WEARABLE DEVICE FOR PREVENTING INJURY DUE TO THROWING

Undergraduate graduation project report submitted in partial fulfillment of the requirements for the

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in

The Department of Electronic & Telecommunication Engineering

University of Moratuwa.

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This is to certify that I/we have read this project and that in my/our opinion it is fully adequate, in scope and quality, as an Undergraduate Graduation Project.

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This declaration is made on October 6, 2017.

Declaration by Project Group

We declare that the dissertation entitled *WEARABLE DEVICE FOR PREVENTING INJURY DUE TO THROWING* and the work presented in it are our own. We confirm that:

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To Our Parents..

Abstract

WEARABLE DEVICE FOR PREVENTING INJURY DUE TO THROWING

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Supervisor: Dr. Pujitha Silva

Keywords: IMU, EMG, Injuries, Overuse, Poor Techniques, Unsupervised Learning, Analytics.

The modern sports arena in comparison to early days have become intensely competitive in nature, which has enhanced the focused on integrating technology towards sports enhancement. The amalgamation of technology with sports could be mainly identified in the areas of sports performance enhancement & sports injury prevention. This project focuses on using existing technologies and concepts to develop a wearable system which could be used for early injury prediction of athletes. The project focus is limited to injuries which occur due to different aspects of throwing which is visible in a range of sports. It has also been identified that overuse & poor techniques are the key drivers of injury. The designed system focuses on extracting the Electromyography (EMG) signals of identified muscle groups and joint angles of the human arm through Inertial Measurement Units (IMU) sensors in order to carry out analysis for injury prediction. The research focuses on obtaining the medical expertise from sports Doctors for medical interpretations in order to develop relationships & patterns to detect injury. Relationships on optimum muscle forces, muscle activation patterns & muscle co-activation patterns have been identified to provide an insight on the phenomena of overuse. Poor techniques of the athletes are monitored through the developed system by performing standard medical tests such as the carrying angle test and optimum operating region tests identified. It is important to note that the researchers focused on the complex dynamic motion of throwing

with resting intervals in between which prompted towards the development of an unsupervised learning algorithm which focused on features related to throwing yet to be explored. The team focuses on fine tuning the developed algorithm through further data acquisition in future. The identified crucial indicators of possible injury are presented through the developed web / mobile application which provides an easily interpretable graphical user interface. The research is of great value towards the athletes at it would enhance the players to perform in their optimum capacity avoiding injuries and the loss of potential sports events due to potential injuries.

Acknowledgments

We wish to extend our heartfelt gratitude to our Project Supervisor Dr. Pujitha Silva for the constant supervision & guidance provided to us which ensured the successful completion of the project. The weekly meetings, progress assessments and the motivation sessions were of great value for us during the challenging obstacles we overcame during the course of the 12 months of the project. Your advices and inspiration would certainly be of great importance for us in life & personal development as a fresh graduate entering the industry.

A special thanks is extended to Dr Mrs.Daminda Attanayake of the Sports Ministry for providing us with the valuable medical advice and insights towards the project, and Mr Damith Warusuwithana, Head Coach of Fingara Cricket Academy for providing us with the practical knowledge related to athletes which ensured a successful approach towards tackling the assigned project objectives.

We would also like to thank the Head of our Department Prof Rohan Munasinghe and all the academic staff for providing their advices and insights towards the project and support extended through providing resources and laboratory facilities. A special thanks to Mrs. Salgado for all the encouragement extended to us in the domains of developing verbal & written skills related to English enabling us to achieve success in the international arena.

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The assistant provided by the voluntary participants during the study is highly appreciated and acknowledged, without which the project would not have been a success. Finally, we also wish to thank all our colleagues who helped us towards the project and for creating a budding environment. We wish all of them a prosperous future.

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Acronyms and Abbreviations

IMU - Inertial Measurement Unit

EMG - Electromyography

ETS - Electromagnetic Tracking System

OLE - Optical Linear Encoding

MER - Maximal External Rotation

SRO - Safety Region of Operation

RMS - Root Mean Square

BCP - Biceps

TCP - Ticeps

DTD - Deltoid

SUP - Supraspinatus

INF - Infraspinatus

SUB - Subscapularis

TMR - Teres Minor

FLX - Flexor carpi Radialis

BRA - Brachioradialis

ZCR - Zero Crossing Rate

PCA - Principal Component Analysis

SVD - Singular Value Decomposition

Chapter 1

INTRODUCTION

In the modern high competitive sports arena, we can identify instances in which talented sportsmen being ruled out of their respective sport due to injuries. If we conduct a survey on the most prominent injuries present we could identify that throwing injuries and hamstring injuries are of most frequent occurrence. Such injuries could deprive the athlete from playing their respective sport for a period of time, and if severe it could also result in the end of his or her sports career.

This has been a major concern in the sports arena where the sports coaches and managers want to ensure that their players are fully fit, so that they will be able to take part and represent their respective teams in crucial and important sports competitions. The root cause of such injuries are due to poor management of players and the inability to monitor the athletes. This project would identify the throwing injuries and evaluate the technology applicable in order to propose a suitable solution.

Throwing could be identified as an integral component in sports such as tennis, cricket, baseball, water polo, athletics etc. Players who have a poor technique when it comes to throwing are more prone for such injuries. Hence the coaches and physiotherapists must focus on identifying these techniques and correcting them to aid the player. Although it should be noted that it is a hard task to identify the technique through the naked eye. Thus in the context of this project, we would obtain necessary data from players and process them to come up with the tendency to get prone to a throwing injury.

1.1 Problem Statement

The modern sports arena is highly competitive in nature and due to the increased number of sports events the number of injuries which affect the athletes have also increased. The injuries could be mainly classified as upper body injuries and lower body injuries.

This final year project would focus on detecting upper body injuries with a main focus on the upper limb of the human arm. In numerous sports it is identified that the action of throwing is quite common and thus the importance of focusing to develop a system to prevent injuries which occur in the human upper limb due to throwing. These injuries are mainly associated with overuse and poor techniques of the athletes.

It could be identified that technology plays a major role in sports in the present day's context which highlights the importance of such a system to enhance the performance of the players as well as safeguard players from potential injuries.

1.2 Primary Objectives

The main objectives of the project could be identified as follows,

1 Developing a wearable device which can extract data from Players.
2 Develop a system to predict upper arm injuries through the development of relationships using obtained data and existing literature.
3 Develop a web/mobile application for visualization.

1.3 Scope

There is a larger number of types of throwing available in modern sporting arena such as Baseball pitching, javelin throw and cricket bowling ect. In this research, the scope is narrowed down to cricket fast bowlers and cricket throwers / fileders. The reason behind is that, In Sri Lanka, it's easy to find injured/ uninjured cricket throwers as well as coaches, physiotherapists, managers and doctors treating players. Further, the scope of the project has been narrowed down due to the time and resource limitations. From an anatomical perspective, the main focus of the project would be on the upper limb up to the Glenohumeral joint and the rotator cuff. The rationale behind the selection is presented as Figure 1.1. According to the research [6] carried out in Imperial college, London, there are 21.7% of probability that an injury can be around Glenohumeral joint. Thus, the respective part of the anatomy is selected.

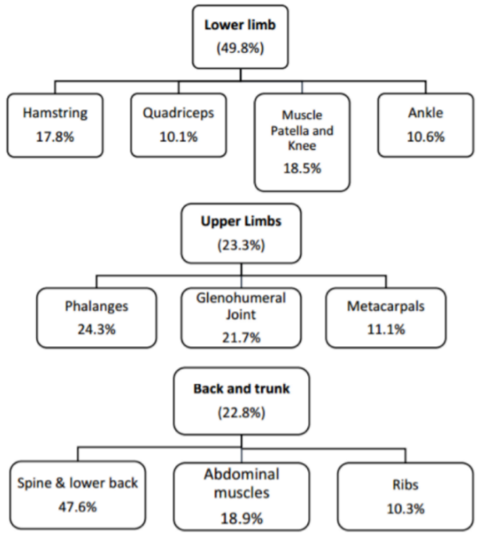


Figure 1.1 Areas of Injury related to Cricket

1.4 Review of Literature

1.4.1 *Identified Literature*

A comprehensive literature review is done with regards to the project. We have divided the complete literature review into several parts.

1.4.1.1 Wearable Technologies to extract Motion data

- IMU (Inertia Measurement Units)

Inertia measurement unit consists of Accelerometer, Gyroscope and Magnetometer. Three common types of accelerometers are available, namely, piezoelectric, piezo resistive, and capacitive accelerometers [1].Piezo-Resistive and capacitive accelerometers can provide dual acceleration components and have higher stability. Therefore, these types of accelerometers are suitable for measuring the motion status in the human gait[2]. Thus, these accelerometers can be used to track the movements in the arm.

- Flexible Goniometer.

A flexible goniometer can be used to measure the relative rotation between two human body segments. The flexible goniometers can be divided into strain gauges, mechanical flexible, inductive, and optical fiber goniometers. [1]

- Electromagnetic Tracking System (ETS)

The electromagnetic tracking system is a kind of 3D measurement device based on Faraday's law of magnetic induction. When an object carrying sensor coils performs a motion inside controlled magnetic fields, the induced voltages in the sensor coils will change, with respect to the change of the object's position and orientation, relative to the source of controlled magnetic fields.[3]

- Sensory Fabrics

The sensing fabric is a combination of sensing technology and fabric, which ranges from very superficially attached electronic components to a substitution of fibers and yarns with sensing properties inserted in normal fabrics, to electronic components made of fabric materials. Compared with other wearable sensors, the sensing fabric is more flexible and comfortable in measuring human posture and movement. [1]

- Optical Linear Encoding. (OLE)

In Optical Linear Encoding, the motion of an optical encoder on a code strip is converted to the limb joints' goniometric data. As described in the project [4], a collection of IMUs with OLE system can be used to capture the motion of the arm.

1.4.1.2. Sensors to Extract Electromyography (EMG) Signals.

To measure the action of the muscles in the lower extremity in a human gait, the EMG was developed to perform an indirect measurement of muscle activity using surface or wire electrodes. These electrodes are a kind of sensor for EMG and can detect voltage potentials to provide information on the timing and intensity of muscle contraction.These sensors been commercialized in combination with wireless technology. [1]

There are few EMG-included devices which can be used as input system for the project. Myo from Thalmic labs [5] is a wearable device which has IMU and EMG sensors included.

1.5 Alternative Strategies and Methodologies

- Image Processing Approach.

The problem identified may have been solved partially by an image processing approach using cameras, Kinect sensors, etc. But practically, in an outdoor cricket stadium, this approach is not feasible.

- Form Factor of distinct wearable bands.

Distinct wearable bands may appear as a good solution but according to the cricket coaches and players, it’s not comfortable to wear when bowling. IN addition, the bands may be instable in fast moving hands.

- Statistical Methods to prevent injuries

This is the method currently used to prevent injuries. The number of deliveries will be counted in this method. However no muscle activity or effort is considered in this method.

1.6 Anatomical Study

1.6.1 *Muscles analyzed.*

The following muscles are identified as prominent muscles which are related to rotation of shoulder and elbow according to the literature and according to the feedback from the Sports Doctors.

The following muscles in rotator cuff is analyzed to examine the Glenohumeral joint and the shoulder movements. Figure 1.2 shows the rotator cuff muscles.

1. Supraspinatus (SUP)
2. Infraspinatus (INF)
3. Subscapularis (SUB)
4. Teres Minor (TMR)
5. Deltoid (DTD)

The following muscles in upper arm and forearm are analyzed in order to examine the behavior of elbow movements. The figure 1.3 shows the muscles in forearm and upper arm analyzed.

1. Biceps (BCP)
2. Triceps (TCP)
3. Flexor carpi Radialis (FLX)
4. Brachioradialis (BRA)

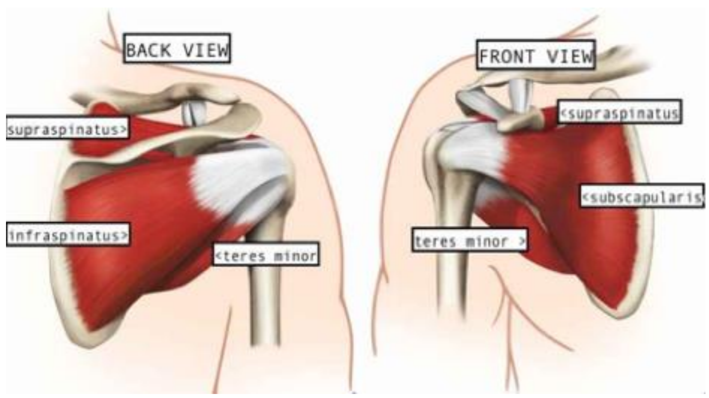


Figure 1.2 Rotator Cuff Muscles

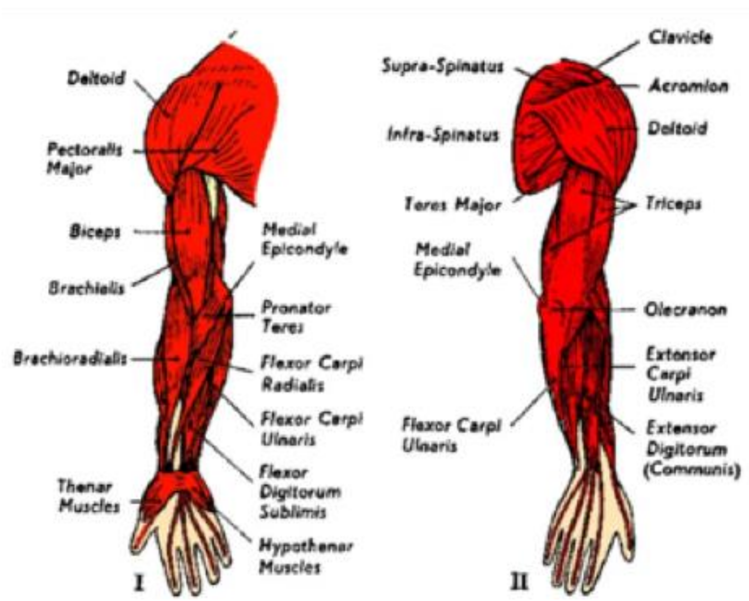


Figure 1.3 Muscles in Upper Arm and Fore Arm.

1.6.2 Parameters analyzed.

Wide range of parameters are analyzed on each muscle in order to get a broad idea about what is happening in the respective muscle causing an injury. In addition to EMG extraction, inverse kinematic techniques with IMU data were used to evaluate several parameters of the muscles such as Normalized Fiber Velocity, Muscle Tendon Length, Active Tendon Force, Passive Tendon Force, Total Muscle Force, Muscle Activation.

1.6.2.1 Parameters identified from EMG.

EMG signal is extracted from each muscle so that the RMS, Mean Frequency, and Zero crossing rate can be identified as factors relating to the muscle activity in the respective muscle.

1.6.2.2 Parameters identified from EMG.

Though the IMU data obtained from our hardware are fed into an algorithm to calculate joint angles and a motion file representing the changes in the motion with respect to the time. This motion file is fed in to OpenSim and thus these parameters are calculated.

- Muscle Tendon Length.

Muscle tendon length varies according to the amount of extension / flexion. If the muscle is extended beyond the optimum range, there is a chance of an injury.

- Active and Passive forces

The basic idea of active and passive force is that passive force represents the amount of energy absorbed by the muscle from the physical energy of the player. In contrast, passive force is generated after extra extensions of the muscles, leading to injuries.

- Muscle Activation

This is another parameter calculated through inverse kinematic techniques. Muscle activation represent how much the muscle is activated which gives and idea that one muscle may have activated than other muscles leading to potential injuries.

Summary

This chapter is a comprehensive introduction for the project specifications. The identified problem statement which is a common occurrence among sporting personalities in the modern context is being discussed thoroughly. Further a scope has been set to carry on the project along with the identified literature review and alternative strategies that address the same problem statement. The main muscles analyzed in Glenohumeral joint, upper arm and forearm are identified. In addition, the parameters of the muscles calculated are describe.

Chapter 2

SOLUTION FOR THE PROJECT

Introduction

The developed solution focuses on the practical aspect of the application as well as the technical, financial, social and legal feasibility of the project. The project integrates the use of an IMU and EMG based system which can be ideally deployed in open environments where the training sessions of fast bowlers and throwers of cricket take place. The solution presented is also advanced as its sole focus is not restricted to statistical methods currently used but rather a focus on classification techniques and unsupervised machine learning techniques would also be integrated. The wearable would be developed considering the form factor and user experience taken into consideration within the use of the device. Hence the developed solution adds great importance and value to the cricket fast bowlers and throwers to predict injuries and enhance performance, thus the uniqueness of the solution.

2.1 Basic Architecture of the Project

The System can be identified as 3 main parts as per the objectives.

1 The hardware to extract IMU & EMG and Data collection
2 The data analysis and classification
3 Data Visualization

Apart from the above main sections of the project, the consultation was done with Mr.Damith Warusawithana, Head Coach, Fingara Cricket Academy in order to get their feedback about the system and with players from the academy to get feedback about the design and details about the injuries. In addition to that, a collaboration was made with Dr.Daminda Attanayake, Doctor for Sports, Ministry of Sports, Colombo in order to get feedback and suggestions about the project. With the Doctors, players, coaches inputs together with existing research results, the research was carried forward and at the end. The designed system obtains the IMU and EMG data of the user during the practice sessions through the wearable device. These data is analyzed along with additional anthropologic data and player profiles obtained. Subsequently all the obtained data is processed to identify crucial relationships and patterns in order to detect anomalies which would occur due to the tendency of injuries. The processed information is visualized through a web application which enables the user to identify potential threats and thus manage the players effectively. Further the processed output of data are shown to sports doctor to get their feedback.

