BIONIC ARM: DATA ACQUISITION AND MAPPING FROM EMG SENSORS

A MINI PROJECT REPORT

submitted by

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BONAFIDE CERTIFICATE

This is to certify that the project work entitled **"BIONIC ARM: DATA ACQUISITION AND MAPPING FROM EMG SENSORS"** is a bonafide record of the work carried out by

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Examiner - I **Examiner - II**

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Bionic Arm: Mapping of elbow and wrist flexion using Neural Networks

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ABSTRACT

KEYWORDS: Transhumeral prosthetic; EMG signals; sensors; Capture unit; Mapping

When a human hand is moved, signals from the brain stimulate the nerves in the hand which causes flexion or retraction of muscles corresponding to different parts of the hand. For a person, whose upper limb is impaired (an amputee) the signals can be detected at the amputated end, though they are very feeble.

This work emphasises on the capture of muscle signals at the amputated end of an amputee using EMG (electromyographic) sensors and other possible sensors; and mapping of these sensor outputs to the corresponding hand movements associated with them; which will be incorporated as the control part in a transhumeral prosthetic.

The first stage, Capture unit, will involve design of the capture circuit that will record the EMG sensor signals in real time; do the required signal processing and send it to a processing unit for mapping. For different virtual movements of the hand (such as flexion of fingers, wrist, elbow; rotation of wrist) the sensors' outputs will be recorded. This part will focus on the identification of control sites in the amputated portion which give significant sensor outputs, mounting of sensors at the amputated portion of the amputee, and development of an arrangement that comprises of the capture circuit and that can fit over the amputated portion. Raw sensor data pertaining to various movements of a virtual hand will be obtained in this stage.

The second part, Mapping unit, will address to the analysis of the obtained data. Different positions of the fingers, wrist and elbow can be categorized as corresponding angular displacements of motors placed at corresponding joints/positions in the prosthetic arm. Various sensors places at different control sites at the amputated region will give raw data in different ranges. These data are to be analysed, processed and mapped to their corresponding categories (different positions of the hand). A mapping procedure should be developed that can analyze the obtained data and classify them according to the categories.

1: INTRODUCTION

The movements of human hand are controlled by the stimuli from brain that controls the flexion and retraction of muscles, tendons and ligaments; which gives rise to different actions. For a person whose upper limb is amputated, the muscle signals that correspond to different hand movements can still be detected at the amputated end.

A transhumeral prosthetic is the one that extends from the upper arm and provides an artificial, structural and functional rehabilitation. The most commonly used means of controlling a bionic arm are EMG (electromyography) [1] [2] and EEG (electroencephalogram). EEG [3] [4] involves capturing the control signals from the brain. However this technique is relatively complex as it requires highly sensitive sensors and the possibilities of erroneous outputs are quite high.

EMG is one of the widely adopted methods for capture of muscle signals. It involves placing the EMG sensors and/or electrodes in the places of remaining muscles (in the amputated region) to capture the control signals. These signals are to be further processed for controlling the prosthetic arm. The experiments are to be tried with a *test person** before trying it on the amputated person.

The hand is considered as a rigid body here [5]. Only voluntary actions of the human hand are considered in this work.

**A test person is the one who has similar hand structure as that of the patient.*

1.1 Need for the Idea

This project is being worked on to design a transhumeral prosthetic arm for Mr Julius Caesar, a known person in our institute campus; whose right hand is amputated from the upper arm. The motto of the idea is to utilise the innovations in the field of engineering and technology to develop a bionic arm that can provide artificial limb rehabilitation for him.

**Right hand is considered in this work*

1.2 Objective

- To work on the Electronics part of a prosthetic arm that involves capture of EMG signals and the Mapping part that maps the signals to their corresponding movements
- To study the human hand anatomy and various movements of a human hand
- To find suitable sensors that can capture EMG signals
- To develop an physical interface between the amputated portion and the prosthetic arm where the sensors can be placed.

2: LITERATURE REVIEW

A study on various sensors, EMG techniques and human hand anatomy were done.

2.1 Current status of Bionics

Most of current existing Bionics use electromyography [6] [7] technology, which is used to detect and measure nerve signals to muscles and muscles' response to the nervous impulse. The instrument used for this purpose is called electromyograph. They are now available in the form of sensors too (EMG sensor), which can be easily connected to the control circuit.

Adaptive control techniques [8] are used in some of the robotic manipulators to detect the presence of ambiguities and non-linearities in robotic models. The techniques have also been implemented in Prosthetics [9] to give precise control of actuators in the prosthetic model.

In some cases, the implementation of a bionic system on a patient may require placing of an Osseointegration [10] [11] , which is a mechanical connection between the bone (where the limb is amputated) and the bionic structure. This technique provides greater stability and weight bearing capacity. It requires less energy expenditure from the patient.

There is a surgery called targeted muscle reinnervation (TMR) which captures signals from the nerves that once stimulated the amputated limb and processes them to actuate the desired movement in the prosthetic [12] [13]. It was observed that the combination of TMR and electromyography techniques yielded better and more accurate results [14] [15].

2.2 A study on Neural Networks

An Artificial Neural Network (ANN) is a network whose network design is modelled to replicate the function of a human neuron. It consists of input layer, one or more hidden layers and an output layer. Each of the layers consists of nodes. The number of nodes in the input layer corresponds to the number of input devices (here, sensors). The number of nodes in the output layer corresponds to the number of categories (in this case, angles) the network should classify. The number of nodes in the hidden layer(s) is chosen in a way to get maximum performance. (Appendix A)

Training of the ANN refers to loading the network with known input data and its corresponding target values. As multiple data are loaded, the network finds a mathematical mapping from the inputs to the targets. This mapping is used to find the output for an input given to the network while testing.

2.3 A study on currently available EMG sensors

Control sites are the regions in the amputated portion where sensors can be placed that can give detectable output

Startups like OYMotion and Myo have introduced EMG bands which are to be fitted on a person's arm to record the muscle sensors. Individual EMG sensors are placed radially on this band and finding the control sites is not necessary, the individual sensors are self-calibrated and the band can be used easily. [16] *(Development of an electromyographic smart prosthetic hand (Parming, & Ghaiad, 2018),* [17] *Wearing-independent hand gesture recognition method based on EMG armband (Zhang et al., 2018)).*

In one work,[18] *Detecting muscle contractions using strain gauges (Zizoua, et al., 2016),* strain gauges have been used for capturing muscle signals due to their appreciable sensitivity to human tactility, Determination of control sites is necessary in this case.

In [19] *Development of a 3D-Printed Bionic Hand with Muscle- and Force Control. (Dannereder, et al., 2018),* [20] *EMG sensor for robotic applications (Tahir,2016),* [21] *Typing with EMG using MyoWare (Clawford & Vavra, 2016)*; Myoware EMG sensors have been used.

