invasively from the skin surface. For this purpose, six pairs of surface electrodes (Ag/AgCl) were used on dominant forearm muscle. The surface EMG data with amplified gain of 2000dB, filtered between 47 and 440 Hz, and sampled at 1024Hz were recorded during the bipolar derivations. Two classifiers, linear discriminant analysis (LDA) and support vector machine (SVM) were tested. For combination of feature set and classification the technique of cross validation was applied. This method shows the comparable results of simple approach of classification in time domain with complex methods of classification of wavelet features.

Muye Pang et al [15] aimed with continues recognition of upper-limb motion for different upper-limb movements. The change in upper-limb movement shows the vital change in amplitude and features of the surface electromyographic (sEMG) signals. The variances in amplitude and features of (sEMG) signals represents the change statuses of upper-limb movement. Five non-invasive electrodes were used on anatomical points of upper-limb to record the EMG signals. For feature extraction an autoregressive model was used. After that to recognize the patterns of upper-limb motion a classifier of back propagation neural network was applied with the help of variant features as training data. Three subjects participated in this real-time experiment. The recognition rate for forearm pronation and supination is lowest during three single movements. Overall this method is effective for upper-limb motion recognition in real-time.

Simone Benatti et al [16] proposed an embedded solution for recognition of real-time EMG based gesture. For this purpose, a wearable device having a multi-level design with hardware and software interfacing components to acquire and process EMG signals for gesture recognition has been developed. For on board processing this system combines the custom analog front end accuracy with low power flexibility and high performance microcontroller. Most expensive active

EMG sensors were used to achieve the high-end accuracy. Four volunteers with seven gestures were selected to validate this approach as to recognize the gesture and recognition accuracy rate with desired classifier. Results show the outstanding recognition capability of SVM with classification rate of 90% which aligned with the system results as 29.7mW consumption, 44 hour continues operation along with battery of 400mAh.

Abdulhamit Subasi et al [17] investigates the different methods of feature extraction for understanding motor unit action potential (MUP) morphology. The (MUPs) in EMG signals have a significant source of information to aces the neuromuscular disorders. Needle electrode was used to record the EMG data from a contracted muscle to investigates its neuromuscular disorder. For classification of EMG signals soft computing techniques had been adopted that will automatically classify the EMG signals into normal, myopathic or neurogenic. For this purpose, three classifiers named as multilayer perceptron neural networks (MLPNN), Adaptive neuro fuzzy inference system (ANFIS) and dynamic fuzzy neural network (DFNN) were compared in order to their accuracy for EMG classification. The results show that the adaptive neuro fuzzy inference system (ANFIS) has a high degree of accuracy, recognition rate and repeatability than (MLPNN) and (DFNN) for classification of EMG signals.

Karan Veer et al [18] proposed the classification and evaluation of surface EMG (SEMG) signals at upper limb for different movements. EMG data acquired from different muscle locations and simulated algorithm was used for interpretation of signals to estimate the parameters. First of all, different arm movements were analyzed then statistical approaches were applied to investigate the relationship between force and muscle. The strength of EMG signal usually depends upon the electrode placement on muscle’s belly. Two electrodes were used to acquire EMG data during muscle activities while the third electrode was used on the surface of bone to neutralize and cancel out the effect of noise that can interfere with the EMG signals acquired by other two electrodes. The methodology involved in this study consists of four steps:

1. Initialization with soft scope interfacing

2. Configuration: depends upon channels and to control the acquisition protocols

3. Execution: Acquired EMG data and send it to workspace

4. Termination: consists of data completion process for detection

For this experiment five amputee males, aged 22-46 years were selected to perform. Two operations elbow flexion and adduction were analyzed for upper limb prosthetic devices. The results based on classification using artificial neural network (ANN) presented for detection of different arm motions (pre-defined) in order to discriminate the different surface electromyogram signals. The output of ANN classifier shows high accuracy and recognition rate of 92.5% for this study. The results of this study also inferred the operations which were easy for arm recognition and for developing a powerful, efficient and flexible prosthetic design.

Derya Karabulut et al [19] comparatively evaluated the time-domain features of EMG signals to estimate the external forces applied to human hands. These time-domain features are consisting of integrated EMG (IEMG), root mean square (RMS) and wave form length (WL). Time-domain EMG features were extracted to classify using artificial neural networks (ANN) to predict the external forces. SEMG sensors were used to carried out the EMG data for six healthy subjects. Two types of muscle contraction:

1. Isometric & isotonic

2. Anisometric & anisotonic

were consider to take EMG data for applied forces. The results obtained from the classifier ANN were statistically evaluated and concluded that the features of IEMG and RMS shows a consistently and satisfactory performance of signal characterization. For RMS and IEMG features there was no any considerable difference in between prediction values of Variation I and II. The results of this study are expected to be useful for extraction and evaluation of different EMG features and motion patterns to control the EMG base motion devices.

Theodora Toutountzi et al [20] proposes the work that intended to develop a system to detect the wandering behavior of men/women through human recognition activity. Attention required on activities to detect the wandering behavior of men which were discover using the technique of data mining on sensor data obtained from MYO armband. MYO armband is a wearable sensor device used to capture the EMG data from muscles to understand the motion activities. For this study nine volunteers took part to perform different actions of walking, running, resting and opening door.

The data obtained from these volunteers was then transfer to computer wirelessly from MYO armband through a Bluetooth device. The MEX file of MATLAB were used to obtain data as MYO works in C/C++ but does not work in MATLAB. To evaluate these motion activities k=10 cross-validation approach were used in frame of SVM, Naïve Bayes and KNN. The classification results were show the significantly high rate of accuracy to extract the set of activities for wandering behavior of men. In future this study will be able to enrich the observing system by increasing the data modes along with pressure density pads, depth imagery and door sensors.

Mithileysh Sathiyanarayanan et al [21] used the MYO armband to utilize its development in the field of healthcare and medicine to improve the system of public health care. To understand this phenomenon a computer-based app known as “MYO diagnostics” is available at MYO market developed by Thalamic labs. A human action or gesture will give a huge amount of data consists of EMG series that cab be analyzed to detect the movement or abnormalities in the muscle. The doctor’s experience against user satisfaction with MYO armband can be classified in terms of effectiveness, satisfaction and efficiency that depends on the error count, metrics task completion and satisfaction scores. For this study twenty-four medical students were participated with system usability scale (SUS) questionnaire model. The outcome of this study will help us to understand the use of MYO armband for physiotherapy analysis by doctors and patients. Another questionnaire model distributed was about to the device usage such as its ease of learning, comfort and stress, social acceptability and its user friendly behavior. The results of this study are capable in development of physiotherapy analysis using MYO armband and different applications of hand gesture at home. The correlation between the muscle signals and system will give the better understanding of myocardium and doctors will be capable to diagnose the abnormalities in early stage.

Xiaoyu Wu et al [22] presents an intelligent intellectual system to recognize the human hand gesture with the help of gesture recognition algorithm and Kinect sensor. This system found on (HOG) histograms of oriented gradients and adaboost learning techniques. An inert hand algorithm was generated to identify or pick the predefine motion of hand area. Kinect sensor was used to track the hand trajectory while hidden markov model (HMM) train and classify the dynamic gesture. After hand area now we need to check whether the area include predefine static gesture or not. As the changing scenes mark the results of static hand recognition so the features of hand extraction must be inconsiderate to light and rotation. The HOG was used to extract the hand features while the adaboost training methods was used to train the models of different hand movement. For dynamic hand gesture recognition, we used the Hidden Markov Method (HMM) to train and recognize our hand gestural sequences. The data set of hands for this study involves the samples of 150 persons through Kinect sensor. We select the right hand for training as both the right and left hand are different. The results show the mean accuracy of detect in real-time video is 90.2%. An application system for operating programs and other parameters by hand is developed through gesture recognition algorithms that is more genius and intelligent than hand operated systems.

Ananta Srisuphab et al [23] analyzes the inertial motion signals in frequency domain with high potential gestural classification. This gestural data consists of both the static and dynamic poses. Applications based on gestural classification and recognition usually found where real time communication, command and control of machines with human activity occur. So to understand the inertial motion data we used a MYO gestural control armband that consists of nine-axis inertial measurement unit (IMU). To collect the experimental data three research students were picked to perform different hand motions. Each student performs 17 hand gesture 20 times. The set of 17 hand gesture contain both the static and dynamic poses as well. So there were 60 record per hand signal and 1020 were recorded in total hand movements. To classify our data different classification approaches (ANN, MLPN and Daubechies wavelet transforms) was adopted. While the discrimination features were effectively discovered in frequency domain by applying Daubechies wavelet transforms. After evaluating the hand motion for different poses and gestural data we achieved the overall accuracy of 88%.

S.Benatti et al [24] introduces an approach to design front-end of analog integrated circuits through real algoroithms of signal processing. It is capable of monitoring the growth of diverse platforms including real time classification and gesture recognition for embedded systems. The study in this paper involves the electromyography (EMG) pattern recognition system with the help of low cost passive sensors, an innovative analog front-end system and low power microcontroller. For data acquisition of EMG bio-potentials, low-cost disposable electrodes were used. The data was acquired with the help of Cerebro AFE and fed into a MCU. The programmable MCU is relatively so simple and inexpensive and relatively has high flexibility. The fed data was then passed through the SVM classifier to recognize the different hand gestures. In this experimental setup, one healthy volunteer was under supervision with 4 EMG passive sensors placed on his forearm. The sampling frequency was set at 1KHZ for each channel with gain of 512. 30% of data was used to train while the remaining 70% was set for testing. The experimental results show the classification accuracy of 92.3%.

Jagdish Lal Raheja et al [25] provides a novel method for recognition of hand gesture using principle component analysis (PCA) through FPGA simulator. Co-simulation tools with Xilinx system generator (XSG) was used to perform simulation. For heterogeneous system design a hardware-software co-simulation methodology was adopted to perform a faster simulation. The processing time for our design system was detected to be 530ns with 100MHz frequency simulated on FPGA. The developed algorithm was implemented 6 images database and a MATLAB code was used to produce a 6×6 projection vector to store in RAM of FPGA. After developing the DB, the system was able to capture an image and produce a projection vector 6×1 which refer to hardware for further process. Results shows a very sound and strong performance with high computing speed and accuracy through deploying PCA on FPGA than other techniques and parameters.

Ali-Akbar Samadani et al [26] develops an innovative inter individual model for recognition of hand gesture using hidden markov model (HMM). This model receives the surface EMG signals from Thalmic lab's product known as MYO armband and classify the corresponding hand gesture. MYO contain 8 surface EMG sensors used to acquire the EMG data from surface the of forearm muscle. For this experiment 25 subjects were chosen to perform the dataset of 10 various hand gestures. This developed recognition model gives the overall accuracy of 79% for hand gesture recognition. The approach used in this paper discriminates between gesture-specific EMG signals and could refer to the design of SEMG- controlled prosthetics to perform the desire gesture. This presented approach encodes gesture specific EMG in HMM with mashup of Gaussian outputs.

Dapeng Yang et al [27] proposed a cataloguing method which is mainly depend upon the support vector machine (SVM) classifier to organize the EMG signals of different 19 hand gestures acquired through six myoelectric electrodes. 3 DOF configuration usually utilize in all hand gestures which make it eligible to move freely like three fingered. The process of training data is very high but the cross-session validation shows typically a low performance. A good or acceptable cross-session validation can be achieved by enhancing the training sessions with fewer modes of gestures. A fast rhythm contraction muscle can make training sessions more useful and give the better prediction accuracy than slow contracted muscle. For different hand grasps tasks, if we directly extract the grasp force from EMG signal than it would be useful for myoelectric prosthetic hand. A six-dimension force/torque JR3 sensor was used to record the force signal directly from the EMG signal by grasping the JR3. 6 EMG surface sensors used in this paper was based on electrodes 13E200=50 by Otto bock. Theses electrodes were attached to AD acquisition card which was embed with PCI slot of computer. Three methods based on local weighted projection regression (LWPR), artificial neural network (ANN) and support vector machine (SVM) were adopted to check the best regression relation among two types of signals. Results shows that SVM shows better performance than ANN and LWPR in case of cross-session validation. Throughout this study using C-SVM method we can achieve the accuracy of 82.5% to recognize the 18 different patterns of active gestures.

Yimin Zhou et al [28] reveals a high level feature extraction method in real time for recognition of hand gesture. In this approach our fingers are designed as cylindrical object due to their parallel edges. The proposed method is a novel algorithm used to extract fingers from salient hand edges. The geometric characteristics of hand describe the hand posture depends upon the finger locations, center of palm location and wrist positions. To localize and extract each finger, an algorithm of weighted radial projection with its origin at wrist position was applied. The system used in this approach can not only extract the features of extensional fingers but also the flexional fingers with rate of high accuracy. During the extraction process the hand rotation and finger angle variation have no any effect on the performance of algorithm. To estimate the angle, orientation and length of each finger we used an angular projection with centered on wrist position. These features directly produced a simple 2D hand model to which we can estimate hand location, finger recognition and hand orientation with the proposed technique used in this study. If this method cannot well detect the salient hand edges, then a false or miss detection for fingers could occur. At end we can say that hand gesture recognition can occur with high efficiency, accuracy and better performance than other methods.

