# Activity Recognition for Quality Assessment of Batting Shots in Cricket using a Hierarchical Representation

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Quality assessment in cricket is a complex task that is performed by understanding the combination of individual activities a player is able to perform and by assessing how well these activities are performed. We present a framework for inexpensive and accessible, automated recognition of cricketing shots. By means of body-worn inertial measurement units, movements of batsmen are recorded, which are then analysed using a parallelised, hierarchical recognition system that automatically classifies relevant categories of shots as required for assessing batting quality. Our system then generates meaningful visualisations of key performance parameters, including feet positions, attack/defence, and distribution of shots around the ground. These visualisations are the basis for objective skill assessment thereby focusing on specific personal improvement points as identified through our system. We evaluated our framework through a deployment study where 6 players engaged in batting exercises. Based on the recorded movement data we could automatically identify 20 classes of unique batting shot components with an average F1-score greater than 88%. This analysis is the basis for our detailed analysis of our study participants' skills. Our system has the potential to rival expensive vision-based systems but at a fraction of the cost.

CCS Concepts: • **Computing methodologies → Supervised learning by classification**; • **Human-centered computing → Ubiquitous and mobile computing systems and tools**; *Information visualization*;

Additional Key Words and Phrases: Activity Recognition, Skill Assessment, Hierarchical models, Sports

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## 1 INTRODUCTION

Wearable technology-based activity recognition has been of great interest in recent times due to the potential of automating the quantification of daily events. For example, various techniques have been used to automatically identify activities of daily living (ADL) – from grooming and bathing based on non-intrusive sensors [46] to more complex and unscripted activities using cameras [39]. Wearable activity recognition has also been used to better

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understand and support users with specific health conditions such as Parkinson's Disease [1] and Dementia [10], including for disease state prediction [14].

Activity recognition technology has also been of great interest in sports with applications for both tracking the performance of individual players [28] and teams [33, 38]. Sports are an interesting context for activity recognition as there are usually several sub-activities, each with their own mechanics, and which may differ according to various circumstances. As such, activity recognition can help with understanding actions of interest and analysing sub-mechanics of specific activities to help with the ever-challenging nature of *scouting* and the development of promising athletes.

In this paper we focus on cricket, a popular sport that consists of a large number of complex activities. Batting plays a key role in the overall game, and as such it is important to have the ability of making suitable judgements regarding the quality of a particular player's batting prowess. Batting is a complicated construct, however, and can be broken down into many types of shots that are played (with over 24 shot categories), thus analysing cricket shots at such a detailed level requires an approach capable of recognising these shots reliably. Therefore, we begin to address this problem by presenting a hierarchical shot analysis system using wearable accelerometers to automatically identify various types of shots.

Four sensors equipped with 3-axis accelerometers, gyroscopes and magnetometers are used for each limb in this framework for detecting these shots. Our hierarchical framework allows us to analyse 5 different levels of batting shot attributes that can directly be linked to a player's ability. Utilising such a framework would also allow players and coaches to analyse the batter's performance, not only by considering the shots played but also by studying whether the feet movement was correct. For example, a shot (like an *off drive*) can be played with or without proper *feet movements* and this detail can be used to distinguish between a skilled batsman and a beginner.

One of the main goals of our work is to provide young amateur cricketers with an opportunity to objectively analyse their batting quality and, using the feedback, eventually assess their skill as compared to *a)* other players; *b)* professional players; but mainly to *c)* track their performance. Currently, expensive vision-based systems such as PitchVision can be used by players to assess their game, but these systems require a semi-professional setup at a training centre in addition to an initial outlay of at least £2,200. While some wealthy cricket organisations can afford such systems for scouting and developing talent, more modestly endowed cricket organisations in poorer nations would benefit from a low-cost solution. Additionally, young cricketers could greatly benefit from a low-cost automatic system to help them assess their batting sessions for raw improvements by addressing weak points – e.g., if they *missed* playing specific shots. From a professional cricketing organisation's point of view, ranking young cricketers is a manual and laborious process for coaches and selectors that can often result in unintentional subjectivity playing a role in the process. A reasonably-priced accelerometer-based system can facilitate this process by reliably and objectively ranking a large number of new players based on batting quality and then selecting a subset for further scrutiny by coaches based on the attributes associated with their shots.

In order to make a suitable assessment of the quality of players, it is very important to understand the activities they are involved in. In an automated system, automatic activity recognition is of paramount importance, therefore most of the skill assessment frameworks rely on accurate activity recognition systems. Cricket games in this context pose a new set of challenges due to a complex activity structure where there are a large number of unique shots that make activity recognition very complicated to achieve. However, without the ability to identify these shots it is impossible to perform reliable automated batting assessment. Automated systems like the one presented in this paper can effectively provide a decision support for coaches and young players to easily track their performance and compare themselves against other players. The ultimate vision is to realise automated skill ranking of players and effectively selections can be made for various teams based on the results of such a quality assessment framework.

The focus of this paper is on an exploration to what extent an inexpensive and thus accessible hardware setup combined with automated sensor data analysis can provide meaningful and objective insights into the performance of ambitious amateur cricketers. Here we present a framework for recognising cricketing shots using an IMU-based setup as a precursor to a quality assessment system. We propose a hierarchical representation of shots that groups activities based on certain aspects of a batting shot such as feet position and shot direction. Multiple visualisation techniques –well-accepted and already used for cricket analysis, for example, on television broadcasting– are then used to show the results of the activity recognition model. Aiming for a general proof-of-concept we evaluate the effectiveness of the two main categories of classification backends (discriminative modelling, and instance based learning) for assessing the quality of cricket shots. The visualisations we create show the types of shot the player uses in a session across a possible range of over 24 unique shot categories that have been identified in the sport of cricket [44]. These visualisations make it easy to understand the strong and weak areas of a player's overall batting session and also provide a method for players to easily compare their session with others. Through comparison between amateur and professional players, and even between multiple sessions belonging to the same player over time, we can therefore end up with a measure of batting quality and performance tracking. In this paper, we present quantitative assessment results that illustrate the value of the proposed analysis framework. The results were based on a carefully designed case study involving participants covering the full range of skill sets – from novices to semi-professional. Our participantsâĂŹ shots were recorded during a series of training sessions and later expert-annotated for automatically identifying the shot types and shot quality. Our automated assessment system is able to consistently replicate the ground truth assessment to a very high degree, which is encouraging as these results provide evidence for the targeted proof-of-concept and essentially render the developed system ready for larger scale deployment. As such this paper, which is the first of its kind that successfully tackles automated quality assessment in cricket (shots), represents the foundations for subsequent, large scale and especially longitudinal quality analysis and tracking studies in amateur cricket. The availability of such a system has substantial potential for the enormous amateur cricket community worldwide – many of which living in underprivileged circumstances and thus not having access to professional coaching. An inexpensive assessment system like the one presented in this paper can help many to gain and maintain skills in their favourite sport and as such to open doors to healthy and happy lives.

## 2 BACKGROUND

### 2.1 Activity Recognition using Wearables in Sports

Automated recognition of relevant activities plays a key role in a number of sports-related application scenarios. Simple event detection, for example, has been explored in golf. Work by [17] used a Hidden Markov Model along with a 6-D IMU for putt detection with the aim of improving golfers' training. The method resulted in a detection rate of 96%, with a sensitivity of 88.8%.

More complicated activity recognition has also been explored by researchers in the field. For example, activity recognition has been used in rugby, where a GPS receiver and an accelerometer in a wearable sensor were used to automatically identify collisions and tackles [20]. The device was located between the shoulder blades of the players, and a combination of Support Vector Machine and Hidden Conditional Random Field models were selected to learn the relationship between the source and the target data to automatically detect collision events. The recall and precision of the system was 93.3% and 95.89% respectively. Other work has looked at recognising aspects of the game, such as scrums and tackles, using Bayes Network, Random Forest, Multilayer Perceptron and a Naïve Bayes classifiers [19]. The Naïve Bayes classifier achieved the highest accuracy with 97.2%, and the overall sensitivity was 100% with a precision of 11.6%. The hardware used for this work consisted of a location positioning system and IMUs for the players.

In swimming, SwimMaster [5] was able to extract swim parameters – including time per lane, swimming velocity, and number of strokes per lane – as well as performing a real-time assessment of the performance using acceleration sensors. The swimmer is then able to use the data to constantly monitor their swimming performance and provide the necessary feedback to achieve their workout goals.

Various work has looked at activity recognition in snowboarding due to the increasing popularity of the sport. A simple setup requiring a gyroscope taped to the board and a mobile GPS receiver allowed the system to recognise turns, placement of the rider, and direction of travel as well as nine other activities [16]. They used a combination of two bespoke algorithms based on the continuous activity recognition approach by [31] and achieved an average accuracy of 90.5%. On the other hand, [11] used an IMU with a Naïve Bayes classifier to recognise a sequence of events that culminated in one of two tricks with an average accuracy of 91.5%. The same hardware was used to detect skateboarding tricks [12], although four different classifiers were evaluated in this work: Naïve Bayes, Partial Decision Tree, Support Vector Machine, and $k$-nearest neighbour. NB and SVM performed best, with an accuracy of 97.8%.

Another system designed to collect sporting data using wearable sensors is ClimbAX [28] – a wearable sensing platform that records a climber's movements and is able to output assessment parameters including stability, control, power and speed, comparable in standard to official expert assessments. [38] evaluated a wearable sensing system to monitor basketball players using multiple inertial measurement units. The system was able to recognise human movements and classify them into walking, jogging, running or sprinting, as well as identifying shooting events.

Activity recognition has also been used for improving personal fitness. RecoFit was designed to monitor repetitive exercise activities such as weight training by using wearable inertial sensors [34]. In the first analysis stage the system discriminates between exercise and non-exercise movements using an L2 Support Vector Machine. Based on this it then recognises and counts the repetition of activities with an overall accuracy of 96%. Similarly, GymSkill used the sensors from smartphones attached to gym equipment to monitor the user's exercises and analysed using a pyramidal Principal Component Breakdown Analysis. Based on the data, the system then presents suggestions for improving the performance [32].

### 2.2 The Sport of Cricket

In this paper, we explore activity recognition with regards to batting in *cricket*, which consists of a large number of complex activities. Figure 1 illustrates the main aspects of how cricket is played at various levels ranging from grass-roots to international cricket at *Test* level. The sport of cricket is arguably the second most popular sport in the world after soccer based on the viewing population [45]; there are an estimated 2-3 billion fans. As an example, the cricket world cup alone in 2015 was watched by 2.2 billion people on television. Some high-profile leagues such as in India have been reportedly valued at $3.6 billion [3]. Several such leagues are also played in other countries including Australia, South Africa, and Pakistan every year.

Cricket is a bat-and-ball game played between two teams of eleven players on a cricket field, at the centre of which is a rectangular 22-yard-long pitch. One team, designated as the batting team, attempts to score as many *runs* as possible, whilst their opponents *field* −that is one of the players throws the ball towards the batsman and others catch the ball− during which they bowl with an aim to get the batting team *out* −that is to force the opposing team into a batting error such as missing the ball and hitting the stumps. A *run* corresponds to a batsman (the player holding the bat and trying to hit the ball that was thrown at them by the fielding team) successfully running from their batting position to the opposite end of the pitch (22 yards as mentioned above). After the batting team is out, the two teams then swap roles. The winning team is the one that scores the most runs during their batting period. With this in mind, it is obvious that batting performance is a very important aspect of the game and as such one that players choose to work on improving continuously.


Fig. 1. Images of cricket played at various levels including (a) Grass-roots, (b) Junior club cricket, (c) Club cricket, (d) Twenty20 International/One-day International cricket and (e) Test cricket. All photos public domain.

