List of Acronyms

Sr. No.	Abbreviations	Full Form
1	AVG	Average
2	BP	Blood Pressure
3	c	Complexity
4	DoF	Degree of Freedom
5	DIP	Distal Interphalangeal
6	DARPA	Defense Advance Research Project Agency
7	EEG	Electroencephalography
8	EMG	Electromyogram
9	f	Fist Position
10	FSR	Force Sensitive Resistor
11	h	Hold Position
12	Kd	Derivative Constant
13	Ki	Integral Constant
14	Kp	Proportionality Constant
15	LOGAVG	Log of Average
16	m	Mobility
17	MCP	Metacarpal Phalange
18	MPL	Modular Prosthetic Limbs
19	p	Pinch Position
20	PCA	Principal Component Analysis
21	pd	Palm Down Position
22	PLA	Polylactic Acid
23	PID	Proportional Integral Derivative
24	PIP	Proximal Interphalangeal
25	pu	Palm Up Position
26	PWM	Pulse Width Modulation
27	r	Rest Position
28	RF	Random Forest
29	RoHS	Restriction of Hazardous Substances Directive
30	RPM	Revolutions Per Minute
31	sEMG	Surface Electromyogram

Sr. No.	Abbreviations	Full Form
32	SMA	Shape Memory Alloys
33	SMP	Shape Memory Polymers
34	SPS	Samples Per Seconds
35	SVM	Support Vector Machine
36	UART	Universal Asynchronous Receiver Transmitter
37	v	Victory Position
38	VAR	Variance

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Contents

CHAPTER 1
1 INTRODUCTION

1.1 Introduction to EMG Signals

The Electromyogram signal is a neuro muscular signal that measures electric potential generated in muscles during their contraction and relaxation representing neuromuscular activities. The amplitude of the signal is in the range of 0-10 mV[1]. Signal frequency range is above 12 Hz. These signals can be recorded from the lower elbow region of the arm for a certain set of gestures. These gestures can be rest, palm-up, palm-down, fist, hold, etc. Various features like average, L2-norm, kurtosis, skewness, etc. can be extracted from these recorded signals. With good analysis tools and algorithms, the EMG signals can be mapped with the control signals for the actuators in Bionic Arm with a high degree of accuracy.

1.2 Introduction to Bionic Arm

The hand is a powerful tool and its loss causes a severe psychological and physical drawback. Despite the significant impact of losing a hand, numbers of amputees requiring prosthesis are too small to push manufacturers to innovate their products, so both the control interfaces and mechanisms have barely changed in the past 40 years. It is proposed to design a cost effective Bionic Arm with 11 DoF. 3DExperience platform would be used for the design of Bionic Arm and using 3D printing technology a light weight Bionic Arm would be printed. Most of the prosthetic arms designed and used in India are very costly yet they fail to provide the high Degree of Freedom. Due to less DoF, the movements of the arm are restricted to only actions like gripping and holding. For this 3D printing technology is used which makes the Bionic Arm light weight as well.

1.3 Motivation

Research on EMG signals is a fascinating field. Study of recorded EMG signals can include various details like transforms, windowing techniques, different digital filtering techniques to better analyze the data. Similarly, just the acquisition of EMG signals can be a different field of research that includes various analog filters, different analog to digital converting techniques, methods for noise and artefact removal, etc.

That being said, there isn't enough research done in this field of biomedical signals, so we wanted to research in this particular field.

Loss of limb for a person can be a devastating experience. The amputees lose control over their lives. They depend on others for their day to day activities. Thus, it can be said the loss of limb causes severe psychological and physiological damage. It diminishes the quality of life of the person.

As engineers we always have wanted to contribute to the society. Thus, as an application of the EMG signal analysis, a Bionic Arm can be built that can mimic hand gestures and movements. Thus, by providing cost-effective low weight Bionic Arm it is aimed to help amputees to overcome their distress

1.4 Objectives

1. To study the human-arm anatomy with reference to different gestures.
2. To study the EMG signals related to lower arm/finger gestures.
3. To acquire the EMG signals from a healthy person (one subject) and create datasets for various pre-decided gestures.
4. To analyze the recorded signals and extract various features from them.

5. To create a machine learning model that can identify these features.
6. To apply the output of the machine learning model to the actuators in Bionic
Arm to actuate the gestures.
7. To design a low cost, high functionality (high Degrees of Freedom) Bionic Arm.
8. To design a lightweight Bionic Arm using 3D print technology.

1.5 Outcomes

A Bionic Arm of 11 DoF was successfully 3D printed and assembled. Three gestures were successfully classified with the accuracy of 94.18% using Support Vector Machine Model of Machine Learning. The classified gesture was successfully actuated by the Bionic Arm. Also the Bionic Arm weighs 600grams which almost meets the standards[2].

1.6 Social relevance of the Project

The outcome of this project is to create a cost effective less weight Bionic Arm that can mimic the hand gestures correctly. This will help lower elbow amputees by providing them a solution that will help them in their day to day tasks. This in turn will give them more independence and improve their quality of life.

CHAPTER 2
2 LITERATURE SURVEY

The contents of this chapter have been divided into two parts. The first part will concentrate on the research and study of EMG signals. The second part will focus on the design of Bionic Arm.

2.1 BIONIC ARM DATA ACQUISITION AND CLASSIFICATION

Many different approaches are presently used to control the Bionic Arm. Some of the widely used approaches are-

1. EEG signal analysis approach.
2. EMG signal analysis approach.

Electroencephalography (EEG) is an electrophysiological monitoring method to record electrical activity of the brain. EEG measures voltage fluctuations resulting from ionic current within the neurons of the brain[3]In EEG signal approach, the brainwaves are sensed from different regions of brain. The Signal frequency range is around 1 to 500 Hz and amplitude is around 50 micro volts[4]. These signals are weak in amplitude and have a lot of noise. Plus, it is hard to distinguish between the signal for left and right hand movements. In EMG signal approach, the brainwaves are sensed near the arm. This signal is produced due to the neural and muscular activity. So the signal is comparatively strong and easy to extract. Since the signal is sensed near the arm there is no problem of right and left hand movement differentiation. In addition to that, processing EEG is complex and consumes more power.

The EMG signal is a biomedical signal that measures electrical currents generated in muscles during its contraction representing neuromuscular activities[5]. The amplitude of the signal is in the range of 0-10 mV[5]. Signal frequency range is above 12 Hz. It is proposed to use EMG signal approach since is easy to implement and gives better signal quality. With good analysis tools and algorithms, the EMG signals can be mapped with the control signals for the servo motors in Bionic Arm with a high degree of accuracy.

There are two ways to extract the EMG signal.

1) Intramuscular EMG (invasive electrode)

2) Surface EMG (non-invasive electrode)

Commercially many different Bionic Arm options are available with a varying degree of freedom in the motions. It is intended to design a Bionic Arm that mirrors as many motions of the actual human hand as possible. For this, study of various actuators and robotic mechanisms will be undertaken to design the Bionic Arm.

2.1.1 Sensors

The requirements for a sensor to successfully acquire EMG signal are as follows [6][4][7].

- It should contain a 10-500Hz Band Pass filter to remove the high frequency noise from the signal.
- It should contain a 50 Hz Notch filter for noise reduction.
- The signal strength of EMG signals is very low. It is in the range of 0-10 mV. Thus the sensor should have an amplifier to amplify the signal strength. [5]
- A high resolution ADC is needed to convert the EMG signal from analog to digital value.

Along with sensors, right electrodes also need to be chosen to obtain accurate readings. There are various types of electrodes available.

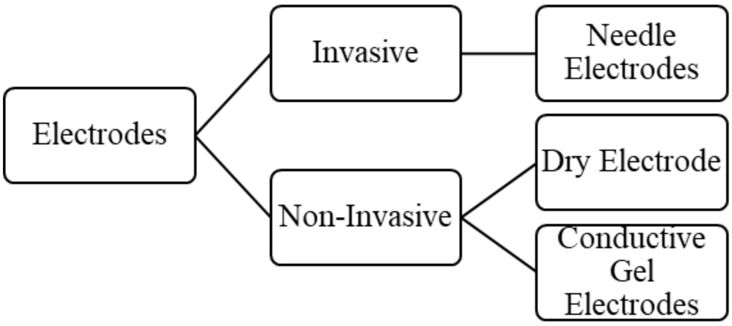


Figure 2-1: Types of Electrodes

Since we are going for sEMG signal extraction, the non-invasive electrodes will be used. The signal extracted with dry electrodes tends to be noisy and weak in strength. Conductive gel electrodes provide better signal extraction as compared to dry electrodes but they need to be replaced regularly since the conductive gel is not long lasting. [7]

2.1.2 Muscle regions

Human hand consists of different muscle groups that are responsible for various hand movements. The following table contains the names of the muscle groups and their functions.

Table 2.1: List of muscle groups and their functions[8][9]

Sr. no.	Muscle group	Actions
1.	Flexor carpi radialis muscle	Flexing of the hand at wrist. Radial deviation of the hand at wrist.
2.	Flexor carpi ulnaris	Flexing of the hand at wrist. Ulnar deviation of the hand at wrist.
3.	Flexor digitorum profundus	Flexing of the fingers.
4.	Flexor pollicis longus	Flexing of the Thumb
5.	Extensor carpi radialis brevis muscle	Extension of the hand at wrist. Radial deviation of the hand at wrist.
6.	Extensor carpi radialis longus muscle	Extension of the hand at wrist. Radial deviation of the hand at wrist.
7.	Extensor carpi ulnaris	Extension of the hand at wrist. Ulnar deviation of the hand at wrist.
8.	Extensor Digitorum	Extension of the hand at wrist. Extension of the fingers.
9.	Extensor pollicis longus	Extension of the Thumb

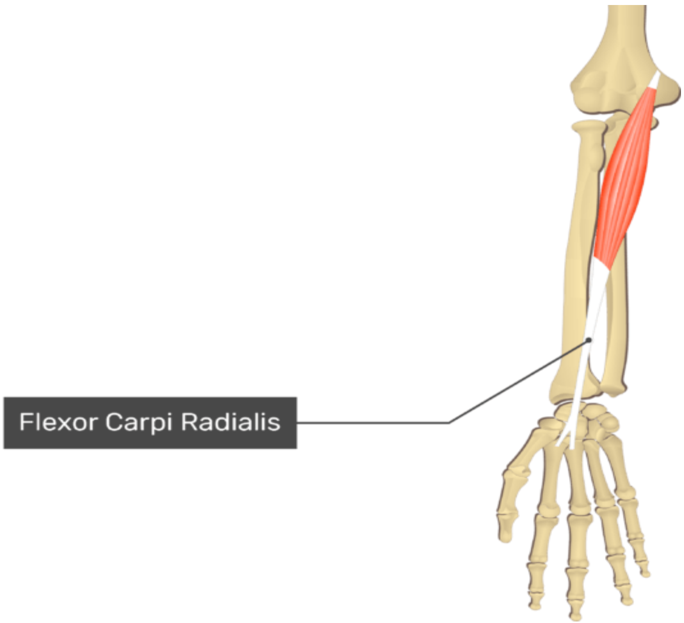


Figure 2-2: Flexor Carpi Radialis[9]

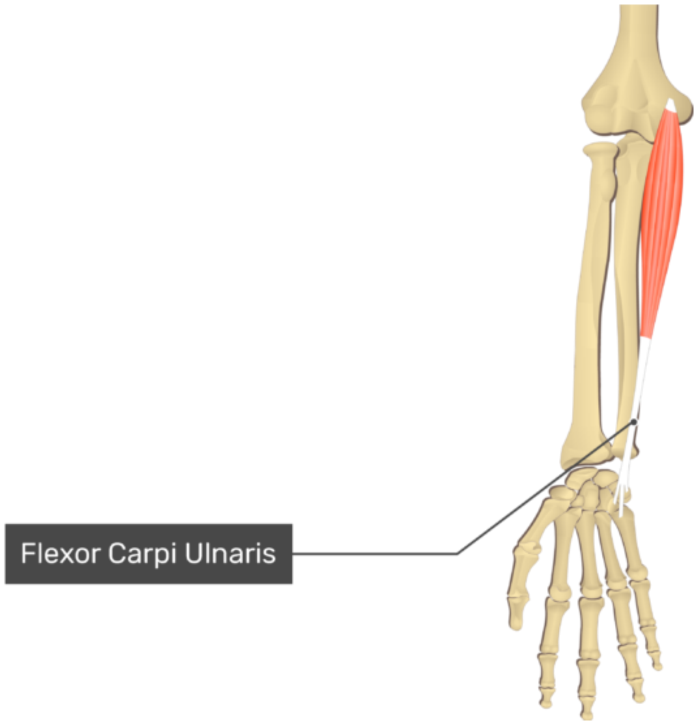


Figure 2-3: Flexor carpi ulnaris[9]

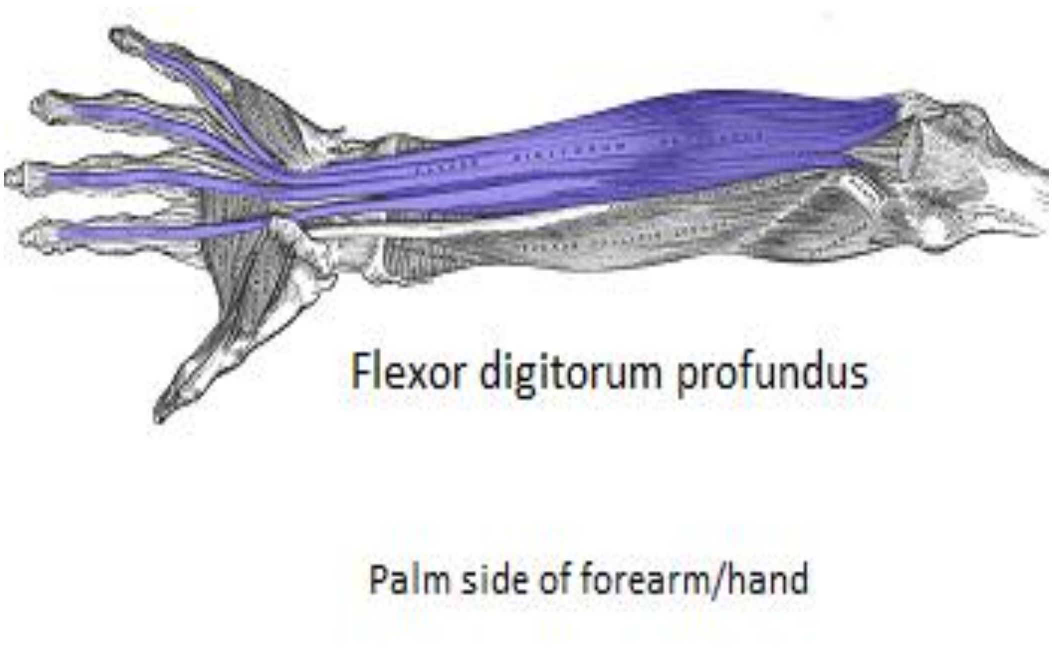


Figure 2-4: Flexor digitorum profundus[8]

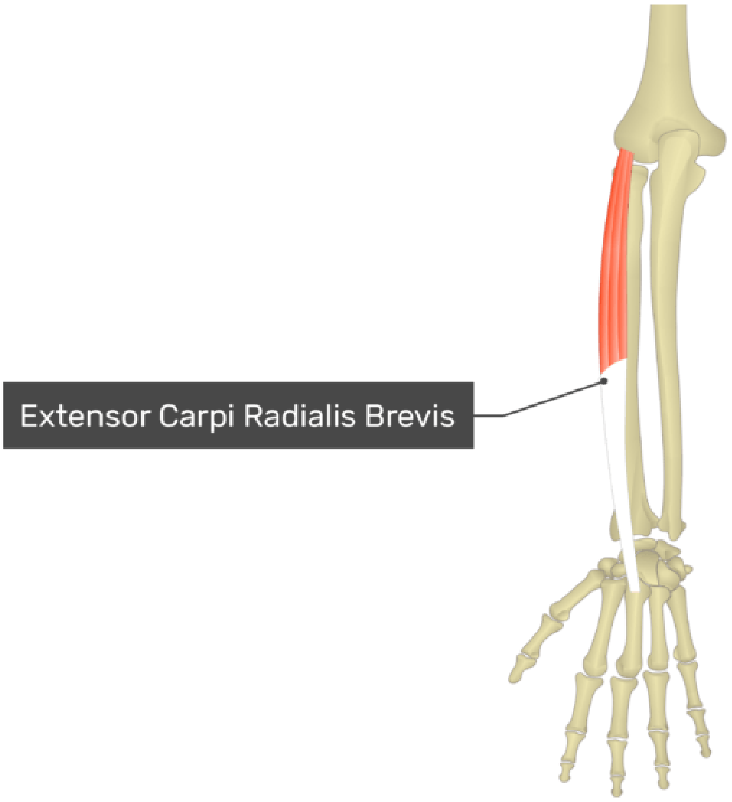


Figure 2-5: Extensor carpi radialis brevis[8]

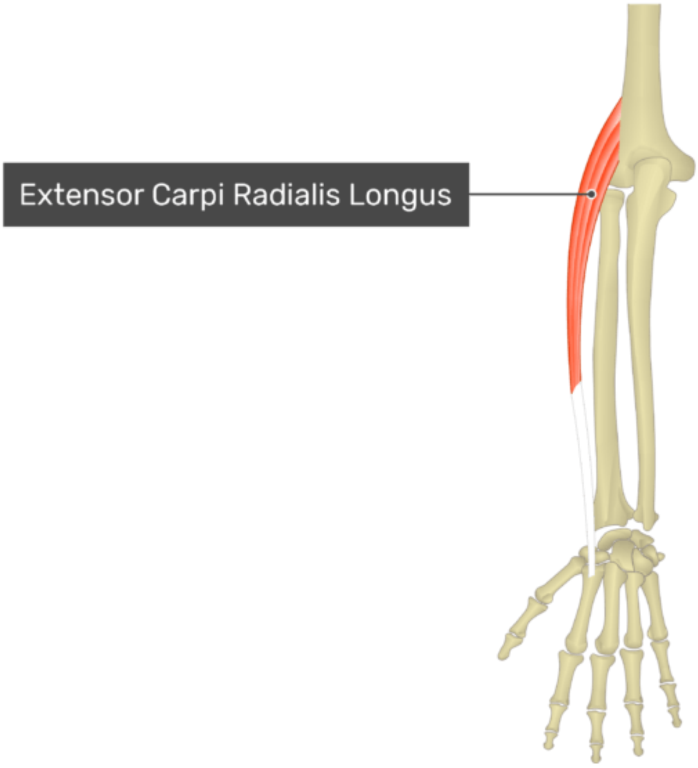


Figure 2-6: Extensor carpi radialis longus

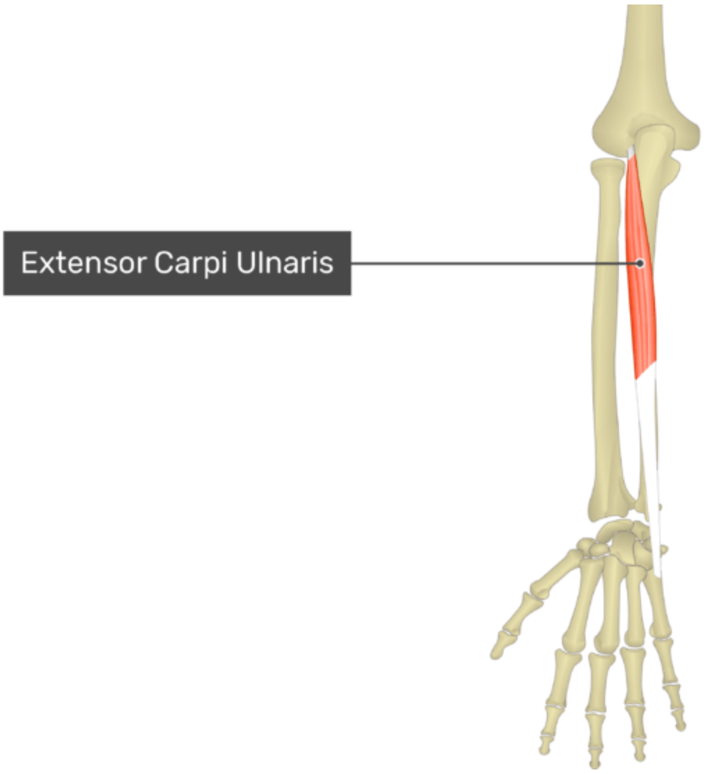


Figure 2-7: Extensor carpi ulnaris

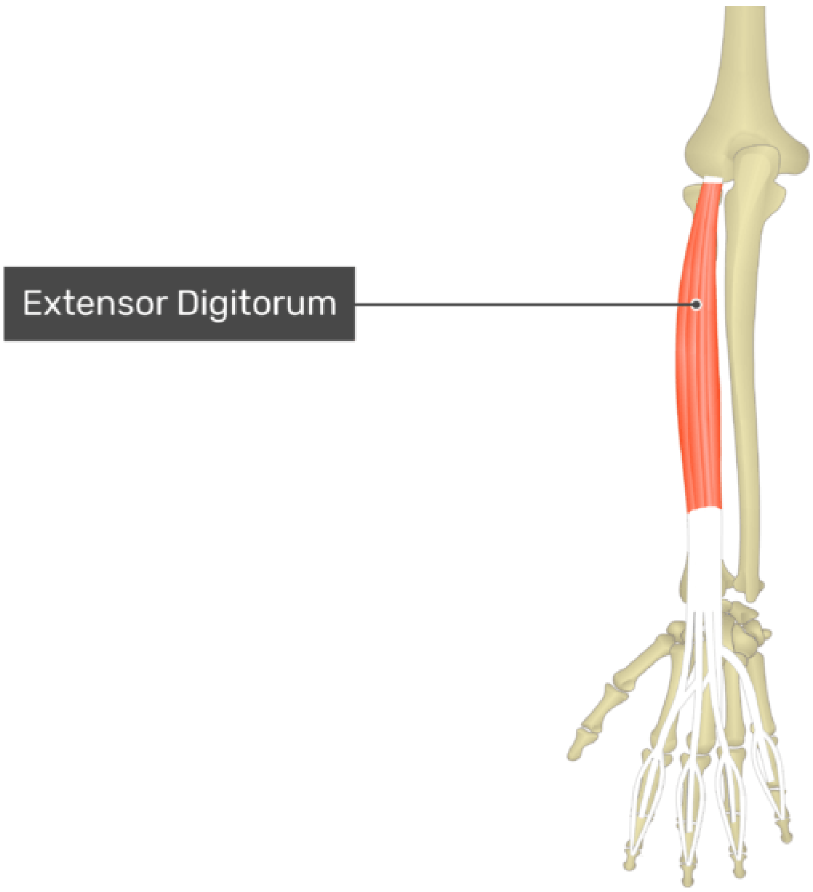


Figure 2-8: Extensor digitorum

2.1.3 Windowing Techniques

The data obtained from ADC after conversion is a continuous stream of numbers. To be able to work on it, the data needs to be divided into small packets first. So, various windowing techniques are used for this purpose. Also for Real time application the window size should be less than 300ms.The two main types of Windowing Techniques are-[4][7][6]

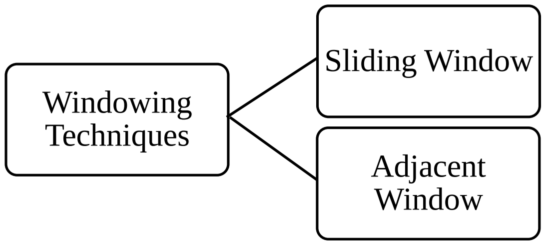


Figure 2-9: Different Windowing techniques

In sliding windowing method, 1-D array of fixed length data in selected from the signal stream and then for the next array window slides by some value. So there is an overlap [4]. In Adjacent windowing method, the 1-D array of fixed length is made by taking adjacent data value from the signal stream. Adjacent windowing method is effective in case of small window sizes. [4]

2.1.4 Noise

The EMG signal extracted from the sensor is not ready to use. It contains a lot of noise that may come from various resources. This may be due to the temperature of the skin, the blood velocity, fats in the body etc. These noises should be taken into consideration and also taken care of. The noises are follows-[10]

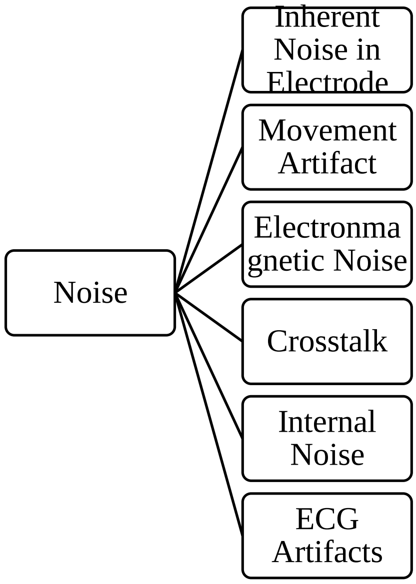


Figure 2-10: Types of noise encountered during signal extraction

2.1.5 Feature Set

To identify the gestures certain features, need to be extracted from the data set. The extracted features should be such that they are easily differentiable and the RES index value in the scatter plot should also be high. Features can be grouped together and Figure 2.5 shows some famous feature sets.

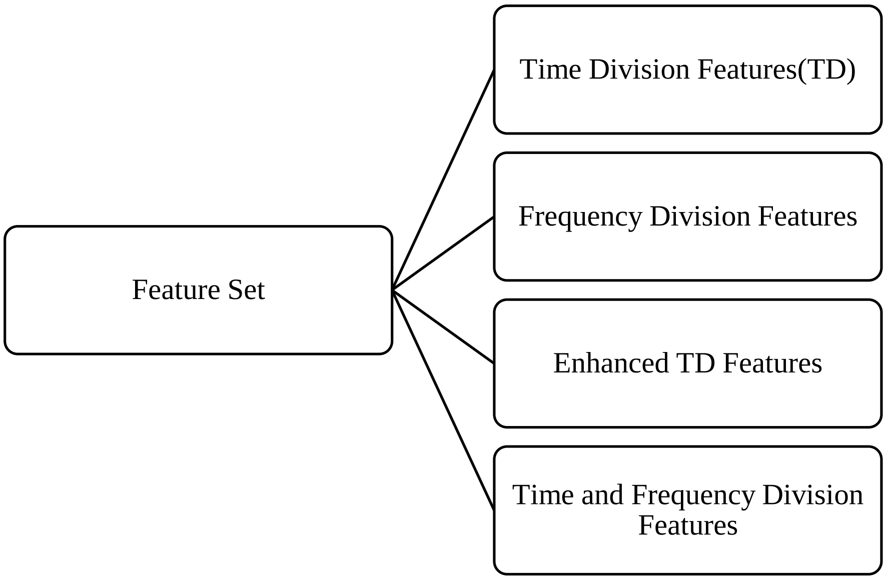


Figure 2-11: Different types feature that can be extracted from EMG signal

2.1.6 Dimensionality Reduction

Some features have high dimensionality and hence dimensionality reduction techniques need to be employed. The following Figure 2.6 shows some of the popular dimensionality reduction techniques. Wavelet based feature reduced in dimension by principal component analysis greatly improves the classification accuracy in myoelectric controlled processing. [6]

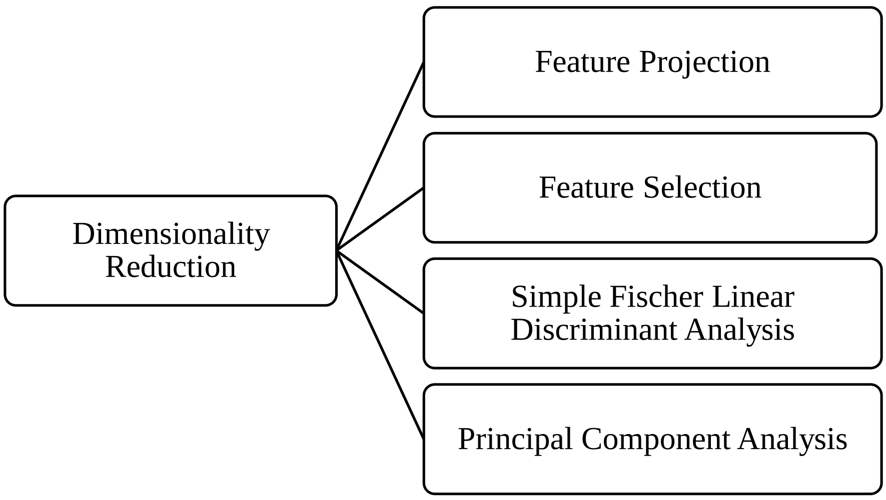


Figure 2-12: Techniques to reduce the dimensionality of the feature set

2.1.7 Classifiers

Machine learning algorithms are used to design classifiers. Classification model is used to classify different hand gestures based upon the feature set that is provided to the classifier. Firstly, the learning data set is given to the classification model. The variables of the model are trained using this data set. Once the classification model is trained it can be used for inference. The following Figure 2-13 shows some of the widely preferred classifiers.

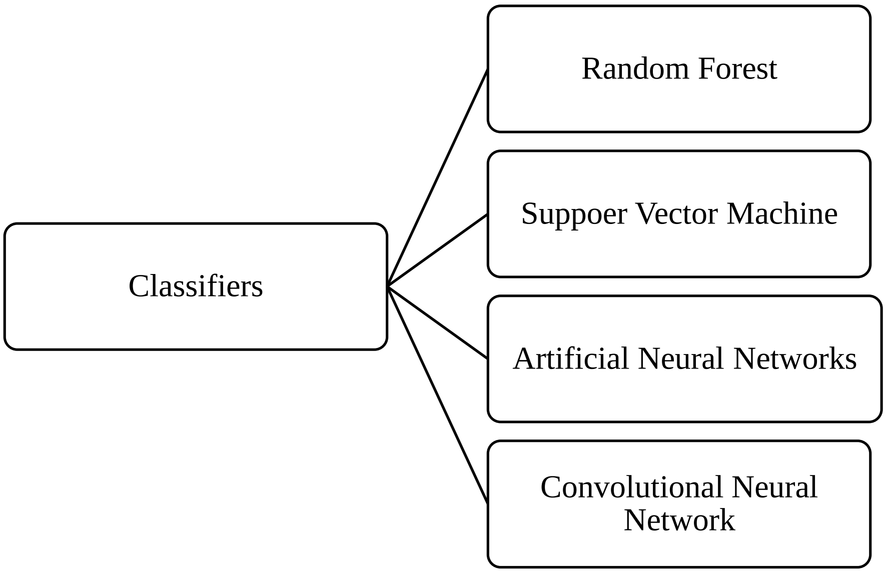


Figure 2-13: Different classifiers available

2.2 BIONIC ARM DESIGN

2.2.1 Introduction

Prosthesis and orthotics are clinical disciplines that deal with artificial limbs(prostheses) for people with amputation and people with muscoskeletal weakness. Bionics is a field of engineering which is inspired from biology. Bionic Arm is by-product of prosthetics and Bionics whose aim is to provide an artificial arm for amputees. Thus, this artificial robotic prosthetic arm provides amputees with artificial hand which can help them to carry out daily activities as efficiently as they used to carry out when they had their biological hand intact to their body. The following literature survey consist of study of designing and building of Bionic Arm.

2.2.2 Prosthetic Arms

The hand is a powerful tool and its loss causes a severe psychological and physical drawback. Despite the significant impact of losing a hand, numbers of amputees requiring a prosthesis are too small to push manufacturers to innovate their products, so both the control interfaces and mechanisms have barely changed in the past 40 years. The most technologically advanced prostheses are myoelectric ones; one or two DoFs, motorized hands (or hooks) are activated by antagonist residual muscle contractions where the EMG signal is picked-up by surface electrodes in the prosthetic socket and processed to functionally open and close the palm (or pronate/supinate the wrist).

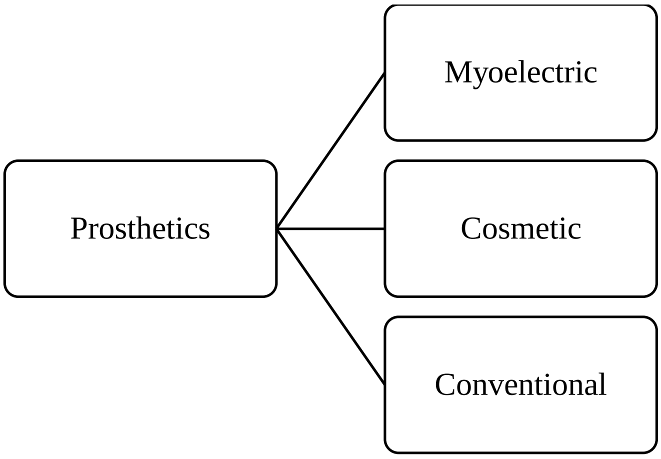


Figure 2-14: Types of prosthetics

Before learning to build highly functional, high DoF and light weight prosthetic arm study of human hand, its working, number of joints, tendon muscle relationship, etc. is needed.

2.2.3 Anatomy of Human Hand

The human hand consists of 4 fingers and a thumb and is the main organ for physical interaction with the environment surrounding the human body. A schematic of the bones in the human hand can be seen in Figure 2-15

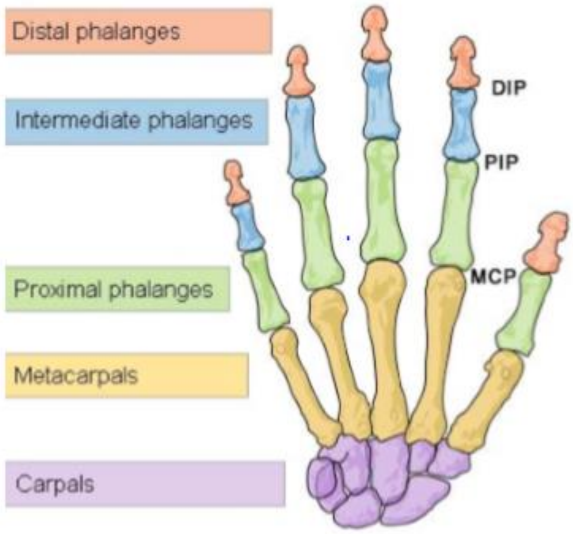


Figure 2-15: Anatomy of Human hand[11]

As mentioned in[11], Every finger has 3 joints, which are-

- DIP (Distal Interphalangeal Joint)
- PIP (Proximal Interphalangeal Joint)
- MCP (Metacarpal Phalangeal Joint)

Fingers are divided in different segments connected by joints called as Phalanx, following are different phalanxes [11]-

2.2.3.1 Metacarpal Phalanx

The metacarpal phalanx (yellow) is connected to the first finger segment (proximal phalanx) with a joint called the metacarpophalangeal joint (MCP-joint). The MCP-joint is able to perform to types of movement, flexion/extension and abduction/adduction. Flexion in this case means bending the finger while extension means extending the finger. Abduction denotes the sideways motion of the finger away from the midline of the hand. The opposite movement, adduction, means moving the finger back against the midline of the hand.

