CommBox: Utilizing Sensors for Real-Time Cricket Shot Identification and Commentary Generation

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***Abstract*—Online cricket commentary has become very popular as the internet provides access to a large number of sports websites. A key challenge for them is to offer their readers an insightful and fast paced live commentary. In this paper, we propose a framework to automate cricket shot identification and commentary generation using sensor data as features for machine learning models.**

I. Introduction

In the contemporary world, Internet has become an integral part of everyone's life. Sports websites have become a major source of information for enthusiasts, who are continuously on the move. An arguable problem for such websites is to have enough man power in order to provide their readers an umpteen amount of sports articles and live commentary across various domains. From our research, we see a need to speed up the streaming of commentary on these websites. In this paper, we propose a framework *CommBox* to automate commentary generation specifically in the domain of cricket.

Previous works in this domain like [1], [2] use cricket videos in order to automate cricket shot identification. However, we leverage the unique patterns observed in sensors [3] as features for a machine learning model to predict cricket shots and thereby, commentary. Particularly, we also utilize unique patterns observed in sound sensors when someone plays a cricket shot to trigger the classifier. The major contributions of our system are manifold:

- We develop a hybrid framework *CommBox* which uses sensors instead of visually assessment of videos to automate cricket commentary.
- We conduct extensive evaluations on different players to demonstrate that the sensors act as a classic indicator to determine uniqueness across different shots even when separate people play the shots.
- Moreover, we display that a sensor based approach outperforms existing video based systems for few shots.

II. Methodology

Our Framework is shown in Fig I. We collect sensor data using wearable sensors, deploy a sensor fusion algorithm and train our classification model after incorporating noisy samples.

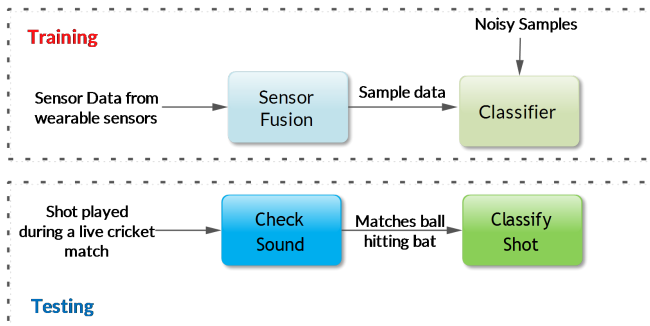

Fig. 1. CommBox Framework

A. Collecting Sensor Data

In order to check if sensors like accelerometer and gyroscope have the potential to be used for identifying cricket shots, we first imitated them using a smartphone. We captured accerelometer, gyroscope and rotation vector data from a smartphone for 3 major shots - cut, straight and pull. Fig II shows the variation of y component of gyroscope reading over the duration in which different shots were played. We see clear differences in the 3 shots at specific points.

However, the sensors have to be used in a realistic fashion in order to utilize them during a live cricket match. A reasonable practical approach is to use wearable sensors. We used MetaWear CPRO[1], a coin sized sensor provided by Mbient Lab[2]. We place it inside a wrist band, which the batsman can wear on their hand. Accelerometer and gyroscope data obtained from these sensors are continuously collected by connecting it to a computing device (phone or laptop).

B. Determining Angular Position in 3D Space

Apart from accelerometer and gyroscope readings, another important feature of our system is the angular orientation of bat/hand in the 3D space.

Angular position can be calculated by determining the position of the gravity vector captured using accelerometer

[1]https://store.mbientlab.com/product/metawear-cpro/
[2]https://mbientlab.com/

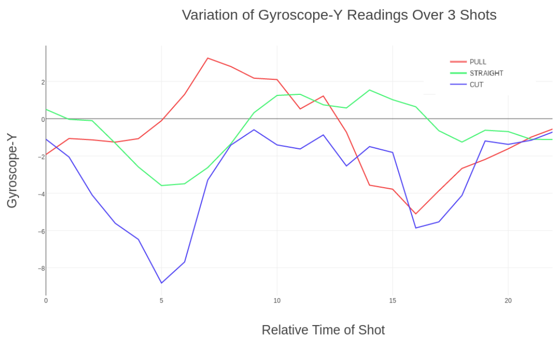

Fig. 2. Variation of Gyroscope-y Reading over 3 shots

or by integrating angular velocity computed using gyroscope over time.

