Analysis of Sensor Locations on Human Body for Wearable Sensor based Activity Classification during Fast Bowling in Cricket

Jayamini Ranaweera and Pujitha Silva
Department of Electronic and Telecommunication Engineering, University of Moratuwa, Sri Lanka

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Abstract: This paper focuses on determining best body sensor position among calf, thigh, upper trunk and forearm when classifying Run Up, Delivery Stride and Follow Through phases during fast bowling in cricket by the usage of a machine learning model. Nine-axis Inertial Measurement Units (IMU) were used to collect data at 350Hz and Madgwick's quaternion based algorithm was used for orientation estimation. The study also focused on determining best quaternion to be considered for such activity classification requirements in fast bowling. Three fast bowlers with Mixed type bowling action were considered for the study. A sliding window with 200 samples/window with 50% overlap collected eight, time domain statistical features from the sensor data and Principal Component Analysis was used to reduce dimensionality of the feature set. A linear kernel based Support Vector Machine classified the features into the three main phases and five-fold cross validation was used to determine model performance. The results indicate that fourth quaternion on calf or forearm is the best quaternion and body position to be considered for activity classification of fast bowling action in cricket.

1 INTRODUCTION

1.1 Phases in Fast Bowling Action

Biomechanical analysis of fast bowling action in cricket reveals that there are three key phases during motion: Run Up, Delivery Stride and Follow Though. As illustrated in Figure 1, each of these phases comprises of sub key motion activities as well.

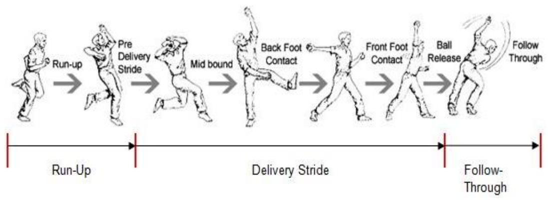

Figure 1: Phases in fast bowling action (Craig, 2013).

In cricket, fast bowlers are more prone to injures. Research (Craig, 2013; Burnett et al., 1998) has demonstrated different types of injuries occurring in each of the key phases during fast bowling. Most injuries in fast bowling occur during Delivery Stride phase. Further, research (Worthington et al., 2013; Wickington et al., 2017) points to biomechanical parameters contributing towards enhancing performance of fast bowlers. Motion analysis can be used to monitor such biomechanical parameters for performance enhancement. Therefore, there is a requirement to analyse the motion of fast bowlers in each phase for the purposes of injury prevention and performance enhancement.

However, wearable sensors (when used for motion analysis) provide continuous data samples during motion. As a result, a model is necessary to segment the data samples into its key phases for analysis purposes.

1.2 Body Sensor Locations

As the first step towards this activity segmentation, it is important to determine which body sensor location would provide the best results during classification of key phases in fast bowling action. Therefore, wearable sensors were placed on different locations on the body during bowling to collect data. However, it was evident that certain locations would provide more deviations of the sensor values during bowling.

Sensor placement for Inertial Measurement Unit (IMU) based bowling action legality classification (Salman et al., 2017) used three IMU sensors placed on upper arm, forearm and wrist. Previous research (Attal et al., 2015; Olguin et al., 2006; Pirttikangas et al., 2006) has conducted extensive analysis to understand the effect of placing sensors on different body locations and their effect on measurement of

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bodily movements. The effect of placing sensors on wrist, thigh, neck, chest, lower back, waist, calf, etc. have been examined. There has been a general tendency to obtain better results when sensors were placed on the waist. It is assumed, that this may be due to the proximity of waist towards the centre of mass in the human body. Further, research (Attal et al., 2015) illustrated that accuracy of human activity recognition decreased when the number of wearable sensors used increased beyond a certain number. Therefore, it was important to determine the best number of sensors to be used for such human activity classification tasks. Following research concentrated on studying the effect of activity classification for sensors placed on the forearm, upper trunk, thigh and calf (Figure 2).

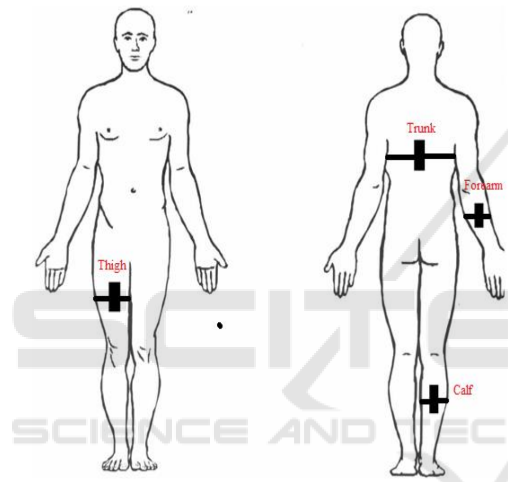

Figure 2: Body sensor placement positions for the study.

