Optimizing a cricket edge detection system using feature extraction from wavelets over the time domain.

R. Rock (rodrick.rock@mycavehill.uwi.edu), A. Als (adrian.als@cavehill.uwi.edu), P. Gibbs (peter.gibbs@cavehill.uwi.edu),
Department of Computer Science, Mathematics and Physics
University of the West Indies (Cave Hill Campus) Barbados
Cavehill, St Michael. Barbados West Indies
CSC’2012

Abstract- In the game of cricket an edge is defined as an inadvertent connection between ball and bat. Edges, which result in the ball carrying directly to a fielder and being caught, warrant the batsman being adjudged out. Unfortunately there are various sounds that on-field umpires may confuse with genuine edges thereby causing the batsman to be erroneously adjudged as being out. In this paper the edge detection system proposed by Rock et al [1] is modified and extended to handle scenarios where there are edges and both the bat and pad are involved. Live audio samples of ball-on-bat, ball-on-pad and cases where both events occur within a narrow time window (<1 sec) will be recorded. Wavelet analysis, feature extraction and neural network classification will then be employed on these samples. Results will show the ability to differentiate amongst the three types of events, which is crucial to the development of a fully automated edge detection system.

Keywords: Cricket, Wavelets, Neural Networks, Edge-detection, feature classification

I. Introduction

The limited overs version of the game of cricket is played between two teams with 11 players on each side. On winning the coin toss, the captain decides whether his team bats or fields first. The conclusion of the allotted number of overs, or when all the batsmen are given out, marks the close of an innings. Each team is allowed one (1) innings. The aim of the team batting first is to score as many runs as possible during their innings. In order to win, they must limit the other team to fewer runs [2]. The test match version of the game is played over multiple (≤ 5) days and is more complex as each team may accumulate runs over multiple (≤ 2) innings. Cricket is the second most popular sport, and the Indian Premier League’s (IPL) 20/20 format
boasts of being the second highest paid sport ahead of the football’s English Premiere League (EPL) [3]. In 2009, the Indian Premier League (IPL) offered paychecks as high as US$1.55 million to top class cricketers for a five-week contract [4]. This figure was eclipsed in 2011 when Gautam Gambhir of the Kolkata Knight Riders was awarded a contract for US$2.4 million [5].

On the field of play, there are two umpires officiating a match. One umpire stands behind the stumps at the bowler's end of the pitch, while the other umpire stands at square leg. At international level there is also a third umpire on the sidelines and a match referee. The umpire at the bowler's end makes decisions on lbw and bat-pad appeals, no balls, wides and leg byes [6]. The square leg umpire will judge stumpings and run outs [6]. At the end of each over, the umpires change position [2]. The third umpire uses TV replays to rule on run outs, stumpings, boundary infringements and close catches. However, the third umpire can only make a decision if requested by the on field umpires. Their involvement in the game has become increasingly influential, with fans and commentators alike calling for technology to be used for every contentious appeal [2]. In the last few years, the ICC has trialed a review system which allowed players to challenge the on-field umpires and have their decisions referred to the third umpire - in Test cricket. The dismissed batsman or the fielding captain could appeal by making a "T" sign with both forearms at shoulder height, each team having a maximum of two unsuccessful challenges per innings [2].

The use of technology serves to protect both players’ careers by avoiding incorrect decisions and the reputation of the game. The snickometer and hotspot are two devices which have been used and to some extent are still being used in cricket mainly for bat pad decisions. These two devices have come under some criticism for their accuracy and the use of them in cricket has not been fully embraced by cricketing administrators [1].

The aim of this paper is to employ wavelet analysis, unique feature extraction methods and artificial neural networks to implement a fully automated decision making system for bat on pad edge and bat/pad decisions, thereby extending and improving the work done by Rock et al in [1]. This will greatly minimize the number of errors currently seen in the game.

II. Background

The use of wavelets to analyze real-world signals (i.e. the constituent frequencies change over time, or have pulses, anomalies or other transient events) is well documented. Although these non-stationary signals may be intermittent and noisy, wavelet analysis can be employed to simultaneously monitor events in both time and frequency [7]. This special attribute makes the use of wavelet analysis more convenient than that of Fourier analysis as tradeoffs between knowing the time occurrence of an event and the constituent frequencies are avoided. The analysis of sound signals using the continuous wavelet transform (CWT) is well documented in the literature [8-10]. In the CWT approach the target signal to be analyzed is correlated with an analysis wavelet thereby producing a set correlation values along a time axis. The analysis wavelet is repeatedly stretched and used in other correlations with the target signal. Each stretching instance results in what is referred to as a scale value (y-axis). Thus this method provides another view of temporal signals as it transforms the regular
time vs. amplitude signal to time vs. scale, where scale can be converted to a pseudo-frequency. Therefore one can examine the temporal nature of audio events and the corresponding frequencies involved simultaneously. The correlation values produced during the transformation process provide critical information on the characteristics of the signal. Therefore by extracting and analyzing these correlation values a distinction can be made between different audio events. In this work, four main features were extracted across time from the CWT. These included the average **pseudo-frequency** for the CWT time range, along with the **standard deviation**, **kurtosis** and **skewness** of the said frequencies. These features were fed into an Artificial Neural Network (ANN) to produce the final result. ANNs are information processing systems that have performance characteristics common to biological neural networks. They consist of a number of interconnected neurons, each with an associated weight. These neurons work together to help solve various problems [11]. One of the main features of the ANN is its ability to take a set of features it has not encountered before and accurately output the desired classification result.