F. Riillo et al [29] presents a methodological study for optimization technique used for classification of surface EMG hand gesture recognition which was effectively implemented through human-computer interfacing device for both the healthy and amputee subjects. The comparison of unsupervised approach of principle component analysis (PCA) and supervised approach of common spatial pattern was taken in account to identify the best classification strategy. A set of low density surface EMG sensors was used on forearm muscle to acquire the EMG data. 20 healthy subjects with five different gestures were participated in this study to compute optimized parameters for both strategies. Different classifiers (LDA, ANN, SVM) were implemented to check the overall accuracy of both techniques. At end the results show that the first approach of unsupervised PCA has the accuracy of 88.8% and the second approach of supervised methodology of CSP shows the rate of accuracy higher than PCA with 89.3%. Statistical analysis of these classification results shows no difference between both approaches.

Xiang Chen et al [30] explore the features of accelerometer necessary for SEMG-based features used for recognition of hand gesture. Experimentations were performed to collect the gesticulation data through both recognizing approaches and to equate their results in recognition of different wrist and finger gestures. Different recognition tests were performed using different set of information as accelerometer and SEMG data separately and with combined sensor data. Results shows that the mixture of accelerometer and SEMG have 5 to 10% improvement in accuracy of recognition of hand gesture than other approach. In this experiment total 24 types of hand gestures including relaxation had been used. These gestures consist of 6 wrist motions, 6 individual finger motion and 11 type of multi finger motion. Five healthy subjects with 3 males and 2 females were recruited for this experiment. The process of recognition consists of gesture action, feature extraction and classification steps. The average classification results of SEMG data (A1+A2) shows the accuracy of 95.6%. The average classification for three combination of data are 98%,97% and 97.9%. The results of this research shows that A1, A2 and A1+A2 comparatively more similar in gesture recognition.

Ali Boyali et al [31] presents the variant novel method and application for classification based on collaborative representation (CRC) in spectral domain to recognize the different hand movements using raw EMG data. For pattern classification the collaborative representation method does not need a large amount of training sample. The training procedure in this technique used with high and subspace clustering method that is used for clustering the representative samples towards their corresponding label classes. An intuitive use of features in spectral domain through circulant matrices are present in this paper. The accuracy of fairly rich gesture depends upon the raw EMG signals that can be improved by analyzing the noise of signal and introducing other filtering techniques. The spectral collaborative representation based classification (SCRC) shows the higher rate of accuracy to recognize the gesture for a set of fairly rich gesture. The recognition results show the best rate of accuracy with 97.3% among the four sets of experiments for each gesture.

Angkoon Phinyomark et al [32] inspects the performance of fifty features including Time-domain (TD) and Frequency-domain (FD) to classify the ten upper hand motions using EMG data. The technique used to transform the raw input EMG data in to a reduced representation feature set is known as feature extraction. Time-domain features can be easily extracted from raw EMG data as it requires low computational load and easy to implement. While the frequency domain features usually have statistical properties of power spectral density (PSD) of EMG signals. The dataset used in this study was provided by University of Paderborn in Germany. The obtained EMG data were recorded using a portable EMG recording device known as NeXus-10, Mind Media BV. Four electrode-pair were used on four positions of forearm (Top, bottom, medial and lateral) to record EMG data with reference (r) at wrist position. The volunteer (non-amputee) performed 11 different upper limb motions including extension, flexion, supination, pronation, radial deviation, open, close, ulnar deviation, pincer grip, index finger extraction and key grip. Different set of features including single feature and multiple features with configuration of myoelectric control using classifiers and data segmentation were presented. The results of this study place the sample entropy at top position of accuracy than other features when compared using (LDA) and a robust classifier. This study reveals the average classification accuracy of fifty features are 93.3%. The best robust feature in single set is SampEn (sample entropy) and in multiple set (SampEn+CC+RMS+WL) is the best robust feature. While TD have better performance than FD in EMG classification pattern and LDA shows higher rate of accuracy than QDA, SVM, MLP-NN, KNN and DT.

Adriano O et al [33] provides a filtering technique for electromyogram (EMG)signals in the form of Empirical Mode Decomposition. It’s a novel method of digital signal processing that can use to decompose the time series into a set of functions as intrinsic mode function. In processing usually

EMG signals are affected by noise which may be in results of different sources like electrodes, cables and due to activity of motor unit from detection point. To reduce this noise different techniques had been adopted in past namely as low-pass differential (LPD) filter, weighted low-pass differential (WLPD) filter and the wavelet approach. The results of a comparative study between Empirical Mode Decomposition (EMD) and wavelet approach shows that EMD could be a successful approach for attenuation of EMG noise. After the analysis of experimental signals, it showed that the power of noise window could be reduces greatly and the energy of signal preserved.

Adel Al-Jumaily et al [34] provides a method of classification for signal output as a potential control stimulus to move the virtual hand prototype. An anatomical structure methodology was adopted that congruent with virtual reality modeling language (VRML). To collect the motor unit action potential (MUAP) on skin area, a highly reliable and responsive surface electromyogram (sEMG) electrodes were used. For EMG based prosthetic and rehabilitation devices a 10-class EMG motion visualize model was built successfully. The anatomical construction of human arm supports this 10-class EMG model as it involves the basic theory of kinematics. For the independently active classes or the classes conjunction with other movements, this model allows for multiple degree of freedom profiles.

Angkoon Phinyomark et al [35] presents the comprehensive and innovative study of thirty seven (37) features of Time domain (TD) and frequency domain (FD) with their properties. The EMG data used in this training were logged from two forearm muscles known as extensor carpi radialis longus muscle and flexor carpi radialis muscle. For this experiment a healthy male subject was selected to accomplish six upper-hand movements (hand open, hand close, wrist flexion, wrist extension, forearm pronation, forearm supination). The results were verified on behalf of scatterplot of different features, classifiers and statistical analysis which shows that time domain features are more redundant than the features of frequency domain. Time domain features can be grouped into four forms as energy and complexity, prediction model, time dependence and frequency according to mathematical property. While on other hand frequency domain features can be intended on basis of statistical parameters of power spectral density (PSD). The first two time-domain features show better results than last two whereas features of frequency domain are not so good for classification of EMG signal. The results of this study can be used for many clinical and engineering approaches.

Chapter 3 PROPOSED METHODOLOGY

3.1 Basic Concept

As we discussed in previous chapters that Electromyography (EMG) is a diagnostic approach to evaluate the health of muscles and neuron cells that use to control them as motor neurons. These motor neurons are responsible to transmit electrical signals through muscles to contract them. EMG can either be used as a diagnostic tool to locate the neuromuscular diseases or to control the prosthetic hand movement. So in our case we are trying to give a novel method to obtain these EMG signals and further classifying them to give a good predictive behavior for an artificial hand or prosthetic hand to move as freely as natural hand movement. Detection, analysis, classification and feature extraction of EMG signals is our mainstream for this research project.

In past, myoelectric control systems have been used to control any upper-limb assistive devices or prosthetic arms by conducting classified EMG signals. Mostly available literature on EMG pattern focus on enhancing the classification accuracy and its usability to control assistive devices or any upper-limb prosthesis. Classification and feature extraction of Electromyography (EMG) signals is a challenging process especially in case of forearm muscle due to different hand movements. Feature extraction from Electromyography (EMG) signal is a well-known technique used to acquire useful information encoded in raw EMG signal which is further deliberately use to control prosthetic hand movement, diagnose muscle diseases and pattern recognition. The characteristics of EMG signals are recognize by using features in both domains as Time-domain (TD) and Frequency-domain (FD). Time-domain (TD) feature extraction is a technique to extract the useful information in sequence data points encoded in EMG signal over specific time interval while Frequency-domain (FD) features are extracted using spectral analysis and power spectral density (PSD) of EMG signal.

3.2 Proposed Technique

In this study, we analyze the EMG signals of various upper-limb movements through different classification approaches. For this purpose, we used a device known as MYO armband that has eight (EMG) sensors for detecting the electrical activities from various parts of forearm muscle. MYO sends EMG data to computer via Bluetooth module (HM-10) from where we can understand the movements of different gesture. In our case we have study the four gesture EMG data including

Stationary, Double Tap, Single finger movement and the Finger spread to analyze its different features and accuracy measures. The block diagram of proposed research has been shown in Figure 3.1.

The approach we adopt in this study is comparatively feasible and cheaper as compared to previous approaches as it uses non-invasive simple device of MYO armband which can be wearable on any size of muscle without shuffling of wires, an embedded controller with least price and an HM-10 Bluetooth module for transmitting data. For further progress in future, we can design a cost efficient prosthetic upper-limb to perform action through this embedded system.

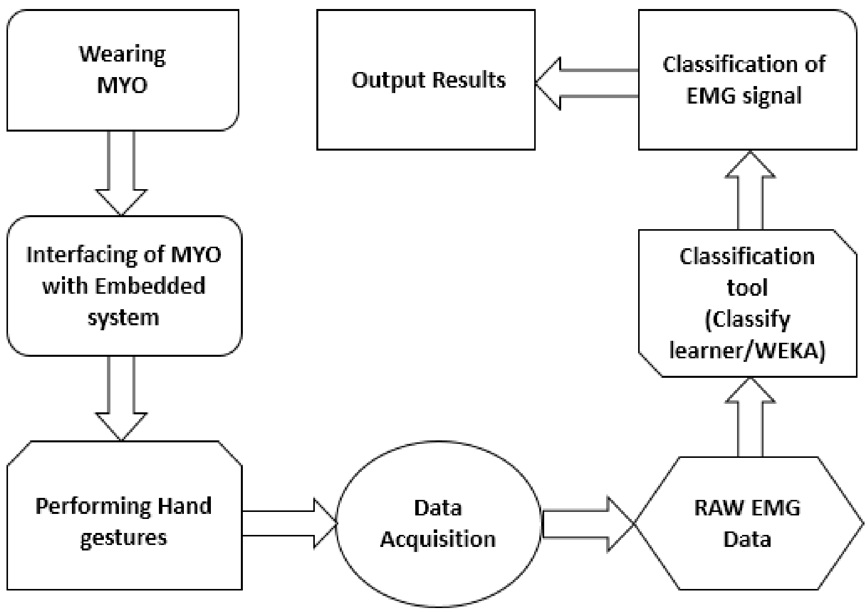


Figure 3.1 Block diagram of proposed methodology

3.2.1 MYO Armband

The MYO armband is an electronic sensor by Thalmic Labs. It is used to acquire EMG signals from human arm and it can be used for gesture recognition. It has a nine-axis inertial measurement unit. Inertial measurement unit (IMU) consists of 3-axis gyroscope, 3-axis accelerometer and 3-axis magnetometer that detects orientation and acceleration of hand or arm. The EMG sensor detect muscle contractions and muscle movement in the arm which corresponds to hand motions. Hand motion can be double tap of the index finger or thumb, wav in, wave out, fist or an open hand.

With the IMU, the MYO can record the pronation, supination and the role of the forearm.

Figure 3.2 MYO Arm Band [42]

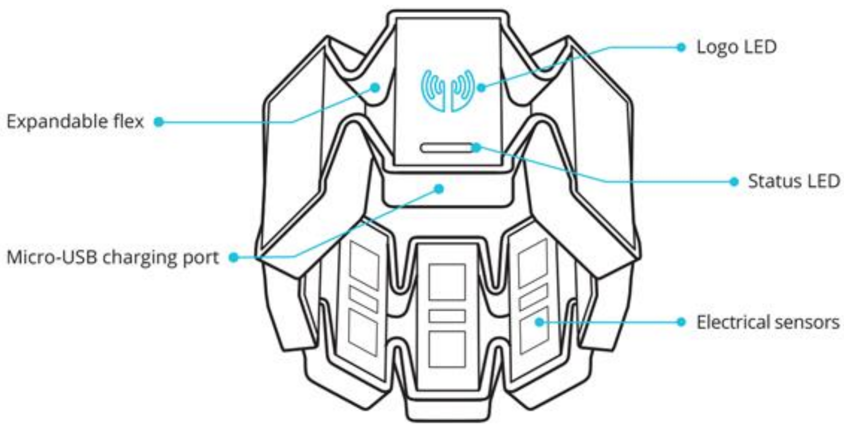


Figure 3.3 Physical Characteristics of MYO [43]

The eight sections of inflatable exterior hold the MYO armband's machineries and are associated using stretchable substantial that permits them to enlarge and contract relative to each other, so that the MYO armband can securely fit each user's unique physiology. The electrical sensors quantify the electrical signals in millivolts mV wandering transversely in user's arm, which further interprets into postures and gestures by MYO.

The USB charging port permit us to charge the MYO armband's interior battery by means of a USB power connecter or a conventional USB port on a computer.

The LED badge displays the synchronization state of the MYO armband. It beats when the MYO armband is not synced. The LED becomes dense and give a long trembling when it synchronizes successfully and the MYO is synced to your arm as well.

