A Wearable System to Analyze the Human Arm for Predicting Injuries Due to Throwing

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Abstract— **There is limited understanding on factors that contribute to throwing related injuries that frequently occur in sports such as Baseball, Cricket and Javelin throwing.**

This preliminary study focuses on the development of a real time wearable system focusing on extracting key parameters related to potential upper arm injuries associated with the throwing action in the game of Cricket. A wearable system is developed to analyze Electromyography (EMG) signals for detecting muscle activity and Inertial Measurement Unit (IMU) data for monitoring the arm motion.

The extracted parameters are then used for analysis, focusing on detecting established indicators of potential injuries. Additionally, an unsupervised learning algorithm is developed towards identifying novel relationships indicating potential injuries.

I. INTRODUCTION

The action of throwing can be identified as one of the basic routines of many sports such as Baseball, Cricket and Javelin throwing. The advent of sport science has extended beyond boundaries of the playing arena, to encompass the analytics, player management and strategic decisions carried out off field.

Previous research on cricket injuries have mostly been limited towards statistical based studies to detect potential injuries using the number of games played and the number of balls bowled [1][2]. The findings include the optimum number of balls to be bowled and games to be played by a player based on continuous player monitoring over multiple seasons. It has also been identified that in cricket, a fielder has a 26.1% chance of upper limb injuries out of total injuries across fielding, batting & bowling [3]. The action of throwing, which includes the more controlled action of bowling, requires the players to throw a hard-solid ball covered in leather weighing between 137.5 - 143.8 grams, typically to a distance of 25 - 90 meters.

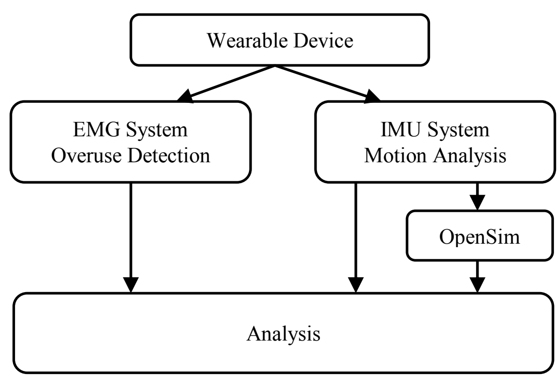
The overuse of muscles and the poor techniques of players have been identified as the main cause of these potential injuries [1-3]. Beyond that there is limited understanding on factors that contribute to throwing related injuries. This study focuses on developing a wearable system for players in order to extract potential indicators of injury for diagnostic and preventative analytics. The scope of the proposed wearable was limited to the throwing action in Cricket, focusing on the glenohumeral joint / rotator cuff muscles, the upper arm and the forearm regions.

II. METHODOLOGY

A. System Design

The system comprises of two sub systems (Figure 1). The Electromyography (EMG) system which identifies muscle activity and an Inertial Measurement Units (IMU) based system to monitor the upper arm motion. Analyzing muscles using EMG in a static environment has widely been carried out in previous research [8]. The focus of such investigations was limited to isometric motions related analysis. In the proposed system in contrast, the analysis is carried out on the actual dynamic motion related to Cricket. Upon the successful development of the wearable system data acquisition was carried out and necessary parameters extracted to identify relationships to focus on predicting potential injuries. The wearable device was designed ensuring minimal interference with the sport. Main muscle groups and joints related to the action of throwing was analyzed with the help of a physician affiliated to the Institute of Sports Medicine, Ministry of Sports Sri Lanka.

Figure 1. System Block Diagram



B. Joint Anatomy

The focus of the research was limited to the upper arm and the glenohumeral joint. It was identified that the stability of the glenohumeral joint is of great importance in preventing potential injuries. The muscles Supraspinatus (SUP), Infraspinatus (INF), Subscapularis (SUB), Teres Minor (TMR) and Deltoid (DTD) were analyzed to assess the active muscle forces and passive muscle forces [4-6].

The upper arm and the forearm were mainly analyzed focusing on the Biceps (BCP), Triceps (TCP), Flexor Carpi Radialis (FLX) and Brachioradialis (BRA) [8]. Although most accurate EMG signals are obtained via fine wire methods, the validity of EMG using surface electrodes has been demonstrated [9] and was considered appropriate for this study.

