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A HIDDEN MARKOV MODEL FOR DETECTION AND CLASSIFICATION OF ARM ACTION IN CRICKET USING WEARABLE SENSORS

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Hidden Markov Models (HMM) have been used for to accurately model, detect and classify key phenomenon. In this manuscript, we propose use of HMM for detection and classification of arm action in the game of cricket. The technique uses sensor data gathered from wearable sensors placed at wrist, elbow and shoulder. The sensor data consists of both displacement and rotational information collected through a combination of accelerometer and gyroscope placed at each joint. A Bluetooth transceiver is attached to the arm in order to wirelessly transfer the gathered data to the base station. A K-means clustering algorithm classifies the current position and angular rotation of the joint for each of the sensor placements. A Markov chain then determines the chain of sequence for a set of joint movements (displacement and angular rotation) to classify it as a specific arm motion. A Hidden Markov Model determines the previous state of arm motion in order to classify the current state and hence, the current action since the movements happen in progression, when following the other. Experiments show an accuracy of up to 100% in correctly determining the arm action against a model built around a trace-set collected from a sports biomechanics expert. The proposed model has applications in cricket coaching and technique adaptation both for novice and trained players.

Key words: Hidden Markov Model, Cricket, Action Classification

1 Introduction

Detection and classification of arm action is an important problem for the game of cricket. Correct arm action recognition may assist coaches who can provide real-time feedback to the players for playing key strokes or delivering a ball to the player. A major problem in cricket is to detect whether an arm action conforms to the guidelines put forth by cricket governing bodies such as International Cricket Council. Many technologies have been used in the past for detecting legality of moves in games. Most of these systems involve cameras with an observer or a computer program for classifying the activity being monitored. A video processor may be configured to identify anomalous or abnormal behavior. As one example of video based anomalous behavior detection, a system may treat stealing or shoplifting as abnormal behavior and use video feature extraction and model based comparison techniques for detecting anomalous behavior.

Other solutions may involve tracking players without using cameras but by monitoring key features and applying pattern recognition techniques for classifying a move. These solutions may execute on a computer based processing device to detect unwanted or unfair betting patterns of players. In this scenario, both known and unknown players may be tracked, wherein game data is collected over a plurality of gaming sessions and analyzed to determine if an alert needs to be triggered for an operator of the game. These systems may have applications in detecting illegal activity in gaming, gambling, or other operations with a high risk of potential fraud.

Sensor based systems are becoming increasingly popular due to their low cost, miniaturized non-obtrusive form factor and higher accuracy. Sensor-based systems may detect contacts between the games equipment and a games object and/or contacts between a games object and a target surface. These systems may comprise sensor means that have been adapted to detect vibrations caused by game contacts and convert them into sensor data. These systems are generally focused on game contacts and not on the legality or illegality of action performed.

These systems have inherent limitation in terms of cost as they need expensive high-resolution cameras to cover all spatial aspects of a play for identifying key features accurately. A camera based approach requires complex computation methods to correctly estimate the location and attributes of the object under observation.

In contrast, the inertial sensors may be used to accurately acquire the location, velocity, angular acceleration data or other attributes, processing the acquired data either in real-time or after the game is over. Inertial sensors are compact in size, portable, and low cost making them easy to use for determining the legality or illegality of a move as per the rules of a game. The accuracy achieved by logging movements using inertial sensors is better than the accuracy achieved by using camera-based systems because the location and viewing angle of a camera may become a limiting factor.

A Wireless Sensor Network (WSN) comprises a number of devices known as wireless sensors that are designed specifically for acquiring data and processing it according to requirements [1]. In context of research, WSN is a major field in which extensive research work is being done nowadays. However, as the technological evolution continues, many unexplored areas are being discovered and thus, present an excellent opportunity for the researchers to expand their knowledge by innovation in the area of wireless sensors and wireless communications.

The latest technology has enabled us to design such compact and versatile devices that can greatly assist us in daily-life activities [2]. Weiser investigated how the pre-existing technologies can be used to integrate the latest information technology in daily-life activities of the people [3]. WSNs are deployed for a variety of applications, most of them related to daily life activities. Extensive research has been conducted in the past decades, and is still going on, particularly in the area of activity recognition.

Activity recognition is a process of identifying certain activities of a subject under study that are being carried out in real-time, by comparing them with the information readily stored in the system. Human Activity Recognition is another perspective of activity recognition in which human activities are recognized by deploying external sensors such as motion, acceleration and video sensors [4]. Usually, the activity recognition process is used for medicine or biomechanics related applications. A WSN for activity recognition of a patient suffering from Parkinson's disease has been discussed by Akay [5] and thus, the movement of various body parts is monitored which eventually helps in the recovery process. Activity recognition can also be used for security purposes or for monitoring the data traffic in a particular space at a particular instant of time as done by Weaver et. al [6]. Recently, inertial sensors are integrated with antenna for developing a compact device capable of performing the body motion analysis [7].