Cricket matches are typically structured into "innings", that is each team take turns for batting in which multiple "overs" (a set of 6 legal bowling deliveries) are involved. The overall goal of the team batting first is to score as many runs as possible (whilst the other team tries to get each batsman out, which triggers the end of the innings or restricts the batting team's score). In the second innings, the batting team chases the target of the first innings' score, which was set by the team batting first, whilst the bowling team tries to restrict scoring or get all of the players out before they reach the target. If the team batting second reaches the target, they win the match. A summarised list of cricket specific terms used in this paper are shown in Table 1[1]. International cricket has three formal formats as summarised below.

**T20I (Twenty-20 International)** With 20 overs (each comprising 6 legal bowling deliveries) per innings, this is the shortest format lasting up to 3 hours (there are 2 innings in which each team bats and scores runs).

**ODI (One Day International)** In this format, there are a total of 50 overs per innings, which can last up to 7 hours. Both of the T20I and ODI formats are played in colored clothing.

**Test** This is the longest format with a maximum of 4 innings played over 5 days and a minimum of 450 overs across all days (weather permitting). There are 3 sessions per day with two breaks for lunch and tea. This is the traditional form of cricket and is played in white clothing. In total there are 10 test playing nations determined by the International Cricket Council.

All of the above formats require different playing strategies in general for example in the shortest format a more aggressive form of the game is required whilst at the Test level, defensive game is necessary. In some

[1]http://www.espncricinfo.com/ci/content/story/239756.html

Table 1. A subset of cricket terminologies as used in this paper

| Term | Description |
|---|---|
| Back foot | Batsman's foot that is nearer to the stump |
| Back foot shot | A shot played when the batsman's weight is on the back foot |
| Bails | A small piece of wood that is placed on top of the stumps |
| Delivery | Bowling act |
| Dismiss | State at which the batsman must cease batting |
| Fielding (team) | the team which is not batting |
| Front foot | Batsman's foot that is nearer to the bowler |
| Front foot shot | A shot played when the batsman's weight is on the front foot |
| Innings | A player's or team's batting or bowling turn |
| LBW | (leg before wicket) A form of dismissal in which the ball hits the leg of the batsman in front of the stumps |
| Leg-side | For a right-handed batsman, the left side of the pitch |
| Off-side | For a right-handed batsman, the right side of the pitch |
| Out | State of the batsman when dismissed |
| Pitch | A rectangular surface in the centre of the ground |
| Pitch (of the ball) | To bounce before reaching the batsman |
| Runs (1) | A single run is scored if a batsman, after hitting the ball, runs the length of the pitch once (2 for running twice) |
| Stumps | One of the three wooden posts |
| Wicket | Interchangeably used for a) stumps (ball hitting the wickets), b) out (bowler takes a wicket), c) pitch (the wicket is good for batting) |

cases, mainly depending on the situation, a defensive game can be the best strategy in the shortest formats if the team loses early wickets. This is to ensure that a batting team plays all of the available overs. Similarly in test cricket, for example, in the 3rd innings of the match and on the 4th day a team might want to quickly score runs to set a target for the bowling team in the 4th innings prior to final session of the day. This will require an attacking game (with the risk of losing wickets which can result in the end of their innings), however if the team succeeds in getting a higher score earlier, it provides sufficient time to get the batting team out in the 4th innings and win the match on the 5th day. If the target is too high and impossible to chase in the 4th innings, the batting team usually employs a defensive strategy and plays for a draw. This strategy, although it seems simple, requires a sound defensive technique since on the 5th day, the cricket pitch has usually deteriorated with cracks. The ball can spin off these cracks extraordinarily and/or have uneven bounce off the surface leading to batsmen getting out (getting caught by a fielder after the ball hits the edge of the bat or getting LBW – see below). On rare occasions, the ball does not even bounce enough for the batsman to judge properly.

There are many factors that should be considered when selecting a shot, such as the feet position relative to the ball, the angle the ball approaches, the spin and speed of the ball, as well as its current trajectory. Judging all these factors in a split second and choosing the best kind of shot to respond with contributes to the difficulties associated with batting in cricket. Figure 2 illustrates the most relevant shot categories around the ground with numbers indicating the indices of these shots colored according to the feet position. Shots in these directions can be played on the front-foot (in which the batsman moves towards the ball to hit it) or the back-foot (in which the batsman moves back).

More complex shots (also known as unorthodox shots) can also be played which are very rewarding in terms of the number of runs but have higher risks associated with them in which the batsman can get out. For example, a batsman can play a *switch-hit* in which a right-handed batsman switches the stance to the one normally associated with left-handed players (and vice-versa) and does this very quickly right before the ball is delivered so that the bowler is unable to adjust the line/length of the ball. In this case, the field which is originally set for a right-handed batsman provides opportunity for the batsman to play scoring shots in the vacant areas of the ground. However, since the batsman is not in his natural stance, the risk of getting out is higher.

Other examples of risky feet positioning involve a batsmen taking multiple steps to get close to the pitch of the ball and hitting the ball hard. Getting close to where the ball pitches, allows the batsman to hit a shot for a

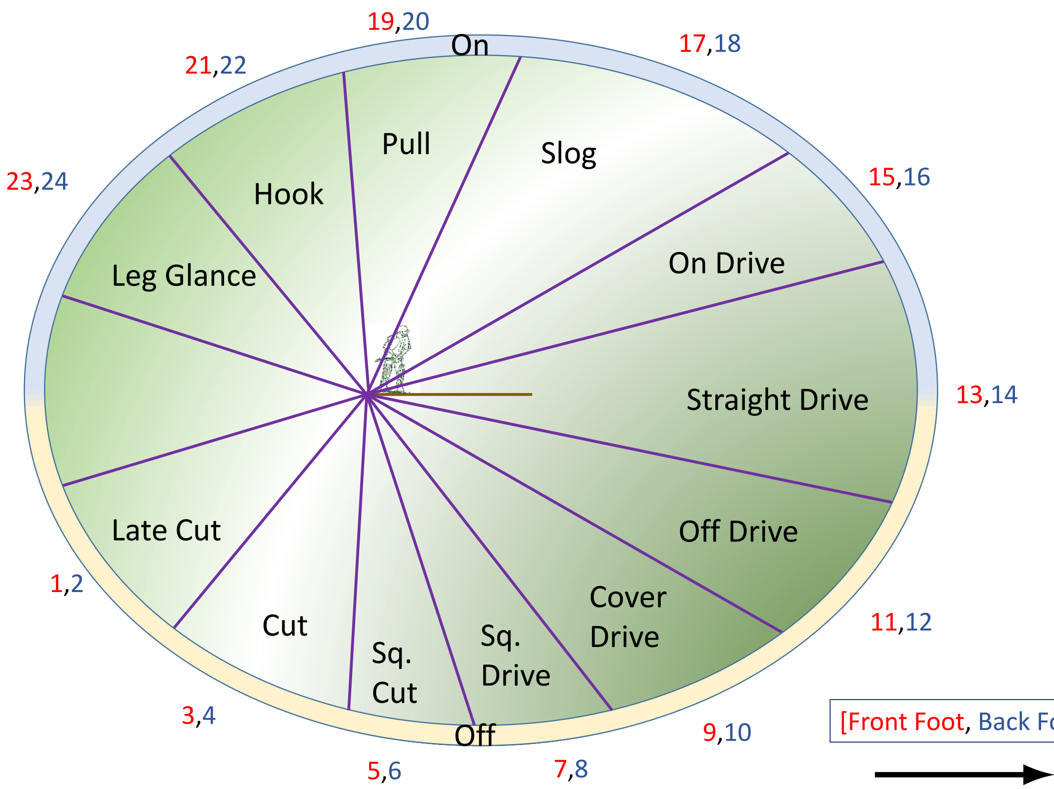



Fig. 2. Shot types around the ground for a right-handed batsman with front-foot and back-foot shots separately labelled (numbers indicating the shot indices). Batting direction is left to right.

maximum number of runs (4 along the ground or 6 runs if the ball is hit so hard, it bounces outside the ground boundary). If the batsman misses the ball, he can get out *stumped*, in which the *wicket-keeper* collects the ball in his gloves and dislodges the *bails* that are placed on top of the three *stumps* before the batsman can get back inside the *crease* (bounded area close to the stumps in which the batsman is safe). Alternatively, whilst playing slow bowling, a batsman can initially come slightly forward towards the ball and when he sees that the ball might not bounce close to him, he moves back (very close to the stumps) allowing the ball to have bounced and spun enabling the batsman to properly see it and hit it for a run-scoring shot. In this scenario both front and back foot movements happen resulting in a very complex shot. There can be multiple risks associated with such a shot for example if the batsman moves back in line with the stumps and the ball hits his legs if he misses then he could be adjudicated as *out* which corresponds to one of the mode of *dismissals* called LBW (leg before wicket). The batsman can also misjudge the distance whilst moving back and forth and hit the wicket with his feet dislodging the bails (which is another mode of dismissal) leading to the batsman getting out. Compiling a list of all shot categories is therefore very difficult. However, a list of the most important shots is shown in Figure 2. This list serves as the basis for the hierarchical representation and thus the automated assessment as it is developed in this paper.

### 2.3 Activity Recognition for Cricket

Activity recognition in cricket is a challenging task due to the complexity of the activities involved. Batting can be broken down into the many types of shots that are played, with over 24 shot categories encapsulating all the possibilities. These categories combine the type of swing and the foot positioning that the player uses based on the direction of the incoming ball. Depending on where the bowler places the ball on its way to the wicket, batsmen employ different tactics to maximise chance of success (scoring runs).

There has been limited previous work looking at activity recognition in cricket. [6] proposed a platform for providing objective feedback to batsmen on their performance using bat-mounted tri-axial accelerometers. The feedback was based on the velocity and twist of the bat, along with an estimated impact time and therefore presented the batsman with a measure of strike quality, rather than any detailed analysis of the shot. In this work, a single shot category of 'defensive drives' was used to analyse the ball's impact when hitting the bat.

On the other hand, [48] have looked at determining the differences between novice and expert batsmen. This work has focused on the batters performing a batting task in a highly-controlled environment where they were required to hit various targets using different bats from a machine-projected ball. This work did not utilise sensors but rather relied on expert observation, and as such this method was time-consuming for both participants and evaluators due to its artificial environment which required setting up. Recent work has approached shot classification in cricket by using motion vectors in video frames with 4 possible shots being recognisable [18]. While the proposed method is convenient as it can be done using standard videos from training sessions rather than with a specialistic setup, the average accuracy of the system was at the lower end (60%).

Somewhat related to cricket is the sport of baseball which is also a bat-and-ball game played between two teams similarly taking turns for batting. However, there are many differences in the way runs are scored and other rules of the game. For batting, the fundamental difference is in the primary goal of the batsman that is mainly dictated by gameplay. In baseball, there are 9 innings played within a few hours whilst in test cricket 4 innings are played over 5 days (30 hours). This means, that in cricket, batsmen are trained to develop their defensive game to be able to survive longer. There are other differences for example in awarding penalty points to batsmen in baseball for swinging and missing the ball (three strikes result in out); in cricket a batsman can bat a lot longer with no penalty for missing the ball. Due to the length of batting durations, a greater range of the types of bowling deliveries, and dynamics of the field, cricket batting requires a very different technique to be able to manoeuvre the ball and score runs. The total number of shots in cricket are therefore higher than in baseball. Coaching systems in baseball such as [35] focus mainly on the path of the swing enabling assessment of batting. In this vision based system, differences between consecutive frames are used for generating the path of the bat and arms. In cricket, such an assessment system can be utilised to assess the swing type, however other relevant factors such as feet movements, and direction of the shot would be cumbersome to infer.