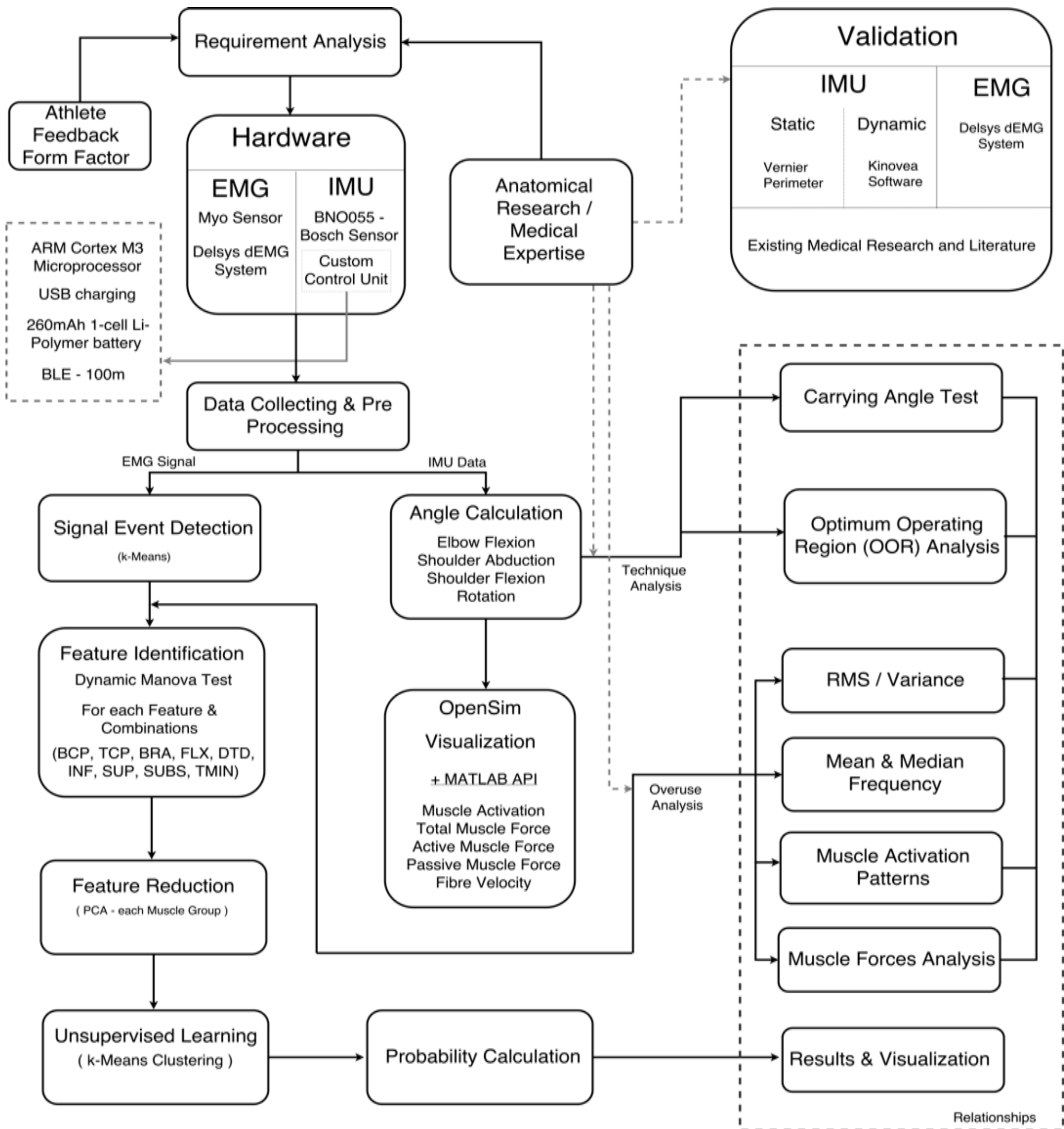


Figure 2.1 Basic Architecture of the Project

2.2 Technical Feasibility of the Solution

- Inertial Measurement Unit (IMU)

High Accuracy IMU Sensors (BNO055 from Bosch) are used to capture motion parameters. IMU sensors consists of Accelerometer, Gyrometer and a Magnetometer. However, the accuracy and the data rate of the inbuilt IMU sensor is not sufficient in capturing high speed motions. Thus, high accurate Accelerometer and a Gyrometer will be used separately, in sensor modules where high rate of data is needed to simulate the motion accurately. BNO055 has its own algorithm, a Kalman implementation so that the absolute orientation is provided. The BNO055 can connects with the microcontroller with I2C which has its own calibration mechanism.

- Electromyography (EMG)

The purpose of EMG sensors is to obtain the EMG Parameters so that the Muscle activity level of upper limb could be analyzed. Further through this analysis, parameters which represent overuse, are identified through Unsupervised Machine Learning techniques where it would be beneficial to predict injuries due to overuse of a Muscle. Moreover, we are obtaining the surface EMG of the Muscles, which will track the electrical activity produced by those during necessary activities. However, the activity of the inner muscles could not be analyzed through this technique. As the EMG measurement system, MYO band from Thalmic labs is used after evaluating several EMG extraction systems. The system needed to be wireless and less costly. Therefore, the ideal option is MYO band which has been used in literature. Apart from the MYO Sensor, The Wired EMG system from Delsys Inc which is available at University of Moratuwa is used for further analysis. Figure 2.2 shows the MYO band sensors used, and Figure 2.3 shows the Delsys Wired EMG system used to extract EMG from Shoulder muscles.

Figure 2.2 Myoband Sensors used to extract EMG wirelessly.

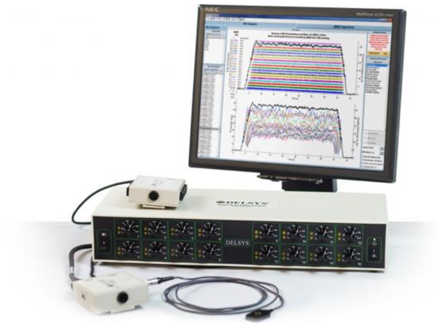


Figure 2.3 Delsys EMG system (wired), used to extract EMG on shoulder muscles.

2.3 Potential Beneficiaries of the Project

Cricket could be identified as a major sport in today's world and thus a greater deal of time, money and effort has been focused upon. Although there does not exist systems which are able to detect injuries of players in advance and thus better manage them. Thus, in essence the system to be developed would be immensely beneficial for the players (fast bowlers) themselves as well as the Coachers, Managers, Physiotherapists for their management of players. It can also be identified that this system can be also used as a medical screening device which would aid the Doctors. It is also expected that the successful development of this project would lead to extending the system towards various other sports, which would ultimately result in catering the needs of many sports athletes and players.

Summary

This chapter presented a proposed solution. The basic architecture of the project includes obtaining IMU and EMG data from the player and processing the above-mentioned data to derive relationships. Further the technical feasibility and the potential beneficiaries of the project was also being considered.

Chapter 3

WEARABLE DEVICE DESIGN

Introduction

This chapter identifies the development of the wearable device used for the acquisition of data to develop the anticipated relationships between the physical parameters extracted and injuries. The developed wearable device can be categorized mainly as the hardware design and the wearable sleeve design. The hardware design identifies the two standalone systems within the device namely the EMG system and the IMU Sensor System. The design phases, design methodologies along with the different design constraints would be discussed in this chapter to identify the most suitable design to accomplish the identified task.

3.1 Wearable Inner Skin Design

The form factor of the wearable design possesses great importance due to the application focused in this project, cricket fast bowling. Through the consultation of cricket fast bowlers, throwers and coaches it was identified that the wearable device should be developed to withstand the high-speed motion artifacts. The wearable developed is able to place the sensors appropriately in a manner such that any relative motion doesn’t exist between the bowler’s arm and the developed wearable. It was identified that the form factor of distinct arm bands to place the sensors were in appropriate due to the slipping of the bands which occurred during fast bowling. It was also identified that the bowlers / throwers comfort also needed to be focused, so that the bowler does not feel any constraint or limitation which would affect his bowling style. The adjustability of the wearable to players of different sizes was also considered during the development of the sleeve. Hence considering all the design constraints a wearable was designed in the form of a cricket inner skin using a material which specifically attaches to the body to reduce any relative motion artifacts. Velcro straps were attached at the identify regions to place the sensors appropriately and thus extract the readings. A pocket was also designed within the wearable to place the main printed circuit of the design and the battery to power up the system. It should be important to note that all identified practical constraints were rigorously analyzed during the design of the wearable.

Figure 3.1 Cricket Wearable

3.2 Hardware Design

The hardware design comprises of two main subsystems namely the IMU Sensor Network and the EMG System. The following section identifies the technical aspects of the designed and developed system as well as the technical specifications of other used systems related to hardware.

3.2.1 IMU Sensor Network

The IMU system is important to obtain the motion input of the players in order to develop relationships between the joint angles as well as the generated muscle forces during fast bowling and throwing. The designed system comprises of three sensor nodes places on the regions of the arm as depicted in the Figure 3.2.

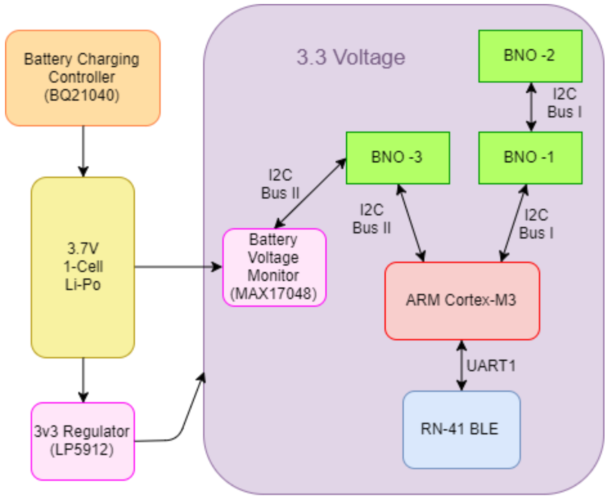


Figure 3.2 IMU Sensor Node System.

The IMU sensor nodes would be connected to the main control unit which would be located at the back of the developed cricket inner skin. The IMU sensor nodes were designed in a miniaturized manner to eliminate the bulkiness which would affect the bowling action of the players. The dimensions and the network design are presented in Figure 3.3.

IMU System

Individual Sensor Unit
< 1cm x 2.5cm x 0.4mm >

Control Unit
< 3cm x 4cm x 1.2mm >

Figure 3.3 IMU Sensor Unit and Control Unit

The main technical specifications of the developed sensor can be listed down as follows. It is important to note that the sensor design was carried out application specific to cater the needs of cricket fast bowling.

- Size and form factor specialized for cricket.
- Design for Higher angular velocity capturing.

Gyroscope	(250 to 4000) degree/s
Accelerometer	(2 to 16) g
Compass	(4800) uT

- Centralized processing unit and distributed sensor network.
- In house processing using ARM Cortex M3 microprocessor, reduces the amount of data communicated, thus fast and efficient and easy to sync motion sensors.
- Battery monitoring with Charging controlling.
- Easy USB charging with mobile phone charger.
- 260mAh 1-cell Li-Polymer battery powered device.
- Bluetooth low energy for low power data transmission up to 100m.
- Power saving mechanics.

For the IMU System we initially design our own system. In the custom system we chose STM32F103C8 microprocessor which has ARM Cortex-M3 architecture. Mainly we selected it because of the following advantages,

- 32-bit register size so it help us to have enough variable size.
- 20 kByte RAM to run our filters and other programs.
- Two hardware I2C serial interfaces to access more Sensor Nodes.
- 72Mhz clock speed to make to speed up the programs.

When we design the system we make sure it is complete wearable device by integrating battery charging and monitor functionality to our system with one cell Lithium Polymer battery. Figure 3.4 - 3.6 depicts the design of the control unit designed by Altium Designer tool.

Initial design for Sensor Nodes of IMU system was a failure due to soldering facilities were not good enough to solder component such a small ICs. Our first design for sensor node consist of following integrated circuits,

- MPU 9250 - IMU sensor
- H3LIS - gyroscope
- ITG 3701 - accelerometer
- P82B715 - I2C bus extender

Figure 3.7 - 3.9 are showing the design of Sensor Node by Altium Designer tool.

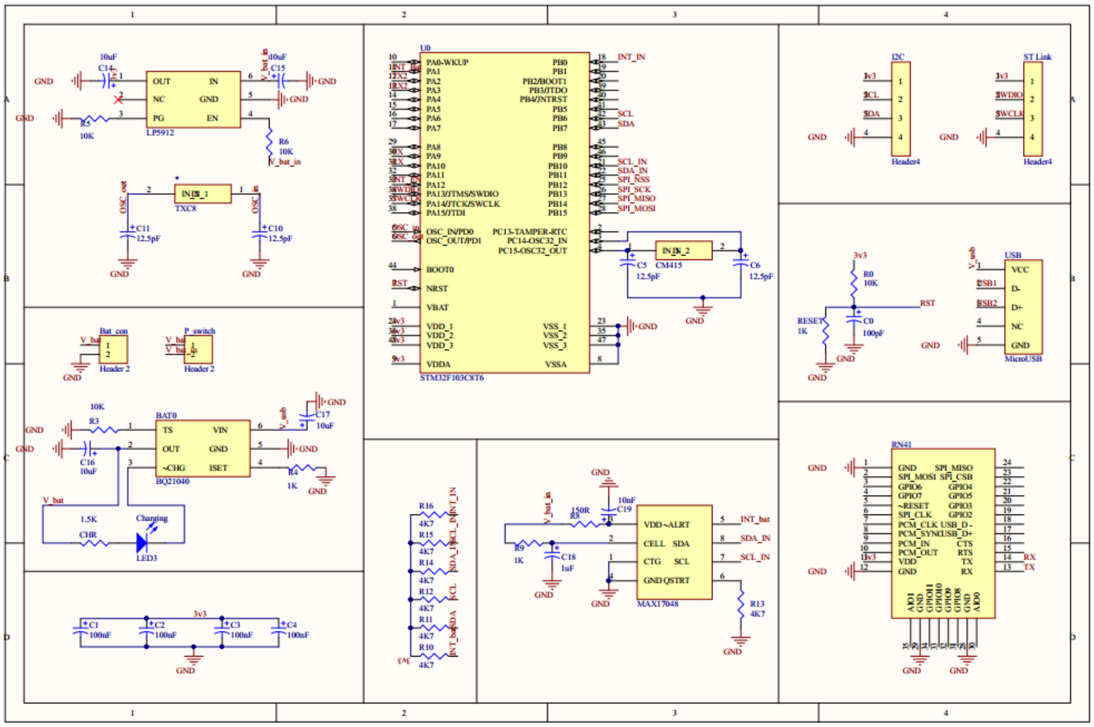


Figure 3.4 Schematic design for Control Unit of IMU system.

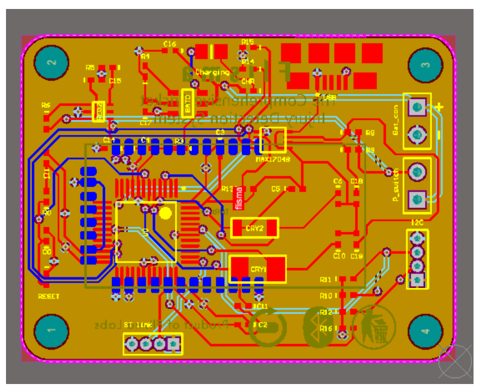


Figure 3.5 2D view of Control unit of IMU system

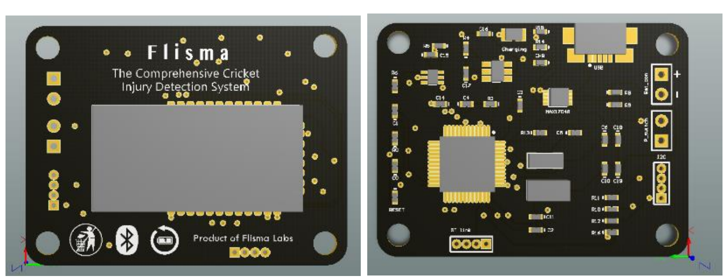


Figure 3.6 3D view of Control unit of IMU system

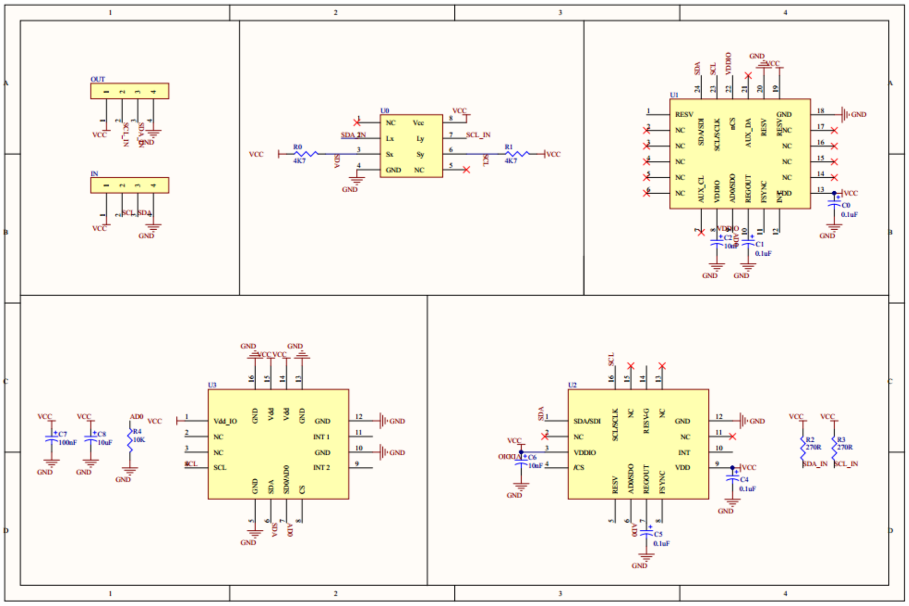


Figure 3.7 Schematics design of Sensor Node

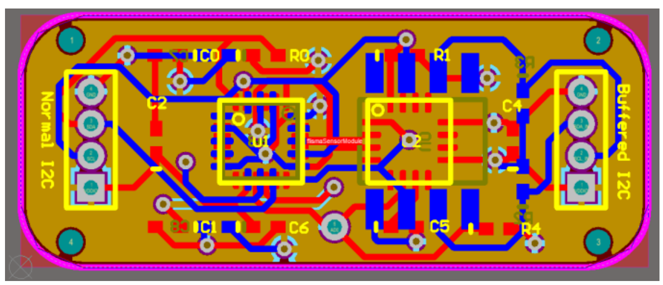


Figure 3.8 2D view of Sensor Node

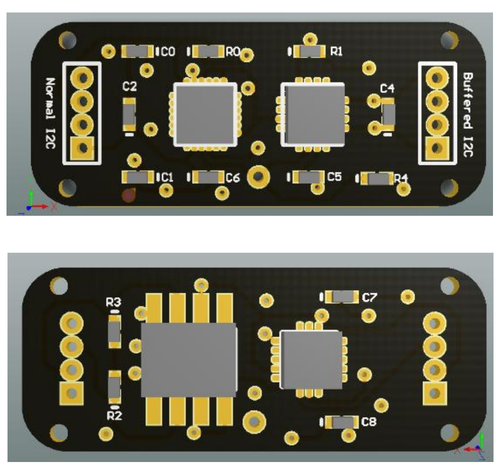


Figure 3.9 3D view of Sensor Node

Since soldering constraint, we had to design temporary IMU system using Arduino Nano board which base on ATmega328 chip. Then we had to develop software I2C interface along with provided hardware I2C interface of that chip. We also choose BNO055 Bosch Sensor module (Figure 3.10) as our sensor node of IMU system due to the soldering constraint.

