The 5th Umpire: Automating Cricket's Edge Detection System

R. Rock, A. Als, P. Gibbs, C. Hunte
Department of Computer Science, Mathematics and Physics
University of the West Indies (Cave Hill Campus)
Barbados

Abstract-**The game of cricket and the use of technology in the sport have grown rapidly over the past decade. However, technology-based systems introduced to adjudicate decisions such as run outs, stumpings, boundary infringements and close catches are still prone to human error, and thus their acceptance has not been fully embraced by cricketing administrators. In particular, technology is not employed for bat-pad decisions. Although the snickometer may assist in adjudicating such decisions it depends heavily on human interpretation. The aim of this study is to investigate the use of Wavelets in developing an edge-detection adjudication system for the game of cricket. Artificial Intelligence (AI) tools, namely Neural Networks, will be employed to automate this edge detection process. Live audio samples of ball-on-bat and ball-on-pad events from a cricket match will be recorded. DSP analysis, feature extraction and neural network classification will then be employed on these samples. Results will show the ability of the neural network to differentiate between these key events. This is crucial to developing a fully automated edge detection system.**

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

I. INTRODUCTION

The revenue generated from sport globally is estimated to reach over $130bn US dollars by the year 2013 [1, 2]. In 2010, Soccer, the world's most popular sport according to [3], was reported by its international governing body, FIFA, to have generated US$1bn on the strength of the successful world cup in South Africa [4]. Cricket is the second most popular sport, and the Indian Premiere League's (IPL) 20/20 format boasts of being the second highest paid sport ahead of the football's English Premiere League (EPL) [5]. In 2009, the Indian Premier League (IPL) offered pay checks as high as US$1.55 million to top class cricketers for a five week contract [6]. This figure was eclipsed in 2011 when Gautam Gambhir of the Kolkata Knight Riders was awarded a contract for US$2.4 million [7].

It is well known that bookmakers have also capitalised on cricket's wide fan-base. The plethora of online betting sites dedicated to cricket, such as bet.com, cricketworld.com, cricket.bettor.com and cricketbetlive.com, to list a few, are evidence of this practice. Unfortunately, the sport has gained notoriety with several of its elite players being charged with bringing the game into disrepute. In the 1999-2000 India-South Africa match fixing scandal, Hansie Cronje, the South African captain admitted to accepting money to throw matches and was subsequently banned from playing all forms of cricket [8, 9]. In August 2010 during the match between England and Pakistan at Lord's Cricket Ground two Pakistani players were accused of match fixing by deliberately bowling three illegal deliveries (i.e. no-balls) at pre-determined times during their bowling spells. It was alleged that Mr. Mazhar Majeed, a property developer and sports agent, orchestrated the events and tipped off betting syndicates so they could place "spot" bets and make profits of millions of pounds [10, 11].

To deter match fixing, and ensure legitimate results, it is not surprising that the use of technology in cricket has steadily increased over the years and now has a major role in adjudicating the outcome of events. However, although the use of technology serves to protect both players' careers by avoiding incorrect decisions and the reputation of the game, its adoption has not been fully embraced by the cricket's administration body. There are a number of devices being used to assist umpires in the adjudication process and for the entertainment of television audiences. One such device is the Snickometer (also known as 'snicko') which English Computer Scientist, Allan Plaskett, invented this in the mid-1990s. The Snickometer is composed of a very sensitive microphone, located behind the stumps, and an oscilloscope (wirelessly connected), which displays traces of the detected sound waves. These traces are recorded and synchronized with the cameras located around the ground. For edge-decisions, the oscilloscope trace is shown alongside the slow motion video of the ball passing the bat. By the transient shape of the sound wave, the viewer(s) first determines whether the noise detected by the microphone coincides with the ball passing the bat, and second, if the sound appears to come from the bat hitting the ball or from some other source. Unfortunately, this technology is currently only used as a novelty tool to give the television audience more information regarding if the ball actually hit the bat. Umpires do not enjoy the benefit of using 'snicko' but must rely instead on their senses of sight and hearing, as well as personal judgment and experience. In many instances, there are coinciding events that may be confused with the sound of ball-on-bat. These include the bat hitting the pad during the batman's swing or the bat scuffing the ground at the same time the ball passes the bat. The shape of the recorded sound wave is the key differentiator as a short, sharp sound is associated with bat on ball. The bat hitting the pads, or the ground, produces a 'flatter' sound wave. The signal is purportedly different for bat-pad and bat-ball however, this is not always clear to the natural eye [12]. It is our submission that as the final decision requires human interpretation of the signal traces, it may be subject to error.