In this paper we focus on the automated recognition of batting shots in cricket using a hierarchical framework utilising low-cost hardware and a simple setup. A similar form of hierarchical analysis framework was deployed in [25], in which occupancy estimation was performed at multiple levels of granularity using environmental sensors. Based on the automated recognition results we generate visualisations that are oriented on the current best standard as it is typically used for illustration in, e.g., television broadcasting of cricket. These automatically generated visualisations are informative through representing each batting session and thus serving, for example, as a decision support for coaches during initial scouting sessions where a bottleneck for amateur players can make the process very time-consuming. Individual players can use the visualisations to improve their range of shots by focusing on less-successful shots, thus improving their overall technical game without the need for expensive professional setups.

# 3 HIERARCHICAL RECOGNITION OF BATTING SHOTS

## 3.1 System Overview

The ultimate vision of our work is the development of an analysis system for the fully automated assessment of cricket skills, which is the basis for autonomous, affordable coaching systems. This is in line with related work where wearable sensing systems and automated sensor data analysis methods have been used for (semi-)automated quality assessments, for example, in other sports as outlined in the previous section.

In this paper we present the fundamental building block of such a skill assessment system for the sport of cricket consisting of an automated recognition system for the analysis of batting shots –arguably the most important technical skill a cricketer has to master for successfully playing the game – and, based on the results of this automated classification step, visualisation and analysis schemes that facilitate objective skill assessments as they are required for devising tailored, that is personalised training programs as professional coaches would develop.

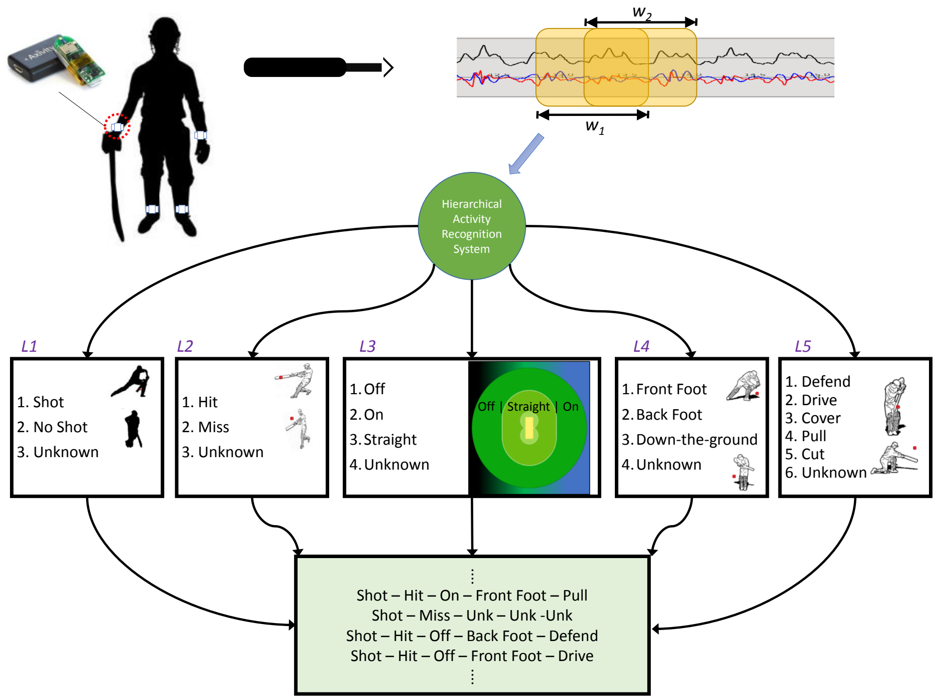
Figure 3 gives an overview of the developed system. A cricket player attaches four sensors – standard, off-the-shelf nine-axis inertial measurement units (IMUs) – to his/her limbs using wrist bands or tape, which is a straightforward process to which most cricket players are used to anyway (given that during batting sessions players are supposed to wear protective equipment). For our deployment we used Axivity WAX9 IMUs [4]. The sensors are wirelessly paired via Bluetooth with an application running on a smartphone where the data is collected and stored. A batting session can then take place as they are typically conducted (either indoors in specific batting arenas or outdoors on any kind of pitch that is large enough for playing cricket) without any disruptions or discomfort to the player. Upon conclusion of the session our analysis system processes the sensor readings from all four devices, recognises the various shot types, and generates visualisations of key performance indicators ("skills") as they are relevant for the analysis of a cricketer's performance. These results form the basis for informed, objective, and personalised coaching programs that tackle individual weaknesses of a player. The advantage of our system is its affordability and ubiquitous applicability, which enables cricketers not only at (semi-)professional level but rather at all levels of expertise down to grass-root movements in remote villages, to enjoy their sport and receive helpful and objective feedback that will form the basis for excelling in the technical skills that are so important for mastering the sport.

## 3.2 Methodology Background

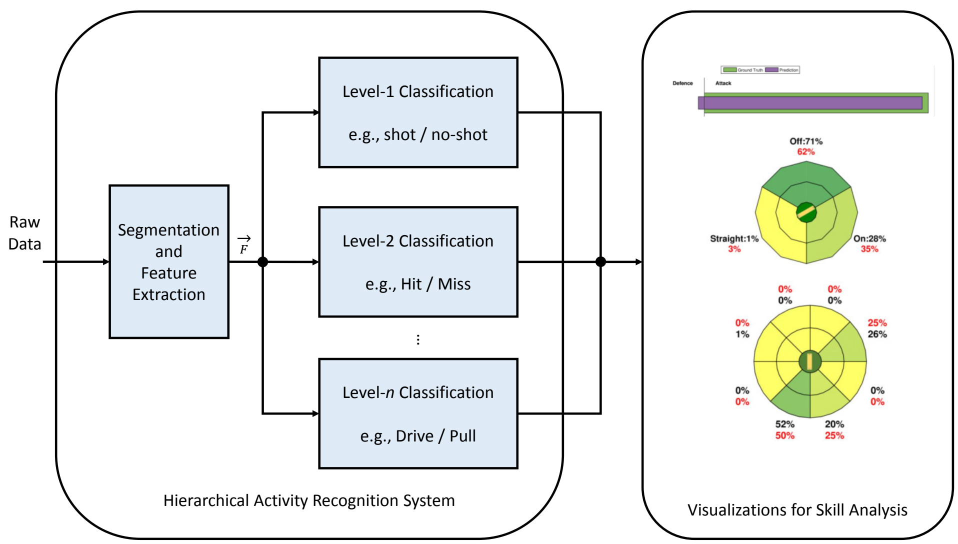
Batting in cricket can result in both intended and unintended shots, with both intended and unintended results. Due to the complexity of batting shots involving several sub-components, our batting shot analysis framework is based on a hierarchical approach. The prerequisite for the overall assessment stage is a system that captures different aspects of the batting shot. According to the background of the game of cricket (as explained in the previous section) and the general best practice in assessing the quality of cricket matches, we formulate these aspects as follows:

*Has the batsman played a valid shot?*
This allows recognition of shots among all the activities performed by a player. Whilst batting, a player *runs* between the two ends of the pitch to score, *walks* to change ends or engage in stretching exercises between shots. Recognition of shots among all the activities performed by players is very useful.

*Has the bat successfully hit the ball or not?*
This enables delineation between hits (shots in which the bat touches the ball) and misses (shots in which the bat




(a) Low-level batting shot analysis




(b) Hierarchical batting shot classification linked to automated visualisation of batting skills.

Fig. 3. Overview of our system for automated batting shot recognition for skill assessment in cricket (see text for description).

misses the ball). Inexperienced players face difficulties in hitting the ball initially which can be improved over time. Experienced players can naturally hit the ball and also hit it in a certain direction of the ground.

*What was the direction of the shot?*
With this, we can observe the ground coverage of a player and identify weak zones around the ground. There are three main sides that a batsman can target including *Off*, *On* or *Straight* (as shown in Figure 2).

*What were the positions of the batsman's feet?*
In order to execute perfect shots, feet positions are very important as such correct and quicker assumption of batting stance enables better shots. For batsmen, this is one of the most important skills and which also takes a long time to master. The goal is to get close to the pitch of the ball in order to nullify the effect of spin (in the case of slow bowling) or swing (in the case of fast bowling). The closer a batsman gets to the pitch of the ball, the better it is. However, in cases where the bowler shortens the length, the batsman then has to move back to allow some more time for him to judge the ball's trajectory and hit it.

*What type of swing was used by the batsman?*
As opposed to the direction of the shot, this defines the type of swing executed to play a shot in a certain direction. There are various types of shots such as drives in which a batsman swings along the line of the ball (this shot mainly covers the straighter regions of the ground). In the case of *cuts* and *pulls*, a batsman swings the bat across the line of the ball; such shots mainly cover the *off* and *on* sides of the ground.

Each of these aspects are modelled separately representing multiple layers of the overall system's granularity. Comparable methods have already been used for assessment in sports such as tennis or badminton [26]. In tennis, for example, shots are analysed at multiple levels of representation by looking at *rallies*, and within each rally representing *hits* on the *near* and *far* side of the tennis court. Such a representation helps in: *a)* understanding various components of an activity; and *b)* modelling them in a machine learning framework to automatically recognise/ predict these activities.

For cricket batting, we define $L = 5$ levels for detecting relevant aspects of a cricket shot. These levels are based on the structure of a cricket shot and can be separately detected:

**L1 – Shot detection**
a) Shot,
b) No-shot,
c) Unknown.

**L2: – Hit detection**
a) Hit,
b) Miss,
c) Unknown.

**L3 –Direction detection**
a) Off,
b) On,
c) Straight,
d) Unknown.

**L4 – Feet position detection**
a) Front foot,
b) Back foot,
c) Down-the-ground,
d) Unknown.

**L5 – Type of shot detection**
a) Defend,
b) Drive,
c) Cover,
d) Pull,
e) Cut,
f) Unknown.

In order to effectively assess a player's batting quality, these 5 levels need to be analysed separately. These levels represent components of a batting shot that collectively, when mastered, result in a successful execution of a shot. For example, a Drive on the Off side (cf. Figure 2) can be played with both front and back foot positioning of the feet. However, if the ball is pitched close to the feet, it becomes a risky shot to play on the back-foot. As such, if the ball misses the bat, it may hit the stumps or one of the legs in front of the stumps, both leading to the batsman getting out, i.e., a failed attempt. In fact, players spend a long time training in nets to get into correct positions to play shots. Analysing these separately can greatly help in defining focus points for improving aspects of the shot that are not (yet) correctly executed by an individual player.

In the context of cricket training, after batting shot recognition has taken place the aforementioned five levels can be analysed separately for assessing batting quality. For example, at each level we can draw a comparison between professional and amateur cricketers, thereby providing feedback which can assist in the coaching of young players. Using this feedback, players can focus their practice on particular areas of their game, and as improvements are made over time they will be automatically observed by our system, allowing players to track their performance. For example, for a beginner, it is important to successfully hit the ball with as many of their shots as possible and therefore level-1 and level-2 would be the most important levels to focus on initially. Extending this for professional players – where every movement is critical to execute the perfect cricketing shot, the type of shot and the technique utilised also become more important – and therefore analysing all 5 levels is relevant.

The main benefits of using a hierarchical approach are two-fold: *a)* it provides activity outputs in a manner that coaches or trainers can easily understand for assessing batting abilities of players; and *b)* it makes the classification approach for activity recognition easier to train, as the number of classes per level are relatively few.