C. EMG Data Extraction System

Two Myo Armband sensors from Thalmic Labs [10 - 11] were placed in parallel to the muscle body of the above muscles of the upper arm and the forearm to extract the raw EMG signals using wireless Bluetooth Low Energy (BLE) at a data rate of 200Hz. In addition to the wearable system for the extraction of EMG signals, a Delsys dEMG System [12] was used to monitor muscle activation patterns in players under a slow-motion bowling action. All of the above identified muscle groups were analyzed using the Delsys system upon careful placement of electrodes. The extracted signals were filtered to eliminate the low frequency motion artifacts and power line interference in the case of the Delsys system.

The exact EMG signal portion related to the activity of throwing was then extracted using a clustering algorithm. The EMG signal readings were applied k-means clustering and separated in to a *n* number of different clusters. The clusters were sorted in an ascending order based on their values, and a cutoff value was identified. The signal between the first occurrence of the cutoff value from the start and end was extracted as the signal related to the throwing action. The number of clusters *n* and the cutoff value were fine tuned to extract the throwing action. This method was used to eliminate any reaction errors of visually starting and stopping the data extraction based on the throwing action manually. It is also beneficial as the time taken for a throw is different among different players due to their techniques and power exerted, which eliminated the use of a fixed time frame. Finally, the EMG signals were analyzed to identify potential relationships. The block diagram related to the signal processing of the EMG signal is presented in Figure 2.

D. IMU Data Extraction System

The IMU system was developed using three BNO055 Bosch sensor modules, an Arduino Nano module and a BLE module. The inbuilt IMU sensors of the Myo Armbands were not used since their data rate was limited to 50Hz compared to 100Hz in the BNO055 sensors which is a limitation in a dynamic motion such as throwing.

The three sensors were placed as presented in Figure 3, on the back of the player, on the upper arm and the forearm, ensuring the complete modeling of the motion of the glenohumeral joint and the upper arm. The system extracts the quaternion coordinates from the sensors and carries out mathematical computations in order to calculate joint angles. The horizontal flexion, vertical flexion, abduction of the shoulder along with the elbow angles are calculated based on the obtained readings of the placed sensors, which are mainly used in analysis related to detecting poor techniques and the calculation of muscle forces using the OpenSim software. The block diagram of the IMU system is presented in Figure 4.

Figure 2. EMG Sub System

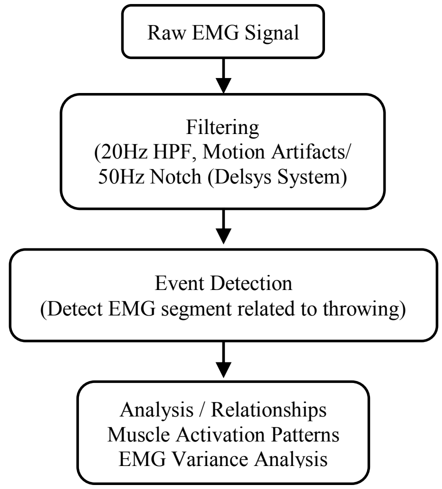


Figure 3. Experimental Setup

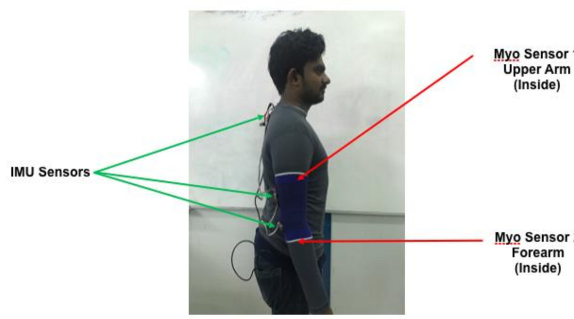
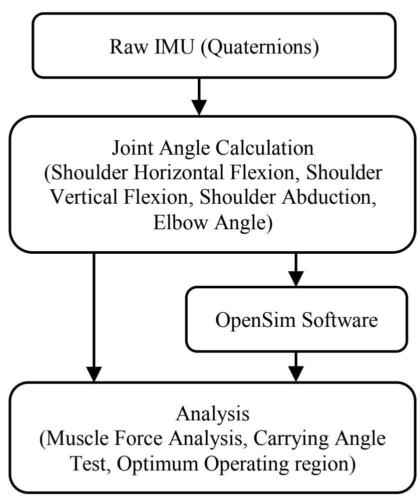


Figure 4. IMU Sub System



E. Experimentational Setup

A total of 3 voluntary test subjects, (ages 19 - 24 years, height 170 - 177 cm) participated in the study. All three subjects were initially required to simulate their respective throwing action in slow motion to extract the EMG from the Delsys dEMG system. The test subjects were then asked to throw a cricket leather ball repetitively as many times as possible towards a constant distance of 25 meters, where the developed wearable system was used to extract the EMG and IMU data. Readings of a total number of 291 throws were recorded across the 3 subjects.