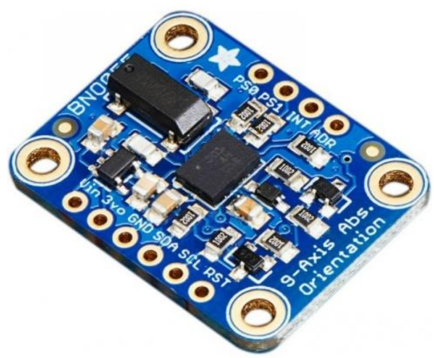


Figure 3.10 BNO055 Bosch Sensor module

Since we wanted a calibrated sensor system, we kept our system power on, our battery charging, and monitoring ability of the system enabled us to achieve that objective. If any case, we lost that power of the system following procedure will restore calibration.

1 Place every sensor module horizontally for about one minute.
2 Move each sensor in a infinity symbol in horizontal plane.
3 Then rotate the sensor module about Y - axis 45 degree and wait for 30 second for two times.
4 Perform this until each sensor stop showing calibrating state in sending data.

We speed up the calibration task by memorizing the previous calibration data in EEPROM of the processing unit.

3.2.2 Electromyography (EMG)

The Electromyography (EMG) of the athletes should be extracted with great accuracy from the muscles identified above. Thus the possible alternative methodologies were brainstormed to identify the most feasible within the project constraints. It was identified that commercial high end wireless EMG systems were present such as Delsys, Myon and BioMetrics Ltd. However, the cost of such systems exceeded the project budget and thus a more cost effective method was analyzed.

Since the injury relationships to be identified was a crucial element of the project the accuracy level of the EMG acquisition was identified as of utmost importance. Thus, the elimination of the option of developing our own sensors which would greatly affect the time constraints of the project as well as the accuracy of the readings. Considering all the possibilities a low cost commercial product which has been used for prior research and which had already been validated was used. The product selected was the Myo Armband developed at Thalmic Labs.

The experimentation was identified to place 2 Myo Armbands on the identified muscle groups and thus obtain the EMG signals for the analysis. The wearable sleeve was developed to facilitate the use of 2 Myo Armbands for data acquisition purposes.

Figure 3.7 Myo Armband

Summary

The designed wearable device was analyzed to meet the practical constraints and the unique features of the developed IMU Sensor Network was discussed within this chapter along with the suitability and the rationale for the use of a Myo Armband for the acquisition of the EMG.

Chapter 4

DATA EXTRACTION

Introduction

This chapter focuses on identifying the methodology of data extraction and the preprocessing required in order to develop the extracted data towards the state of analysis. It should be noted that publicly accessible data sets were unavailable for the specific action of throwing and fast bowling which the project focused upon. Thus, the data sets were developed from scratch for analysis.

During the project time period a total of 6 voluntary test subjects participated in the study. Three of the players were asked to throw a cricket leather ball repetitively towards a constant distance of 25 meters while the rest carried out the action of fast bowling. The test subjects ranged from ages 19 - 24 years, with a height of 170 - 177 cm. The Experimentational setup of the IMU & EMG sensors are presented in Figure 4.1. An application was developed to log the IMU & EMG data of the respective bowls with their timestamp in order to sync the data obtained from the two standalone systems. The application was developed in a manner such that any false readings, device disconnections would be identified and alerted if occurred.

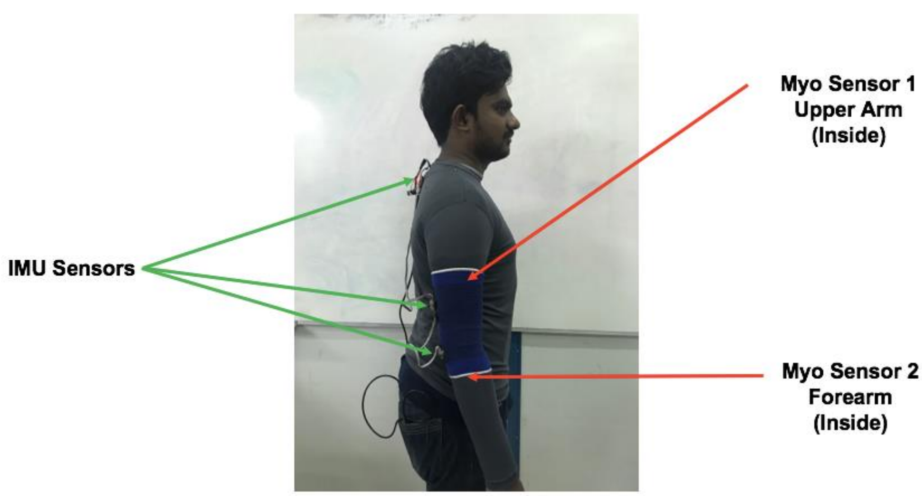


Figure 4.1 Experimentational Setup

4.1 EMG Signal Pre-Processing

The raw EMG signal was obtained through the Myo sensors placed on the identified 4 muscles in the arm. The signal was subjected to standard filtering in order to eliminate the motion artifacts and noise from AC voltage sources. (during data acquisition via the Delsys System) A 20 Hz High Pass Butterworth filter was used to eliminate the motion artifacts and a notch filter at 50 Hz to avoid line interference.

The EMG signal was processed afterwards in order to identify the event of throwing within the EMG signal. A number of methods were evaluated to extract the part of the signal corresponding to the throwing action. First a method to set fixed threshold for extraction was used which was inefficient. Afterwards a method of cross correlation and clustering was used. The clustering method provided better results in extracting the relevant part of the EMG signal. The processed and extracted signal is used for the analysis presented in the next section. The block diagram of the EMG signal preprocessing is presented in Figure 4.2 below.

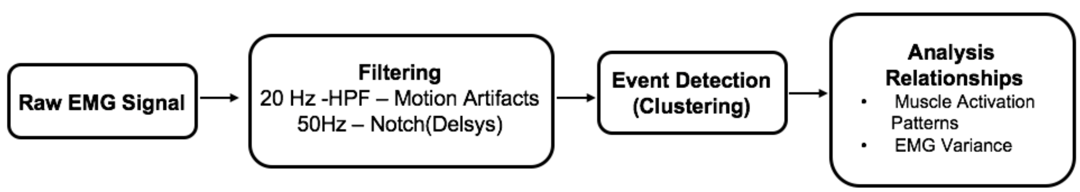


Figure 4.2 EMG Signal Pre – Processing

4.2 IMU Mathematical Model Development

The basic block diagram of the IMU preprocessing is presented in Figure 4.3.

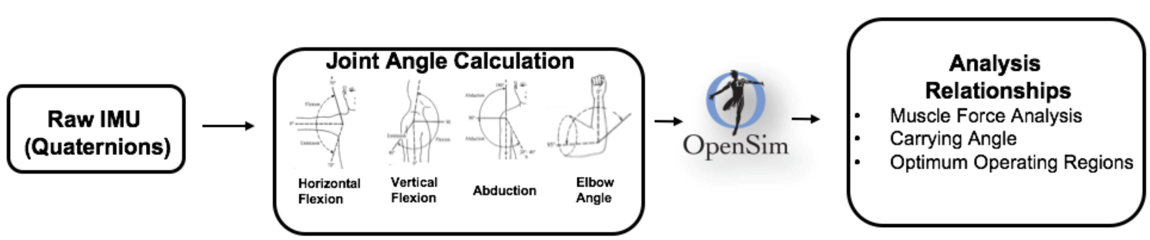


Figure 4.3 IMU Signal Pre – Processing

Shoulder joint is one of the Complex Joint in the Human Body which contains four bony structures and four joints with 20 Muscle Sub Regions. We narrowed down our focus to Glenohumeral Joint and the Elbow Joint in our research. Hence, the Joint Angles associated with Shoulder are as follows (Figure 4.4).

- Protraction/Retraction Angle : When the Scapula is moved anteriorly along the Chest Wall, protraction/Retraction occurs.
- Flexion/ Extension Angle : The motion of Humerus along the Sagittal Plane is known as the Flexion/Extension.
- Abduction/ Adduction Angle : The motion of the Humerus in the Frontal Plane is known as Abduction/Adduction.

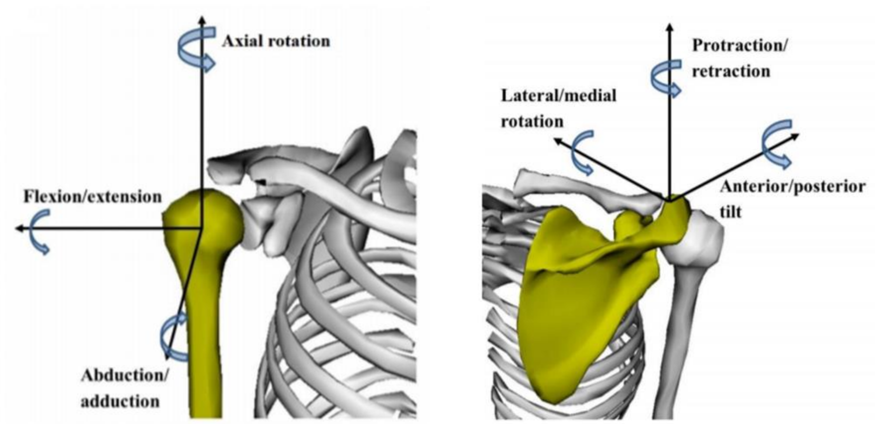


Figure 4.4 Representation of Joint Angles in Shoulder

Further the Elbow Flexion Angle, the angle between the Upper Arm and the Forearm with one DOF (Degree of Freedom) is also taken into consideration.

From the data obtained from the IMU Sensors, we developed our own Mathematical Model to calculate the above mentioned Joint Angles. The data obtained from the BNO055 IMU Sensors are quaternions, a four – dimensional complex number to represent the orientation in the Absolute Frame (Quaternion data are obtained to avoid the consequences of Gimble Lock). Thus, the placements of the IMU Sensors are shown in Figure 4.5.

Accordingly, the three IMU Sensors are placed such that the coordinate system frames are parallel to each other. This makes the calculation of Joint Angles effective.

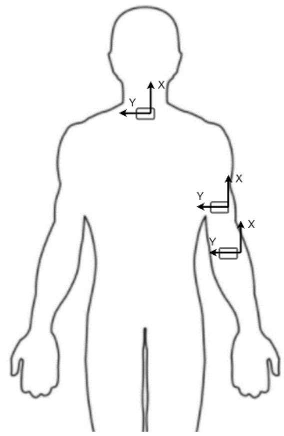
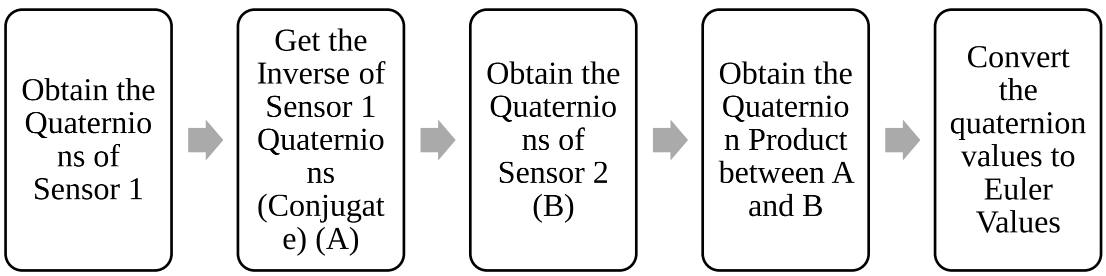


Figure 4.5 IMU Sensor Placement

To calculate the Joint Angle between two quaternions the following steps are being followed.



The Quaternion Product can be determined through the Hamilton Rule. The three Euler Angles, Yaw, Pitch and Roll accounts for the angle change along the Z, Y and X axis. Hence the final Euler Values of the above algorithm outputs the Euler Rotation Angles of Sensor 2 (B) relative to Sensor 1 (A). These Euler angles must be accounted for offsets to obtain the accurate values. Considering the sensor placements, the following joint angles can be obtained.

Euler Angles of Sensor 2 (Sensor Placed in Upper Arm) relative to Sensor 1 (Sensor placed in the Neck).

- Yaw: Shoulder Abduction/Adduction
- Pitch: Shoulder Flexion/Extension
- Roll: Shoulder Protraction/ Retraction

Euler Angles of Sensor 3 (Sensor Placed in Upper Arm) relative to Sensor 2 (Sensor placed in the Neck).

- Pitch Angle: Elbow Flexion

Summary

This Chapter identifies the Data Acquisition and Pre-Processing Steps that needed to be carried out in order to use the data for Analysis purposes. This preprocessing consists of two major components; EMG Data Processing and IMU Data Processing and our Research has focused on developing models to get required information.

Chapter 5

RESULT AND ANALYSIS

Introduction

Identifying relationships between injury and obtained parameters could be identified as an important aspect of the project. This chapter would identify the possible analysis categories and techniques which would be carried out during the project. The analysis component of the project could be broadly classified as EMG based analysis and IMU based analysis. The sections 5.1 and 5.2 would focus on identifying EMG and IMU analysis respectively. The identified relationships presented in this chapter would reflect the basic principles of the anatomical study which was identified above in this report.

5.1 EMG Based Analysis

The initial EMG based analysis was carried out through the use of existing sample data repositories. [11] Upon the successful identification of key features embedded within the EMG signal, initial algorithms were developed and relationships between injury and the EMG signal was identified.

The EMG sensor placement was identified through the Anatomical Study. Seven key muscles were identified which has greater probability of injuries occurring due to the action of throwing. The identified muscles are the Biceps (BCP) , Triceps (TCP) , Deltoid (DTD) , Supraspinatus (SUP), Infraspinatus (INF) , Subscapularis (SUB) , Teres Minor (TMR) , Flexor carpi Radialis (FCR) and Brachioradialis (BRA). [12] [13] The EMG signal extracted from these muscles would then be used to identify the basic EMG features and relationships related to fatigue.

The Delsys dEMG system was used to analyze all the above muscle groups in order to identify the muscle activation patterns in a slow-motion action of throwing and fast bowling. In order to analyze the muscles in the real time environment Myo Sensors were used and the focus was restricted to four muscles groups BCP, TCP, FLX and BRA due to the practical limitations. The application of EMG sensors on the shoulder during the action of fast bowling & throwing proved to be a tedious task thus the focus was compromised towards the Upper Arm & Forearm.

5.1.1 Basic EMG Features

The main features of the EMG signal can be listed down as follows.

- I-EMG (Full wave / Half wave rectified)
- A-EMG
- RMS-EMG
- P-EMG
- Linear Envelope
- Frequency Analysis
- Mean Frequency
- Statistical Parameters (Mean, Std Dev, Corr)
- Zero crossings

The initial data set was used to study the above characteristics and identify their nature. Upon the extraction of data sets related to throwing and fast bowling the above identified basic features of the EMG signal was used for analysis purposes.

5.1.2 Fatigue Index

Through the literature review it was identified that the mean frequency of the EMG is related to static muscle fatigue. The calculation of the mean frequency of the EMG can be analyzed along with the repetitive motion of the fast bowlers to identify and set thresholds, through which early injury detection could be focused on.

It was expected that the parameter Fatigue would be a clear indication of injuries occurring due to the overuse of the muscles. However, when the activity of throwing is concerned, it cannot be compared with a static activity, which is more of a dynamic nature. Research on such dynamic activities have been limited thus the importance of analyzing EMG in novel methods. Initially the research focused on verifying whether the existing findings of muscle fatigue was applicable in the focused activity. In order to carry out verification the mean frequencies and median frequencies of each muscle groups were visualized with the number of throws. (Figure 5.1 – 5.2) It was identified that the proven relationship was evident in some muscle whereas in some it was not visible and showed different relationships. The reason is mainly due the resting period which occurs between throws and fast bowling. Hence other methods were analyzed to determine injuries in throwing which are presented in the following sections.