Applications

The Applications of MYO are almost boundless. MYO is essentially a remote device that only regulate the output through your EMG signals.

- You can use it to control PPT slides, regulate music, Scroll webpages and documents etc.
- To Play games
- Use it as a distant device to turn on/off your electrical appliances using Embedded circuits
- To Initiate robots, drones around your neighbor hood
- Use it as a PC remote etc.
- In field of biomedical to check the status of healthy and damage muscles, wandering behavior or in movement of prosthetics.
- Use with your mobile phone apps to assist you in number of fields

3.2.2 Arduino

Arduino is an open-source podium used for edifice numbers of electronic developments. Arduino encompasses of reciprocally a physical programmable circuit board (frequently stated as a microcontroller) and a section of software, or IDE (Integrated Development Environment) that runs on your processer, used to engrave and upload computer code to the physical program board.

The Arduino board has become prevalent among people preliminary with electronics. Contrasting utmost other programmable circuit boards, the Arduino does not require a discrete section of hardware (called a programmer) to load new code onto the board. In Arduino you can purely customize a USB cable to upload your code directly. Moreover, the software of Arduino IDE customizes the basic version of C++ that make it easier to understand the program. Lastly, Arduino offers an average form factor that disrupt the functions of the micro-controller into a more available package. The Uno is among the most common board in the Arduino family and a prodigious choice for the learners as shown in Figure 3.4.

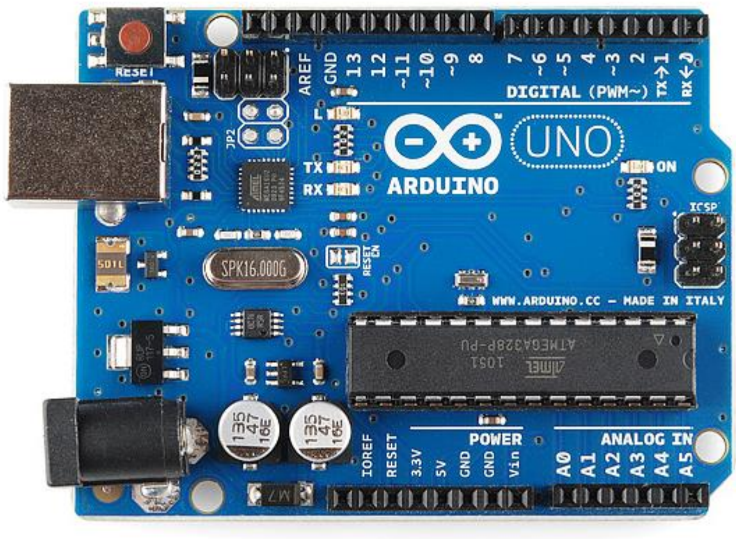


Figure 3.4 Arduino UNO Controller [44]

Why Arduino?

1. Arduino has an accessible user experience with number of different projects and applications
2. The Arduino software is more feasible for trainees, yet stretchy enough for unconventional users as well.
3. It runs on Mac, Windows, and Linux. Teachers and students can use it to build low cost scientific projects or to get started with programming and robotics.

Inexpensive

Arduino boards are comparatively cheap associated to other microcontroller podiums. The minimum luxurious version of the Arduino module can be accumulated by hand, and even the cost of pre-assembled Arduino units is less than $50.

Cross-platform

Windows, Macintosh OSX, and Linux are fundamental operating systems for Arduino software (IDE). Utmost microcontroller systems are bound to Windows only.

Pins (5V, 3.3V, GND, Analog, Digital, PWM, AREF)

Arduino has several spaces for pins where you connect cables to design a circuit (probably in aggregation with a breadboard and some wire). They generally have plastic ‘headers’ with black color that let you to just plug a wire precisely into the board. The Arduino has numerous diverse types of pins, each of which is categorized on the board and used for different functions.

- **GND**: GND is abbreviated for ‘Ground’. Arduino has number of GND pins on board, from where you can use its space to ground or earth your circuit.

  5V & 3.3V: 5-volt power is being provided by 5-volt pin and 3.3 volt from 3.3-volt pin. 3.3 volt and 5 volts is the main configuration supply for Arduino.

- **Analog**: Analog in Pins comprises the area from A0 to A5 (UNO Controller). Analog Signal can be converted into digital signal via temperature sensor and can easily be measured.

- **Digital**: “Transversely Digital pins ranges from 0 to 13 on the UNO controller board and can be used for both digital input and digital output

- **PWM:** Other digital pins like (3, 5, 6, 9, 10, and 11 on the UNO) act as normal digital pins, and can be used for Pulse-Width Modulation (PWM). Pretending is being done by these pins.

- **AREF**: Analog Reference is an unaided pin. Peri phal reference voltage is being set from this pin that is (between 0 to 5 Volts).

TX/RX/LEDs

The term TX is used for transmitting and RX is abbreviating for receiving. For serial communication these patterns seem pretty in electronics to specify the pins.

Main IC

IC is the backbone and usually refer as a brain of Arduino. Its principal working is to analyze the software and perform action according to given command. The main IC on Arduino board deviate to some scope from board to board type, but is frequently from the ATmega family of IC's from the ATMEL (Microcontroller) company.

3.2.3 HM-10 Bluetooth module (CC2541)

The HM-10 is a tiny SMD Bluetooth 4.0 module with operating on 3.3v. The IC embedded on HM 10 module is T1CC2540/CC2541 SOC (System on chip). The HM-10 module is developed by Jinan Huamao and is among various other Bluetooth devices they yield including the HM-11 module which is operationally identical to HM-10 but has a minor footmark with rarer pins wrecked out. There are 2 forms of the HM-10 module; the HM-10C BLE module and the HM-10S BLE module as shown in Figure 3.5.

There are no pads on the bottom side of HM-10C module. It has 26 pads rather than 34 which make it less inexpensive to yield. There may be other alterations (such as the type of crystal used) due to the date of manufacture. Both modules operationally have the same attitude and performance.

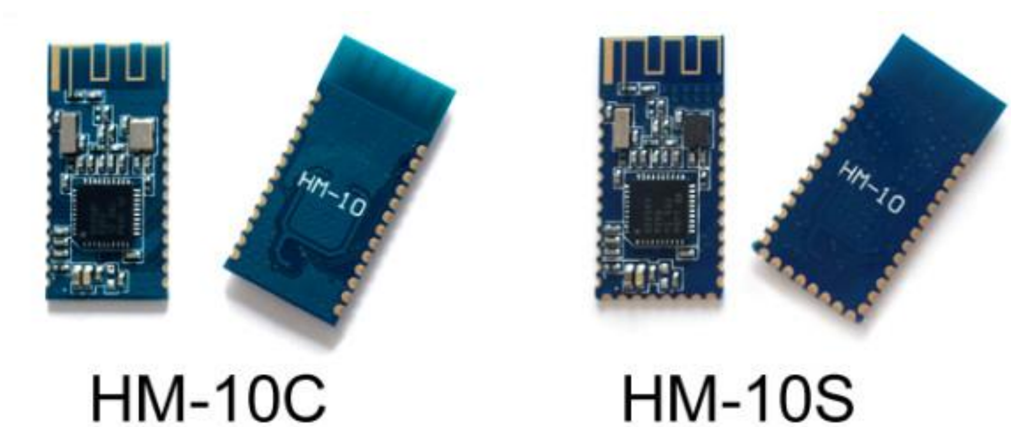


Figure 3.5 HM-10 Bluetooth Modules [45]

Integrates of HM-10 Bluetooth module

It has the subsequent specification circuitry for transmission and receiving signals and data.

- +2.5v to +3.3v
- Entails up to 50mA
- Consume about 9mA when in an active state
- Customize 50-200uA when asleep
- RF power: -23dbm, -6dbm, 0dbm, 6dbm
- Bluetooth version is based on 4.0 BLE
- Default baud rate for the serial connection is 9600
- Default PIN is 000000
- Default name is HMSoft
- Based on system on chip CC2540 or the CC2541

The HM-10 has turn out to be a very prevalent Bluetooth 4 BLE module among Arduino. In share owing to the standard UART serial connection that makes it fairly advance in connecting to an Arduino board. The UART coating is a virtuous thing and a depraved thing, it consents affluence use of it but on other side it furs the BLE layer so you have no control over the actual BLE side of things. HM-10 Bluetooth module has only 4.0 version. So, it is unable to communicate with other Bluetooth devices like 2/2.1 modules (HC-06 and HC-05).

3.3 Interfacing MYO with Arduino

Different embedded system can be utilizing to interface the MYO armband but in our approach we used the Arduino UNO controller board to interface the MYO armband. To aces the raw EMG data we used an external HM-10/CC2541 BLE blue tooth module that must be flash out with MyoBridge firmware before communicate to MYO as shown in Figure 3.6. In order to make Arduino enable with MYO we used the library of MyoBridge that includes the EMG, IMU and hand pose functions. The EMG data transfer rate is at 200 Hz while for IMU it comes out at 50 Hz. That's why in our dataset we get 4 time more EMG data than IMU data as shown in Figure 3.7. In this experiment we selected 4 healthy male subjects of age (25-55) to perform four hand gestures including stationary, double tap, single finger movement and finger spread. These four gestures will further use to classify the different hand movements.

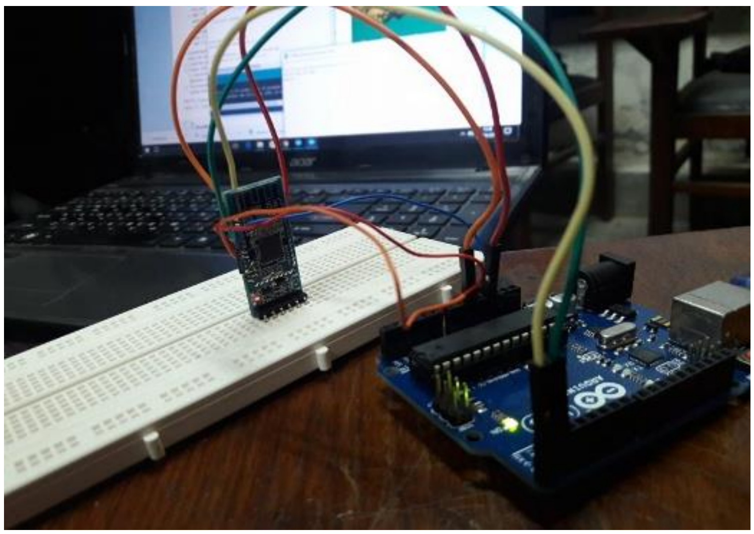


Figure 3.6 Hardware interfacing of MYO

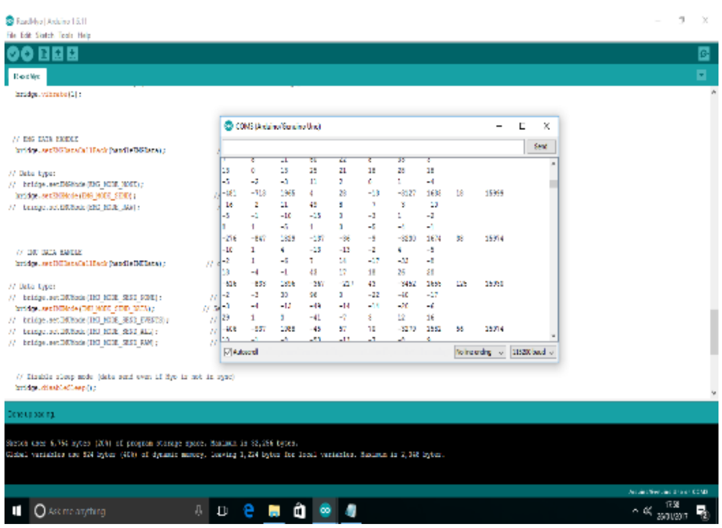


Figure 3.7 8-channel EMG and IMU data

3.4 Classification and recognition of Hand-gesture

In this section we describe the classification approaches used for EMG signal classification. The aim of this system is to classify the various hand movements with higher rate of accuracy. As in our case we have study the four gesture EMG data including Stationary, Double Tap, Single finger movement and the Finger spread as shown in Figure 3.8. For this purpose, we used seven numbers of classifiers to classify our hand movements based on classification tools of WEKA, Rapid minor and classify learner in MATLAB.

Figure 3.8 Four-gesture hand movement

3.4.1 Quadratic Discriminant Analysis (QDA)

Quadratic discriminant analysis (QDA) is used to classify or distinguish the dimensions of two or more classes of objects within a surface quadrature. Quadratic discriminant analysis (QDA) is a very close linked group of linear discriminant analysis (LDA), where it has been noticed that the dimension from each class are normally dispersed. Contrasting from LDA however, in QDA there is no postulation that the covariance of each of the classes is identical. When the normality postulation is true, the best conceivable test for the hypothesis that a given measurement is from a given class is the likelihood ratio test. As we mention that QDA is not that much dissimilar from

LDA excepting that you assume that the covariance matrix can be diverse for each class and so, we will estimate the covariance matrix Σk separately for each class k as k =1, 2, ..., K.