Activity recognition can be used for certain applications in sports technology. Previously, Aerts [8] has developed a wearable device for monitoring different factors like velocity, acceleration, body temperature, etc., for sports like jogging, swimming, cycling and similar sports. Recently, inertial sensors have been extensively deployed for various applications, and activity recognition is one of them. The use of inertial sensors for activity recognition purpose has been further extended for deployment in particular fields of sports and training; swimming, golf, sprint-running and tennis to name a few. Sports regulatory bodies have also shown keen interest in developing compact devices that can be easily used for training and monitoring of developing players and athletes [9-10]. Cricket is one major sport in which researchers are carrying out advance level studies in order to develop an efficient device that can be specifically used to monitor and detect legality of a move during a bowling action [9, 11]. Researchers like Portus and Wixted [9, 11] are working in collaboration with some testing facilities to achieve a solution for monitoring and detecting an illegal bowling action performed by a player on-field, instead of doing the same at a dedicated facility and under unnatural circumstances.

Wixted et. al. [11] have proposed a method for elbow axis alignment to compare the output of sensors for known data sets for legal and illegal deliveries, and the system was validated with the help of a video based motion capture system. Another approach of detecting the illegal bowling action has been discussed by Wixted et. al. [9] by monitoring the angle of bowling arm during a delivery, by comparing the data collected from MEMS devices with that obtained using Vicon markers. Research is also being carried out in determining the accuracy of wearable sensor device data in comparison with the data obtained using the testing facilities available today.

Although the problem of designing an efficient and compact device to detect the legality of bowling action in the game of cricket has been addressed by many researchers [9-10], however, the coaching technique using miniature sensors has not been given much attention. Further, the equipment cost made the solution unviable for use by the developing players or for personal training purposes. The use of video based system in well-established laboratories was also of concern for personnel due to privacy issues. Besides, the use of cameras limited the application in terms of viewing angle possibility with a fixed number of camera devices.

As mentioned earlier, coaching is also necessary to properly train the bowlers to comply with the rules of cricket. Most of the time, the coaching is done by showing the videos of experienced bowlers to the developing players. Some players also practice in the vicinity of biomechanics laboratory specialized for monitoring the bowling action. Nowadays, inertial sensor based devices are used for coaching in sports like sprint running [12], tenpin bowling [13], baseball [14], etc. Similar coaching strategy can also be applied for coaching the cricket bowlers using inertial sensors.

As mentioned in the work by Eric Guetenberg et. al. [15], parameter extraction is also possible without direct calculation of angle and position to identify an activity. Our system is different from the one proposed by Eric Guetenberg et. al. [15] as the acquired data from inertial sensors is used to train the HMM to generate the corresponding template for checking the validity of a test data set against it. The identification of key events is not necessary since the training data set is acquired only for one particular action, signifying only a specific bowling style. This paper is based on an activity recognition system specifically designed for coaching a cricket bowler. The Micro-Electro-Mechanical Systems (MEMS) based Inertial Motion Units (IMUs) namely gyroscope and accelerometer, are used in this system. The data is collected from the sensors wirelessly and is passed on to a computational unit where it is compared with another data set that complies with the standards specified by the regulatory body (International Cricket Council (ICC), in this case). Care is taken that the rule of arm extension angle not exceeding 15 degrees [16] is followed in the standard data set, based on which the test data is classified as incorrect if it is not closely correlated to the standard data set. Section II of the paper discusses the design challenges that are faced at the system level, followed by a description of implementation methodology of the proposed system in section III. The test scenarios and experimental setup for testing the implemented system is discussed in section IV, whereas the results and a discussion on critique are provided in section V. The conclusion of the proposed system and the results is covered under section VI.

2 Key Design Considerations

Proper coaching and training of a player in a game requires very precise details about parameters associated with movement so as to correctly follow the rules of the game. The technical challenges that are faced at every stage, from component level design to the system level design, while designing a system for training a bowler for a particular bowling action can be divided into two major categories; device level and, data processing and classification inference level, both of which are discussed as follows:

2.1 Device Design

Keeping in view the work reported in literature [11], the designing of inertial sensor was accomplished by thorough investigation of each related parameter. MEMS based IMUs namely gyroscope and accelerometer are preferable to use because of their compactness in size, minimal power consumption and motion data capturing characteristics [17, 18]. Sensor data resolution is the next important parameter, as it specifies the number of samples of acceleration and angular velocity obtained to correctly model the action. However, care must be taken that higher data resolution may not lead to extra power consumption.