## 3.3 Segmentation and Feature Extraction

We build separate predictive models for each level within our hierarchy, where each level employs a similar, supervised classification approach. Raw data is initially segmented using a sliding window approach, with a window length of $w = 1.6$ seconds (derived from a systematic evaluation performed for a range of values originating from the length of batting shots in our dataset). A range of features are then calculated to abstract from the raw data to our feature space. These features are then utilised in parallel for hierarchical classification. As explained in the previous section, in the context of our cricket shot classification framework we have $L = 5$ levels and therefore five classifiers. Classifiers are trained hierarchically with the same feature vectors but different labels each that are used specifically for each individual level (described in Figure 3), resulting in five recognition models, each of which focussing on a different aspect of the batting shot.

These features must be able to capture the unique characteristics important to the five levels in our hierarchy. Our 4-sensor setup is ideal in this context as most of the body movements can be captured to a sufficient quality for accurate recognition. For the accelerometer features $\vec{f_a}$, we use statistical features such as the mean $\mu$, median $\widetilde{x}$, standard deviation $\sigma$, and range $x_1, x_n$ of each axes to capture the underlying distribution of the sensor data. For each axis of our four 3-axes sensors we therefore produce $(\mu, \sigma, \widetilde{x}, x_1, x_n)$.

Additionally, we also include the ECDF representation $f_i$ (Equation 1), which samples from the empirical cumulative distribution function to provide $d = 15$ coefficients per axis which includes information about the data distribution within a frame [13]. The ECDF representation of raw sensor data is provenly beneficial as it captures the real distribution of sensor data in a compact and meaningful way [13, 27, 40].

$$\mathrm{ECDF} = \{x, \exists j : P_c^j(x) = p_j\} \tag{1}$$

$$C = \{p_i\} \in \mathbb{R}^d_{[0,1]}, p_i < p_{i+1} \tag{2}$$

We also use additional representations that are important for understanding more complex shots: Signal energy (Equation 3), signal entropy (Equation 4), total squared jerk (Equation 5), and fast Fourier transform (FFT) coefficients ($d = 16$) calculated on each axes.

$$E = \frac{1}{N} \sum_{i=1}^{N} x^2 \tag{3}$$

$$I = \sum_{i=1}^{N} x \log(|x|) \tag{4}$$

$$J = \sum_{i=1}^{N} D_x x \tag{5}$$

Other features are also calculated for each sensor utilising multiple axes including RMS of acceleration (Equation 6), RMS velocity (Equation 7), and the maximal pairwise cross-correlation between the acceleration axes (Equation 8) [9].

$$R_a = \frac{1}{N} \sum_{i=1}^{N} \sqrt{(x^2 + y^2 + z^2)} \tag{6}$$

$$R_v = \frac{1}{N} \sum_{i=1}^{N} \sqrt{(\int xdx)^2 + (\int ydx)^2 + (\int zdx)^2} \tag{7}$$

$$CC_{(x,y)} = \max_{d=1}^{n-1} (\frac{1}{N} \sum_{i=1}^{N} x_i \cdot y_{i-d}) \tag{8}$$

By combining all of these features we end up with feature vector $\vec{f_a} \in \mathbb{R}^{d=106}$ for each accelerometer:

$$\vec{f_a} = \left(\mu, \sigma, \widetilde{x}, x_1, x_n, C, E, I, J, FFT_c, R_a, R_v, CC_{(x,y)}\right)^T \tag{9}$$

For the gyroscope and magnetometer we focus on a smaller subset of the total features in order to reduce the overall dimensionality of the feature vector while including additional information. This subset includes mean, median, standard deviation, signal energy, and entropy. For each of these sensors we calculate these features on the magnitude of the sensor rather than individual axes, resulting in $\vec{f_g} \in \mathbb{R}^{d=5}$ and $\vec{f_m} \in \mathbb{R}^{d=5}$, each containing the following ($\mu$, $\sigma$, $\widetilde{x}$, $E$, $I$).

Finally, we then combine the features via concatenation so that the features for each sensor combine to form a sub-feature vector representing the overall sensor $\vec{f_s}$ (Equation 10). Features from the overall representation for all 4 of our sensors are then concatenated to form the overall feature vector $\vec{F} \in \mathbb{R}^{d=464}$ (Equation 11).

$$\vec{f_s} = \{\vec{f_a}, \vec{f_g}, \vec{f_m}\} \tag{10}$$

$$\vec{F} = \{\vec{f_1}, \vec{f_2}, \vec{f_3}, \vec{f_4}\} \tag{11}$$

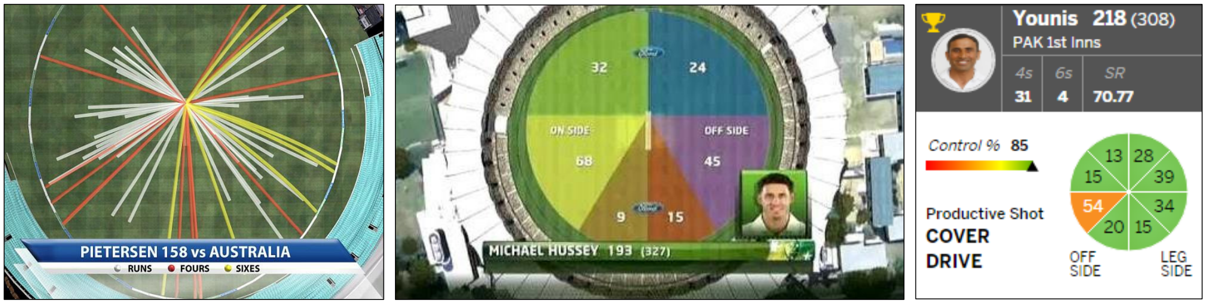



Fig. 4. (L) Wagon Wheel representing each shot with a line, used in TV broadcasting. (C) Wagon Wheel showing the proportion of runs scored in key areas around the pitch. (R) Wagon Wheel with more granular proportion of runs around the pitch.

## 3.4 Hierarchical Classification

Five separate models are built for recognising the various aspects of a batting shot. These aspects are represented by each level in our hierarchy. Given the exploratory character of this paper we have evaluated the effectiveness of the predominant approaches as classification backends in our system, namely: discriminative models (Decision Trees, and Support Vector Machines – SVM), and instance based learning model (k-Nearest Neighbour classifier).

Ground truth annotation was collected from video footage and used for training and validating our models. Labels are assigned for every frame extracted using the aforementioned sliding window procedure thereby employing majority voting (necessary due to overlapping subsequent frames). Overall, ground truth annotation is based on the hierarchical labelling scheme as detailed in Section 3.2 for which an example batting shot can look like; *Shot-Hit-FF-Off-Cut*, representing all 5 levels of the representation hierarchy.

Utilising our feature matrix $\vec{F}$ we train five distinct models. For the purpose of evaluating more than one classifier to determine the best possible set of 5 models, we repeat this modelling process in separate experiments for the three classification paradigms previously mentioned. Each of our five models use a different label which corresponds to the five different levels in our representation hierarchy, allowing us to capture different aspects of the batting shot. By modelling the different aspects separately (the five levels) we significantly reduce the number of classes that we intend to recognise with a single model. For $k$-NN we optimise the value of $k$, and for Support Vector Machines we perform a grid search procedure for optimising the cost and gamma parameters of the RBF kernel [43].

## 3.5 Visualisations

The visualisations produced by our framework are oriented on the standard "Wagon Wheel chart" that is widely used by international cricket teams for training as well as by cricket broadcasters to summarise a batter's performance. Versions of this chart have been used in the game for over one hundred years [30], thus indicating the value of the depicted information and formatting. The traditional Wagon Wheel presents the cricket pitch from a bird's eye view, and draws straight lines from the wicket to the final destination of each ball, resulting in a summary of a batter's innings (see Figure 4(L)). Other versions have simply reported the percentage or number of runs scored in key areas (see Figure 4(CR)), again resulting in a concise summary of the batter's performance. These two Wagon Wheel styles can both be used to assess weaknesses and dominance of batsmen, for example

Fig. 5. Front-on view of a batting net session where this dataset was collected. Off and on sides are towards the left and right of the image respectively.

by showing Michael Hussey's preference for on side pulls when scoring (see Figure 4(C); note Michael Husssey is a left-handed batsman) or Younis Khan's cover-drives (see Figure 4(R)).

With this in mind we decided to follow the de facto visualisation techniques in cricket, thus assuring that all players and coaches would have an instant understanding of the results. The bar charts employed in other visualisations, i.e. Front/Back foot preference (see Figure 8) and Attacking vs. Defensive Shots (see Figure 9) bar charts were designed to be as intuitive as possible for players and coaches. While these graphs were not grounded on established visualisations within the sport, we used a simple two-way bar chart to indicate the proportion of attacking and defensive shots (or front vs. back foot) – thus effectively relaying the binary options. While no formal evaluation was carried out for these bar graphs, feedback from non-cricketing colleagues verified the intuitiveness of the visuals. These bar graphs, in conjunction with the Wagon Wheel visualizations, provide a complete representation of batting shots.

# 4 EXPERIMENTS

## 4.1 Dataset

To evaluate our system and to validate its general effectiveness, we conducted a study where we invited participants to a local (indoor) cricket centre that features dedicated practice areas –so-called batting nets– where cricketers can practice batting to improve their abilities for match situations. A bowling machine shoots balls towards the batter thereby varying speed and direction such that the player can practice the various skills relevant for good batting. Figure 5 gives an impression of the setting in the cricket centre where we ran our data recording session.

Our study was conducted in these dedicated batting areas and participants wore the sensing system as described before while engaging in batting sessions. Although we collected our dataset in batting nets, the system has been designed for deployments during match situations where identical shots are played. The only difference is in the running activity between shots which can be treated as another activity type and can be added to the classification system. Activity recognition for walking and running is widely studied in the literature and very good accuracies are achieved in recognising these activities [42].

For a total of 6 participants (5 males and 1 female; average age: 27.50 (±4.46)) we collected data over 11 sessions, which translates into almost 3 hours of raw sensor data. Arguably, this dataset is relatively small and as such

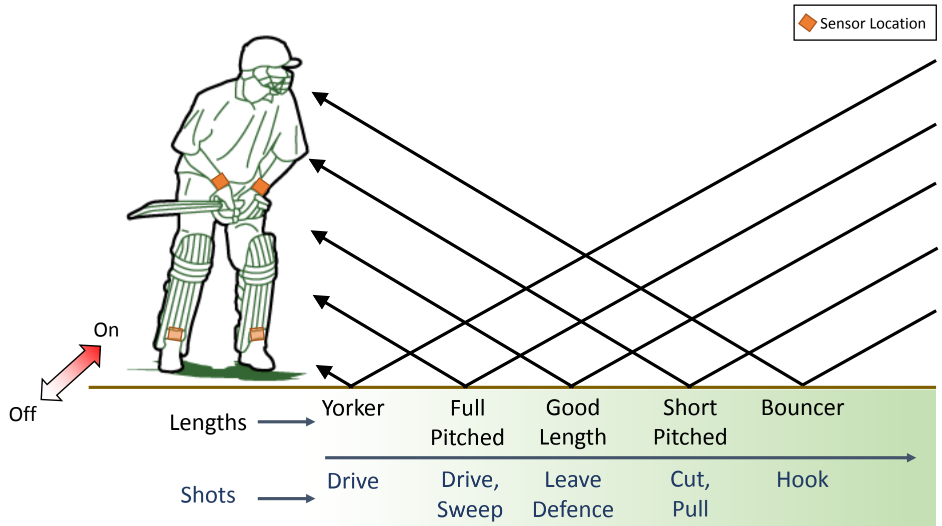



Fig. 6. Illustration of the bowling *lengths* during our batting sessions. Some preferred shot types for those lengths are also illustrated. Decision regarding off and on side is usually made based on the *line* of the ball.

does not qualify as a large-scale user study. However, the focus of this paper is on the exploration of general feasibility of an automated cricket skill assessment system based on inexpensive sensing infrastructure and machine learning based sensor data analysis. As such our focus was more on a detailed evaluation for a cohort of participants that span the full range of experience and existing cricket skills as one would expect for the intended target user groups – amateurs who would benefit substantially from an automated and especially consistent feedback procedure. Typically this population does not have any access at all to qualified feedback not to mention coaching. The aim of the work presented in this paper is to develop a prototypical system that can subsequently be used for large scale deployments thereby specifically targeting longitudinal studies that, for example, track the performance of whole teams over the course of, e.g., a complete cricket season. The evaluation conducted for this paper will lead to important insights that will allow us to realistically judge the capabilities of our system.