An application was developed to log the IMU & EMG data of the respective throws with their timestamp in order to synchronize the data obtained from the two standalone systems. The application was developed in a manner such that any false readings, device disconnections could be identified and alerted if occurred. The extracted data was then used for injury predictive analysis.

III. RESULTS & ANALYSIS

The prediction of the potential injuries can be carried through two different approaches; first, to observe established relationships related to muscle function and injury. The second was to focus on detecting new relationships based on the extracted parameters.

Optimum Operating Region (ORR) of the human arm, Carrying Angle Test, Muscle Forces Analysis, EMG Variation Analysis and Muscle Activation Patterns were identified as relationships already identified through literature [13-15]. The research also focused on the development of an Unsupervised Learning Algorithm towards overuse prediction.

A. Muscle Activation Pattern Analysis

The analysis of muscle activation patterns was carried at the outset of the research using the Delsys dEMG system in order to identify the behavior of the main muscle groups. Through the initial analysis of the aforementioned muscles, observations were made on their level of activations at different stages of the action of throwing under slow motion. The results were also analyzed with the help of medical experts to identify important findings.

During the analysis of the rotator cuff muscles it was identified that the muscles Deltoid, Infraspinatus and Supraspinatus activate at the point of the release of the ball compared to the Subscapularis muscle which activates well in advance which is expected due to the arm raising motion prior to throwing. The muscle activation patterns related to the rotator cuff muscles are presented in Figure 5.

It was also identified that the muscle activation patterns provide important insights of a person's throwing technique. These patterns could be analyzed in order to monitor the players to ensure that the stability of the rotator cuff is maintained during throwing, and to make necessary changes to the players technique if needed. Through these observations healthy muscle activations as well as activations with potential risk were identified. Figure 6 presents the forearm & upper arm muscle activation of a healthy subject, which according to identified medical relationships, are positive due to the synchronous activation of the muscles in synergy. Conversely Figure 7 presents a muscle activation where less synergy is shown between the muscles which is an indicator of potential risk. Other parameters of the EMG signals were not analyzed since the sole focus of this analysis was on the slow motion of the throwing action and the understanding of the behavior of the different muscle groups.

Figure 5. Rotator Cuff - Muscle Activation Patterns (From top to bottom: Deltoid, Subscapularis, Infraspinatus, Supraspinatus)

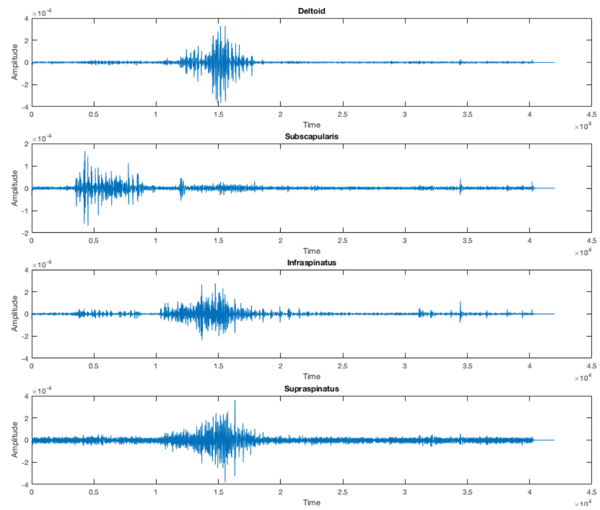
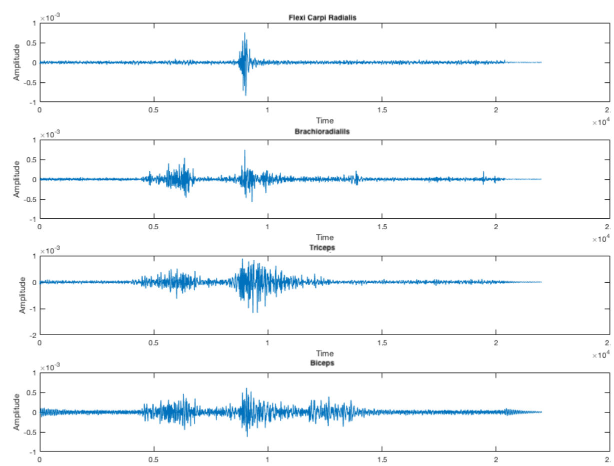


Figure 6. Healthy Muscle Activation Patterns (Flexi Carpi Radialis, Brachioradialis, Triceps, Biceps)