2.2 Communication Protocol

Once the components are properly calibrated, a suitable technique needs to be chosen for communicating the data collected by the device to the processing module. The chosen wireless communication technology should meet the requirements for adequate data rate, proper networking, data aggregation process, low power consumption, greater communication range and most importantly the accuracy. Greater the accuracy of data acquired, the more reliable is the system functioning. Keeping in view all these constraints, the best suitable communication technology is chosen to be Bluetooth Class 2. Its transmission range is between 10 meters to 33 feet, power consumption is very low (about 25mW), and most importantly its operating frequency lies in the unlicensed spectrum [19]. Also, Bluetooth is feasible for use in most WSNs [20] and also because high data rate communication is required over a short range as it is an efficient technology for reducing end-to-end data transmission time [21]. Furthermore, the Adaptive Frequency Hopping (AFH) capability in Bluetooth technology makes it feasible for usage with other technologies operating in the 2.4 GHz spectrum, without interference [19]. The prime advantage of using inertial sensors coupled with wireless technology is the ease of mobility. Such devices can be easily used by coaches to train the developing players as well as by the players themselves while playing on field. Another advantage of such device design is that privacy of a player is not affected, since only the data associated with the bowling action is captured, instead of the player profile as done in the video based activity recognition processes. Moreover, the security of the player is not invaded since no information about physical features of the player is used for checking the bowling action.

2.3 Machine Learning

After successful acquisition of accurate data, the main task is to define sequence of steps to process the data and finally, to determine the correctness of action associated with it. The acquired data is first calibrated by passing it through a filter, which removes the noise in the data as well. The calibrated data is then refined using data estimation techniques commonly employed for mathematical analysis.

After noise removal and data refinement, the preprocessed data will contain two types of values; one for acceleration in the x, y and z axes, and the second for angular velocity obtained through gyroscope. This preprocessed data is used for feature extraction on the basis of which the classification engine will work. The classification engine comprises certain algorithms that have been deployed in the previous literature for machine learning. The choice of classification algorithm depends on the accuracy of detection required as well as the features extracted from the data. High level accuracy is required for this system to correctly classify the bowling action as correct or incorrect, therefore such algorithm is to be chosen that ensures an accuracy of nearly 100 percent.

3 Methodology

Based on the design challenges, discussed in the previous section, the proposed methodology can be divided into the following sub-categories:

3.1 Device Architecture

The initial WSN design is limited to three sensors to be placed on the arm. The sensors are similarly structured and are capable of acquiring data. The IMU is calibrated for a data rate of 150Hz so that data samples can be collected accurately without significant power consumption, however the calibration can be increased till 400Hz at the cost of greater power consumption. The data transmission is accomplished using Bluetooth class2. A microprocessor is used for interfacing the IMU and the Bluetooth transmission module to complete the device level design.

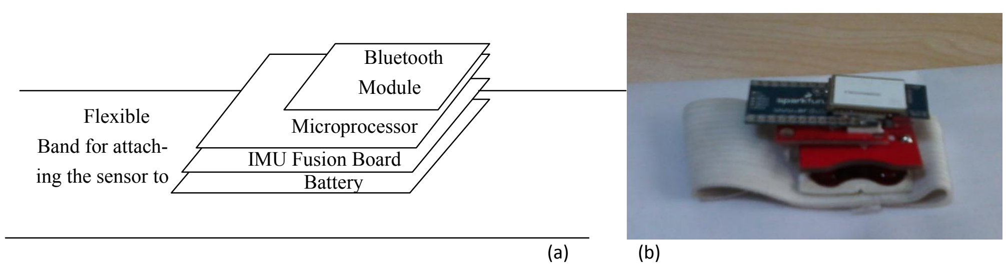


Fig.1. The sensor module (a) schematic and (b) final form

The schematic of the sensor is shown in figure 1 (a). The sensor is made up of four separate parts; and all of them are connected in such a way that the sensor, as a whole, is compact and comfortable for use in lab environment or on-field. The microprocessor, Arduino Pro-Mini, is connected to the IMU 3000 Fusion Board. Transceiver operation is completed by the use of Bluetooth class2 compatible module. The whole assembly is connected to a 3.6 Volt rechargeable Lithium battery, placed at the bottom of the wearable sensor device and all the boards are connected in overlapping fashion to achieve compactness. The combined assembly is attached to a flexible band, so as to support its fixture on the desired body part. Figure 1(b) shows the sensor module used for the experiment discussed in this paper.

The placement of these sensors on the arm has to be carefully decided so as to correctly determine the anomaly in action, if any. Since the objective is to test the arm extension angle with respect to a standard data set, the three sensors are to be placed on the upper arm, the elbow joint and the wrist of the subject under test. This placement of three sensors will ensure maximum accuracy in determination of correctness of the delivery. Figure 2 shows the sensors placed at the upper arm, elbow joint and the wrist of a test subject.