1.3 Inertial Measurement Units

Most of the research on activity classification (Groh et al., 2015; Aoki et al., 2013; Wu et al., 2016) with wearable sensors have focused on using Inertial Measurement Units (IMU's) which comprises of a three-axis accelerometer, three-axis gyroscope and three-axis magnetometer. The range of accelerometer, gyroscope, magnetometer values and resolution depend on the specific application. IMU's used for trick classification (Groh et al., 2015) during snowboarding used +/- 16g accelerometer and +/- 2000^{o} /s gyroscope with 16-bit resolution. When the movement speed increases accelerometer range needs to increase accordingly. Fast bowling in cricket requires a sampling rate of beyond 300Hz. However, a major constraint at present is finding IMU's with greater accelerometer ranges. In most IMU based applications, magnetometer is also included to help eradicate drifting errors which are caused due to gyroscopic drifting. Magnetometer assists to provide the earth's horizontal magnetic field and accelerometer provides the vertical acceleration due to gravity which act as the base for drift compensation (Roetenberg, 2006). Another key parameter for IMU selection is its physical size. Since, majority of the IMU based applications are wearable, most studies (Salman et al., 2017; Groh et al., 2015; Gowda et al., 2017) have focused on physically smaller IMU's. IMU developers have managed to reduce the size of the component while also increasing their performance parameters. Hence, 9-axis IMU's were used as relevant wearable sensors for this research. This was achieved by using Kairos (Gawsalyan, et al., 2017; Kathirgamanathan et al., 2018) motion analysis system for data collection.

1.4 Orientation Estimation Algorithm

The outputs from the Kairos motion analysis system were four quaternion values per each sensor. The orientation estimation algorithm used in the system was based on Madgwick's orientation estimation filter (Madgwick, 2010) (quaternion based). By visualization, it is easier to understand a quaternion with reference to the rotation created by rotating frame B to A as illustrated below in Figure 3. In a nutshell, it represents the orientation of frame B with reference to frame A.

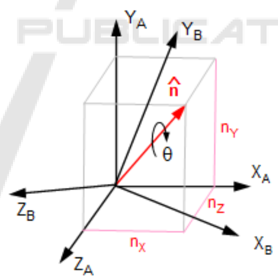

Figure 3: Quaternion rotation (Norris, 2011).

$$q = q_1 + q_2 i + q_3 j + q_4 k = [q_1, q_2, q_3, q_4]$$
$$q_1 = \cos(\theta/2)$$
$$q_2 = n_x \times \sin(\theta/2)$$
$$q_3 = n_y \times \sin(\theta/2)$$
$$q_4 = n_z \times \sin(\theta/2)$$

Where,

q_1 = quaternion real component

q_2, q_3, q_4 = quaternion imaginary components

i, j, k = imaginary vectors with i^2 = j^2 = k^2 = -1

θ = rotation angle

n_x, n_y, n_z = rotation axis components

As a result, in this research, the effect of each quaternion on each body sensor location for activity classification of three key phases in fast bowling was analysed.

1.5 Activity Classification in Cricket

Most common classification related problem for bowling is centred at determining if a certain bowling action is legal or not. Vision based systems are generally used to segment the bowling window to analyse the legality of bowling actions. However, modern research (Attal et al., 2015) has also used wearable sensors to collect three-dimensional rotational data and used supervised classification techniques such as k-Nearest Neighbour, Naïve Bayes, Support Vector Machines, etc. to classify the legality of bowling actions. Initial research (Rowlands et al., 2009) on usage of wearable sensors in cricket has used inertial sensors placed at the centre of mass of a 'Front On' fast bowler to determine Run Up speed, Pre-Delivery Stride length and Hip Rotational Angle.

2 METHOD

This research focuses on extraction of time domain statistical features from IMU data, which act as inputs to a supervised classifier to classify the three main phases of Run Up, Delivery Stride and Follow Through for every quaternion at each of the four specified body locations. Five-fold cross validation was used to determine model performance. The body locations and corresponding quaternions were analysed for their performance during classification. The body position which produces best classification results can be considered as the suitable location to collect data for such classification tasks in fast bowling. Therefore, a pattern recognition algorithm was developed to determine the best on body sensor position.

2.1 System Design

As illustrated in Figure 4, the system initiates with IMU sensors (MPU 9250) being placed on the specific locations collecting quaternion data at 350Hz. The collected data were sent wirelessly by an ESP 8266 microcontroller to a PC to be stored in a .csv file in real time for post processing. Data were collected for each of the three phases (Run Up, Delivery Stride and Follow Through). During post processing, a sliding window collected time domain features from the data followed by a dimensionality reduction step. The dimensionally reduced data set was fed into a supervised classifier and its corresponding performance was analysed. Data from each quaternion on every specified body location were classified and the body position and quaternion with best performance was selected. R programming language was used for all machine learning aspects of the analysis.