Quadratic discriminant function:

$$\delta_k(x) = -\frac{1}{2}\log|\Sigma_k| - \frac{1}{2}(x-\mu_k)^T\Sigma_k^{-1}(x-\mu_k) + \log\pi_k \qquad (1)$$

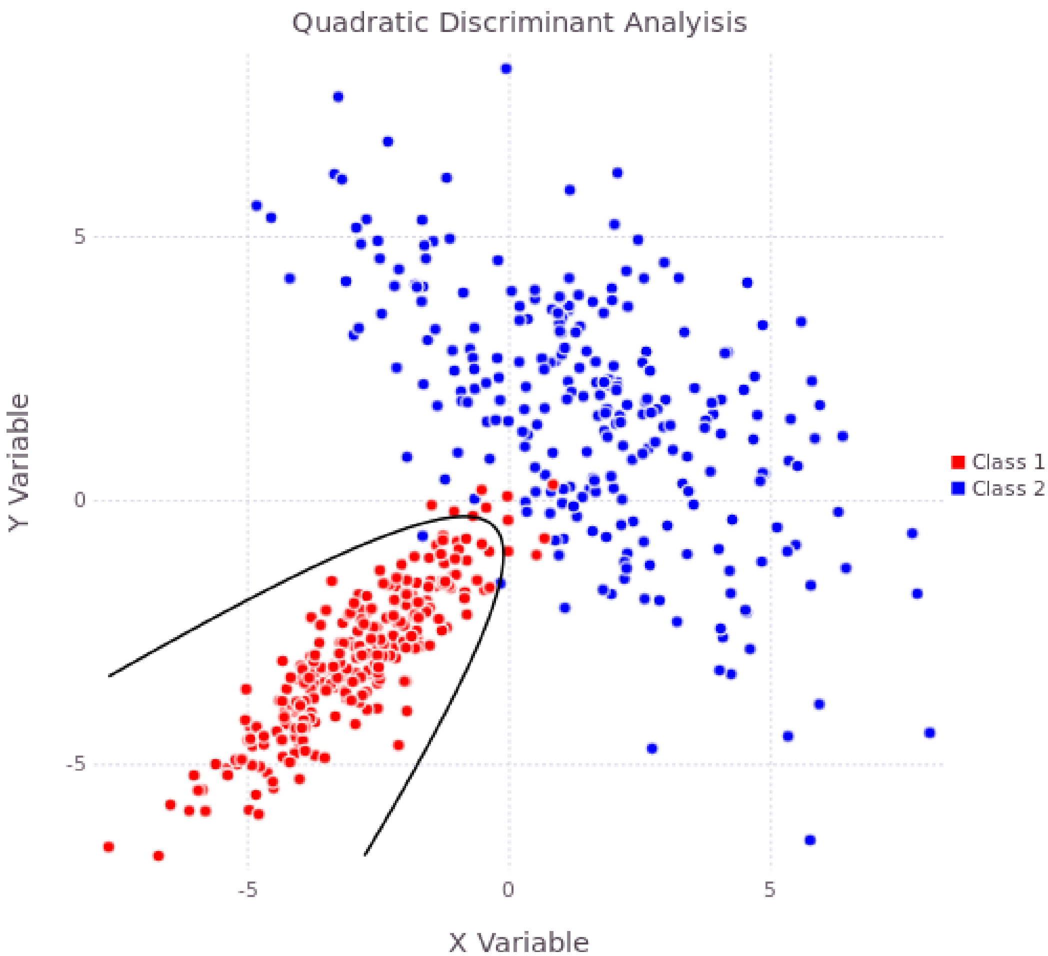


Figure 3.9 Quadratic Discriminant Analysis (QDA) [46]

This discriminant function is basically a second order classifier. The pattern of classification is parallel as well. You just bargain the class k which capitalize on the quadratic discriminant function.

The decision boundaries are quadratic equations in x.

Classification rule:

$$\hat{G}(x) = \arg\max_k \delta_k(x) \tag{2}$$

QDA have significantly more parameters than LDA because it has more litheness for the covariance matrix as it inclines to fit the data better than LDA. So, for QDA assessment, you would have a discrete matrix of covariance for each class. If you have numerous classes and not enough sample points for it, then it will be problematic.

3.4.2 SVM Classifier

Support vector machine is basically a supervised learning model with specific learning algorithms used to compute the data for classification. In contrast with linear classification SVM can also use for non-linear classification using the feature of kernel trick.

A binary classifier is a function f: X → Y which nominates every point as x ∈ X with some y ∈ Y. Both linear SVM and Quadratic SVM based on kernel version classifiers.

$$f(x) = \sum_i \alpha_i y_i (\mathbf{x}_i{}^\top \mathbf{x}) + b \tag{3}$$

Where w > x + b = 0 and c (w > x + b) = 0 define the same plane, we can choose the normalization of w for both cases as positive and negative support vectors. Choose normalization such that:

$$\mathbf{w}^\top \mathbf{x}_+ + b = +1$$

$$\mathbf{w}^\top \mathbf{x}_- + b = -1$$

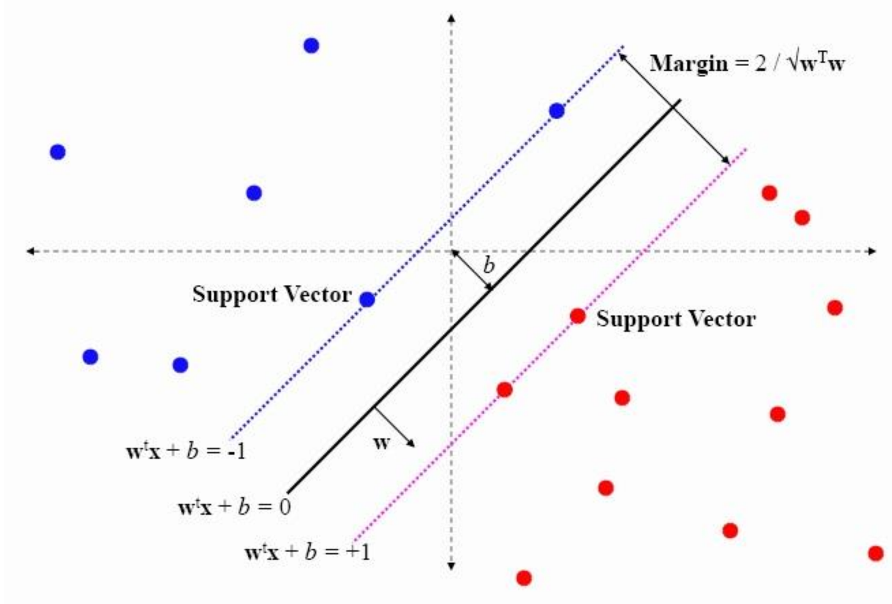


Figure 3.10 Description of SVM classifier [47]

Margin is given as:

$$\frac{\mathbf{w}}{||\mathbf{w}||}\cdot\left(\mathbf{x}_{+}-\mathbf{x}_{-}\right)=\frac{\mathbf{w}^{\top}\left(\mathbf{x}_{+}-\mathbf{x}_{-}\right)}{||\mathbf{w}||}=\frac{2}{||\mathbf{w}||}$$

Learning algorithm of SVM can be formulated as:

$$\max_{\mathbf{w}}\frac{2}{||\mathbf{w}||}\ \text{subject to}\ \mathbf{w}^{\top}\mathbf{x}_i+b\ \begin{array}{ll}\geq 1 & \text{if } y_i=+1\\ \leq -1 & \text{if } y_i=-1\end{array}\ \text{for } i=1\ldots N$$

$$\min_{\mathbf{w}}||\mathbf{w}||^2\ \text{subject to}\ y_i\left(\mathbf{w}^{\top}\mathbf{x}_i+b\right)\geq 1\ \text{for } i=1\ldots N$$

3.4.3 Ensemble (Bagged Tree)

An ensemble classification method is a supervised learning approach that synthesize the multiple predictions of various machine learning algorithms together to attain better predictive performance than single algorithm. Bagging or Bootstrap Aggregation can be used to train data for prediction and to reduce the variance of high variance algorithms like classification and regression tree (CART). Decision trees are very sympathetic and acute towards trainee data. If there any changed occur in training data, then it also effects the resulting decision tress which in turn change the results of prediction. In case of bagged decision trees, we are less apprehensive toward the single tress overfitting the trainee data. For efficiency and higher accuracy, the single particular decision trees should grow deep with each leaf-node containing a few trainee samples. For classification or regression of data we have (Xi,Yi) $(i = 1,...,n)$, where $Xi \in IRd$ mention the d-dimensional predictor variable and the response $Yi \in IR$ (regression) or $Yi \in \{0, 1,...,J - 1\}$ (J-class classification). For regression the target function is $IE[Y |X = x]$ and for classification of multivariate functions it should be $IP[Y = j|X = x]$ $(j = 0,...,J - 1)$.The function estimator which in turn the resultant of base procedure is given as

$$g(\cdot) = hn((X1,Y1),..., (Xn,Yn))(\cdot): IRd \rightarrow IR, \qquad (4)$$

The variables for bagged trees algorithm only include the number of samples and number of tress to count. Models having huge amount of data may take time to train data but it will not follow the overfitting in training data.

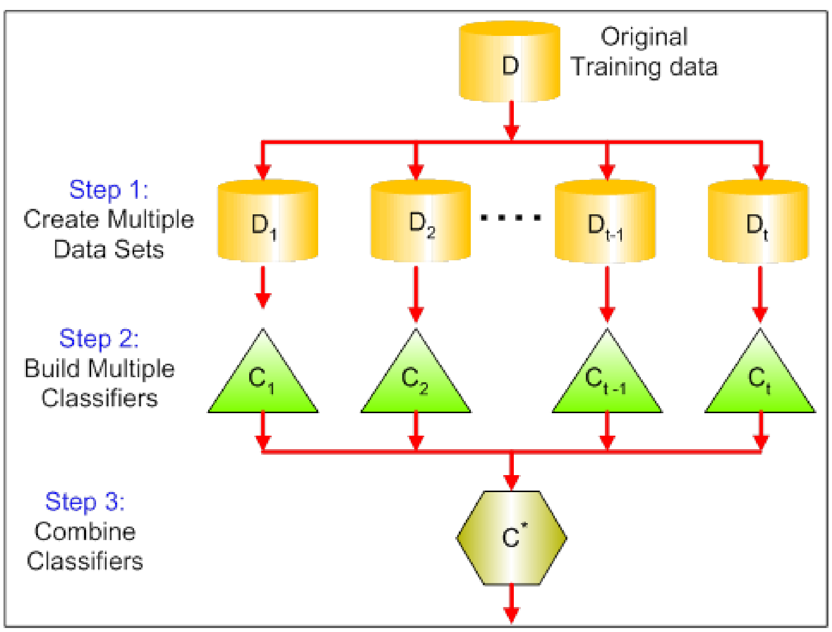


Figure 3.11 A model of Ensemble (Bagged Tree) [48]

3.4.4 Random Forest

Random forest is the improved version of bagged decision tress. Combination of multiple predictions from various models can give the better prediction rate from the uncorrelated sub-models or weakly correlated models of prediction. In decision trees algorithm a problem arise especially in CART that they are greedy algorithms so they pick a variable to split through greedy algorithm to minimize the error. There's a lot of similarities in pattern and design configuration for decision tress in case of bagged tree and they have a high correlation in their prediction level. While in case of random forest they changed the algorithms as sub-trees learned in their training process so their resulting predictions have less correlation among these sub-tresses. The algorithm used for training in case of random forest applies the same approach as used by bagging or bootstrap aggregation trees to learn. If the data set is given as

X = x1, ..., xn with responses Y = y1, ..., yn, bagging to select a random sample of trainee data and try to fit trees to these samples: For b = 1, ..., B:

Where sample with replacement, B training examples from X, Y call as Xb, Yb and train a decision or regression tree fb on Xb, Yb. then after training predictions of unseen data can be achieved by computing the prediction average of individual trees on x'.