The implemented system works according to a procedure outlining several steps. The first among them is to acquire real-time data from the sensor using Bluetooth. This is achieved by interfacing the Bluetooth module attached to the sensor, to the computation machine where either it is stored to be used later, or is processed on real-time basis. This data is pre-processed through calibration by a filter using signal processing techniques and then interpolated to smooth out the filtered data [22].

The output of preprocessing block gives a six tuple data; i.e., triple axis (X, Y, Z) acceleration and angular velocity. From this data, useful information has to be obtained for further processing. After detailed research and extensive literature review [14] following features were decided on:

- Mean
- Mode
- Standard Deviation
- Peak to Peak Value
- Minimum
- Maximum
- First and Second derivative

Figure.2. Placement of sensors on the test subject's arm

These features are supposed to be evaluated at each data point and therefore take a shape of a multi-axis waveform. The resulting wave is then fed to the algorithmic block comprising the algorithms as elaborated in the following sub-section.

3.2 Classification Technique

The training of a bowler for a specific bowling action is accomplished by adopting the technique of un-supervised machine learning, in which the algorithms are first trained according to the available set of data known to be accurate and the sample data is matched with the trained data set in order to check any anomalies. Unsupervised machine learning was opted over supervised learning due to its advantage in not binding the user or developers to manually train the data.

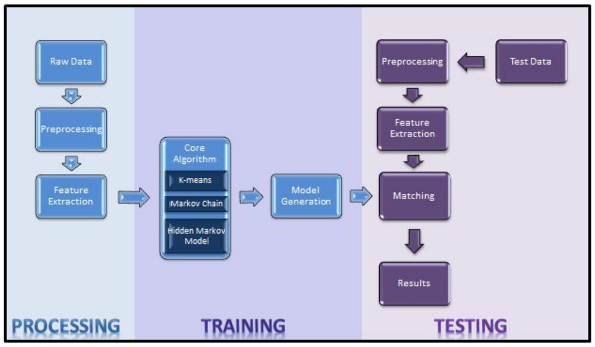


Figure 3: Algorithm flow with discrete steps of processing, training and testing

Figure 3 describes the flow of algorithm. Raw data is processed for noise removal and feature extraction. This is followed by training of the algorithm using a combination of K-means, Markov and Hidden Markov model. The generated model is then compared against test data for correct classification of action. As mentioned above, the implemented system uses these three algorithms for training and model generation; however, certain other algorithms can also be used. Details as to how each of these algorithms contributes towards accurate action detection follow:

K-Means Clustering Algorithm

The k-means clustering algorithm has been used in two ways in the presented work; one as a classification algorithm, the other as a means for generating observations for other classification algorithms (i.e. MM and HMM).

K-means is an unsupervised method of clustering where a set of data is clustered into k clusters. The algorithm has no prior knowledge of which cluster the data may belong to. The only inputs to the algorithm are the data and the desired number of clusters denoted by ‘k’.

Typically, for k-means the data is not 1 dimensional. Each dimension represents a feature. A simple flow graph for a 1 dimensional k-means is illustrated in Figure 4. Note that for 2-dimensional data, each row represents a data record and each column represents a feature.

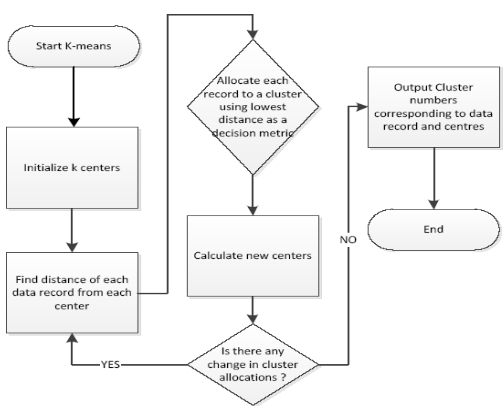


Figure 4: K-Means clustering algorithm

The number of clusters 'k' for k-means clustering was decided based on the number of 'events'. The event extraction is accomplished by using the 'min-max' algorithm. This algorithm is based on the concept that any local minima or maxima in the data represent a noticeable change in movement. Using this information the data is divided into 'events'. Each event is then fed into the clustering algorithm.

As a classification algorithm, the three-dimensional data was clustered and a template was generated in the form of k-means string for comparison. The data was clustered and a string of the form 'xxxx……xxx' was formed where 'x' can be any number ranging from 1 to k.

The k-means clustering is also used for generating the observations for MM and HMM. In order to cluster the events, a variation of the basic k-means algorithm was coded which could cluster three dimensional data. Each data record is k-means clustered and hence quantized. This reduces the number of values for the dataset as well as makes it easier to generate observations for the MM and HMM algorithms.