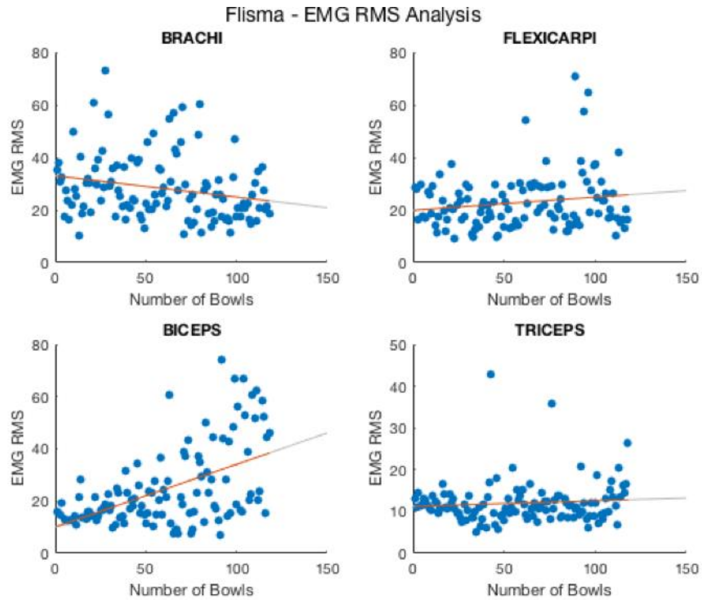


Figure 5.1 RMS Value Visualization of Focused Muscles

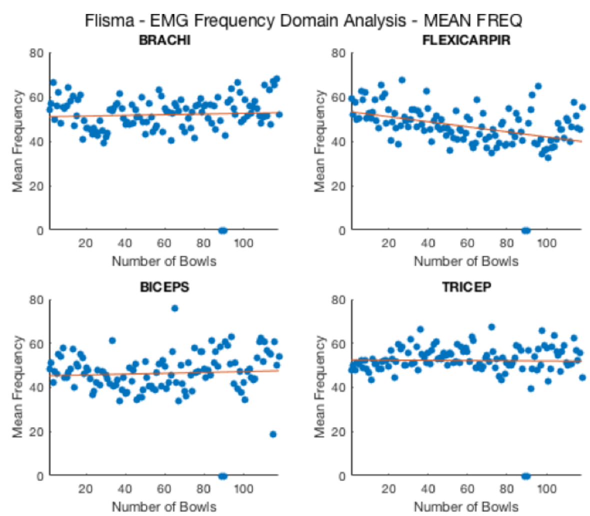


Figure 5.2 Mean Frequency Visualization of Focused Muscles

5.1.3 Muscle Activation Pattern Analysis

In addition to the EMG data extracted from the Myo Sensors a Delsys dEMG System was used to monitor the muscle firing patterns which was able to provide further insight into the players muscle conditions and muscle usage during the assigned task. It was evident through careful examination and medical expertise the muscle should activate in tandem in order to carry out the task effectively without any potential of injury. The Figure 5.3 identifies the muscle activation patterns of a health subject who is not prone for potential injuries where as in Figure 5.4 a muscle activation pattern is shown where there is inconsistent muscle activity. The perfect muscle activity could be distinguished through the high amplitude segment which occurs at fixed time periods, where as in Figure 5.4 such perfect activity is not visible within the Brachioradialis muscle.

It is also important to note that this analysis could be well used to improve sports performance through identified the important muscle groups to carry out the particular task in the sport and thus evaluate the muscle conditions of the players. Necessary exercises could be focused upon using the observations of the above analysis. Hence it is important to highlight the importance not only limiting to the injury prediction aspect but also related to the sports performance enhancement aspect.

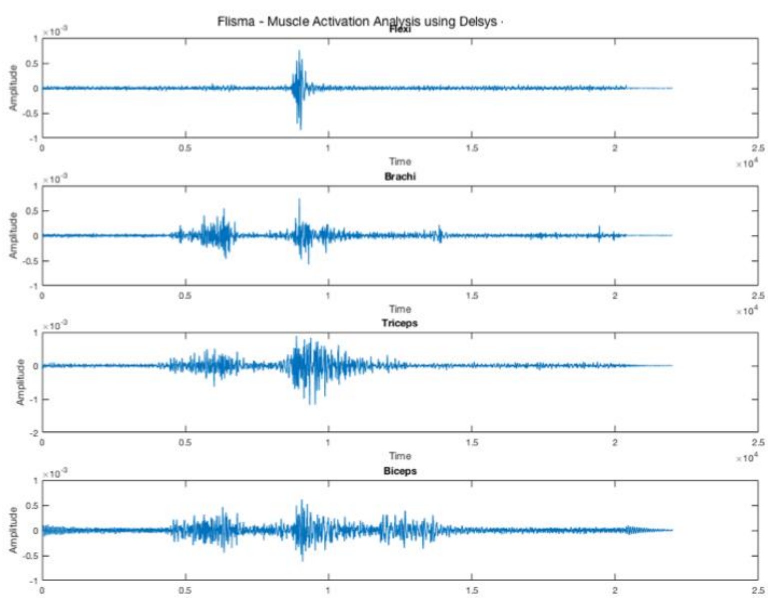


Figure 5.3 Healthy Muscle Activation Pattern

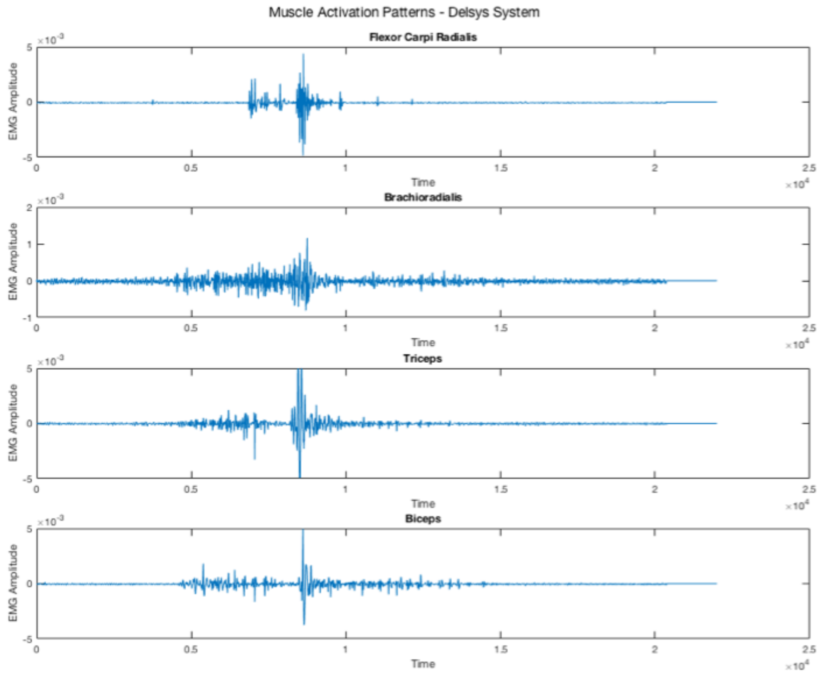


Figure 5.4 Muscle Activation Pattern With Potential Risk

5.1.4 EMG Co - Activation Analysis

A significant research finding in the project could be identified as the muscle coactivation patterns. Through careful analysis of the muscle group reactions it was identified that some muscles undergo a phenomenon of fatigue, whereas the rest focuses on providing the additional force required to complete the required task. Due to this condition some muscles are fatigued and reach a dangerous level of potential injury. Upon receiving medical expertise to analyze the observed result further it was identified that this could lead to the player having injuries in the overused muscle. In such a scenario the healing procedure would require additional time in comparison to a normal injury where all the muscles are injured.

It was identified that the RMS value provides an insight of the above mentioned variation of muscle activity. As observable in Figure 5.5 the power which the muscles generate starts to diverge at the middle period from 60 - 80 bowls. Thus, it is expected that within this period there is significant changes in the muscle forces which could be mainly due to overuse. Hence this analysis could be used as a method to test the capacity of a player to avoid the possible overuse which courses injuries. Moreover, it should be noted that the identified overuse point differs from player to player due to the physique and action differences. This was also confirmed through the research which identified different overuse ranges for different players. It was also identified that healthy muscle activations as discussed in section 5.1.3 leads to better overuse ranges, where the player is able to operate for a longer period relatively to a person with a compromised muscle activation during throwing.

The Figure 5.6 provides the standard deviation of the muscle RMS values which is able to identify the exact point of overuse. An analysis of this nature will be valuable to measure the physical capacity of a person and avoid the injuries which occurs due to overuse.

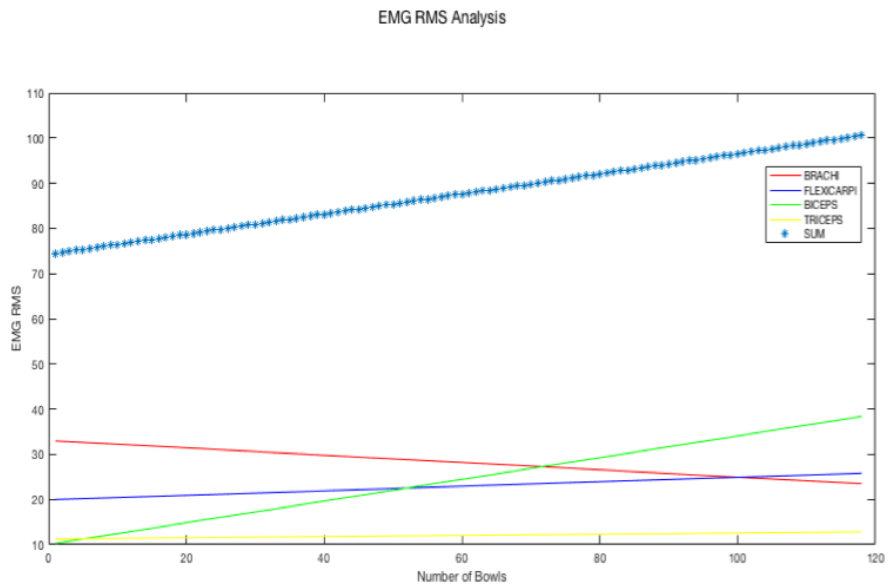


Figure 5.5 EMG RMS Analysis

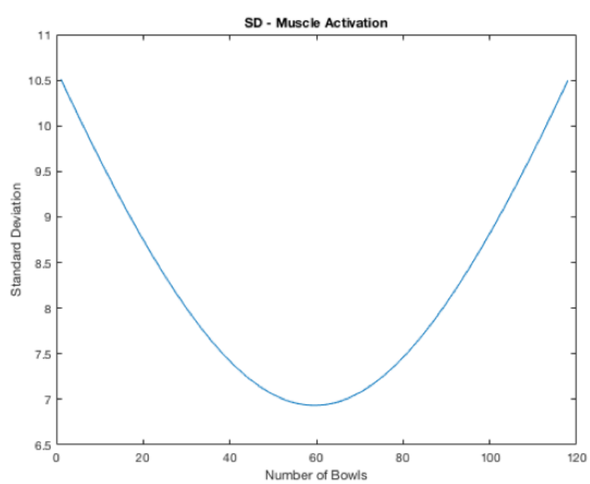


Figure 5.6 Standard Deviation of Muscle RMS Values

5.1.5 Unsupervised Learning Model

Throughout the research conducted it was identified that due to the challenging dynamic action and resting period during fast bowling and throwing, identifying unique features for analysis impossible. Thus, an unsupervised learning model was developed in order to learn the main features itself and identify possible relationships.

The 4 main analyzed muscles BCP, BRA, TCP, FLX was used for the analysis and the algorithm was provided with main key features of the signal such as the RMS, ZCR, Mean & Median Frequency components of each muscle. After initial scaling of the data and application of Singular Value Decomposition (SVD) the number of features were reduced, and it is expected that the identified principal components of each muscle group replicated the nature of each muscle group and its characteristics.

Upon the feature reduction of each muscle, the identified features of each muscle were combined, and analysis carried out through PCA and k-means clustering methods. The results obtained through the clustering was able to identify a key pattern which could be related to overuse. The two clusters were mainly around the bowls thrown initially and then towards the latter part of the throws. However, a perfect distinguish of such a characteristic was not visible. (Figure 5.7). It should also be noted that the algorithm would provide much more better results through more data sets and hence the interpretation of the observation further analysis.

However, it is important to note that through unsupervised learning it has been able to identify a pattern which is worth of analyzing in future research projects to achieve better results through more data acquisition. The block diagram of the unsupervised learning algorithm is presented in Figure 5.8.

The cumulative probability was calculated in order to distinguish the observed clusters. (Figure 5.9) It is expected to derive a threshold to identify the overuse point occurring. It is important to note that through further analysis the proposed unsupervised learning could be enhanced effectively.

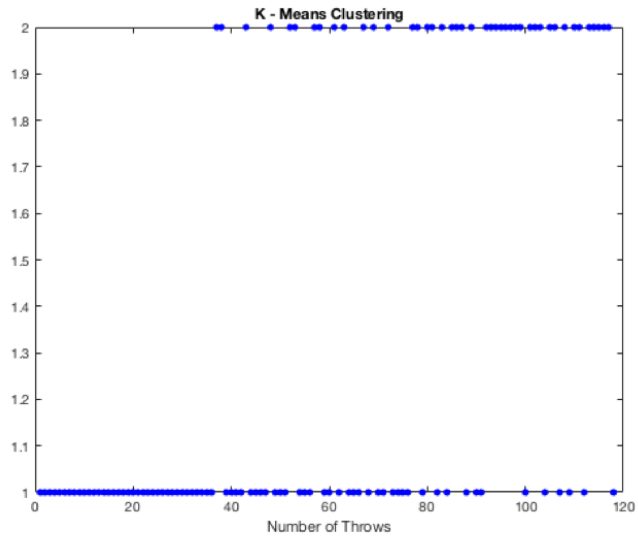


Figure 5.7 Clustering Results - Unsupervised Learning Algorithm

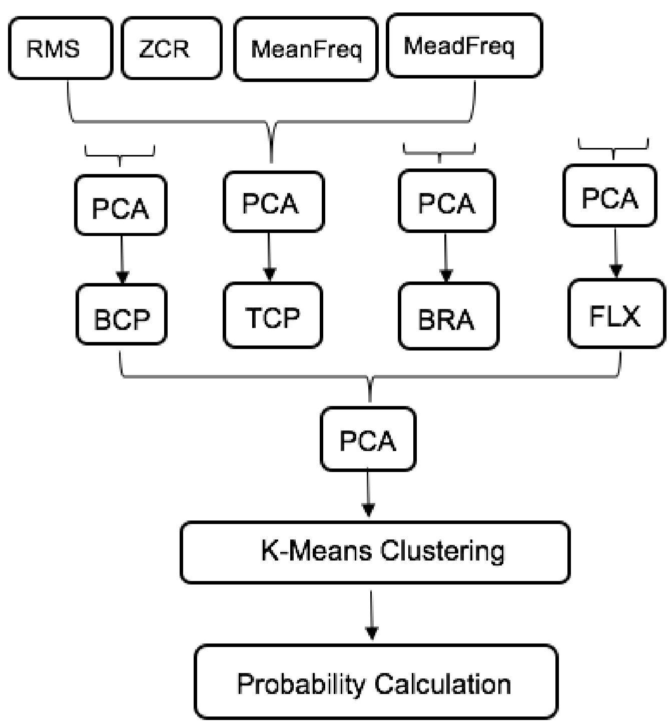


Figure 5.8 Unsupervised Learning Algorithm

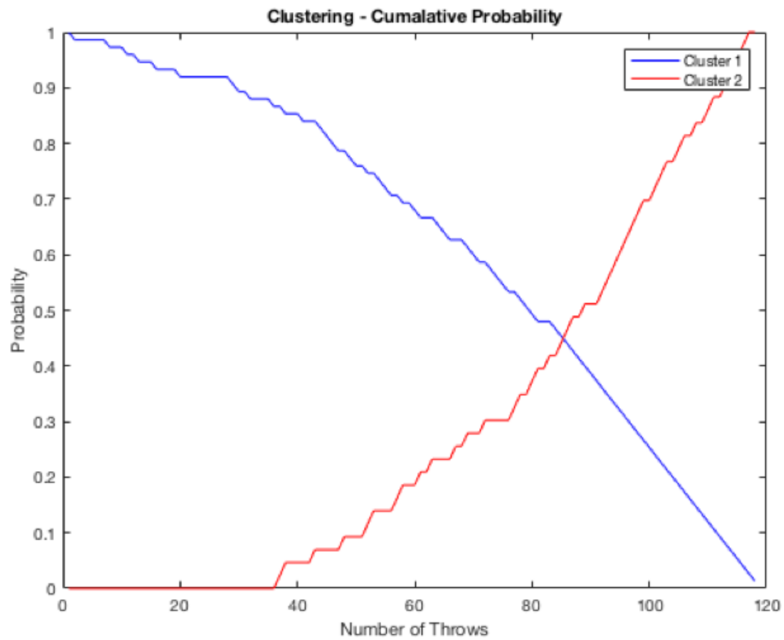


Figure 5.9 Cumulative Probability Calculation - Unsupervised Learning Algorithm

5.2 IMU Based Analysis

The information obtained from the inverse kinematics operations mentioned above can be used to calculate the Musculotendon parameters such as Muscle Forces, Tendon Lengths, Contraction Velocity and Activation of Muscles. To perform these operations, a standard opensource software named 'OpenSim' is used. OpenSim, a freely available musculoskeletal modeling and simulation application and libraries specialized for these purposes, by providing: musculoskeletal modeling elements, such as biomechanical joints, muscle actuators, ligament forces, compliant contact, and controllers. The model used to analyze the Rotator Cuff muscles in the shoulder is WU Shoulder model [17]. It is a generic rigid-body upper-limb musculoskeletal model which the Muscle-Tendon path Information are optimized using the experiments performed in vitro. The Muscles that Are being analyzed using Inverse Dynamics performed through Matlab – OpenSim Interface are; Deltoid, Supraspenatus, Infraspenatus, Subscapularis.

5.2.1 Simulation in OpenSim

The joint angles which are calculated using the above Mathematical Model can be used to simulate the motion in the OpenSim Simulator. To perform this, a Motion File has to be created. The Motion file header for the WU shoulder model should contain the elements; Number of Data Rows, Number of Data Columns, Range and Degrees/Radians. The content of the Motion File comprises of Angles for each joint, for each time stamp. Hence based on the Joint angles we calculate, the columns we should insert angle data are ; sternoclavicular_r1 (Shoulder Protraction/ Retraction) , sternoclavicular_r3 (Shoulder Flexion/Extension), shoulder_ele (Shoulder Abduction/Adduction) and elbow_flexion (Elbow Flexion). The standard frequency needed for the model to work precisely is 50Hz. However, through the IMU System developed, 100Hz are supplied which is sufficient to simulate the system accurately.

5.2.2 Analysis Using OpenSim and Matlab

The OpenSim Matlab Scripting API is used to analyze the motion using several Musculotendon parameters which are critical in detecting the tendency for injury. In order to connect Matlab with OpenSim, system configurations and Environment Variable had to be adjusted. The Muscle inverse dynamics performed by Matlab scripting consider the parameters such as; Normalized Fibre Velocity, Muscle Tendon Length, Active Tendon Force, Passive Tendon Force, Total Muscle Force, Muscle Activation. The steps followed in obtaining these parameters are as mentioned in Figure 5.10. For the Optimization, Sum of Muscle Activation is being used as the objective function, and as the input; Muscle Force-Length-Velocity is being used. The above operation performed in Matlab will provide the parameters to analyze the Muscle forces in the Rotator Cuff Muscles.