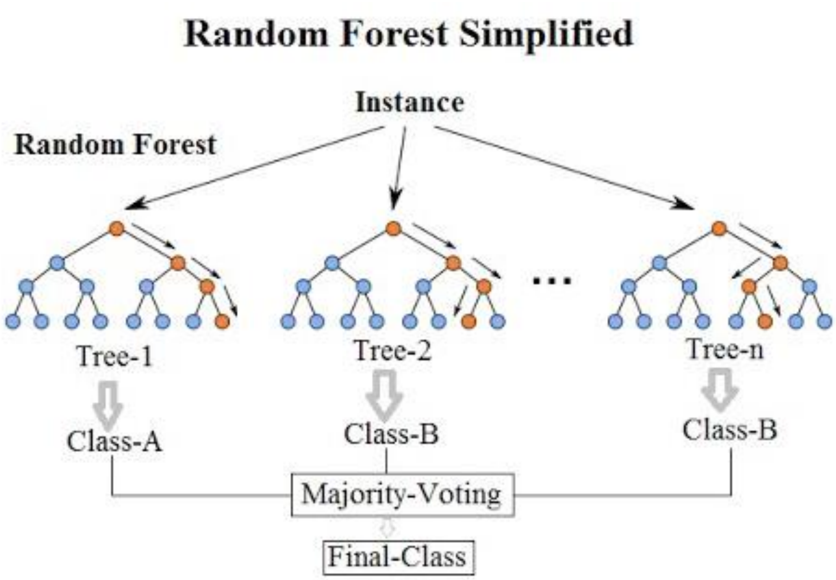


Figure 3.12 Random Forest based Classification [49]

3.5 Feature Extraction methodology

Classification and feature extraction of Electromyography (EMG) signals is a challenging process especially in case of forearm muscle due to different hand movements. Feature extraction from Electromyography (EMG) signal is a well-known technique used to acquire useful information encoded in raw EMG signal which is further deliberately use to control prosthetic hand movement, diagnose muscle diseases and pattern recognition. The characteristics of EMG signals are recognizing by using features in both domains as Time-domain and Frequency-domain. Time-domain (TD) feature extraction is a technique to extract the useful information in sequence data points encoded in EMG signal over specific time interval while Frequency-domain (FD) features are extracted using spectral analysis and power spectral density (PSD) of EMG signal.

As discussed in previous part that the EMG data used in this study were carried out from four healthy male subjects performing 4-different hand gestures. For this purpose, we adopt a simple approach of getting EMG data from MYO through an embedded microcontroller. Data acquisition is being carried through 8 channel MYO armband via HM-10 Bluetooth module on an embedded controller as shown in Figure 2.6. The gain of EMG signals is used to extract its features in both Time-domain and Frequency-domain. Feature extraction is a well-known approach to transform raw input data in to a reduced set of features which contain the useful information of signal. Time-domain features are usually faster and implemented easily because they do not require any transformation. Features in time-domain are extensively use in the field of biomedical engineering, medical researches and practices. Time-domain features have better classification performance and less computational complexity than features in Frequency-domain. Frequency-domain represent the statistical properties of power spectral density in EMG signal.

Thirteen features of Time-domain and frequency-domain has been proposed in this paper. These features have been analyzing linearly and non-linearly with specific parameters. To estimate the power and attributes, we take the power spectral density (PSD) of EMG signal.

3.5.1 Features in Time-domain

- **Mean absolute value (MAV)**

Mean absolute value (MAV) is a very well-known feature used in evaluation of EMG signals. It is same like as integrated EMG feature used in the detection of surface EMG signal. It is also known as average rectified value (ARV), Integral of absolute value (IAV) or average absolute value (AAV). MAV is basically a reckon of summation absolute value and measurement of level contraction in EMG signal. It perceives the mean of EMG amplitude over length of signal.

$$\text{mean}(\mu) = \frac{1}{N}\sum_{n=1}^{N} x_n \tag{5}$$

- **Variance of EMG signal (VAR)**

Variance is another statistical power tool used to measure EMG signal. Variance is measured as the expectation of average square deviation of random variable from their mean. Variance is also defining as the measure of power density of an EMG signal.

$$\text{var} = \frac{1}{N-1}\sum_{n=1}^{N} (x_n - \mu)^2 \tag{6}$$

- **Standard Deviation (SD)**

Standard deviation (SD) is a Time-domain statistical approach to measure the dispersion of data from its mean. It is measure as the square root of variance by estimating the variation among data points to its mean. If data are outlying from its mean, then it shows the higher deviation with in the data set.

$$\text{std}(\sigma) = \sqrt{\frac{1}{N-1}\sum_{n=1}^{N} (x_n - \mu)^2} \tag{7}$$

- **Skewness**

Skewness is defined as a measurement of symmetry of signal for both cases, more precise symmetry or lack of symmetry on either side of center point or it may be simply defined as the estimation of third order cumulative.

$$skew = \frac{\frac{1}{N}\sum_{n=1}^{N}(X_n - \mu)^3}{\sigma^3} \tag{8}$$

- **Kurtosis**

Kurtosis is defined as the measure of probability distribution of random variables or the estimation of fourth order cumulative.

$$kurt = \frac{\frac{1}{N}\sum_{n=1}^{N}(X_n - \mu)^4}{\sigma^4} \tag{9}$$

- **Standard Error (SE)**

Standard deviation from its sampling distribution of a signal is known as its standard error (SE) which claims the deviation of sample from its mean.

$$\mathrm{SE}_{\bar{x}} = \frac{s}{\sqrt{n}} \tag{10}$$

- **Mean absolute deviation (MAD)**

Mean absolute deviation is a statistical approach to find the average interval among each data value of a data set from its mean. It is used to find the variations in data set.

$$\mathrm{MAD} = \frac{1}{N}\sum_{n=1}^{N}|x_n - ORT| \tag{11}$$

3.5.2 Features in Frequency-domain

- **Mean Frequency**

Mean frequency is a regular frequency of the spectrum defined as the sum of the product (SOP) of EMG power spectrum and frequency, divided by sum of spectrogram intensity.

$$MNF = \sum_{j=1}^{M} f_j P_j \Big/ \sum_{j=1}^{M} P_j \tag{12}$$

- **Median frequency**

Median frequency splits the spectrum in to two regions with same amplitudes on both sides. Its spectrum is calculated first as the summation of the intensity of whole signal divided by 2 and then cumulative intensity of selected frequency should exceed the calculated value of previous step.

$$\sum_{j=1}^{MDF} P_j = \sum_{j=MDF}^{M} P_j = \frac{1}{2}\sum_{j=1}^{M} P_j \tag{13}$$

- **Power Bandwidth**

The power bandwidth is basically the frequency range or upper frequency limit of a signal for which the rated output power can manage to at least half of the full rated power without any distortion.

- **Total Harmonic Distortion (THD)**

THD is defined as the sum of power of all harmonic components to the power of fundamental frequency. Total harmonic distortion (THD) is in fact the estimation of harmonic distortion present in signal.

- **Signal-to-Noise Ratio (SNR)**

The ratio of signal power to noise power is known as signal-to-noise ratio (SNR). It is quoted for electrical signals and often expressed in decibels.

$$\mathrm{SNR_{dB}} = 10\log_{10}\left(\frac{P_{\mathrm{signal}}}{P_{\mathrm{noise}}}\right) \tag{14}$$

- **Power spectral Density (PSD)**

The power spectral density (PSD) of a signal indicates the presence of power in signal as a function of frequency, per unit frequency. PSD is often expressed in watts per hertz (W/Hz). The PSD of a signal is basically the average of the Fourier transform magnitude squared, over a wide-range time interval.

$$S_x(f) = \lim_{T\to\infty} E\left\{\frac{\mathbf{1}}{\mathbf{2}T}\left|\int_{-T}^{T} x(t)e^{-j2\pi ft}\,dt\right|^{\mathbf{2}}\right\} \tag{15}$$

Summary

After classification we proposed the methodology of feature extraction of Electromyography (EMG) signal using MYO armband. For this purpose, we acquire raw EMG data from forearm muscle through MYO gesture control. Four healthy male subjects were participated in this experiment to perform four different hand gestures including stationary, double tap, single-finger and finger-spread hand movement as shown in Figure 2.8. From these different hand gestures, we extract our features in both Time-domain (TD) and Frequency-domain (FD) to analyze the characteristics of our EMG signal. Time-domain features show the statistical analysis and information carried in EMG signal over specific time interval while Frequency-domain features involve the measurement and variables which explain the different aspect of frequency spectrum in EMG signal. For normal distribution of EMG spectrum, the median frequency and mean frequency will be the same while any deviation from normal spectrum will show the opposite values of both median and mean frequencies. After feature extraction in both domains we classify our EMG signal under supervision of Neural Network (NN), Linear discriminant analysis (LDA), Quadratic discriminant analysis (QDA), Support vector machine (SVM) and attribute selected classifier in WEKA. The recognition utility of these features shows a very high rate of accuracy as in case of attribute selected classifier.

Chapter 4 RESULTS AND ANALYSIS

4.1 Experimental Parameters

In this study we observe the behavior of four hand gestures including the stationary, double tap, single finger movement and finger spread to understand the attributes and features of hand movements using number of classifiers.

Different classification approaches named as LDA, QDA, SVM, NN, Ensemble (Bagged Tree), Random forest, Gradient boosted and subspace KNN were adopted in our case to utilize and classify the hand movements as given in Table 2.

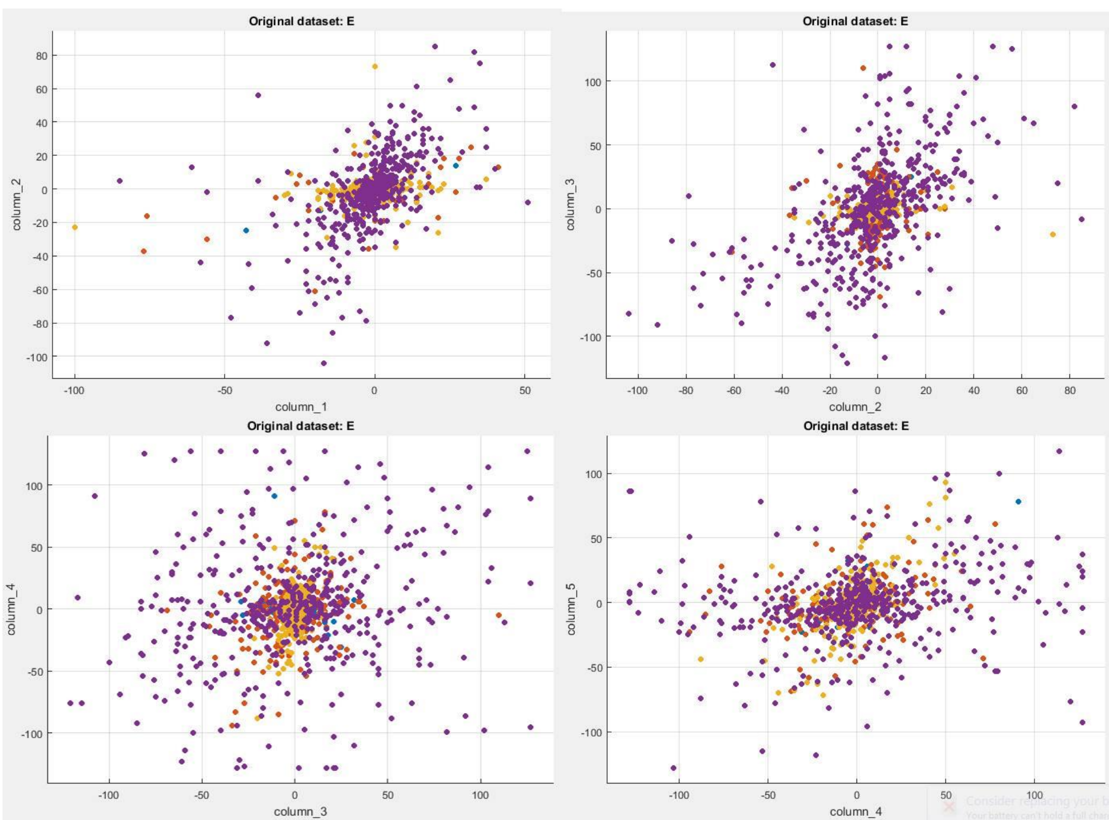
To employ the classification approach, we used 5 fold cross-validation technique in our model of classify learner with four class EMG data. The scatter plot of four class EMG signals in classify learner is shown in Figure 4.1 where we can see the scatter plot of EMG data among each channel of MYO (As column 1= channel 1, column 2 = channel 2 and so on). In our model of classify learner we define a response variable to classify the predictive behavior of four class EMG signal. For this reason, we mark our four class hand-gestures as 0 for stationary, 1 for double tap, 2 for single finger movement and 3 for finger spread as response variable as shown in Table 4.1, While in case of WEKA, we used 10 fold cross-validation approach to classify our EMG data as shown in Figure 4.5.

Table 4.1 4-class Hand gestures

Sr. No.	Movements	Variables
1	Stationary	0
2	Double Tap	1
3	Single finger Movement	2
4	Finger Spread	3

4.2 Experimental Results of classification

Results of this experiment shows the high rate of accuracy with F-measure, MCC and ROC. As from the results we conclude that the ensemble bagged tree shows the higher rate of accuracy among the listed classifiers with 83.9% as given in Table 4.2. The confusion matrix and True (TPR) and false rate (FPR) of four class EMG data has shown in Figure 4.2 and Figure 4.3 respectively. The recognition rate of various hand movements after classification give 92% for stationary, 68% for double tap, 83% for single finger movement and 82% for finger spread gesture. While in case of Random Forest it gives the recognition accuracy for each gesture as 91% for stationary, 67% for double tap, 83% for single finger movement and 82% for finger spread as given in Table 4.3.