Markov Models

A MM is a probabilistic model that consists of a sequence of states. It is defined by the following parameters:

P_i: The probability of starting in a particular state
A: The state transition probability matrix which describes the probability of being in state *i* after state *j*

These are used to generate a model for MMs. The training data is first clustered according to the events using the special three dimensional k-means algorithm. The clustered data serves as training data for the sequence of states and hence both the state transition matrix and initial probability matrix. These parameters are then stored in a file to be used later.

For a three state model the matrices are as follows:

Initial Probability Matrix:

$$[\pi_1 \quad \pi_2 \quad \pi_3]$$

State Transition Matrix: (each row represents previous state, each column next state)

$$\begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix}$$

For each state S_i the transition probability to state S_j is a_{ij}, where

$$a_{ij} = \frac{No.of\ transitions\ from\ i\ to\ j}{Total\ No.of\ transitions\ from\ i\ to\ all\ states}$$

For each state S_i the initial probability is π_i, where

$$\pi_i = \frac{No.of\ training\ sequences\ starting\ with\ i}{Total\ No.of\ training\ sequences}$$

Here, the states 'S' are the average numbers of extremes in the whole data set. For clustering purposes, cluster all the events or states, identified together, individually for the entire data set and store their centers. Then k-means clustering is applied, keeping time as the feature, and each state is allotted a number.

The probability *P* of a sequence *O* of length *n*, with $\{a, \pi\}$ given, is found by

$$P = \pi_{O(1)} \prod_{i=1}^{n-1} a_{O(i)O(i+1)}$$

Using the probability *P*, the algorithm is trained for the given data set initially, and afterwards, the new data set, i.e., the one acquired on real-time basis, is compared with the initially given data set. For clustering purpose, the distance metric is decided as logarithm of the forward probability *P* and the new data set's distance metric is compared with a threshold value. If majority of the data set clusters are greater than or equal than the threshold, the activity is recognized as correct. Else, an anomalous action is detected.

Hidden Markov Models

In most real world scenarios, one cannot determine all possible states for a particular occurrence. To model the hidden states, Hidden Markov Models are mostly used. An HMM is a generative probabilistic model used for generating hidden states from observed data [23, 24]. HMMs imply that there is a set of hidden elements between the known and the unknown states that connect them together. These hidden elements are known as hidden states; whereas the known elements are known as observations. In order to simplify the problem the known states are considered to be hidden states. This forms the basis of the HMM which can then be improved by adding or removing states and modifying corresponding probabilities.

An HMM models probabilistically the following parameters:

Pi: The probability of starting in a particular state
A: The state transition matrix
B: The confusion matrix (the probability of a certain observation occurring given a particular state)

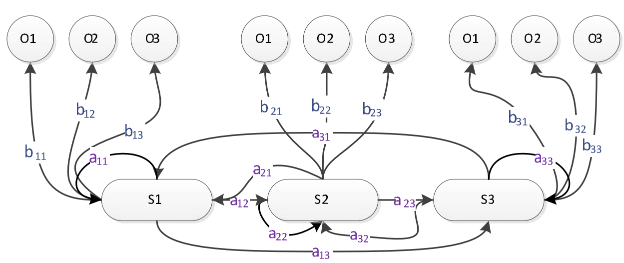


Figure 5: Visual representation of HMM for action classification

The HMM parameters are very similar to MM parameters except the confusion matrix. State information is derived in the same way as done in MM. Observation information is derived by extracting features and quantizing them into *k* levels, resulting in *k* observations for each state.

For a three state model with three observations the matrices are as follows:

Initial Probability Matrix:

$$[\pi_1 \quad \pi_2 \quad \pi_3] \qquad \text{(A)}$$

State Transition Matrix: (each row represents previous state, each column next state)

$$\begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \qquad \text{(B)}$$

Confusion Matrix: (each row represents state, each column observation)

$$\begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix} \qquad \text{(C)}$$

For each state S_i the transition probability of observation O_j is b_{ij}, where

$$b_{ij} = \frac{No.of\ observations\ j\ for\ state\ i}{Total\ No.of\ observations\ for\ state\ i} \qquad (1)$$

For each state S_i the transition probability to state S_j is a_{ij}, where

$$a_{ij} = \frac{No.of\ transitions\ from\ i\ to\ j}{Total\ No.of\ transitions\ from\ i\ to\ all\ states} \qquad (2)$$

For each state S_i the initial probability is π_i, where

$$\pi_i = \frac{No.of\ training\ sequences\ starting\ with\ i}{Total\ No.of\ training\ sequences} \qquad (3)$$