However, these approaches have certain limitations. An accelerometer measures all forces acting on the object and is too noisy for positioning of any kind. The integration computed using gyroscope is approximate and the measurement has tendency to *drift* as it does not return to zero when the object is moved back to its original position.

To avoid both accelerometer noise and gyroscope drift, we employ *Complementary Filter* which is a sensor fusion technique. It applies low-pass filtering on accelerometer data and high-pass filtering on gyro output [4]. The angle update rule is defined as follows:

$$\phi_{n+1} = 0.98 * (\phi_n + integrated\_gyro) + (0.02 * acc)$$

C. Data Sampling

The sensor records accelerometer and gyroscope readings continuously at its sampling rate. However, for shot classification, we only need the readings during the time when the shot is played. In order to detect if the batsman has hit the ball we use a sound sensor. The microphone embedded in a smartphone is placed in the batsman's pocket for measuring the sound intensity. We found that the sound produced by the bat hitting the ball is of high intensity when measured using a microphone in near proximity and of a specific frequency. For our system, we only use intensity and check if it exceeds a threshold to conclude that batsman has hit the ball. We take x samples before and x samples after the ball hits the bat so as to capture the full bat swing. We take equally spaced p samples from the collected data. Accelerometer, gyroscope and angle computed from complementary filter are then chosen as features for shot classification.

III. Experimental Setup

For training purposes, we restrict our domain to classify 5 different cricket shots. We picked three very different shots: cut, pull shot and straight drive. In order to generalize our model, we included two more shots, cover-drive and on-drive which confuse with cut and pull. The training and testing was done in a playground. To avoid unnecessary sensor damage, we used a plastic cricket ball, which we found to produce equally good hitting sounds similar to a seasoned cricket ball. We train a SVM with linear kernel on 50 shots of each category played by one player. We take the value of x as 100 and p = 25.

Also, batsman frequently does *warm-up back swings* during his stance which conflicts with sound of ball hitting the bat. We extend our classifier to incorporate this by generating such noisy examples.

TABLE I
Classification Accuracies (acc: Accelerometer, gyro: Gyroscope, comp: Comparative Filter)

Experiment	Feature Used			
	acc	gyro	comp	comp+gyro
3 Shots	88.80 %	90.84 %	82.23 %	**96.52 %**
5 Shots	80.94 %	86.27 %	69.49 %	**90.57 %**

IV. Evaluation

Table I shows 10-fold cross validation accuracies of our system for 3 shots and 5 shots classification. We find best results when we use comparative filter along with gyroscope as our features. Our system has better accuracies as compared to recent video based methods for shot identification [2] (86.54 %).

We then tested our trained model on a different batsman with different playing style. We find a low accuracy of 47.32 %. However, if we train on both the batsmen and identify player as well as shot, we find a promising score of 90.69 % (3 shots, Comparative Filter and Gyroscope as features). These results show that sensors are a nice indicator to determine uniqueness across different shots even if the shots are played by different batsman.

V. Conclusion and Future Work

The goal of this work was to develop a sensor based framework to automate cricket shot identification. In particular, we used gyroscope, accelerometer and sound sensors to identify the shots and comment appropriately. More importantly, we demonstrate our approach outperforms the existing systems for certain shots and performs slightly better for confusing shots like on-drive and cover-drive.

In future, we plan on classifying missed shots, identify edges and determine the runs scored. Although further work remains to be done, we can conclude automated cricket commentary can be done using a sensor based system.

References

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