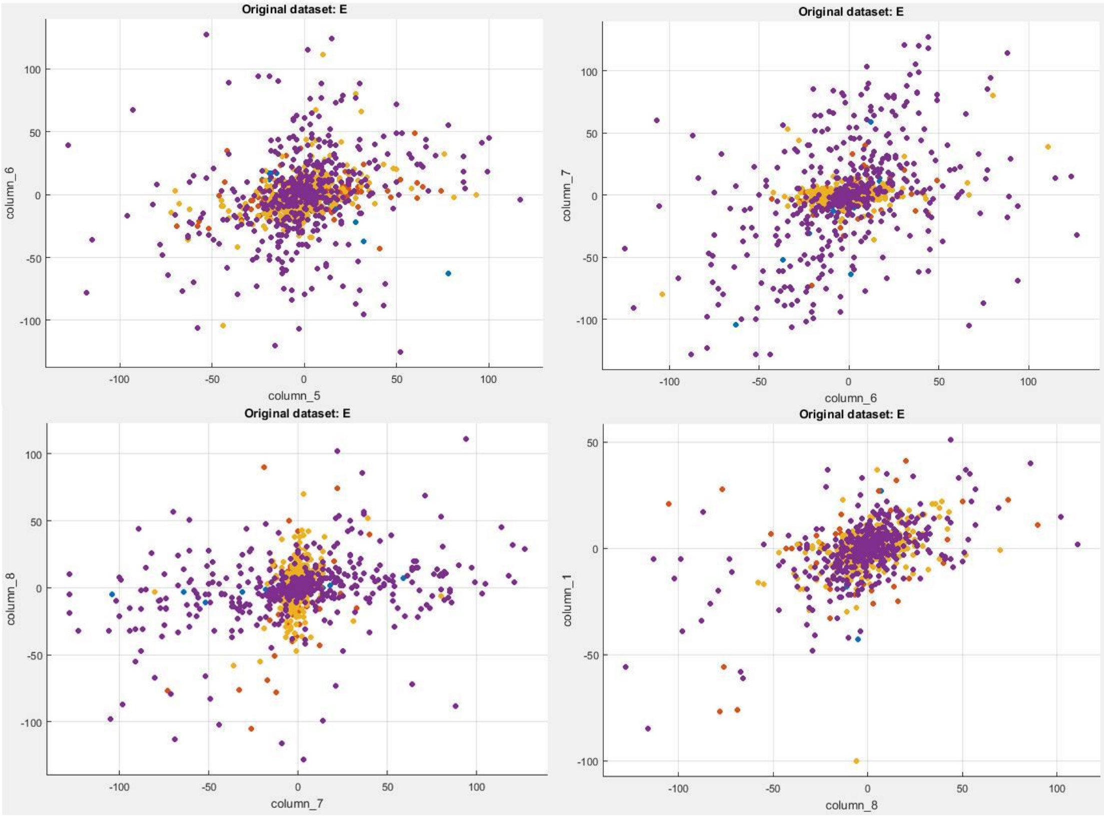


Figure 4.1 8-channel EMG scatter plot

The classification results of other classifiers are given in table [2].

Table 4.2 Results of Classification

Sr. No.	Classification Algorithm	Performance
1	QDA	72.4%
2	Quadratic SVM	82.6%
3	Fine Gaussian SVM	80.1%
4	Random Forest	83.3%
5	Gradient Boosted (Tree)	81.2%

6	Ensemble (Bagged Tree)	83.9%
7	Ensemble (Subspace KNN)	80.4%

4.2.1 Region of convergence (ROC)

Region of convergence (ROC) curve is castoff to find the quality and accuracy of running classifier. The marker on plot exhibits the performance of classifier as it shows the true positive rate (TPR) and False positive rate (FPR) of running classifier as shown in Figure 4.4. For example, if it states the behavior of False positive rate (FPR) as 0.25 then its mean that the classifier picks the 25% incorrect observations for positive class. In turn if the true positive rate (TPR) signify the behavior of classifier as 0.75 then actually it shows that the classifier picks 75% correct observations for positive class.

Table 4.3 Recognition rate for Hand-gestures

Sr. No.	Classification Algorithm	Stationary	Double Tap	Single finger movement	Finger- spread
1	Ensemble (Bagged Tree)	92%	68%	83%	82%
2	Random Forest	91%	67%	83%	82%