5.2.3 Results of the IMU Analysis

IMU Data were obtained for 6 subjects (3 Throwing and 3 Fast Bowling) with 120 deliveries for throwing. The following Figures (Figure 5.11 – 5.14) depicts the Muscle Forces for each Muscle in the Rotator Cuff calculated following throwing of one bowler.

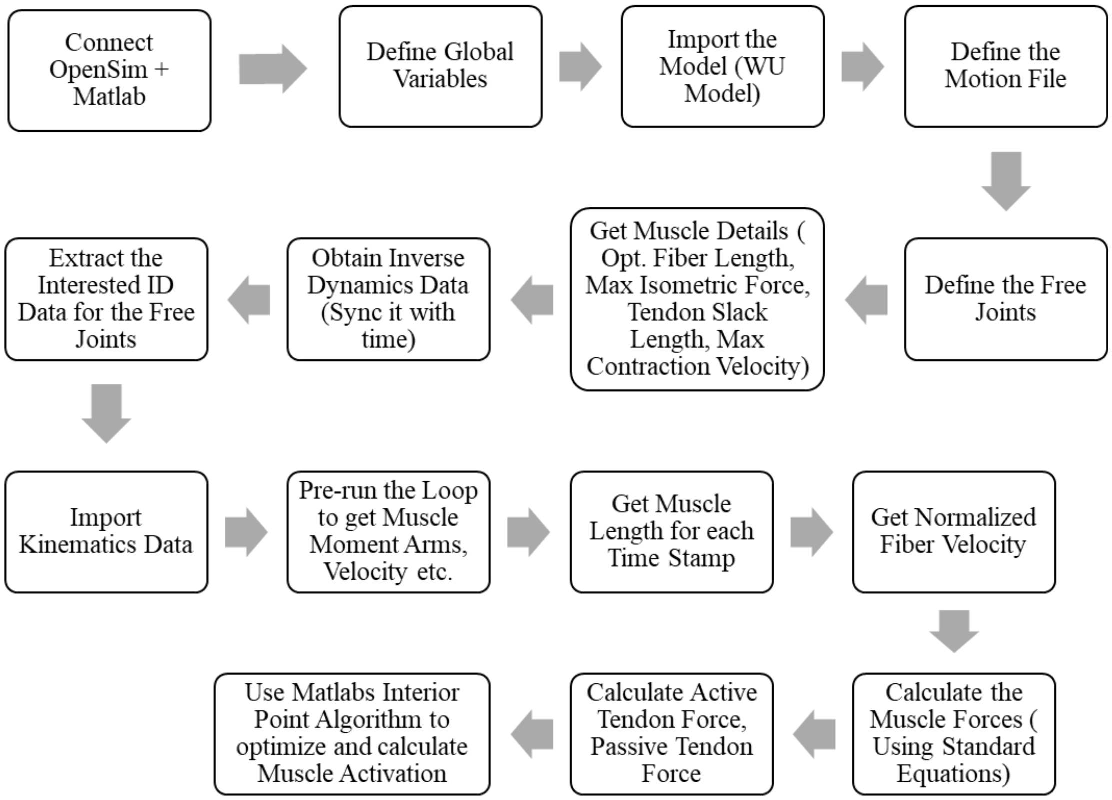


Figure 5.10 Steps followed in Matlab to obtain Parameters

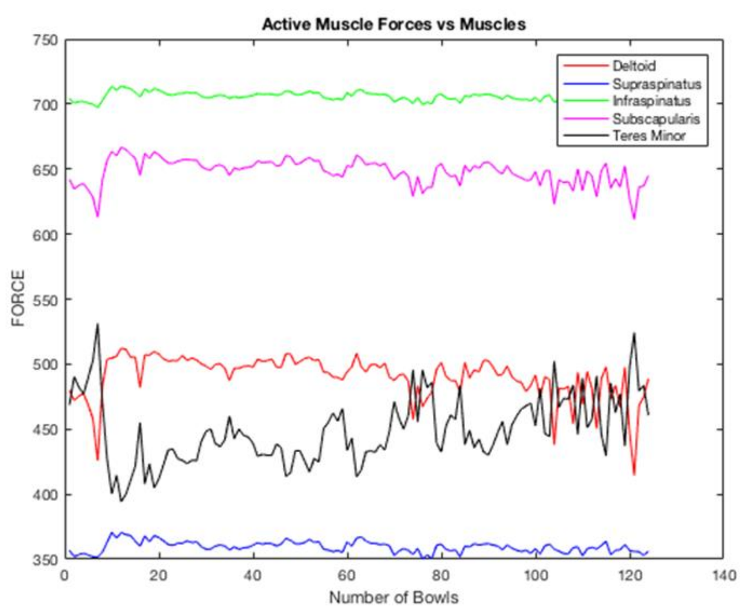


Figure 5.11 Active Tendon Forces of Muscles

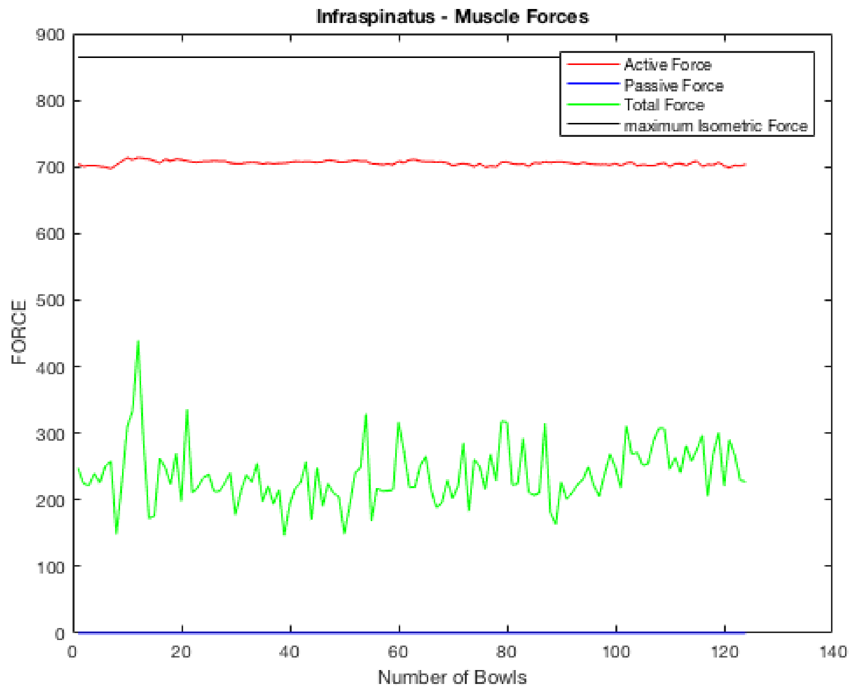


Figure 5.12 Muscle and Tendon forces of Infraspinatus

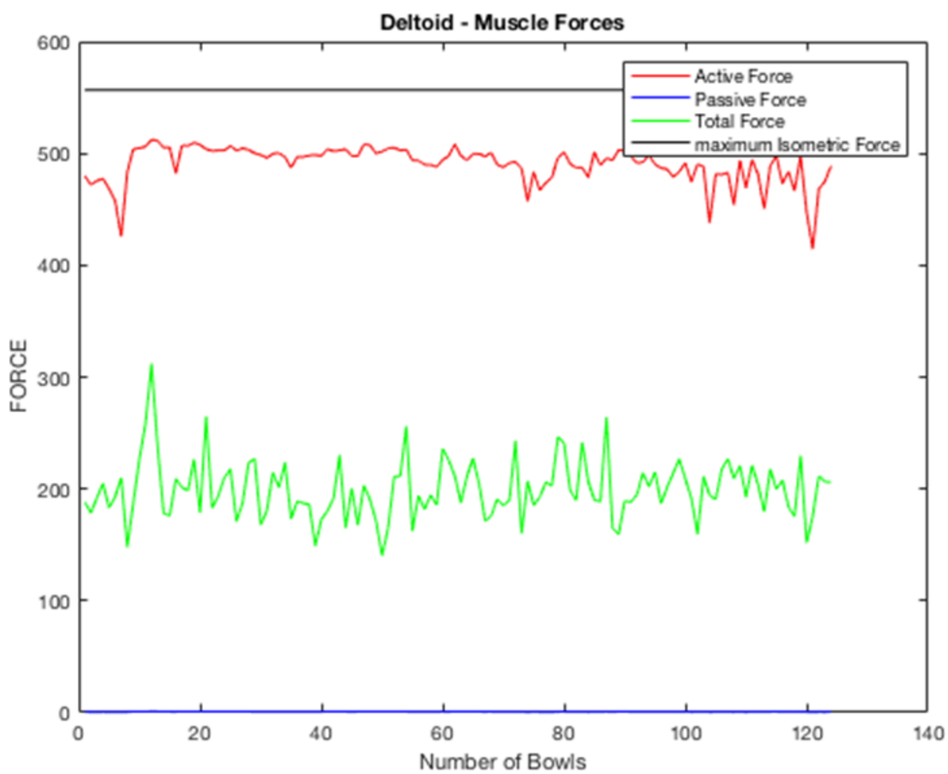


Figure 5.13 Muscle and Tendon forces of Deltoid

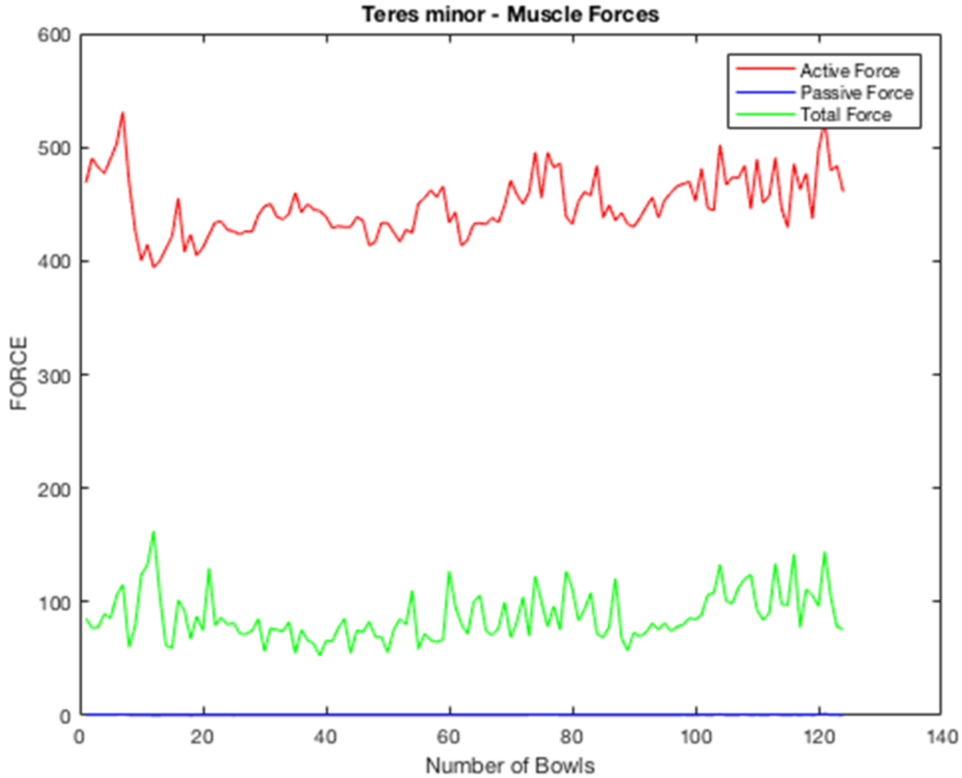


Figure 5.14 Muscle and Tendon forces of Teres Minor

To perform the analysis from the obtained information, we use the Standard Length-Tension curve of a Muscle (Figure 5.15) as the standard benchmark. This curve demonstrate how the Muscle length affects the force production of the whole Muscle.

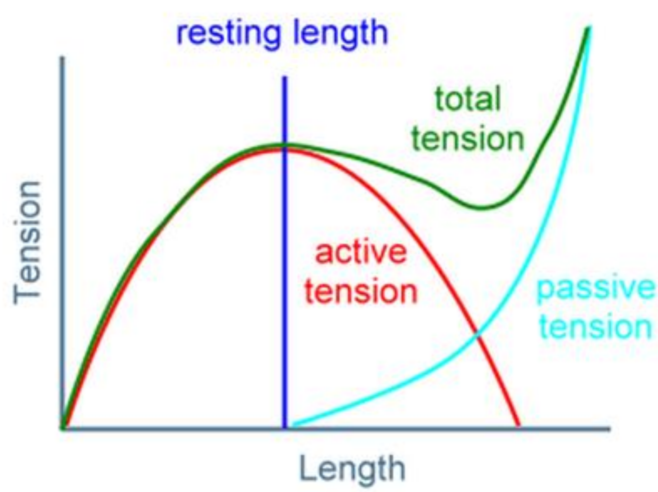


Figure 5.15 Length Tension Curve of a Muscle

Accordingly, the Active Force is generated by the Contractile element of a Muscle in the presence of external interference. As a muscle is stretched in the absence of a contraction, there is some length at which the muscle begins to resist the stretch. As the stretch of the muscle increases, the muscle exerts a larger pull against the stretch. This pull is attributed to the elastic recoil of the passive structures within the muscle, such as the investing connective tissue. These components are known as the parallel elastic components. The tendons at either end of the muscle also provide a force against the stretch. These are described as the series elastic components. The combined effects of muscle contraction and stretch of the elastic components are represented mechanically by a contractile element in series and in parallel with the elastic components. Thus the side effects of generating Passive Force is risky with a high probability of getting prone to injury.

For the results we obtained, it is apparent that the Passive Muscle force is always lower than the Active forces. This proves the fact that, the player is not prone to injury in terms of Muscle Forces and Velocity.

Moreover, in order to examine the Passive forces we generated it by bringing the IMU System, into unrealistic position by a human arm so that the Muscles would stretch beyond its maximum capacity producing Passive Force. The following figure depicts the Passive Forces generated in each Muscle Tendon for the above-mentioned activity.

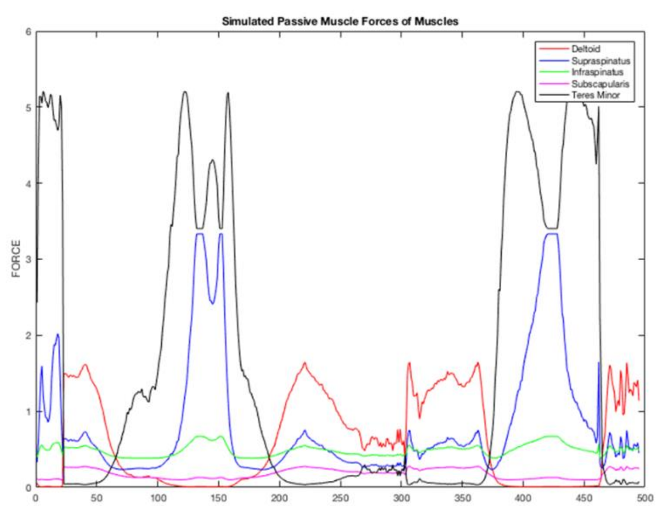


Figure 5.16 Passive Forces generated in Muscles

Thus, it is concludable that the Passive forces are not generated during normal throwing, which indicates that the probability of getting injury due to Muscle Over Stretching because of the posture is nearly zero. However further studies needed to be done using more data samples in order to derive an absolute assumption.

5.3 Web / Mobile Application

One of the expected deliverables of the project is the Web/Mobile application to be used by Coaches and Players. This application looks user friendly and presents the facts that is being obtained from the EMG/IMU analysis in a meaningful method.

5.3.1 Technologies Used

The web/mobile application is a node.js based application. The file server and backend is based on node.js. The front end is based on HTML, Javascript and CSS.

Apart from the basic web technologies, many 3rd party libraries are used to make the application attractive and optimized. The bootstrap library is used in order to make the application responsive effectively, so that the application can be view on desktop and mobile browsers without any damage to the appearance. The Figure 5.17 gives a glance of the technologies used.

Figure 5.17 Technology stack used for Web/Mobile Application

5.3.2 Features

<u>Muscle Usage</u>

The muscle Usage of four main muscles (TCP, BCP, FLX, BRA) are visualized in a pie graph. The RMS values are converted to percentages. This visualizes which muscle has been prominent and which is not. According to the rationale presented above at the report, when one muscle is highly working than the others, there is a high chance that muscle is getting injured. This can be easily visualized.

The javascript libraries - Chart.js Chart JS 2, EChart JS are used to draw attractive graphs on the web application. In addition, fully 3d rotatable model of human arm with respective muscles analyzed is shown in the app for a better understanding about the muscles. This model is taken from biodigital.com.

Raw EMG

The signals of the EMG extracted from TCP, BCP, FLX, BRA are visualized in this part. The features - Muscle Usage and Raw EMG can be seen in Figure 5.18.

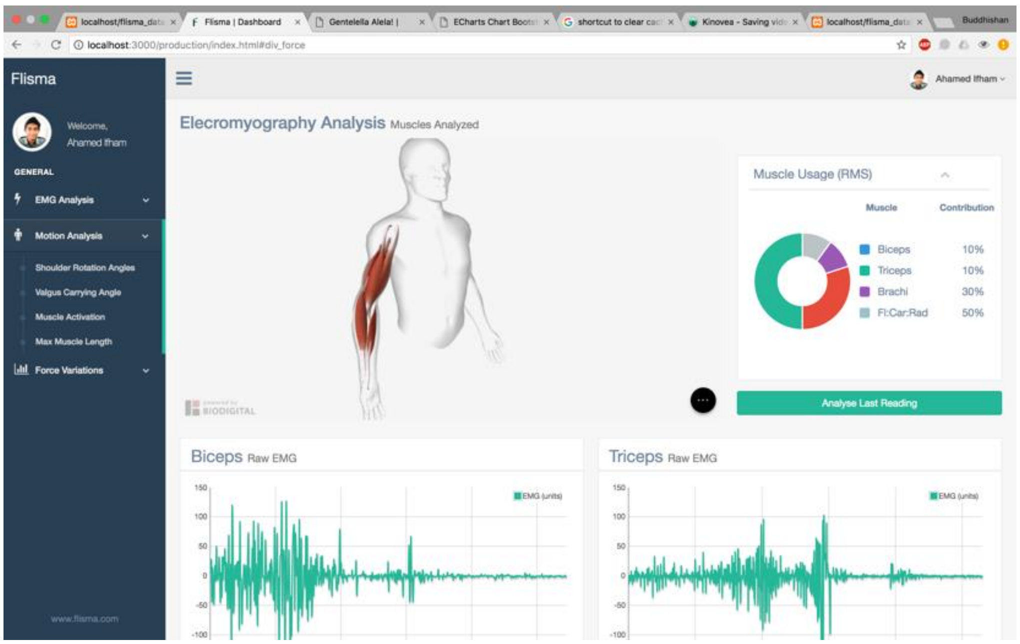


Figure 5.18 Features - Muscle Activation & Raw EMGs.