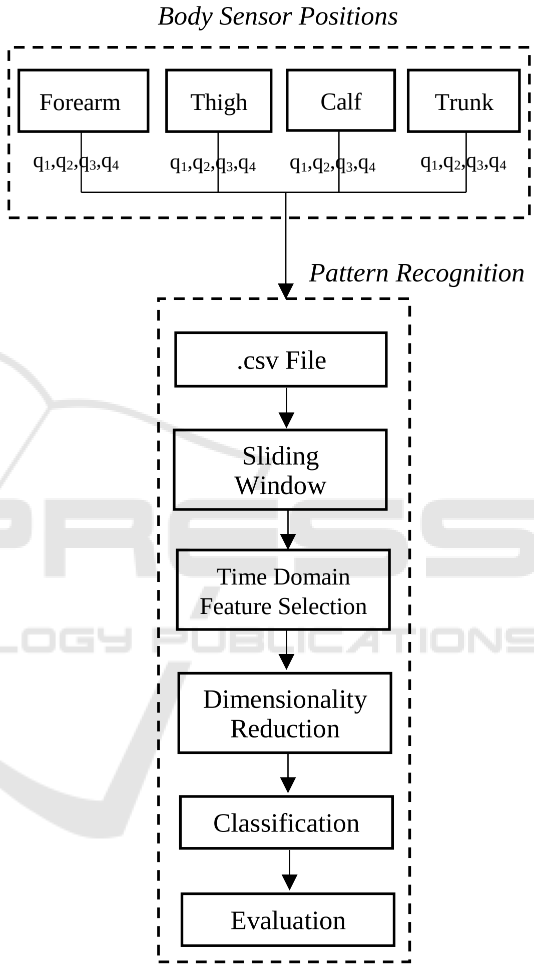

Figure 4: System flow diagram.

2.2 Signal Processing and Connectivity

Microcontrollers are generally used as the signal processing unit in motion analysis systems. Further, wireless transmission of orientation data, visualization and analysis on a secondary computer ease the data collection process. Therefore, a Wi-Fi based ESP 8266 microcontroller was used in this research as the brain of the system to run the orientation estimation and data transmission algorithms. As illustrated in Figure 5, the Kairos motion analysis system comprises of an ESP 8266 module integrated with a MPU 9250 IMU.

For this application, User Diagram Protocol (UDP) was used to transmit data from microcontroller to computer. It was possible to achieve sampling and transmission rates of better than 350Hz. However, a drawback of UDP was the loss of certain data packets during transmission (in some instances). A Python based socket programming application was developed to collect the transmitted data and store in a .csv file in the computer before being input to the machine learning model. Finally, a 180mAh Lithium Polymer battery was used to power the circuit after analysing peak power consumption during operation.

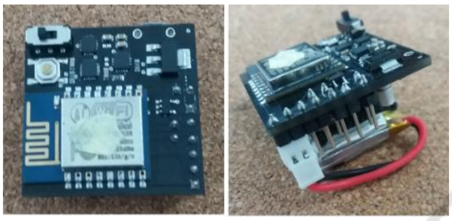

Figure 5: IMU Sensor with battery and ESP module.

2.3 Data Collection

Three participants were selected for the initial data gathering to determine body sensor position that would provide best accuracy results for classification. All participants belonged to 'Mixed type' fast bowling action type and were active cricketers at the instance of data collection. Official consent was obtained from each participant to participate in the data gathering and to take photos and videos during the session. Table 1 represents age, height and weight for the three participants.

Table 1: Fast bowlers age, height and weight distribution.

Bowler	Age	Height (cm)	Weight (Kg)
1	27	164	63
2	17	172	60
3	17	170	65

Sensors mounted using Velcro straps were placed on specific body positions (Figure 6,7) and the subjects were requested to bowl with the sensors. As specified previously, four positions on the body were considered as potential sensor placement areas.

- Thigh – Sensors were placed on the front leg (left leg for right arm bowlers and vice versa).
- Forearm – Sensors were placed on the bowling arm (right arm for bowlers delivering with right arm and vice versa).
- Trunk – Sensors were placed on the upper trunk.
- Calf – Sensors were placed on the front leg (same as the thigh).

Figure 6: Second bowler.

Figure 7: Third bowler.

2.4 Definition of Classes for Supervised Classification

One critical parameter for the classification model was to derive the separate classes for every phase: Run up, Delivery Stride and Follow through. Therefore, data gathering was conducted separately for each phase. Data collection was initiated and ended visually for each phase (Figure 8).

- Full delivery – 5 iterations per subject
- Run Up – 4 iterations per subject
- Delivery Stride - 4 iterations per subject
- Follow Through - 4 iterations per subject

Table 2: Data gathering sequence per class.

Segment	Beginning	End
Run Up	First Clap	Pre-Delivery Stride end
Delivery Stride	Mid Bound Start	Ball Release
Follow Through	Ball Release	Final Clap

The beginning and end for each phase was defined as specified above in Table 2.

Figure 8: Illustration of Delivery Stride phase.

2.5 Feature Selection

A sliding window was used to obtain features for the classification model. Each window comprised of 200 samples and a window overlap of 50% was used (Figure 9). This was done independently for every quaternion on each body sensor position.

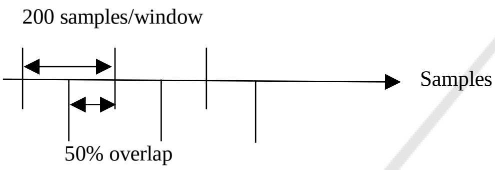

Figure 9: Sliding window for feature collection.

Time domain statistical features were used for this analysis. Hence, eight, time domain statistical features were calculated for each sliding window: Mean, Median, Variance, Skewness, Kurtosis, Median Absolute Deviation, Root Mean Square and Interquartile Range.