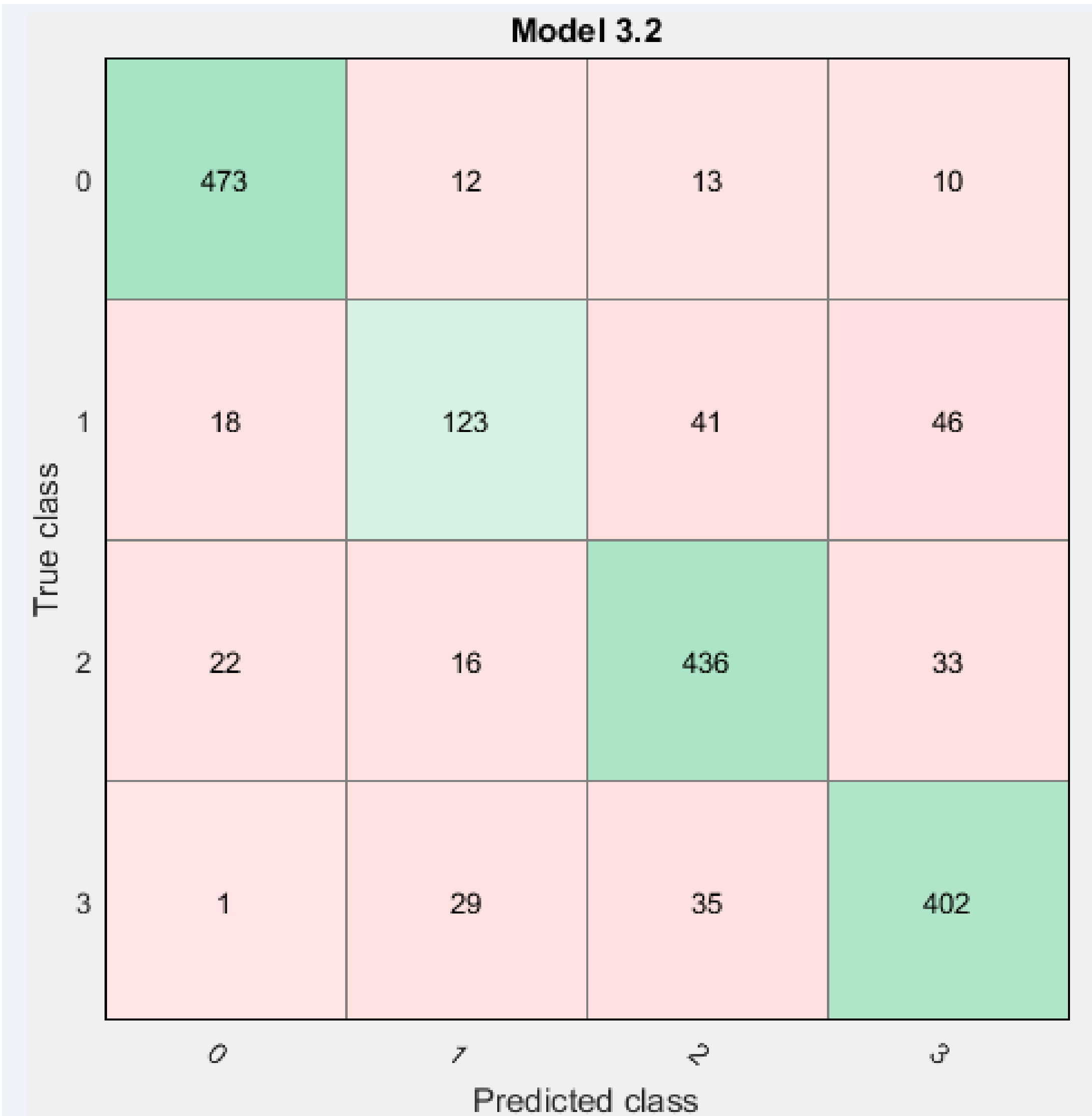


Figure 4.2 Confusion Matrix of Four-Hand gestures

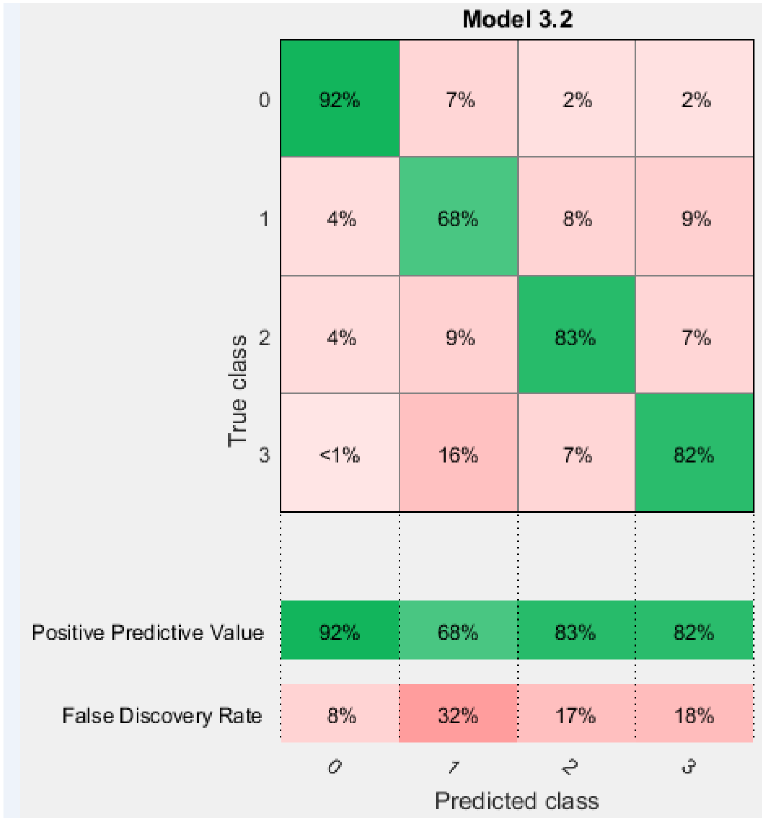


Figure 4.3 True and False rate of predictive classes

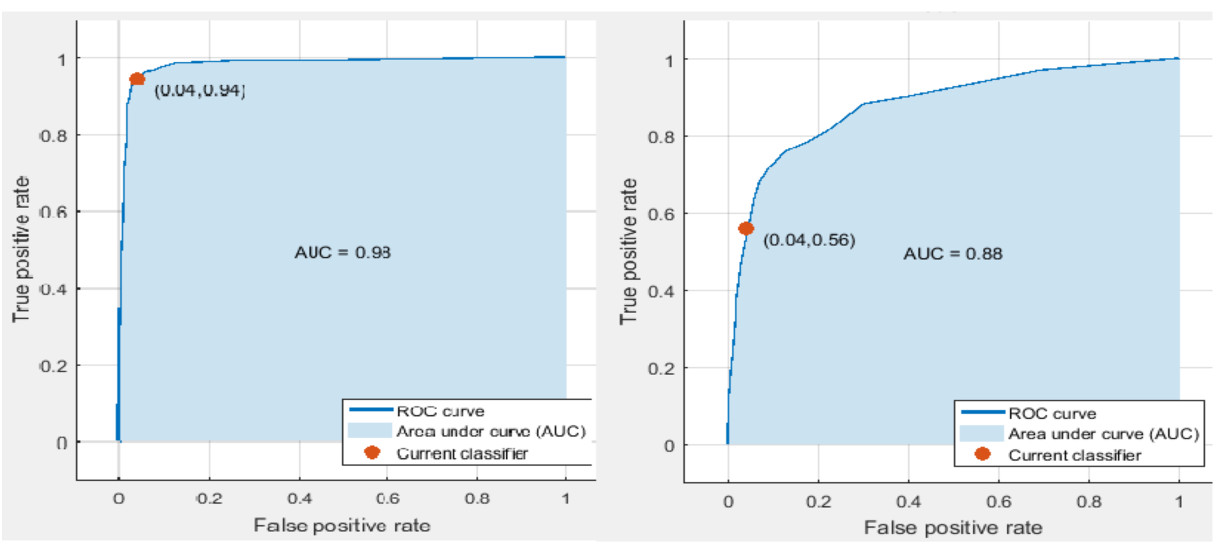


Figure 4.4 ROC curve for Stationary/Double Tap Hand-gesture

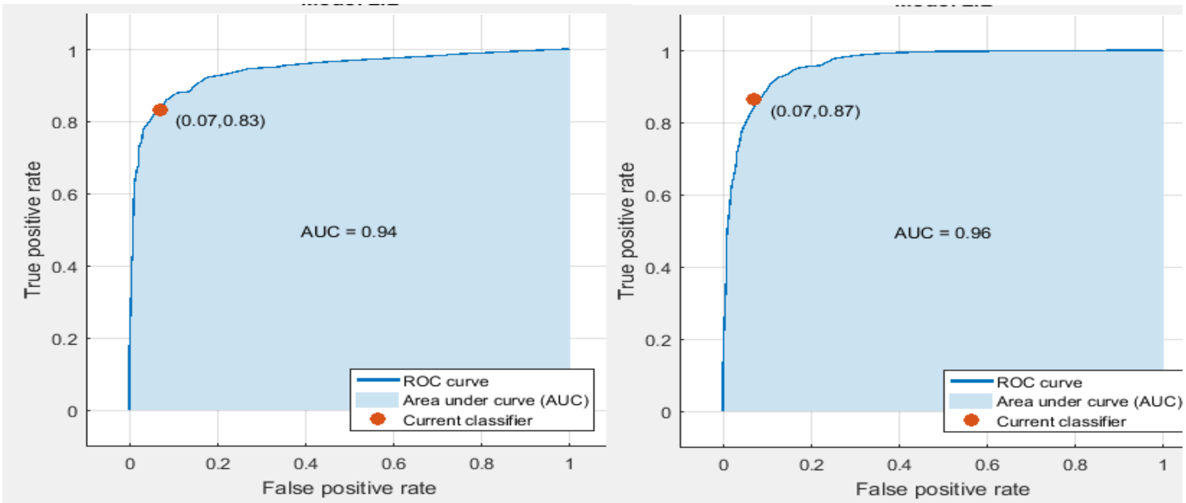
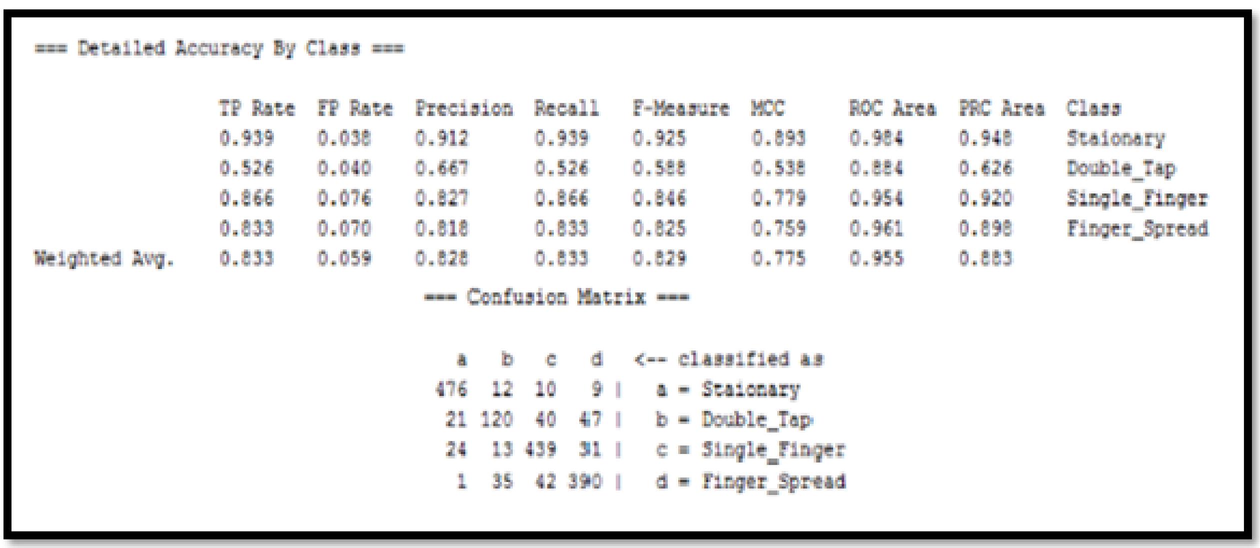


Figure 4.5 ROC curve for Single finger mov. /Finger spread Hand-gesture

The top left corner with right angle of curve represents the perfect results with no misclassification rate. While the point lies with 45 degree of curve line shows the poor results of classification. The AUC (area under curve) is actually the measurement of recognition, classification and quality of classifier results. Large area under curve (AUC) represents the superior results of classification while small area under curve indicates the inferior performance of classifiers.



=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0.939	0.038	0.912	0.939	0.925	0.893	0.984	0.948	Staionary
	0.526	0.040	0.667	0.526	0.588	0.538	0.884	0.626	Double_Tap
	0.866	0.076	0.827	0.866	0.846	0.779	0.954	0.920	Single_Finger
	0.833	0.070	0.818	0.833	0.825	0.759	0.961	0.898	Finger_Spread
Weighted Avg.	0.833	0.059	0.828	0.833	0.829	0.775	0.955	0.883	

=== Confusion Matrix ===

a	b	c	d	<-- classified as
476	12	10	9	a = Staionary
21	120	40	47	b = Double_Tap
24	13	439	31	c = Single_Finger
1	35	42	390	d = Finger_Spread

Figure 4.6 Classification results of WEKA

4.3 Experimental Parameters of Feature Extraction Methodology

This section explains the behavior and classification results of used classifier in extracting features of EMG signal in Time-domain and Frequency-domain. As we mentioned in previous chapters that for this study four healthy male volunteers took part in performing four different hand-movements. These hand-movements were relatively based on stationary, Double tap, single finger movement and fingers spread as shown in Figure 3.8.

The EMG signals of these hand-movements were further extracted and used to generate feature extraction in Time-domain and Frequency- domain. Analysis based on feature extraction of electromyogram (EMG) signals becomes an utmost criterion before interpretation. As the EMG signal depend upon time and force with amplitude variations, so the normalization of EMG signal is necessary to define its characteristic properties and features in both domain. Subsequently, before extracting features from signal the frequency-domain parameter power spectral density (PSD) is determined and analyzed; for a given signal. The power spectral density of a EMG signal shows the power (energy per unit time) falling within given frequency limits.

The power spectral density (PSD) of 8-channel EMG signals for 4-hand gesture shows the strength and disorderly action potentials of EMG signal with increasing rates and amplitude overlaps at 60Hz frequency in Figure 4.7 to Figure 4.10.

There is no activation in muscle's action potentials at rest position while on contraction of muscles it acquires more and more action potentials. That's why in Figure 4.7 and Figure 4.8 we can see the more strength and saturation of double tap signals (in blue) than stationary EMG signal (in red).

Similarly, in case of single finger movement and finger spread, the muscle fibers produce more MUAP's as contraction level of muscles increases. Figure 4.9 explains the PSD of more contracted gestures of single finger movement (in green) and finger spread (in black) with high disorder of actions potentials and varying amplitudes that show the strength and saturation of EMG signals. In comparison of 4-gesture hand movement we can see the more strength and alignment of 8-channel EMG signals in case of Figure 4.10 as it shows the more contraction of muscles.

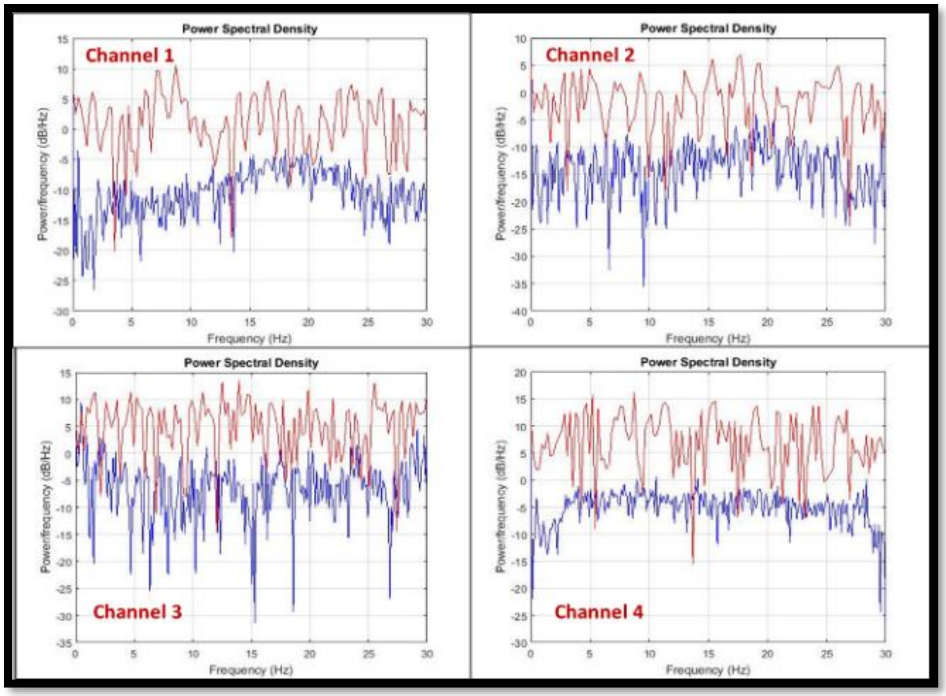


Figure 4.7 PSD of EMG signals (Stationary vs Double Tap)

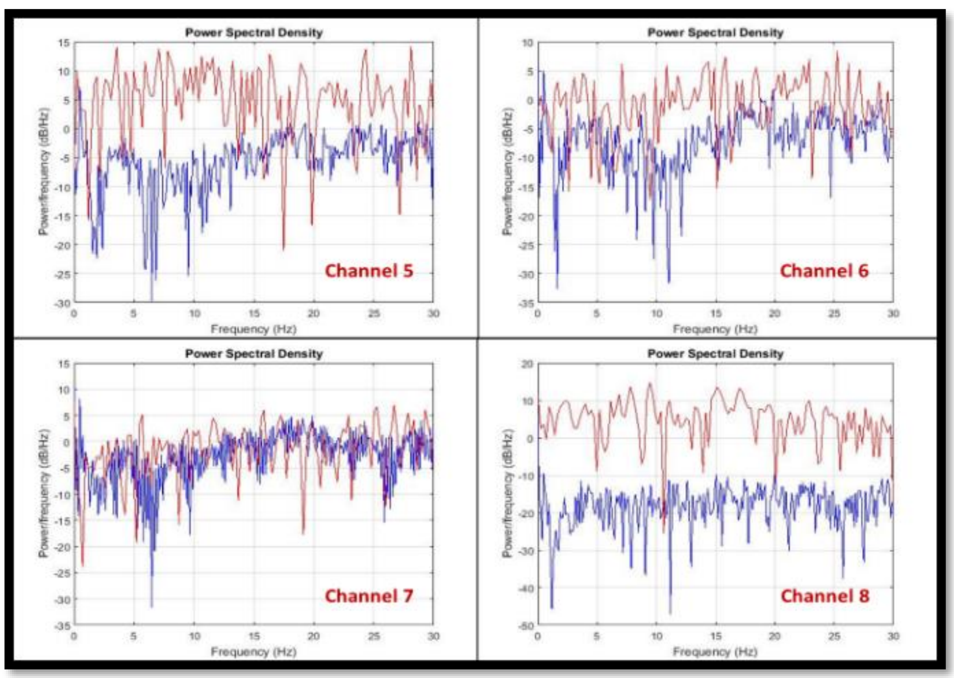


Figure 4.8 PSD of EMG signals (Stationary vs Double Tap

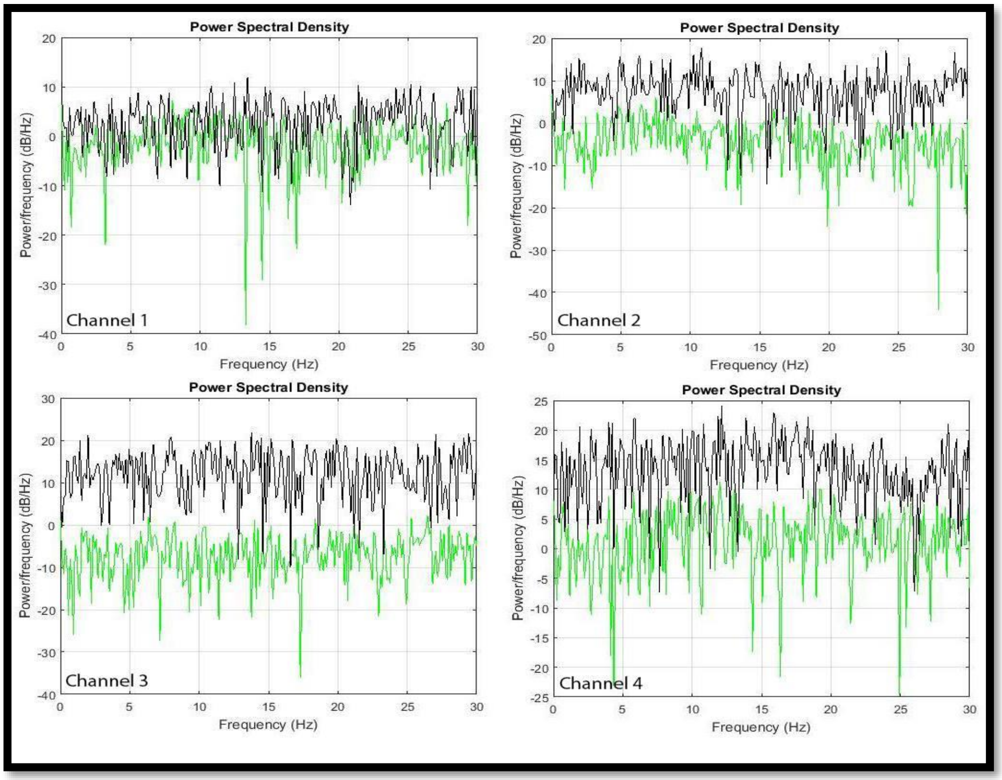


Figure 4.9 PSD of EMG signals (Single finger mov. vs Finger spread)