The aim of this paper is to employ wavelet analysis, feature extraction and artificial neural networks to implement a fully automated decision making system for bat on pad and bat on ball (i.e. edge) decisions, thereby extending the work done by Rock et al in [13]. It is expected that this will give teams a fairer chance on the outcome of a match (game) by minimising the number of these decision errors currently observed in the game.

II. BACKGROUND

It is well known that the continuous wavelet transform (CWT) may be used to analyse audio signals [14, 15]. The CWT 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. This method allows for the examination of the temporal nature of audio events and the corresponding frequencies involved. In essence, the correlation values, produced during the transformation process, provide critical information on the characteristics of the signal. By exploiting these characteristics a distinction can be made between different audio events. In particular, the five (5) features extracted from the Wavelet Transform are the **maximum correlation coefficient** and its associated **pseudo-frequency** for several CWT scale ranges, along with the **standard deviation**, **kurtosis** and **skewness** of the said correlation coefficients. These features were fed into a Neural Network to produce the final result.

Neural networks have been employed over the years in a wide range of areas. These areas range from forecasting to extracting patterns from imprecise or complicated data, which human and other pattern recognition techniques may have missed. For the purpose of this paper we will be examining the pattern recognition and classification capabilities of an Artificial Neural Network (ANN). An ANN is an information-processing system that has certain performance characteristics in common with biological neural networks. It consists of a large number of interconnected neurons, each with an associated weight. These neurons work together to help solve various problems [16]. 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 output after it has been well trained.

There are many instances where Neural Networks are being applied. There has been extensive research of their use in the medical arena, specifically in the classification of heart and lung sounds. There has also been extensive research in the Computer Science field. Hadi [17] used a Multilayer Perceptron Neural Network to classify features obtained from heart sounds by the Wavelet transform, and a high correct classification rate of 92% was achieved. Borching [18] developed a chord classification system using features extracted from the wavelet transform and classified by a Neural Network. A high recognition rate was achieved even under a noisy situation.

Kandaswamy [19] using feature extraction from the wavelet transform and classification found that results using the Neural Network out performed conventional methods of classification of lung sounds. Though all classes of lung sounds were not used in the experiment, results showed this method was worth exploring.

No known instances where Neural Network classification has been applied in the area of cricket were uncovered in the literature. The approach adopted in this work is to utilise Neural Networks to classify features that has been extracted from bat on ball and bat on pad sound files using the Continuous Wavelet Transform. This can then be used to accurately determine the source of the noise 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. This approach can then be expanded throughout the sporting world improving the quality and minimising the errors observed at various events.

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.

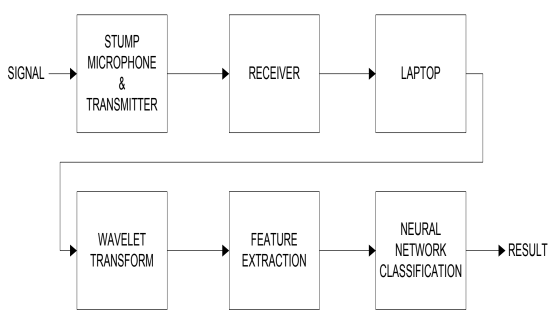

Figure 1: Schematic of experimental setup.

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

TABLE I. EQUIPMENT PARAMETERS

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

MATLAB programs were written to perform the CWT analysis and extract the following features: main maximum correlation value (x_{corr}) and the associated pseudo-frequency (P_{freq}) from selected CWT scale ranges along with the standard deviation (σ), kurtosis (k) and skewness (sk_n) of the said correlation coefficients. These features were used as input to the fully connected 5-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.