B. EMG Variation Analysis

The EMG signal was analyzed based on different criteria. Upon the analysis of the total root mean square (RMS) value of the BRA, FLX, BCP, TCP muscles along with the individual muscle values across the iterative throws, it was identified that for each subject after a certain point of throws the standard deviation between the RMS values of the 4 muscle groups shows significant increase. (Figure 8)

Upon further analysis of the individual EMG signals it was identified that after a certain number of throws the RMS values of the muscles start to diverge, enabling some muscles to exert more power to carry out the throw, whereas the fatigued muscles start to exert lower power. (Figure 9) The observation was able to detect a threshold which identifies potential injury risk due to the muscle fatigue of the players. The findings were also cross referenced with the same medical practitioner upon analysis. The detected threshold varies among the test subjects, which is due to the different physiques and capabilities of the individuals.

Figure 7. Muscle Activation with Potential Risk Patterns (From top to bottom: Flexi Carpi Radialis, Brachioradialis, Triceps, Biceps)

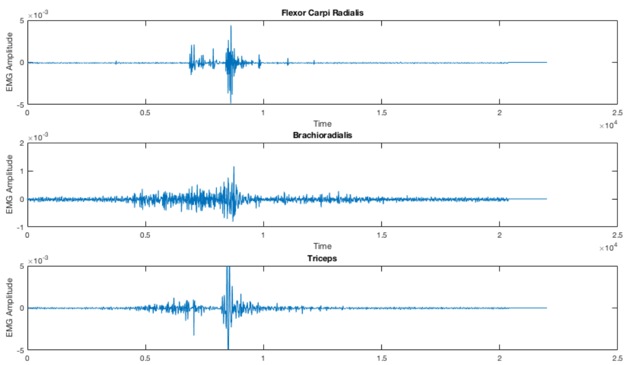


Figure 8. The Fluctuation of Standard Deviation (of Total RMS of Muscle Groups) across Number of Throws

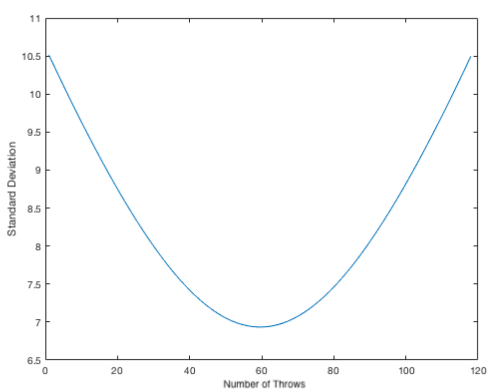
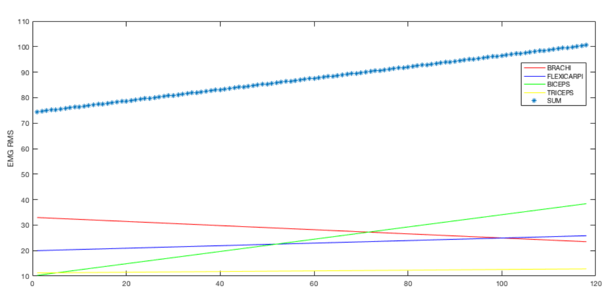


Figure 9. Variation of the RMS Value of Extracted EMG Signals



C. *Joint Angle Analysis*

The Optimum Operating Region (ORR) [13] [14], and the Carrying Angle [15] are measures developed in order to ensure the safe operation of the human arm. Specific limits have been identified to avoid potential injuries due to the poor techniques of the players. A key focus of the developed system was identified as continuously monitoring these angles in order to ensure that the players are operating in a safe region. It was identified that upon overuse of the arm due to throwing there is a chance of induced poor techniques hence the importance of continuously monitoring the identified angles. The system monitored four main joint angles of the human arm, namely the horizontal flexion, vertical flexion, abduction of the shoulder along with the elbow angles. These angles were calculated through a mathematical model using the extracted raw IMU data. The accuracy of the system is of great importance towards the measurement of these joint angles. Thus, a static validation was carried out using a Vernier Perimeter which identified a mean error of 0.634 degrees in the developed system which was deemed sufficient towards the specified task. The identified join angles were also plotted real time for monitoring purposes.

D. *Active / Passive Muscle Force Analysis*

The application of Myo Armband sensors on the rotator cuff muscles was not practical due to the complexity of the shoulder joint and the dynamic nature of throwing. Hence in order to analyze the rotator cuff muscles, an inverse kinematics approach was carried out using the OpenSim software. The calculated joint angles were given as a motion file to the WU shoulder model within OpenSim to simulate the motion and thus calculate the active /passive muscle forces. However, there were inherent limitation since the WU shoulder model was designed for males between the ages of 25-38, weight 56-85kg and a height of 1.7-1.75m [16].