Inertial Measurement units (IMUs) are being used to detect the minimal displacement of amputated portion. [22]*(Relation of accelerometer and EMG recordings for the measurement of upper extremity movement* (*Keil, Elbert & Taub, 1999*)).

2.4 A study of Human hand anatomy

A detailed study on the location and types of bones (for understanding the structure) and muscles (for understanding the control of movements) in a human hand and arm (Figure 2.1) [23] [24] is indispensible for the design of bionic arm.

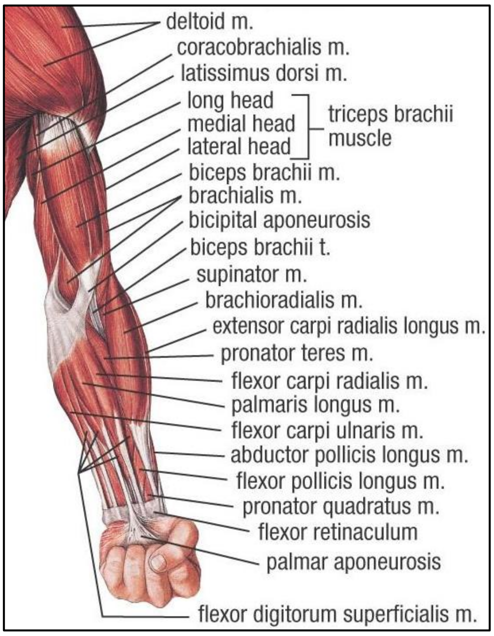


Figure 2.1 Muscle structure of human upper arm *(Courtesy: Extremetech)*

2.4.1 Flexion and Extension of Elbow joint

Brachialis muscle, brachiorradialis, Biceps brachii long are responsible for flexion of elbow; and Triceps brachii, anconeous are responsible for extension of elbow. (Figure 2.2)

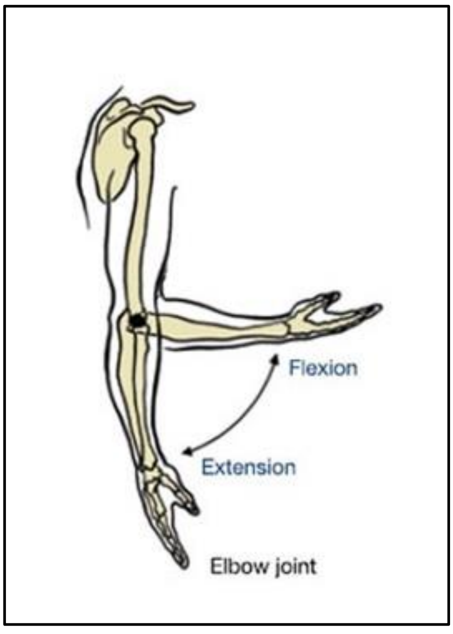


Figure 2.2. Flexion and extension of elbow *(Courtesy: American Council on Exercise, ACE Fitness)*

2.4.2 Flexion and Extension of Wrist joint

Brachialis, flexor carpi radialis, Biceps brachii long, palmaris longus, flexor carpi ulnaris, flexor digitor superficialis, Flexor digitorum profundis are responsible for flexion of wrist; and Extensor indicis, retinaculum(ligament), Extensor retinaculum, Extensor carpi ulnaris muscle, Extensor Digitorum Muscle are responsible for extension of wrist [25] (Figure 2.3).

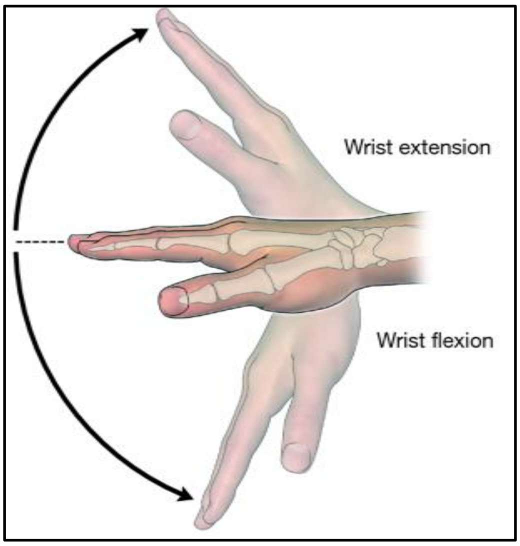


Figure 2.3 Flexion and extension of a wrist *(Courtesy: Access Physiotherapy)*

2.4.3 Turning of Wrist

Pronator teres, pronator quadratus are responsible for pronation of wrist; supinator muscle is responsible for supination of wrist.

Control points for the placement of sensors are determined. Here, control points refer to the points of joint in a human hand and arm (Figure 2.4).

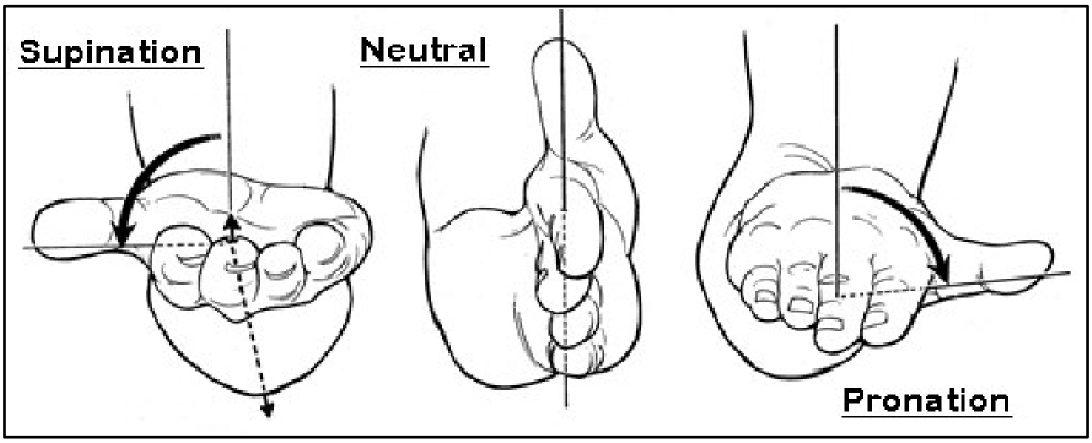


Figure 2.4 Rotation of a wrist [26] *(Courtesy: GroundUp Strength)*

2.4.4 Grasping and releasing of hand

Extensor digitorum, Flexor digitorum profundis are responsible for grasping; and Extensor retinaculum, Extensor digitorum muscle are responsible for releasing.

- Phalanges bones are responsible for the flexion (bending) of fingers

3: PATIENT SURVEY

The amputated person was interviewed regarding his requirements. He currently uses a wooden mannequin for structural support. It is supported by a cloth interface (between the amputated part and the wooden cavity) and a nylon strap that can be adjusted around his left shoulder. The amputated part has not been in contact with any other material than the cloth. The mannequin model can support small activities like pushing, carrying small loads and it weighs about 500g.