2.6 Feature Scaling

A standardization step was required prior to dimensionality reduction for features which were out of scale. In this approach, mean and standard deviation of entire feature vector was calculated. The dataset was scaled by subtracting every element by the mean and dividing by the standard deviation.

2.7 Dimensionality Reduction

2.7.1 Principal Component Analysis (PCA)

To minimize over fitting and for visualization purposes PCA was used for dimensionality reduction. PCA transforms the original variables into a new set of small variables without losing the most important information of the original data. Owing to requirements of visualization in this study, the original dataset was transformed into two principal components. This was achieved by assuming directions with largest variances as the most important. In this instance PC1 (First Principal Component) and PC2 (Second Principal Component) were generated and they were orthogonal to each other with PC1 acting as the most important direction.

2.8 Classification

2.8.1 Support Vector Machine (SVM)

Support Vector Machine (SVM) has been used as a classification (Attal et al., 2015; Fei et al., 2004) and regression algorithm. Throughout literature (Attal et al., 2015; Fei et al., 2004) SVM's have been used for human movement classification as a supervised classifier. However, literature (Attal et al., 2015) illustrates that k-NN classifier has performed better in human movement classification tasks compared to SVM's in certain instances. But in this scenario, the requirement was to compare one classifier against different datasets. In k-NN, selecting correct 'k' number across all datasets was challenging. Hence a SVM was more suitable in this instance. Following characteristics in SVM were also considered for its selection.

- Suitable for instances with less number of classes. In this instance, there were three classes (bowling phases).
- Suits classification with higher number of features. Current classification consisted of eight features.
- When there is non-uniform weighing among features.

In SVM's, features are mapped into high dimensions and a corresponding hyperplane is selected to best classify the results. However, it was noted that application of PCA reduced dimensionality prior to classification. Therefore, a linear 'kernel' was used for the SVM for classification.

2.9 Evaluation

Five-fold Cross Validation was used to evaluate every model. The dataset was divided into five subsets where one of them acted as the test set and the others as training sets. For each subset Accuracy, Precision and Recall were calculated. This was repeated five times and the average of each parameter was considered as the final value. Finally, F-measure was calculated from the averages of Precision and Recall. Body sensor position and quaternion providing best values among the evaluation parameters were selected as the suitable quaternion and best on body sensor position.

$$Accuracy = \frac{(T_p + T_n)}{T_p + T_n + F_p + F_n}$$

$$Precision = \frac{T_p}{T_p + F_p} \qquad Recall = \frac{T_p}{T_p + F_n}$$

$$F - Measure = \frac{2 \times Mean\ Precision \times Mean\ Recall}{(Mean\ Precision + Mean\ Recall)}$$

Where,

T_p = True Positive $\quad T_n$ = True Negative

F_p = False Positive $\quad F_n$ = False Negative

The above parameters were derived based on the confusion matrices generated for each classification.

Table 3: Example 3x3 confusion matrix.

	Run Up	*Delivery Stride*	*Follow Through*
Run Up	13	0	1
Delivery Stride	6	31	1
Follow Through	9	0	27

From the matrices (example in Table 3), Accuracy would be indicated by sum of diagonal values (correctly classified instances) divided by total number of instances. Precision would be defined from the confusion matrix as the ratio of number of correctly classified instances per phase (class) to the number of predictions per phase. Whereas Recall would be the ratio of number of correctly classified instances per phase to the number of instances per phase.

3 EXPERIMENTAL RESULTS

3.1 Original Data Patterns

The first step was to observe the data patterns generated from the IMU sensors when each fast bowler completed his action. The experiment initiated with data collection from sensors on calf, followed by thigh, trunk and forearm.

Collecting data from trunk was a challenge due to the difficulty in holding the sensors steady during delivery. Further, the sensors were positioned in a way not to discomfort the bowler during delivery.

The experiment was conducted at 'Cric Sri Lanka' indoor cricket academy. The head coach of the academy was present and was given the responsibility to observe the deliveries. This was done to highlight if any variations were observed in the bowler's actions from the normal action. The bowlers were requested to perform their deliveries with the intention of hitting a stump placed at the batmen's end. This was done to generalize each delivery from the bowlers.

Figures 10, 11, 12 and 13 illustrate the patterns generated from first bowler, during full delivery, for every quaternion at calf, thigh, forearm and trunk. The graphs illustrate normalized quaternion value on y-axis and the relevant sample number on the x-axis.