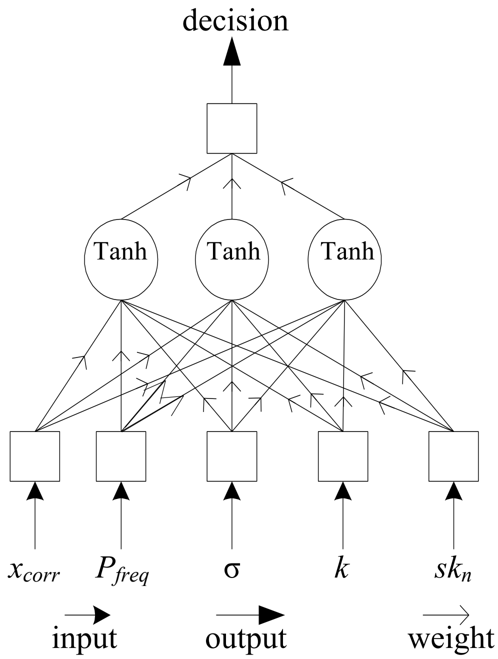

Figure 2: 5-Input Multi-Layered Perceptron

The network was trained with 260 data samples using a backpropagation algorithm. The data set was divided into 130 incidences of bat-on-ball signals and 130 of bat-on-pad. Moreover, testing was done on 40 previously unknown signals. The output from the network was a decision on whether the ball hit the bat (1) or the pad (0).

IV. RESULTS

Recordings of the impact of ball hitting bat and ball hitting pad were successfully compiled and analysed. Figure 3 shows the plot of the mean squared error (MSE) of the network after each complete presentation of the training data to the network (i.e. epoch). The epoch number is shown on the X-axis and the MSE is shown on the Y-axis. The MSE of the training (T) set is shown in white diamonds and that of the cross validation (CV) set is shown in black squares. Ideally, a neural network is deemed to be well trained when both lines gradually decrease to zero. Results from the graph showed that the neural network was trained reasonably well.

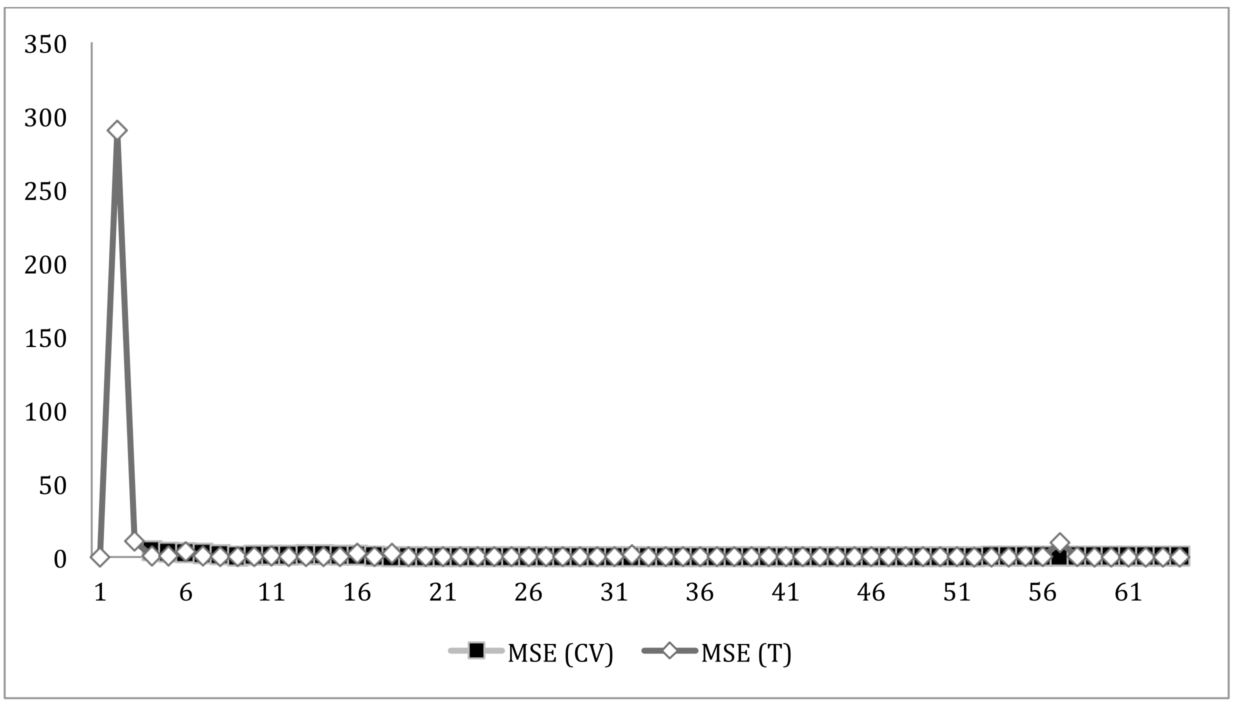

Figure 3: Graph of mean error versus number of epoch

Figure 4 shows the plot of desired output and actual output versus number of samples used for testing. The samples (40) used for testing originated from data the neural network was not exposed to previously. Note there is only one error (26th sample, white diamond) thus indicating 97.5% accuracy.