The person wishes to do activities such as opening packet, steering, driving and basic hand gestures.

Different Sensors were tried on the test person for capturing muscle signals that gave considerable changes for different hand gestures.

These points are very important while designing the interface material between his amputated portion and the prosthetic that the material should not cause kind of discomfort and the total load of the prosthetic arm should bebearable.

4: SELECTION OF SENSORS

Different sensors were tried to capture the muscle signals. They were tried on the test person’s right, upper arm.

4.1 EMG band

GForce EMG band from OYMotion was tried. It gave binary outputs for 6 different actions (Figure 4.1) indicated by 6 corresponding LEDs as shown in Table 4.1.

Figure 4.1 OYMotion Gforce EMG Band

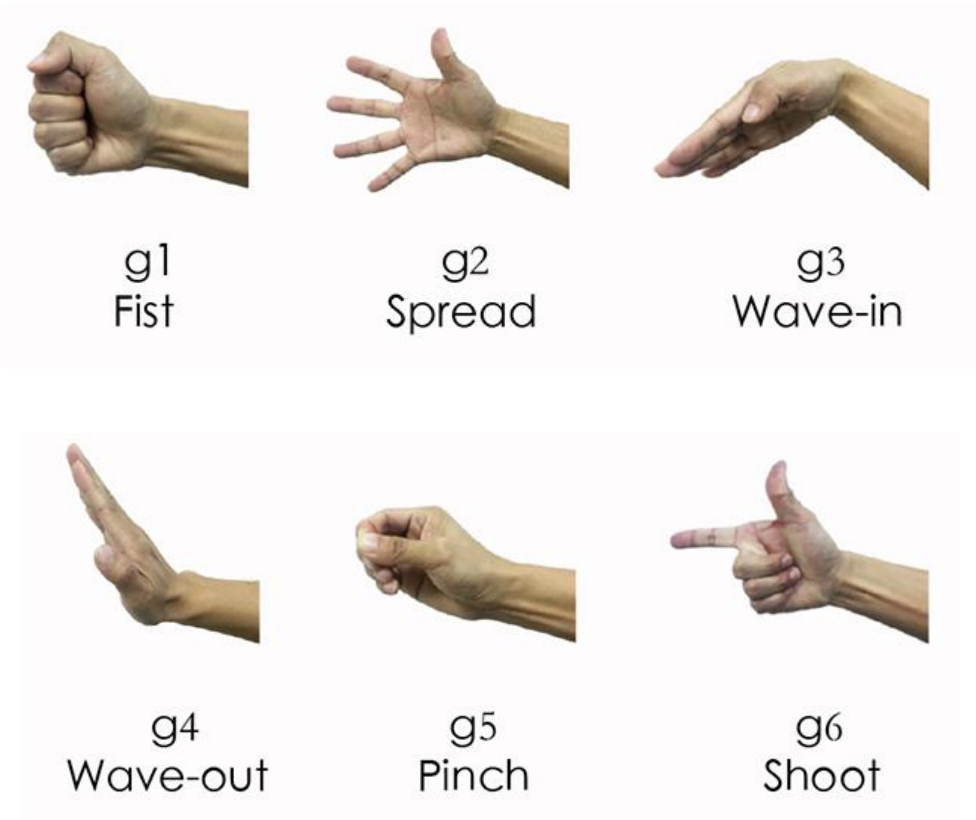


Figure 4.2 Gestures detectable by OYMotion EMG band

Table 4.1 Hand gestures corresponding to the LEDs in the Bluetooth module

LEDs on the module	Corresponding Actions
LED1	Fist
LED2	Spread Fingers
LED3	Wave In
LED4	Wave Out
LED5	Pinch
LED6	Shoot

The output of the EMG band was wirelessly transmitted to a Bluetooth module which can be interfaced with Arduino microcontroller board to get the gesture.

Experiments were done with the test person wearing the EMG band and the outputs were recorded in Arduino serial monitor, that displayed each gesture when it was done; and in “gForce app” which viewed the gestures as corresponding movements of a virtual app along with the x, y and z movements as shown in Figure 4.3.

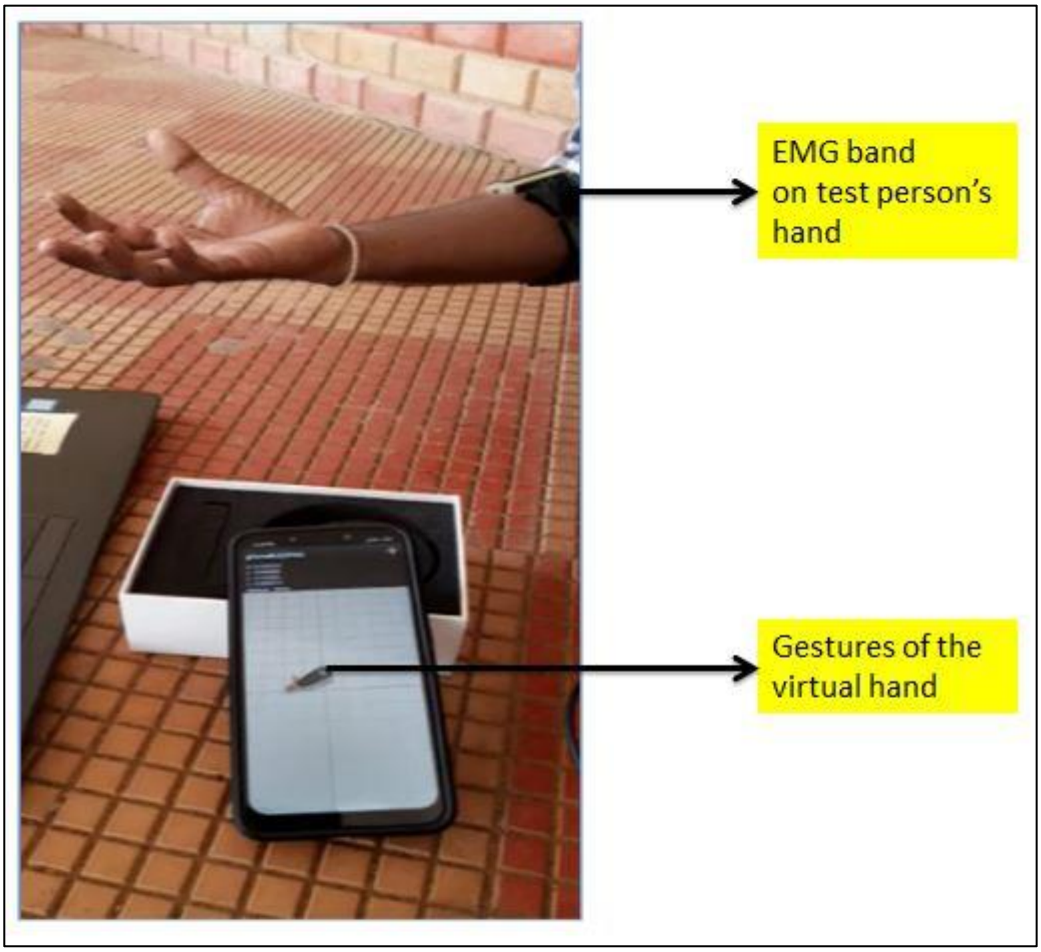


Figure 4.3 Movements of the virtual hand

The EMG band gave considerable outputs when tried on the test person. However, when it was also tried on the amputated person, it was not able to detect any muscle signals. The reason is that, the band gave relatively high accurate outputs when the band was worn on the lower arm and did not give any outputs when it was worn on the upper arm.

