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An Event Detection based Video Summarization for Cricket Video

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Abstract : As viewers interestingly consume sports videos significance of video summarization is increasing nowadays. In sports video summarization brief form of a sports game is constructed and the interesting segments from lengthy sports videos are highlighted. This research is undertaken to detect and classify exciting events of cricket matches like four runs, six runs and wicket fall. First, cricket video is divided into shots, and keyframes from each shot are detected. To reduce processing time all other processes are applied to keyframes. In the following stage reply segments are identified and removed from further consideration. Keyframes are classified into different views. Finally, scoreboard text is detected to identify run and wicket differences. If the run difference is equal to 4 or 6 and the wicket difference is equal to 1, then frames between such keyframes are used to build the match's highlight. The wicket fall segment of the video is further classified into a different type using text recognition based approach. The proposed technique is modest and efficient. Experiments and results reflect the effectiveness of the proposed method. The wicket classification technique using text detection and recognition is a novel contribution that achieves 100% precision and 93% recall. Proposed method found novel and generalized to classify all different types of wicket fall using a single approach.

***IndexTerms* - Sports video summarization, Sports event detection, Sports video analysis, Wicket fall classification, Cricket highlight generation.**

I. Introduction

The rising quantity of video content causes a problem to convey essential information. Video summarization allows us to efficiently access video content through numerous fields. Sports video summarization targets to shrink a large sports video into a brief and informative video summary that contains important and thrilling events of the sports game. It aims to offer a concise overview of the match that covers key events and avoid watching the whole sports video [1]. Sports video summarization applies to the different sports domains to capture exciting events from full-length match videos. Automatically generated highlight by video summarization is used in sports video broadcasting, game analysis and sports news [2]. Summarized videos are most pleasing to capture more followers on social media. Caused by the intricate nature of the cricket game, different match duration and various playing environments, automatic analysis of cricket is demanding [3]. Although significant advances are noted in the field of cricket event detection and analysis, there are some glitches where attention is required to improve the effectiveness of the present techniques. One of the main complications with cricket video summarization is the unavailability of labeled datasets for cricket analysis. For the evaluation of new findings, a benchmark dataset is essentially needed.

The majority of present research on cricket pays attention to the detection of main events such as replays, four runs, six runs and wicket fall, so there is a scope to discover small-grained events [4]. Detailed classification of dismissal into different types like run out, caught or boundaries into cover drive, square cuts, etc. can be focused for meticulous annotation of cricket highlights. Moreover analyzing cricket based on various types of shots can be utilized by sports analysts as well as coaches [5].

Techniques that apply domain knowledge and use information from the temporal structure of cricket video can lead to precise event detection and classification system. As annotated data are scarce, non-learning-based techniques can be explored to diminish the need for training of models. For the concrete implementation of event detection methods, techniques that work in real-time with constrained environments are to be developed. Most of the available techniques are analyzing each frame of a cricket video which is inefficient. Keyframes can be selected from the video as a representative frame and further processing can be applied to it to reduce time requirement [6].

Exciting events in sports broadcast videos reside in only a trivial percentage of the whole video. It is observed that watchers are not much interested in dull segments of sports video. Thus automatic event detection, video annotation and highlight generation are extremely advantageous [7]. With the evolution in technology like machine learning, deep learning and multimedia exploration, research on sports video summarization is progressing. For improving the watching experience, numerous researchers are working on the formation of personalized and refined video summaries.

It is perceived that during the thrilling events, because of the spectator's excitement and the commentator's voice audio volume increases. Cricket highlights can be generated using excitement detection. S. C. Premaratne et al. [8] discussed audio-based cricket event detection. They considered audience cheer-up noise and the voice of the commentator to be interrelated with interesting events. So these audio features are used and Hidden Markov Model is trained to classify key events. This approach can be used for broadcast cricket video indexing.

Ali Javed et al. [9] extracted acoustic-local binary patterns from a broadcast cricket audio stream and then classify exciting and non-exciting clips using Support Vector Machine. Similarly, the loudness audio feature can also be used for excitement detection [10]. A. Bhalla et al. [11] collected audio samples from each frame and the largest audio samples are used to generate an exciting video summary. Muhammad Haseeb Nasir et al. [12] proposed non-learning based technique for key event detection. To identify changes in score and wicket information image averaging is used. To remove noise from the image morphological operations are applied and then OCR is used to identify the noteworthy change in wicket and score. Finally, a summary of the video is created using frames between the keyframes.