2.2.3.2 Proximal Phalanx

The proximal phalanx (green) is connected to the metacarpal phalanx through the MCP-joint. On the other side of the finger segment it is connected to the second finger segment (intermediate phalanx) with a joint called the proximal interphalangeal joint (PIP-joint). The PIP-joint only has one axis of motion and is therefore called a hinge joint. Flexion and extension of the PIP-joint means bending and stretching the first finger joint.

2.2.3.3 Intermediate and Distal Phalanx

The intermediate (blue) and distal (red) phalanges are the middle and outer segments of the finger, respectively. They are connected with the distal interphalangeal joint (DIP-joint) which is a hinge joint like the PIP-joint.

2.2.4 Robotic approach to the human hand

There are several aspects of the human hand that makes it very hard to imitate in a robotic application. First of all, the human hand has a very complex kinematic model. The fingers alone possess 21 DoFs. In addition to the finger, movement of the palm includes 6 DoF, 27 for the whole hand [11]. The movement of the palm itself is rarely seen in robotic hands; a solid palm is often used instead. In addition to the high degree of freedom, the finger is also very sensitive to external input. To imitate all the nerves on the surface of the finger is very complicated. Normally, a number of touch sensors are seen instead.

Thus, mimicking human hand's functionality in prosthetic arm is a difficult task and a great amount of research is undertaken to create an anthropomorphic prosthetic arm.

To implement high functionality anthropomorphic prosthetic hand which will be controlled by myoelectric signals or EMG signals, efficient and light weight actuators are needed.

2.2.5 Needs of Amputees from Bionic Arm

After referring to [12],[13] detailed study of problems perceived by the amputees was done. As our design is only specified for lower elbow amputees the study was only limited to problems perceived by lower elbow amputees. Recently development of myoelectric prostheses has mostly focused on increasing the number of DoFs while increasing joint speed and torque. However, these devices achieve improved dexterity at the cost of increased weight, size, and complexity. There is trade-off between the dexterity of Bionic Arm and the weight, size of the Bionic Arm. In[13]they have suggested that the weight of Bionic Arm should be around 500 grams. In [13], R.F Weir et al consulted different amputees and has proposed following rules of thumb for design of prosthetic arm-

1. The total weight of prosthesis should be around 500 grams. A lighter prosthetic arm is always beneficial for amputees as they can easily use the device for carrying out daily activities without any hardships.
2. The Bionic Arms should incorporate main functional grasps like Power Grasp, Pinch Grasp and Lateral Grasp.
3. The design and control of Bionic Arm should be compliant enough.
4. Simple and robust finger kinematic design should be implemented.
5. The exact need of amputees should be mapped and then specified design for that person should be initiated. This approach gives a better design output which will be definitely compliant to the amputee.

In [12] the author has proposed that prosthesis should be sophisticated enough to imitate the movements of human arm. The author stated that it's not trivial endeavor to reduce the weight and size of the Bionic Arm while increasing the degrees of freedom of the Bionic Arm. But designer should design in such a way that he must partially achieve both the goals and satisfy the needs of the amputees.

2.2.6 Grasps

For designing an artificial human hand there is need to study the human arm and its functionality. Human hand carries out different grasps to pick and handle different objects in our daily life. Thus, for designing purpose of Bionic Arm, study of different grasps was done. The Cutkosky grasp taxonomy was referred[14]. Mark Cutkosky wrote a paper in 1989 where he classified a set of manufacturing grasps in order to evaluate analytical models of grasping and manipulation with robotic hands. This taxonomy is widely used by robotic scientists and engineers who undertake designing of robotic arm. The following image is the hierarchical tree of grasps referred from Mark Cutkosky's paper-

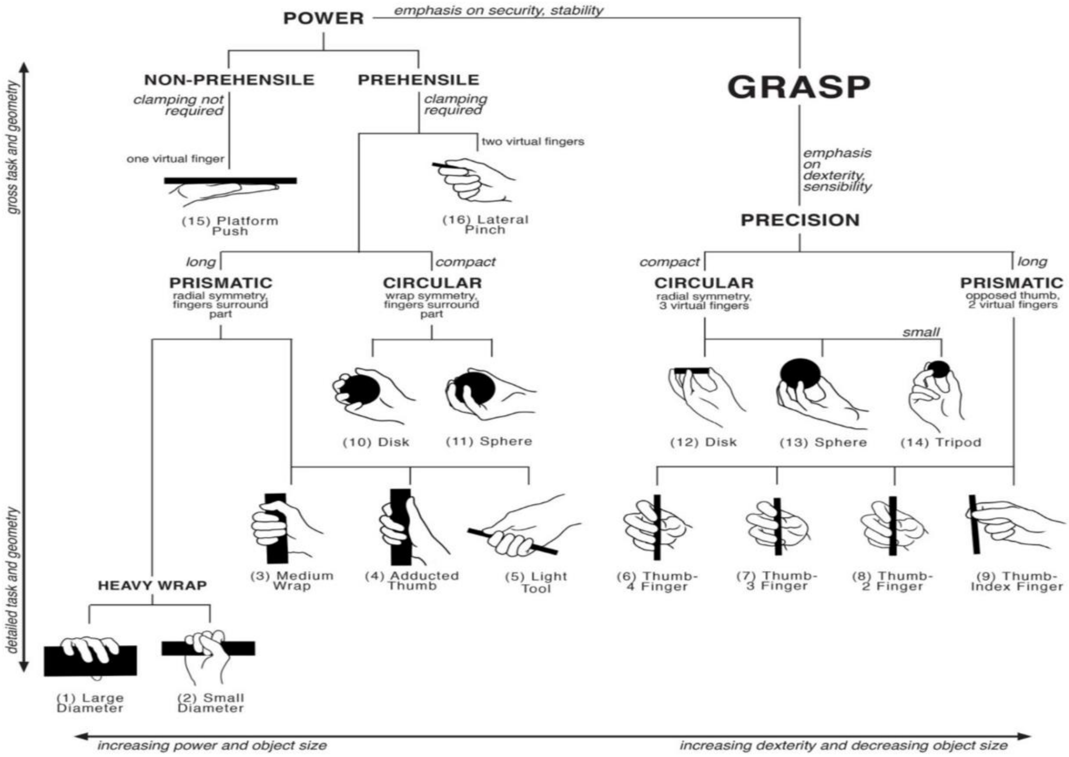


Figure 2-16: Hierarchy of grasps [14]

Following is the list of important grasps studied and their use in everyday life-

- POWER GRASP- for picking heavy weights.
- PRECISION GRASP- for picking cherry from trees.
- LATERAL GRASP-for picking spoon laterally.
- INDEX Pointing for typing.
- Basic Gesture likes counting.

2.2.7 Survey on Commercial and Research Prosthetic Arms

In [13]Weir et al has made comparison analysis on different types of commercial Prosthesis and Bionic Arms designed by research institutes. Following Prosthetic arms were studied-

- Vincent hand by Vincent Systems.
- iLimb hand by Touch Bionics.
- BeBionic hand by RSL Steeper
- Michelangelo Hand**.**

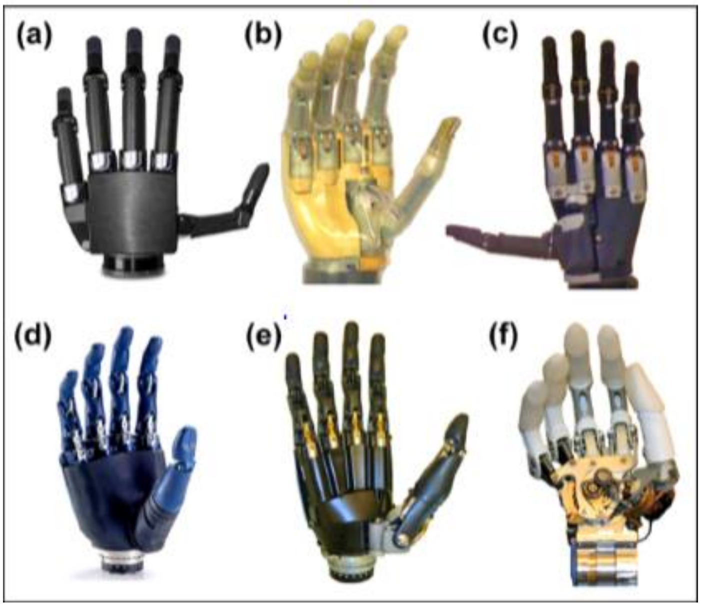


Figure 2-17: Prosthetic Arm Comparative study[13]

2.2.7.1 Comparative Analysis

In [13] general characteristics of commercial prosthetic hands is stated. Vincent Hand was designed for 6 DoF and DC motor worm gear was used for actuation. Adaptive Grip was the feature. BeBionic hand is the most successful commercial prosthetic arms which used DC Motor Worm Gear for actuation method. Bebionic used carbon fiber body which lead to reduction in weight. It only weights 465 gram. iLimb by touch bionic is also successful commercial prosthetic arms which consists of features like Wi-Fi control and adaptive grasps.

After studying these prosthetic arms, it is analyzed that all these companies used custom made expensive actuators which increases the total cost of entire device. Though they were light enough and had compliant actuation, they were very expensive which can't be afforded by middle-class and below middle-class people. Thus, work on cost effective Bionic Arm is an undergoing research.

2.2.7.2 Modular Prosthetic Limbs

Figure 2-18: Modular Prosthetic Arm [15]

Modular Prosthetic Limbs are till now the most advanced prosthetic arm designed by researchers in John Hopkins University which was funded by DARPA. MPL is the most advanced prosthetic limb which achieved intuitive feedforward control through EMG sensor band and it also incorporated feature of natural sensory feedback to the user. MPL is the most expensive Bionic Arm which is successfully tested on an amputee. It incorporated more than 100 sensors on the Arm including force, contact and temperature sensor. No doubt it is the most advanced artificial limb.

2.2.8 Actuators

Following are common different types of actuators that can be used in prosthetics-

- Hydraulics-

  Hydraulics, a widely used form of general actuation is hydraulic systems. A hydraulic system typically consists of a pump, a reservoir, a valve and an actuator. Hydraulics are bulky and include oils which will make difficult for amputee to use it as prosthetics.
- Pneumatics-

  In pneumatics, a pressurized gas is used to create actuation, typically by filling a cylinder with air. Pneumatic valves and cylinders are bulky so they cannot be used in prosthetic applications.
- Intelligent material used as actuator (Soft Robotics)-

  Intelligent material used as actuator are not seen in common life, these include Shape Memory Polymers (SMP) and Shape Memory Alloys (SMA). Some polymers change shape when subjected to voltage and thus due to shape change actuation is incorporated. Shape memory alloys are also used similarly to actuate. Thus, such intelligent material can be used in prosthetics for creating actuation at joints. Such actuation method closely mimics the muscles of our finger and brings us close to the goal of anthropomorphism. Advantages of such actuators is low cost and simplicity. But such actuators incorporate joule heating effect for shape change and actuation, such actuation mechanisms are not safe for prosthesis application and it will require insulation. Moreover, high DoF and robustness in prosthetics cannot be obtained using these actuators. We referred to [16],[17], these companies manufactured SMA and SMP. SMP technologies, Japan, manufactured SMP material which had molding point around 55 centigrade but due to its exorbitant price it was hard to be affordable for the project.

  Thus, intelligent material used as an actuator had to be dropped for this application.

Electric actuators provide sufficient torque, force, robustness and flexibility and are suitable for this application. Following are different electric actuators that can be incorporated in prosthetic arms-

- DC Motors
- BLDC Motors
- Servo Motors
- Stepper Motors
- Linear actuators

2.2.9 Review on Tactile Sensor

In [18],tactile sensing technology has been reviewed. Tactile sensor or Force sensor detects pressure or force applied on the surface of the sensor. It provides information related to the interaction forces between object and fingers of robotic arm. Tactile sensor taken in closed loop, helps in precise control of force applied on the object by the fingers of robotic arm. Biological human hand also has many senses like the human hand can detect hotness or coldness of the object, pressure applied on the finger and pain on the finger. Tactile sensors are incorporated by engineers and researchers working on prosthetic arms and Bionic Arms, to have precise object handling and manipulation. Tactile sensors help to control force imparted on the object. For Bionic Arm, having control on force imparted on the object is important because an amputee interacts with different types of objects like hammer, flower, eggs etc. If the Bionic Arm applies same amount of force for holding hammer on holding an egg, it will destroy the egg. One axis and 3 axis tactile sensors are available in market. 3 axis tactile sensors are used for calculating normal and tangential forces simultaneously, which also helps in detecting slippage of object from the fingers. But the 3-axis tactile sensor are expensive, so mostly people prefer to use single axis tactile sensor Thus, use of tactile sensor in field of prosthetics is important.

Following are different types of tactile sensors [18]-

- Piezo resistive sensor.
- Capacitive sensors.
- Piezoelectric sensors.
- Quantum Tunnel Effect Sensors.
- Optical Tactile sensors.

Amongst these sensors, following is the description of piezo resistive sensor and capacitive sensors-

- Piezo resistive Sensor

Piezo resistive effect is a physical process during which electrical resistance changes when the material is mechanically deformed. There are several technologies based on piezoelectric sensors. Force Sensitive Resistor (FSR) is based on piezo resistive effect. In FSR when the sensor is deformed, the resistance changes. The FSR voltage divider configuration can be given as input to the analog to division converter of microcontroller for calculation of force applied on the sensor.

FSR have advantages like low cost, flexible and simple to manufacture but it has many disadvantages like it has less repeatability after multiple deformation. The sensitivity of sensor also reduces due to wear and tear of the sensor. Thus, FSR are not accurate solution for precise force measurement.

- Capacitive Force Sensor

Capacitive sensors consist of two conductive plates separated by compressible dielectric material. When force is applied on the object the gap between the plates changes and capacitance is also changed. The change in capacitance is detected and inferences are made for how much force is applied.

Capacitive sensor technology has several advantages over resistive, including greater stability in terms of repeatability and durability, and can measure low levels of pressure with accuracy. Capacitive sensor gives linear output; it facilitates measurement of proportional force.

Thus, capacitive sensor is more accurate than FSR and good for long term prototyping in Bionic Arms.

2.2.10 Grasp Control

Bionic Arm helps amputees to live a normal life and become less dependent on others. For amputees to carry out their daily activities, it is important for the Bionic Arm to have firm grasping skills on different types of object as their principal feature. Thus, having good grasping skills and improved dexterity leads to achieving the purpose of an artificial human hand.

To achieve good grasp, it is important to devise grasping control algorithm or grasping control mechanism. To achieve a stable grasp following prerequisites should be followed[19]:

To hold the object properly, minimum grip force should be applied. The minimum grip depends on the weight and surface friction of the object trying to be lifted. Grip force is naturally adjusted by human hands when it feels that object is slipping from the hands. When an object slips, it generates vibrations which can be measured and quantified. This is susceptible to noise, but is still viable with adequate filtering.

To hold heavy object maximum force should be applied. The maximum grip force depends on the mechanics of the hand and the maximum force that can be applied by the actuators/motors. Depending upon how much force can be applied by the Bionic Arm, there must be a standard grip strength which cover range of scenarios.

Haptic feedback could play a role here. Firstly, by providing feedback in terms of pressure and secondly by amplifying the vibrations caused by slipping. This approach allows to have natural feedback to the amputees.

Having these prerequisites followed leads to good base for achieving stable grasp of the Bionic Arm on any object.

CHAPTER 3

3 SYSTEM ARCHITECTURE

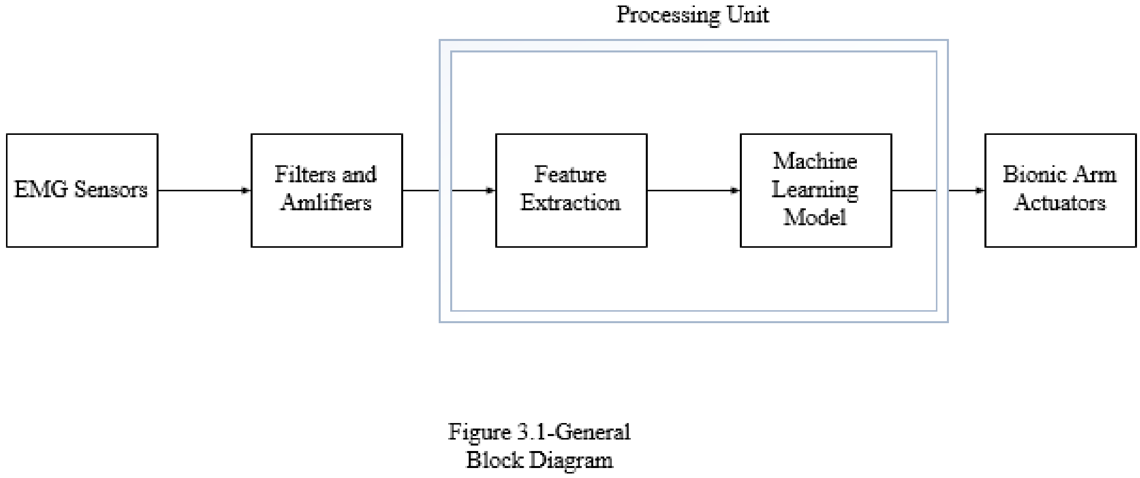


Figure 3-1: General Block Diagram

The main hardware component in the extraction of EMG signal is the Electromyogram Sensors shown in Figure 3.1. The signals are collected from the surface of the arm using electrodes. This type of Electromyogram is called Surface Electromyogram (sEMG). These channels of EMG signals are filtered and amplified to reduce noise and increase signal strength. The amplified EMG signals are given to the Processing Unit. In the Processing Unit different features are extracted from the EMG signal and are used to train a Machine Learning Model. Once the model is trained the features are applied to the trained model and inferences can be made about the expected gesture. According to the output gesture the control signals for the Bionic Arm actuators are calculated and are given to the Bionic Arm.

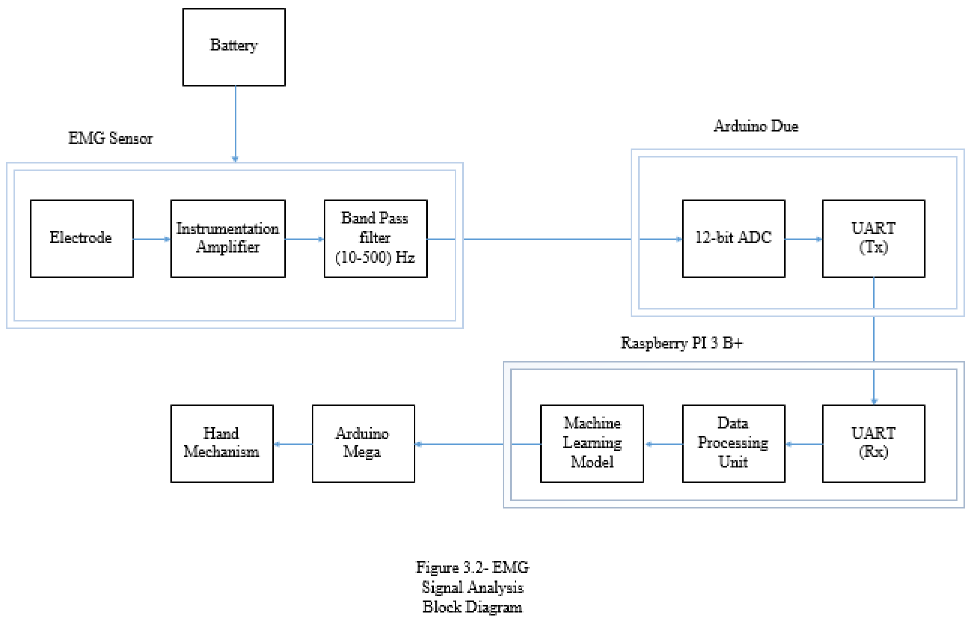


Figure 3-2: EMG Signal Analysis Block Diagram

In EMG signal analysis, first block is Electrodes, as denoted in Figure 3.2 Electrodes are used to detect muscle activity. These electrodes will be placed on skin. Different EMG signals corresponding to different hand gestures can be sensed by this placement of electrodes. The data obtained after filtering and amplification is then passed through a 12-bit ADC to obtain a string of digital values.

To differentiate between various hand gestures, we need to identify different features. Different features are mapped on a scatterplot. It is used to classify the features as good or bad. The good features are then selected. This process of feature evaluation, Scatter plot mapping and feature selection comes under the block of Feature Extraction.

Once the features are selected, they are used to create data set. For machine learning, we need to create various datasets like Training Data set, Validation Data set and Testing Data set. Training Data set is used to train to the machine learning model. Validation Data Set is used in loop with training model for validation purpose. Once the model is trained it is tested on Test Data Set to observe its accuracy.

Machine Learning algorithms are used to generate a model. This model is used to determine the hand gesture. The accuracy of the model depends on the Machine Learning algorithm selected to generate the model. Once the model is trained, features are applied to it and the output is generated. The generated output is in the form of 1-D array corresponding to the probability of different hand gestures. A threshold value of probability is used to select the correct hand gesture

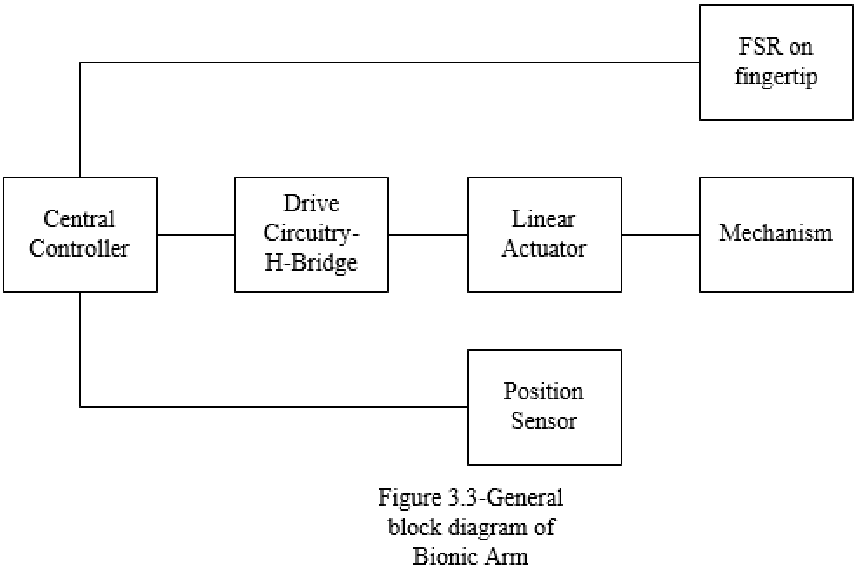


Figure 3-3: General block diagram of Bionic Arm

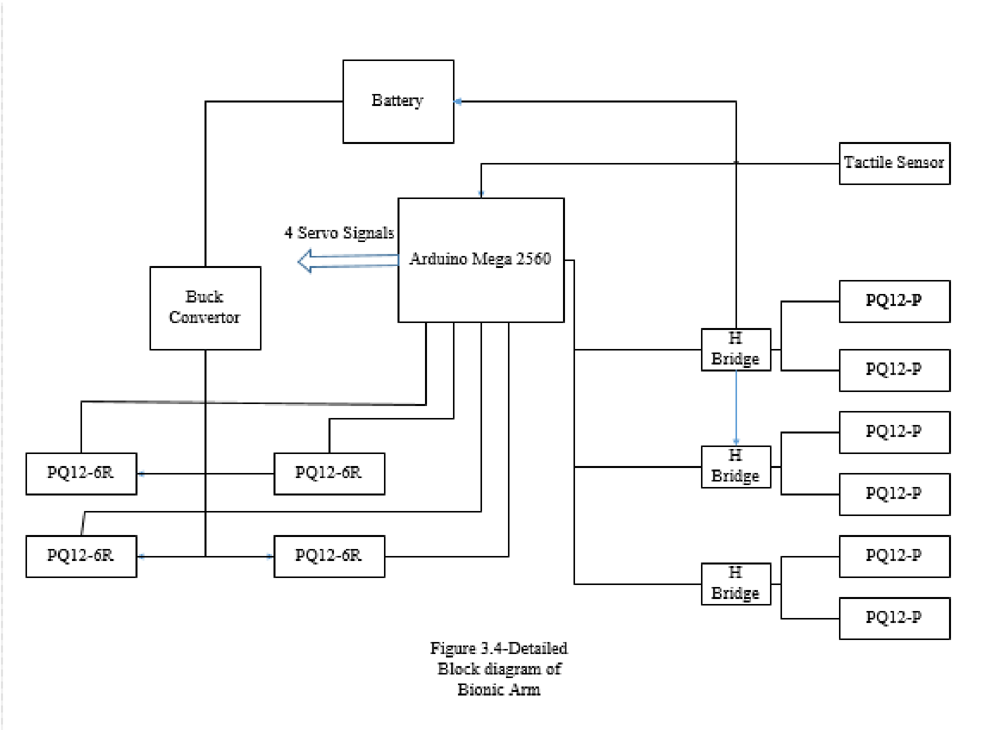


Figure 3-4: Detailed Block diagram of Bionic Arm

The signals from the ML model are in the form of digital signals and these digital signals are given to the Arduino Mega 2560 module.

CHAPTER 4
4 SYSTEM SPECIFICATIONS

The system specifications are as follows:

1) The input given to the overall system should have these following specifications:
    a) The Bionic Arm should be controlled by EMG signals.
    b) The voltage range of the input signal in EMG is about 0-10mV.
    c) The frequency of the input signal is about 0-500Hz.
2) The maximum weight of the Bionic Arm should be around 700 grams which can be achieved using 3D printing.
3) The Bionic Arm should be a dexterous 11 DoF arm The arm should be able to perform:
    a) Relax Hand
    b) POWER Grasp.
    c) LATERAL Grasp.
    d) Fist.
    e) Little Finger flexion.
    f) Ring Finger flexion.
    g) Middle Finger flexion.
    h) Forefinger flexion.
    i) Thumb flexion.
    j) Victory.
    k) Pinch.
    l) Hold.
4) The Machine Learning model should be able to classify 3 gestures viz. rest, pinch and fist.

CHAPTER 5
5 RESEARCH AND ANALYSIS

5.1 Selection of Muscle Sensor

After an extensive market research on the commercially available EMG sensors, their [20]specifications cost in the market and considering their availability in India, two EMG sensors were shortlisted for the acquisition of data from human body.

The two sensors that were shortlisted are as follows-

1. MyoWare Muscle Sensor-by Advancer Technologies
2. DF Robot Gravity-Analog EMG Sensor by OYMotion.

Apart from their differences in specifications and their design, the major difference in them is the type of electrode used to sense the neuromuscular signal. MyoWare Sensor uses the conductive gel electrodes and DF Robot sensor uses dry electrode.

Figure 5-1: MyoWare Sensor[20]

Figure 5-2: DF Robot Gravity Sensors[21]

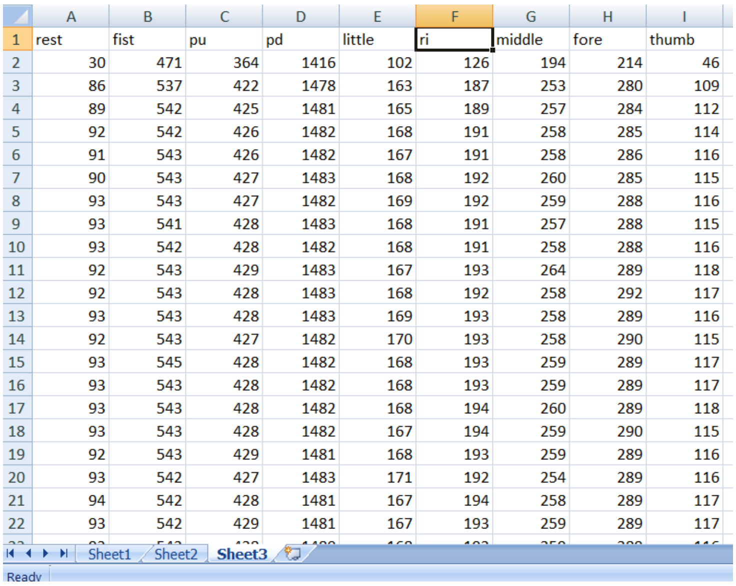
5.1.1 Differences in MyoWare muscle sensor and DF Robot Gravity Sensor[21][20]

Table 5.1: Comparison of MyoWare Muscle Sensor and DF Robot Muscle Sensor o

PARAMETERS	MYOWARE	DF ROBOT
Supply Voltage	3.3V-5V	3.3V-5.5V
Output modes	EMG Envelope and Raw signal	Raw Signal
Type of Electrodes	Conductive Gel	Metal dry electrodes
Adjustable Gain	Present	Absent
Availability in the Country	Available in India	Not Available in India
Cost	Rs.3,700/-	Rs.3,598/-

5.1.2 Results of MyoWare sensor

The MyoWare sensor was placed on specific regions that were identified through some literature survey. Various gestures were decided and were performed and a continuous reading for about 2000SPSwas taken and stored in an excel sheet as shown below.



	A	B	C	D	E	F	G	H	I
1	rest	fist	pu	pd	little	ri	middle	fore	thumb
2	30	471	364	1416	102	126	194	214	46
3	86	537	422	1478	163	187	253	280	109
4	89	542	425	1481	165	189	257	284	112
5	92	542	426	1482	168	191	258	285	114
6	91	543	426	1482	167	191	258	286	116
7	90	543	427	1483	168	192	260	285	115
8	93	543	427	1482	169	192	259	288	116
9	93	541	428	1483	168	191	257	288	115
10	93	542	428	1482	168	191	258	288	116
11	92	543	429	1483	167	193	264	289	118
12	92	543	428	1483	168	192	258	292	117
13	93	543	428	1483	169	193	258	289	116
14	92	543	427	1482	170	193	258	290	115
15	93	545	428	1482	168	193	259	289	117
16	93	543	428	1482	168	193	259	289	117
17	93	543	428	1482	168	194	260	289	118
18	93	543	428	1482	167	194	259	290	115
19	92	543	429	1481	168	193	259	289	116
20	93	542	427	1483	171	192	254	289	116
21	94	542	428	1481	167	194	258	289	117
22	93	542	429	1481	167	193	259	289	117

Sheet1 Sheet2 Sheet3

Ready

Figure 5-3: MyoWare Muscle Sensor Initial Readings

Figure 5-3 shows the data of sensors placed on the back-hand. The gestures defined were relax, fist, palm up, palm down, and movement of all the individual fingers. As it can be seen from Figure 5-3, one particular gesture has a constant set of readings.

5.1.3 Results of DF Robot Sensor

The DF Robot sensor was placed on specific regions that were identified through some literature survey. Various gestures were decided and were performed and a continuous reading for about 2000SPSwas taken and stored in an excel sheet as shown below.

	A	B	C	D	E	F	G	H	I
1	r	f	pu	pd	l	ri	m	i	t
2	435	463	466	466	498	452	457	460	438
3	436	462	466	466	499	452	457	460	439
4	435	462	466	466	499	452	457	460	439
5	435	462	466	466	499	452	458	460	439
6	435	462	466	466	499	452	458	461	439
7	435	462	466	466	499	453	458	461	439
8	435	462	465	465	499	453	458	461	439
9	435	461	465	465	499	453	458	461	439
10	435	461	465	465	499	453	458	461	439
11	435	461	465	465	499	453	458	462	439
12	435	461	465	465	499	453	458	462	439
13	435	461	464	464	499	453	458	462	439
14	435	461	464	464	499	453	458	462	439
15	435	461	464	464	500	454	458	462	440
16	435	460	464	464	500	454	458	462	440
17	435	460	464	464	500	454	457	462	440
18	434	460	464	464	500	454	459	462	440
19	434	460	464	464	500	454	459	462	440
20	434	460	463	463	500	454	459	462	440
21	435	460	464	464	500	454	459	462	441
22	435	459	463	463	501	455	459	462	441
23	434	459	463	463	500	454	459	461	440
24	434	459	463	463	500	455	459	461	441
25	434	459	463	463	501	455	459	462	441
26	434	459	462	462	501	455	459	461	441
27	434	458	462	462	500	455	459	461	441
28	434	459	462	462	501	455	459	461	442
29	434	458	462	462	501	455	459	461	442
30	435	455	461	461	503	458	460	463	446
31	436	451	461	461	504	461	461	473	450
32	436	448	456	456	504	466	461	480	453

Figure 5-4: DF Robot Sensor Readings

Figure 5-4shows the data of sensors placed a particular muscle. The gestures defined were relax, fist, palm up, palm down, and movement of all the individual fingers. As it can be seen from Figure 5-4, just by looking at the readings none of the gestures are classifiable.

5.1.4 Results of MyoWare Sensor Graphically

It has been observed that various gestures that have been plotted in Figure 5-5show represent data in a better way which gives a sense of confidence that the data obtained from MyoWare Sensor is classifiable.

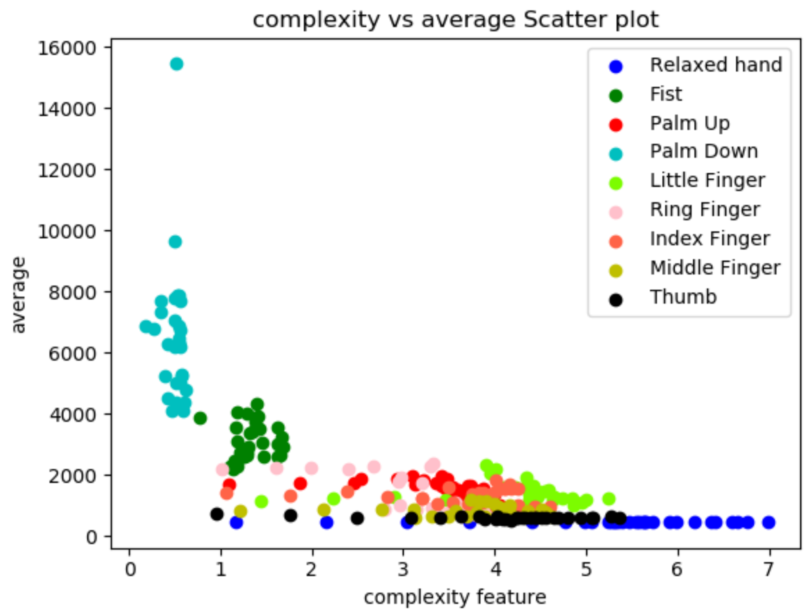


Figure 5-5: Complexity vs. Average on the data obtained from MyoWare Sensor

5.1.5 Result of DF Robot Sensor Graphically

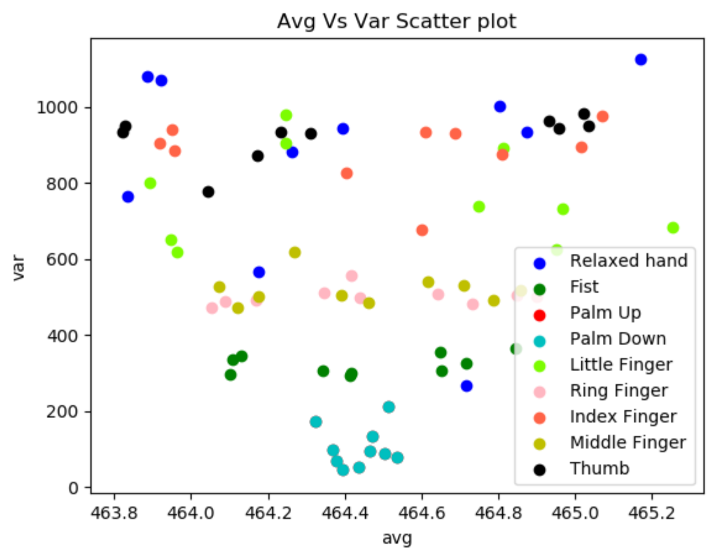


Figure 5-6: Average vs. Variance on data obtained from DF Robot Sensor

5.1.6 Comments on the obtained results

It has been observed that the readings and graphical representation of the MyoWare Sensor is more capable of distinguishing the gestures. The DF robot sensor seems to be less reliable and its reading and graphical representation is not that clear and decisive. One of the major difference that is been concluded is the type of use of electrodes. Even though the conductive gel electrodes need to be renewed every time before taking the readings, the readings are noise free than that taken by dry cell electrode. Dry cell electrode may have long life but they are prone to noise.