4.2 Bioamp – DAQ System (Electromyogram Instrument)

Biomechanical Laboratory, School of Chemical and Biotechnology

Bioamp-DAQ System EMG instrument was tried on the test person. 3 electrodes were attached to the test person's upper arm. These electrodes were connected to the input channel of DAQ through a probe. The captured signals were amplified using a Bioamplifier and were recorded in numerical and graphical forms in the PC (Figure 4.4).

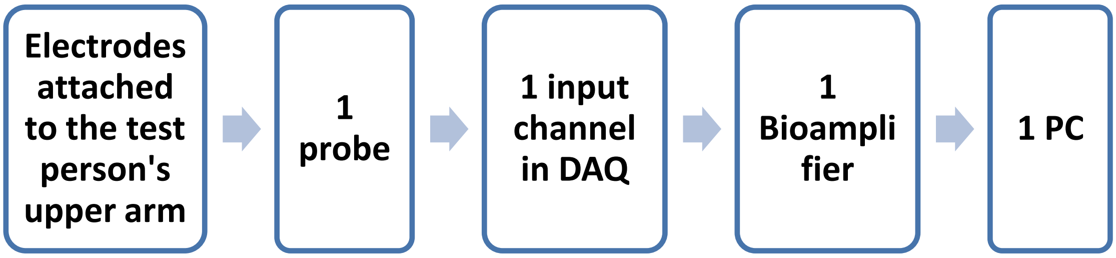


Figure 4.4 Data flow using EMG instrument

The DAQ system has a maximum capacity of 16 input channels and the software used to record the EMG readings is Chart5. A digital high-pass filter of cut-off frequency 60Hz was used to remove the low frequency noise signals.

More the EMG data, more inputs will be obtained for different gestures. Due to the availability of only one Bioamplifier, data collection was limited to only one input channel in the DAQ. The first channel in the DAQ is 0V (reference signal) and the 2nd channel was used to record the EMG signals. The DAQ and theBioamplifier are shown in Figure 4.5.

Figure 4.5 Bioamplifier (top) and the DAQ (bottom)

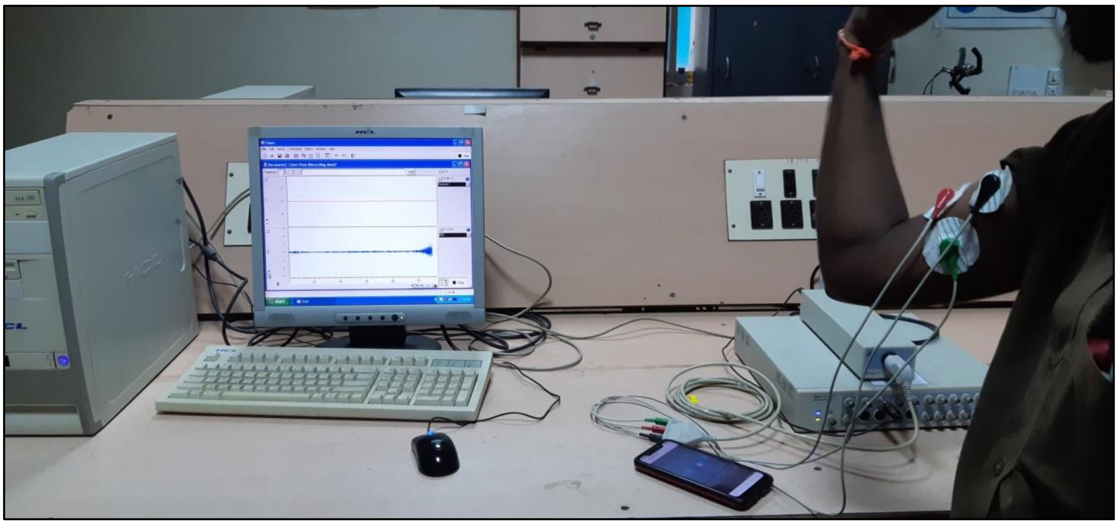


Figure 4.6 Recording EMG signals from upper arm using Bioamp EMG instrument

The instrument data collected from the EMG instrument (Figure 4.6) were given as training data to neural networks in MATLAB to find the percentage of accuracies in mapping to different gesture for one particular joint (Figure 4.7 to Figure 4.11).