Rotation Angle Analysis

In this section all the angles that is measure on shoulder and the elbow are presented with respect to the limits. When a respective angle goes beyond the prescribed limits (as per literature), it tends to an injury.

The Figure 5.19 shows the optimum angle ranges described in existing research studies. [16]

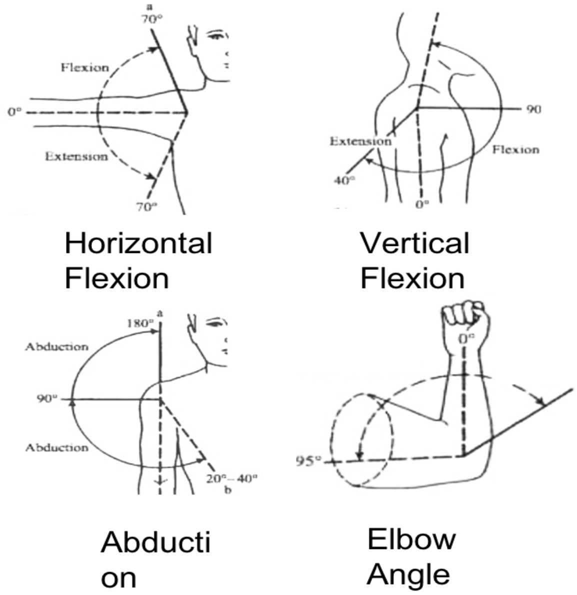


Figure 5.19 Range of Rotation arm angles without an injury

<u>Valgus Carrying Angle</u>

According to the researchers [15] Valgus Carrying angle can be identified as a straightforward measurement of a potential injury. The angle should lie between 5-15 degrees for men and 10-15 for women. If the angle is getting increased, It indicates and Injury. The web application can show the angle. The Figure 5.20 shows how VCA can affect to an injury.

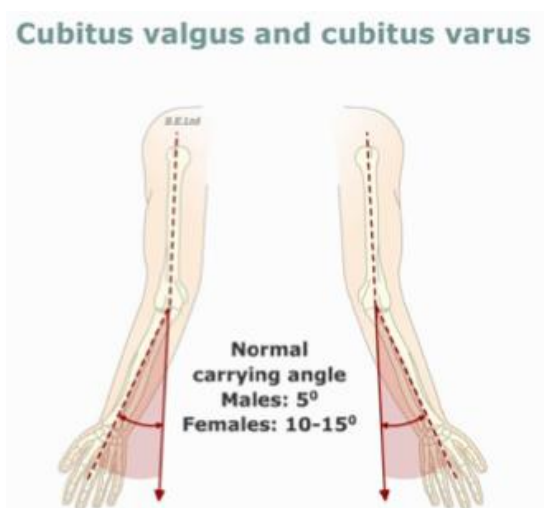


Figure 5.20 Valgus Carrying Angle Test

Muscle Activation

Muscle activation is another indicator visualized in the App. The percentage of activation of each muscle is shown in a bar graph for the muscles analyzed using openSIM. This indicates information whether one or several muscles activated than others which depicts a cause to an injury.

Muscle Forces

The changes in active and passive forces are drawn in 4 graphs for each muscle in rotator cuff and deltoid. If passive forces are available, it indicates a potential injury. The visualizations of the Rotation angle analysis, VCA, Muscle activation and Muscle Forces are shown in Figure 5.21.

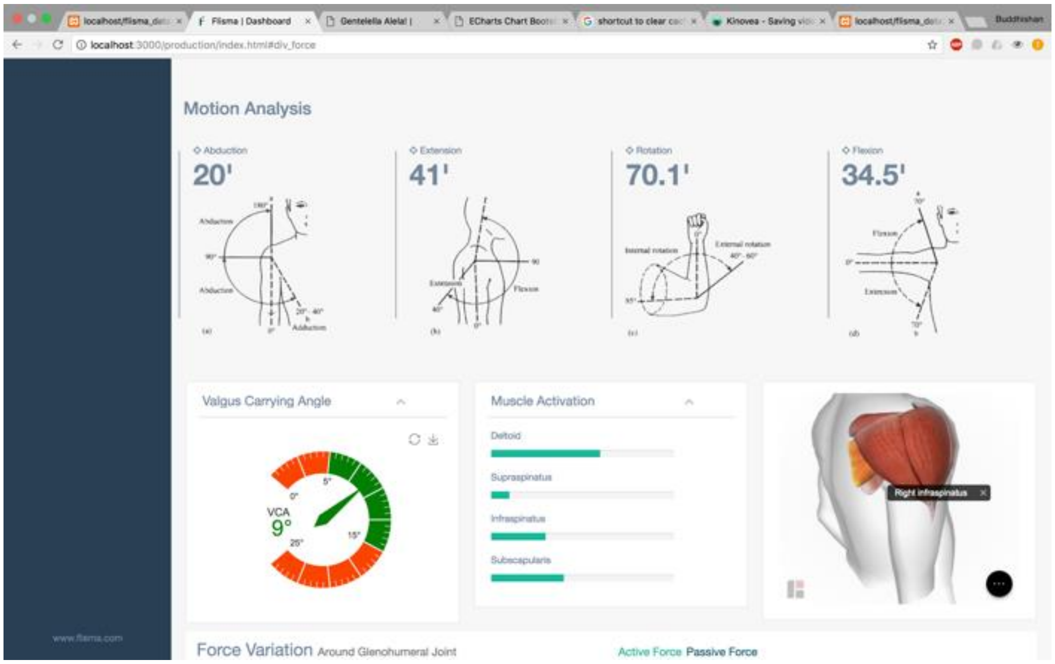


Figure 5.21 The visualizations of the Rotation angle analysis, VCA, Muscle activation and Muscle Forces.

5.3.3 Realtime Myo Sensor Visualization Tool

A node-based web app was created in order to visualize the raw EMG data captured using the Myo Sensor. This app is able to run on any browser and able to connect to Myo SDK in order to communicate with the Sensors.

In addition, the library bootstrap is used in order to make sure that the app is visible nicely both in desktop browsers and mobile browsers. The screenshot of the Realtime EMG plot is shown in Figure 5.22.

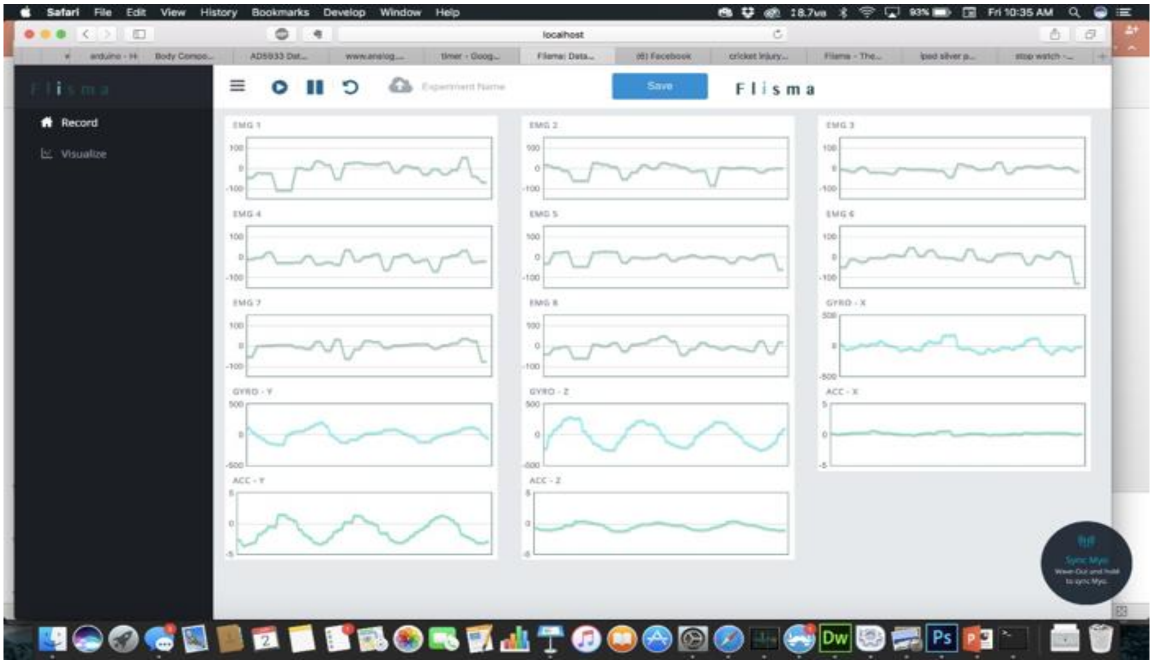


Figure 5.22 Application to visualize Real Time Data

5.3.4 Real time 3D Motion Tracking Application

An application was created using Blender 3D software. A human model was imported from Makehuman.org which allows to create a customized human model according to our requirement. The Blender allows to use Python code to connects with the Bluetooth Serial port in order to communicate with the hardware system. Figure 5.23 shows the Blender Application which tracks the arm movements real time.

Figure 5.23 Realtime Arm tracking app using Blender 3D and Python

Summary

This Chapter consists the Results and Analysis of the research carried out. One major component of the analysis is, EMG Signal analysis which concluded that as the Number of throwing passes a certain threshold, one Muscle will dominate the activity which would lead to the fatigue nature of the Muscle. The IMU Analysis derived certain parameters including Active Muscle Force, Passive Muscle Force and Activation of Muscle which didn’t depicted a greater variation as the number of bowls increased. Further this chapter describes the third Objective of the Project, to create a Web/ mobile application to visualize the data and information generated through the system. One application was made to visualize the data with attractive graphs. And another application was made to visualize the real time EMG and IMU data. 3rd Application is created using Blender in order to track and visualize the Upper Arm movements. Wide area of technologies has been used to develop the respective Applications.

Chapter 6

DISCUSSION AND CONCLUSION

The project identified analysis & tests which can be used in order to detect early indications of potential injuries. A portion of identified analysis were based on the existing medical literature, where the developed system was of great use in extracting the inputs required to carry out these tests. For such applications the device could be used as solely a data extraction tool which has been validated for its accuracy. The aforementioned tests could be mainly identified as tests which focus on the techniques of the athletes.

In contrast to the above tests, the analysis based on the overuse aspect focuses on individual athletes. The overuse threshold varies with the physical capabilities of each player and their internal characteristics. Hence the overuse analysis developed through the project is ideally focusing on individual athletes. The analysis such as the muscle activation patterns, co activation patterns and maximum force threshold relationships are able to provide a significant understanding about the athletes' potential for injury. Hence the above developed novel analysis would be of great essence towards injury prediction.

It should also be noted that such analysis has not been conducted in the dynamic complex nature of the application of the throwing motion with the resting phases in between. Hence the identification of exact features related to fatigue was impossible. The focus on the unsupervised learning algorithm enables to narrow down the possible features and develop a method to identify fatigue. The developed algorithm provided results which can be further analyzed with more data sets. The results have proven that there exists a relationship between the extracted parameters and muscle fatigue.

In conclusion the analysis and relationships identified through the research study are of great importance towards the prediction of potential injuries. However, the unsupervised learning algorithm developed could be fine-tuned further through analyzing more volumes of data. Further, it has been identified that the results and observations of the above results may also be used towards sports performance enhancement which would be an important area to focus on for greater value addition.

The developed wearable system is also of great importance which ensured the successful development of aforementioned analysis. The wearable system was developed with cost constraints. The system could be practically implemented, and the data extraction was carried out with reasonable accuracy and quality. The IMU system static validation provided a reasonable accuracy of +- 0.634 degrees. However, it’s important to note that the system should be validated against a gold standard device for its dynamic validation. The EMG Myo sensors used towards the system provides reasonable accuracy for healthcare applications and research which was validated through previous research.

In conclusion, the project resulted in the development of a robust wearable system for data extraction under practical sporting scenarios. The analysis conducted on top of the developed system is of great value and provides great insights towards the future analysis which can be conducted. The project has also identified many possible avenues for the extension and possible research in sports enhancement and injury prediction.

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Validation – Research

1. OpenSim Software for Simulation

Open-source Software to Create and Analyze Dynamic Simulations of Movement. by Scott L. Delp , Frank C. Anderson , Allison S. Arnold , Peter Loan , Ayman Habib , T. John , Eran Guendelman , Darryl G. Thelen (NIH Center for Biomedical Computation at Stanford University.)

2. WU Shoulder Model for Simulation

Subject-specific musculoskeletal modeling in the evaluation of shoulder muscle and joint function. Wu W1, Lee PVS1, Bryant AL1, Galea M1, Ackland DC2. (PhD Thesis – University of Melbourne)

3. Myo Armband EMG Extraction / Medical Applications

Myo Gesture Control Armband for Medical Applications, 16 October 2015, Department of Computer Science and Software Engineering University of Canterbury

4. Surface EMG vs Fine - Wire Electrodes

A Comparison of EMG Signals from Surface and Fine-Wire Electrodes During Shoulder Abduction , Bala S Rajaratnam1*, James CH Goh2 and V Prem Kumar2 ,1School of Health Sciences (Allied Health), Nanyang Polytechnic, Singapore ,2Faculty of Medicine, Department of Orthopaedic Surgery, National University of Singapore, Singapore.

5. Carrying Angle Test

Increased Valgus Carrying Angle at the Elbow correlates with Shoulder and Elbow injuries in Professional Pitchers: A Prospective Study, Sarav S. Shah, MD,1 Jeffrey A. Goldstein, MD,1 Spencer Stein, MD,1 Isaac Gammal, MD,1 Roger Gerland, MSPT, ATC,2 Jean-Paul C. Lucke, DO,3 and Steven Rokito, MD1 (Orthopaedic Journal of Sports Medicine)

6. Optimum Operating Region

Handbook of Physical Measurements, By Judith Hall, Judith Allanson, Karen Gripp, Anne Slavotinek.

7. Anatomical Study. (Identification of Muscle Groups)

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APPENDIX

1. Calculating the Joint Angles using quaternions

```
% Flisma Labs (c) 2017
% Chirath Hettiarachchi
% Calculate the Angles using quaternions for the OpenSim Model using the
% serial data

% Sensor 1 - Body
% Sensor 2 - Shoulder
% Sensor 3 - Elbow

clear all;
close all;
addpath(genpath('libraries/'));

delete(instrfindall);
s = serial('/dev/cu.wchusbserial1420');
%s = serial('/dev/tty.RNBT-A83A-RNI-SPP');
s.BaudRate=115200;
fopen(s);

% displaying the initial values from the code.
disp(fscanf(s,'%s'))
disp(fscanf(s,'%s'))
disp(fscanf(s,'%s'))

%Obtaining the actual data
true = 9;
counter = 3;

plot_window = 100;
time = 1:plot_window;
marker = 0;

Elbow_Angle  = zeros(plot_window,3);
Shoulder_Angle = zeros(plot_window,3);

elbow_initial = [0 0 0];
shoulder_initial = [0 0 0];
twist_initial = [0 0 0];

figure
```

```
subplot(1,2,1)
title('ELBOW')
subplot(1,2,2)
title('SHOULDER')
grid on;
xlim([0 100])
ylim([-180 180])

while true > 0

    k = fscanf(s,'%s');
    try
        c  = textscan(k, '%f', 'Delimiter', ',');
    catch
    end

    temp = cell2mat(c);
    [m,n] = size(temp);

    %Ensure the required data is received.
    if m == 21

        %For the plotting
        if(marker < plot_window)
            marker = marker+1;
        else
            marker = 1;
        end

        %Storing all the received data
        rolling(counter,1:21) = temp';

        %Obtaining the Quartinions
        q1 = [rolling(counter,10) rolling(counter,11) rolling(counter,12)
rolling(counter,13)];
        q2 = [rolling(counter,14) rolling(counter,15) rolling(counter,16)
rolling(counter,17)];
        q3 = [rolling(counter,18) rolling(counter,19) rolling(counter,20)
rolling(counter,21)];

        %the elbow angles respective to sensor 2
        q2_inv = [q2(1) -1*q2(2) -1*q2(3) -1*q2(4)];
        %ElbowRespect_2 = quaternProd(q3,q2_inv);
```

```
ElbowRespect_2 = quaternProd(q2_inv,q3);
ElbowRespect_2 = quatern2euler(ElbowRespect_2);

%the shoulder angles respective to sesor 1
q1_inv = [q1(1) -1*q1(2) -1*q1(3) -1*q1(4)];
%ShouldRespect_1 = quaternProd(q2,q1_inv);
ShouldRespect_1 = quaternProd(q1_inv,q2);
ShouldRespect_1 = quatern2euler(ShouldRespect_1);

%final elbow / shoulder angles
Elbow_Angle(marker,:) = ElbowRespect_2 - elbow_initial;
Shoulder_Angle(marker,:) = ShouldRespect_1 - shoulder_initial;

%checking the z (yaw) angles to adjust the pitch
z = -1*Shoulder_Angle(marker,1);
if (z <= 90) && (z >= -90)
   Shoulder_Angle(marker,2) = Shoulder_Angle(marker,2);
elseif (z > 90) || (z < -90)
   Shoulder_Angle(marker,2) = 180 - Shoulder_Angle(marker,2);
end

%checking the z (yaw) angles to adjust the pitch of the elbow!!
z2 = Elbow_Angle(marker,1);
if (z2 <= 90) && (z2 >= -90)
   Elbow_Angle(marker,2) = 180+Elbow_Angle(marker,2);
elseif (z2 > 90) || (z2 < -90)
   Elbow_Angle(marker,2) = -1* Elbow_Angle(marker,2);
end

subplot(1,2,1)
plot(time,Elbow_Angle);
title('Elbow Angle');

subplot(1,2,2)
plot(time,Shoulder_Angle);
title('Shoulder Angle');

%Final array of angles required
Angles(counter,:) = [Elbow_Angle(marker,2) -1*Shoulder_Angle(marker,1)
Shoulder_Angle(marker,2) -1*Shoulder_Angle(marker,3)];

%disp(counter)
disp('  E-Pitch|    S-Yaw|  S-Pitch|  S-Roll|')
```

```
        disp(Angles(counter,:))

        counter = counter + 1;
        pause(0.001);

    else
        disp(k)
    end



end
fclose(s);
```