V. CONCLUSION

Results show the neural network performed exceptionally well rendering a correct classification of 97.5% for data not previously encountered. It is believed that better results may be obtained by optimising the choice of features that are extracted from the wavelet transform and used to train the neural network. This will be the subject of future work. Technology must be used judiciously if it is to gain support of the players and administration. For example consider the case in the recently concluded 2nd Test match between India (I) and the West Indies (WI) in Barbados were the on field umpire consulted the third umpire regarding the legality of a delivery from Fidel Edwards (WI), which ultimately resulted in Raul Dravid (I) being given out to a no-ball. Ironically, the wrong television reply of the bowling delivery was used. This supports the efforts pursued in this paper to completely remove the human factor from the data gathering and information-processing portion of the adjudication process. The 5th umpire system will provide a decision, which will greatly assist the on-field umpire, with whom the final decision resides.

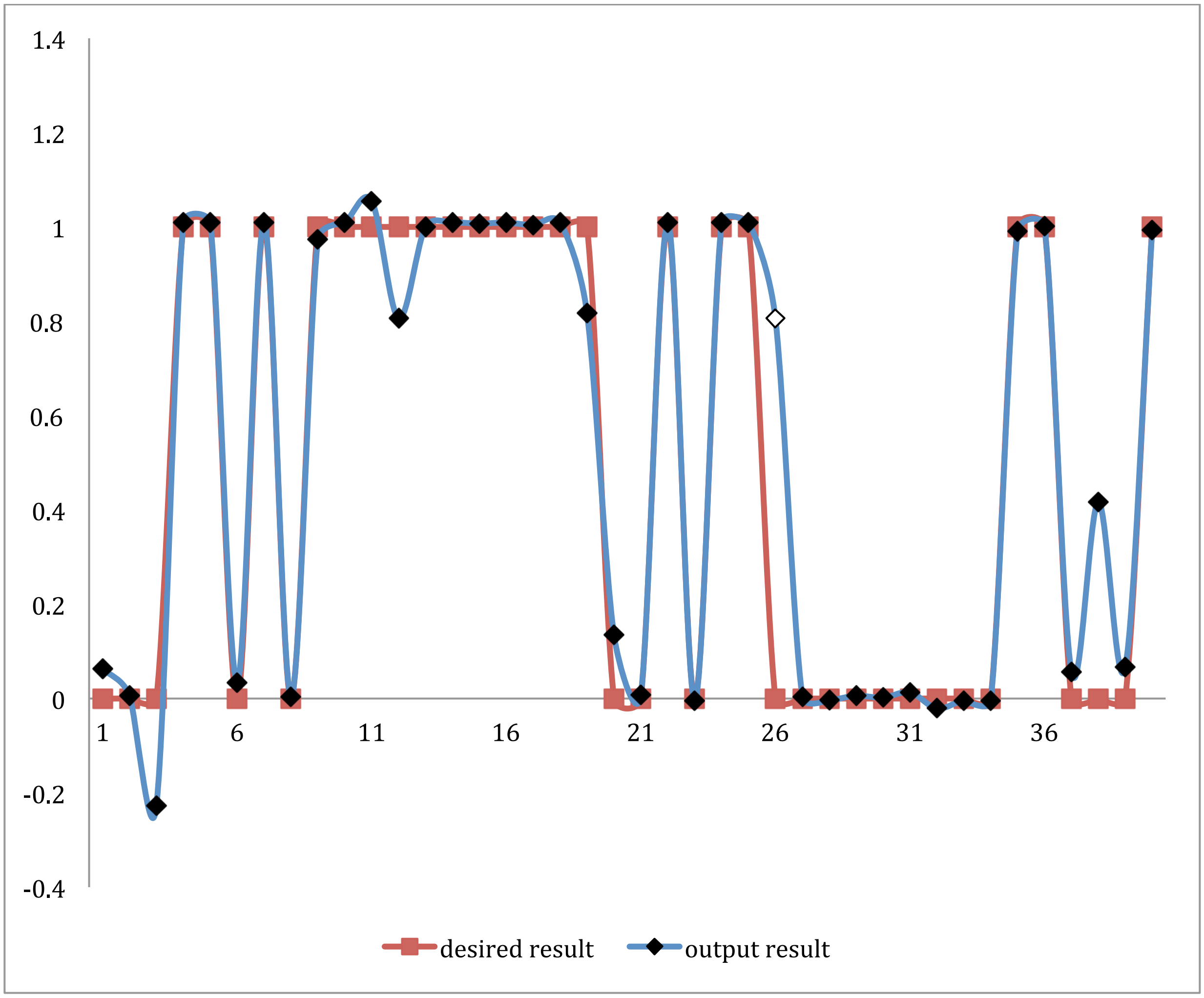

Figure 4: Graph and results of actual and desired results for the forty test data samples

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 (i.e. snickometer, hawk-eye, TV replays).