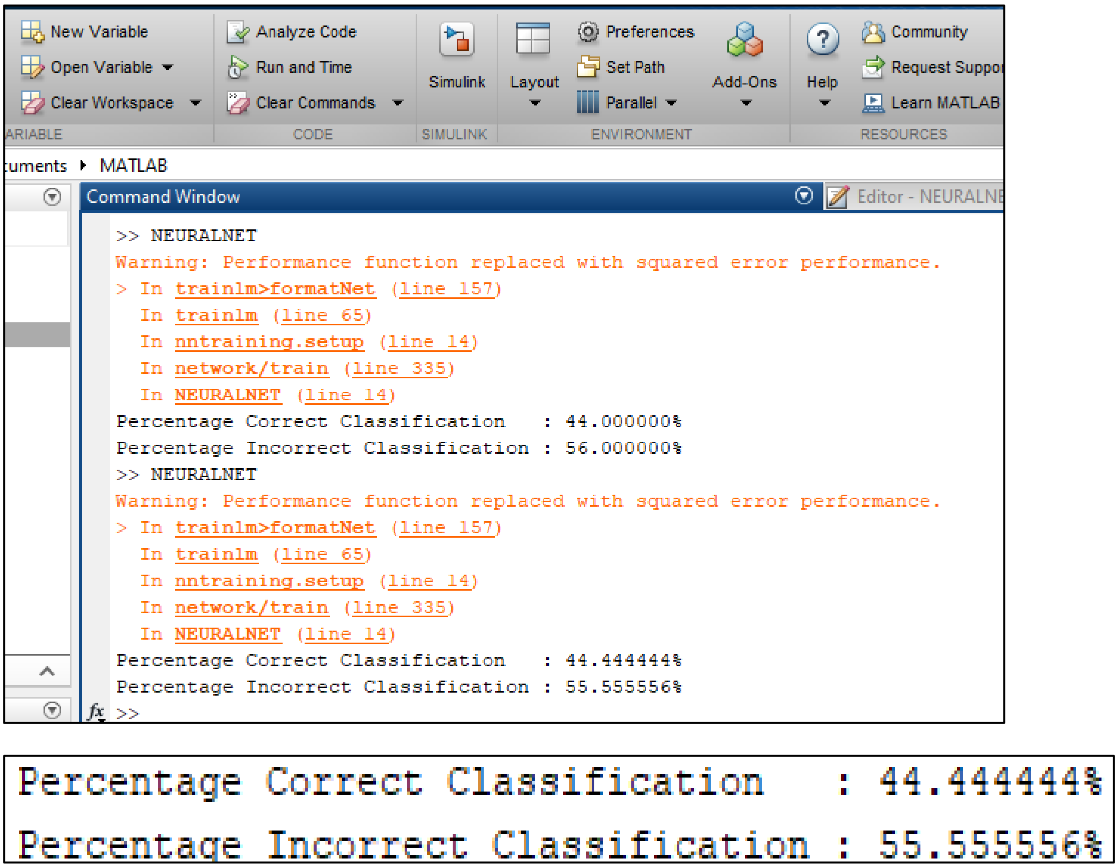


Figure 4.7 Neural Network in MATLAB for mapping of **elbow flexion** using Bioamp EMG instrument

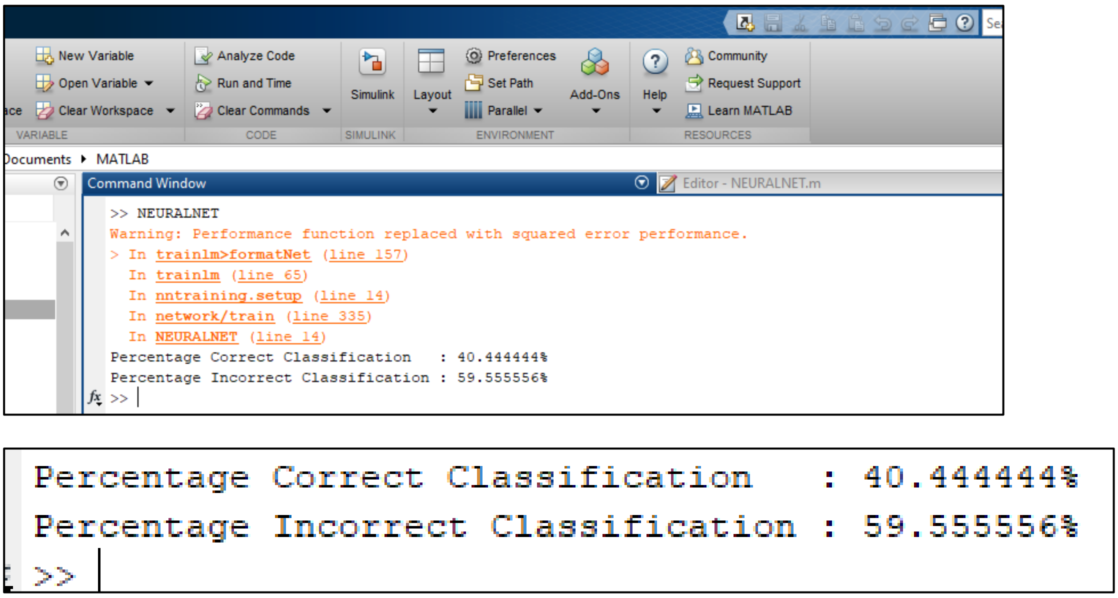
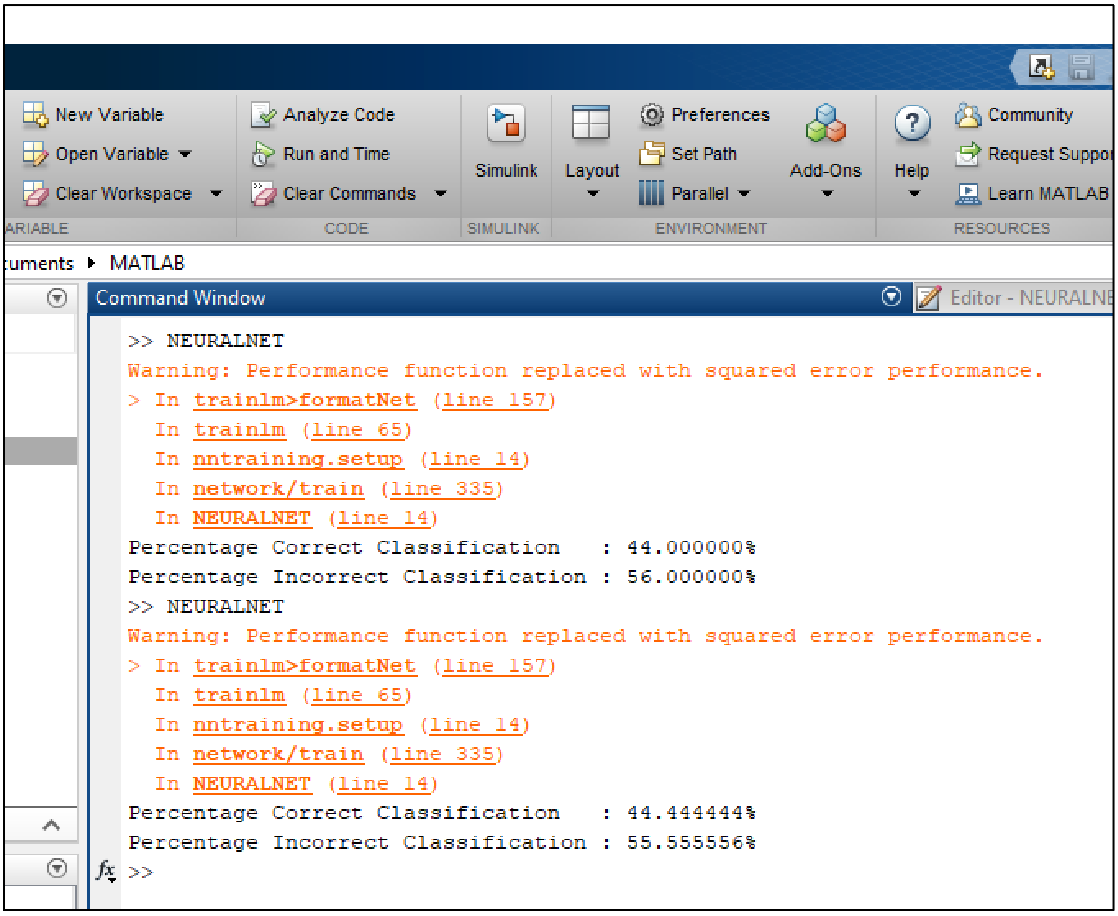