Here, the states 'S' are the average numbers of extremes in the whole data set. For running the forward algorithm, given the observation sequence *O*, and parameters $\{\pi, a, b\}$, we can calculate the probability or likelihood of *O* as shown in figure 5 given as:

$$a_1(i) = \pi_i b_{iO(1)} \qquad (4)$$

for $i = 1{:}N$, where N is the number of states, and

$$a_{t+1}(i) = \sum_{j=1}^{N} a_t(j) a_{ij} b_{iO(t+1)} \qquad (5)$$

for $j = 1{:}N$ and $t = 1{:}T$, where T is the length of the observation. The probabilities are found by:

$$P_a = \sum_{j=1}^{N} a_T(j) \tag{6}$$

For expectation maximization, backward algorithm was implemented on HMMs. Given the observation sequence O, and parameters $\{\pi, a, b\}$, we can calculate the probability or likelihood of O as:

$$\beta_T(i) = 1$$

for $i = 1{:}N$, where N is the number of states, and

$$\beta_t(i) = \sum_{j=1}^{N} \beta_{t+1}(j) a_{ji} b_{jO(t+1)}$$

for $j = 1{:}N$ and $t = 1{:}T$, where T is the length of the observation. The probabilities are found by:

$$P_\beta = \sum_{j=1}^{N} \beta_1(j) b_{jO(1)} \pi_j$$

For calculating the best path in HMMs, the Viterbi algorithm has been used. Given the observation sequence O, and parameters $\{\pi, a, b\}$, we can calculate the best sequence W, of O as:

$$a_1(i) = \pi_i b_{iO(1)}$$

for $i = 1{:}N$, where N is the number of states, and

$$a_{t+1}(i) = max_j\left[a_t(j) a_{ij}\right] b_{iO(t+1)}$$

for $j = 1{:}N$ and $t = 1{:}T$, where T is the length of the observation.

$$\omega_{t+1}(j) = argmax_j\left[a_t(j) a_{ij}\right]$$

$$p* = max_j[a_T(j)]$$

$$\omega_T(j) = argmax_j[a_T(j)]$$
$$W_t = argmax_i[w_t(i)]$$

W_t is the best path state sequence. The number of hidden states is decided on the basis of local extremes present in the data set and feature extraction is done which is later quantized feasibly. The distance metric for k-means clustering comprises two factors; the logarithm of forward probability, and the log probability obtained from Viterbi algorithm (the best path sequence). The decision metric is the threshold, the same method as done in MMs. If the resulting clusters of data set lie above or equal to the threshold, the data set for the subject under study is recognized as correct action, otherwise it is detected as incorrect.

Based on the above analysis, the states are determined using the average number of extremes in the whole data set, whereas the observations are derived using the k-means clustering algorithm on the extracted events for HMM. For the three sensors placed on the arm of the test subject, the mathematical notations are detailed in table 1.

TABLE I
MEANINGS OF NOTATIONS USED

Symbol	Meaning
k	Number of clusters into which the data is divided
pi	Probability of a state being an initial state
a	State transition probability
b	Probability of being in a state given an observation
P	Probability of an observed sequence given an HMM

4 Test Scenarios And Experimental Analysis

To test the functional and computational efficiency of the system, different scenarios can be implemented. For example the proposed system can be tested for fast bowling, spin bowling, medium pace bowling, etc. However, this paper discusses the test case for medium pace bowling only, due to ease of analysis. The experimentation is performed using three sensors placed on right arm of the subject at the wrist, elbow joint and the upper arm. The placement of the sensors is decided by keeping in view the objective of comparing the arm extension angle with a standard data set. The comparison results will assist the test subject in training himself for that specific bowling action complying with the rules set forth by ICC [16]. A total of 40 samples have been collected, from which 23 correct samples are used for training the algorithm, while the remaining 17 samples have been used for testing upon the trained model. The sampling rate of the sensor data is 150 Hz and all the samples are transmitted via Bluetooth serial communication and are recorded in a file stored in PC. In this way, the data stored in the file can be utilized for on-spot processing as well as for comparison with other test data sets to check for improvement after the training process.

As mentioned in previous sections, the real-time data is filtered, then processed using k-means algorithm. The resulting data after applying k-means is processed through HMM and finally, the likelihood is calculated using Viterbi Algorithm. The whole procedure is designed as a GUI (graphical user interface) on MATLAB and the results are presented as a graph showing the test data, accompanied by the likelihoods obtained after processing. Table 2 enlists the different parameter settings for the experimental setup.