Our participants' cricket experience and expertise ranged from beginners (first time batting) to players with semi-professional batting experience. We have categorised each player into one of four categories, *beginner*, *intermediate*, *experienced*, and *semi-professional* players, detailed below:

P1: Experienced (>10 years of batting experience):
Player 1 had played cricket at both school and college levels playing as a lead batsman. With several years of experience in unprofessional cricket, player 1 was capable of playing most of the shots comfortably.

P2: Intermediate (>5 and <10 years of batting experience):
Player 2 had only played cricket at the school level and was able to play some of the shots comfortably. Player 2 had a particular difficulty with feet movements for example, most of the shots were played with incorrect feet positions.

P3: Beginner (<5 years of batting experience):
Player 3 had only played cricket at the school level for a short time. However, player 3 was able to play shots with both front foot and back foot successfully.

Table 2. Dataset summary

| P | Gender | Sessions | Total Shots | Total shots per activity within the hierarchical shot representation | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | L1 | | L2 | | | | L3 | | | L4 | | | L5 | | | |
| | | | | Shot | No-shot | Hit | Miss | Leave | Prac. | Off | On | Str. | FF | BF | DG | Defend | Drive | Cover | Pull | Cut |
| 1 | Male | 4 | 364 | 273 | 91 | 208 | 57 | 8 | 83 | 80 | 89 | 34 | 102 | 147 | 16 | 60 | 71 | 12 | 33 | 41 |
| 2 | Male | 1 | 56 | 52 | 4 | 32 | 16 | 4 | 0 | 22 | 19 | 3 | 44 | 4 | 0 | 4 | 8 | 3 | 2 | 10 |
| 3 | Male | 1 | 95 | 72 | 23 | 61 | 9 | 2 | 21 | 41 | 18 | 6 | 35 | 35 | 0 | 5 | 11 | 21 | 16 | 14 |
| 4 | Female | 1 | 161 | 98 | 63 | 59 | 35 | 4 | 59 | 20 | 41 | 28 | 55 | 38 | 1 | 5 | 35 | 13 | 24 | 7 |
| 5 | Male | 2 | 74 | 66 | 8 | 56 | 10 | 0 | 8 | 46 | 19 | 0 | 44 | 22 | 0 | 1 | 52 | 6 | 4 | 1 |
| 6 | Male | 2 | 222 | 143 | 79 | 90 | 47 | 6 | 73 | 25 | 97 | 5 | 96 | 40 | 1 | 10 | 40 | 10 | 25 | 5 |
| ∑ | | | 947 | 704 | 243 | 506 | 174 | 24 | 244 | 234 | 283 | 76 | 376 | 286 | 18 | 85 | 217 | 65 | 104 | 78 |

P4: Semi-professional (> 10 years of batting experience including club level experience):
Player 4 was an experienced player who was able to play most of the shots with correct feet positions; depending on the bowling length, player 4 was able to very quickly change stance and play shots. Player 4 actively plays as a batsman at the county club level. Shots played by player 4 were also timed perfectly in most cases (high power shots).

P5: Beginner (<5 years of batting experience):
Player 5 had no exposure to playing cricket prior to data collection and played cricket for the first time. In most shots, player 5 preferred driving the ball but had difficulty in playing other kinds of shots.

P6: Beginner (<5 years of batting experience):
Player 6 had a good knowledge of cricket but very little experience of playing cricket. In particular, player 6 had difficulties with feet movements and getting into the correct position for a shot.

A detailed breakdown of the collected dataset is given in Table 2. Each session was on average $15.63 \pm 5.44$ minutes long, where sensors (each equipped with an accelerometer, a gyroscope and a magnetometer) were placed on all four limbs of the players (as illustrated in Figure 6; note that sensors on the lower limbs were placed behind the protective pads). Due to the high speed motion of batting shots, sampling rate of 100Hz was used (higher than required for standard HAR models [23]). The bowling machine we used served balls with speeds varying between 40 to 70mph, representing a range of bowling styles from slow *spin* (where a bowler bowls slow and spins using the wrist and/or fingers) to *fast* bowling. Line (direction of the ball in line with the pitch) was varied slightly between straight and off-side depending on the spin and swing generated by the machine. Also, length (point in front of the batsman where the ball is pitched) was varied between 'short pitched' and 'full pitched' (cf. Figure 6).

Players were given complete freedom to execute any desired shots but were encouraged to play as many varieties of valid shots as possible. Videos for each session were recorded for annotation purposes and an initial synchronisation ritual was executed for temporal alignment between the sensors and the camera to facilitate the annotation: a vigorous shake of the sensors in plain view of the camera that enabled subsequent manual alignment of the separate timelines of both the sensors and the video footage (see [41] for details).

## 4.2 Annotation Protocol

We annotated each batting shot to give us information on each of the levels in our hierarchy. By default any segment of the data not annotated as a batting shot was classified as the 'unknown' class described in our first level. For every shot that was picked out as a batting shot (Level 1: Shot/No shot), we annotated whether the shot successfully hit the ball or not (Level 2: Hit/Miss), the direction of the shot (Level 3: Off/On/Straight), what kind of footing was employed (Level 4: Front foot/Back foot/Down-the-ground) and finally what type of shot

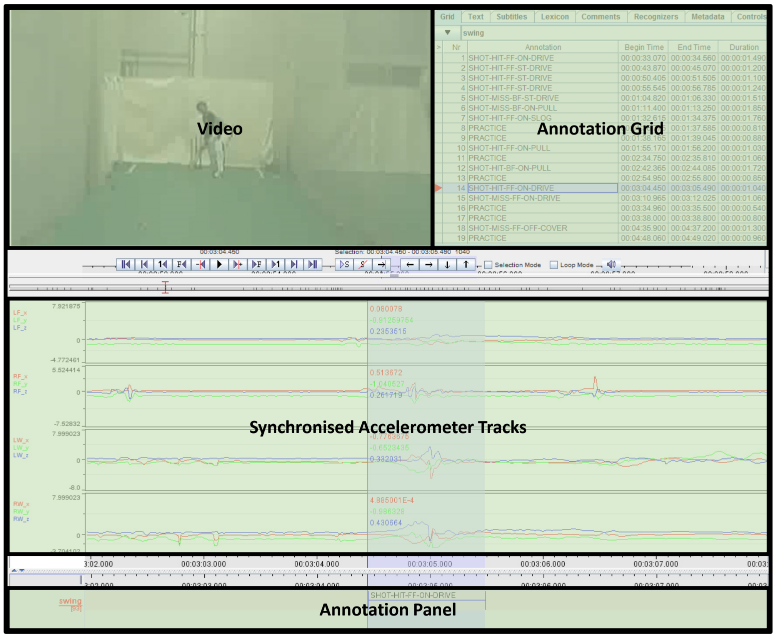



Fig. 7. Screen-shot of the annotation software indicating various panels including the video synchronised accelerometer data (note, gyroscope and magnetometer data is not indicated in this but is utilised in our recognition framework). Annotated shots with their start/end times and duration are also indicated.

it was (Level 5: Defend/Drive/Cover/Pull/Cut). The final label therefore contained information for all 5 levels. Annotations were performed using the ELAN annotation software[2]. A screen-shot of the software in operation is shown in Figure 7. Batting shots were annotated by two annotators with knowledge of cricket shots and rules of cricket. After annotation of a session by one annotator, the other annotator verified the annotated shots. In the case of disagreements, shots were reviewed multiple times to reach consensus. Most of the disagreements arose from confusion caused by the direction of the batting shot and the direction in which the ball went (this was mainly caused by the ball hitting the edge of the bat and going in unintended directions). This was resolved by taking the ball direction as the true clue for shot category annotation (which is also consistent with the batting visualizations that professional cricketers have access to in which direction of the ball is mainly considered irrespective of the type of bat swing).

## 4.3 Evaluation Methodology

As discussed in Section 3, for the batting type classification we performed recognition using three standard classification techniques: Decision Trees; $k$-Nearest Neighbours; and Support Vector Machines. We employed a leave-one-participant-out approach for classification in order to demonstrate realistic general applicability of the proposed system [15]. For each level, separate classifiers were trained to output activities per level (see Figure 3). An average class-weighted F1-score was used to compare the results of these techniques as below:

[2]https://tla.mpi.nl/tools/tla-tools/elan/

Table 3. Leave-one-player-out results for batting classification; each row represents the test results for an individual player by training the models using all sessions of the other players.

| P | Hierarchical activity recognition results for batting shots | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | L1 | | | L2 | | | L3 | | | L4 | | | L5 | | |
| | DT | k-NN | SVM | DT | k-NN | SVM | DT | k-NN | SVM | DT | k-NN | SVM | DT | k-NN | SVM |
| 1 | 86.30 | 90.60 | 90.72 | 83.57 | 87.42 | 82.22 | 87.96 | 89.09 | 88.91 | 86.70 | 87.75 | 90.02 | 86.24 | 86.75 | 88.36 |
| 2 | 88.94 | 93.54 | 84.92 | 86.56 | 88.97 | 85.14 | 88.58 | 87.85 | 89.04 | 90.57 | 90.88 | 90.13 | 87.36 | 87.36 | 87.88 |
| 3 | 89.93 | 91.23 | 82.91 | 87.27 | 89.44 | 83.33 | 90.13 | 90.41 | 87.60 | 89.88 | 90.00 | 87.10 | 87.70 | 88.93 | 87.46 |
| 4 | 74.81 | 76.68 | 65.98 | 68.95 | 71.72 | 66.10 | 82.76 | 83.35 | 82.56 | 84.39 | 86.20 | 90.18 | 82.79 | 84.54 | 82.75 |
| 5 | 90.84 | 92.28 | 85.02 | 86.15 | 88.84 | 86.30 | 91.95 | 91.71 | 89.06 | 90.12 | 91.45 | 90.91 | 91.24 | 92.31 | 92.93 |
| 6 | 88.62 | 90.37 | 83.44 | 86.59 | 88.66 | 83.70 | 87.75 | 86.96 | 85.52 | 88.11 | 88.57 | 90.80 | 87.69 | 89.55 | 91.62 |
| $\mu$ | 86.57 | 89.11 | 82.16 | 83.18 | 85.84 | 81.13 | 88.18 | 88.22 | 87.11 | 88.29 | 89.14 | 89.85 | 87.17 | 88.24 | 88.50 |
| $\sigma$ | 5.96 | 6.20 | 8.40 | 7.08 | 6.95 | 7.50 | 3.09 | 2.93 | 2.61 | 2.40 | 2.00 | 1.40 | 2.72 | 2.66 | 3.57 |

$$F1_c = \frac{2}{|C|} \sum_{i \in C_i} |C_i| \cdot \frac{p_i \times r_i}{p_i + r_i} \tag{12}$$

where $C$ is the set of all classes whilst $p_i$ and $r_i$ are the precision and recall values that can be calculated as follows:

$$p_i = \frac{tp_i}{tp_i + fp_i}, r_i = \frac{tp_i}{tp_i + fn_i} \tag{13}$$

where $tp_i$, $fp_i$ and $fn_i$ are the true positives, false positives and false negatives for a given class $i \in C$ respectively. Results of the automated batting type classification are given in what follows.