Hence due to all these aspects and analysis it is decided that MyoWare Sensor would be used to record signals.

5.2 Experimenting whether Electromyogram is a Neuromuscular Signal

EMG refers to the collective electric signal from muscles, which is controlled by the nervous system and produced during muscle contraction. The signal represents the anatomical and physiological properties of muscles; in fact, an EMG signal is the electrical activity of a muscle's motor units. [5]

In the beginning of the report the term EMG has been associated with Brainwaves. It is difficult to comprehend whether the EMG signal obtained is actually a neuromuscular signal or a mere signal resulted from muscular activity.

In order to prove that the EMG signal is a neuromuscular signal, an experiment was conducted. In this experiment, the subject wearing the sensor was asked to make hand movements according to his/her wish. The result of this hand movement was observed on the serial plotter of the Arduino IDE. When the subject performed hand motions on his/her own, the serial plotter displayed a waveform of considerable amplitude and with desirable variations in voltage

On the other hand, when the subject's hand was in normal relaxed phase and an external stimulus was applied on it, the result was totally different. When a second person tried to forcefully perform hand motions on the subject's hand i.e. without his/her wish, the reading on the serial plotter did not display a considerable voltage. Also the waveform obtained was quite plain and the only variations that were observed were because of the noise in the whole setup.

5.2.1 Comments

After performing the above experiment, it was concluded that if the subject does not person hand gestures on his/her own desire or his/her own wish, the "neurons" do not play a vital role in the overall process and hence the obtained signal is not a neuromuscular signal. Whereas, when the subject performs hand gestures by his/her own wish, the signal obtained is quite significant. This is because the neurons get activated here and the resulting signal turns out to be neuromuscular signal.

5.3 Raw Signal Output and Enveloped Signal Output of the MyoWare Sensor

In the selected MyoWare Muscle sensor, there are two kinds of signals that can be obtained from the sensor.

1. Raw Signal-Raw signal refers to the actual signal in the human body which is detected and extracted out as it is i.e. without performing any external processing on it.
2. Enveloped Signal-Enveloped signal is an amplified, rectified and an integrated raw signal.

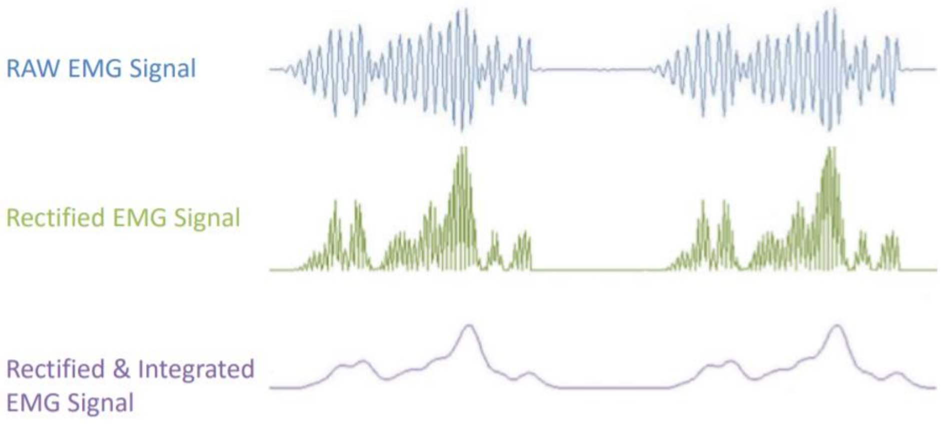


Figure 5-7: RAW EMG and Enveloped EMG[20]

The raw signal is a very vague signal and contains a lot of noise. But since the EMG signal itself is a very low voltage, low frequency signal, there may be a possibility of losing minute variations that are important. The enveloped signal is a pretty clear signal that shows consistent variations in accordance to the hand gestures and it is considerably noise free.

In order to decide which of these will be more useful as an input to the whole system, both the raw and the enveloped signals were compared and conclusions were drawn from it. It was concluded that for the recording of signals for this project, the enveloped signals will be used.

5.4 Noise Sources

The various noise sources observed were as follows

5.4.1 Power Line Interference

Power line interference is the high amplitude 50Hz noise interference produced by the AC supply lines connected to the acquisition system. This noise also contains high frequency harmonics. The readings obtained from the sensor when powered by this 240V, 50Hz supply were observed to have high amplitude. Thus the power line interference was affecting the signals.

The solution to this was to use battery for the supply voltage. Readings observed when the sensor was powered by battery was of reasonable amplitudes.

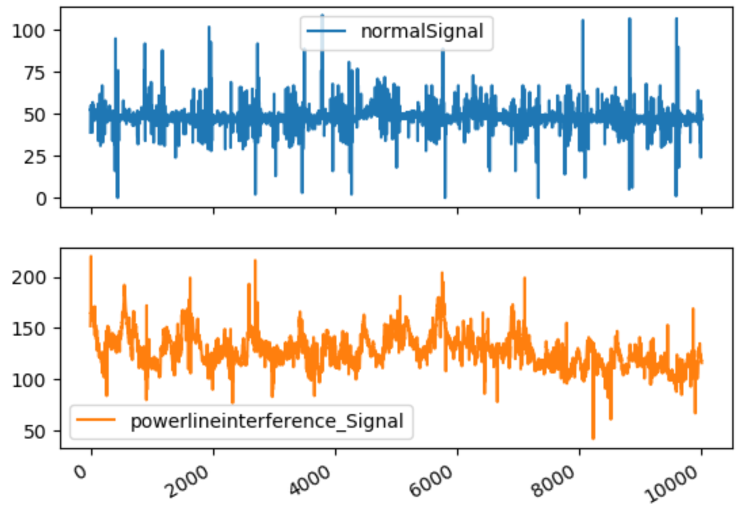


Figure 5-8: Effect of Power line Interference

In the above figure the blue signal shows the value of EMG signal recorded when the sensor is powered by a battery. As seen the amplitude of the signal is in the range of 0-100 units. The orange signal represents the signal when the sensor is powered by 50Hz power supply. It can clearly be seen that the amplitude range is from 0-200 units. Thus the effect of power line interference can be clearly seen.

5.4.2 Motion Artefacts[10]

Human movements while taking readings affect the signal quality. This is termed as motion artefacts. It may occur due to voluntary or involuntary muscle contraction or relaxation. It may also occur during respiration.

To tackle the problem of motion artefacts orientation of the hand is kept fixed throughout the data acquisition phase. The subject is required to sit relaxed with the arm by his/her side. This keeps the motion artefacts to a minimum.

5.4.3 Skin impedance[10]

The contact between skin and electrodes created a low-pass filter. Due to the presence of this low pass filter, the high frequency components present in the signal get attenuated.

Thus the signal may lose some of its characteristics. This problem occurs due to the impedance mismatch between skin and electrode surfaces.

As a solution to this problem, we decided to use conductive gel electrodes. The conductive gel electrodes reduce the skin impedance and also provide a path for the current to flow from the skin to the electrode.

5.5 EMG Signals-Isometric and Isotonic[4]

EMG signals are recorded for various muscle contractions and relaxation periods. There are two types of muscle contractions depending on whether the muscle length changes during the data acquisition period or not. They are as follows

- Isometric contraction-In isometric contraction there is no change in muscle length since the muscle extends at a constant rate. Thus it is sometimes also termed as static contraction. This type of contraction generates static EMG signal.
- Isotonic contraction-In isotonic contractions the muscle length changes and movement occurs. It is termed as dynamic contraction. This type of contraction generates dynamic EMG signal.

We tried both the EMG signal recording methods.

Figure 5-9shows isotonic reading for fist gesture. Here the hand is first at relaxing position and then the gesture is carried out. Thus it effectively shows one isotonic contraction.

Figure 5-10 shows multiple isotonic contractions for the fist gesture. The signal amplitude changes from 0 to500 units (approx.) multiple times during one recording of the EMG signal.

Figure 5-11shows an isometric reading for fist gesture. During recording of isometric readings, the subject first makes the gesture and then the recording is started. Thus the amplitude change is minimal; 160 to 200 units (approx.) in our case.

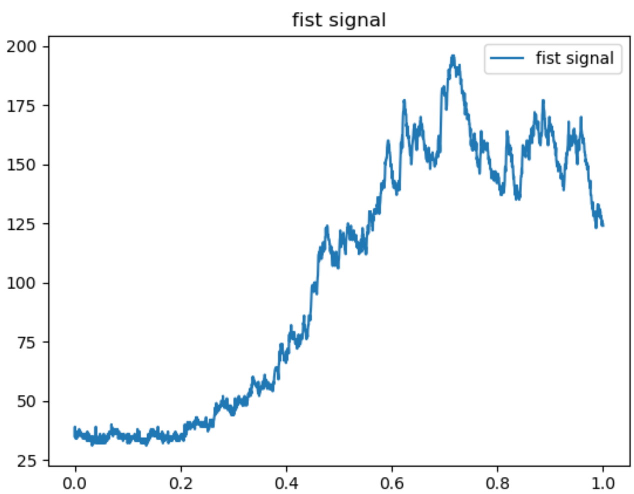


Figure 5-9: Isotonic reading taken for fist gesture

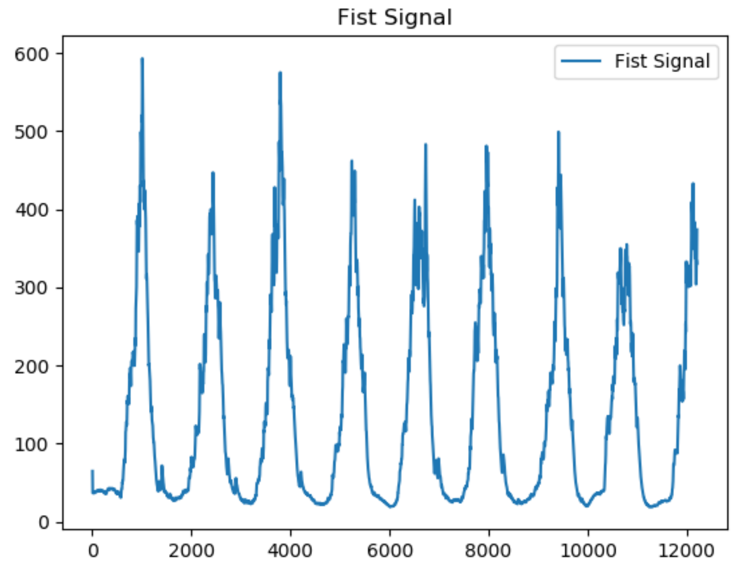


Figure 5-10: Multiple isotonic readings for fist gesture

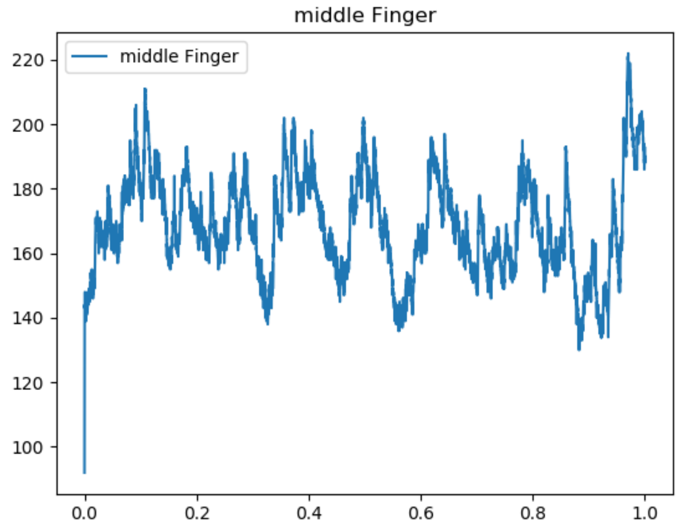


Figure 5-11: Isometric reading taken for middle finger

Figure 5-12shows the scatter plot of different gestures as shown taken for isotonic readings. Figure 5-13shows the scatter plot for the same gestures taken for isometric readings. Both the scatter plots are plotted using average and variance as features for comparison. It can be clearly seen that the gestures aren't clearly separated for isotonic readings; whereas for isometric readings points for one gesture form a cluster and these clusters are separate from the clusters of different gestures.

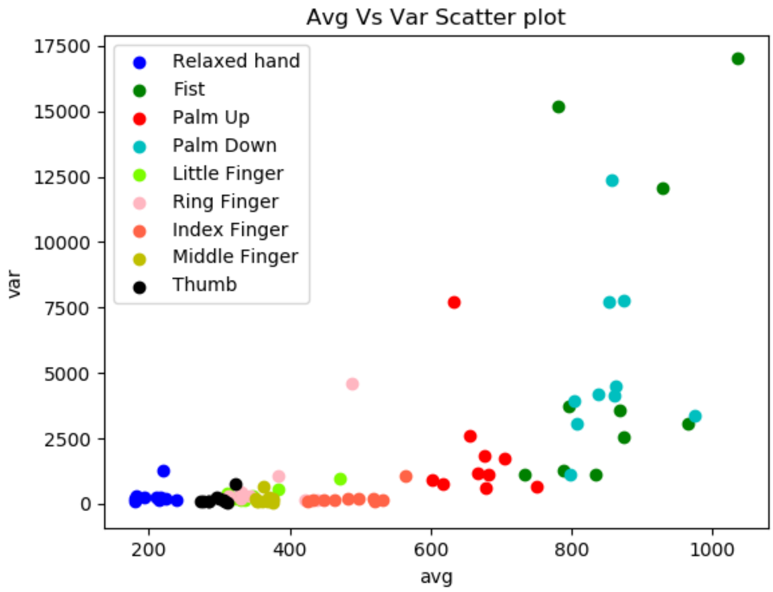


Figure 5-12: Scatter plot for isotonic readings

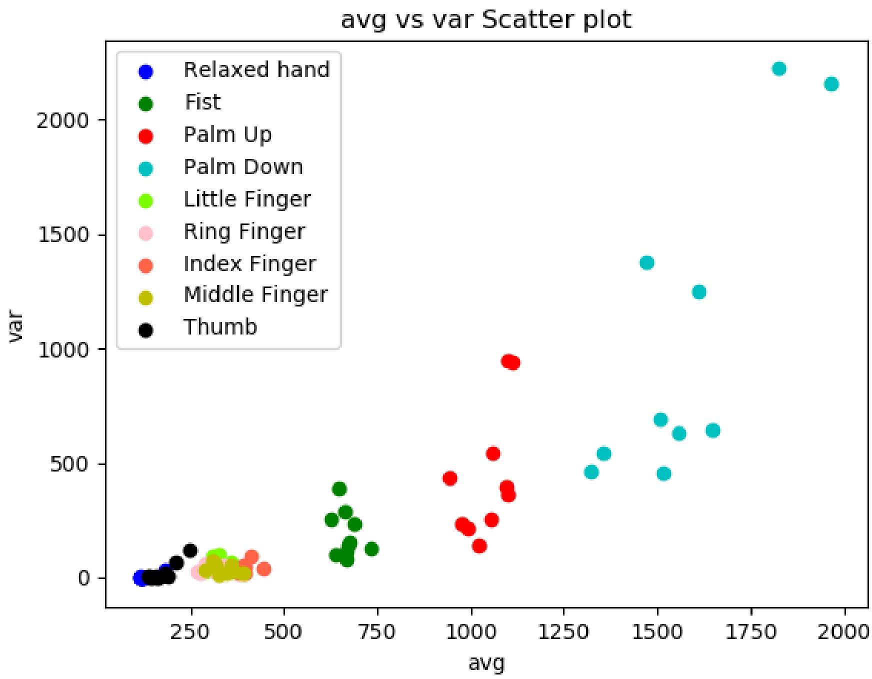


Figure 5-13: Scatter plot for isometric reading

Thus for the project and experimentation purpose it is decided to go with isometric method to record EMG signals.

5.6 Organizational visits

To gain more insight on the existing technologies and to check the feasibility of the project we visited various organizations.

5.6.1 Dassault Systems, Pune

Figure 5-14: Dassault Systemeś

We visited Dassault Systems, regarding the sponsorship terms and conditions. Also experts of company helped us gain valuable insights regarding the project. The terms of the project and the feasibility of the project was discussed. The overall outcome of this meeting was to go ahead with the project.

5.6.2 Artificial Limb Centre (Wanowrie, Pune)

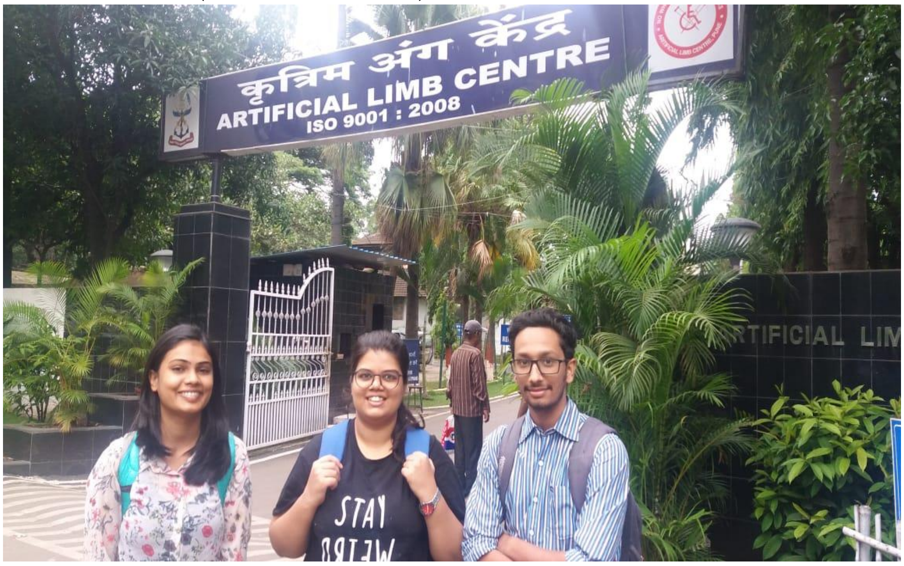


Figure 5-15: Artificial Limb Centre

The next visit was to Artificial Limb center in Pune. This organization provides low cost Bionic Arm to amputees. The Bionic Arms provided by ALC provide very less degrees of freedom. A meeting with the physiotherapist was also done in order to get his/her insights regarding the anatomy of hand and muscle region. Figure 4.16 shows the Bionic Arm provided by ALC for amputees. The arm provided by the ALC was at subsidized cost of around Rs.1,60,000/-but it provided just one degree of freedom.

Figure 5-16: Artificial Limb Centre's Bionic arm

5.6.3 Dee Dee Labs, Pashan, Pune

We visited a start-up called Dee Dee labs which is a start-up working on the EMG controlled Bionic Arms. We met the head of the organization who is working on this idea since past 4 years. We approached them in order to have some insights regarding the process but since their project was going through a patent, they could not tell us much.

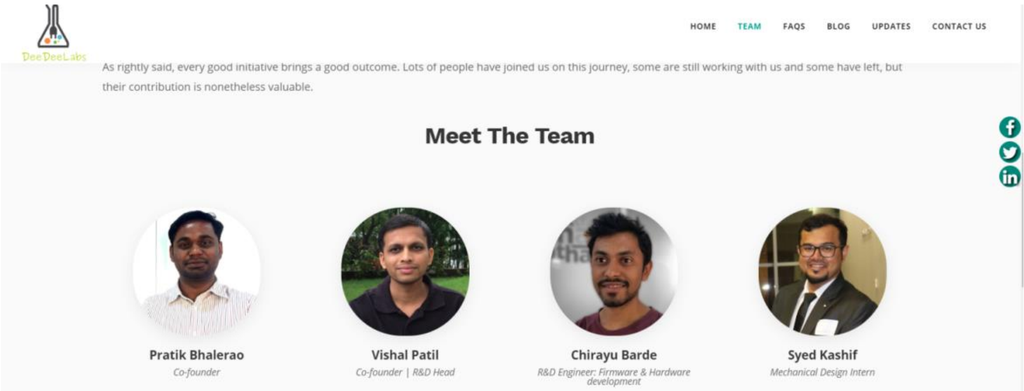


Figure 5-17: Dee Dee Labs Team[22]

5.6.4 Robo-Labs

Robo-Labs, Pune is a research lab that concentrates in the field of robotics. It has a robotic arm which is controlled by flex sensor. It used a servo string mechanism.

5.7 Sensor array band

Previously, we saw muscle region based sensor placement. There the proper muscle region selection is very necessary. Also the orientation of sensors affects the signal quality. Every time the Bionic Arm is worn by the user, he/she has to take care of placing the sensors properly on the muscle regions. When not done with extreme care, the classification accuracy of the Machine Learning is adversely affected. As a solution to this, it was decided to use sensor array band. It reduces the work needed to find the muscle regions every time the readings need to be taken.

In sensor array band, we use multiple sensors which are placed around the circumference of the arm while aligned horizontally parallel to each other. Here this orientation is fixed by using a band that holds the sensors in place. Sensor array band can have n number of sensors in it. As the number of sensors in the band increases, more informative signals can be recorded. The limitation on the number of sensors in the band is present due the size of the sensors and the perimeter of the band.

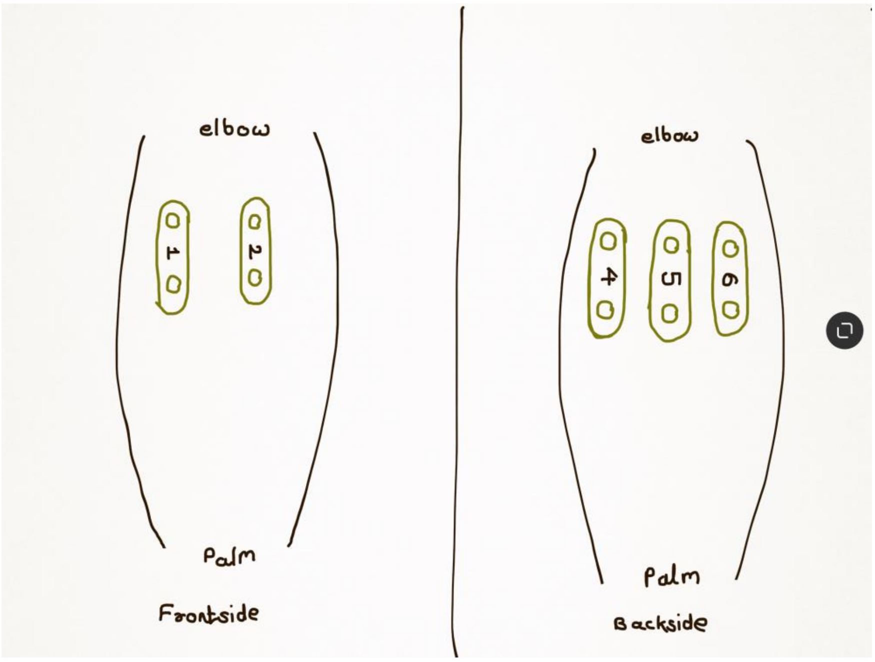


Figure 5-18: 5 Sensor Band Placement

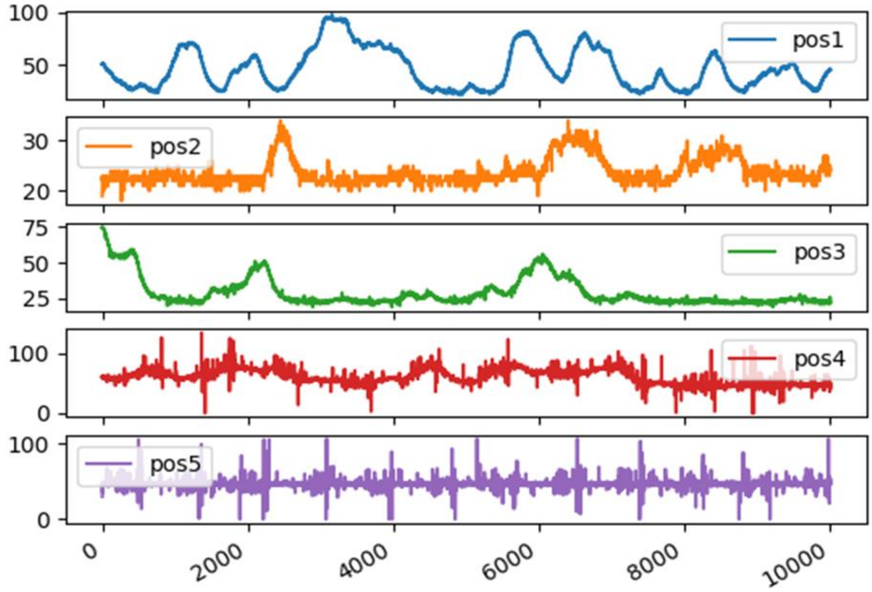


Figure 5-19: Relax signal extracted from 5 sensors

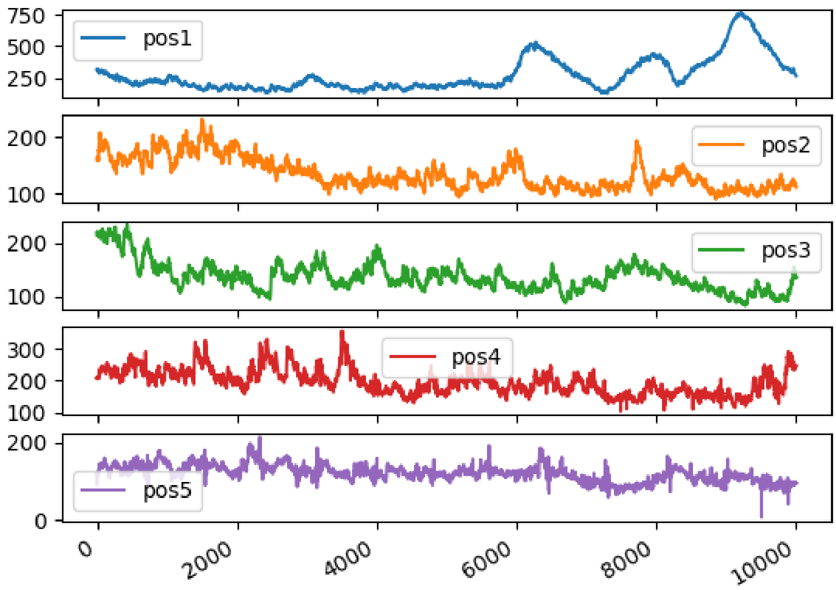


Figure 5-20: Fist signal from 5 sensors

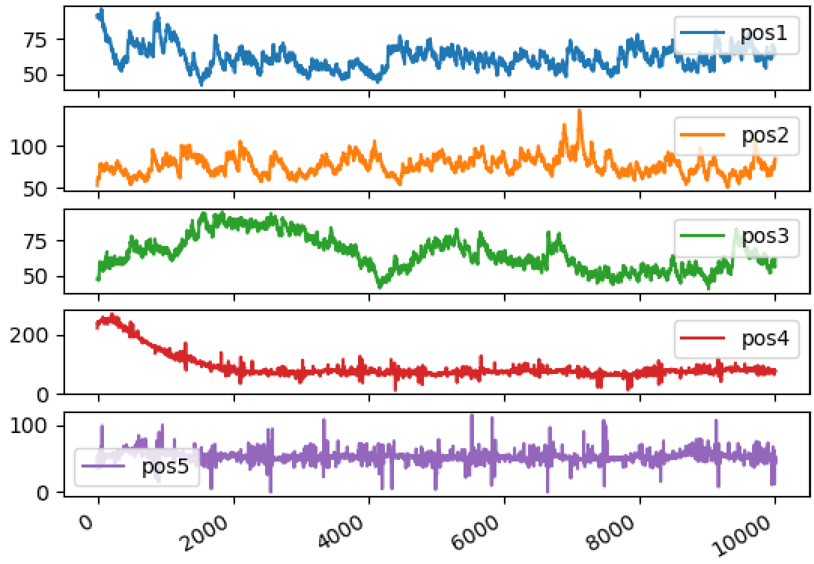


Figure 5-21: Little Finger signal from 5 sensors

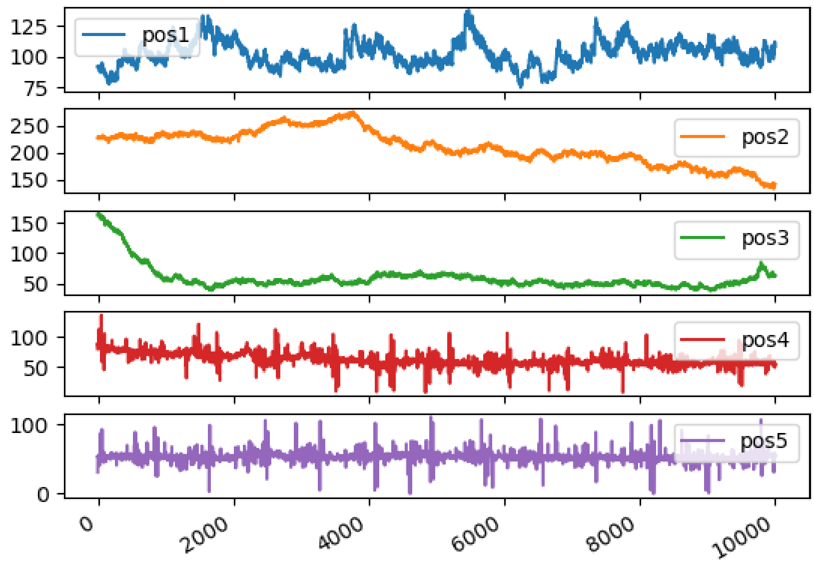


Figure 5-22: Index finger signal from 5 sensors

5.8 ADC resolution's effect on the EMG signal

Arduino Uno has a 10-bit Delta sigma ADC which provides 1024 distinct levels for the representation of the analog signal. The reference voltage used here by default is 3.3V. So the 3.3V corresponds to 1024, 0V corresponds to 512, 1.65V corresponds to 788, -3.3V corresponds to 0 and so on.

If the input to this ADC is in the range of ±3.3V, the output of ADC is clearly visible in the range of 0 to 1023. Likewise, if the input signal is in the range of ±1.65V, the output ranges between 256 to 788. So if the input range goes on decreasing there is less number of distinct output levels to represent the signal in digital form. Hence small variations are ignored and the analog to digital conversion is lossy.

Arduino Due has a 12-bit Delta sigma ADC which provides 4096 distinct levels for the representation of the analog signal. The reference voltage used here by default is 3.3V. So the 3.3V corresponds to 4096, 0V corresponds to 2048, 1.65V corresponds to 3072 and -3.3V corresponds to 0 and so on.

The amplitude of EMG signal is in the range of ±10mV, which is amplified by the instrumentation amplifier of gain 'G' and then given as input to the ADC block. So if G is low then high resolution ADC's should be used

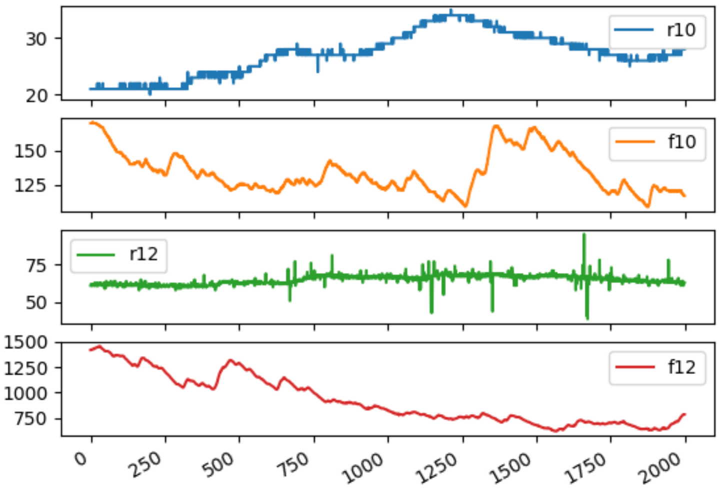


Figure 5-23: ADC Resolution results

5.9 Ninapro results[23]

The Ninapro project is an ongoing work that aims to aid research on advanced hand myoelectric prosthetics with publicly available datasets.
The databases are obtained by jointly recording multi-modal data, including e.g. surface electromyography (sEMG) signals, hand kinematics, hand dynamics while the subjects perform a predefined set of up to 53 movements..

Dataset 1 includes data from 27 intact subjects.
Dataset 2 includes data from 40 intact subjects.
Dataset 3 includes data from 11 transradial amputees (with amputation levels as represented in the figure at the end of the page).
Dataset 4 includes 10 intact subjects recorded with "Cometa" electrodes.
Dataset 5 includes 10 intact subjects recorded with two ThalmicMyo armbands, putting them on the same forearm simultaneously.
Dataset 6 contains repeatability data from 10 intact subjects repeating data acquisitions 2 times per day for 5 days.
Dataset 7 contains data from 20 intact subjects and 2 transradial amputees.

Despite intact subjects results can be used as a proxy measure for hand movement classification of hand amputees (Atzori et al., EMBC 2014),. Considering the data from amputees, several clinical parameters related to the amputation can significantly influence results, as described in Atzori et al., Journal of Rehabilitation Research and Development, 2016. This fact should be properly considered while analyzing the data and presenting the results.

It will constitute a standard, widely accepted benchmark for novel myoelectric hand prosthesis control methods.