Figure 4.8 Neural Network in MATLAB for mapping of **wrist flexion (wave in, normal, wave out)** using Bioamp EMG instrument



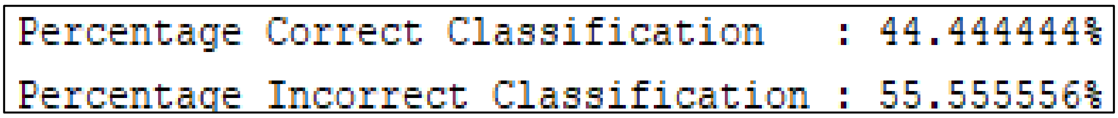


Figure 4.9 Neural Network in MATLAB for mapping of **elbow flexion** using Bioamp EMG instrument

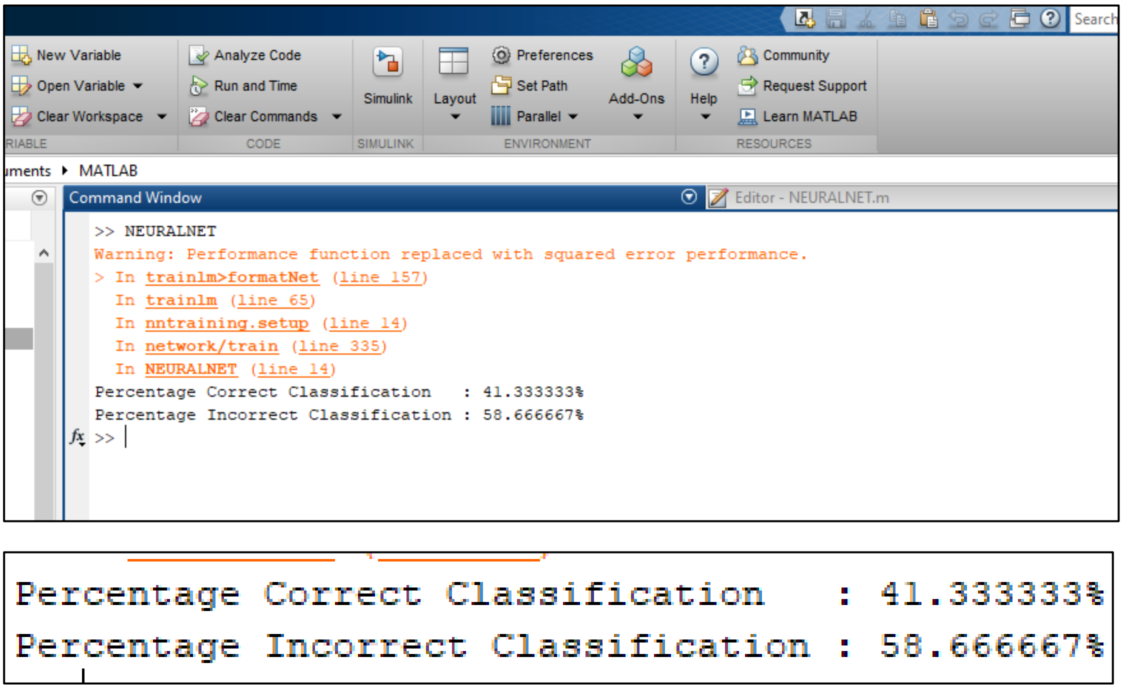


Figure 4.10 Neural Network in MATLAB for mapping of **pronation, neutral position and supination of wrist** using Bioamp EMG instrument

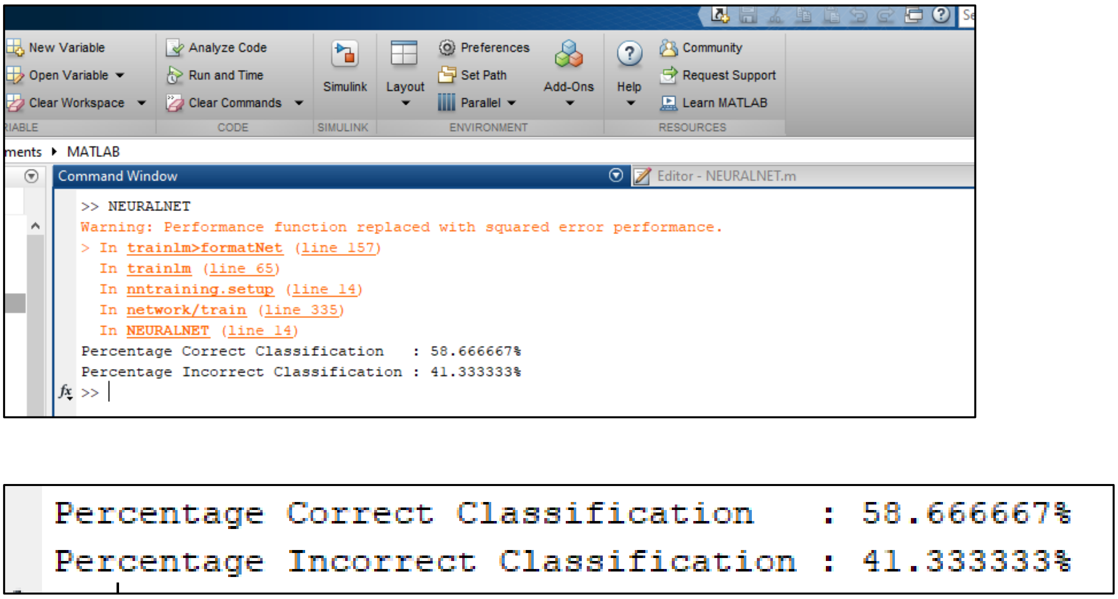


Figure 4.11 Neural Network in MATLAB for mapping of **opening and closing of fingers** using Bioamp EMG instrument

The reason for the low values of accuracy in mapping is that the instrument was able to detect only the transition from one gesture to another, i.e. the EMG instrument was able to give high values when the test person switched between gestures. The instrument readings (measured in millivolts) was nearly the same for different movements in the same joint.

4.3 Myoware Muscle Sensors

Each Myoware Muscle sensor (Figure 4.12) has electrodes that were placed on the test person’s upper arm to recor sensor data for different gestures.