There are many instances where the CWT and neural network classification has been used. Kaewkongka [12] obtained a recognition rate of 90% success of rotodynamic machine conditions for four machine operating conditions using features extracted from the continuous wavelet transform and fed into a neural network. Kilby used the wavelet transform to enhance features extracted from the surface electromyography (SEMG) [13]. These features were taken from the time-based information as well the scale (i.e. pseudo frequency) axes. Using the extracted features of the dominant (pseudo) frequencies from the wavelet transform and the related scales, they were able to train and validate an artificial neural network for SEMG classification. Kotani [14] used the wavelet transform and neural network classification to perfectly detect the surging sound (non-stationary signal) which leads to the destruction of a dryer machine.

Other than the work by Rock et. al in [1] there are no known instances where CWT and Neural Network classification has been applied in the area of cricket were uncovered in the literature. The Neural Networks are utilized to classify the features that are extracted from the sound files using the CWT. This classification can then be used to accurately determine both the order and the source of the events in a cricket match. The automated sound detection technique can greatly decrease the number of incorrect decisions being made in the game, which may ultimately protect a player’s career.

**III. Methodology**

The equipment setup, shown in Figure 1, is identical to that used for international matches and was configured at various hardball cricket grounds throughout Barbados. The microphone transmitter is covered in a small hole directly behind the stumps. The receiver and the laptop are assembled inside the players’ pavilion. The recordings, made using the laptop’s sound recorder program, are stored as a 16-bit pulse coded modulation (PCM) .WAV file, sampled at 44,100 kHz (stereo) for later processing.
Figure 1: Schematic of experimental setup.

The key specifications for equipment used in recording the audio data are listed in Table 1.

<table>
<thead>
<tr>
<th>EQUIPMENT</th>
<th>KEY PARAMETERS</th>
</tr>
</thead>
<tbody>
<tr>
<td>WL184 Supercardioid Lavaliere Condenser Mic</td>
<td>Supercardioid pickup pattern for high noise rejection and narrow pickup angle</td>
</tr>
<tr>
<td>Shure SLX14/84 Wireless Lavaliere Microphone System</td>
<td>SLX1 Body pack Transmitter:</td>
</tr>
<tr>
<td></td>
<td>518 - 782 MHz operating range</td>
</tr>
<tr>
<td></td>
<td>SLX4 Wireless Receiver:</td>
</tr>
<tr>
<td></td>
<td>960 Selectable frequencies across 24MHz bandwidth</td>
</tr>
<tr>
<td>Mobile Precision M6400 Notebook Computer</td>
<td>Precision M6400, Intel Core 2 Quad Extreme Edition QX9300 2.53GHz, 1067MHZ</td>
</tr>
</tbody>
</table>

MATLAB programs were written to perform the CWT analysis and extract the following features: the average pseudo-frequency (Pfreq) from the selected CWT time range along with the standard deviation (σ), kurtosis (k) and skewness (skn) of the said frequencies. The average pseudo-frequency was obtained from using the frequencies corresponding to the highest correlation values of the wavelet transform in each time interval. These features were used as input to the fully connected 4-input Multi-Layer Perceptron neural network depicted in Fig. 2. The network consists of a single hidden layer with three neurons each of which employed the tanh transfer function.

The network was trained with 232 data samples using a backpropagation algorithm.
The data set was divided into 116 incidences of bat-on-ball signals and 116 of ball-on-pad. Testing was done on 44 previously unknown signals. The output from the network was a decision on whether the ball hit the bat or the pad. Note that some of the audio samples included both bat-on-ball and ball-on-pad noises occurring in quick succession (<1 sec). These were analyzed as two separate events. The chronological nature of the decisions output from the ANN could then be used to determine the outcome of an appeal for LBW or bat/pad.

IV. Results

Three types of recordings were successfully complied and analyzed. These included the impact of ball hitting bat, ball hitting pad and cases where both events occur within a narrow time window (<1 sec). Figure 3 shows the plot of desired output and actual output versus number of samples used for testing. In this work, the average pseudo-frequency along with the standard deviation, kurtosis and skewness were extracted across time instead of scale as was done in [REF]. There are two rationales for this modification. Firstly, in the case where both events occur within a narrow time window, there has to be a clear differentiation as to when in time these two events occurred. Secondly the observation was made that as the ball passes the bat or pad, the signal properties change. The extracted features from across the time domain best represented these changes and provided the better results. The Neural Network then successfully classified these features with a one (1) and zero (0) representing ball-on-bat and ball-on-pad, respectively. A threshold value of 0.5 was used in separating data, as anything above 0.5 was considered 1 and anything below 0.5 was considered 0. The line with the diamond markers represents the expected results whereas the line with x’s is the actual results output from the neural network. The neural network performed exceptionally well. Observe that in Figure 3 the neural network output for some of the ball-on-bat cases deviate from the expected results. However, the threshold value ensures that all the deviations were still correctly classified. This resulted in a 100% correct classification for data not previously encountered.
V. Conclusion

Results show the neural network performed exceptionally well rendering a correct classification of 100% for data not previously encountered. It is believed that better results may be obtained from training the neural network with more sound files.

The methods used in this paper to completely remove the human factor from the data gathering and information-processing portion of the adjudication process will provide an edge detection system, which is a lot more accurate than the ones currently being used in the game of cricket.

![Graph and results of actual and desired results for the forty test data samples](image)

Figure 3: Graph and results of actual and desired results for the forty test data samples

VI. Acknowledgment

The authors would like to acknowledge Mr Simon Wheeler (Executive Producer/Director of TWI and IMG media company), Mr Mike Mavroleon (Senior Engineer IMG media) and Mr Collin Olive (Asst. Sound Engineer IMG media) for their direction in acquiring the equipment needed to record the data samples used in this paper. These are the persons responsible for technological aspects of the broadcast of international cricket.

References