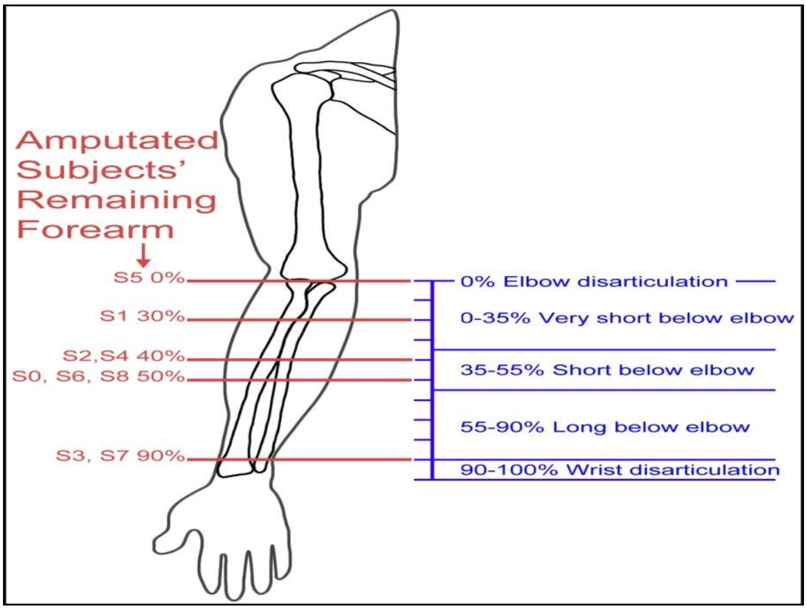


Figure 5-24: Human Arm Amputation Details[23]

The codes that were written for analysis was also implemented on the Ninapro database and the results are as follows-

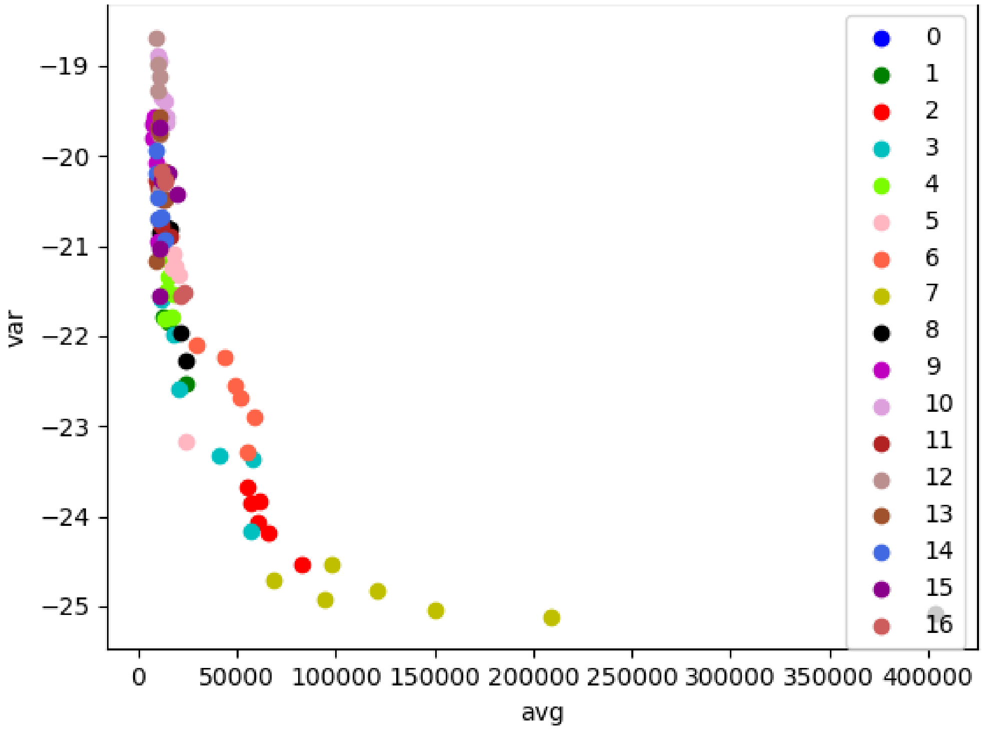


Figure 5-25: Database 3 Subject1

5.10 Gestures

In the initial signal recording stage 9different hand gestures were fixed. They were as follows-

Gesture Set 1

- Rest
- Fist
- Palm up
- Palm down
- Little finger
- Ring finger
- Middle finger
- Index finger
- Thumb

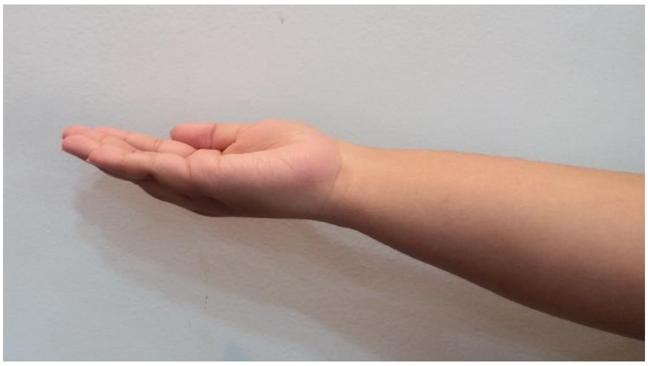


Figure 5-26: Rest

Figure 5-27: Fist

Figure 5-28: Palm up

Figure 5-29: Palm down

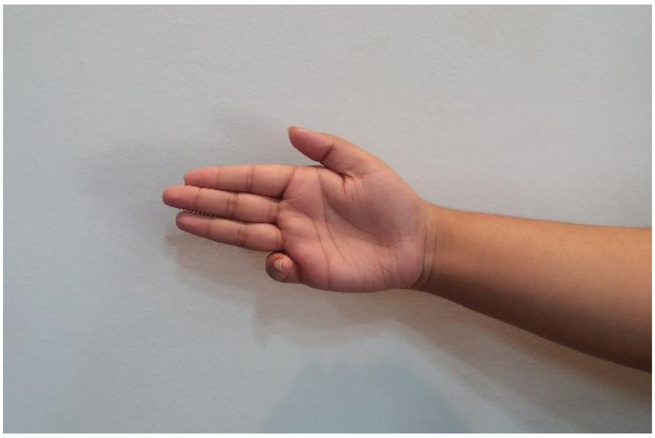


Figure 5-30: Little Finger

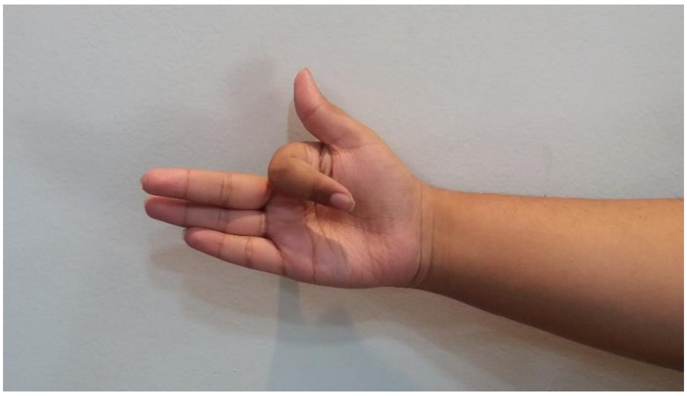


Figure 5-31: Index Finger

Figure 5-32: Middle Finger

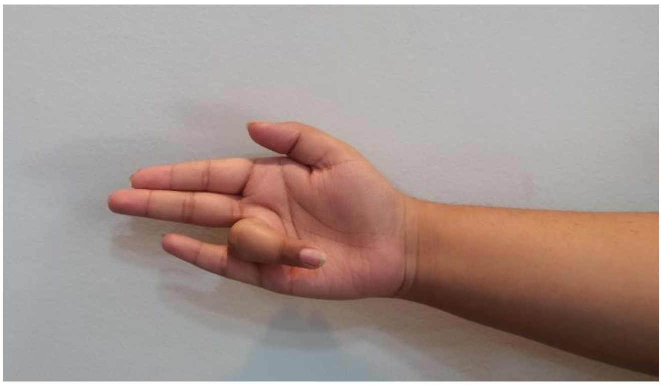


Figure 5-33: Ring Finger

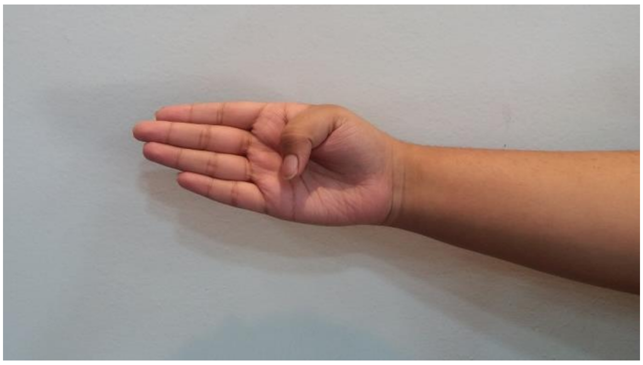


Figure 5-34: Thumb

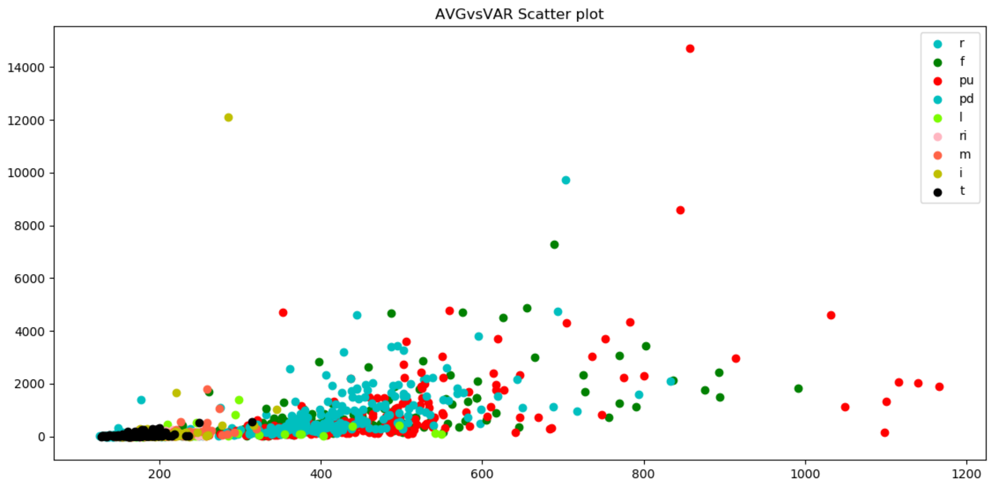


Figure 5-35: Scatter plot for 9 gestures

The 9 gestures selected have been plotted in the scatter plot given in Figure 5-35. As it can be seen the readings of the gestures overlap each other and no clear distinction can be seen. This will lead to an inaccurate machine learning model and the model will not be able to classify the gestures accordingly.

Also these gestures have little practical use in daily life. Thus to increase functionality of the Bionic Arm and to increase classification accuracy, a new gesture set was defined.

This new gesture set contains some gestures from the previous 9 gestures and some new gestures. These new gestures have more practical application as compared to the previous ones. These new seven gestures are as follows.

Gesture Set 2

- Rest
- Fist
- Palm up
- Palm down
- Hold
- Victory
- Pinch

Figure 5-36: Rest

Figure 5-37: Hold

Figure 5-38: Fist

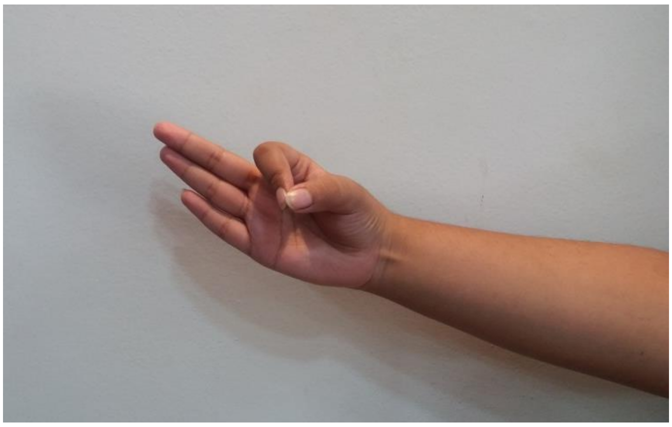


Figure 5-39: Pinch

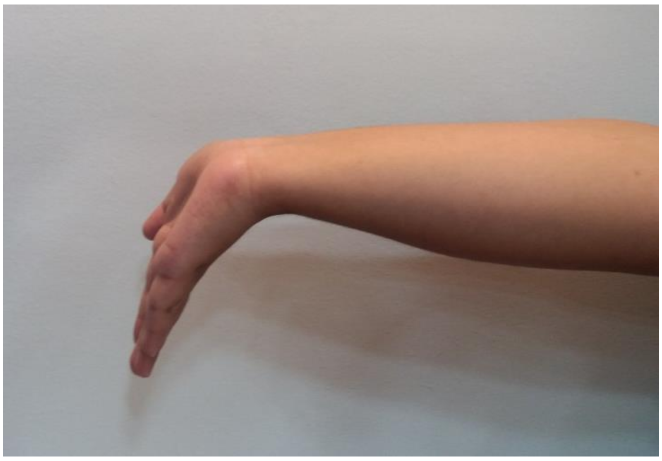


Figure 5-40: Palm down

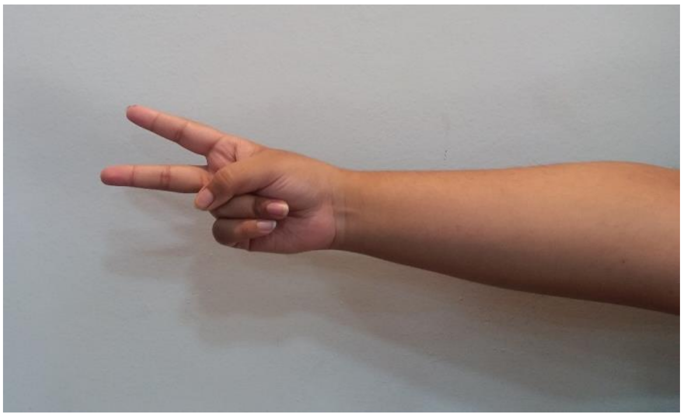


Figure 5-41: Victory

Figure 5-42: Palm up

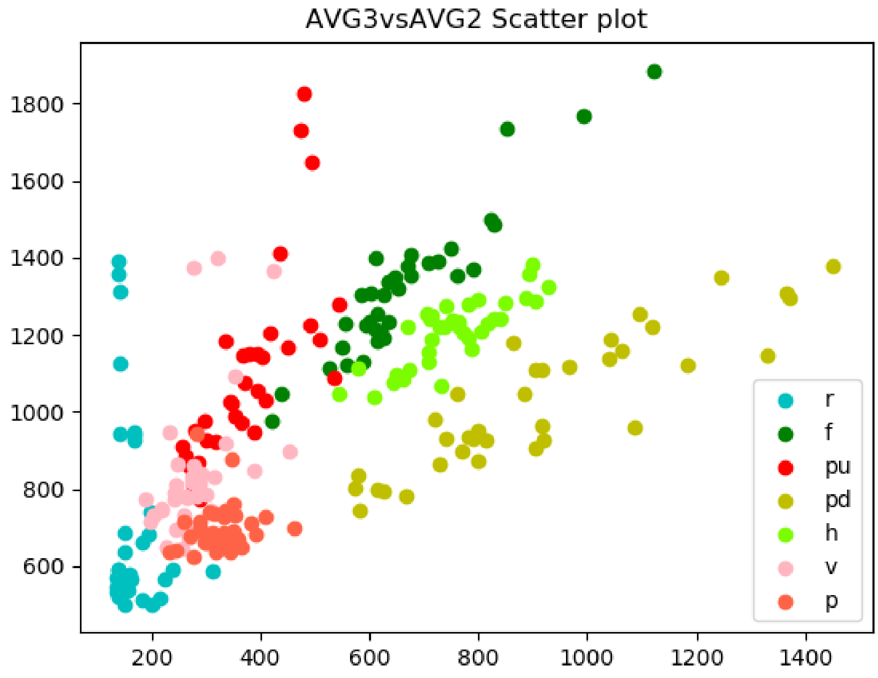


Figure 5-43: Scatter plot of AVG3 vs. AVG2

Figure 5-43shows the scatter plots for the 7 gestures plotted for AVG3 and AVG2 features. It can be clearly seen that the gestures form separate classes and there is minimum overlap between different gestures. Thus better classification accuracy might be obtained.

In addition to these gestures like hold, victory and pinch have practical applications. Hold can be used to hold a bottle or other things. Pinch gesture can be used to lift small things like keys, etc.

5.11 Feature Extraction

Different Features can be used to represent information in the EMG signal. We classify these gestures based on the values of the features. These features need to be carefully chosen to make the machine learning model efficient.

In our project, we applied different Time-domain features to represent our data. Initially we choose the features mentioned in the Table 5-2.

Table 5-2: Various Features and their Formulae

Feature Name	Formula
Average	$f(x) = \frac{1}{N}\sum_{i=0}^{N} x_i$
Variance	$f(x) = \frac{1}{N}\sum_{i=0}^{N}(E[x] - x_i\,)^2$
Mobility	$f(x) = \sqrt{\frac{Variance(\frac{d(x)}{dt})}{Variance(x)}}$
Complexity	$f(x) = \frac{Mobility(\frac{d(x)}{dt})}{Mobility(x)}$
Wavelength	$f(x) = \sum_{i=0}^{N}(x_i - x_{i-1})$

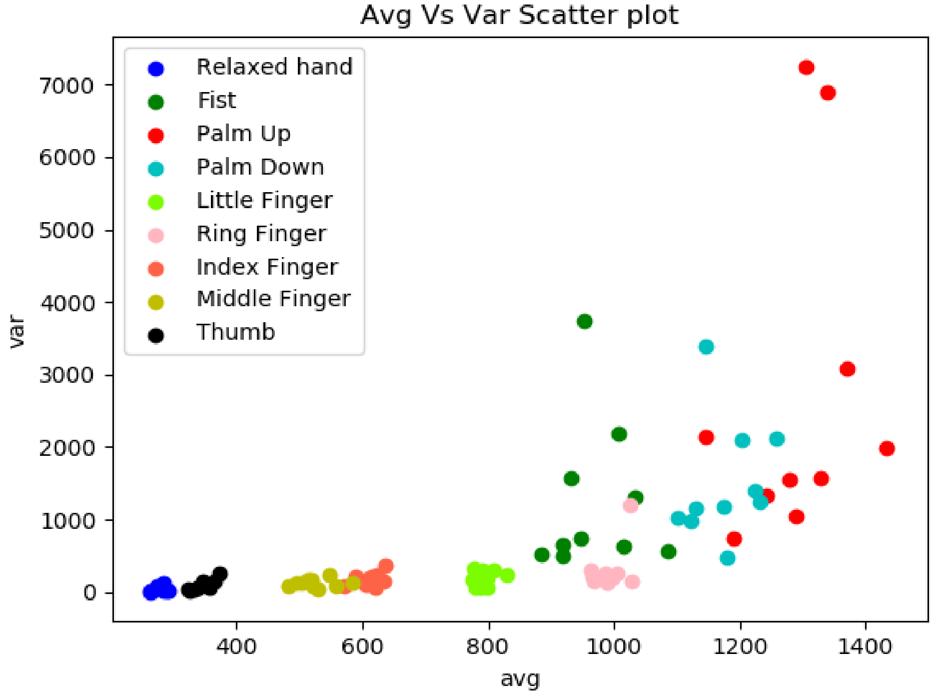


Figure 5-44: Scatter plot of AVG vs. VAR

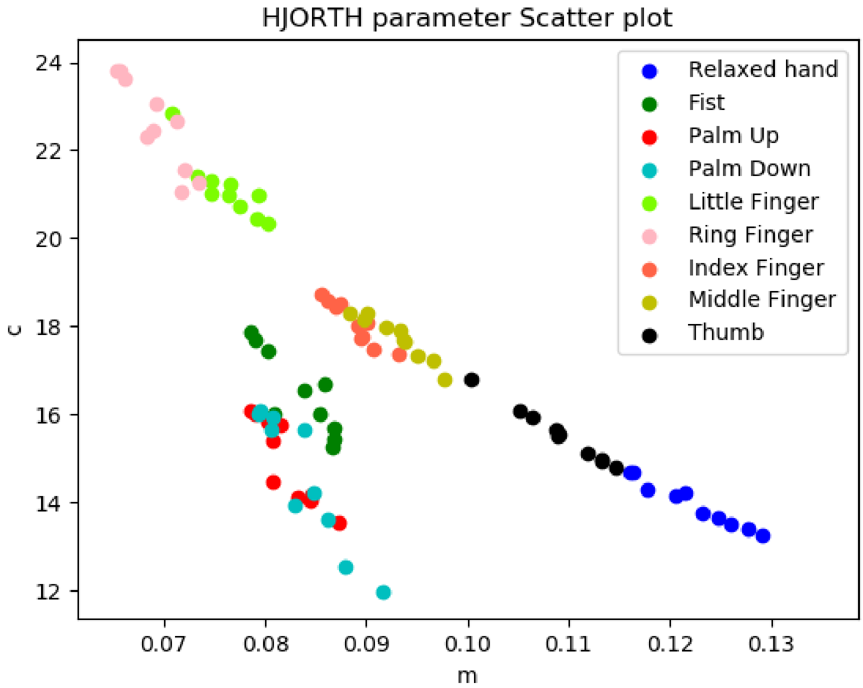


Figure 5-45: Hjorth Parameters scatter plots

5.12 Fitness Function

Fitness function is code written to check the how fit is the feature to be taken forward for the model.

The Fitness code was executed on the features and its value was noted down.

5.13 Dimensionality Reduction Algorithms

Dimensionality reduction is a statistical technique in Machine Learning that helps to reduce the random variables and helps in obtaining principal variables.

Two dimensionality reduction algorithms were experimented on the obtained data.

1. Principal Component Analysis (PCA)
2. Linear Discriminant Analysis (LDA)

PCA tries to find the direction of maximal variance and LDA tries to maximize the ability of separation between the classes.

Two dimensionality reduction algorithms were tested on the data in order to reduce the number of dimensions and check whether it makes the gestures more classifiable.

The results are as follows-

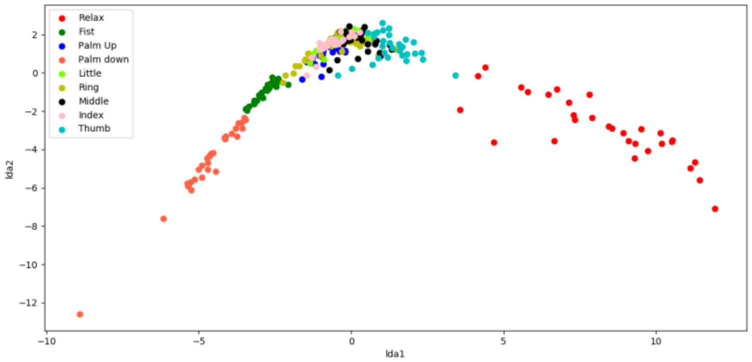


Figure 5-46: Linear Discriminant Analysis Scatter Plot

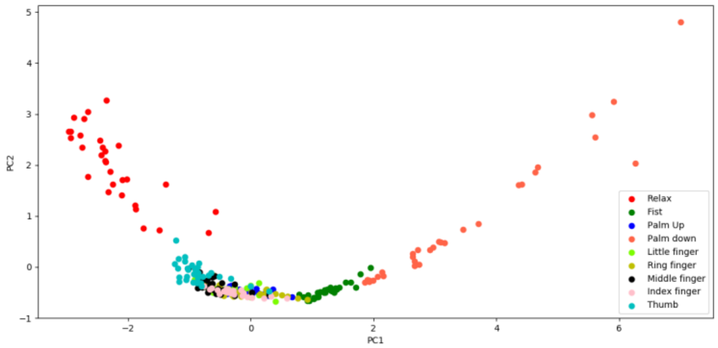


Figure 5-47: Principal Component Analysis Scatter Plot

The number of features were reduced here while maintaining the useful information in the features.

5.14 Data Acquisition, Signal Analysis and Modelling Flow

5.14.1 Data Acquisition

Acquiring data from one sensor placed on one particular muscle was not a feasible solution for data acquisition. Therefore, a band of sensors was formed by placing the sensors parallel, around the circumference of the lower elbow region of the arm. In total 10 sensors were used for acquiring data. The 10 sensors were divided in two sets of bands. The first band comprised of 6 sensors and the second band comprised of 4 sensors. The sensors were placed in such a way that all major muscle regions were covered.

The advantage of using array band was that finding a particular muscle was a tedious job and forming a band reduced this work.

The sensors were secured using a medical BP band so that the sensors are fixed to their position and there is no noise present. The reference terminal of each sensor was brought to a common point and given to the corner elbow bone.

When the whole setup is done, the subject is asked to hold one particular gesture for one second. The reading is recorded in that period at a sampling rate of 2000 SPS. Thus we get an excel sheet stating reading of all 10 sensors in those particular gestures using the Arduino Due board.

A large data was acquired across few days. The following Table 5-3contains the details of the date and number of sets on which the particular readings were recorded

Table 5-3: Whole Data Details

Sr.No	Date	Number of Sets
1.	12/05/2019	5
2.	13/05/2019	45
3.	14/05/2019	25
4.	15/05/2019	12
5.	28/05/2019	9
6.	31/05/2019	25
7.	01/06/2019	25
8.	03/06/2019	9
Total-	8 Days	155

	A	B	C	D	E	F	G
1	r	f	pu	pd	h	v	p
2	0	0	0	262	0	0	0
3	33	195	148	280	238	59	64
4	62	400	219	77	247	109	68
5	22	267	43	51	368	14	31
6	105	139	122	409	187	117	111
7	57	226	240	243	359	147	96
8	74	339	404	178	306	198	129
9	437	789	721	424	659	574	405
10	84	183	171	165	170	114	106
11	66	280	105	374	462	171	152
12	86	321	162	748	529	226	139
13	62	218	173	295	260	88	93
14	86	430	241	89	244	111	91
15	16	288	52	82	375	18	24
16	106	130	117	405	206	127	108
17	64	230	246	243	374	183	110
18	88	357	421	187	295	193	127
19	429	798	717	439	661	535	398
20	75	174	162	163	178	128	120
21	83	276	120	360	476	168	175

SET1 SET2 SET3 SET4 SET5 SET6 SET7 SET8 SET9

Figure 5-48: 14/05/19 Sheet9

5.14.2 Data conditioning

The data that is acquired from the Arduino Due board is in a very scrambled format to make it easy for single channel serial transmission. Thus we need to condition the data in order to unscramble it and to represent it properly for the next analysis. The input to the data conditioning block is 10 scrambled streams of data. Data Conditioning block converts this stream of data into 7 excel sheets, each sheet represents individual gesture. In each sheet, 10 columns of 2000 rows are formed, each column representing the individual sensor. This is done for all the 155 sets.

The final output is one excel sheet per gesture.

	A	B	C	D	E	F	G	H	I	J	K
1		1	2	3	4	5	6	7	8	9	10
2	0	0	33	62	22	105	57	74	437	84	66
3	1	86	62	86	16	106	64	88	429	75	83
4	2	83	57	75	26	107	64	78	443	72	64
5	3	92	69	74	17	105	77	78	432	87	68
6	4	88	59	87	19	106	64	91	429	73	70
7	5	90	59	75	19	119	63	79	470	75	67
8	6	88	69	80	5	106	76	87	430	71	77
9	7	94	56	75	32	120	64	86	442	68	69
10	8	94	78	72	18	111	79	73	429	76	85
11	9	88	59	86	18	107	66	90	425	72	68
12	10	99	53	74	20	127	65	78	438	85	68
13	11	92	68	75	20	110	75	79	443	72	82
14	12	89	57	75	27	113	64	78	441	68	67
15	13	97	64	75	19	115	70	77	429	82	73
16	14	88	57	83	28	107	63	84	428	77	42
17	15	95	60	75	26	113	64	78	435	81	67
18	16	89	62	82	18	112	74	74	426	73	84
19	17	88	58	82	0	107	66	81	442	71	67
20	18	85	71	76	21	121	63	78	433	87	67
21	19	88	60	85	18	108	71	92	426	72	75
22	20	92	59	81	27	136	61	88	439	73	58

r f pu pd h v p

Figure 5-49: 14/05/19 Data Conditioning SET1

In this way one excel sheet represents one gesture's readings of all the 10 sensors.

5.14.3 Set combination

In Set Combination we combine the readings of all the sets excel files into a single excel file. The input given to set combination is the output of the data conditioning file.

	A	B	C	D	E	F	G	H	I	J	K
1		1	2	3	4	5	6	7	8	9	10
2	0	0	33	62	22	105	57	74	437	84	66
3	1	86	62	86	16	106	64	88	429	75	83
4	2	83	57	75	26	107	64	78	443	72	64
5	3	92	69	74	17	105	77	78	432	87	68
6	4	88	59	87	19	106	64	91	429	73	70
7	5	90	59	75	19	119	63	79	470	75	67
8	6	88	69	80	5	106	76	87	430	71	77
9	7	94	56	75	32	120	64	86	442	68	69
10	8	94	78	72	18	111	79	73	429	76	85
11	9	88	59	86	18	107	66	90	425	72	68
12	10	99	53	74	20	127	65	78	438	85	68
13	11	92	68	75	20	110	75	79	443	72	82
14	12	89	57	75	27	113	64	78	441	68	67
15	13	97	64	75	19	115	70	77	429	82	73
16	14	88	57	83	28	107	63	84	428	77	42
17	15	95	60	75	26	113	64	78	435	81	67
18	16	89	62	82	18	112	74	74	426	73	84
19	17	88	58	82	0	107	66	81	442	71	67
20	18	85	71	76	21	121	63	78	433	87	67
21	19	88	60	85	18	108	71	92	426	72	75
22	20	92	59	81	27	136	61	88	439	73	58

Figure 5-50: 14/05/19 Set Combination SET1

5.14.4 Averaging the Signal

The data of set combination is further averaged. Averaging the EMG Signal is found to be useful as all the important information in individual signals are added together and the common signals are reduced substantially. This reduces the overall computation.

The averaging the signals is done in the following way-

Output1= EMG5+EMG6+EMG7

Output2= EMG8+EMG9+EMG10

Output3= EMG1+EMG2

Output2= EMG3+EMG4

The output of this block is four excel sheets, each for one average signal.

	A	B	C	D	E	F	G	H
1		r	f	pu	pd	h	v	p
2	0	94	281.8	217.3	246.3	299.6	150.3	116.2
3	1	109.5	322.2	241.1	301.1	359.8	177.7	138.5
4	2	106.9	326	241.7	302.6	361.4	176.3	136.8
5	3	109.9	333.3	240.3	302.3	364	177.2	138.2
6	4	108.6	330.7	241.4	303.3	364.2	177.3	138.1
7	5	111.6	329.9	239	303.1	364.3	176.2	140.4
8	6	108.9	329.5	238.6	303.1	365.2	175	138.2
9	7	110.6	331.1	240.5	307.6	367.9	178	137.7
10	8	111.5	326.6	239.3	304.7	362.1	174.4	139
11	9	107.9	331.5	237.7	305.9	363.8	176.4	138.5
12	10	110.7	333.7	238.3	305.2	363.2	171.1	139.7
13	11	111.6	333.1	236.8	303.3	365.1	173.7	137.9
14	12	107.9	331.8	235.8	301.3	363.4	170.5	136.9
15	13	110.1	333.7	237.8	302.7	363.8	171.6	141.8
16	14	105.7	333.9	238	302.5	363.8	172.4	138.9
17	15	109.4	337.1	233.5	302.3	362.4	170.4	137.6
18	16	109.4	340	236.8	299.2	364.4	171.8	137.1
19	17	106.2	341.4	237.8	302	363.3	170.8	138.4
20	18	110.2	344.7	237.1	299.9	360.8	169.7	138.6
21	19	109.5	348.9	236.2	298.3	362.6	169.6	137.7
22	20	111.4	348.8	237.9	296.1	364.6	170.5	138.8

Sheet1

Figure 5-51: 14/05/19 Average Signal

5.14.5 Feature Extraction

The input given to this block is the four excel sheets-Output1.xlsx, Output2.xlsx, Output3.xlsx and Output4.xlsx.

Various features were extracted from the data. Average, Log of Average, L3 Norm, Variance etc. are a few examples of the features. The features from each output excel file are separately extracted and are saved into separate excel files. The output of this block is 4 excel files and their description is as follows.

Features1 → Output1

Features2→ Output2

Features3→ Output3

Features4→ Output4

	AVG	LOGAVG	L3	Label
0	109.722	4.69795	871.4753	r
1	122.2724	4.806251	971.6481	r
2	129.779	4.865833	1030.626	r
3	117.8088	4.769063	937.1043	r
4	194.224	5.269012	1545.801	r
5	192.2874	5.258991	1527.34	r
6	185.6566	5.223899	1474.527	r
7	168.9032	5.129326	1342.026	r
8	108.9196	4.69061	864.8234	r
9	113.7066	4.733621	902.9125	r
10	110.5	4.705016	877.8147	r
11	108.7814	4.68934	863.6909	r
12	156.8596	5.055351	1246.885	r
13	153.5406	5.033965	1218.866	r
14	151.5072	5.020633	1202.799	r
15	147.6172	4.994622	1172.073	r
16	109.139	4.692622	868.5487	r
17	115.5622	4.749809	917.4135	r
18	120.643	4.792836	958.3754	r
19	130.7744	4.873474	1038.702	r
20	108.134	4.683371	858.573	r

Sheet1

Figure 5-52: 14/05/19 Features

5.14.6 Plotting the Scatter plots for classification

In order to have a visual idea of all the gestures and its classification capability, the data from the features' excel sheet was plotted against each other with all the possible permutations and combinations to see whether different gestures are classifiable. This is done because it is difficult to visualize the hyper-plane, so instead the hyper-plane is visualized in 2D plot.

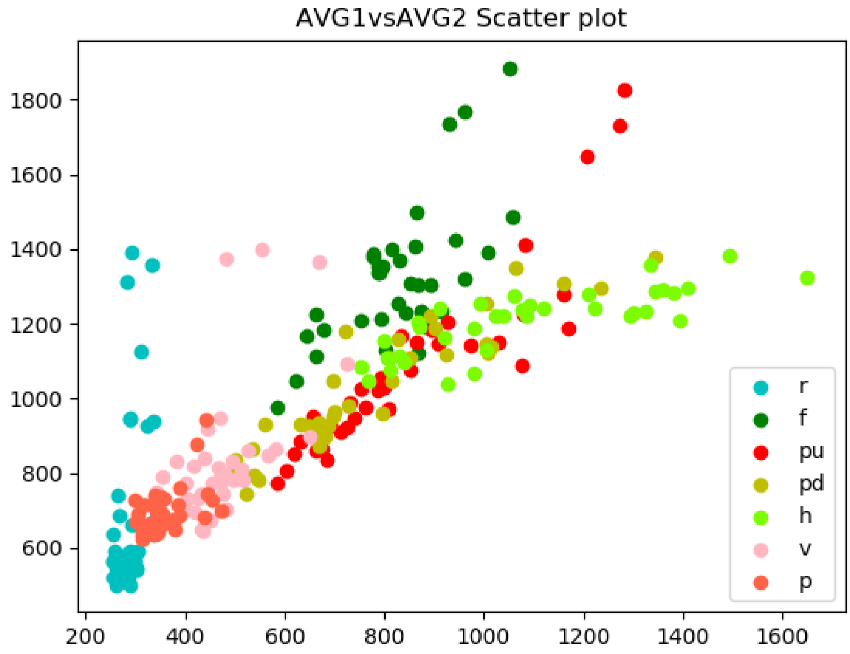


Figure 5-53: 14/05/19 Scatter Plot for AVG1 vs. AVG2

5.14.7 Training the Model

In the training phase of the model, the feature set was split into training data set and testing data set in the ratio of 5-1. The training data set is used to train the machine learning model. Firstly, the data set is normalized and is then fed to the model for training. Both the trained model and the transformation matrix are saved as .pkl files. These models are then used later for the process of prediction.