## 4.4 Results: Classification of Batting Types

Results for these individual levels using all three classifiers (individually) are shown in Table 3. On average 88.30% class-weighted F1 score was achieved using the best performing classifiers per level. Results across all the players and all levels for all classification methods are shown including their means with the standard deviations across all levels. Average results are computed across all participants which also indicate the expected performance of these classifiers on all levels if data from a new participant is tested using the trained models.

Our results indicate a very high reliability at all levels and for all classification methods with no significant difference in performance. This means that any of the evaluated classification techniques can be used to train models at all levels of our representation hierarchy to classify batting shots. A batting shot can thus be reliably classified using such sensors and our method by splitting it into various categories. This approach can be readily applied in domains where activities can similarly be represented such as in baseball or tennis [26].

Our proposed system is modelled in a manner to reflect generalization i.e., the leave-one-participant-out cross validation technique enables us to have models that will increasingly get more general as data from new participants is used. Performance of a personalized approach i.e., a model specific for each user might yield better performance but it has a significant limitation in the number of models that are required to be trained.

Reliable results from these levels are of significant importance as it is based on these results that coaches or players can infer about the performance in the overall context of the game. Based on the output of the automated shot recognition systems, players can retrospectively analyse their shot statistics not only individually but also

Table 4. Aggregated results using the hierarchical representations using the leave-one-player-out cross-validation scheme.

| P | Attack-Defence | | | Feet Positions | | | Ground Coverage[1] | | | Ground Coverage[2] | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | L1-L2-L5 | | | L1-L2-L4 | | | L1-L2-L3 | | | L1-L2-L3-L4-L5 | | |
| | DT | k-NN | SVM | DT | k-NN | SVM | DT | k-NN | SVM | DT | k-NN | SVM |
| 1 | 77.29 | 85.14 | 86.62 | 78.72 | 85.79 | 87.30 | 78.62 | 86.33 | 88.72 | 75.89 | 84.89 | 86.35 |
| 2 | 86.19 | 87.13 | 88.45 | 86.23 | 88.14 | 89.91 | 85.93 | 86.73 | 87.94 | 84.62 | 86.31 | 87.58 |
| 3 | 85.64 | 85.27 | 85.91 | 86.51 | 87.05 | 88.48 | 85.40 | 86.58 | 87.11 | 83.85 | 85.68 | 85.94 |
| 4 | 67.76 | 71.86 | 72.55 | 66.85 | 70.39 | 70.75 | 67.19 | 71.38 | 73.39 | 64.97 | 69.85 | 70.46 |
| 5 | 85.60 | 88.64 | 89.25 | 85.33 | 88.70 | 89.45 | 85.55 | 88.67 | 89.68 | 83.53 | 87.35 | 88.11 |
| 6 | 83.50 | 85.27 | 86.62 | 83.70 | 87.10 | 86.87 | 85.14 | 86.06 | 88.31 | 82.60 | 85.49 | 86.41 |
| $\mu$ | 81.00 | 83.89 | 84.90 | 81.23 | 84.53 | 85.46 | 81.31 | 84.29 | 85.86 | 79.24 | 83.26 | 84.14 |
| $\sigma$ | 7.28 | 6.05 | 6.18 | 7.60 | 7.00 | 7.30 | 7.45 | 6.39 | 6.17 | 7.68 | 6.62 | 6.75 |

[1]Off-On-St, [2]Octants

their combined effect resulting in generating focus points that players or coaches can utilize to improve game performance. In this paper, we demonstrate not only how to automatically recognize activities but also utilizing the results of the automated system in a manner that can be used for quality analysis and trend tracking in batting.

In order to perform such analysis of batting in cricket, various shot categories within the hierarchical representation need to be aggregated. For example for feet position analysis, levels 1, 2 and 4 need to be analysed. Table 4 shows the aggregated results for all scenarios discussed in this paper. Predictions from each level are separately produced and then collectively considered for calculating the class-weighted F1-scores. These aggregated results, although showing a slight drop in performance, are very promising as also indicated by the visualizations below.

### 4.5 Quality Analysis of Batting Sessions

With our approach, key statistics and visualisations related to a player's batting style can be generated, which are the basis for assessing the quality of a player. In what follows we provide an exemplary exploration of some of the key analyses that can be performed using our automated system, which illustrates the practical utility of our system in general and the low-level batting short classification in particular.

*4.5.1 Feet Position Analysis.* When batting in cricket, a player's feet are positioned to ultimately guide the ball in the correct direction. Even executing the upper-body mechanics to perfection can result in an unexpected shot if the player's feet are not placed appropriately. Using our system, feet positions can be analysed using levels-1, 2, and 4 of the representation hierarchy where all the *hits* are considered (ignoring *miss* and deliberate *leave* type shots). In our dataset, we found that players 1 and 2 have a balanced playing style with an almost equal distribution of “front foot" and “back foot" shot types (see Figure 8). Players 5 and 6 have opposite tendencies in playing back foot and front foot shots respectively.

With such information, players can practice shots to improve on both kinds of feet positions. Figure 8 also shows our model's results with regards to feet position (using the same representation hierarchy) showing a positive correlation with the actual distribution of feet positions.

*4.5.2 Attacking and Defensive Shot Analysis.* A player can play aggressively to try and score runs (*attacking*) or they can be more cautious and play *defensive* shots to prevent getting out. Such an analysis of attack against defense can also be performed for individual players using our system (see Figure 9). This is achieved using

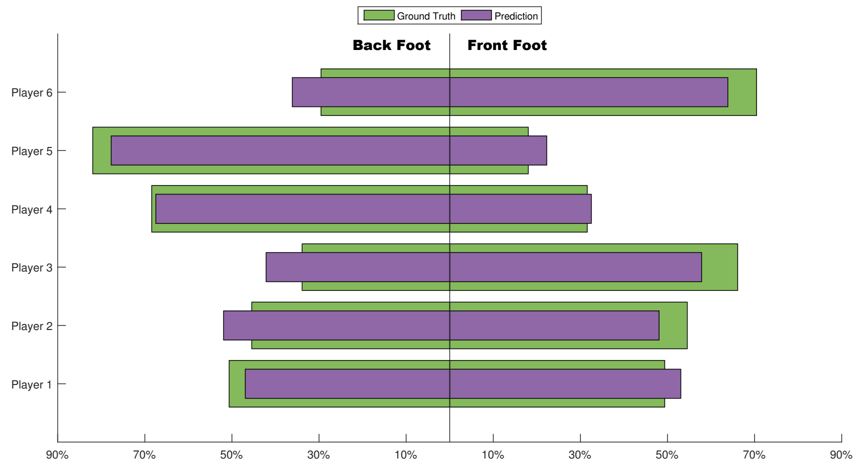



Fig. 8. True and predicted percentages of shots played on either back foot or front foot for individual players across all of their batting sessions. This was generated using the results of our automated analysis framework at level-4 of the representation hierarchy.

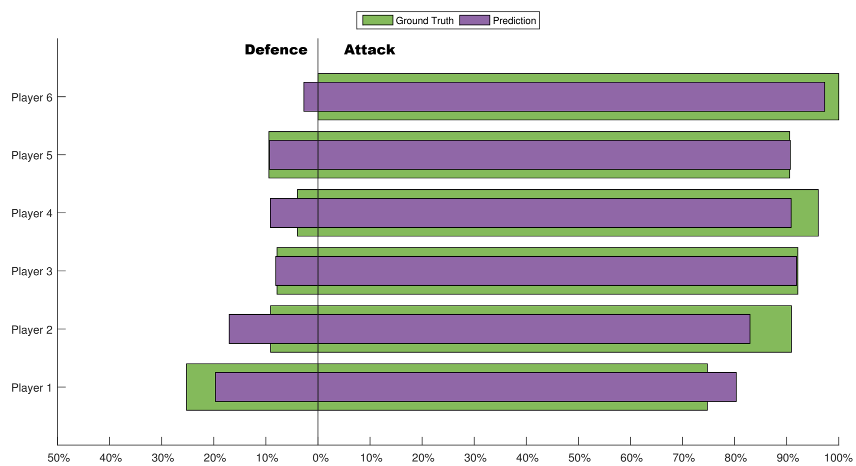



Fig. 9. True and predicted percentages of shots to compare attacking against the defensive shots for individual players across all of their batting sessions. This was generated using the results of our automated analysis framework at level-5 of the representation hierarchy by comparing the shot 'Defend' against all other shots.

level-1, level-2, and level-5 of the representation hierarchy where all the valid shots are compared against the defensive shot. In most cases, our participants played different kinds of attacking shots with player 1 playing the most number of defensive shots. This is of particular importance in cricket as there are various formats in which cricket is played, some of which require a more attacking game. For example, in the *T20* format, which lasts for a few hours, most of the players generally play an aggressive game whilst in the *test* format (which can last for up to 5 days), players generally engage in a more defensive game.

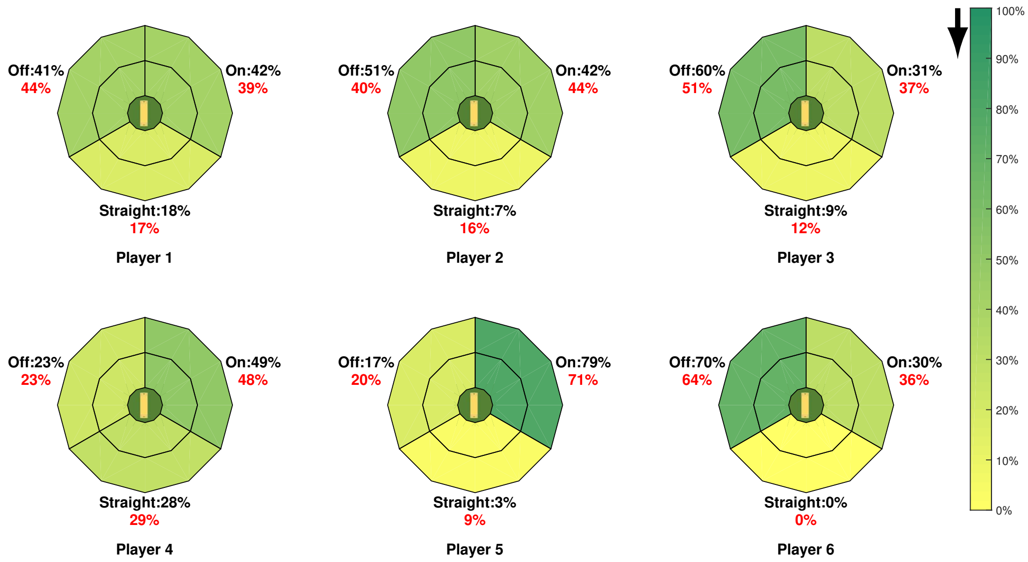



Fig. 10. Analysis of shots illustrating the percentages of shots played in a certain direction utilising the representation hierarchy. Prediction results also showing the percentages of shots in a certain direction using the proposed system and are shown in red. Black arrow indicates the batting direction.

Depending on the format a player is interested in, our approach can automatically help in tracking a particular form of batting style and practice shots that are of more interest. For example, in an aggressive game scenario, players would focus more on hitting shots that would yield higher number of runs which has an associated risk of getting *out* whilst in defensive game scenarios, players would prefer hitting shots along the ground, reducing the risk of getting out caught (a batsman gets out when the ball is caught by a member of the opposition team before it hits the ground).