TABLE II
PARAMETER SETTINGS FOR EXPERIMENTAL SETUP

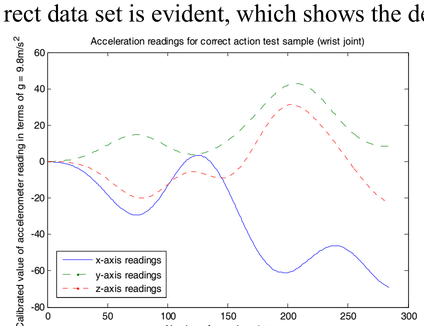
Parameter	Value
k	5
No. of observations	280
Order of filter	100
Normalized frequency of filter	0.005 Hz

5 Results And Discussion

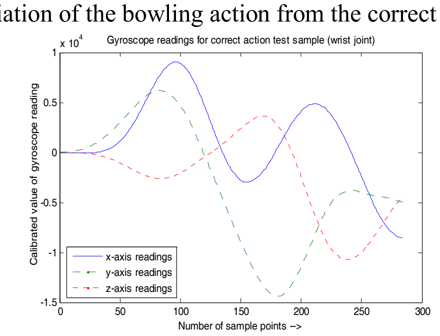
The data was initially classified based upon the trained model obtained through k-means algorithm. The classification accuracy obtained using k-means model was about 66%, keeping edit distance as the distance metric and a threshold value as the decision metric. To improve the data classification accuracy, the same data set was used for training a Markov Chain Model and the data samples were tested for classification accuracy. 68.09% accuracy was achieved, considering logarithm of calculated forward probability P as the distance metric and a threshold value as a decision metric.

To further improve the classification accuracy, Hidden Markov Model was used and a model template was generated by training the HMM using the same training data set as used in previous two algorithms. At present, the training data set is treated separately for the three locations, i.e., wrist, elbow joint and upper arm, rather than using a concatenated data set comprising the data for the three locations altogether. The accuracy of correct data classification greatly depends on correct placement of sensors. Therefore, the sensor placement must be checked very carefully while collecting either the training data set or the test data set.

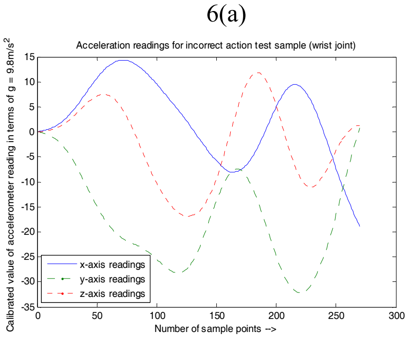
Figure 6 shows the plots of accelerometer and gyroscope's readings for one correct data set of wrist joint, three for triple axes gyroscope and three for x-, y-, z-axes accelerometer. The same set of readings is plotted for an incorrect data set for wrist joint, as shown in figure 7. The irregularity in plot for incorrect data set is evident, which shows the deviation of the bowling action from the correct bowling action.



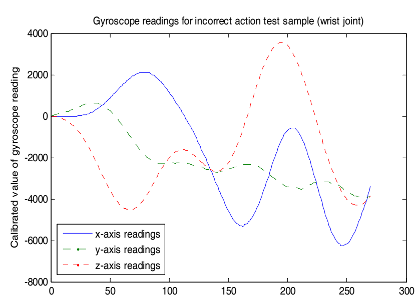
6(a)



6(b)



7 (a)



7 (b)

Figure 6. Plot of (a) triple axis accelerometer and (b)gyroscope readings for correct bowling action's data set for wrist joint .

Figure 7. Plot of triple axis accelerometer (a) and gyroscope (b) readings for incorrect bowling action's dataset for wrist joint.

Figure 8 shows the classification graph for wrist joint for 17 data sets. As seen from the figure, the data is classified 100% accurately. Particularly, in this case, medium paced bowling action has been performed which does not involve variable wrist joint movement; that is why the wrist joint movement is classified as either correct or incorrect with 100% accuracy.

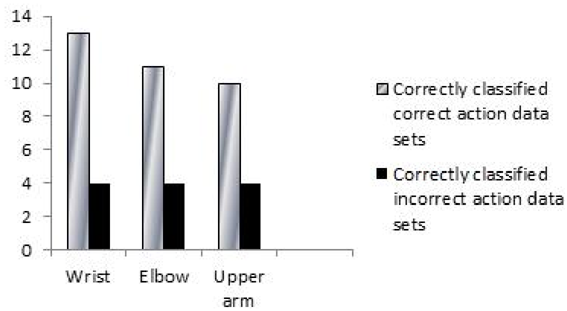


Fig.8. Classification results for correct and incorrect action data sets for wrist, elbow joint and upper arm

Similar tests were performed on the data samples for elbow joint and upper arm and the classification results achieved using HMM trained model are shown in table III, whereas graphical representation is given in figure 7. Overall, 17 data sets were used, out of which 14 were for correct action. The wrist data was classified correctly with 100% accuracy, elbow joint data with 88.24%, whereas the upper arm data was 82.35% correctly classified. The overall classification accuracy, for all three joints is thus evaluated as 90.2%.