5.15 Data Acquisition

5.15.1 Six sensor results

An array of six sensors was created by placing the six sensors parallel as shown in the

Figure 5-54. This array was placed on the upper part of the arm covering the circumference of the arm. Readings from all the six sensors are recorded in parallel for one specific gesture for one recording. They are then copied to the excel sheet. Each sheet containing six columns which store the value of EMG signals from six sensors. In such a way one sheet per gesture is used to store the data.

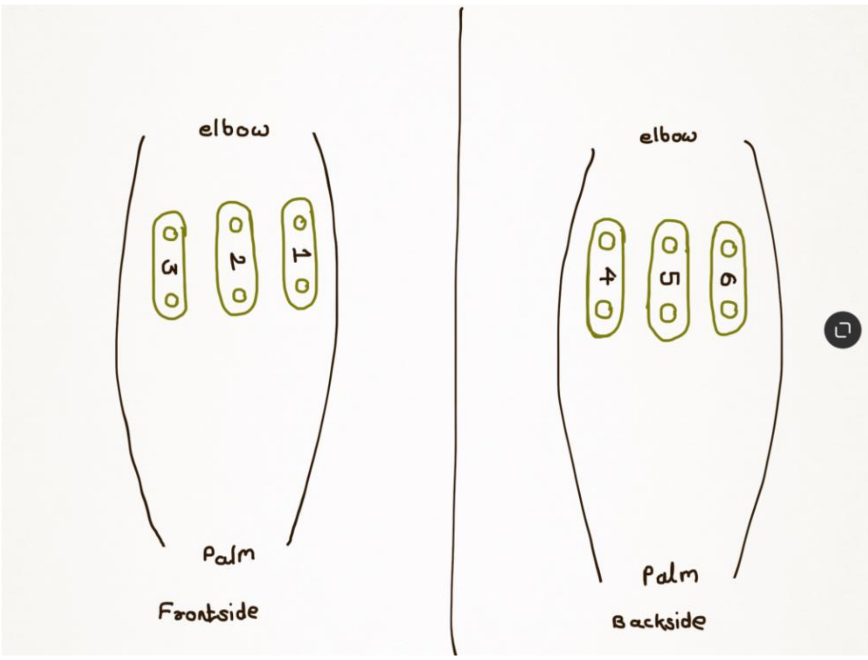


Figure 5-54: 6 Sensors placement

The following Figure 5-55 is a snapshot of the values of EMG signal for 6 sensors for rest gesture.

	A	B	C	D	E	F	G	H
1		**1**	**2**	**3**	**4**	**5**	**6**	
2	**0**	108	85	95	449	302	118	
3	**1**	108	65	94	460	289	107	
4	**2**	106	83	103	465	288	106	
5	**3**	109	83	95	447	294	109	
6	**4**	109	74	95	447	288	109	
7	**5**	114	75	95	447	292	111	
8	**6**	110	85	108	451	292	113	
9	**7**	111	84	104	467	291	120	
10	**8**	108	87	99	451	292	107	
11	**9**	121	73	103	465	296	112	
12	**10**	120	74	94	448	288	120	
13	**11**	108	81	96	446	300	112	
14	**12**	115	72	98	455	286	123	
15	**13**	108	87	98	447	300	109	
16	**14**	110	73	106	447	302	108	
17	**15**	109	75	106	458	317	108	
18	**16**	108	76	107	451	301	103	
19	**17**	113	75	109	451	301	106	
20	**18**	109	79	111	450	298	106	
21	**19**	106	80	112	448	296	107	
22	**20**	110	83	114	452	292	116	
23	**21**	106	84	113	449	290	114	

r | f | pu | pd | l | ri | m | i | t

Figure 5-55: Acquired Values from 6 sensors array for rest gesture

The following Figure 5-55 is a snapshot of the values of EMG signal for 6 sensors for fist gesture.

	A	B	C	D	E	F	G	H
1		**1**	**2**	**3**	**4**	**5**	**6**	
2	**0**	193	781	1711	1629	1004	918	
3	**1**	186	789	1716	1626	1009	909	
4	**2**	187	780	1747	1622	1011	906	
5	**3**	184	792	1725	1623	1019	904	
6	**4**	187	782	1720	1634	1020	899	
7	**5**	187	784	1718	1620	1010	893	
8	**6**	190	795	1719	1622	1009	892	
9	**7**	190	779	1713	1624	994	883	
10	**8**	156	782	1681	1617	998	874	
11	**9**	190	764	1677	1622	991	879	
12	**10**	177	769	1648	1603	987	865	
13	**11**	189	745	1627	1600	984	869	
14	**12**	174	749	1599	1612	1001	865	
15	**13**	173	741	1584	1623	1006	860	
16	**14**	147	735	1556	1617	1010	855	
17	**15**	171	717	1541	1602	1000	837	
18	**16**	171	705	1527	1610	995	815	
19	**17**	170	709	1506	1610	973	808	
20	**18**	172	702	1501	1637	984	797	
21	**19**	167	705	1470	1618	978	792	
22	**20**	176	689	1467	1609	971	781	
23	**21**	169	669	1444	1594	957	768	

r | f | pu | pd | l | ri | m | i | t

Figure5-56: Acquired values from 6 sensors array for fist gesture

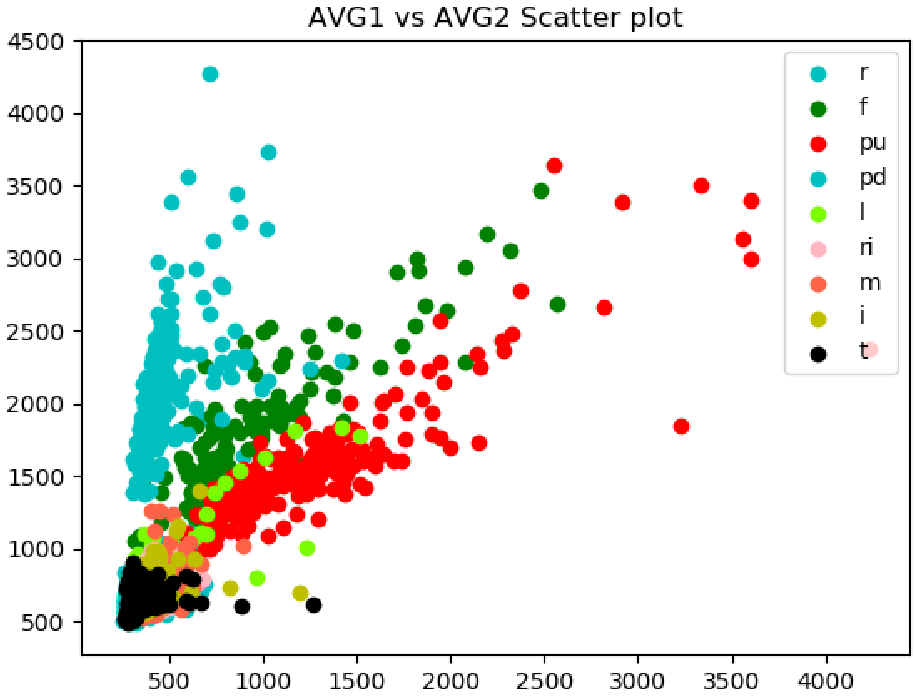


Figure 5-57: Scatter Plot for 6 Sensors of AVG1 vs. AVG2

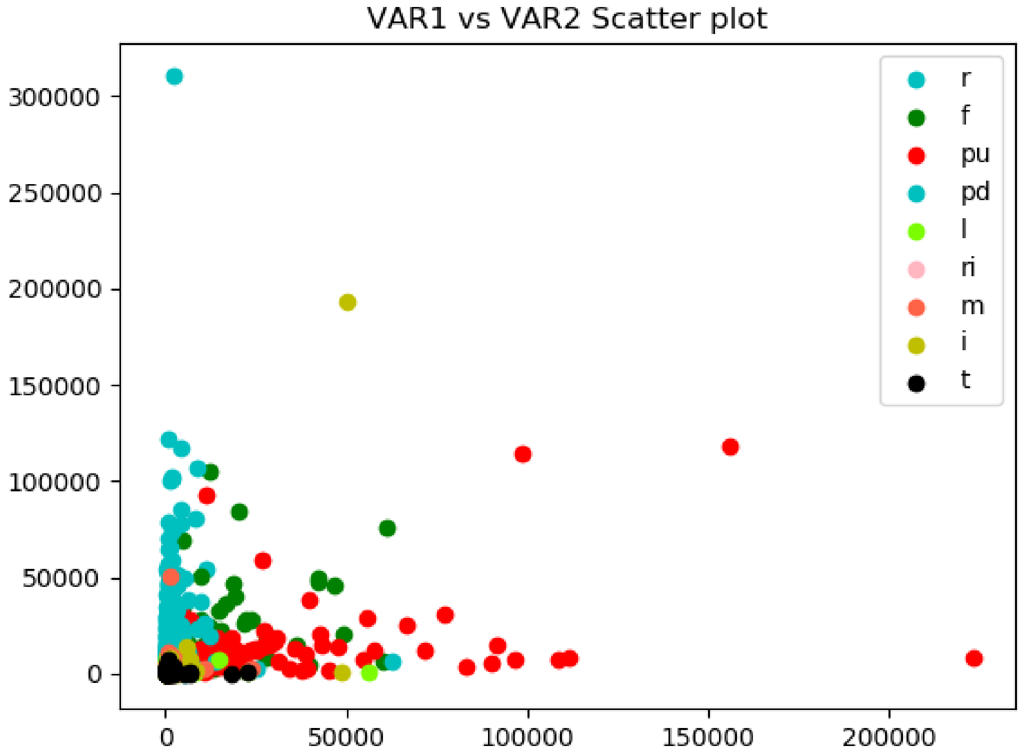


Figure 5-58: Scatter Plot for 6 Sensors of VAR1 vs. VAR2

5.15.2 Four Sensor Results

An array of four sensors was created by placing the four sensors parallel as shown in the Figure 5-59. This array was placed on the lower part of the arm covering the circumference of the arm. Readings from all the four sensors are recorded in parallel for one specific gesture for one recording. They are then copied to the excel sheet. Each sheet containing four columns which store the value of EMG signals from four sensors. In such a way one sheet per gesture is used to store the data.

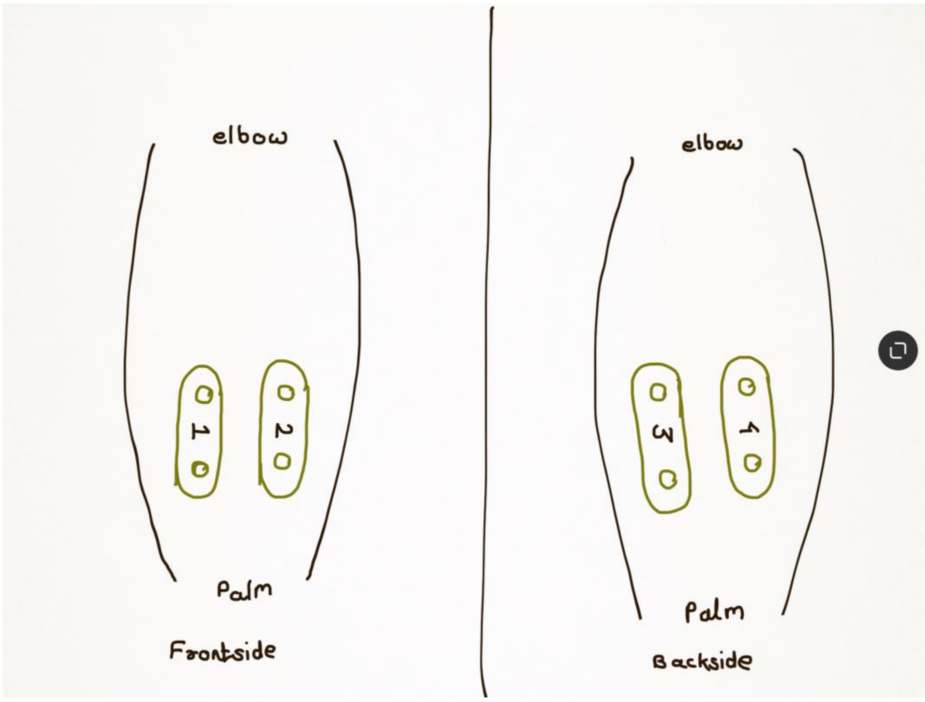


Figure 5-59: Placement of 4 sesnsors

	1	2	3	4
0	87	50	77	21
1	87	48	77	22
2	85	47	75	23
3	85	47	76	22
4	85	48	79	21
5	87	54	84	24
6	93	53	79	27
7	88	56	78	23
8	90	50	60	25
9	90	56	76	16
10	88	52	80	22
11	86	43	85	23
12	87	50	79	34
13	85	49	76	28
14	87	49	78	24
15	94	48	77	24
16	90	56	75	24
17	90	53	78	22
18	87	49	84	23
19	86	49	79	31
20	85	49	78	27
21	84	43	80	15
22	94	48	76	23
23	90	56	75	23
24	87	49	86	21
25	88	50	83	24
26	86	52	78	31
27	85	48	79	25
28	88	46	77	23
29	94	49	76	23
30	88	56	77	21

Figure 5-60: 4 sensor readings for rest gesture

	1	2	3	4
0	241	306	449	97
1	237	305	459	101
2	240	309	456	100
3	241	315	448	103
4	240	305	448	103
5	247	303	450	106
6	239	306	451	103
7	240	306	449	102
8	244	299	450	102
9	250	314	456	101
10	253	318	461	101
11	251	317	465	99
12	253	318	461	96
13	250	313	468	97
14	252	316	465	95
15	246	313	476	94
16	247	317	468	94
17	243	311	466	99
18	241	313	465	92
19	241	313	469	98
20	240	322	469	92
21	240	316	464	99
22	236	321	461	92
23	238	315	455	96
24	242	320	453	89
25	235	311	448	95
26	230	312	445	87
27	232	310	438	94
28	229	310	437	87
29	231	301	429	93
30	225	306	429	88

Figure 5-61: 4 Sensors readings for fist gesture

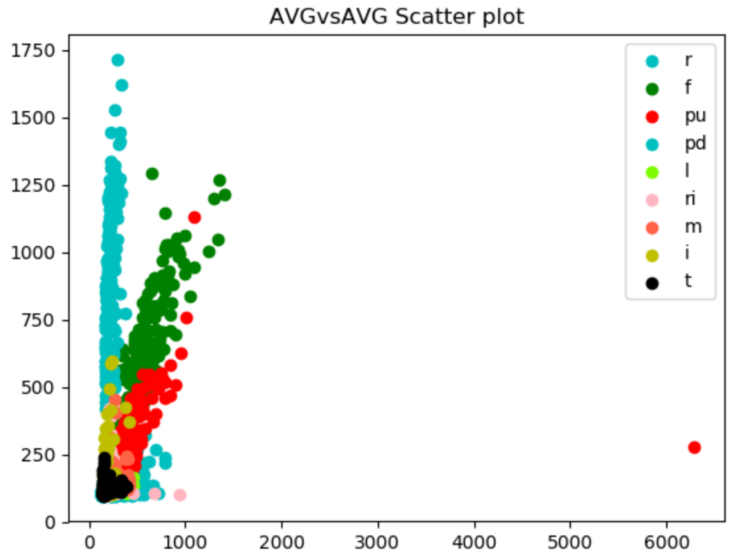


Figure 5-62: 4 Sensor Scatter Plot AVG vs. AVG

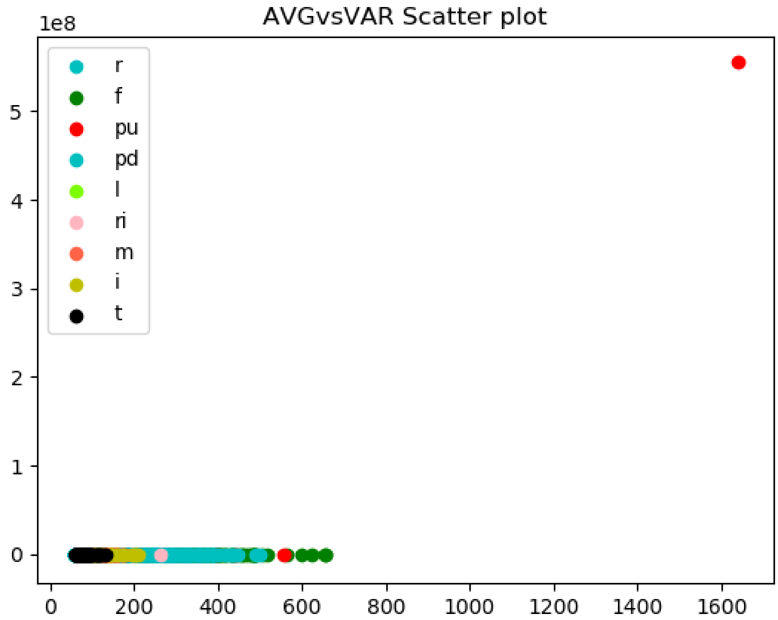


Figure 5-63: 4 Sensor Scatter plot for AVG vs. VAR

5.15.3 10 Sensors

Two sensor bands of 6 Sensors and 4 sensors respectively are used here. Six sensor band is placed close to the elbow as the circumference of the hand is large there and needs more sensors to cover the whole area. It covers the muscle groups like Flexor carpi radialis muscle, Flexor carpi ulnaris, Extensor carpi radialis muscle and Extensor carpi ulnaris muscle groups. Four sensor band is place just below the Six sensor band to cover the remaining muscle regions like Flexor digitorum profundus, Flexor pollicis longus, Extensor digitorum profundus and extensor pollicis longus muscle groups.

The signals from the sensor band is given to the Arduino Due where Delta-Sigma type 12-bit ADC is used to sample the EMG signal at 2kSPS. Then these digital EMG signals are combined sequentially and sent to the computer using UART with baud rate of 2,50,000 bits per sec. Then using Python3.6, signals are processed and unscrambled. Then the EMG signals are averaged to reduce the computation. Averaging the EMG signal is found to be useful as all the important information in individual EMG signals are added together and common signals are reduced substantially.

The averaging of the signals is done as following,

Output1 = EMG5 + EMG6 + EMG7

Output2 = EMG8 + EMG9 + EMG10

Output3 = EMG1 + EMG2

Output4 = EMG3 + EMG4

This averaging scheme was found to be effective as each average represents different muscle groups. Output1 represents signals from Extensor carpi radialis and Extensor carpi ulnaris muscle regions. Output2represents signals from Flexor carpi radialis and Flexor carpi ulnaris muscle regions. Output3 represents signals from Extensor digitorum profundus and Extensor pollicis longus muscle regions. Output4 represents signals from Flexor digitorum profundus and Flexor pollicis longus muscle regions.

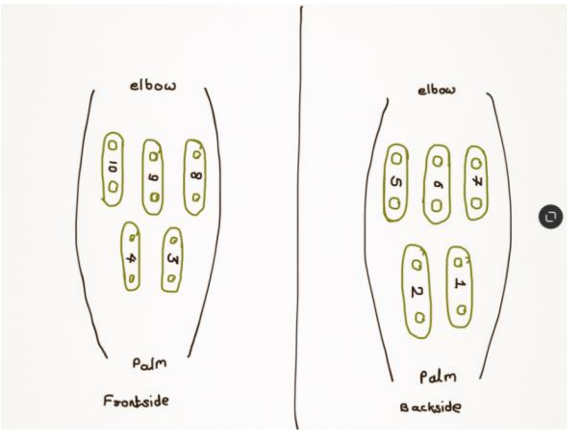


Figure 5-64: 10 Sensor Placement

Then the averaged signals are then used to extract features. The features are extracted from Output1 are called as Feature1 and so on. Then the scatter plots were plotted on the features extracted from the averaged signals. Scatter plots are very useful tool to visual see the clusters of the gestures based on the features extracted.

The following scatter plots were plotted on the database recorded on 12th May. The Average and LogAverage are used as the features here.

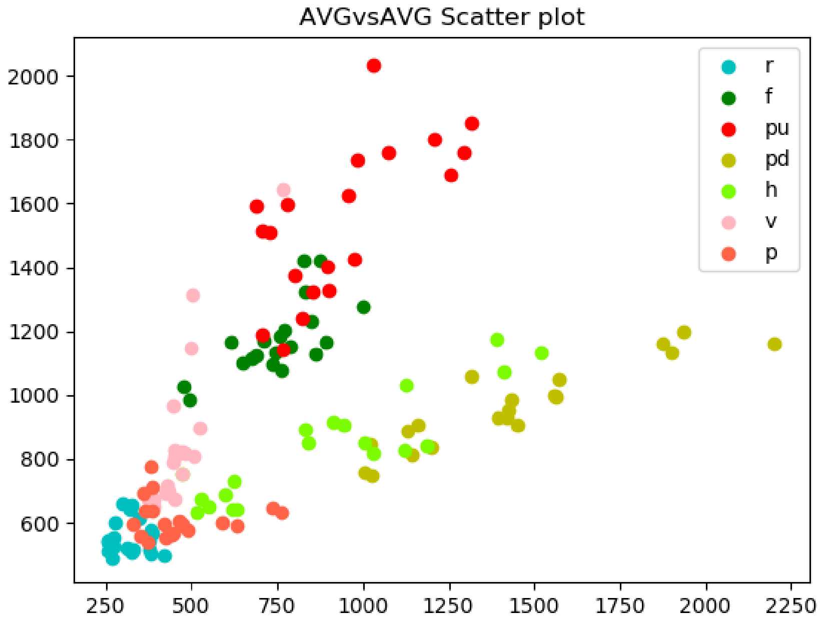


Figure 5-65: 10 sensor Scatter Plot AVG vs. AVG

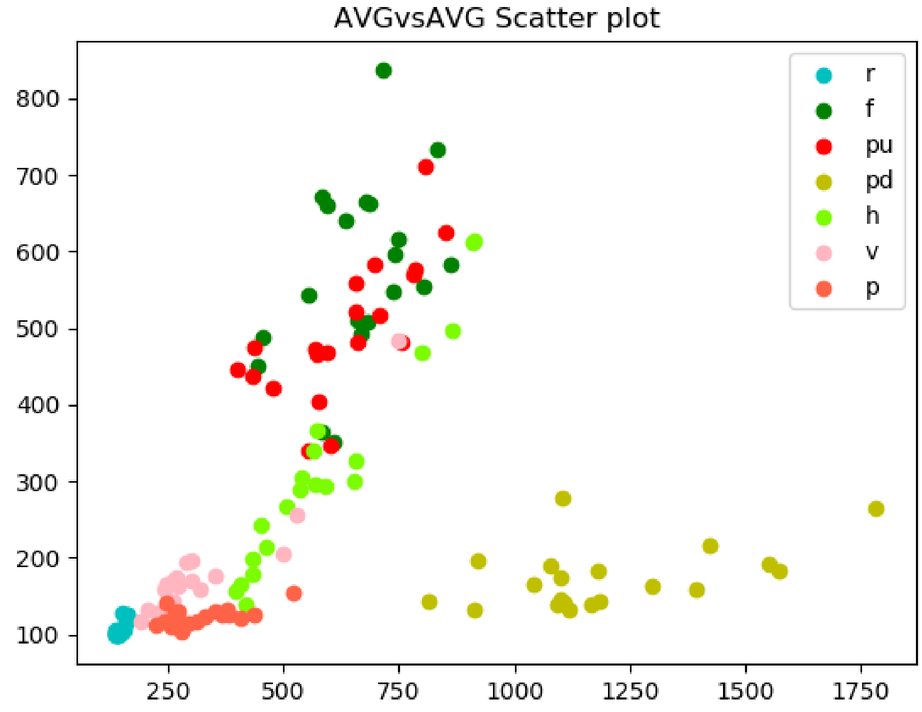


Figure 5-66: 10 Sensor Scatter Plot AVG vs. AVG

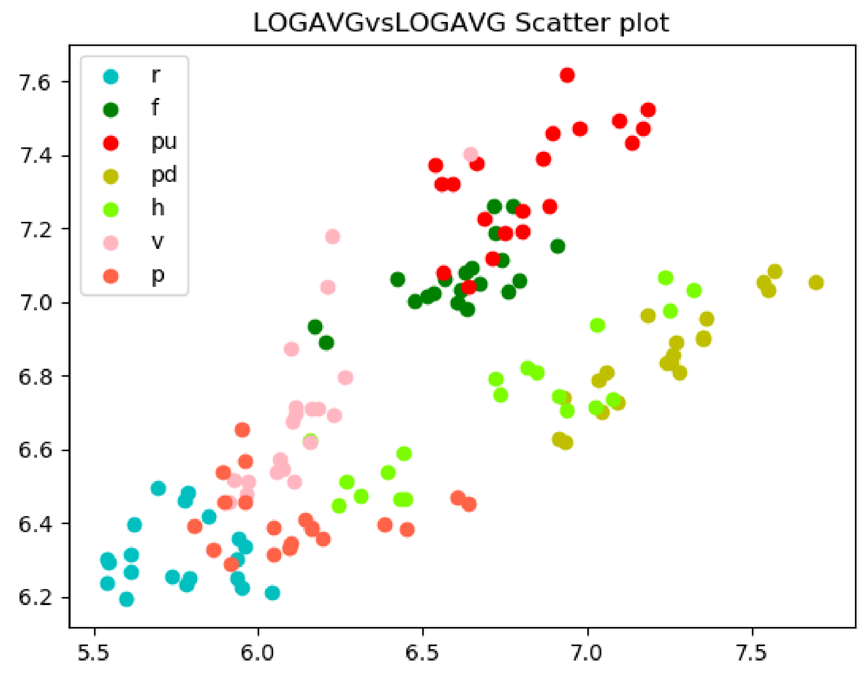


Figure 5-67: 10 sensors LOGAVG vs. LOGAVG

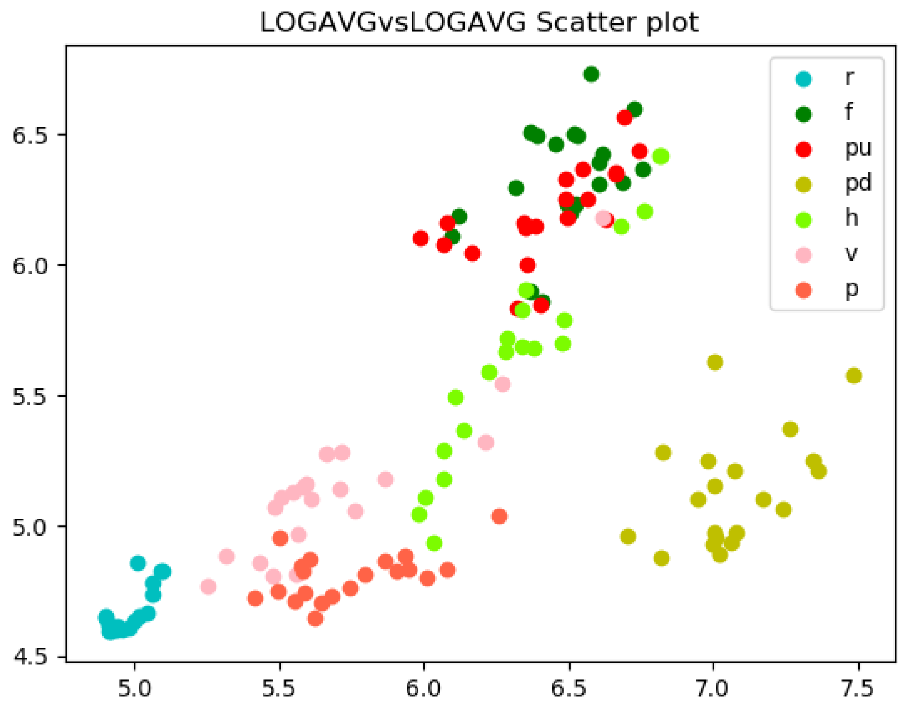


Figure 5-68: 10 Sensor Scatter Plot LOGAVG vs. LOGAVG

5.16 Statistical analysis of the whole acquired data

Statistical analysis of the acquired data is done for two purposes-

1. To observe the muscle fatigue on the subject's arm.
2. To observe the repetitiveness of the acquired data during the whole data acquisition process.

Statistical analysis here refers to combining all the features extracted from the acquired data and finding the median of that particular data. The data that was acquired consist of two features, Average and Log of Average. These two features were combined in one excel sheet and median of that data was taken to analyze the repetitiveness and muscle fatigue.

The amount of data taken is very large. The statistical analysis was carried out on the data taken from date13/05/19 to date 03/06/19. The whole data consist of 155 sets, each set consisting 7 gestures and each gesture is sampled at 2000 SPS. Everyday data is divided into number of sheets, each sheet consisting 9 sets of data.

Therefore, in order to observe the first aim i.e. muscle fatigue, each and every set was analyzed individually and then the values of each feature with respect to each gesture was analyzed in order to check whether the muscle gets tired after some duration and this affects the value of the features. The snapshots of these observations are given below.

	A	B	C	D	E	F	G	H	I	J
1		features1_A	atures2_A	atures3_A	atures4_A	ures1_LOG	ures2_LOG	ures3_LOG	ures4_LOGAVG	
2	0	312.951	510.409	139.113	102.472	5.746039	6.235211	4.935283	4.629588	
3	1	743.967	847.432	589.437	413.049	6.611957	6.742208	6.379162	6.023525	
4	2	914.163	1003.095	563.965	445.587	6.818009	6.910845	6.334992	6.099368	
5	3	1558.504	885.14	1232.188	183.944	7.351481	6.785745	7.116529	5.214619	
6	4	940.98	734.061	598.264	327.959	6.846914	6.598591	6.39403	5.792887	
7	5	600.46	700.848	364.511	171.469	6.397694	6.552291	5.898524	5.144312	
8	6	500.113	558.501	320.835	131.699	6.214731	6.325247	5.770893	4.880518	

Figure 5-69: Date-13/05 Sheet 1

	A	B	C	D	E	F	G	H	I	J
1		features1_A	atures2_A	atures3_A	atures4_A	ures1_LOG	ures2_LOG	ures3_LOG	ures4_LOGAVG	
2	0	275.96	551.42	163.32	103.551	5.620256	6.312436	5.095534	4.640058	
3	1	578.667	1039.259	647.267	461.088	6.360719	6.946252	6.472736	6.133404	
4	2	713.712	1319.915	591.183	474.667	6.570399	7.18517	6.382121	6.162507	
5	3	1197.96	961.688	1090.399	153.101	7.088371	6.868683	6.99425	5.031026	
6	4	661.541	1025.371	685.191	343.769	6.494569	6.932601	6.529693	5.839963	
7	5	448.698	798.751	325.775	165.706	6.106347	6.683048	5.786203	5.11021	
8	6	456.846	658.747	329.802	143.618	6.124345	6.490338	5.798384	4.967153	
9										

Figure 5-70: Date-13/05 Sheet 2

The above data sheets depict the data taken in one particular day. First a sheet of 9 sets was formed and then a sheet of 18 sets was formed. If the readings are tallied, a general trend is observed that the feature values are decreasing with the time. It was concluded that this was due to muscle fatigue. After a certain set of readings, the muscle gets tired and starts impacting the reading extracted from the sensor. Hence muscle fatigue has a huge impact on the readings.

The second aim was to check the repetitiveness. In order to check the repetitiveness of the readings, a combined excel sheet was made and then date wise readings and features were compared. The excel sheet that was made is as follows-

							Whole Data Statistics analysis								
	r	f	pu	pd	h	v	p		r	f	pu	pd	h	v	p
Features1								Features2							
13-May	354.84	853.39	846.22	1147.9	1001.29	539.86	500.44	13-May	616.5	1138	1196	753	948	757	609
14-May	268	662	646	505	787	432	322	14-May	608	1206	983	852	1168	810	662
15-May	306	840	902	826	844	497	434	15-May	574	986	929	791	888	727	644
28-May	340	1069	1090	990	1388	624	522	28-May	321	1082	832	857	1050	522	545
31-May	251	871	651	858	671	405	413	31-May	215	805	454	536	564	285	271
1-Jun	261	759	816	947	814	489	423	1-Jun	214	828	523	546	692	329	290
3-Jun	264	804	921	784	861	504	345	3-Jun	220	821	551	491	673	358	292
	r	f	pu	pd	h	v	p		r	f	pu	pd	h	v	p
Features3								Features4							
13-May	181	853	566	950	743	311	314	13-May	114	449	238	141	321	171	128
14-May	141	597	329	648	741	283	306	14-May	101	672	259	193	503	139	117
15-May	141	718	487	760	622	317	324	15-May	100	644	309	206	479	174	135
28-May	146	765	469	1035	872	351	439	28-May	102	923	401	233	735	216	166
31-May	140	668	489	559	488	280	277	31-May	104	630	269	235	395	162	137
1-Jun	149	608	663	614	604	335	284	1-Jun	103	671	388	213	478	178	144
3-Jun	145	612	712	520	607	364	223	3-Jun	103	605	357	236	416	215	170

Figure 5-71: Statistical Analysis of Whole data date wise

							Sheet 9 Statistics analysis								
	r	f	pu	pd	h	v	p		r	f	pu	pd	h	v	p
Features1								Features2							
13-May	312	743	914	1558	940	600	500	13-May	510	847	1003	885	734	700	558
14-May	281	828	797	710	1050	468	350	14-May	575	1313	1027	971	1220	787	683
15-May	306	840	902	826	844	497	434	15-May	574	986	929	791	888	727	644
28-May	340	1069	1090	990	1388	624	522	28-May	321	1082	832	857	1050	522	545
31-May	250	1080	912	903	704	408	393	31-May	215	953	688	582	574	312	276
1-Jun	257	756	839	906	783	481	409	1-Jun	214	812	537	523	709	345	277
3-Jun	264	804	921	784	861	504	345	3-Jun	220	821	551	491	673	358	292
	r	f	pu	pd	h	v	p		r	f	pu	pd	h	v	p
Features3								Features4							
13-May	139	589	563	1232	598	364	320	13-May	102	413	445	183	327	171	131
14-May	151	629	366	893	747	273	326	14-May	101	766	306	222	594	131	132
15-May	141	718	487	760	622	317	324	15-May	100	644	309	206	479	174	135
28-May	146	765	469	1035	872	351	439	28-May	102	923	401	233	735	216	166
31-May	139	854	671	606	511	279	270	31-May	105	705	433	258	408	183	146
1-Jun	143	603	689	598	580	332	271	1-Jun	10	644	399	211	475	179	135
3-Jun	145	612	712	520	607	364	223	3-Jun	103	605	357	236	416	215	170

Figure 5-72: Statistical Analysis of first 9 sheet

From this analysis we can observe that all some features depict a sense of repetitiveness and some don't. Hence by keenly analyzing the excel sheets, it was concluded that Feature3 and Feature4 show a repetitive nature and hence these features were finalized to train the machine learning model to have a better accuracy.