*4.5.3 Ground Coverage Inference.* Ground coverage is an important metric that reveals the direction of shots played by a batsman. With our approach, we can do this either using: *a)* shot direction (focusing on *L*3 for example *Off* or *On* side shots); and/ or *b)* shot types (focusing on L5 for example *drives* and *pulls*). For players who are new to the game and at a stage where it would be difficult to recognise all specialised shot categories, ground coverage can be analysed using only the batting shot direction (i.e., using information upto *L*3) which is associated with the three main areas around a batsman.

Figure 10 shows the distribution of shots around the ground divided into 3 main areas named as *off*, *on* and *straight* (see also Figure 2, which highlights these regions, too). This distribution is derived using level-1, level-2, and level-3 of the representation hierarchy considering all *shots* in level-1 and all *hits* in level-2.

Most of the shots are usually played according to the type of the incoming ball (see Figure 6 for various types of bowling lengths for example). Shot analysis, therefore, can be performed in order to see how batsmen execute their shots in response to the kind of bowling they are exposed to. In our results, we can see that most of the shots played by the players are either on the *off* or the *on* side of the pitch. Player 5 has largely played on-side shots (79% of the time and hierarchically classified using our approach as 71%), whilst for player 6 off-side shots are favoured more. Player 4 has a good shot distribution all around the ground including straight shots played 28% of the time.

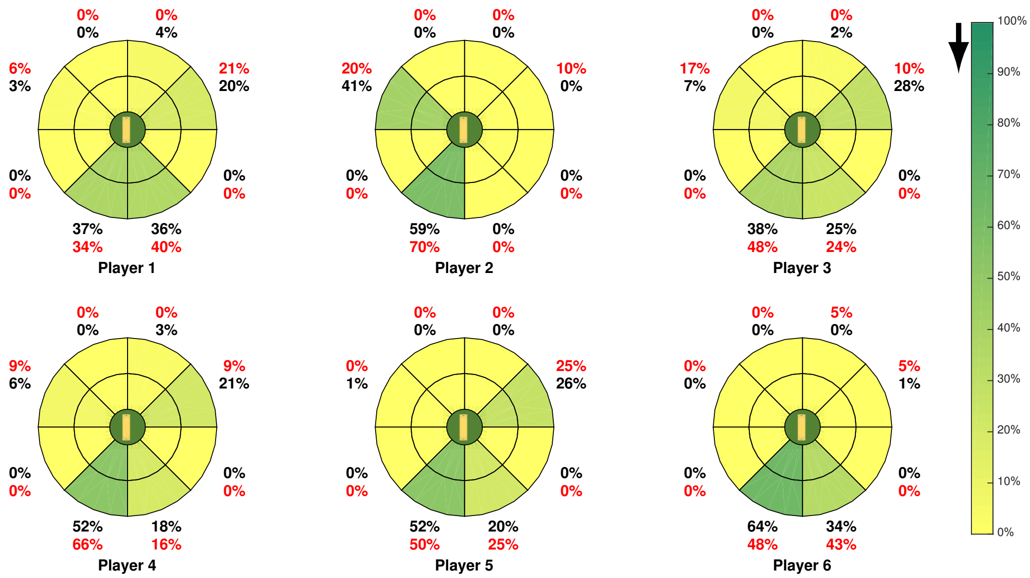



Fig. 11. Shot analysis showing percentages of shots played around the ground with prediction results shown in red. There are 8 octants and is a standard representation used in professional cricket to analyse the number of runs scored in various directions. Batting direction is indicated by the black arrow.

Table 5. Label schemes for constructing the octant visualisations based on the proposed hierarchical representation approach.

| Octant | Angle Range | Labels scheme per octant |
|---|---|---|
| 1 | 0°– 45° | L1 (SHOT) & L2 (HIT) & L3 (ON) & L4 (FRONT \| BACK) & L5 (PULL) |
| 2 | 45°– 90° | L1 (SHOT) & L2 (HIT) & L3 (ON) & L4 (FRONT \| BACK) & L5 (LEG GLANCE) |
| 3 | 90°– 135° | L1 (SHOT) & L2 (HIT) & L3 (OFF) & L4 (FRONT \| BACK) & L5 (LATE CUT) |
| 4 | 135°– 180° | L1 (SHOT) & L2 (HIT) & L3 (OFF) & L4 (FRONT \| BACK) & L5 (CUT) |
| 5 | 180°– 225° | L1 (SHOT) & L2 (HIT) & L3 (OFF) & L4 (FRONT \| BACK) & L5 (COVER DRIVE) |
| 6 | 225°– 270° | L1 (SHOT) & L2 (HIT) & L3 (OFF \| STRAIGHT) & L4 (FRONT \| BACK) & L5 (DRIVE) |
| 7 | 270°– 315° | L1 (SHOT) & L2 (HIT) & L3 (ON \| STRAIGHT) & L4 (FRONT \| BACK) & L5 (DRIVE) |
| 8 | 315°– 360° | L1 (SHOT) & L2 (HIT) & L3 (ON) & L4 (FRONT \| BACK) & L5 (SLOG) |

For more skilled players, greater granularity of shot direction analysis is very important. Our system is capable of providing shot distribution around the ground in this manner as illustrated in Figure 11, and constructed using a label scheme shown in Table 5. This label scheme is based on the presence of certain types of shots around the ground. For example, for Octant 6 (which is located south west of the ground between 180°-225°) there are *shots* (*L*1) that are *hits* (*L*2) on either the *Off*-side or *Straight* (*L*3) and are either *front* or *back* foot (*L*4) *drives* (*L*5).

These octant-specific shots are then shown as percentages of all shots around various parts of the ground. There are very few shots played towards the north side of the ground behind the batting direction (illustrated using the black arrow) that usually indicate either on-side leg-glances (a delicate touch shot in which the ball is angled by the batsman behind them) and off-side edges (usually a miss-hit) that goes towards north-west of the ground). This shows a very good representation of the types of shots a batsman is good at or can improve upon.

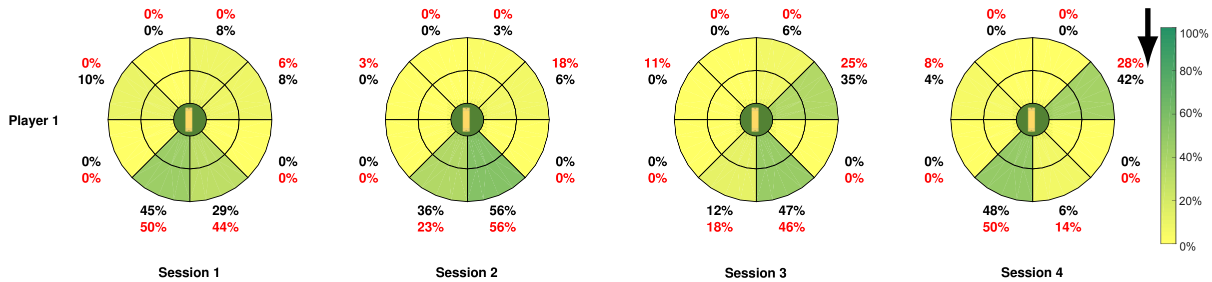



Fig. 12. Session-wise illustration of shots around the ground for player 1. Prediction results using the proposed method are shown in red. Black arrow indicates the batting direction

For example, player 1 has a good distribution of straighter shots and also off and on drives, but very little cut shots towards the off-side. As a coach, this would be one area to focus on by reconfiguring the bowling machines to bowl at such *lines* and *lengths* where the batsman is encouraged to play this type of shot.

In the case of player 2, there is an opposite picture suggesting that player 2 is largely a straight and off-side player and improvement on the on-side game is required. Note the discrepancy between Figures 10 and 11 is due to the defensive shots which are not included in Figure 11; the main focus for this visualization is to determine the potential scoring shots. This is important as a team within which players collectively score more wins the game, however a defensive game is equally important to ensure staying not-out. Also note that the cover-drive and slog regions are empty as no such shots in these areas were executed by the players which illustrates another additional focus point for the players to practice on. For player 2, it suggests that the majority of shots played towards the on side are defensive shots and would greatly benefit from practising shots such as the pull or on-drive.

*4.5.4 Batting Trend Analysis and Focus Point Generation.* Players and coaches need to be able to digest a session's-worth of shots and forge an action plan to improve weaker shots. In order to track batting trends in a player, the proposed framework can also be utilised to observe session-wise changes in shots. Figure 12 shows such a session-wise distribution of shots for Player 1. Not only does this reflect the change in the configuration of the bowling machine during these sessions but also the change in strategy of shots by the player. In sessions 1 and 2, the bowling machine was kept at a full to good length (see Figure 6) and therefore straighter drives south of the ground are the most favoured and can clearly be observed.

In session 3, bowling speeds were slowed down to spin (particularly off-spin where the ball after bouncing on the pitch turns west to east). This encourages the player to play shots on the *on* side mainly, either straighter on-drives or shots towards the east. In session 4, faster bowling speeds were configured initially on a full/yorker length and later on a short-pitched length (see Figure 2). This resulted in initial straighter shots, mainly the off-drive as the bowling line was also on the off side. However, most of the short pitched balls were played employing the pull shot towards the east of the ground.

Utilizing the proposed system, such tactical changes in gameplay, which are of great importance for a player or a coach, can be analysed. Players can observe the change in their gameplay in response to various conditions (e.g., bowling speeds, spin, line and length) and focus their training by practising shots that they feel need further improvement.

Table 6 provides an overview of all of our players with their preferred feet positioning and shot tendencies. Players 1 and 2 have a balanced gameplay in terms of their feet positioning (as also illustrated in Figure 8). However there is a difference in their preferred shot tendencies; player 1 preferring Straight and On sides whilst

Table 6. Focus points for all players summarised based on the analysis of the output of our proposed system including Hit/Miss ratio; higher value indicating majority of shots hitting the bat.

| Player | Feet preference | Shot Tendencies | Hit/Miss Ratio | Focus points |
|---|---|---|---|---|
| 1 | Balanced | Straight & On | 3.51 | Off side |
| 2 | Balanced | Straight & Off | 1.81 | On side & Improve hit percentage |
| 3 | FF | Straight & On | 7.47 | Off side (BF drives or BF Pulls) |
| 4 | BF | Straight & Off | 2.15 | On side (FF drives) & Improve hit percentage |
| 5 | BF | Straight & On | 1.86 | Off side (FF drives) & Improve hit percentage |
| 6 | FF | Straight | 5.29 | Off and On side (using BF) |

player 2 prefers Straight and Off sides. Player 1 also has a higher hit to miss ratio of 3.51 indicating higher percentages of shots played in a given session compared with Player 2's 1.81.

Based on the automated analysis our system provided, not only players can be ranked but also different focus points can be generated. Based on feet positions, shot tendencies and strike rates, we have defined focus points specifically tailored for individual players. For example, Player 5, who has a poor strike rate (hit/miss ratio) not only needs to improve this by practising more to hit the ball but also to play on the Off side more using the front-foot in particular.

In the absence of our system, achieving such a detailed level of analysis can be very time consuming for coaches and players. Considering the complexity of shots, it is difficult to gain a comprehensive understanding of a player's batting prowess by a simple direct observation where shots would have to be manually noted either real-time or using a video of the session. A variety of vision-based systems are available to some coaches to support them in the data collection and analysis. However, these alternative systems aimed at (semi-)professional players are either very expensive to deploy, require an expert manual setup, or are otherwise not accurate enough to generate meaningful measures of low-level activities. With our approach, we can achieve the rudimentary measures of shot classification and present it as a visual package at a fraction of the cost for both amateur cricketers (who would otherwise have no way of assessing their batting) and professional cricketers (as a low-cost alternative).