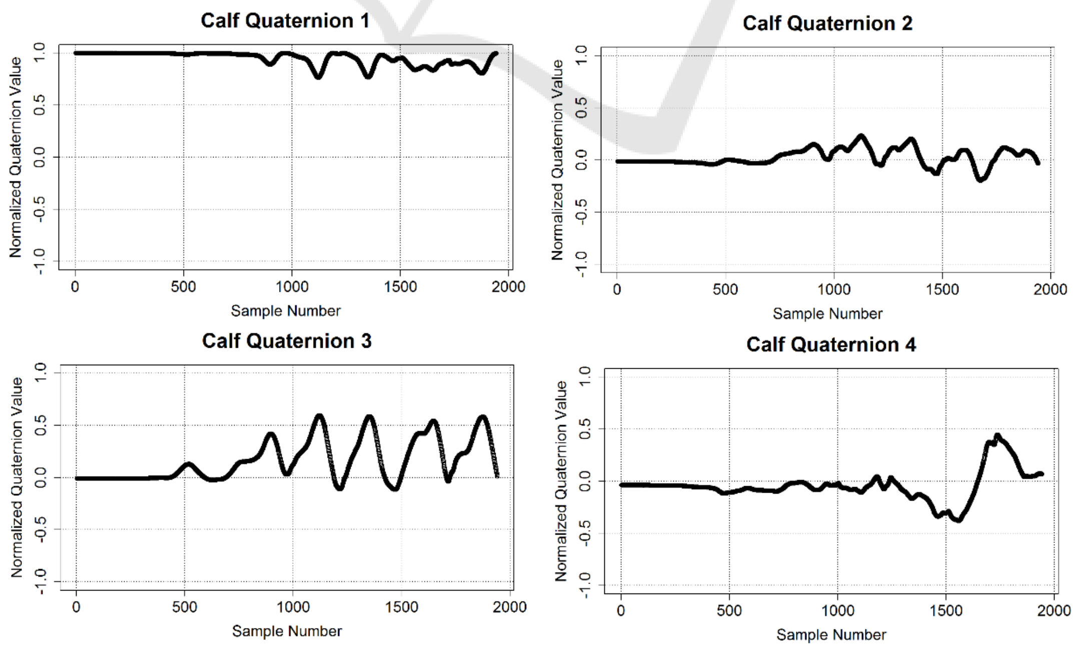

Figure 10: Quaternion illustration of sensor data from calf for fast bowler 1.

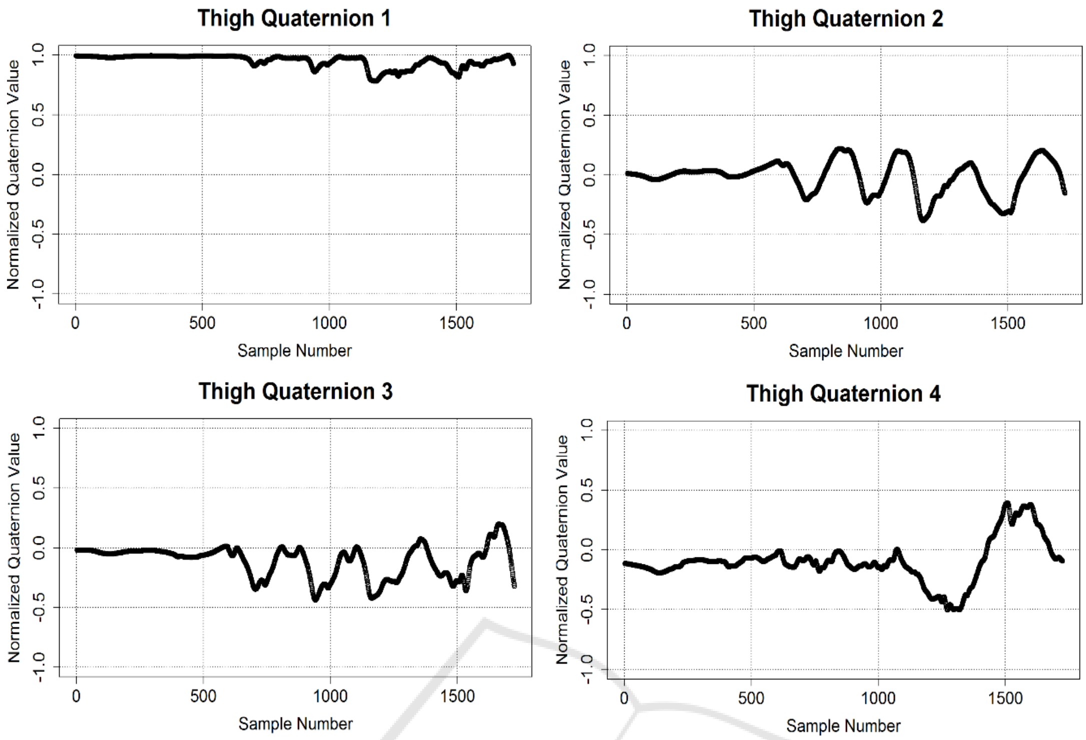

Figure 11: Quaternion illustration of sensor data from thigh for fast bowler 1.