The calculated active muscle forces were then compared with the maximum isometric forces for each rotator cuff muscle to analyze and compare whether they were within the identified limits [17]. The passive muscle forces were also monitored to ensure that the passive forces are always below their respective active forces ensuring the player is not prone to injury.

E. *Unsupervised Learning Algorithm*

The identified previous analysis focused on monitoring relationships among the different extracted parameters to avoid potential injuries. Alternatively, in this method, the focus was to identify new relationships that would provide some indications of overuse which would eventually lead towards potential injuries. It is important to identify such new relationships which would be player agnostic compared to the already established fixed relationships identified above. Hence an unsupervised learning algorithm was developed to detect the point of overuse effectively. It was initially assumed that with the increase of the number of repetitive throws, there exists a point where the muscles would be at a stage of fatigue which would increase the risk of potential injury.

The extracted EMG signals from the BCP, TCP, BRA, FLX muscles were used towards the analysis where the Root Mean Square, Zero Crossing Rate (ZCR), Mean Frequency and the Median Frequency calculated for each muscle group and each throw. Principal Component Analysis was used for these identified features, where finally k-means clustering was used to identify throws related to 2 different clusters. The two different clusters were hypothesized to represent the Non-Fatigue and Fatigue states.

The expected result was observed in a subject who carried out 118 repetitive throws, where the initial throws were clustered together representing the healthy number of throws, and the latter throws clustered representing possible overuse. The clusters based on the number of throws is presented in Figure 10. In order to clearly identify the splitting point of the clusters a cumulative probability was calculated and presented in Figure 11. Through the use of the cumulative probability it was identified that around the 90th throw there is a 0.5 probability of the throw being clustered as overuse.

However, it should be noted that this observation was not seen among the other subjects, which could be mainly due to the insufficient number of repetitive throws. Further data extraction is required from additional players in order to derive a definitive observation. The learning model can be further enhanced through the addition of IMU based data and player specific anthropometric data.

IV. Conclusion & Future Work

The system developed using low cost sensors shows promise in extracting key parameters required towards the prediction of potential injuries. The obtained parameters were capable of analyzing and monitoring the relationships identified through previous research. These identified relationships and the proposed system for data extraction forms a preliminary framework for sports, where the human arm undergoes significant amount of stress and workload. The study can be further improved through the addition of the scapular motion, to study the scapula compensation during the humerus movement.

Figure 10. Clustering Results of the Repetitive Throws.

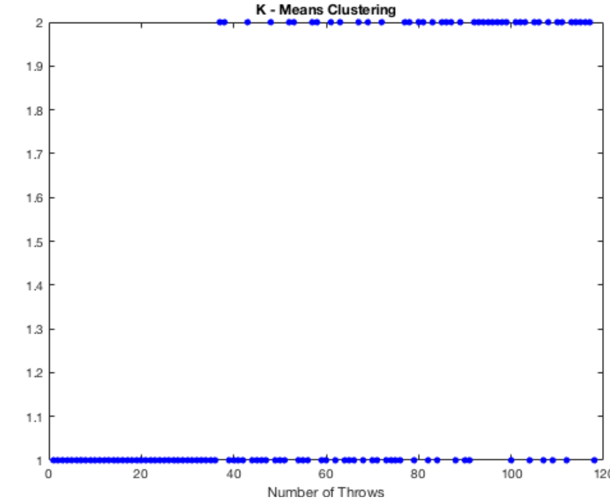
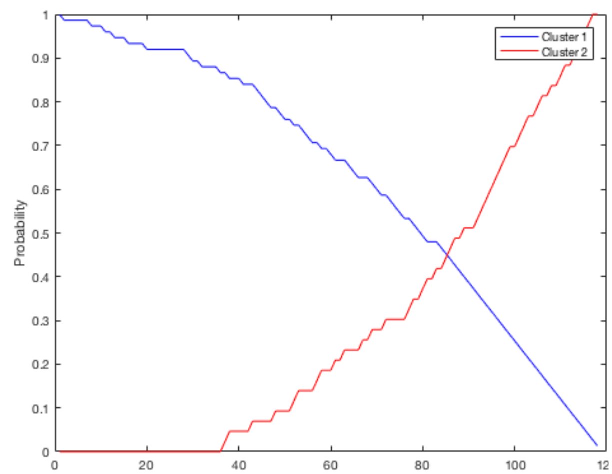


Figure 11. Cumulative Probability of being in given Cluster



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