2. Muscle Activation Pattern Visualization Using Delsys dEMG System

```
% Visualize & Analyse the EMG Obtained from the Delsys System - Muscle
% Firing Patterns
% by Chirath Hettiarachchi
% copyrights Flisma Labs.

close all;
%format shortG
format long
addpath(genpath('libraries/filters/'));
addpath(genpath('libraries/extra/'));
addpath(genpath('libraries/transform/'));

%Sampling Freq 4000Hz, No filters used.
%Channel 12 - Felxi       - Array Column 2
%Channel 13 - Brachi      - Array Column 3
%Channel 14 - Triceps     - Array Column 4
%channel 16 - Biceps      - Array Column 5

EMGFILES = dir('../DelsysData/*.csv');
```

```
NumberOfFiles = length(EMGFILES);

%TODO -> Preallocating for optimization
%To Overcome the issue of file ordering
SORTED_EMGFILES = {};
for file = 1 : length(EMGFILES)
    temp = EMGFILES(file).name;
    SORTED_EMGFILES{file} = temp;
end
SORTED_EMGFILES = natsortfiles(SORTED_EMGFILES);
SORTED_EMGFILES = string(SORTED_EMGFILES);
%disp(SORTED_EMGFILES);

for x = 1 : NumberOfFiles

    file = strcat('../DelsysData/' , SORTED_EMGFILES(x));
    A=dlmread(file,',',33,0); % Reading from line 33

    %Apply Butterworth Filter / HPF
    A(:,2) = Butterworth(6, 20, 4000, A(:,2),'high');
    A(:,3) = Butterworth(6, 20, 4000, A(:,3),'high');
    A(:,4) = Butterworth(6, 20, 4000, A(:,4),'high');
    A(:,5) = Butterworth(6, 20, 4000, A(:,5),'high');

    %Implement a Notch Filter to remove the 50Hz Noise component.
    A(:,2) = NotchFilter(A(:,2));
    A(:,3) = NotchFilter(A(:,3));
    A(:,4) = NotchFilter(A(:,4));
    A(:,5) = NotchFilter(A(:,5));

    %figure
```

```
    %plot(A(:,2));

    %[f, p1] = FFT(4000,A(:,2));
    %plot(f,p1)

    %Plotting each every iteration muscles emg amplitude.
    figure;
    suptitle({'Flisma - Muscle Activation Analysis using Delsys - Ahamed'})
    for index = 2 : 5
    subplot(4,1,index-1)
    plot(A(:,index));
    if index == 2
        name = "Flexi" ;
    elseif index == 3
        name = "Brachi";
    elseif index == 4
        name = "Triceps";
    else
        name = "Biceps";
    end
    title(name);
    xlabel('Time')
    ylabel('Amplitude')
    end

end
```

3. Unsupervised Learning Algorithm

```
% Myona (c) Flisma 2017
% by Chirath Hettiarachchi
% copyrights Flisma Labs.
% Unsupervised Clustering

close all;
format long
addpath(genpath('libraries/filters/'));
addpath(genpath('libraries/myo/'));
addpath(genpath('libraries/extra/'));
addpath(genpath('libraries/transform/'));
addpath(genpath('libraries/actionDetect/'));
addpath(genpath('libraries/features/'));

%Myo Armband EMG Sampling rate 200Hz

%Read all the csv files stored in Data Folder
EMGFILES = dir('../MyoData/*.csv');
NumberOfFiles = length(EMGFILES);

%TODO -> Preallocating for optimization
%To Overcome the issue of file ordering
SORTED_EMGFILES = {};
for file = 1 : length(EMGFILES)
    temp = EMGFILES(file).name;
    SORTED_EMGFILES{file} = temp;
end
SORTED_EMGFILES = natsortfiles(SORTED_EMGFILES);
SORTED_EMGFILES = string(SORTED_EMGFILES);
```

```
%Learn without PCA, all features together
[A,B,C,D,E] = FeatureCalculation(SORTED_EMGFILES);




%%%%%%%%%%%Calculating PCA for each of the muscles seperately
%%% PCA Muscle A
array = A;
[m,n] = size(array);
X = (array-repmat(mean(array),[m,1]))';
[U,S,V] = svd(X);
temp = S(1:n,1:n);
sum = 0;
for i = 1:n
    sum = sum + temp(i,i);
end
sum_val = 0;
val = 0;
for index = 1:n
    sum_val = sum_val + temp(index,index);
    val = sum_val / sum ;
    if val > 0.99
        components = index;
        break
    end
end
%disp(components);
Reduced_Features = U(:,1:components);
A = X' * Reduced_Features;

%%% PCA Muscle B
```

```
array = B;
[m,n] = size(array);
X = (array-repmat(mean(array),[m,1]))';
[U,S,V] = svd(X);
temp = S(1:n,1:n);
sum = 0;
for i = 1:n
   sum = sum + temp(i,i);
end
sum_val = 0;
val = 0;
for index = 1:n
   sum_val = sum_val + temp(index,index);
   val = sum_val / sum ;
   if val > 0.99
      components = index;
      break
   end
end
%disp(components);
Reduced_Features = U(:,1:components);
B = X' * Reduced_Features;

%%% PCA Muscle C
array = C;
[m,n] = size(array);
X = (array-repmat(mean(array),[m,1]))';
[U,S,V] = svd(X);
temp = S(1:n,1:n);
sum = 0;
for i = 1:n
```

```
    sum = sum + temp(i,i);
end
sum_val = 0;
val = 0;
for index = 1:n
    sum_val = sum_val + temp(index,index);
    val = sum_val / sum ;
    if val > 0.99
        components = index;
        break
    end
end
%disp(components);
Reduced_Features = U(:,1:components);
C = X' * Reduced_Features;

%%% PCA Muscle D
array = D;
[m,n] = size(array);
X = (array-repmat(mean(array),[m,1]))';
[U,S,V] = svd(X);
temp = S(1:n,1:n);
sum = 0;
for i = 1:n
    sum = sum + temp(i,i);
end
sum_val = 0;
val = 0;
for index = 1:n
    sum_val = sum_val + temp(index,index);
    val = sum_val / sum ;
```

```
    if val > 0.99
        components = index;
        break
    end
end
%disp(components);
Reduced_Features = U(:,1:components);
D = X' * Reduced_Features;



%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%% FINAL CLUSTERING %%%%%%
All_Features = cat(2,A,B,C,D);

%Write the final array to file
csvwrite('EMG_ALL_FEATURES',All_Features);

[m,n] = size(All_Features);
X = (All_Features-repmat(mean(All_Features),[m,1]))';
[U,S,V] = svd(X);

temp = S(1:n,1:n);
sum = 0;
for i = 1:n
    sum = sum + temp(i,i);
end
sum_val = 0;
val = 0;
for index = 1:n
    sum_val = sum_val + temp(index,index);
```

```
    val = sum_val / sum ;
    if val > 0.99
        components = index;
        break
    end
end

%disp(components);
% Reduced Feature Vector
Reduced_Features = U(:,1:components);
New_Features = X' * Reduced_Features;

%[idx, C] = kmeans(New_Features,2);

%cityblock, cosine , correlation
[idx,c] =
kmeans(New_Features,4,'Distance','correlation','MaxIter',100000,'Display','final','Replicat
es',10);
figure;
plot(idx,'b.','MarkerSize',12);
title('K - Means Clustering');
xlabel('Number of Throws')



cluster_1 = zeros(1,length(idx));
cluster_1_count = 0;
cluster_2 = zeros(1,length(idx));
cluster_2_count = 0;

%idx output either 1 or 2
for index = 1:length(idx)
```

```
    if idx(index) == 1
        %If cluster 1
        cluster_1(index) = 1;
        cluster_1_count = cluster_1_count + 1;
    else
        %If cluster 2
        cluster_2(index) = 1;
        cluster_2_count = cluster_2_count + 1;
    end
end


count_cluster_1 = 0;
count_cluster_2 = 0;
for index = 1:length(idx)
    if cluster_1(index) == 1
        count_cluster_1 = count_cluster_1 + 1;
        cluster_1(index) = count_cluster_1 / cluster_1_count;
    else
        cluster_1(index) = count_cluster_1 / cluster_1_count;
    end
    if cluster_2(index) == 1
        count_cluster_2 = count_cluster_2 + 1;
        cluster_2(index) = count_cluster_2 / cluster_2_count;
    else
        cluster_2(index) = count_cluster_2 / cluster_2_count;
    end
end

N = 1:length(idx);
```

```
figure
plot(cluster_1,'b');
hold on;
plot(fliplr(cluster_2),'r');
title('Clustering - Cumalative Probability');
xlabel('Number of Throws')
ylabel('Probability')
legend('Cluster 1','Cluster 2');

figure
plot(fliplr(cluster_1),'b');
hold on;
plot(cluster_2,'r');
title('Clustering - Cumalative Probability');
xlabel('Number of Throws')
ylabel('Probability')
legend('Cluster 1','Cluster 2');
```

4. RMS Analysis Algorithm

```
% RMS value based Analysis of EMG
% by Chirath Hettiarachchi
% copyrights Flisma Labs.

close all;
format long

addpath(genpath('libraries/filters/'));
addpath(genpath('libraries/myo/'));
addpath(genpath('libraries/extra/'));
addpath(genpath('libraries/transform/'));
addpath(genpath('libraries/actionDetect/'));
```

```
addpath(genpath('libraries/features/'));


%Myo Armband EMG Sampling rate 200Hz

%Read all the csv files stored in Data Folder
EMGFILES = dir('../MyoData/*.csv');
NumberOfFiles = length(EMGFILES);

%TODO -> Preallocating for optimization
%To Overcome the issue of file ordering
SORTED_EMGFILES = {};
for file = 1 : length(EMGFILES)
   temp = EMGFILES(file).name;
   SORTED_EMGFILES{file} = temp;
end
SORTED_EMGFILES = natsortfiles(SORTED_EMGFILES);
SORTED_EMGFILES = string(SORTED_EMGFILES);

%suptitle({'Flisma - EMG RMS Analysis ';''})

EMG_RMS_BRACHI = zeros(1,NumberOfFiles);
EMG_RMS_FLEXICARPIR = zeros(1,NumberOfFiles);
EMG_RMS_BICEPS = zeros(1,NumberOfFiles);
EMG_RMS_TRICEPS = zeros(1,NumberOfFiles);

for file = 1 : length(SORTED_EMGFILES)

   temp = SORTED_EMGFILES(file);
   disp(temp);
   filename = strcat('../MyoData/' , temp);
```

```
    %filename = strcat('../Data/' , EMGFILES(file).name);
    try
        M = csvread(filename ,1,0);
    catch
    end
    [timestamp_myo1,timestamp_myo2, BRACHI, FLEXICARPIR, BICEPS, TRICEPS]
= DetectMyoSeperate(M);

    %Applying a High Pass Filter at 20Hz
    BICEPS = Butterworth(6, 20, 200, BICEPS,'high');
    TRICEPS = Butterworth(6, 20, 200, TRICEPS,'high');
    BRACHI = Butterworth(6, 20, 200, BRACHI,'high');
    FLEXICARPIR = Butterworth(6, 20, 200, FLEXICARPIR,'high');



    %Detecting the Muscle Action
    BICEPS = ActionDetect_Clustering(BICEPS,8,3);
    TRICEPS = ActionDetect_Clustering(TRICEPS,8,3);
    BRACHI = ActionDetect_Clustering(BRACHI,8,3);
    FLEXICARPIR = ActionDetect_Clustering(FLEXICARPIR,8,3);



    %Obtaining the RMS value for each Bowlong Iteration.
    EMG_RMS_BRACHI(file) = rms(BRACHI);
    EMG_RMS_FLEXICARPIR(file) = rms(FLEXICARPIR);
    EMG_RMS_BICEPS(file) = rms(BICEPS);
    EMG_RMS_TRICEPS(file) = rms(TRICEPS)
```

```
end

%[idx,C] = kmeans(EMG_RMS_BICEPS',2);
%plot(idx,'b.','MarkerSize',12);
%
% array = EMG_RMS_BICEPS';
% Y = pdist(array,'euclidean');
% Z = linkage(Y,'average');
% %c = cluster(Z,'maxclust',2);
% dendrogram(Z);

% %%%%%%%%%%%%%%%%%%%%%%%%%%% Anova Analysis
%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% m = length(EMGFILES);
% level = floor(m * 0.10);
% threshold = m - level;
% Group = zeros(1,m);
% for index  = 1:m
%     if index <= threshold
%         Group(index) = 1;
%     else
%         Group(index) = 2;
%     end
% end
%
% p = anova1(EMG_RMS_BRACHI,Group);
% disp('brachi')
% disp(p)
%
% p = anova1(EMG_RMS_FLEXICARPIR,Group);
% disp('flexi')
```

```
% disp(p)
%
% p = anova1(EMG_RMS_BICEPS,Group);
% disp('biceps')
% disp(p)
%
% p = anova1(EMG_RMS_TRICEPS,Group);
% disp('triceps')
% disp(p)

figure
plot(EMG_RMS_BRACHI,'r');
hold on;
plot(EMG_RMS_FLEXICARPIR,'g');
hold on;
plot(EMG_RMS_BICEPS,'b');
hold on;
plot(EMG_RMS_TRICEPS,'y');
legend('BRACHI','FLEXICARPI','BICEPS','TRICEPS');



% %%%%%%%%%%%%%%%%%%%%% RMS of Each Muscle & Regression
%%%%%%%%%%%%%%%%%%%%%
figure
suptitle({'Flisma - EMG RMS Analysis ';'';''})
subplot(2,2,1)
scatter(1:length(EMG_RMS_BRACHI), EMG_RMS_BRACHI, 'filled');
lsline
p1 = polyfit(1:length(EMG_RMS_BRACHI),EMG_RMS_BRACHI,1);
y1fit = polyval(p1,1:length(EMG_RMS_BRACHI));
```

```
hold on;
plot(y1fit);
disp(p1)
title('BRACHI')
xlabel('Number of Bowls')
ylabel('EMG RMS')

subplot(2,2,2)
scatter(1:length(EMG_RMS_FLEXICARPIR), EMG_RMS_FLEXICARPIR, 'filled');
lsline
p2 = polyfit(1:length(EMG_RMS_FLEXICARPIR),EMG_RMS_FLEXICARPIR,1);
y2fit = polyval(p2,1:length(EMG_RMS_FLEXICARPIR));
hold on;
plot(y2fit);
disp(p2)
title('FLEXICARPI')
xlabel('Number of Bowls')
ylabel('EMG RMS')

subplot(2,2,3)
scatter(1:length(EMG_RMS_BICEPS), EMG_RMS_BICEPS, 'filled');
lsline
p = polyfit(1:length(EMG_RMS_BICEPS),EMG_RMS_BICEPS,1);
y3fit = polyval(p,1:length(EMG_RMS_BICEPS));
hold on;
plot(y3fit);
disp(p)
title('BICEPS')
xlabel('Number of Bowls')
ylabel('EMG RMS')
```

```
subplot(2,2,4)
scatter(1:length(EMG_RMS_TRICEPS), EMG_RMS_TRICEPS, 'filled');
lsline
p = polyfit(1:length(EMG_RMS_TRICEPS),EMG_RMS_TRICEPS,1);
y4fit = polyval(p,1:length(EMG_RMS_TRICEPS));
hold on;
plot(y4fit);
disp(p)
title('TRICEPS')
xlabel('Number of Bowls')
ylabel('EMG RMS')



%%%%%%%%%%%%%%%%%%%%%%%%%%%%%% Ploting the combination of Muscles
%%%%%%%%%%%
figure
suptitle({'EMG RMS Analysis ';'';''})
plot(y1fit,'r');
hold on;
plot(y2fit,'b');
hold on;
plot(y3fit,'g');
hold on;
plot(y4fit,'y');
hold on;
plot(y4fit + y1fit + y2fit + y3fit,'*');
legend('BRACHI','FLEXICARPI','BICEPS','TRICEPS','SUM');
xlabel('Number of Bowls')
ylabel('EMG RMS')
```

```
%The total RMS values of the muscles.
Sum = EMG_RMS_BRACHI + EMG_RMS_BICEPS ;
figure
scatter(1:length(Sum), Sum, 'filled');
lsline

Muscle_variance = zeros(NumberOfFiles,2);
for i = 1:NumberOfFiles
    %temp = [EMG_RMS_TRICEPS(i) EMG_RMS_BICEPS(i)
EMG_RMS_FLEXICARPIR(i) EMG_RMS_BRACHI(i)];
    temp = [y4fit(i) y1fit(i) y2fit(i) y3fit(i)];
    S = std(temp);
    M =mean(temp);
    Muscle_variance(i,1) = M;
    Muscle_variance(i,2) = S;
end

figure
plot(Muscle_variance(:,2));
title('SD - Muscle Activation');
xlabel('Number of Bowls')
ylabel('Standard Deviation')

figure
plot(Muscle_variance(:,1));
title('Mean - Muscle Activation');
xlabel('Number of Bowls')
ylabel('Mean')
```