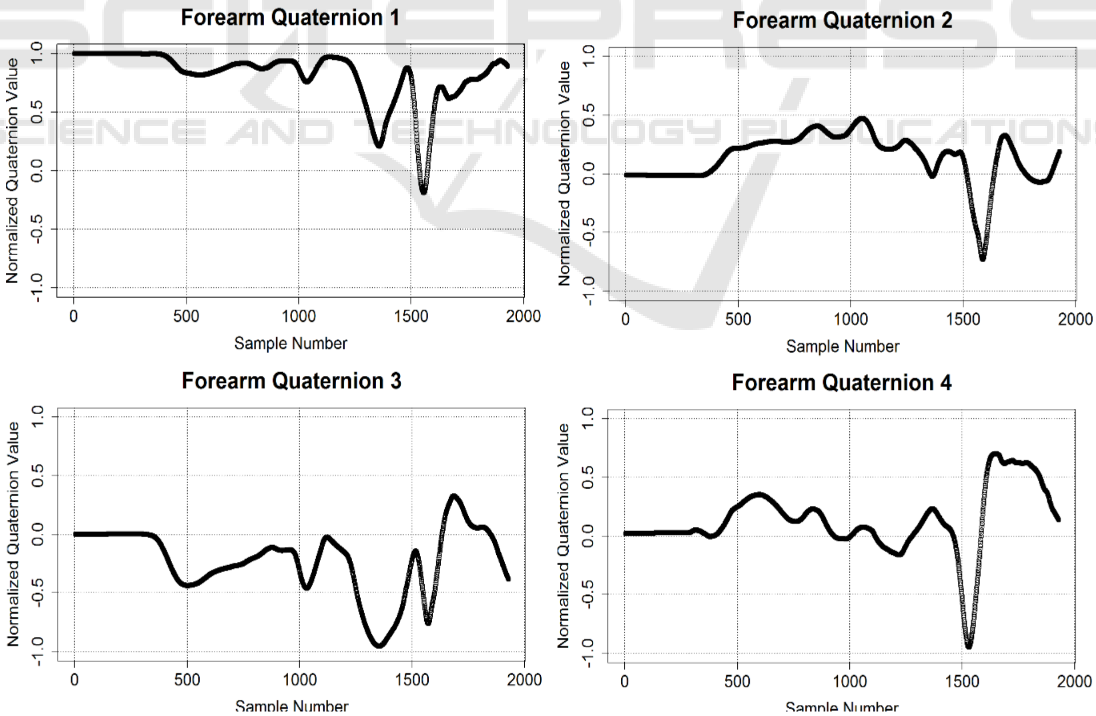

Figure 12: Quaternion illustration of sensor data from forearm for fast bowler 1.

The initial graphs developed from the sensor on the calf (Figure 10) demonstrated fluctuations among all quaternions. Quaternion 1, 2 and 3 demonstrated consistent deviations and fourth quaternion showed sudden variations in the graph, which may indicate boundaries for different phases in bowling. Graphed data plot from thigh (Figure 11) demonstrated similarities to the data from the calf. Only fourth quaternion demonstrated higher variations in the plot. From the sets of data received from trunk (Figure 13), quaternion 3 and quaternion 4 demonstrated higher variations. All quaternion data from forearm (Figure 12) demonstrated higher fluctuations/variations throughout the plot. However, it was difficult to determine separability of phases and performance by observing the original plots. Hence it was necessary to observe the results from the machine learning model to determine best sensor location for classification of three key phases in fast bowling.

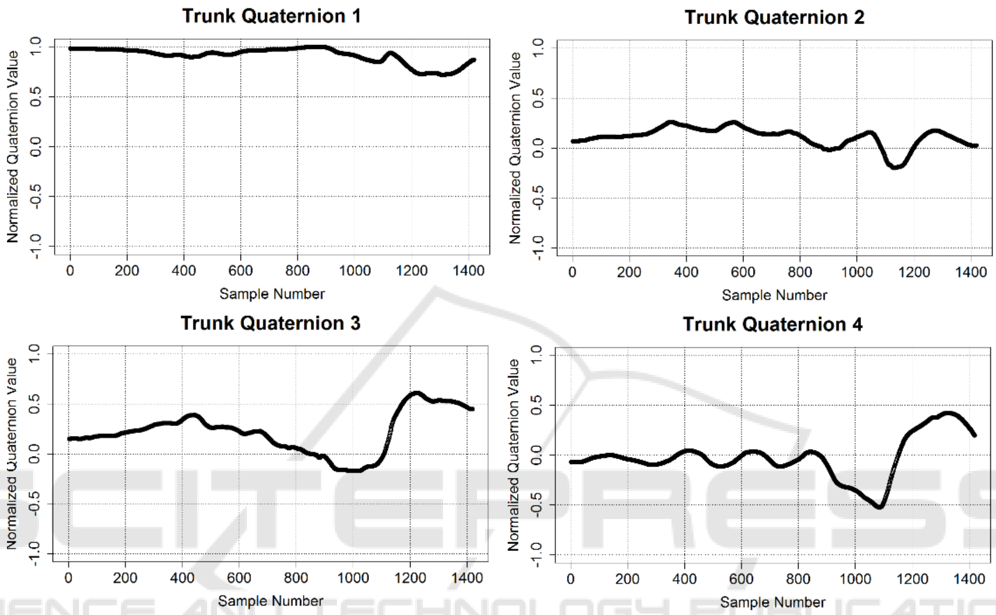

Figure 13: Quaternion illustration of sensor data from trunk for fast bowler 1.

3.2 Classification Results

Table 4: Performance parameter results from classification.