Figure 4.12 Myoware muscle sensor

It was observed that this sensor gave considerable changes in output for different actions. (Figure 4.13 and Figure 4.14)

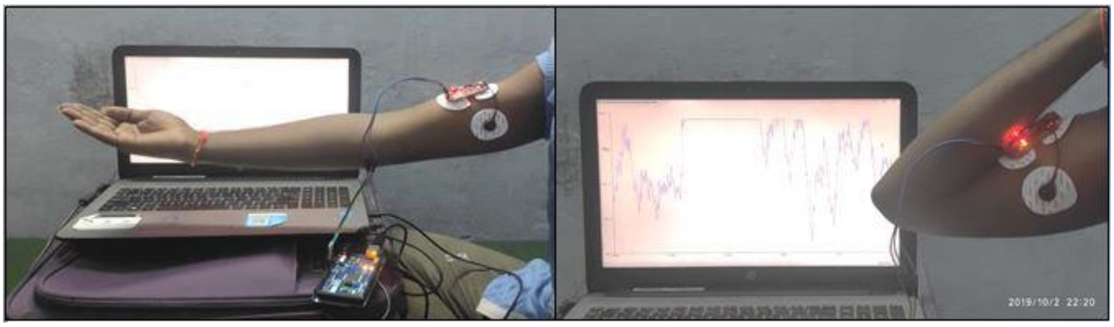


Figure 4.13 Flexion and extension of elbow

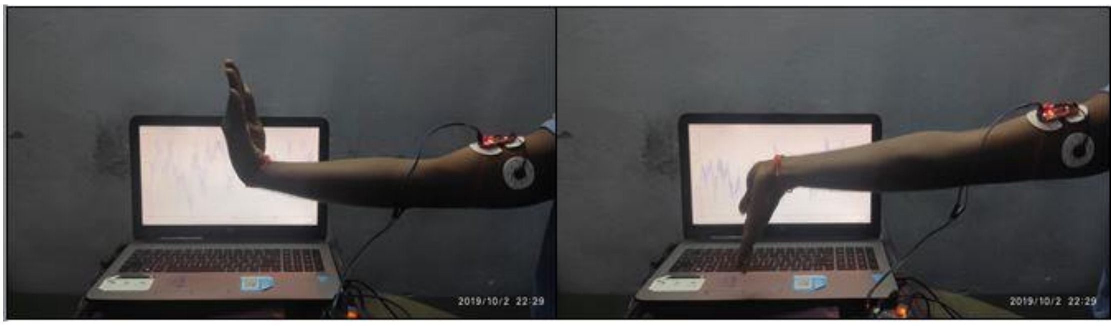


Figure 4.14 Flexion and extension of wrist Wave In and Wave Out

4.4 Inertial Measurement unit

3 Axis accelerometer gives the rotation of an object in X, Y, Z axes. This sensor can be mounted at the amputated end to capture the rotation of shoulder joint which is a major movement. This sensor is to be placed at the extreme portion of the cavity in the prosthetic part.

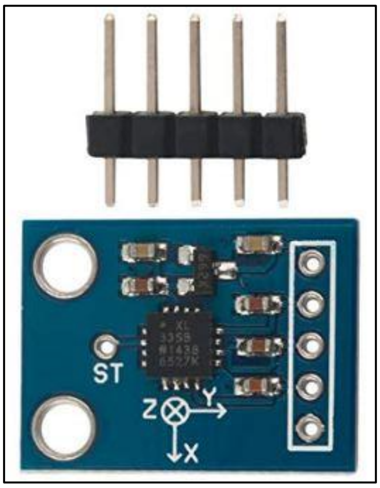


Figure 4.15 Adxl335 3 Axis Analog Output Accelerometer Module Angular Transducer

4.5 Strain Gauge

As mentioned in literature review (3.1), strain gauges (figure 4.16) could be placed on the control sites of the amputated portion or embedded in the cloth interface that contacts with the control sites to capture the small muscle signals.

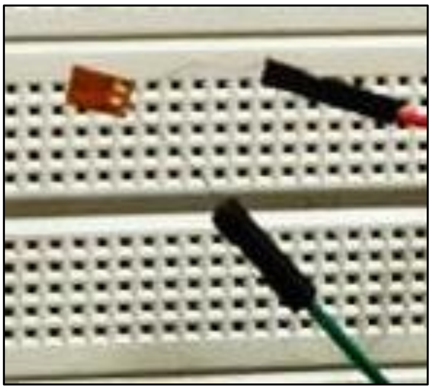


Figure 4.16 Strain Gauge

4.6 Sensor Glove

8 Strain gauges were attached to an elastic glove that can be worn on the amputated portion (Figure 4.17). 8 sensor data could be very useful for mapping different combination of upper arm muscle flexion to different gestures. When sensors are embedded in all parts of the cloth/belt strap that in contact with the amputated region, more input data could be obtained.

Figure 4.17 Sensor glove

5: CONCLUSION AND FUTURE SCOPE

It was observed from the experiments that one particular sensor could not cater the requirement of capturing muscle signals from the amputated region and the nearby regions. Some sensors were independent of the control sites (EMG band), while some of them requires locating the control sites (strain gauges, Myoware sensor). The inertial measurement unit (IMU) could be placed at the tip of the amputated end to measure the possible deflection of the half upper arm. His could be very useful for elbow flexion. The EMG band gave considerable outputs when placed on the lower arm of the test person, while it didn't so when placed on the upper arm of the amputated person. Arduino MEGA 2560 was used as the microcontroller board for all the sensors mentioned in this work. It does not the capability to store training data and test situ-in when neural networks are used. Thus, a new microcontroller should be sought. If a cloth is used as the interface material between the amputated end and the prosthetic arm, it may lose its elasticity due to prolonged use and the sensors will be in the same position (control sites). When compared with other interface materials such as silica sheet, plastic, rubber; a few variants of plastics such as Orthoplast can be used for flexible and customizable molds. Kydex and Nyoplex are high temperature plastics which are found to be suitable for upper extremities [27].

The mapping part can be considered as a Regression problem (Appendix B) under supervised machine learning wherein the traing stage will require the amputated person to flex his muscles for different (imaginary) movements and the sensor data should be recorded. The testing stage will involve the actual implementation of the trained network into the prosthetic system. An orthotic doctor should also be consulted to verify the correctness of the procedure.

The list sensors provided in Table 4.2 are planned to be used for capturing different gestures and controlling the corresponding joint motors.

Table 5.1 List of Proposed Sensors

S.No.	Sensor	Location of sensor	Gesture to be captured
1	Myoware muscle sensor	Shoulder and neck junction	Flexion of elbow, rotation of wrist
2	Strain gauge	Around the amputated portion	Fingers' flexion. Wrist rotation
3	Inertial measurement unit	At the tip of the amputated portion	Elbow flexion

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APPENDIX A

NEURAL NETWORKS

A.1 Introduction to Neural Networks

A neural network is collection of interconnected neurons. They are designed in a way analogous to that of a human brain in order to accomplish parallel processing and natural perception. These networks are used in cases involving data classification and pattern recognition. Input data is loaded into the network. The network takes in the data, which is called machine perception, labels them and clusters them into various categories. The pattern they recognise are numerical vectors, which can be translated to the requirement of a real world application such as output pulses to a motor, picture (a 2D vector of pixels), a sound track, etc.