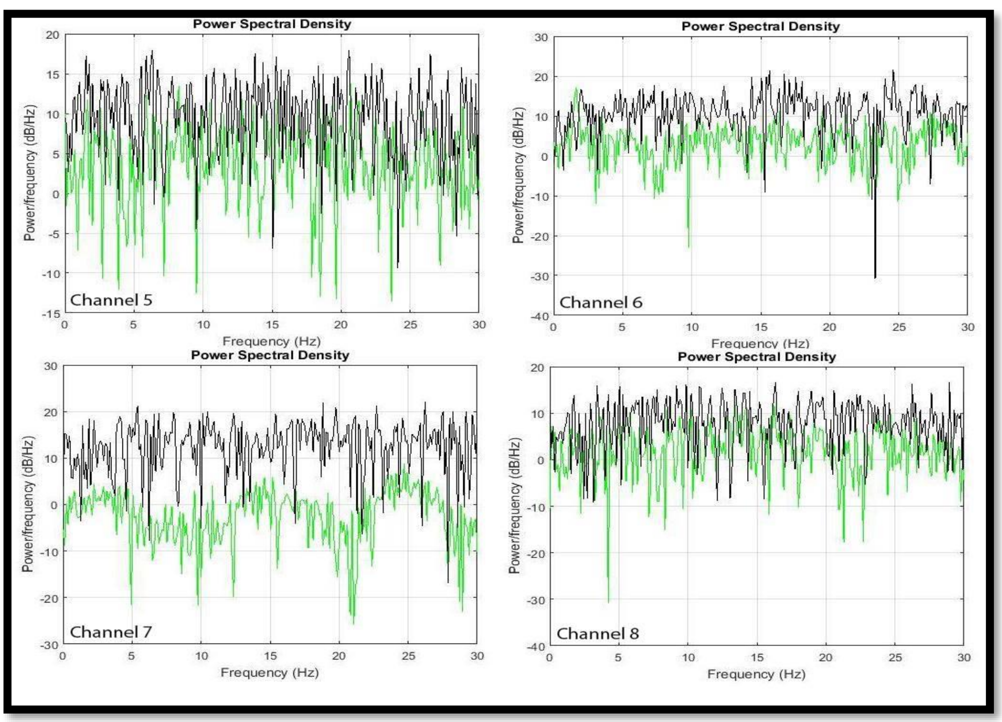


Figure 4.10 PSD of EMG signals (Single finger mov. vs Finger spread)

4.4 Classification Results of EMG signal features in Time-domain and Frequency-domain

Based on acquired classification approaches of various classifiers the behavior of each group of time-domain and frequency-domain were tested. The classification based on attribute selected classifier shows the higher rate of accuracy as compared to previous approaches with 93.8% on platform of WEKA. The average classification results of all features in both time-domain and frequency-domain for 4-gesture hand movement are given in Table 4.

To classify the thirteen features EMG data, we used 10-fold cross validation approach in WEKA. For this purpose, we also trained our sample at ratio of 60% to train with ratio of 40% to test or to evaluate the remaining data. Among listed classifiers of WEKA attribute selected classifier was the only one with higher predictive values of True positive class, precision, FC-Measure and ROC (Region of convergence) area as given in Figure 4.8.

Table 4.4 Classification results of EMG features

Time domain features			Frequency domain features	
Sr.	Feature	Performance	Feature	Performance
1.	Mean absolute value(MAV)	100%	Mean frequency	100%
2.	Variance	100%	Median frequency	100%
3.	Standard deviation (SD)	75%	Power Bandwidth	100%
4.	Skewness	100%	THD	100%
5.	Kurtosis	80%	SNR	100%
6.	Standard Error	100%		
7.	Mean absolute deviation (MAD)	75%		

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	Mean (MAV)
	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	Sample Variance
	0.750	0.023	0.750	0.750	0.750	0.727	0.980	0.799	Standard Deviation
	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	Skewness
	1.000	0.023	0.800	1.000	0.889	0.884	0.989	0.800	Kurtosis
	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	Standard Error
	1.000	0.022	0.750	1.000	0.857	0.856	0.996	0.917	MAD
	0.000	0.000	0.000	0.000	0.000	0.000	0.989	0.500	MAD
	0.750	0.000	1.000	0.750	0.857	0.856	0.997	0.950	Mean Frequency
	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	Median Frequency
	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	Power Bandwidth
	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	THD
	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	SNR
Weighted Avg.	0.938	0.005	0.926	0.938	0.928	0.926	0.997	0.947	

Figure 4.11 Classification results of WEKA

A confusion matrix in Figure 4.9 shows the performance of classification model on test data set for which the true positive values are known.

=== Confusion Matrix ===

a	b	c	d	e	f	g	h	i	j	k	l	m	<-- classified as
4	0	0	0	0	0	0	0	0	0	0	0	0	a = Mean (MAV)
0	4	0	0	0	0	0	0	0	0	0	0	0	b = Sample Variance
0	0	3	0	1	0	0	0	0	0	0	0	0	c = Standard Deviation
0	0	0	4	0	0	0	0	0	0	0	0	0	d = Skewness
0	0	0	0	4	0	0	0	0	0	0	0	0	e = Kurtosis
0	0	0	0	0	4	0	0	0	0	0	0	0	f = Standard Error
0	0	0	0	0	0	3	0	0	0	0	0	0	g = MAD
0	0	1	0	0	0	0	0	0	0	0	0	0	h = MAD
0	0	0	0	0	0	1	0	3	0	0	0	0	i = Mean Frequency
0	0	0	0	0	0	0	0	0	4	0	0	0	j = Median Frequency
0	0	0	0	0	0	0	0	0	0	4	0	0	k = Power Bandwidth
0	0	0	0	0	0	0	0	0	0	0	4	0	l = THD
0	0	0	0	0	0	0	0	0	0	0	0	4	m = SNR

Figure 4.12 Confusion Matrix of thirteen EMG features in both domains

4.5 Comparative Analysis

In field of biomedical engineering various design techniques and approaches have been used to develop an efficient and cost-effective solution for handicaps. For this purpose, some developers use invasive electrodes on muscles to acquire EMG data and some give preference to non-invasive design techniques through a controller or DAQ board. MYO arm band is a latest approach and become very wide use in number of studies. As we mentioned above in previous chapter that although previous design techniques improve the results of accuracy and reduce the cost of prosthetic design but still it requires some improvement in cost of design. The comparison of different approaches used so far has been given below in Table 5. As compared to previous approaches we give an idea of MYO arm band as a motion device for various upper-limb movements through an embedded system and an external Bluetooth module with a good performance classifier. The overall system developed in our case is relatively cheaper non-invasive and give good performance too than other costly systems with high rate of accuracies. We basically classify the four basic and general hand movements to study the liability of our system. Results of this study shows comparatively good performance in detecting 4-hand movements with accuracy of more than 80% to 92%. More over this study can be used in future to develop a cheap prosthetic design for amputee.

Table 4.5 Comparison of different approaches used for classifying hand movement

Sr. No.	Technique/Apparatus	Gestures/purpose	Classifiers	Accuracy
1.	11 electromagnetic Sensors on a glove	Free hand movement,	Using GUI to explore gesture in real time	NA/ just connecting of prosthetic hand
2.	6 surface EMG sensors	3 Grasping things (Mug, Marker, Rectangle) At 3	LDA,QDA,SVM,ANN, KNN	83-91%

		diff. places to observe	and Random forest	
3.	Multiscale principle component analysis Surface EMG sensors	Normal, Myopathy, ALS (Types of muscles to detect) to classify data of these muscles	C4.5, CART and Random forest decision tree	96%
4.	Surface electrodes with DAQ board and 16-bit A/D converter	59-person data with 19 normal, 20 myopathy patients and 20 neuropathy patient to classify	MLP and SVM under the supervision of PCA and FFT to enhance accuracy	85.4%
5.	MYO arm band with Bluetooth using MEX file Bridging with (Laptop)	9 subjects Walking, Running, Resting and open door (To check wanderness) a disease	SVM, Naïve bias and KNN	More than 90%
6.	MYO with help of Apple map connector (App)	Zooming, focusing and panning the map navigation using 5 gestures of MYO (Fist, Finger spread, wave in, wave out and Double Tap)	Questionnaire based study	NA

7.	8 surface EMG sensors locate on forearm	Six gestures/wrist flexion, wrist extension, hand supination, hand pronation, hand opening, and hand closing	Discrete wavelet transforms (DWT) of EMG signals with unconstrained parameterization of mother wavelet using SVM to classify	5% misclassification rate
8.	Low cost passive sensors, an innovative analog front-end system and low power microcontroller	6 gestures/power grip, precision grasp, open hand, pointed index and flexion/extension of the wrist	LDA, ANN and SVM	92%
9.	Six pairs of surface electrodes (Ag/AgCl)	9 gestures/wrist flexion, wrist extension, thumb close, making a fist, fingers spread, 4-finger close, forearm supination, forearm pronation, open, and no motion	LDA and SVM (WT/SVM-OVO)	92.3%
10.	MYO armband	To control virtual robotic arm	NA	NA

		generated in unity 3D		
11.	Three dimensional (3D) printed prosthesis with MYO	To provide an affordable, practical, and convenient solution for amputees.	NA	NA
12.	Five non-invasive Surface electrodes	3 Movements/upper arm flexion and extension, forearm pronation and supination and palmar flexion and dorsiflexion	AR model, Back propagation Neural networks (BPNN	81-90%

4.6 Comparative Analysis of Feature extraction with previous studies

As compared with previous studies we used more feasible, noninvasive and cost-effective approach to acquire EMG data using a band MYO gesture control rather to use electrodes with high signal to noise ratio. MYO gesture control has 8 channel EMG sensors with 9-axis inertial measurement unit to measure the EMG signals wirelessly through an embedded system. So, in our case there’s no resistance, low motion artifacts and no shuffling of wires because it’s an elastic product that can be wear on any size of forrarm. [1] Cemil Altın and Orhan Er study a biological EMG signal for different gestures. They filtered and classify the hand movement using the feature extraction methodology by extracting features in both wrist flexion and wrist extension cases. Classification was made using K Nearest Neighbor algorithm (KNN). The dataset used in this study is acquired by the EMG signal acquisition tool. Overall 90 % accuracy was obtained by K Nearest Neighbor algorithm purposed for signal classification. While in our case extracting features from the above classified results of four hand gestures we acquire the overall accuracy of 93.8% using attribute selected classifier in WEKA which shows the better results than the features of time domain and frequency domain used by Cemil Altın and Orhan Er. Table 6 shows the comparison and overall performance ratio of features in time and frequency domain for both studies.

Table 4.6 Comparative Analysis of both studies

Time-domain Features				Frequency-domain features		
Sr.	**Feature**	**Performance (By Cemil Altın and Orhan Er*)**	**Performance (In this study)**	**Feature**	**Performance (By Cemil Altın and Orhan Er*)**	**Performance (In this study)**
1.	Mean Absolute Value (MAV)	91%	100%	Mean Frequency (MF)	65%	100%
2.	Variance	79%	100%	Median Frequency (MDF)	83%	100%
3.	Standard Deviation (SD)	81%	75%	Power Bandwidth	_____	100%
4.	Skewness	72%	100%	THD	_____	100%
5.	Kurtosis	74%	80%	SNR	35%	100%
6.	Standard Error (SE)	_____	100%			
7.	Mean Absolute Deviation (MAD)	83%	75%			

Chapter 5 CONCLUSION AND FUTURE WORK

The goal of this study is based on classification and recognition of hand movement for various upper-limb movements. For this purpose, a novel method has been proposed to acquire the EMG signals from forearm muscle with the help of MYO gesture control on an embedded platform through a Bluetooth module. 4 healthy male subjects were participated in this study to perform four different hand gestures. After acquiring EMG data from these participants' 5-fold cross validation approach was used to classify these hand movements. The results based on classification using Ensemble (Bagged Tree) give the high rate of accuracy among other classifiers with better recognition rate for various hand movements.

This study also comprises thirteen different features of Time-domain and Frequency-domain from EMG signals were extracted and evaluated for 4-gesture hand movements. Extracted features were further classified under supervision of various classifiers on WEKA to predict the behavior of gesture. Attribute selected classifier is one among the other classifiers with higher performance and accuracy of 93.8%. For this scope, attribute selected classifier was trained by 10 fold-cross validation approach with 60% training data and 40% test data to predict the features of four-class EMG signals in both domains (TD & FD). From results it is concluding that features in frequency-domain shows the ultimate dominance and signal characterization rather features in time-domain. The finding of this study will further use to predict the behavior of EMG in pattern recognition and to investigate and evaluate the relation between different feature vectors and motion patterns. The obtained results will precede to contribute in process of classification of EMG signals for assistive devices or powered human arm prosthetics.

The results of this study can also be used in future to develop an efficient, cost effective and flexible assistive device or prosthesis.

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