Evaluation Parameter	**Forearm**				**Trunk**			
	Q1	***Q2***	***Q3***	***Q4***	***Q1***	***Q2***	***Q3***	***Q4***
Accuracy (%)	93.02	89.76	83.79	96.39	78.14	92.24	78.34	93.92
Standard Deviation (+/- %)	1.77	2.79	2.8	2.11	2.39	3.35	4.87	3.16
Precision (%)	93.18	89.97	84.35	96.45	79.02	92.56	81.53	93.63
Recall (%)	92.9	89.51	84.37	96.22	78.29	91.84	78.32	94
F-Measure (%)	93.04	89.74	84.36	96.34	78.66	92.19	79.89	93.81
Evaluation Parameter	**Thigh**				**Calf**			
	Q1	***Q2***	***Q3***	***Q4***	***Q1***	***Q2***	***Q3***	***Q4***
Accuracy (%)	73.73	58.57	54.44	89.17	96.38	85.67	75.9	99
Standard Deviation (+/- %)	4.26	3.87	4.61	2.53	1.57	0.66	3.84	0.2
Precision (%)	74.54	58.97	59.75	89.37	96.43	85.9	78.27	99
Recall (%)	73.5	58.43	54.1	89.03	96.37	85.34	76.57	99
F-Measure (%)	74.02	58.7	56.79	89.2	96.4	85.62	77.41	99

Q1 – Quaternion 1 *Q2 – Quaternion 2* *Q3 – Quaternion 3* *Q4 – Quaternion 4*

The results from Table 4 indicate that forearm and calf provided best classification results when classifying Run Up, Delivery Stride and Follow Through phases of fast bowling action in cricket. In all body positions, the fourth quaternion has produced good performance results with best Accuracy, Precision, Recall and F-Measure results. The fourth quaternion on calf has produced the best Accuracy, Precision, Recall and F- Measure of 99%. Fourth quaternion on forearm, also produced a good Accuracy level of 96.39%. During the study, it was observed that among the three phases, Run Up had more data points in comparison to the other two phases. Hence, Synthetic Minority Over-Sampling Technique (SMOTE) (Chawla et al., 2002) was used to balance the data sets by oversampling data in Delivery Stride and Follow Through phases after applying PCA to eradicate the errors that may be caused due to unbalanced classes (phases) on the SVM classification model. Corresponding results have been visualized in Figure 14.

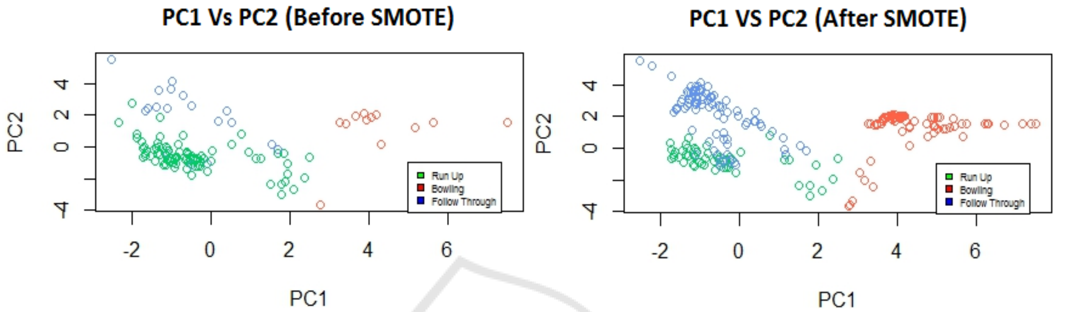

Figure 14: Balancing of data sets by using SMOTE.

3.3 Visualisation of Classification Results

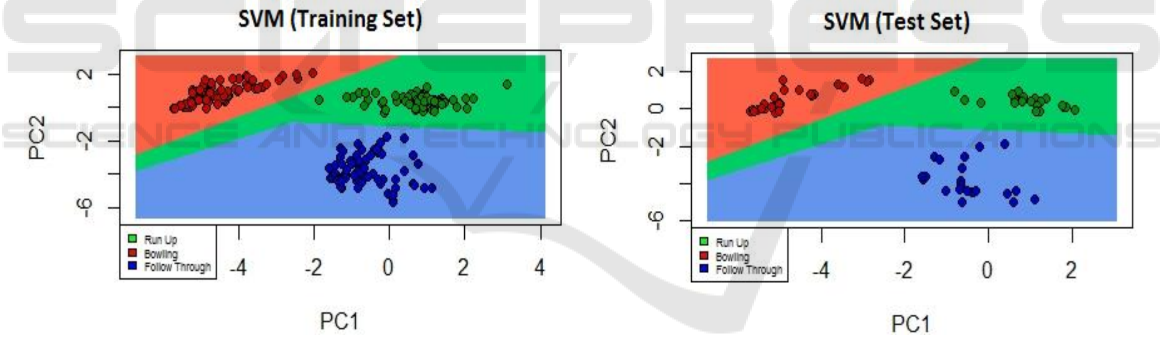

Figure 15: Training set vs Test set plot of fourth quaternion data from calf.