5.17 Machine Learning Modeling

5.17.1 Support Vector Machines[24]

SVM or Support Vector Machine is a linear model for classification and regression problems. It can solve linear and non-linear problems and work well for many practical problems. The idea of SVM is simple-The algorithm creates a line or a hyper plane which separates the data into classes.

Thus SVM tries to make a decision boundary in such a way that the separation between the two classes is as wide as possible. A hyper plane in an n-dimensional Euclidean space is a flat, n-1 dimensional subset of that space that divides the space into two disconnected parts**.**

Parameters are arguments that you pass when you create your classifier. Following are the important parameters for SVM.

1]C-

It controls the tradeoff between smooth decision boundary and classifying training points correctly. A large value of c means you will get more training points correctly.

2]Gamma-

It defines how far the influence of a single training example reaches. If it has a low value it means that every point has a far reach and conversely high value of gamma means that every point has close reach.

Thus by changing the value of gamma, the accuracy was checked.

Table 5-4: C=10. Gamma=0.1

	r	f	pu	pd	h	v	P
R	76	22	0	1	10	0	4
f	9	70	1	2	9	0	0
pu	0	0	94	0	0	8	12
pd	0	2	0	96	1	0	0
h	0	6	1	0	82	0	4
v	0	0	1	0	0	102	1
p	0	7	25	0	8	0	74

Accuracy=0.815934065934065

Table 5-5: C=30. Gamma=0.4

	r	f		pu	pd	h	v	P
R	84	18	1	1	6	0	3	84
f	9	70	1	1	10	0	0	9
pu	1	0	96	0	0	6	11	1
pd	1	3	0	94	0	0	1	1
h	1	5	0	1	78	0	8	1
v	0	0	2	0	0	101	1	0
p	0	6	19	0	8	0	81	0

Accuracy=0.8296703296703297

Table 5-6: C=60 Gamma=0.6

	r	f	pu	pd	h	v	P
R	85	16	3	1	5	0	3
f	12	64	0	2	13	0	0
pu	0	0	98	0	0	6	10
pd	1	4	0	94	0	0	0
h	1	6	0	1	80	0	5
v	0	0	2	0	0	101	1
p	1	2	16	0	8	0	87

Accuracy=0.8365384615384616

Table 5-7: C=100. Gamma=1

	r	f	pu	pd	h	v	P
R	93	10	1	0	6	0	3
f	4	78	0	1	6	0	2
pu	0	0	99	0	0	5	10
pd	0	5	0	94	0	0	0
h	3	3	0	1	82	0	4
v	0	0	3	0	0	101	0
p	0	0	18	0	6	1	89

Accuracy=0.8736263736263736

As result, it was concluded that at gamma=1 and C=100, maximum accuracy was obtained.

5.17.2 Random Forest[25]

Random Forest is a flexible, easy to use machine learning algorithm that produces, even without hyper-parameter tuning, a great result most of the time. It is also one of the most used algorithms, because its simplicity and the fact that it can be used for both classification and regression tasks.

One big advantage of random forest is, that it can be used for both classification and regression problems, which form the majority of current machine learning systems.

The Hyper parameters in random forest are either used to increase the predictive power of the model or to make the model faster.

1. Increasing the Predictive Power

Firstly, there is the n_estimatorshyperparameter, which is just the number of trees the algorithm builds before taking the maximum voting or taking averages of predictions. In general, a higher number of trees increases the performance and makes the predictions more stable, but it also slows down the computation.

Another important hyper parameter is max_features, which is the maximum number of features Random Forest considers to split a node. Sklearn provides several options, described in their documentation.

The last important hyper-parameter we will talk about in terms of speed, is min_sample_leaf. This determines, like its name already says, the minimum number of leafs that are required to split an internal node.

2. Increasing the Models Speed

The n_jobshyper parameter tells the engine how many processors it is allowed to use. If it has a value of 1, it can only use one processor. A value of "-1" means that there is no limit. random_statemakes the model's output replicable. The model will always produce the same results when it has a definite value of random state and if it has been given the same hyper parameters and the same training data.

Lastly, there is the oob_score(also called oob sampling), which is a random forest cross validation method. In this sampling, about one-third of the data is not used to train the model and can be used to evaluate its performance. These samples are called the out of bag samples. It is very similar to the leave-one-out cross-validation method, but almost no additional computational burden goes along with it.

Table 5-8: lda components=2. Max depth =4

	r	f	pu	pd	h	v	P
R	30	55	0	1	24	0	3
f	15	60	1	0	15	0	0
pu	0	1	92	0	0	7	14
pd	0	4	3	92	0	0	0
h	5	23	3	0	48	0	14
v	0	0	1	0	0	99	4
p	0	9	35	0	1	0	69

Accuracy=0.6730769230769231

Table 5-9: lda components=3. Max depth =6

	r	f	pu	pd	h	v	P
R	73	28	1	1	7	0	3
f	12	58	3	1	16	0	1
pu	0	3	98	0	0	3	10
pd	0	4	3	91	1	0	0
h	5	8	3	0	70	0	7
v	0	0	2	0	0	100	2
p	0	7	27	0	8	0	72

Accuracy=0.771978021978022

Table 5-10: lda components=4. Max depth =8

	r	f	pu	pd	h	v	P
R	72	30	2	1	3	0	5
f	5	77	1	0	8	0	0
pu	0	0	100	0	0	3	11
pd	0	5	1	93	0	0	0
h	0	8	1	0	79	0	5
v	0	0	3	0	0	100	1
p	0	6	18	0	8	1	81

Accuracy=0.8269230769230769

Table 5-11: lda components=8. Max depth =9

	r	f	pu	pd	h	v	P
R	87	13	1	2	3	0	7
f	6	78	1	1	5	0	0
pu	0	0	101	0	2	5	6
pd	1	3	4	91	0	0	0
h	0	5	1	0	81	0	6
v	0	0	1	0	0	102	1
p	0	0	9	0	6	0	99

Accuracy=0.8777472527472527

It was observed that SVM gave a better accuracy than the random forest mechanism.

5.18 Machine Learning Modelling for 7 Gestures

5.18.1 Model 1-SVM Model trained on database of 12th May to 15th May

Table 5-12: Database details of SVM Model trained on database of 12th May to 15th May

Sr.No.	Date	Number of sets	Number of data points
1	12th May 2019	5	140
2	13th May 2019	45	1260
3	14th May 2019	25	700
4	15th May 2019	12	336
Total	4 days	87	2436

Training data set-1948 data points

Testing data set-488 data points

Table 5-13: Confusion matrix for SVM training on database of 12th May to 15th May

\	r	f	pu	pd	h	v	P
r	93	10	1	0	6	0	3
f	4	78	0	1	6	0	2
pu	0	0	99	0	0	5	10
pd	0	5	0	94	0	0	0
h	3	3	0	1	82	0	4
v	0	0	3	0	0	101	0
p	0	0	18	0	6	1	89

Accuracy= 0.8736

5.18.1.1 SVM Model 1 tested on database of 28th May 2019.

Testing data set-252 data points

Table 5-14: Confusion Matrix SVM Model tested on database of 28th May 2019

\	r	f	pu	pd	h	v	P
r	23	4	0	0	9	0	0
f	2	26	0	0	8	0	0
pu	3	4	5	4	17	0	3
pd	3	2	0	26	5	0	0
h	7	13	0	0	14	0	2
v	3	0	0	0	24	9	0
p	0	11	7	0	12	0	6

Accuracy= 0.4325

5.18.1.2 SVM Model 1 tested on database of 31st May 2019.

Testing data set-700 data points

Table 5-15: Confusion Matrix SVM Model tested on database of 31st May 2019.

\	r	f	pu	pd	H	v	P
r	60	28	0	0	12	0	0
f	34	60	0	0	6	0	0
pu	0	0	0	0	100	0	0
pd	0	61	0	0	39	0	0
h	4	46	0	0	50	0	0
v	0	0	0	0	100	0	0
p	0	0	0	0	100	0	0

Accuracy= 0.2428

5.18.1.3 SVM Model1 tested on database of 1st June 2019

Testing data set-700 data points

Table 5-16: Confusion Matrix SVM Model tested on database of 1st June 2019

\	r	F	pu	Pd	H	v	P
r	77	4	0	0	19	0	0
f	36	63	0	0	1	0	0
pu	3	0	2	0	95	0	0
pd	0	67	0	5	28	0	0
h	4	39	0	17	40	0	0
v	0	0	0	0	100	0	0
p	0	8	0	0	92	0	0

Accuracy= 0.2671

5.18.2 Model 2-RF Model trained on database of 12th May to 15th May

Table 5-17: Database details of RF Model trained on database of 12th May to 15th May

Sr.No.	Date	Number of sets	Number of data points
1	12th May 2019	5	140
2	13th May 2019	45	1260
3	14th May 2019	25	700
4	15th May 2019	12	336
Total	4 days	87	2436

Training data set-1948 data points

Testing data set-488 data points

Table 5-18: Confusion matrix of RF Model trained on database of 12th May to 15th May

\	r	f	pu	pd	h	v	P
r	87	13	1	2	3	0	7
f	6	78	1	1	5	0	0
pu	0	0	101	0	2	5	6
pd	1	3	4	91	0	0	0
h	0	5	1	0	81	0	6
v	0	0	1	0	0	102	1
p	0	0	9	0	6	0	99

Accuracy= 0.8777

5.18.2.1 RF Model 2 tested on database of 28th May 2019.

Testing data set-252 data points

Table 5-19: Confusion Matrix RF Model tested on database of 28th May 2019

\	r	f	pu	pd	h	v	P
r	28	4	0	0	4	0	0
f	5	28	0	0	3	0	0
pu	5	1	10	1	3	10	6
pd	3	2	0	28	3	0	0
h	0	5	3	0	28	0	0
v	0	0	0	1	0	35	0
p	0	2	19	0	8	1	6

Accuracy= 0.6468

5.18.2.2 RF Model 2 tested on database of 31st May 2019.

Testing data set-700 data points

Table 5-20: Confusion Matrix RF Model tested on database of 31st May 2019

\	r	f	pu	pd	h	v	P
r	59	38	0	0	0	0	3
f	4	45	34	1	0	8	8
pu	0	0	23	0	0	77	0
pd	0	50	50	0	0	0	0
h	1	34	53	2	0	8	2
v	0	0	1	1	0	98	0
p	0	0	51	0	0	49	0

Accuracy= 0.3214

5.18.2.3 RF Model 2 tested on database of 1st June 2019.

Testing data set-700 data points

Table 5-21: Confusion Matrix RF Model tested on database of 1st June 2019

\	r	F	pu	pd	h	v	P
r	90	10	0	0	0	0	0
f	20	61	10	2	0	7	0
pu	2	1	34	0	0	63	0
pd	0	40	38	19	0	3	0
h	0	45	27	23	0	2	3
v	0	0	0	2	0	98	0
p	0	0	64	0	0	35	1

Accuracy= 0.4828

5.19 MACHINE LEARNING MODELLING FOR 3 GESTURES

As seen before the accuracy of the machine learning models to classify all the 7 gestures accurately was very less. Also in the statistics section it was seen that the values of gestures like palm-up, palm-down, fist and hold overlapped with each other. This further decreased the accuracy of the machine learning model.

As a solution to this the number of gestures was narrowed down to 3. These gestures are-

- Rest
- Fist
- Pinch

5.19.1 Model 3-SVM Model trained on database of 12th May to 15th May and 31st May 2019 using all four features

Table 5-22: Database Details SVM Model trained on 12th May to 15th May and 31st May 2019 using all four features

Sr.No.	Date	Number of sets	Number of data points
1	12th May 2019	5	60
2	13th May 2019	45	540
3	14th May 2019	25	300
4	15th May 2019	12	144
5	31st May 2019	25	300
Total	5 days	112	1344

Training data set-1075 data points

Testing data set-271 data points

Table 5-23: Confusion Matrix SVM Model trained on database of 12th May to 15th May and 31st May 2019 using all four features

/	r	f	p
r	72	2	0
f	10	73	2
p	1	6	103

Accuracy= 0.9219

5.19.1.1 SVM Model 3 tested on database of 28th May, 1st June and 3rd June 2019

Testing data set-271 data points

Table 5-24: Confusion Matrix tested on database of 28th May, 1st June and 3rd June 2019

/	r	f	p
r	172	0	0
f	17	151	4
p	11	38	123

Accuracy= 0.9418

5.19.2 Model 4-SVM Model trained on database of 12th May to 15th May and 31st May 2019 using Feature3 and Feature4

Table 5-25: Database details SVM Model trained on database of 12th May to 15th May and 31st May 2019 using Feature3 and Feature4

Sr.No.	Date	Number of sets	Number of data points
1	12th May 2019	5	60
2	13th May 2019	45	540
3	14th May 2019	25	300
4	15th May 2019	12	144
5	31st May 2019	25	300
Total	5 days	112	1344

Training data set-1075 data points

Testing data set-271 data points

Table 5-26: Confusion Matrix SVM Model trained on database of 12th May to 15th May and 31st May 2019 using Feature3 and Feature4

/	r	f	p
r	71	1	2
f	3	80	2
p	1	9	100

Accuracy= 0.9330

5.19.2.1 SVM Model 4 tested on database of 28th May, 1st June and 3rd June 2019

Testing data set-271 data points

Table 5-27: Confusion Matrix tested on database of 28th May, 1st June and 3rd June 2019

/	r	f	p
r	172	0	0
f	14	153	5
p	0	11	161

Accuracy= 0.9418

5.19.3 Model 5-RF Model trained on database of 12th May to 15th May and 31st May 2019 using all four features

Table 5-28: Database details of RF Model 5 trained on database of 12th May to 15th May and 31st May 2019 using all four features

Sr.No.	Date	Number of sets	Number of data points
1	12th May 2019	5	60
2	13th May 2019	45	540
3	14th May 2019	25	300
4	15th May 2019	12	144
5	31st May 2019	25	300
Total	5 days	112	1344

Training data set-1075 data points

Testing data set-271 data points

Table 5-29: Confusion Matrix of RF Model 5 trained on database of 12th May to 15th May and 31st May 2019 using all four features

/	r	f	p
r	72	2	0
f	5	79	1
p	0	10	100

Accuracy= 0.9330

5.19.3.1 RF Model 5 tested on database of 28th May, 1st June and 3rd June 2019

Testing data set-271 data points

Table 5-30: Confusion matrix of RF Model 5 tested on database of 28th May, 1st June and 3rd June 2019

/	r	f	p
r	172	0	0
f	37	76	59
p	2	7	163

Accuracy= 0.7965

5.19.4 Model 6-RF Model trained on database of 12th May to 15th May and 31st May 2019 using Feature3 and Feature4

Table 5-31: Database details of RF Model 6 trained on database of 12th May to 15th May and 31st May 2019 using Feature3 and Feature4

Sr.No.	Date	Number of sets	Number of data points
1	12th May 2019	5	60
2	13th May 2019	45	540
3	14th May 2019	25	300
4	15th May 2019	12	144
5	31st May 2019	25	300
Total	5 days	112	1344

Training data set-1075 data points

Testing data set-271 data points

Table 5-32: Confusion Matrix of RF Model 6 trained on database of 12th May to 15th May and 31st May 2019 using Feature3 and Feature4

/	r	f	p
r	71	1	2
f	3	80	2
p	1	9	100

Accuracy= 0.9330

5.19.4.1 RF Model tested on database of 28th May, 1st June and 3rd June 2019

Testing data set-271 data points

Table 5-33: Confusion Matrix of RF Model 6 tested on database of 28th May, 1st June and 3rd June 2019

/	r	f	p
r	74	0	0
f	4	79	2
p	0	12	98

Accuracy= 0.9011

Table 5-34 shows the comparison of two different machine learning models, i.e., SVM and RF. The models have been trained on the combined data of 12th May, 13th May, 14thMay, 15th May, 31st May. The training accuracies of the model are mentioned under the column train. The model has been trained on the combined data of 28th May, 1st June and 3rd June. The testing accuracies have been mentioned under the test column.

Accuracies using different features was also calculated and is mentioned as different rows of Table 5-34.

Table 5-34: Comparison of accuracy for SVM and RF model

3 gestures	SVM	SVM	RF	RF
Features	Train	Test	Train	Test
F1,F2,F3,F4	92.19	86.43	93.3	79.65
F1	81.41	85.46	76.95	81.97
F3	91.07	88.17	89.21	87.98
F4	83.64	87.2	81.41	84.88
F3,F4	93.3	94.18	93.3	90.11

It is seen that the accuracy for SVM model using a combination of Feature3 and Feature4 is highest.

CHAPTER 6
6 BIONIC ARM LITERATURE SURVEY

6.1 Introduction

The aim of the project is to build a high DoF Bionic Arm which will be light in weight. Achieving high dexterity is a herculean task, so a step by step approach was undertaken. For incorporating dexterity in artificial robotic hand, the fingers of the hand should have more than one DoF. So initially the work initiated with designing and implementation of 1 DoF finger. The design of Bionic Arm is divided into 3 phases, following is the detail description of the phases-

6.2 Design Phase 1

The design process of Bionic Arm initiated with single DoF finger actuated by string mechanism. The string was actuated by high torque servo motors. The string mechanism consisted of a nylon string which was passed through the finger in such a way that when the string is pulled by adequate force, the finger flexes. Thus, providing a flexion and extension motion of finger.

Figure 6-1: Single DoF finger actuated by servo motor.

Figure 6-2: NRS 995 servo motor used for experimenting[26]

Specifications of servomotor [26]-

- Dimension-40.7mm x 20.5mm x39.5mm
- Torque-15.5kg/cm at 4.8V, 17kg/cm at 6V
- Dual bearing with metal gear
- Motor weight-60gms
- Operating speed-0.15sec/60 degree
- Operating voltage-4.8V to 6V
- Temperature range-0-55C
- 0.6 ms for 0-degree Rotation
- 2.2 ms for 180-degree Rotation

After pulling the strings, actuation is observed at PIP, DIP and MCP joints. Though the actuation is not an independent one, the movement at DIP and PIP are passive DoF.

6.2.1 Advantages

- Simple Mechanism due to use of servo motor and strings,
- Servo motor is easy to control.
- The total weight of the hand can be close to 500 grams.
- Simple Kinematics of the finger.

6.2.2 Disadvantages

- The mechanism is mainly based on the quality of strings; highly tensile strings are required which can endure millions of cycles of pulling forces. So, a high tensile string is required. But as amputees heavily use the artificial hand, the servo string mechanism will fail in long terms as string will fail to provide that tensile strength due to wear and tear.
- As it is only 1 DoF per finger, it has less dexterity.
- String-servo motor mechanism can only give flexion and extension motion and lack of feedback in servo motors leads to inefficient actuation.

Thus, it was concluded that servo string mechanism cannot be used to design fingers with more than one active DoF.

6.3 Design Phase 2

After experimenting with servo string mechanism, design phase 2 was initiated. In phase 2 of design, after considering the advantages and disadvantages of previous mechanism it was decided to continue with the same finger model. This time rather than using a servo motor, Johnson DC motor was used. The purpose of using a DC motor was to incorporate precise control over flexion and extension motion of the finger. Here for actuation of finger, rather than using single string, a twisted string was used. The DC motor was coupled to two strings and the rotatory motion of DC motor twisted the strings leading it to linear actuation which flexed the finger.Twisted string actuation method was referred from [27].

Specifications of Johnson DC Motor-

- Base Motor RPM-18000
- Operating Voltage-6-18 V
- Rated Voltage-12 V
- Rated Torque-7.5 kg-cm
- Stall Torque-30 kg-cm
- Gearbox Dimensions-25×37 (LxW) mm

Figure 6-3: Twisted String Actuation using DC motor

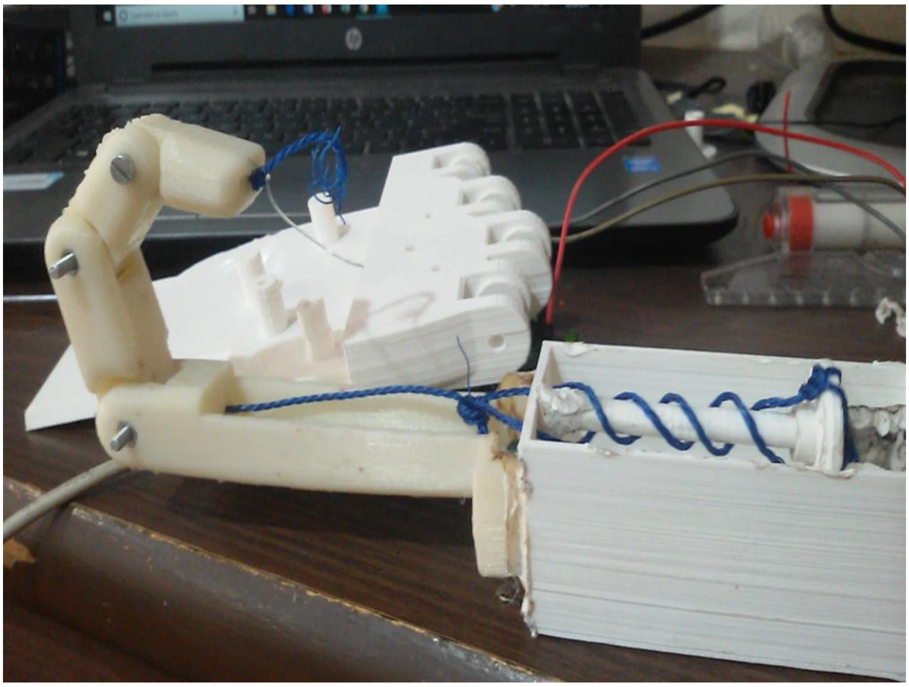


Figure 6-4: Finger mounted on holder, holding Johnson DC motor

6.3.1 Advantages

- Johnson DC motor provided enough torque which was converted to force imparted on the tip of the finger.
- Precise angular control of the finger.
- Adequate grasping was achieved.

6.3.2 Disadvantages

- Johnson DC motor provided enough torque but at the cost of its high weight due to heavy metal gears. 60 RPM motor weighted 164 grams. So, weight of single finger mechanism was about 180 grams. This will lead to overall weight of arm up to 1kg.
- High weight was not acceptable as it is not suitable for amputee to use such a heavy artificial arm.
- The author in [27] has used Maxon motors with planetary gears. Maxon motor are costly and are not feasible for low cost Bionic Arm design.
- Less dexterous.

Thus, this mechanism was not feasible solution for the problem statement.

6.4 Design Phase 3

6.4.1 Need for Design Phase 3

- After experimenting on two mechanisms, a better mechanism for fingers was required which will provide more DoF and dexterity.
- While maintaining the dexterity, goal of light weight prosthetic was also to be achieved.
- Though DC motor and Servo motors are famously used for actuation in robotic arms and prosthetic arms, a different type of light weight and high force imparting actuator was needed to address the problem statement.
- Thus, it paved the roads for the design phase 3.

6.4.2 Introduction

- After thorough research, an idea for different type of mechanism, actuated by light weight and high force imparting actuator was initiated.
- After deep research about electric motors and actuators, linear actuators from Actuonix Motion Devices Inc. [28] were found.The company provided variety of linear actuators varying from different size and weights.
- Amongst many actuators, the PQ12 linear actuators were noteworthy, thanks to their small form factor and light weight.
- The idea was to convert linear motion of actuator to the angular motion at the joints of the fingers so as to provide flexion and extension motion.
- As the actuator had small size it could be fitted inside proximal phalange of finger and in the palm, which could make a 2 DoF finger.
- Thus, this mechanism has potential to improve dexterity of the Bionic Arm and also to keep the weight of the Bionic Arm close to 500 grams.

6.4.3 Block Diagram of Proposed System

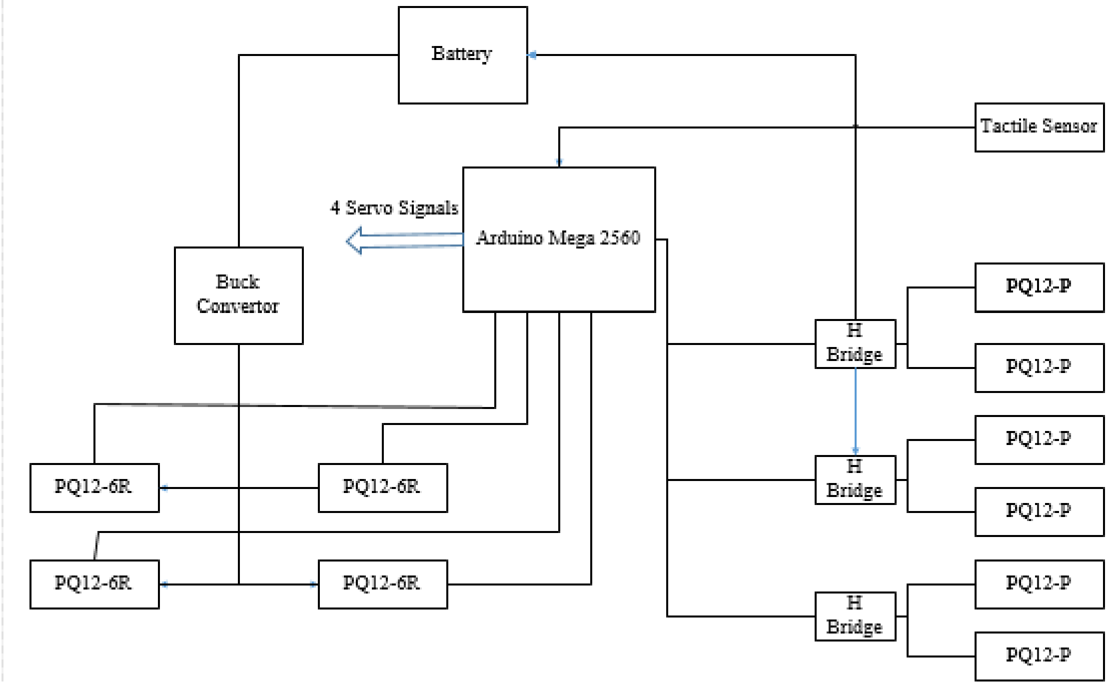


Figure 6-5: Block Diagram of Proposed System

6.4.4 Working of the Bionic Arm-

As finalization of incorporating of linear actuator in the Bionic Arm was done, detail working of Bionic Arm is as follows-

6.4.4.1 Working of PQ12 Linear Actuator

Linear Actuator consist of following parts-

- DC Motor
- Gears
- Lead Screw

Figure 6-6: PQ12 Linear actuator[28]

In linear actuator linear motion is obtained from conversion of rotational motion of DC motor. The DC motor is connected to set of gears which improves the torque, while the set of gears are also connected to lead screw. The lead screw moves in linear direction. So as the motor rotates, lead screw moves in linear direction.

6.4.5 Mechanism Design and incorporation of Linear Actuators in the mechanism-

Linear Actuator works on the principle of slider crank mechanism. These slider crank mechanisms provide linear movement. This linear movement has to be converted into rotatory motion. So, to have angular motion at joints of finger, a revolute joint is introduced by a small link at the MCP and PIP joints of the finger. The finger mechanism was designed in 3DExpereince platform, which provided many tools like Part Design, Assembly Design, Mechanical System Design.

Thus, using 3DExperience entire Bionic Arm was designed.

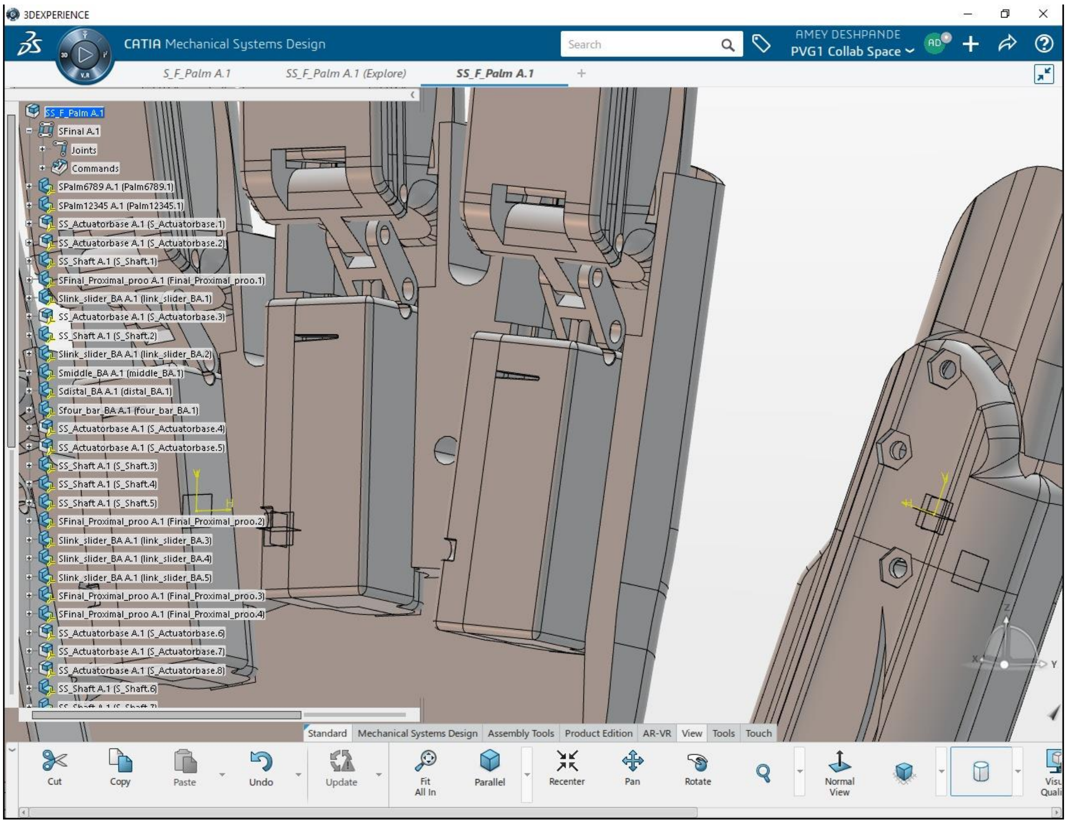


Figure 6-7: Linear actuator connected to a revolute joint link for actuation at MCP joint.

Here to improve the DoF, PQ12 actuator is placed in proximal phalange of a finger to actuate PIP joint and another PQ12 actuator is placed in the palm to actuate MCP joint. Thus, each finger is actuated by two Linear actuators and each finger thus has two active DoFs.

The Figure 6-7describes the mechanism of MCP revolute joint. A small link was designed which converted linear actuation into rotatory actuation. The link was connected to the shaft of the linear actuator by a screw. When linear actuator extends up to 16 mm, the finger was rotated about that link for 90 degrees. Thus there was rotation for 0-90 degrees at MCP joint, which also mimicked the human finger rotation at MCP joint.

Figure 6-8: Actuator in Proximal Phalange for actuation at PIP joint

The above Figure 6-8describes actuation at proximal joint. Here a separate DoF is introduced at PIP joint. An independent DoF at proximal joint helps for stable pinch and lateral grasp. This also improves the dexterity of the Bionic Arm. A linear actuator is placed in proximal phalange of the finger. The design was such that when the actuator extends, the upper part of the proximal joint was supposed to rotate for 90 degrees.

One more feature added to this joint was that it was connected to the DIP joint of the finger by a link. The famous four bar mechanism was implemented between PIP and DIP joint. The implementation of four bar mechanism lead to the relative movement of DIP joint with respect to PIP joint Due to this motion, an intuitive finger motion was implemented which had an anthropomorphic design.

Figure 6-9: Thumb assembly and actuation on servo motor

The thumb is an important part of human hand. Without thumb, it would be impossible to achieve any kind of grasp. So, the goal was to improve the dexterity of the thumb. In human hand thumb has 5 DoFs but implementing 5 DoFs in thumb was not an easy task. So only main and important DoF/movement of thumb had to be selected. After studying the role of thumb in object grasping ,3 DoFs were selected. Following were the 3 DoF selected-

- Flexion extension motion(1-DoF) of thumb was implemented by mounting thumb on a servo motor which rotated from 0 to 90 degrees.
- One linear actuator was placed in thumb phalange to actuate DIP joint of thumb (1 DoF). The actuation at this joint was important for pinch grasp
- Another linear actuator was placed in another thumb phalange for actuation at MCP joint (1 DoF). The actuation at this joint was important for lateral grasp

Thus, 3 DoF for thumb was implemented.

Figure 6-10: Bionic Arm assembly (11 DoF.)

Total DoFs in the Bionic Arm-

- Each finger has two DoFs, so total DoF including all fingers is 8
- Thumb takes an important part of our hand and all the stable grasps are achieved due to thumb. A decision was taken to increase the DoF of thumb. So, thumb had 3 DoF.
- The thumb of Bionic Arm has actuation at IP joint and MP joint as well as flexion and extension movement of finger was implemented using servo motor fixed in palm.
- Thus, total DoFs in the Bionic Arm is 11.

6.4.5.1 Bionic Arm Electrical Specification

6.4.5.1.1 Power Supply

For prototyping of the Bionic Arm we used Orange 5200mAh 3S 40C LiPo Battery of 11.1V.

Specifications-

- Weight -360.0g
- Voltage -11.1V
- Dimensions -28x44x137(mm)

It can provide 5.2 A current continuously for 1 hour.

Battery Calculation-

Though, 5200mAh of battery is used following calculations are for 2200 mAh LiPo battery.

Following assumptions have been done while calculating the battery calculations of Bionic Arm-

- Bionic Arm can be used by people of different profession. An amputee can be a carpenter who will extensively use the bionic arm which will lead to imparting of lot of force on the object and can cause fast battery discharge. While an amputee can be IT engineer who hardly applies a large amount of force.
- So, for battery calculation it is assumed that average amount of force will be imparted on every joint.

Power Calculations-

- Calculations for average force imparted by MCP joints and PIP joints of all fingers are 20 N and 10N respectively-
- Current Consumption of PQ12P (63-1) at 20N=65mA
- Current Consumption of PQ12P (30-1) at 10N=100mA
- Current Consumptions of PQ12-6R Servo at 10 N=100mA
- Total Power dissipated by 5 PQ12P (63-1) actuators =3.9 W
- Total Power dissipated by PQ12P (30-1) actuators =1.2 W
- Total Power dissipated by 4 PQ12R -Servo actuator=2.4 W
- Power dissipated by MG90 Servo motor= 0.5 W
- Total Power dissipated-8W
- No of Hours the 2200mAh battery will last=(12*2200mAh)/8 W=3.3 hours.

A 5 V, 5A buck converter was used to power the linear actuator servos and to supply power to feedback potentiometers of 6 feedback actuators.