We note that the proposed system is suitable for both indoor and outdoor batting sessions, as the types of batting shots played indoors or outdoors are exactly the same. We evaluated the performance of our system in an indoor net session solely for ground truth annotation purposes.

## 4.6 Influence of Bowling Type

The bowling line and length play a major role in a batsman's shot choice of batting, as well as in the method the shot is played (see Figure 6). For example, a short length ball is more likely to be *pulled*, i.e., shot towards the *on* side of the ground played using a back-foot stance, whilst a full length ball is more likely to be driven (usually played straight down the ground). Thus, knowing the type of the delivery is important for understanding the resulting shot. Our proposed system does not automatically record the length of the deliveries, but a well-organised and systematic batting session will portray this information. Then, separate visualisations will be created for each type of delivery (i.e. short length, good length, and full length). While this approach would perhaps be most effective when using a bowling machine due to consistency in deliveries, it is possible to collect the data using a bowler. The ideal method for structuring the batting session would be to systematically cycle through all delivery types, thus splitting the session into three sub-sessions based on bowling types. The appropriate instructions would then be relayed to either the bowler or the coach responsible for overseeing the session.

### 4.7 Run-time Analysis

In order to assess the computational performance of the proposed framework (run-time analysis), we consider a deployment scenario that enables quality analysis of batting shots. In order to meaningfully assess cricket batting, session-wise analysis must be performed (i.e., not at the sample level). This level of assessment granularity allows capturing trends in cricket batting including strengths and weaknesses of a batsman. For example, for scouting purposes, where a large number of players are required to be assessed, a final statistical representation of batting quality is of greater importance (instead of manually analysing hundreds of shots that a player plays). This has to be performed, not only session wise, but also longitudinally (across multiple sessions) to assess batting quality including trends in improvements for example.

In our dataset, the average length of a batting session is $15.63m \pm 5.44$. All the shots played during these batting sessions (see also Table 2) can be recognised in less than 2 seconds (per player and per level) on average using a pre-trained model (see Section 3). Although the proposed system is capable of producing recognition results in under 62ms per shot, session-wise assessment performance is more valuable. This performance was recorded during the testing phase of our experiments for all folds (leave-one-player-out cross validation) and all levels of the representation hierarchy. We performed our analysis on a desktop workstation with an i7 950 processor clocked at 3.07GHz and 12GB DDR3 RAM. The system utilises multiple cores to provide greater performance and is suitable for any stationary deployment. For mobile deployments state of the art processors can achieve similar performance, enabling nearly-immediate feedback. For mobile deployments a pre-trained model can be deployed directly on a mobile device.

In professional cricket, batting duration can vary a lot from lasting a single delivery (if a batsman gets out with the first ball bowled) to days in test cricket (the longest batting recorded in cricket history lasted for 970 minutes over 4 days [3]). With our approach, statistical analysis of shots can be provided as soon as a batting session is over. Considering the longest ever batting session of 970 minutes, our approach can produce results in 129.3 seconds per level if all the shots are recognised at the end of the session. However, predicting shots as soon as the data is recorded can also be performed allowing an even quicker feedback at the end of a batting session.

## 5 DISCUSSION

The overarching goal of our work is focused on developing technology that enables participation and positive impact for everyone with specific attention to under-represented groups. This paper contributes to the wider context of facilitating for the amateur and hobby sports community to foster wider uptake and sustained engagement that promotes healthier living and societal engagement. Cricket is a tremendously popular sport with millions and millions of supporters and hobby players all over the world. As with so many amateur sports, professional assessment and coaching in cricket is typically not widely and easily accessible. It is the intention behind our work to eventually overcome this shortage of professional support by developing and deploying inexpensive thus widely accessible yet accurate and consistent automated assessment means that enable cricket enthusiasts to objectively reflect upon their skills and as such to develop as players. As an additional benefit the automated, objective assessment using an analysis system like the one we are developing will allow for entirely new ways of engagement, such as through remote scouting as described below.

In this paper we presented the first exploration regarding the general effectiveness of an automated cricket assessment system that consists of inexpensive, wearable movement sensors and an automated, machine-learning based sensor data analysis framework. We proposed a hierarchical shot recognition mechanism for accurately identifying cricket shots with the aim of providing an objective, automated assessment system for coaches and players. The proposed system is important for cricket due to the popularity and wide-reach of the sport [45], but also because of the financial inequalities that are common across the participating countries. The proposed system

[3]http://stats.espncricinfo.com/wi/content/records/284006.html

and hardware are inexpensive and relatively simple to set up, and thus can be used in developing countries and by individuals who cannot afford expensive setups. Teams like the West Indies rely on players from a network of islands, but each individual island is relatively financially unstable compared to other cricketing countries like India where domestic leagues generate billions of dollars over the course of two months [29]. This is also true for developing cricket countries as well such as Zimbabwe, Afghanistan, and Kenya, where an overall lack of finances makes it difficult for scouts to reach geographically-isolated talent. However, there is a wealth of talent that rises from these countries, and a scalable and affordable system like the one proposed in this paper would help reach youth players who otherwise would go unnoticed. Scouting can also be an issue in wealthier countries like Australia and India, where large numbers of amateur players require the limited attention of scouts and coaches. There is also a case to be made about the blind evaluation of cricketers, as there are concerns about the representativeness of specific backgrounds at an elite level [36]. The presented system enables fair and objective skill assessment.

Our system can provide a measure of batting quality through an analysis of the results of our activity recognition system. By providing a detailed breakdown of the different aspects and types of shot categories used in a session, we open up for a comparison between players. Using each aspect of the shot: bat-and-ball contact, foot positioning, direction and shot type we can provide information to the players, which can be used to draw a comparison between skilled and unskilled batsman. By highlighting the areas that are most profoundly different between the amateur player and the professionals we provide feedback which can assist the coaching of amateur players. Using this feedback players can focus their practice and track their improvements over time. For a beginner-level player, it is most likely they will need to focus on the most important aspect for that level: hitting the ball. Extending this for professional players – where each type of shot can be important to use in the appropriate scenario – they will be interested to know if their shot success suffers for certain types of shot, meaning the full breadth of the information our system offers becomes important.

We developed informative visualisations analysing feet positions, attack/defence and distribution of shots around the ground. These visualisations are automatically produced after a batting session and players/coaches can observe weak points to improve upon. These visualisations can then be utilised by coaches to filter through large numbers of players without the need to invest large amounts of time attending to batting sessions, or to evaluate players from far away geographical locations without having to commit to lengthy travel. This is especially important at early grass-roots levels where there is an influx of players and a limited number of scouts. Using these visualisations, a coach can get an immediate picture of each aspiring cricketers' technical prowess before deciding on whether to invest any further time with observations and/or development.

The low-cost hardware and resulting visualisations can also be used by the individual players themselves to improve their game. It is well known that a person's feelings can affect the recollection of memories (e.g. [21]), and this no different during lengthy cricket batting sessions where valuable details can be forgotten or misremembered – for example shots played well or shots missed. When players can conveniently access detailed graphics depicting their performance they can then tailor future training sessions to improving their weaker shots.

### 5.1 The System in Action: A Vision for Cricket Kenya

To illustrate the system's potential in facilitating remote scouting of players, we present the following deployment scenario. While every club employs their own distinct practices, we base this scenario on the reported infrastructure information and likely practices.

Kenya is an up-and-coming cricketing nation with hopes of becoming a full member of the elite cricket group (the International Cricket Council). However, travelling throughout the country can be challenging due to limited railway routes and the poor condition of roads [37]. Thus, when a player displays some potential in a remote area of the country, a coach from Cricket Kenya (the central organisation in the country) may be unwilling or even unable to travel a long distance to evaluate the potential of one player. Cricket Kenya are based in the capital, Nairobi, which is generally well-connected to most areas of the country, and is also served by two airports. However, accessing smaller towns is not always straightforward. Based on Cricket Kenya's published Development Program, schools and universities are important sources for talent [7]. Just focusing on universities, a visit to Egerton University would take three and a half hours, while a visit to Meru University would take nearly five hours. Scouting universities further afield would take five and a half hours (University of Kabianga) and just shy of seven hours for Maseno University. With regards to schools and colleges, there are hundreds in Kenya spread out all over the country.

Therefore, instead of subjecting a scout to travel for long durations, the institution (e.g. school, university, local cricket club) could simply request the sensors from Cricket Kenya who would then mail these small items. Coaches at the institution could then download our app (which was not within scope of this paper) onto their smartphones (internet access in Kenya is the highest per-person in Africa [47]) in preparation for the batting sessions. Once the sensors arrive, the sessions can take place like any other batting sessions and all the data will be recorded and analysed on the smartphone. Coaches then have the option of uploading the data to Cricket Kenya's servers (approximately 10 megabytes for a standard 15 minute session) or simply sending it on a memory card alongside the returned sensors. Coaches at Cricket Kenya can then evaluate the player's performance before deciding whether to travel for a formal appraisal.

Of course, the process would be even simpler if the institution owned the sensors, which is not unrealistic given the low cost of the hardware. In this case, the institution would simply need to upload the collected data onto Cricket Kenya's servers for analysis. In the case of poor internet connectivity, the data could be mailed to Cricket Kenya on an inexpensive memory card.

## 5.2 Limitations & Future Work

Although our system provides a thorough representation of batting shots, there are certain aspects of batting that also need to be assessed in order to fully judge a player's batting calibre. These include, batting stance which is the position a batsman assumes before playing a shot. Correct stance results in good shots played around the ground. Similarly, batting shots can be modelled as a function of the bowling type. Our system could be implemented alongside a similar recognition system for bowling, which would provide even more context to the batting metrics and allow an even better automatic understanding of batting decisions. In essence, such a combination would help coaches automatically evaluate the mental responsiveness of the player – i.e. their response to different bowling types – which is another key performance indicator for batting skills.

As a future work, other aspects of cricket, including bowling and fielding, can also be analysed using the proposed system by representing these activities hierarchically. For example, understanding various types of bowling and sub-activities within it can be of great value. For batting skill assessment, i.e., understanding the quality level of a player, other aspects – in addition to the range of shots utilised – are also important to consider, such as the mental aspect of the game. Other complex interactions can also be analysed such as understanding the types of shots played by a batsman as a response to the type of bowling used by the bowler. Related to this is the response time with respect to the ball leaving a bowler's hand and the location of the ball hitting the bat in a shot can also be considered. A generalised approach such as [22, 24] can also be utilised in this context to assess the quality of gameplay and rank players according to their skill levels. The method proposed in this paper can also be used in other sports (such as baseball) by employing transfer learning techniques such as [2, 8] (originally proposed for singles and doubles tennis with extension to badminton).

## 6 CONCLUSION

The game of cricket is very popular worldwide, and while some countries are wealthy enough to sustain the scouting and development of elite players, there are many that cannot afford the state-of-the-art technology required to compete. We explored the suitability of an inexpensive sensor-based system and machine learning based sensor data analysis techniques that require minimal setup to aid the development of cricket batters by automatically recognising batting activities and visualising the results in standard diagrams summarising batting sessions with the aim of improving weaknesses in their game. The generated visualisations are based on those used by international coaches and broadcasts, and can help both players and coaches to pinpoint weaknesses in the batting game by observing the distribution of shots and the foot movement associated with the shots. These visualisations allow hobbyist players who don't have access to a coach to hone their skill at cricket. Additionally, the diagrams could allow scouts to obtain a overall sense of a player's ability without being physically present, facilitating their ability to perform preliminary scouting on a variety of players who would otherwise not be considered due to geographical constraints. The system presented in this paper is the first of its kind that enables automated and objective assessment of batting skills in cricket using an inexpensive sensing infrastructure and robust, machine learning based analysis techniques.

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