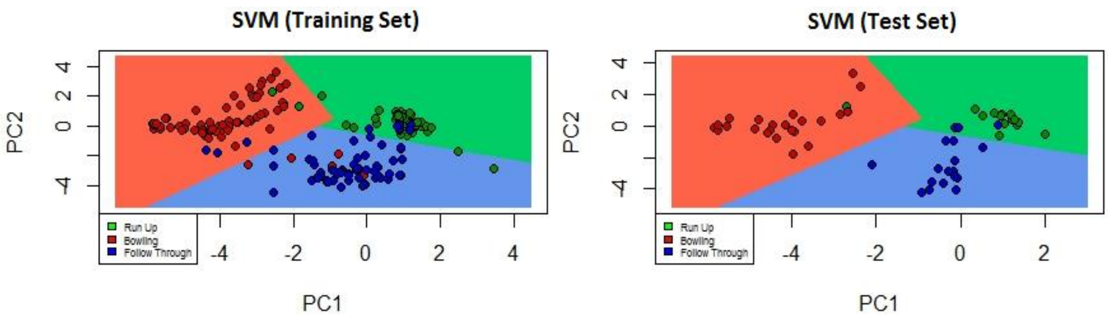

Figure 16: Training set vs Test set plot of fourth quaternion data from thigh.

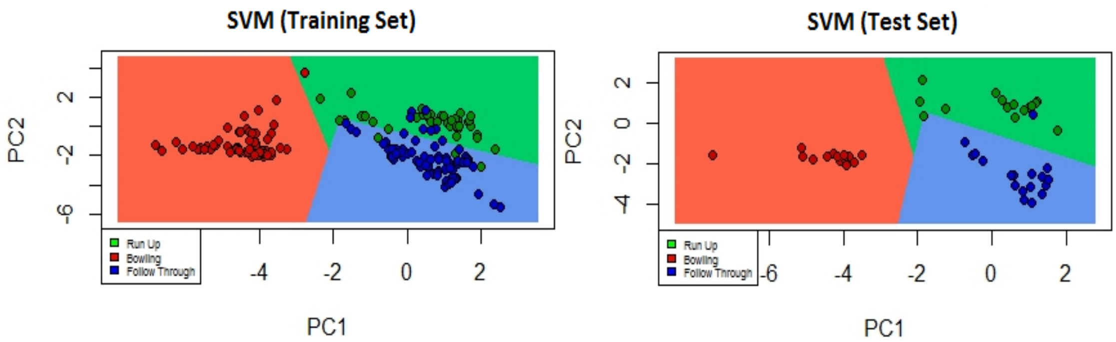

Figure 17: Training set vs Test set plot of fourth quaternion data from trunk.

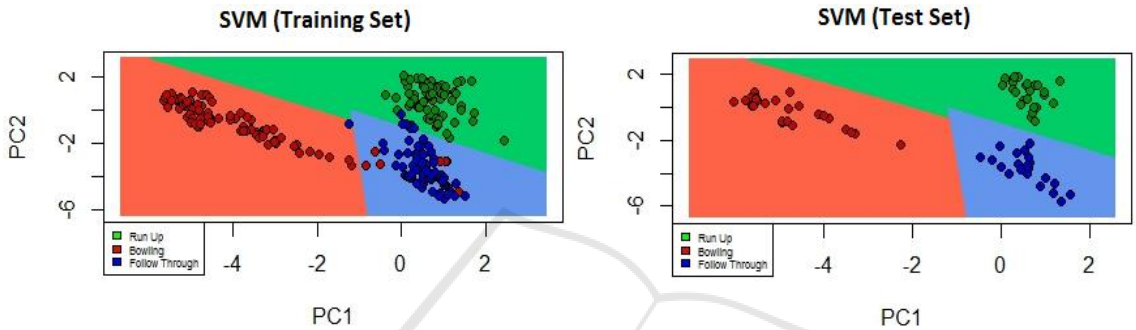

Figure 18: Training set vs Test set plot of fourth quaternion data from forearm.

Above visualization results in Figures 15,16,17 and 18 presents fourth quaternion plots for every on-body sensor position derived from five-fold cross validation. Corresponding training and test sets have been plotted in relation to the subset providing best results among the five subsets. Hence, it is clearly visible that calf and forearm demonstrates best classification results from SVM classifier.

4 CONCLUSION

This paper introduces an analysis towards the determination of best Inertial Measurement Unit (IMU) body placement position to classify the three main phases (Run Up, Delivery Stride and Follow Through) of fast bowling action in cricket. The results indicate that both forearm and calf are suitable positions among calf, thigh, trunk and forearm for placing sensors in relation to activity classification of fast bowling in cricket. However, calf provides best overall performance from the SVM based classification model. Among all the quaternions considered the fourth quaternion provides best results among all quaternions. Hence it can be concluded that fourth quaternion on calf or forearm can be considered for future similar applications of activity classification in cricket. However, there is a case to continue the study further to determine the effect of using raw tri-axial accelerometer, gyroscope and magnetometer values in the classification. Further, the effect of using a more derived measurement such as a yaw, pitch and roll can also be considered.

The above experiment used individual sensors for each on body position. Further, there is a requirement in future, to study the effect of using multiple sensors for similar activity classification of fast bowling action in cricket. The results from the study (Olguin et al., 2006) indicate a rapid increase in accuracy when a second sensor is added for classification. This trend of increase in classification accuracy continues when all three sensors are used for classification. Although the study (Olguin et al., 2006) uses an unsupervised classification method, there is a definite case to add a secondary sensor to increase classification accuracy of the discussed model in the current research. The results indicate that fourth quaternions on calf and forearm can be used for this purpose, since they represent high individual classification accuracies and represent upper and lower body segments. Finally, in future, the effect on model performance can be studied by increasing the number of participants and repeating the experiment.

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