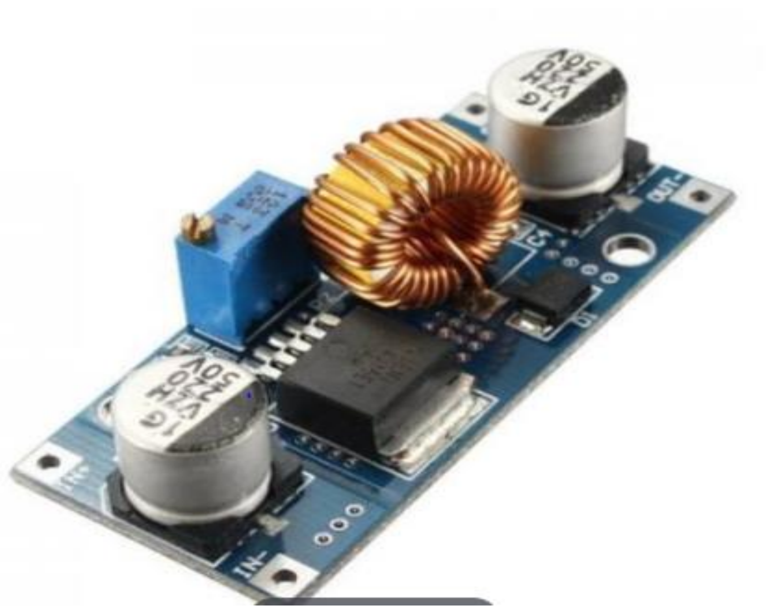


Figure 6-11: Buck Converter[29]

6.4.5.1.2 Linear Actuator Specifications

In the Bionic Arm 11 Linear Actuator are used. For MCP joint of finger lots of force is required as entire finger is actuated on MCP joint actuator. So, for MCP joint 63-1 Gear ratio is selected. Higher gear ratios impart forces up to 45 N on the joint. For PIP joint lower Gear Ratio is used that is 30-1 that can impart forces up to 20 N.

MCP joints of all fingers are actuated by 63-1 feedback linear actuator. Potentiometer feedback is used to detect the position of actuator. Feedback helps to have precise control.

To incorporate pinch grasp 30-1 feedback PQ12P actuator is used at PIP joint of index finger while for all PIP joints of other fingers are actuated by linear Servos for easy controlling.

PQ12 Specifications			
Gearing Option	30:1	63:1	100:1
Peak Power Point	15N@15mm/s	30N @ 8mm/s	40N @ 6mm/s
Peak Efficiency Point	8N @ 20mm/s	12N@12mm/s	20N @ 8mm/s
Max Speed (no load)	28mm/s	15mm/s	10mm/s
Max Force (lifted)	18N	45N	50N
Max Side Load	5N	10N	10N
Back Drive Force	9N	25N	35N
Stroke	20 mm		
Input Voltage	6 or 12 VDC		
Stall Current	550mA @ 6V, 210mA @ 12V		
Mass	15g		
Operating Temperature	-10°C to +50°C		
Positional Repeatability	±0.1mm		
Mechanical Backlash	0.25 mm		
Audible Noise	55dB @ 45cm		
Ingress Protection	IP-54		
Feedback Potentiometer	5kΩ±50%		
Limit Switches	Max. Current Leakage: 8uA		
Maximum Duty Cycle	20%		

Figure 6-12: PQ12 Specifications[28]

Figure 6-13: Actuonix PQ12P Linear Actuator

6.4.5.1.3 Microcontroller

The main controller used for controlling of Bionic Arm is Arduino Mega 2560, The reason for using Arduino Mega 2560 is due to because it has 13 PWM pins and 15 analog pins. These number of pins were required by the Bionic Arm, as it has to control many actuators simultaneously. So, Arduino Mega 2560 is a perfect controller for this application.

Specifications of Arduino Mega 2560[30]-

- 8-bit Microcontroller
- 15 analog pins
- 10-bit ADC
- 16 MHz clock
- Baud Rate up to 115400 SPS
- 54 digital pins
- 4 UART

6.4.5.2 Tactile Sensors

Tactile or Force sensor are to be used to detect slight pressure or contact at the tips of the finger. Different types of tactile sensors are available in market, testing of two types of tactile sensors are done-

- Resistive based force sensor
- Capacitive Based force sensor.

Figure 6-14: Force Sensitive Resistor (FSR)[31]

Figure 6-15: Capacitive Force Sensor [32]

6.4.5.2.1 Specification of Force Sensitive Resistor

Force Sensitivity Range	~0.2 to 20N	Dependent on mechanics
Break Force (Activation Force)	~0.2N min	Dependent on mechanics and FSR build
Part-to-Part Force Repeatability	± 6% of established nominal	With a repeatable actuation system, single lot.
Single Part Force Repeatability	± 2% of initial reading	With a repeatable actuation system
Hysteresis	+ 10% Average	$(R_{F+} - R_{F-})/R_{F+}$
Long Term Drift	< 5% per $\log_{10}$(time)	Tested to 35 days, 1kg load
Force Resolution	Continuous	Depends on measurement electronics
Stand-Off Resistance	> 10MΩ	Unloaded, unbent
Switch Travel	0.05mm	Typical; depends on design
Device Rise Time	<3 microseconds	Measured with drop of steel ball
Maximum Current	1 mA/cm^2 of applied force	
EMI / ESD	Generates no EMI; not ESD sensitive	

Figure 6-16: Specifications of FSR [31]

6.4.5.2.2 Specification of Capacitive Force Sensor

Typical Signal to Noise Ratio (SNR)	500:1
Force Resolution	< 0.2% of Full Scale (FS)
Maximum Force	300% of FS
Typical Repeatability Error	< 1.0% (1 sigma of FS)
Operating Temperature	-40°C – 200°C
Temperature Sensitivity	Up to 0.2%/°C
Linearity Error	< 2.0%
Drift	< 2% per logarithmic time scale
Hysteresis	< 4.0%
Response Time	< 1ms(Measured using Oscilloscope)
Contact Surface Material	Polyimide
Sensor Thickness	0.35mm
Tail Length	50mm
Typical Baseline Capacitance	8mm: 75 pF; 15mm : 230 pF @ 100kHz
Typical Capacitance Change	8mm: 2.2 pF; 15mm : 5.5 pF @ 100kHz
ESD Sensitivity	Not sensitive to ESD
Material Grade	UL grade 94 V-1 or better

Figure 6-17: Capacitive Sensor Performance [32]

- Update Rale->300Hz
- Analog Out-0.5-1,5V
- Digital Interface-I2C (100kHz)
- 10 Voltage-3.3V
- Supply Voltage-3.7-12V
- Input Current-2.5mA running at 3MHz
- Weight-Sensor 0.23g/ Electronics 1.6g
- RoHS-Compliant
- Operating Temperature--40°C-85°C

6.4.5.2.3 FSR characteristics

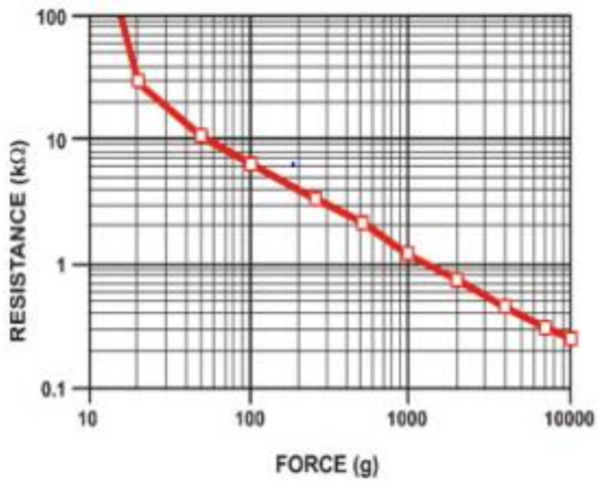


Figure 6-18: FSR Sensor Characteristics.[31]

6.4.5.2.4 Capacitive Sensor Characteristics

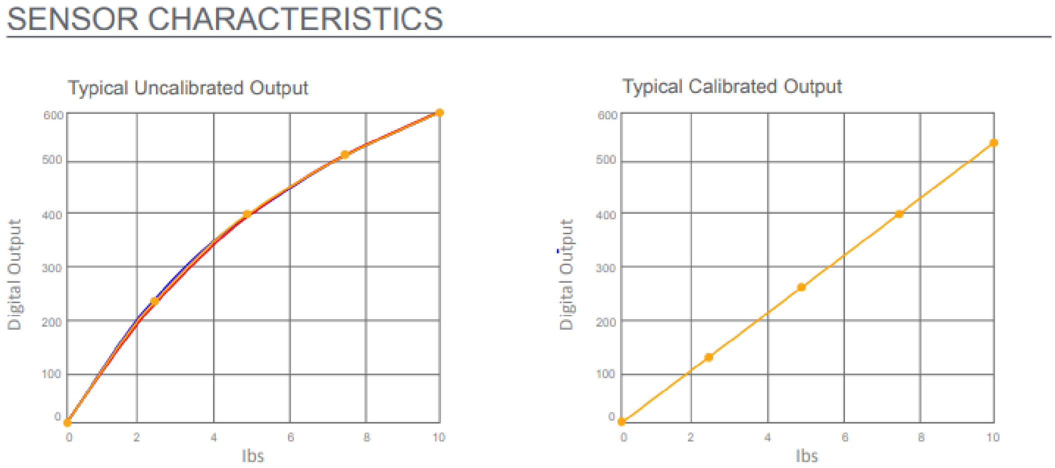


Figure 6-19: Capacitive Sensor Characteristics [32]

6.4.5.3 Mechanical Specifications-

All the 3D parts of Bionic Arm are 3D printed in Product Innovation Lab. PLA filament was used to print the parts of Bionic Arm. PLA material is used as it is light weight and it is strong enough.

6.4.5.3.1 Weight analysis

Following are the weight of each part of the Bionic Arm-

- Distal=3g
- Middle=5g
- Proximal=12g
- Link=0.5 g
- Four Bar Link=1g
- PQ12 actuator-15g
- MG90S Servo Motor=9g
- Thumb Distal=5g
- Thumb base=28g
- Thumb proximal=12g
- Palm=140g
- Weight of entire finger including actuator=38 g
- Weight of thumb including two actuators and one servo motor=84g
- Total Weight of screws and Nuts=50 g
- Weight of electronics (microcontroller, motor drivers) =20g
- Weight of Battery(2200mAh) =150 g

The total weight will be equal to sum of weight of all 3d parts of 4 fingers, thumb, palm, 11 actuators, links, screws, nuts and the total weight is-486grams

Including Battery and electronics total weight will be-656 grams

6.4.5.4 Hardware Design

All the feedback linear actuators were controlled by dual H bridge board. Following H bridge boards were used-

- L298N Board
- Cytron's MDD 10A Board.

By using H bridge circuitry polarity is changed and due to change in polarity the linear actuator extends and retracts. Thus, flexion and extension motion occur due to extension and retraction of linear actuator respectively.

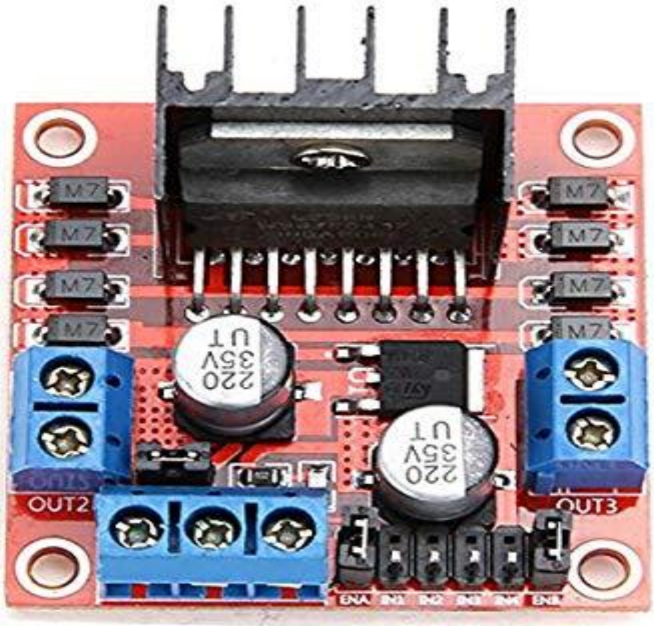


Figure 6-20: L298N Board[33]

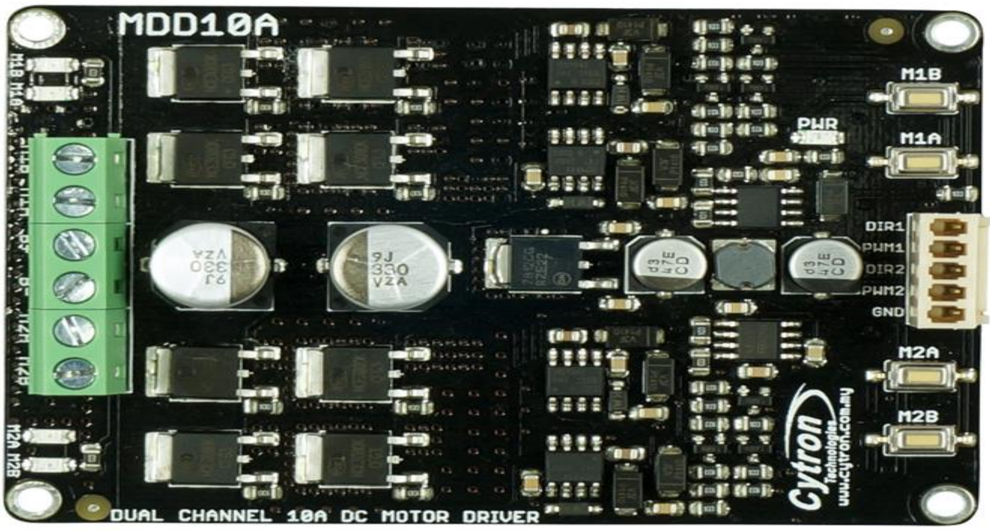


Figure 6-21: Cytron MDD 10 A[33].

For controlling 6 feedback PQ12P actuators two MDD 10 A boards were used and one L298N was used.

4 Linear Servos were directly controlled by 4 PWM signal of Arduino Mega respectively.

6.4.5.5 Software Design of the Bionic Arm

6.4.5.5.1 Introduction

Bionic Arm is controlled by Arduino Mega 2560. Arduino IDE is used to program the Arduino Mega 2560. The main thing to be controlled is to control 11 actuators simultaneously and by controlling different actuators, grasp like Power Grasp, Pinch Grasp and Lateral Grasp are implemented.

It is a herculean task to control so many actuators at a time and thus controlling the fingers of the bionic arm.

Algorithm to control linear actuator-

1. START
2. Send the appropriate PWM signal.
3. Select duty cycle to control the speed of actuation.
4. Apply digital signal to the board to control the direction of actuation of linear actuator.
5. Compile the code.
6. END.

6.4.5.5.2 Algorithm for Position Control of Linear Actuator

1. START
2. Get the current position of linear actuator's position from the analog pin of ARDUINO MEGA 2560.
3. Set the Setpoint position of linear actuator.
4. Apply the PWM signal until the actuator shaft reaches the final setpoint. Continuously check for potentiometric feedback value from analog pin
5. After reaching the setpoint stop the actuator.
6. STOP

6.4.5.5.3 Proportional Integral Control of Linear Actuator

PID control is the smart way of controlling a machine or a plant in control system terminology. PID control helps in smooth and stabilized control of the plant. In PID control the value which is taken feedback is to be controlled. In this scenario, position signal is taken as feedback value and in return position is controlled.

In PID P stands for Proportional control, I for Integral control and D for derivative control.

For some cases P controller is needed or sometimes PI controller is needed. So by entering the proper values of Kp, Ki and Kd constants system needs to be tuned.

6.4.5.5.3.1 Control Algorithm

1. START
2. Initialize Kp, Ki, Kd constants.
3. Using millis() find current time elaspsed time t.
4. For every t seconds-
    - Find error between current and final value
    - Find derivative error term

- Find integral error term
- Send control signal.
- Check error

6.4.5.5.3.2 Grasp Algorithm

For an amputee wearing bionic arm to handle and manipulate objects needs an proper algorithm when the bionic arm comes in the contact with the object. After taking inference from EMG signal the Bionic Arm should apply adequate force on the object so as to properly hold the object without crushing it.

Following is the algorithm of Grasp

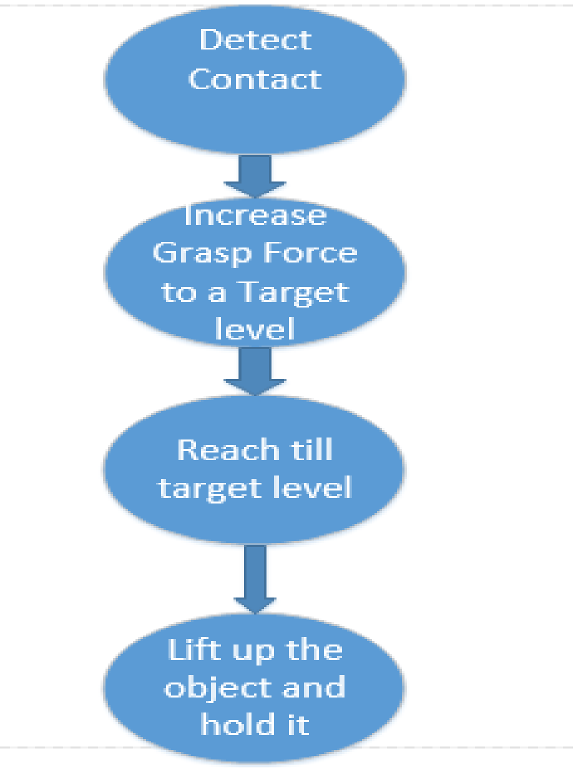


Figure 6-22: Grasp Algorithm

CHAPTER 7

7 SIMULATION AND TESTING

7.1 Introduction

While designing the Bionic Arm simulating tools like MATLAB and Dymola of 3DExperience were used. In MATLAB simulation Linear Actuator was simulated and results were found.

Following are snaps of the simulation from Simulia (MATLAB)-

- An example of linear actuator model was simulated with reference to[34]:

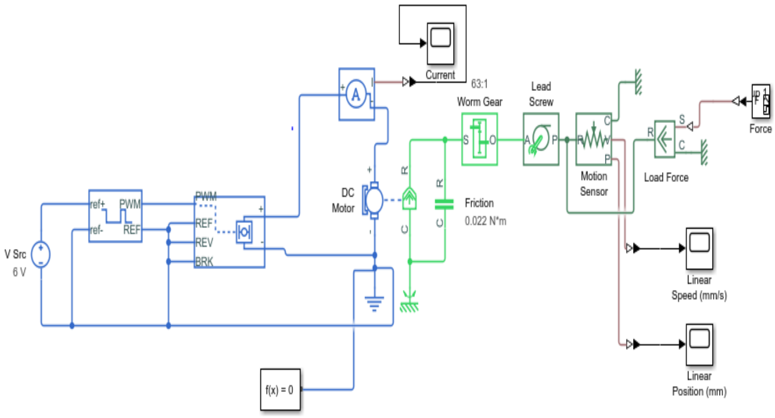


Figure 7-1: Simulation of Linear actuator in MATLAB software

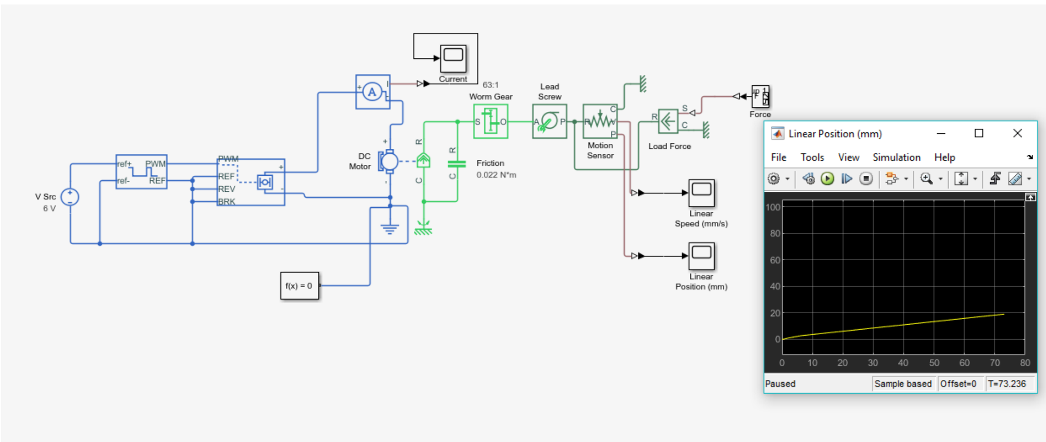


Figure 7-2: Open Loop Control

7.2 Dymola Simulations

Dymola is used for implementing behavior modelling of the plant, in this case finger of the Bionic Arm. In Dymola behavior of revolute joint is given to the PIP, DIP and MCP joint

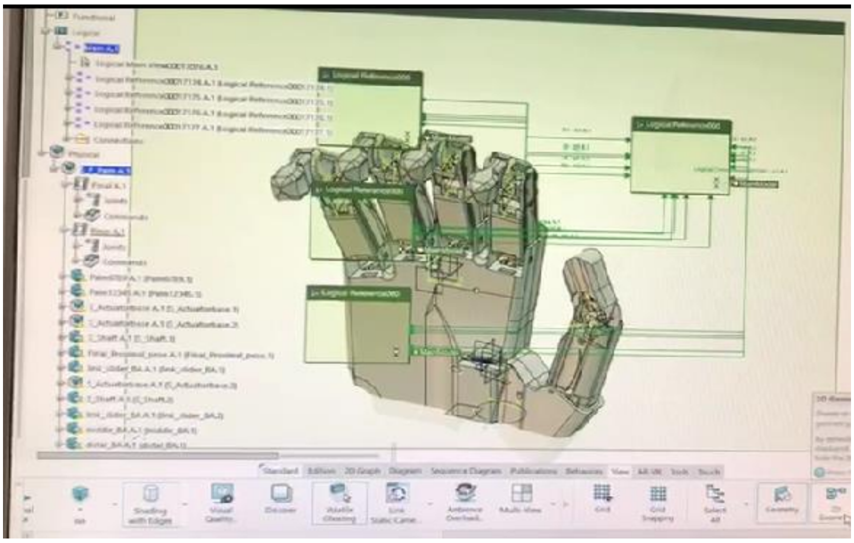


Figure 7-3: Behavior modelling in Dymola app of 3DExperience platform

7.3 Hardware Testing

7.3.1 Actuation at PIP joint

Hardware testing of the Bionic Arm is done by step by step. Following procedure was followed. First the linear actuator was tested for PIP Joint-

Simple control of linear actuator was implemented for actuating PIP Joint.

Figure 7-4: Linear Actuator actuating at PIP Joint

Here with actuation at PIP joint, using a four-bar linkage DIP joint was also actuated with reference to PIP Joint. Due to incorporation of four bar mechanism anthropomorphisms was achieved as it mimicked the real movement at PIP and DIP joints. Thus, testing of PIP joint is successfully done. Adequate force is applied by the DIP joint

7.3.2 Actuation at MCP Joint

After successfully actuation at PIP joint, actuation at MCP joint is achieved and PQ12P 63-1 is used at MCP joint.

Thus entire testing of 2 DoF finger is achieved and adequate force is applied.

Figure 7-5: MCP Actuation.

Figure 7-6: Finger grasping a tape.

7.3.3 Testing of thumb flexion extension

Thumb is mounted on servo motor and is actuated successfully. There were problems of jitter and unstable movement but after using metal gear MG90 servo motor, we achieved good thumb movement.

Figure 7-7: Thumb Extension

Figure 7-8: Thumb Flexion

7.3.4 Testing of Power Grasp

After assembling of all the fingers and thumb to the palm entire hand was assembled. For the first time all the 11 actuators were assembled and tested. All linear actuators are interfaced to motor driver and Arduino Mega 2560. First there were some loose connection problems then after some troubleshooting, we got the connections right and the power grasp was tested by actuating all the actuators at a same time.

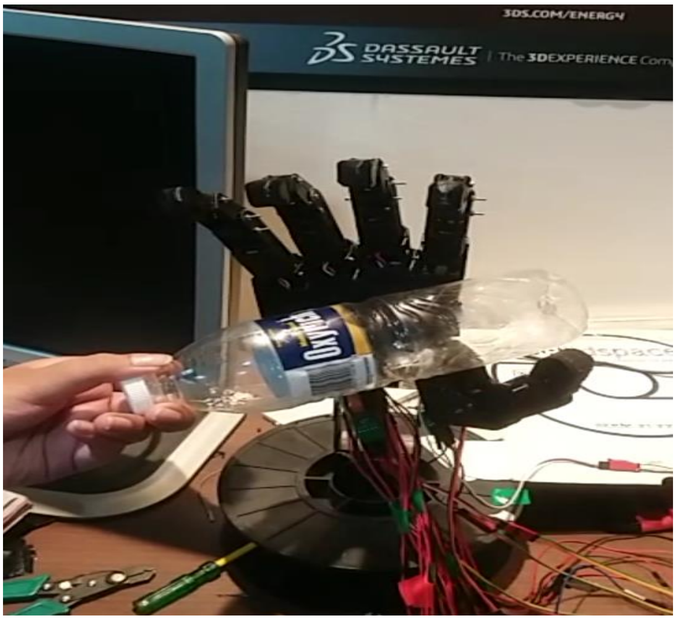


Figure 7-9: Initiation of Power Grasp

Figure 7-10: Bionic Arm Grasping a bottle

7.3.5 Testing of Pinch Grasp

After incorporating position feedback of linear actuator precise control of linear actuator is observed. After getting successful results, pinch grasp was implemented bt actuation MCP and PIP joints of linear actuator and DIP joints of thumb. By incorporating position control successful pinch grasp of glue was done.

Figure 7-11: Pinch Grasp of Bionic Arm holding a glue stick

7.3.6 Testing of Lateral Grasp

Lateral Grasp is used to grasp object on the lateral surface of the fingers. Testing of lateral grasps was successful.

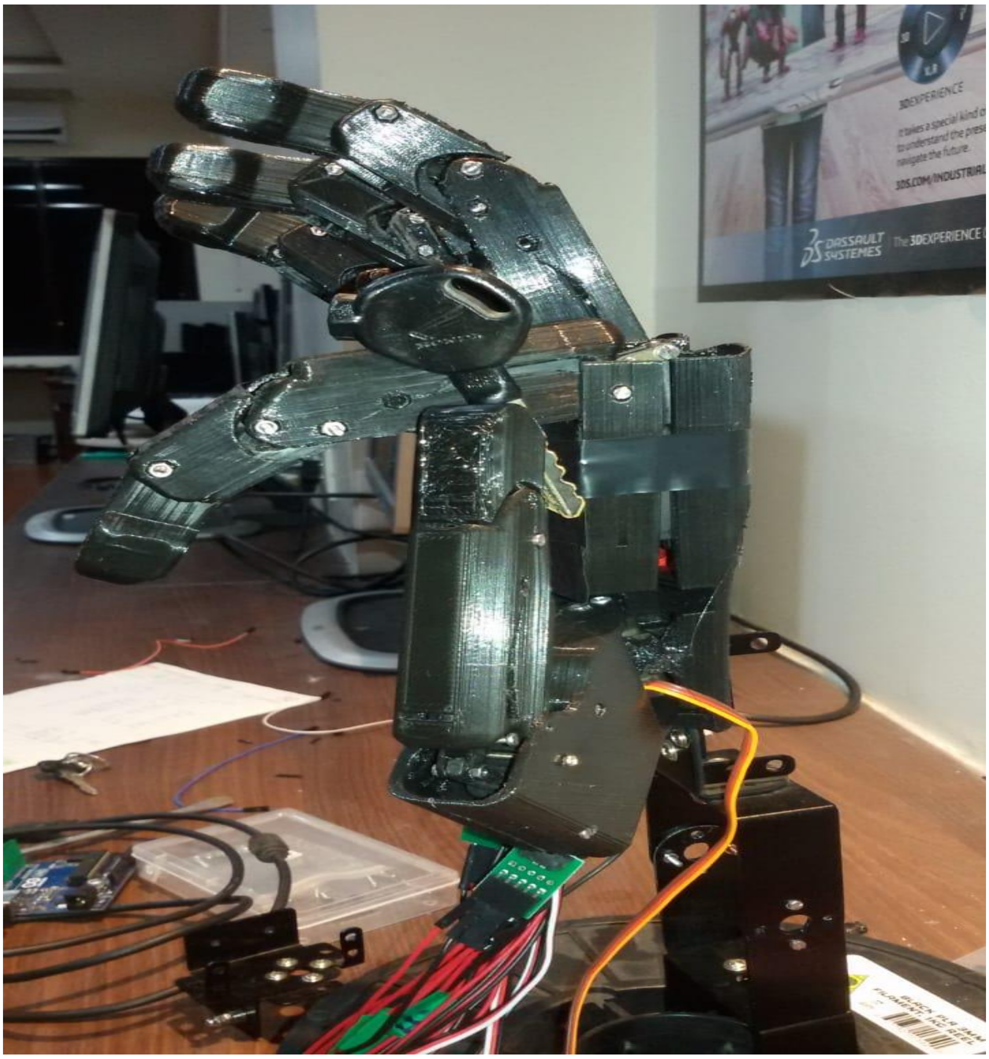


Figure 7-12: Lateral Grasp of a key.

7.3.7 SingleTact Sensor testing

Capacitive sensor was tested and when pressure was applied on it, its voltage was increased. It always gave accurate readings and also repeatable ones.

It always gave accurate readings and also repeatable ones.

Figure 7-13: SingleTact Sensor

Figure 7-14: Pressure applied on SingleTact Sensor

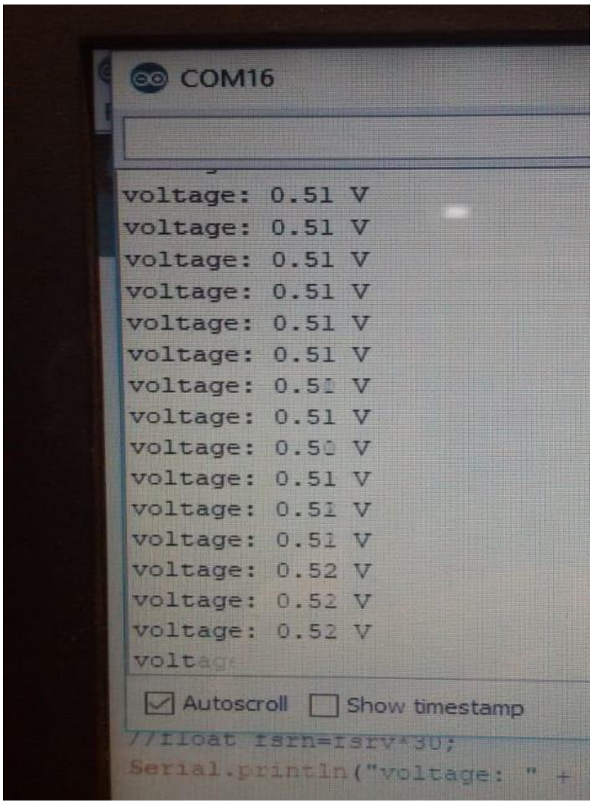


Figure 7-15: Voltage at the output of sensor when applied with no pressure

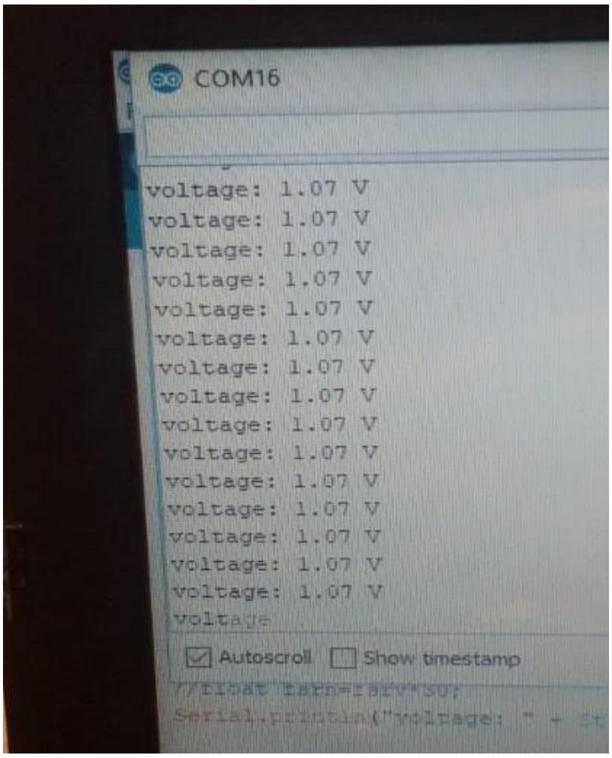


Figure 7-16: Voltage at the output of Sensor when pressure is applied.

Thus, after testing of Single Tact sensor it gave repeatable and accurate results

CHAPTER 8
8 RESULTS

1) After experimenting with 6 and 4 sensors bands, it was finalized to use a four sensor band for data acquisition.
2) Amongst the four feature sets applied, Feature3 and Feature4 gave discrete and repetitive results for the particular gestures. Hence they were selected for further modelling.
3) Amongst the two machine learning techniques used, RF model gave better efficiencies when tested on all 7 gestures but this efficiency in general was not up to the mark.
4) To improve the efficiency some gestures were dropped. The new gesture set contains 3 gestures. Gesture Set 3 is as follows-
    - Rest
    - Fist
    - Pinch

    These gestures are of practical use and are successful on the hardware as well.
5) When the machine learning models were tested on these 3 gestures, SVM model gave higher accuracy. The accuracy of the final SVM model for 3 gesture classification using Feature3 and Feature4 is 94.18%.

    The confusion matrix is as follows-

Table 8-1: Confusion matrix of the final SVM model

\	r	f	p
r	172	0	0
f	14	153	5
p	0	11	161

6) The Bionic Arm was successfully designed and assembled.
7) 11 DoFs were achieved.
8) The Bionic Arm incorporated POWER, PINCH and LATERAL Grasps perfectly and successfully.
9) All the fingers were actuating correctly as per the design.
10) Tactile Sensor was tested successfully and repeatable results were obtained.

CHAPTER 9
9 CONCLUSION

11 DoF Bionic Arm was successfully designed and controlled with the help of 4 EMG Sensor band. 3 Gestures namely relax, fist and pinch were classified with accuracy of 94.18%. Only four features were used for the classification. These features were modelled using the SVM technique. As a result of that, 3 gestures were successfully classified and the Bionic Arm was able to imitate the gestures exactly.

Three Bionic Arm mechanisms were designed and tested.

These were as follows-

- Servo String Mechanism
- Twisted String Mechanism
- Linear Actuator Mechanism

It is concluded that linear actuator mechanism is a better mechanism because it was more reliable and was able to impart adequate force on the object. Also complex gestures like pinch and power grasp which were hard to implement with the previous two mechanisms, which were successfully implemented with Linear Actuator Mechanism.

In addition to that, the whole Bionic Arm weighs about 600grams which is under mentioned needs of the amputees.

Hence the whole EMG Analysis part and Bionic Arm hardware was interfaced successfully.

CHAPTER 10
10 FUTURE SCOPE

Currently an 11 DoF Bionic Arm has been designed which can be controlled using EMG signals. As discussed earlier the DoF is one of the important parameter when it comes to designing a Bionic Arm. The project holds a lot of social as well as technological scope in future. This project has a huge scope So, the scope of different aspects of the project has been described separately in the following parts.