REFERENCES

1. Ben Klayman, L.G. *Global sports market to hit $141 billion in 2012*. 2008 [cited 2011 17/08]; Available from: http://www.reuters.com/article/2008/06/18/us-pwcstudy-idUSN1738075220080618.
2. Clark, J. *Back on track? The outlook for the global sports market to 2013*. [cited 2011 17/08]; Available from: http://www.scribd.com/doc/46262710/Global-Sports-Outlook#outer_page_2.
3. *World's Most Popular Sports* [cited 2011 17/08]; Available from: http://www.mostpopularsports.net/.
4. Zurich, *61st FIFA Congress FIFA Financial Report 2010* 2011.
5. *IPL 2nd highest-paid league, edges out EPL*. 2010 [cited 2011 17/08]; Available from: http://timesofindia.indiatimes.com/iplarticleshow/5736736.cms.
6. Peter J. Schwartz, C.S. *The World's Top-Earning Cricketers*. [cited 2011 January, 1st]; Available from: http://www.forbes.com/2009/08/27/cricket-ganguly-flintoffl-business-sports-cricket-players.html.
7. *Income of IPL 2011 Players* [cited 2011 17/08]; Available from: http://www.paycheck.in/main/salarycheckers/copy_of_income-of-ipl-2011-players.
8. *Hansie Cronje*. 2003 [cited 2011 17/08]; Available from: http://www.espncricinfo.com/southafrica/content/player/44485.html.
9. Varma, A. *Match-fixing - At the turn of the century, cricket felt a tremor stronger than any it had known till then*. 2011 June 11, 2011 [cited 2011 17/08].
10. Quinn, B. *Match-fixing allegations hit England v Pakistan Test at Lord's, guardian.co.uk*. 2010 [cited 2011 15/08]; Available from: http://www.guardian.co.uk/sport/2010/aug/29/match-fixing-allegations-england-pakistan.
11. Richard Edwards, M.B., Murray Wardrop. *Cricket match-fixing: suspicion falls on 80 games as 'fixer' bailed*. 2010 [cited 2011 15/08]; Available from: http://www.telegraph.co.uk/sport/cricket/7971107/Cricket-match-fixing-suspicion-falls-on-80-games-as-fixer-bailed.html.
12. Wood, R.J. *Cricket Snicko-Meter* 2005 [cited 2010 January, 21st]; Available from: http://www.topendsports.com/sport/cricket/equipment-snicko-meter.htm.
13. R. Rock, A. Als., P. Gibbs, C. Hunte, *The 5th Umpire: Cricket's Edge Detection System*, in *CSC'11 - 8th Int'l Conference on Scientific Computing* 2011: Las Vegas, Nevada. p. 6.
14. Lambrou, T., et al., *Classification of audio signals using statistical features on time and wavelet transform domains*, in *Acoustics, Speech and Signal Processing, 1998. Proceedings of the 1998 IEEE International Conference on*. 1998.
15. Schclar, A., et al., *A diffusion framework for detection of moving vehicles.* Digital Signal Processing. **20**(1): p. 111-122.
16. Fausett, L., *Fundamentals of Neual Networks Architectures, Algorithms and Applications*. 1994: Prentice Hall
17. Hadi, H.M., et al., *Classification of heart sounds using wavelets and neural networks*, in *Electrical Engineering, Computing Science and Automatic Control, 2008. CCE 2008. 5th International Conference on*. 2008.
18. Borching, S. and J. Shyh-Kang, *Multi-timbre chord classification using wavelet transform and self-organized map neural networks*, in *Acoustics, Speech, and Signal Processing, 2001. Proceedings. (ICASSP '01). 2001 IEEE International Conference on*. 2001.
19. Kandaswamy, A., et al., *Neural classification of lung sounds using wavelet coefficients.* Computers in Biology and Medicine, 2004. **34**(6): p. 523-537.