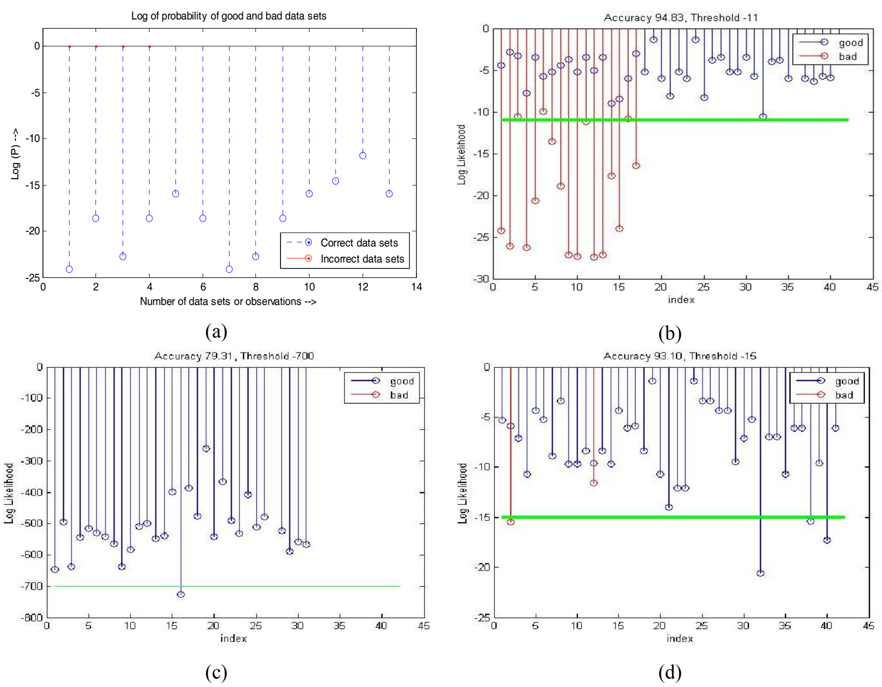


Fig. 9. a) Log probability of the test data set given a trained Hidden Markov Model (HMM), b) Non-overlapping window c) Threshold selection and accuracy d) Overlapping window

These results are presented using bowling action for only medium paced bowling. The results may vary if trials are performed using other bowling actions. Also note that since the presented model is trained for only a particular bowling action, other bowling actions, though classified as legal bowling actions by ICC, will be placed under 'incorrect' data if tested against the presented model. Thus, depending on the different bowling actions, a trained model can be developed against each action and the test data can be classified using appropriate model.

The accuracy of classification is heavily dependent on the training data set. It is necessary that the training data set should be collected from the bowler who correctly follows the ICC rules for arm extension during a delivery. The more accurate the training data set, higher is the probability of correct classification of a test data set as correct or incorrect bowling action. Highly accurate results can be obtained by using the data sets taken from bowling actions of professional bowlers complying strictly with the rules of ICC.

We use both overlapping and non-overlapping window in order to train our algorithm. Figure 9 shows the accuracy achieved with each window selection (figure 9b,d) and significance of correct threshold selection in accuracy of the algorithm (figure 9c).

TABLE III
TABULAR REPRESENTATION OF RESULTS FOR LOG (P)

Sr. No.	Wrist	Elbow	Upper Arm
1	-24.0864	-24.0742	-24.8297
2	-18.6467	-28.8333	-67.9762
3	-22.7265	-32.0061	-40.7668
4	-18.6467	-25.6606	-40.0131
5	-15.9266	-19.3148	-48.5757
6	-18.6467	-28.8333	-45.6162
7	-24.0864	-20.9013	-Inf
8	-22.7265	-24.0742	-33.5059
9	-18.6467	-28.8333	-Inf
10	-15.9266	-22.4878	-40.7668
11	-14.5664	-28.8333	-48.1557
12	-11.8445	-24.0742	-32.7015
13	-15.9266	-55.1607	-42.0157
14	-Inf	-Inf	-Inf
15	-Inf	-Inf	-Inf
16	-Inf	-Inf	-Inf
17	-Inf	-Inf	-Inf

6 Conclusion

A system for coaching of cricket bowlers has been proposed by using the HMM model. A compact design for inertial sensors has been proposed to acquire data for training the HMM model and consequently, for test data acquisition, to test the bowling action. The system is tested for medium paced bowling action and overall accuracy of 90.2% has been found while validating the test data set against the trained HMM model. To achieve better coaching results, similar strategy can be extended to the sensor placement on all key body parts in order to correctly train a bowler for a specific bowling action. This system can be extended for implementing an algorithm for efficient calculation of angle and position so as to correctly detect the illegality in bowling action in case of non-compliance of the rules of the game.

(Note: Since the probability of each bad data set was computed as zero and log (0) gives the value '-Inf', therefore it is not visible in Fig. 9)

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