10.1 Future scope for the EMG sensor design

In the present situation there aren't good quality EMG sensors present in the market. The ones that are there have very less reliability. Also technical documentation of the sensors available in the market is not exhaustive. Also sensors present outside India are very costly and thus not viable for use for a low-cost Bionic Arm. The sensors used in this project were unreliable, noisy and the technical details were not properly mentioned in the datasheet.

Thus, design and development of EMG sensors in house will be of great use for the next batch of students. It will be cheap and reliable too. This in-house EMG sensor can also lead to the design of other Bio signal acquisition system.

10.2 Future scope for the EMG signal analysis and classification

Various noise reduction techniques can be used to refine the EMG signals. Combination of hardware and digital filters can be used for the same.

We have explored the time domain features but the frequency domain features and advance time domain features are remaining. These features can be explored to get better prediction accuracy.

Neural networks and deep learning can be used to increase the prediction accuracy. More number of gestures can also be classified using these non-linear classifiers.

Finally, the total time required for the processing and classification of EMG signal can also be worked on to make it more responsive and real time.

10.3 Future scope for the Bionic Arm

The idea of using these EMG signals as a control signal and using it as a helping aid to the amputees is a big thing in it itself to achieve. Yet the future scope for this particular phase of the project would be increasing the DOFs. Currently, the project has achieved 11 DOFs, which includes movements of the fingers and the human palm as a whole.

Other than increasing DoFs in the arm, various algorithms and transformation techniques can be applied which may give better results than the current techniques.

Development in the Bionic Arms and the challenge related to that mainly lies in the structure of the arm. It is really difficult to imitate an exact human arm with number of miniature motors. Different structures have been proposed and currently the ball and socket technology is used. A lot of research is being carried out regarding refining the technology of the design of the Bionic Arm. Advanced 3D printing techniques and coating techniques have to be developed.

The Bionic Arms available today provide a mental control over the arm but there is no sensory feedback. Sometimes the corresponding muscle may not get actuated accurately and hence there can be a sensory feedback in order to get proper results.

Another advancement that can be added in the arm for the amputees is the feeling of the material it touches. While gripping or holding an object, a Bionic Arm may hold it too tightly or to loosely. For example, the arm must have a feedback that may be able to differentiate between whether it is holding a glass or a pillow. Depending on the material the arm will apply the appropriate amount of pressure in gripping it.

Soft Robotics is a new field which has huge prospects. Usage of soft material like SMA and SMP for prosthetic arm will be a great prospect as the Bionic Arm will look more like a original human hand rather than an artificial robotic hand.

Camera can be mounted on the Bionic Arm and computer vision can be implemented. Control of Bionic Arm on basis of object detection through image processing can help to develop complex grasps of complex shaped objects.

10.4 Future scope for prosthetics

The present myoelectric technology is appropriate for arms. The bionic legs face a lot of technological problems. The movement of knees, feet and ankles in normal walking are more autonomous and they bear entire load of the body, so mechanism and actuators imparting high torque are required. Thus, detail research on leg prosthesis is needed and has a good future prospects for leg amputees.

CHAPTER 11
11 BILL OF MATERIALS

11.1 Research Phase Bill of Material

Table 11-1: Research Phase Bill of Material

Sr. No.	Name	Quantity	Total Cost including GST
1.	MyoWare Muscle Sensor	12	53940=00
2.	ADS1220 24-BIT, LOW NOISE ADC BREAKOUT BOARD	5	9501=52
3.	ADS1262 32-BIT, BIT PRECISION ADC BREAKOUT BOARD	2	9190=00
4.	Asus Tinker 90MB0QY1-M0UAY0 Socket RK3288 Gaming Motherboard	2	10938=00
5.	Force Sensor	2	5048=04
6.	Force Sensor DAQ	1	3798=42
7.	Raspberry Pi B+	2	5980=00
8.	16-Channel 12-bit PWM/Servo Driver w/ I2C interface	1	350=00
9.	PQ12-R Micro Linear Servos6V	4	43,896=00
10.	PQ12-P Linear Actuators with feedback(Gear ratio-30-1)12V	4	43,896=00
11.	PQ12-P Linear Actuators with feedback(Gear ratio-63-1)12V	6	65,844=00
12.	PQ12 Cable Adapter with "P" Extension cable	11	4,212=60
13.	Mini Servo 2.5 kg	2	524=00
14.	5A DC-DC Step Down Buck Module	2	300=00
15.	Miscellaneous Laser Cutting 100 X 175 X THK 2MM MS	1	379=00
16.	Orange 5200mAh 3S 40C LiPo Battery	1	4389=00
17.	SkyRC IMAX Balanced Charger	1	3290=00
18.	TLE94112EL Shield Half Bridge Driver	1	3391=00
19.	MSP430 Launch Pad	2	2828=00
20.	WOL 3D Filament PLA	2	2180=00
21.	Arduino Mega	1	885=00

22.	Mastech MAS830L Digital Pocket Multimeter	1	568=00
23.	Medico EMG Electrodes Pack of 500	1	2500=00
24.	MyoWare Muscle Sensor	3	14,379=00
25.	Miscellaneous -Sandisk SD card 16Gb	2	1000=00
26.	MG 90Servo	3	920=40
27.	Miscellaneous-Male to Male Wire	10	47=20
28.	Miscellaneous-Jumper Wires + Single stranded wire(30m)	250	879=00
29.	Miscellaneous-Screws and nuts	80	287=00
30.	Miscellaneous-Screws and nuts	70	266=00
31.	Miscellaneous-Multi Strand wire(20m), 3pin connector and PCB	30	448=00
32.	Miscellaneous-XC60Connector and Flux	4+1	207=00
33.	Miscellaneous-Male to Male Jumpers	50	118=00
34.	BP Belt	1	50=00
35.	Gravity EMG sensor SEN0240	1	3597=00
36.	Force Sensor	1	677=00
37.	DC motor	1	472=00
38.	Arduino Due	1	1652=00
39.	Medico ECG (pack of 50pcs)	1	365=00
		Total-	3,03,192=58

11.2 One-unit Bill of Material

Table 11-2: One-unit Bill of Material

Sr. No.	Name	Quantity	Total Cost including GST
1.	MyoWare Muscle Sensor	4	17980=00
2.	Raspberry Pi B+	1	2990=00
3.	PQ12-R Micro Linear Servos6V	4	43,896=00
4.	PQ12-P Linear Actuators with feedback(Gear ratio-30-1)12V	1	10,974=00
5.	PQ12-P Linear Actuators with feedback(Gear ratio-63-1)12V	6	65,844=00
6.	PQ12 Cable Adapter with "P" Extension cable	11	4,212=60
7.	16-Channel 12-bit PWM/Servo Driver w/ I2C interface	1	350=00
8.	Mini Servo 2.5 kg	2	524=00
9.	5A DC-DC Step Down Buck Module	2	300=00
10.	Miscellaneous Laser Cutting 100 X 175 X THK 2MM MS	1	379=00
11.	Orange 5200mAh 3S 40C LiPo Battery	1	4389=00
12.	SkyRC IMAX Balanced Charger	1	3290=00
13.	MSP430 Launch Pad	2	2828=00
14.	WOL3D Filament PLA	2	2180=00
15.	Arduino Mega	1	885=00
16.	Medico EMG Electrodes Pack of 500	1	2500=00
17.	Miscellaneous -Sandisk SD card 16Gb	1	500=00
18.	MG 90Servo	3	920=40
19.	Miscellaneous-Male to Male Wire	10	47=20
20.	Miscellaneous-Jumper Wires + Single stranded wire(30m)	250	879=00
21.	Miscellaneous-Screws and nuts	80	287=00
22.	Miscellaneous-Screws and nuts	70	266=00
23.	Miscellaneous-Multi Strand wire(20m), 3pin	30	448=00

	connector and PCB		
24.	Miscellaneous-XC60Connector and Flux	4+1	207=00
25.	Miscellaneous-Male to Male Jumpers	50	118=00
26.	BP Belt	1	50=00
27.	Arduino Due	1	1652=00
		Total-	1,68,896=2

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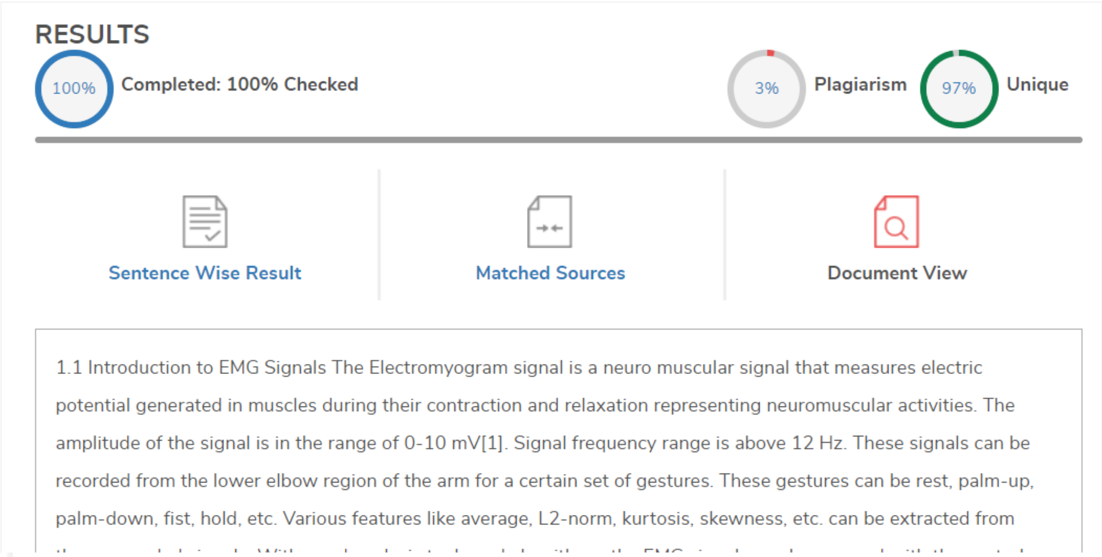
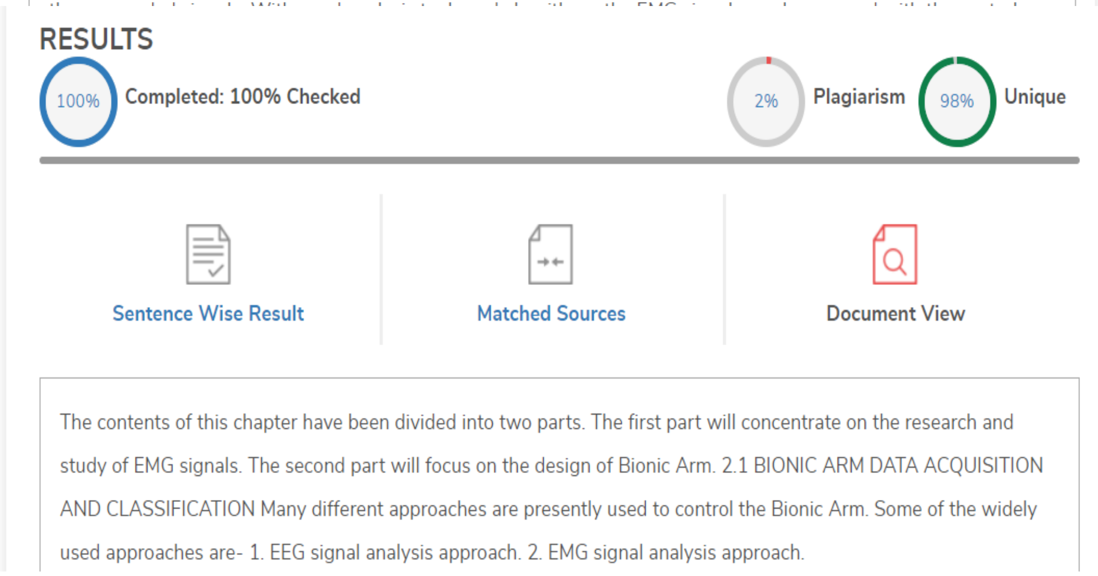
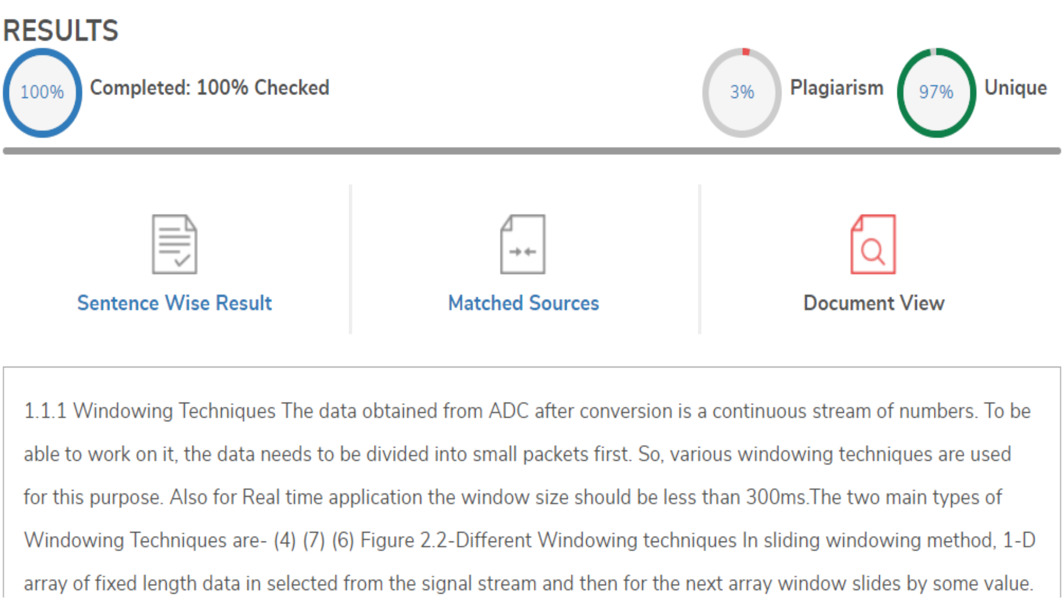
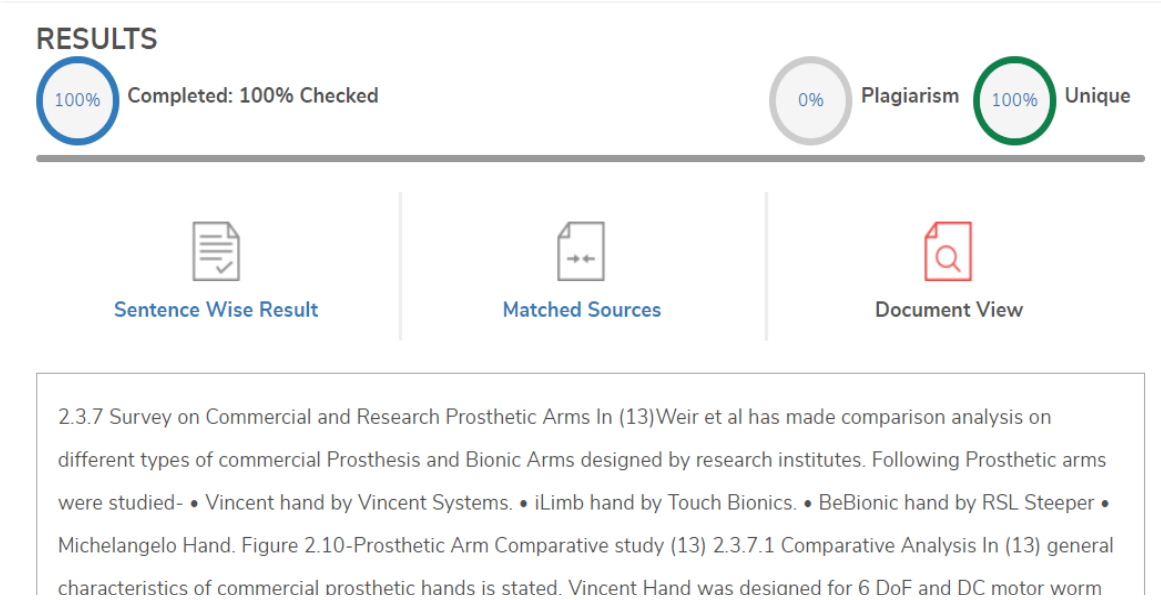
APPENDIX

PLAGIARISM REPORT









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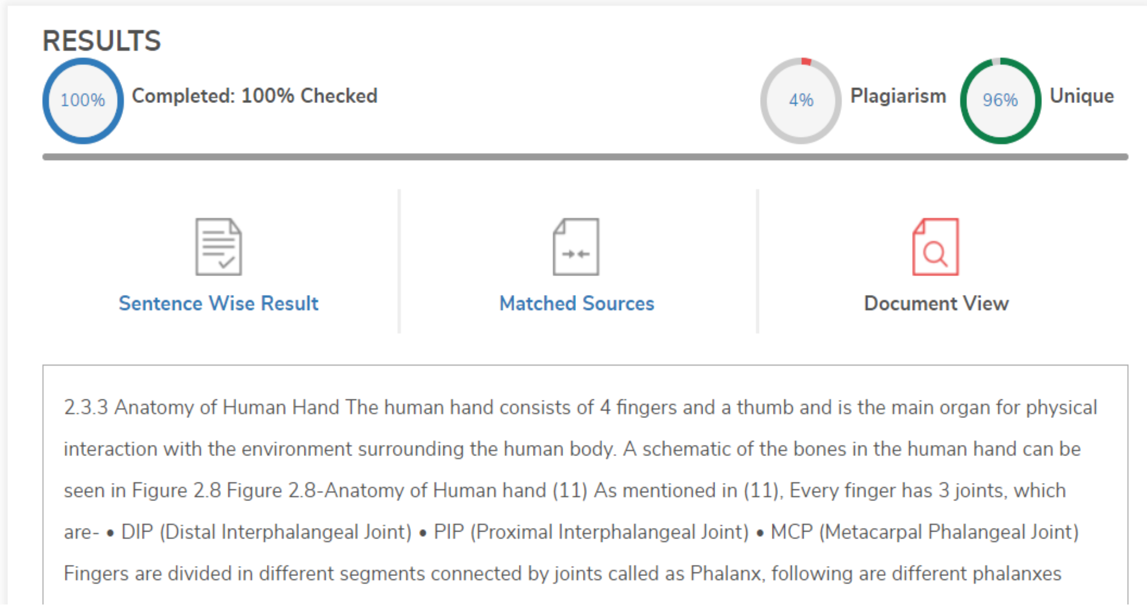
2.3.7 Survey on Commercial and Research Prosthetic Arms In (13)Weir et al has made comparison analysis on different types of commercial Prosthesis and Bionic Arms designed by research institutes. Following Prosthetic arms were studied- • Vincent hand by Vincent Systems. • iLimb hand by Touch Bionics. • BeBionic hand by RSL Steeper • Michelangelo Hand. Figure 2.10-Prosthetic Arm Comparative study (13) 2.3.7.1 Comparative Analysis In (13) general characteristics of commercial prosthetic hands is stated. Vincent Hand was designed for 6 DoF and DC motor worm



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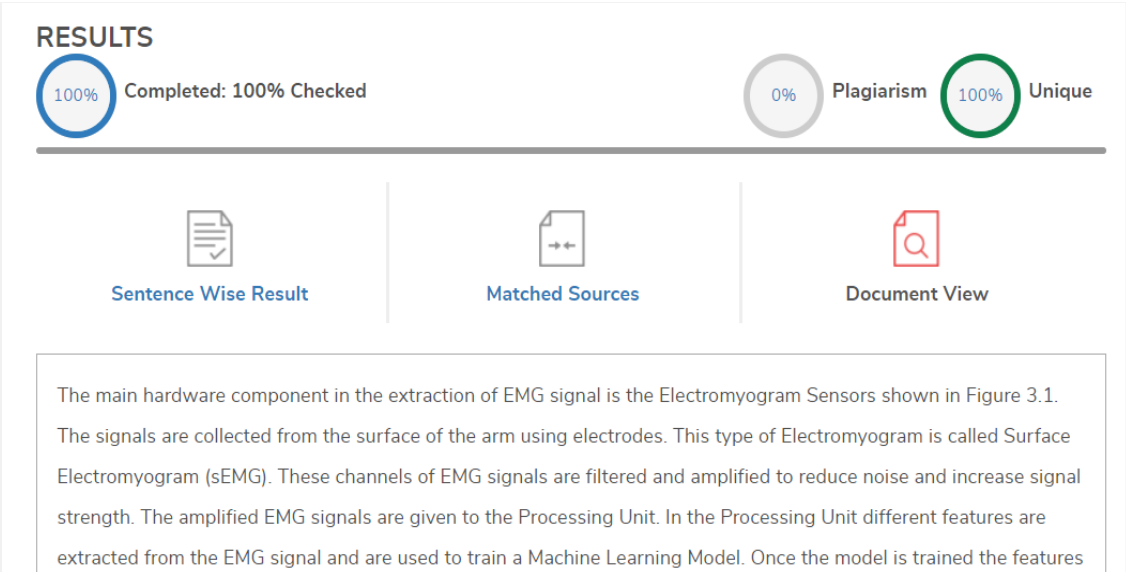
2.3.3 Anatomy of Human Hand The human hand consists of 4 fingers and a thumb and is the main organ for physical interaction with the environment surrounding the human body. A schematic of the bones in the human hand can be seen in Figure 2.8 Figure 2.8-Anatomy of Human hand (11) As mentioned in (11), Every finger has 3 joints, which are- • DIP (Distal Interphalangeal Joint) • PIP (Proximal Interphalangeal Joint) • MCP (Metacarpal Phalangeal Joint) Fingers are divided in different segments connected by joints called as Phalanx, following are different phalanxes



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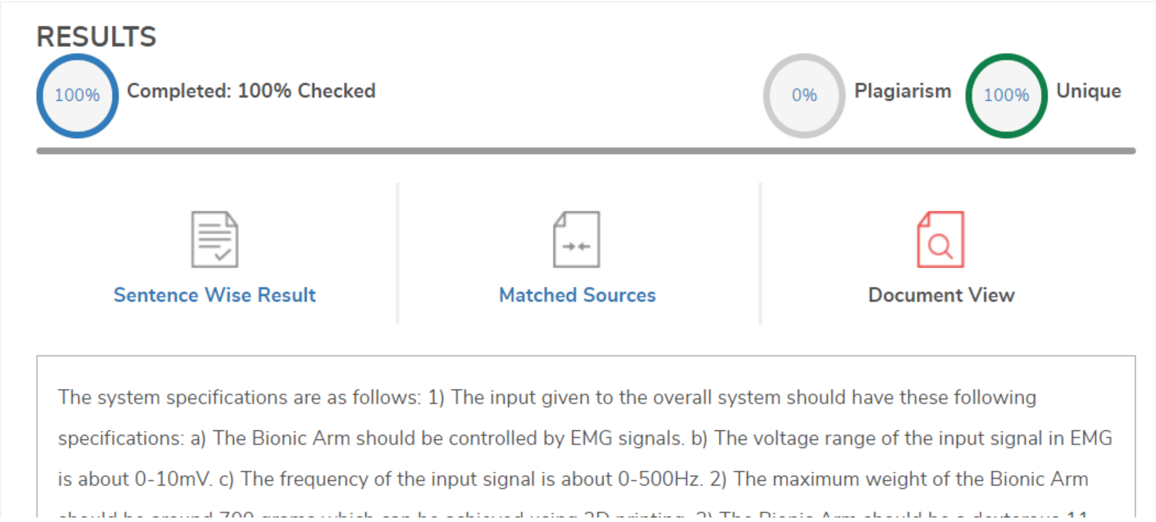
The main hardware component in the extraction of EMG signal is the Electromyogram Sensors shown in Figure 3.1. The signals are collected from the surface of the arm using electrodes. This type of Electromyogram is called Surface Electromyogram (sEMG). These channels of EMG signals are filtered and amplified to reduce noise and increase signal strength. The amplified EMG signals are given to the Processing Unit. In the Processing Unit different features are extracted from the EMG signal and are used to train a Machine Learning Model. Once the model is trained the features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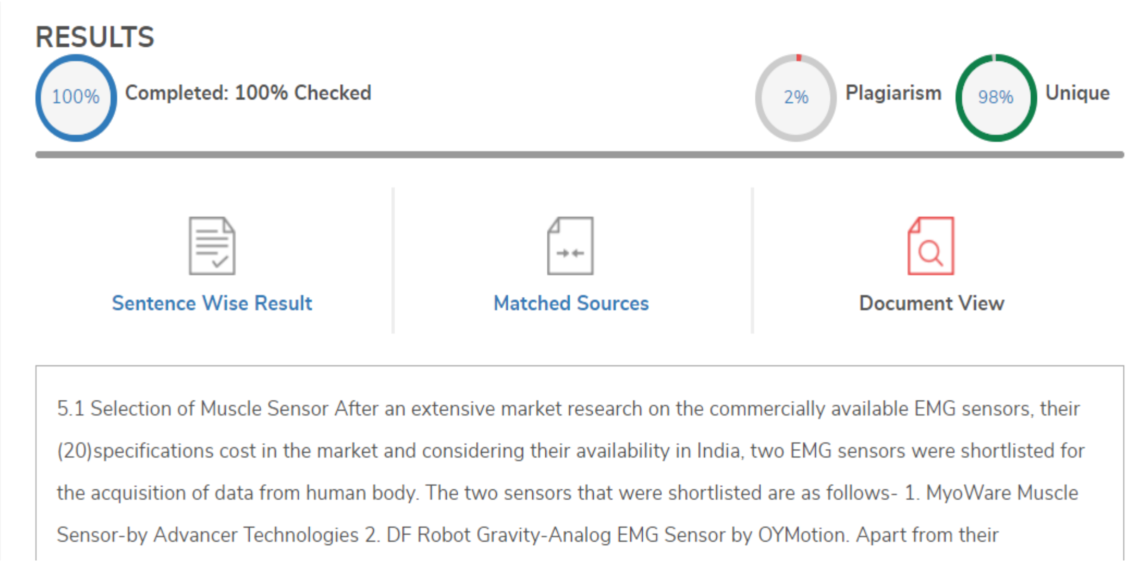
The system specifications are as follows: 1) The input given to the overall system should have these following specifications: a) The Bionic Arm should be controlled by EMG signals. b) The voltage range of the input signal in EMG is about 0-10mV. c) The frequency of the input signal is about 0-500Hz. 2) The maximum weight of the Bionic Arm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5.1 Selection of Muscle Sensor After an extensive market research on the commercially available EMG sensors, their (20)specifications cost in the market and considering their availability in India, two EMG sensors were shortlisted for the acquisition of data from human body. The two sensors that were shortlisted are as follows- 1. MyoWare Muscle Sensor-by Advancer Technologies 2. DF Robot Gravity-Analog EMG Sensor by OYMotion. Apart from their

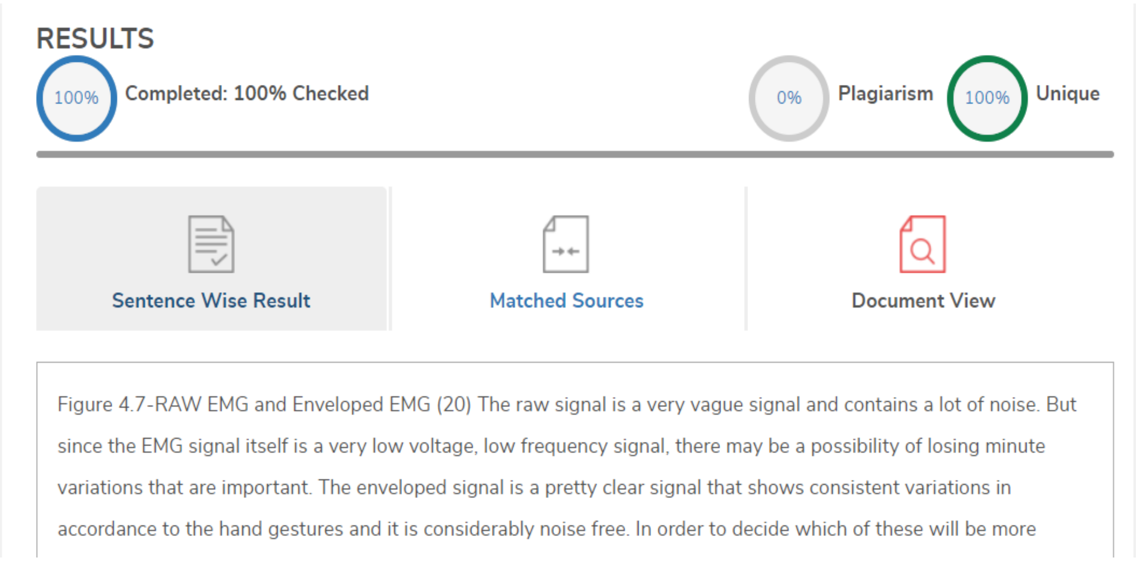
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Figure 4.7-RAW EMG and Enveloped EMG (20) The raw signal is a very vague signal and contains a lot of noise. But since the EMG signal itself is a very low voltage, low frequency signal, there may be a possibility of losing minute variations that are important. The enveloped signal is a pretty clear signal that shows consistent variations in accordance to the hand gestures and it is considerably noise free. In order to decide which of these will be more

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5.6 Organizational visits To gain more insight on the existing technologies and to check the feasibility of the project we visited various organizations. 5.6.1 Dassault Systems, Pune Figure 4.14-Dassault Systemeś We visited Dassault Systems, regarding the sponsorship terms and conditions. Also experts of company helped us gain valuable insights regarding the project. The terms of the project and the feasibility of the project was discussed. The overall outcome of

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The 9 gestures selected have been plotted in the scatter plot given in Figure 4.35. As it can be seen the readings of the gestures overlap each other and no clear distinction can be seen. This will lead to an inaccurate machine learning model and the model will not be able to classify the gestures accordingly. Also these gestures have little practical use in daily life. Thus to increase functionality of the Bionic Arm and to increase classification accuracy, a new gesture set

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5.13.2 Data conditioning The data that is acquired from the Arduino Due board is in a very scrambled format to make it easy for single channel serial transmission. Thus we need to condition the data in order to unscramble it and to represent it properly for the next analysis. The input to the data conditioning block is 10 scrambled streams of data. Data Conditioning block converts this stream of data into 7 excel sheets, each sheet represents individual gesture. In each sheet, 10 columns of 2000 rows are formed, each column representing the individual sensor. This is done for all the 155 sets. 5.13.2.1 Code for Data Conditioning import pandas as pd sheet1=

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5.13.7 Training the Model In the training phase of the model, the feature set was split into training data set and testing data set in the ratio of 5-1. The training data set is used to train the machine learning model. Firstly the data set is normalized and is then fed to the model for training. Both the trained model and the transformation matrix are saved as .pkl files. These models are then used later for the process of prediction. 5.13.7.1 Code for training model- 5.13.7.1.1 Using Support Vector Machine import numpy as np import pandas as pd from sklearn.externals import

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5.14.3 10 Sensors Two sensor bands of 6 Sensors and 4 sensors respectively are used here. Six sensor band is placed close to the elbow as the circumference of the hand is large there and needs more sensors to cover the whole area. It covers the muscle groups like Flexor carpi radialis muscle, Flexor carpi ulnaris, Extensor carpi radialis muscle and Extensor carpi ulnaris muscle groups. Four sensor band is place just below the Six sensor band to cover the remaining muscle regions like Flexor digitorum profundus, Flexor pollicis longus, Extensor digitorum profundus and

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Table 4 9lda components=2. Max depth =4 r f pu pd h v P R 30 55 0 1 24 0 3 f 15 60 1 0 15 0 0 pu 0 1 92 0 0 7 14 pd 0 4 3 92 0 0 0 h 5 23 3 0 48 0 14 v 0 0 1 0 0 99 4 p 0 9 35 0 1 0 69 Accuracy=0.6730769230769231 Table 4 10lda components=3. Max depth =6 r f pu pd h v P R 73 28 1 1 7 0 3 f 12 58 3 1 16 0 1 pu 0 3 98 0 0 3 10 pd 0 4 3 91 1 0 0 h 5 8 3 0 70 0 7 v 0 0 2 0 0 100 2 p 0 7 27 0 8 0 72 Accuracy=0.771978021978022 Table 4 11lda components=4. Max depth =8 r f pu pd h v P R 72 30 2 1 3 0 5 f 5 77 1 0 8 0 0 pu 0 0 100 0 0 3 11 pd 0 5 1 93 0 0

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As seen before the accuracy of the machine learning models to classify all the 7 gestures accurately was very less. Also in the statistics section it was seen that the values of gestures like palm-up, palm-down, fist and hold overlapped with each other. This further decreased the accuracy of the machine learning model. As a solution to this the number of gestures was narrowed down to 3. These gestures are- • Rest • Fist • Pinch 5.18.1 Model 3-SVM

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6.1 Introduction The aim of the project is to build a high DoF Bionic Arm which will be light in weight. Achieving high dexterity is a herculean task, so a step by step approach was undertaken. For incorporating dexterity in artificial robotic hand, the fingers of the hand should have more than one DoF. So initially the work initiated with designing and implementation of 1 DoF finger. The design of Bionic Arm is divided into 3 phases, following is the detail

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6.4.3 Block Diagram of Proposed System Figure 5.5-Block Diagram of Proposed System 6.4.4 Working of the Bionic Arm- As finalization of incorporating of linear actuator in the Bionic Arm was done, detail working of Bionic Arm is as follows- 6.4.4.1 Working of PQ12 Linear Actuator Linear Actuator consist of following parts- • DC Motor • Gears • Lead Screw Figure 5.6-PQ12 Linear actuator (28) In linear actuator linear motion is obtained from conversion of

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6.4.5.1 Bionic Arm Electrical Specification 6.4.5.1.1 Power Supply For prototyping of the Bionic Arm we used Orange 5200mAh 3S 40C LiPo Battery of 11.1V. Specifications- • Weight -360.0g • Voltage -11.1V • Dimensions -28x44x137(mm) It can provide 5.2 A current continuously for 1 hour. Battery Calculation- Though, 5200mAh of battery is used following calculations are for 2200 mAh LiPo battery. Following assumptions have been done while

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7.1 Introduction While designing the Bionic Arm simulating tools like MATLAB and Dymola of 3DExperience were used. In MATLAB simulation Linear Actuator was simulated and results were found. Following are snaps of the simulation from Simulia (MATLAB)- • An example of linear actuator model was simulated with reference to (34): Figure 6.1-Simulation of Linear actuator in MATLAB software Figure 6.2-Open Loop Control 7.2 Dymola Simulations

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1) After experimenting with 6 and 4 sensors bands, it was finalized to use a four sensor band for data acquisition. 2) Amongst the four feature sets applied, Feature3 and Feature4 gave discrete and repetitive results for the particular gestures. Hence they were selected for further modelling. 3) Amongst the two machine learning techniques used, RF model gave better efficiencies when tested on all 7 gestures but this efficiency in general was not up to the mark. 4) To improve the efficiency some gestures were dropped. The new gesture set contains 3 gestures. Gesture Set 3 is as