5. Mean / Median Frequency Analysis Algorithm

```
% Frequency Domain Analysis of EMG
% by Chirath Hettiarachchi
% copyrights Flisma Labs.

close all;
format long
addpath(genpath('libraries/filters/'));
addpath(genpath('libraries/myo/'));
addpath(genpath('libraries/extra/'));
addpath(genpath('libraries/transform/'));
addpath(genpath('libraries/actionDetect/'));

%Myo Armband EMG Sampling rate 200Hz

%Read all the csv files stored in Data Folder
EMGFILES = dir('../MyoData/*.csv');
NumberOfFiles = length(EMGFILES);

%TODO -> Preallocating for optimization
%To Overcome the issue of file ordering
SORTED_EMGFILES = {};
for file = 1 : length(EMGFILES)
   temp = EMGFILES(file).name;
   SORTED_EMGFILES{file} = temp;
end
SORTED_EMGFILES = natsortfiles(SORTED_EMGFILES);
SORTED_EMGFILES = string(SORTED_EMGFILES);

%suptitle({'Flisma - EMG Frequency Domain Analysis ';''})
```

```
MEANFREQ_BRACHI = zeros(1,NumberOfFiles);
MEANFREQ_FLEXICARPIR = zeros(1,NumberOfFiles);
MEANFREQ_TRICEPS = zeros(1,NumberOfFiles);
MEANFREQ_BICEPS = zeros(1,NumberOfFiles);

MEADIANFREQ_BRACHI = zeros(1,NumberOfFiles);
MEADIANFREQ_FLEXICARPIR = zeros(1,NumberOfFiles);
MEADIANFREQ_TRICEPS = zeros(1,NumberOfFiles);
MEADIANFREQ_BICEPS = zeros(1,NumberOfFiles);

for file = 1 : length(SORTED_EMGFILES)

    temp = SORTED_EMGFILES(file);
    filename = strcat('../MyoData/' , temp);

    %disp(file)
    %disp(temp)

    %filename = strcat('../Data/' , EMGFILES(file).name);
    try
        M = csvread(filename ,1,0);

        [timestamp_myo1,timestamp_myo2, BRACHI, FLEXICARPIR, BICEPS,
TRICEPS] = DetectMyoSeperate(M);

        %Applying a High Pass Filter at 20Hz.
        BICEPS = Butterworth(6, 20, 200, BICEPS,'high');
        TRICEPS = Butterworth(6, 20, 200, TRICEPS,'high');
        BRACHI = Butterworth(6, 20, 200, BRACHI,'high');
        FLEXICARPIR = Butterworth(6, 20, 200, FLEXICARPIR,'high');
```

```
    %Detecting the Muscle Action
    BICEPS = ActionDetect_Clustering(BICEPS,8,3);
    TRICEPS = ActionDetect_Clustering(TRICEPS,8,3);
    BRACHI = ActionDetect_Clustering(BRACHI,8,3);
    FLEXICARPIR = ActionDetect_Clustering(FLEXICARPIR,8,3);

    %Obtaining the mean & median frequency of each Bowling Iteration.
    MEANFREQ_BICEPS(file) = meanfreq(BICEPS,200);
    MEANFREQ_TRICEPS(file) = meanfreq(TRICEPS,200);
    MEANFREQ_BRACHI(file) = meanfreq(BRACHI,200);
    MEANFREQ_FLEXICARPIR(file) = meanfreq(FLEXICARPIR,200);

    MEADIANFREQ_BICEPS(file) = medfreq(BICEPS,200);
    MEADIANFREQ_TRICEPS(file) = medfreq(TRICEPS,200);
    MEADIANFREQ_BRACHI(file) = medfreq(BRACHI,200);
    MEADIANFREQ_FLEXICARPIR(file) = medfreq(FLEXICARPIR,200);

catch
end

%%% PLotting various graphs related to EMG %%%
%subplot(5,5,file)
%MUSCLE_GROUP = BICEPS;
%GRAPH_TITLE = "BICEPS ";

%TODO -> IMPLEMENT AS SEPERATE FUNC

%Plot the normal EMG vs Time
%plot(MUSCLE_GROUP)
%title([GRAPH_TITLE num2str(file) ])
%xlabel('Time')
```

```
%ylabel('Amplitude')
%axis([0 1000 -Inf Inf])

%Plot the EMG in Frequency Domain
%Obtain the Fast Fourier Transform.
%[f, p1] = FFT(200,MUSCLE_GROUP);
%plot(f,p1)
%title([GRAPH_TITLE num2str(file) ])
%xlabel('Frequency')
%ylabel('Amplitude')

%Plot Fullwave Rectified EMG vs Time
%fullrect = abs(MUSCLE_GROUP);
%plot(fullrect)
%title([GRAPH_TITLE num2str(file) ])
%xlabel('Time')
%ylabel('Amplitude')

%Plot Half Rectification of the EMG vs Time
%halfrect = max( MUSCLE_GROUP, 0 );
%plot(halfrect)
%title([GRAPH_TITLE num2str(file) ])
%xlabel('Time')
%ylabel('Amplitude')

%Plot the envelope of the signal
%[yupper,ylower] = envelope(fullrect,10,'peak');
%[yupper,ylower] = envelope(fullrect);
%plot(yupper)
%title([GRAPH_TITLE num2str(file) ])
%xlabel('Time')
```

```
    %ylabel('Amplitude')

    %hist(f)
end

%%%%%%% Analyze Median Vs Mean Frequency%%%%%%%%
% figure
% suptitle({'Flisma - MEAN vs MEADIAN FREQ';'';''})
% subplot(2,2,1)
% %scatter(1:length(MEANFREQ_BRACHI) ,MEANFREQ_BRACHI, 'filled');
% %lsline
% plot(1:length(MEANFREQ_BRACHI) ,MEANFREQ_BRACHI,'blue');
% hold on;
% %scatter(1:length(MEADIANFREQ_BRACHI) ,MEADIANFREQ_BRACHI, 'filled');
% plot(1:length(MEADIANFREQ_BRACHI) ,MEADIANFREQ_BRACHI,'red');
% legend('MeanFreq','MedianFreq');
% xlim([1 NumberOfFiles])
% title('BRACHI')
% xlabel('Number of Bowls')
% ylabel('Frequency')
%
% subplot(2,2,2)
% plot(1:length(MEANFREQ_FLEXICARPIR) ,MEANFREQ_FLEXICARPIR,'blue');
% hold on;
% plot(1:length(MEADIANFREQ_FLEXICARPIR)
,MEADIANFREQ_FLEXICARPIR,'red');
% legend('MeanFreq','MedianFreq');
% xlim([1 NumberOfFiles])
% title('FLEXICARPIR')
% xlabel('Number of Bowls')
% ylabel('Frequency')
```

```
%
% subplot(2,2,3)
% plot(1:length(MEANFREQ_BICEPS) ,MEANFREQ_BICEPS,'blue');
% hold on;
% plot(1:length(MEADIANFREQ_BICEPS) ,MEADIANFREQ_BICEPS,'red');
% legend('MeanFreq','MedianFreq');
% xlim([1 NumberOfFiles])
% title('BICEPS')
% xlabel('Number of Bowls')
% ylabel('Frequency')
%
% subplot(2,2,4)
% plot(1:length(MEANFREQ_TRICEPS) ,MEANFREQ_TRICEPS,'blue');
% hold on;
% plot(1:length(MEADIANFREQ_TRICEPS) ,MEADIANFREQ_TRICEPS,'red');
% legend('MeanFreq','MedianFreq');
% xlim([1 NumberOfFiles])
% title('TRICEPS')
% xlabel('Number of Bowls')
% ylabel('Frequency')

%%%%%%%%%%%Visualization%%%%%%%%%%%%%
% Mean Frequency Visualization
figure
suptitle({'Flisma - EMG Frequency Domain Analysis - MEAN FREQ';'';''})
subplot(2,2,1)
scatter(1:length(MEANFREQ_BRACHI) ,MEANFREQ_BRACHI, 'filled');
lsline
p = polyfit(1:length(MEANFREQ_BRACHI),MEANFREQ_BRACHI,1);
y1fit = polyval(p,1:length(MEANFREQ_BRACHI),'r');
hold on;
```

```
plot(y1fit);
disp(p)
xlim([1 NumberOfFiles])
title('BRACHI')
xlabel('Number of Bowls')
ylabel('Mean Frequency')

subplot(2,2,2)
scatter(1:length(MEANFREQ_FLEXICARPIR) ,MEANFREQ_FLEXICARPIR, 'filled');
lsline
p = polyfit(1:length(MEANFREQ_FLEXICARPIR),MEANFREQ_FLEXICARPIR,1);
y2fit = polyval(p,1:length(MEANFREQ_FLEXICARPIR),'r');
hold on;
plot(y2fit);
disp(p)
xlim([1 NumberOfFiles])
title('FLEXICARPIR')
xlabel('Number of Bowls')
ylabel('Mean Frequency')

subplot(2,2,3)
scatter(1:length(MEANFREQ_BICEPS) , MEANFREQ_BICEPS, 'filled');
lsline
p = polyfit(1:length(MEANFREQ_BICEPS),MEANFREQ_BICEPS,1);
y3fit = polyval(p,1:length(MEANFREQ_BICEPS),'r');
hold on;
plot(y3fit);
disp(p)
xlim([1 NumberOfFiles])
title('BICEPS')
xlabel('Number of Bowls')
```

```
ylabel('Mean Frequency')

subplot(2,2,4)
scatter(1:length(MEANFREQ_TRICEPS) ,MEANFREQ_TRICEPS, 'filled');
lsline
p = polyfit(1:length(MEANFREQ_TRICEPS),MEANFREQ_TRICEPS,1);
y4fit = polyval(p,1:length(MEANFREQ_TRICEPS),'r');
hold on;
plot(y4fit);
disp(p)
xlim([1 NumberOfFiles])
title('TRICEP')
xlabel('Number of Bowls')
ylabel('Mean Frequency')



figure
suptitle({'Flisma- EMG Mean Freq Analysis ';'';''})
plot(y1fit,'r');
hold on;
plot(y2fit,'b');
hold on;
plot(y3fit,'g');
hold on;
plot(y4fit,'k');
hold on;
plot(y4fit + y1fit + y2fit + y3fit,'*');
legend('BRACHI','FLEXICARPI','BICEPS','TRICEPS','SUM');
xlabel('Number of Bowls')
ylabel('EMG Mean Freq')
```

```
%Meadian Frequency Visualization

% figure
% suptitle({'Flisma - EMG Frequency Domain Analysis - MEADIAN FREQ';'';''})
% subplot(2,2,1)
% scatter(1:length(MEADIANFREQ_BRACHI) ,MEADIANFREQ_BRACHI, 'filled');
% lsline
% title('BRACHI')
% xlabel('Number of Bowls')
% ylabel('Median Frequency')
%
% subplot(2,2,2)
% scatter(1:length(MEADIANFREQ_FLEXICARPIR)
,MEADIANFREQ_FLEXICARPIR, 'filled');
% lsline
% title('FLEXICARPIR')
% xlabel('Number of Bowls')
% ylabel('Median Frequency')
%
% subplot(2,2,3)
% scatter(1:length(MEADIANFREQ_BICEPS) , MEADIANFREQ_BICEPS, 'filled');
% lsline
% title('BICEPS')
% xlabel('Number of Bowls')
% ylabel('Median Frequency')
%
% subplot(2,2,4)
% scatter(1:length(MEADIANFREQ_TRICEPS) ,MEADIANFREQ_TRICEPS, 'filled');
% lsline
```

```
% title('TRICEP')
% xlabel('Number of Bowls')
% ylabel('Median Frequency')
```

6. ZCR Analysis Algorithm.

```
% Analysing the EMG based on the Zero Crossing Rate
% by Chirath Hettiarachchi
% copyrights Flisma Labs.

close all;
format long
addpath(genpath('libraries/filters/'));
addpath(genpath('libraries/myo/'));
addpath(genpath('libraries/extra/'));
addpath(genpath('libraries/transform/'));
addpath(genpath('libraries/actionDetect/'));

%Myo Armband EMG Sampling rate 200Hz

%Read all the csv files stored in Data Folder
EMGFILES = dir('../MyoData/*.csv');
NumberOfFiles = length(EMGFILES);

%To Overcome the issue of file ordering
SORTED_EMGFILES = {};
for file = 1 : length(EMGFILES)
   temp = EMGFILES(file).name;
   SORTED_EMGFILES{file} = temp;
end
SORTED_EMGFILES = natsortfiles(SORTED_EMGFILES);
SORTED_EMGFILES = string(SORTED_EMGFILES);
```

```
ZCR_BRACHI = zeros(1,NumberOfFiles);
ZCR_FLEXICARPIR = zeros(1,NumberOfFiles);
ZCR_BICEPS = zeros(1,NumberOfFiles);
ZCR_TRICEPS = zeros(1,NumberOfFiles);

ALL_ZCR_BRACHI = zeros(1,NumberOfFiles);
ALL_ZCR_FLEXICARPIR = zeros(1,NumberOfFiles);
ALL_ZCR_BICEPS = zeros(1,NumberOfFiles);
ALL_ZCR_TRICEPS = zeros(1,NumberOfFiles);

ZC_BRACHI = zeros(1,NumberOfFiles);
ZC_FLEXICARPIR = zeros(1,NumberOfFiles);
ZC_BICEPS = zeros(1,NumberOfFiles);
ZC_TRICEPS = zeros(1,NumberOfFiles);

%figure
%suptitle({'ZCR Analysis - BRACHI';'';''})



for file = 1 : length(SORTED_EMGFILES)

  temp = SORTED_EMGFILES(file);
  filename = strcat('../MyoData/' , temp);

  try
  %filename = strcat('../Data/' , EMGFILES(file).name);
    M = csvread(filename ,1,0);
  catch
  end
```

```
[timestamp_myo1,timestamp_myo2, BRACHI, FLEXICARPIR, BICEPS, TRICEPS]
= DetectMyoSeperate(M);

%Applying a High Pass Filter at 20Hz
BICEPS = Butterworth(6, 20, 200, BICEPS,'high');
TRICEPS = Butterworth(6, 20, 200, TRICEPS,'high');
BRACHI = Butterworth(6, 20, 200, BRACHI,'high');
FLEXICARPIR = Butterworth(6, 20, 200, FLEXICARPIR,'high');

%Detecting the Muscle Action
BICEPS = ActionDetect_Clustering(BICEPS,8,3);
TRICEPS = ActionDetect_Clustering(TRICEPS,8,3);
BRACHI = ActionDetect_Clustering(BRACHI,8,3);
FLEXICARPIR = ActionDetect_Clustering(FLEXICARPIR,8,3);



%ZCR for BRACHI
previous = 0;
counter = 0;
for index = 1 : length(BRACHI)

    if BRACHI(index) >= 0
        present = 1;
    else
        present = -1;
    end

    transition = abs(present-previous) / 2;
    counter = counter + transition;
    previous = present;
```

```
    ZC_BRACHI(index) = floor(counter);
    ZCR_BRACHI(index) = floor(counter) / index;

end

%ALL_ZCR_BRACHI(file) = mean(ZCR_BRACHI);
ALL_ZCR_BRACHI(file) = ZCR_BRACHI(end) / length(BRACHI);

% subplot(2,1,1)
% plot(BRACHI);
%subplot(5,5,file)
%plot(MUSCLE_GROUP);

%ZCR for FLEXICARPIR
previous = 0;
counter = 0;
for index = 1 : length(FLEXICARPIR)

    if FLEXICARPIR(index) >= 0
        present = 1;
    else
        present = -1;
    end

    transition = abs(present-previous) / 2;
    counter = counter + transition;
    previous = present;

    ZC_FLEXICARPIR(index) = floor(counter);
    ZCR_FLEXICARPIR(index) = floor(counter) / index;
```

```
    end

    %ALL_ZCR_FLEXICARPIR(file) = mean(ZCR_FLEXICARPIR);
    ALL_ZCR_FLEXICARPIR(file) = ZCR_FLEXICARPIR(end) /
length(FLEXICARPIR);

    % figure
    % suptitle({'ZCR Analysis - FLEXICARPIR';'';''})
    % subplot(2,1,1)
    % plot(FLEXICARPIR);
    % subplot(2,1,2)
    %subplot(4,4,file)
    %plot(ZCR_FLEXICARPIR);

    %ZCR for BICEPS
    previous = 0;
    counter = 0;
    for index = 1 : length(BICEPS)

        if BICEPS(index) >= 0
            present = 1;
        else
            present = -1;
        end

        transition = abs(present-previous) / 2;
        counter = counter + transition;
        previous = present;

        ZC_BICEPS(index) = floor(counter);
        ZCR_BICEPS(index) = floor(counter) / index;
```

```
end
%ALL_ZCR_BICEPS(file) = mean(ZCR_BICEPS);
ALL_ZCR_BICEPS(file) = ZCR_BICEPS(end) / length(BICEPS);

% figure
% suptitle({'ZCR Analysis - BICEPS';'';''})
% subplot(2,1,1)
% plot(BICEPS);
% subplot(2,1,2)
%subplot(4,4,file)
%plot(ZCR_BICEPS);

%ZCR for TRICEPS
previous = 0;
counter = 0;
for index = 1 : length(TRICEPS)

    if TRICEPS(index) >= 0
        present = 1;
    else
        present = -1;
    end

    transition = abs(present-previous) / 2;
    counter = counter + transition;
    previous = present;

    ZC_TRICEPS(index) = floor(counter);
    ZCR_TRICEPS(index) = floor(counter) / index;
```

```
    end
    %ALL_ZCR_TRICEPS(file) = mean(ZCR_TRICEPS);
    ALL_ZCR_TRICEPS(file) = ZCR_TRICEPS(end) / length(TRICEPS);

    % figure
    % suptitle({'ZCR Analysis - TRICEPS';";"})
    % subplot(2,1,1)
    % plot(TRICEPS);
    % subplot(2,1,2)
    %subplot(4,4,file)
    %plot(ZCR_TRICEPS);

    %subplot(5,5,file)
    %plot(ZCR_BICEPS);



end



figure
suptitle({'ZCR Analysis - MEAN ZCR PER MUSCLE VS TIME';";"})
subplot(4,1,1)
plot(ALL_ZCR_BRACHI);
title('BRACHI')
xlabel('Number of Bowls')
ylabel('Zero Crossing Rate')
subplot(4,1,2)
plot(ALL_ZCR_FLEXICARPIR);
title('FLEXICARPIR')
xlabel('Number of Bowls')
ylabel('Zero Crossing Rate')
```

```
subplot(4,1,3)
plot(ALL_ZCR_BICEPS);
title('BICEPS')
xlabel('Number of Bowls')
ylabel('Zero Crossing Rate')
subplot(4,1,4)
plot(ALL_ZCR_TRICEPS);
title('TRICEPS')
xlabel('Number of Bowls')
ylabel('Zero Crossing Rate')
```