A neural network consists of one input layer, one output layer and one or more than one hidden layers. The number of nodes (neurons) in input layer is the number of input sources (such as sensors, input pulses). The number of nodes in the output layer is the number of categories to which the data is required to be classified.

A.2 A Neuron in a Network

A neuron (also known as node) is the basic element of a neural network. It is capable of transferring data bi-directionally and also has mathematical computation capability. It is very similar to a human neuron. It takes in data (similar to dendrites in a neuron), transmits it across the neuron (axon) and passes it out (synaptic junction) to the adjoining neuron.

A.3 Back Propagation Algorithm

The Back Propagation Algorithm (BPA) is the most widely used algorithm for data classification and clustering using neural networks. It involves a series of bi-directional data passes between the layers. A forward pass takes places from the input layer to the output layer, through the hidden layer(s) and a backward pass takes place from the output layer to the input layer, through the hidden layer(s).

Numerical values called weights are assigned to every connection between two nodes. At the end of every backward pass, the weights are reassigned. This process continues until a certain minimum error between the targets and the outputs is reached.

An important parameter called learning rate is used in the reassigning of the weight values.

A.4 Training a Neural Network

Training of a neural network involves loading the network with a collection of input values and a collection of target values (for classification). The number of data values for input and target should be the same. More the number of data given to the network, better will be its performance.

The network is trained n number of times, where n is the number of data given to the neural network. It develops a mapping between the input dataset and the target dataset.

MATLAB provides a neural network toolbox and many data classification techniques, such as Neural Net Clustering, Curve Fitting, Neural Net Fitting, Neural Ney Pattern Recognition, Neural Net Time Series and some others. While MATLAB provides

Neural Network features with an easier user interface, Python provides a more advanced and flexible platform for implementing neural networks.

A.5 Parameters of a Neural Network

Performance of a neural network is determined by the extent of correctness with which it maps an input value to the required output category. More the performance of a neural network, lesser will be the errors between the output values and the target values.

The parameters which can be varied to tune the network's performance are:

- Learning Rate: Increasing the learning rate increases the convergence of the neural network towards the target. But if the learning rate is increased way too high, the neural network might bounce off the optimal performance.

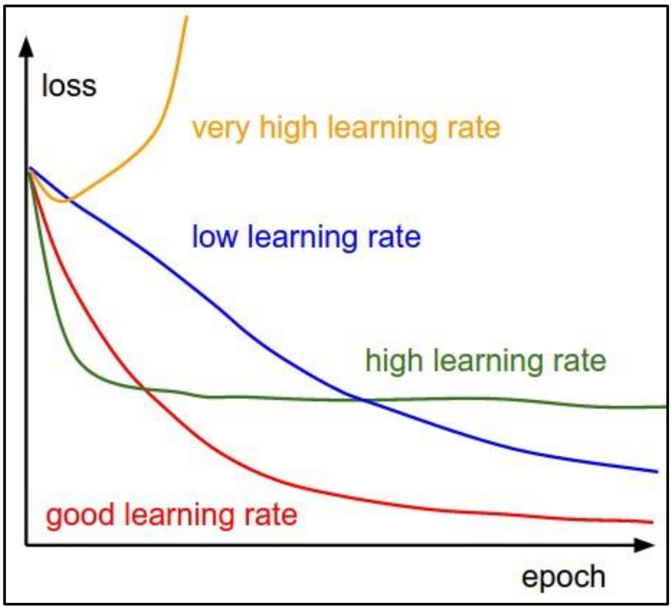

Figure A.1. Effect of learning rate on the performance of the neural network (Courtesy: Towards Data Science, Medium)

Note: In the Figure A.1, the x-axis corresponds to epoch, which refers to the number of times the network is trained with the datasets. And, the y-axis corresponds to performance of the neural network.

- The number nodes in hidden layer(s): Increasing the number of nodes in a hidden layer greatly contributes to optimization of the network's performance. Although more number of nodes in hidden layer(s) take a lot of training time, it yields more accurate results.
- The number of hidden layers: Increasing the number of hidden layers increases the performance to some extent. The network tends to give more accurate results with more number of hidden layers and lesser number of nodes in hidden layer(s) (increasing the network size breadthwise or horizontally) or lesser number of hidden layers and more number of nodes in hidden layer(s) (increasing the network size lengthwise or vertically).

APPENDIX B

SUPERVISED MACHINE LEARNING

B.1 Introduction to Machine Learning

Artificial Intelligence (AI) is the field of Computer Science that is concerned with the development of intelligent machines and intelligent computer systems that can think and work like human beings. It includes features like perception of environment, decision making, natural language processing (NLP) and computer vision.

Machine learning is a subset of AI that emphasises on learning and improving from performance, without being explicitly programmed. In conventional programming methods, the logic has to be formulated by the programmer. In machine learning, the machine learns (gets trained) from the input and target datasets, and formulates a logic that can map the inputs to the desired targets.

B.2 Types of Machine Learning

The major cdivisions of Machine learning is Supervised learning and Unsupervised learning.

- Supervised Machine Learning: The learning algorithm is provided with input datasets labelled with the desired output datasets. The goal of the algorithm is to find a mapping between the input datasets and the output datasets. The algorithm finds a best fit classification line that can divide the input data into partitions of different output category.
- Unsupervised Machine Learning: The learning algorithm is not provided with any labelled datasets. The goal of the algorithm is to find a mapping on its own. The learning algorithm tends to cluster input data into clusters defined by similar characteristics.

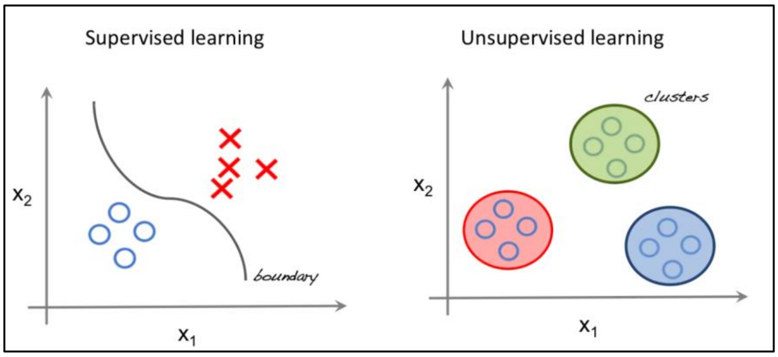

Figure B.1. Supervised and Unsupervised Machine Learning

B.3 Regression Problem

The Regression problem is a type of supervised machine learning that deals with continuous output variables. For example, output of an analogue sensor.is continuous in nature. Classifying sub-ranges of the sensor values to different categories is a regression problem. The input of a regression problem is required to be continuous and have a constant slope.