In cricket, significant events are generally signed by an umpire. So, umpire gestures can be used to categorize different events in cricket. A. Ravi et al. [13] discussed event classification using umpire pose identification. They created a dataset made up of different gestures of an umpire. Six, wicket, wide and no-ball events were classified using SVM classifier. Features are extracted using CNN inception V3 and VGG19. Similarly, CNN, Inception V3 and Deep CNN were utilized to discover third umpire decisions by M. Kowsher et al. [14]. To identify and recognize the umpire's action and non-action gesture, Histogram Oriented Gradient feature oriented non-linear Support Vector Machine classification of deep features is utilized by Suvarna Nandyal et al. [15].

The developments in video summarization techniques have transformed with the advancement in deep learning methods [16]. P. Shukla et al. [10] extracted features from pre-trained AlexNet's fc7 layer and trained multiclass linear SVM for the detection of the scoreboard. A. Bhalla et al. [11] proposed a method to detect run and wicket information using OCR and CNN.

The objective of this research is to identify interesting broad events like boundaries, six and wicket fall. We have further classified the mode of dismissal using non-learning based approach with temporal context modeling. Our approach is working with representative frames to reduce processing time.

II. METHODOLOGY

We have proposed a system for cricket video summarization using the hierarchical framework shown in Figure 1. The figure illustrates that the cricket video is initially divided into frames. These extracted frames are used for shot boundary detection. Once shot boundaries are detected, every shot's first frame is preserved as a representative frame of that shot and identified as a keyframe. All further processing is applied to these keyframes. After shot boundary detection, replay and play frames are classified. As replay segments of the video show redundant information in slow motion, we have detected and removed replay segments from further consideration. Shot boundary detection and replay detection methods are discussed in our previous work [17].

After replay removal, all play frames are further classified as field view and non-field view frames. In cricket, at the start of balling, pitch views are shown. So it is necessary to detect pitch as a mark of delivery of a new ball. The pitch view detection technique is applied to all field view frames and from that, frames showing pitch are extracted. All non-field view frames are classified as close-up or crowd frames. Finally, the score caption detection technique is applied for event detection. The highlight is built for that segment of the video where a significant change in run score or wicket score is identified. The detailed methods for the event detection framework are described in the following subsections.

2.1 Shot Classification

Sports video events cover different shots in sequential order. Shot view classification is an elementary requisite for high-level analysis of sports video [2]. To classify various shots usually, visual cues are used. All keyframes belonging to play segments are fed into the shot classification framework. Initially, our work classified cricket views into field view and non-field view. Pitch views are extracted from field view frames and then non-field view frames are classified into crowd and close-up views. In the following subsection, cricket view classification algorithms are discussed.

Figure. 1 Event Detection Framework

2.1.1. Field view detection

Generally, the field view covers a large green area. The field view and the non-field view are classified by examining the green pixel ratio similar to [18]. Algorithm 1 shows steps for field view detection. RGB frames are converted into HSV images. As the field color is different in each cricket video, we need to check the hue range for the green color. Once the hue range is decided, the peak value of green is observed and a number of pixels having a hue value nearby the green peak are summed and used to identify the Green Pixel Ratio (GPR) [19]. If the GPR value is high, the keyframe is classified as a field view frame otherwise; it is classified as a non-field view frame. The algorithm for field view detection is shown below.

Algorithm 1. Field view detection

$I_{RGB} \leftarrow PlayFrame$

$I_{HSV} \leftarrow RGBtoHSV(I_{RGB})$

$GreenWindow \leftarrow InputGreenRange$

$G_{Peak} \leftarrow \ Max(GreenWindow_{Start}: GreenWindow_{End})$

$$GPR = \frac{Total\ number\ of\ pixel\ having\ hue = Gpeak \pm 2}{Total\ number\ of\ pixels\ in\ the\ frame} \times 100$$

$If\ GPR > Th_{Field}\ then\ FieldFrame\ \leftarrow PlayFrame$

$Else\ NonFieldFrame\ \leftarrow PlayFrame$

2.1.2. Pitch view detection

The pitch view covers a large pitch area, so the pitch color ratio is more significant than other colors. For the detection of pitch view, RGB frames are converted into HSV images. As the pitch color is dissimilar in each cricket video, we need to check the hue range for the soil color. Steps for pitch view discovery are given in Algorithm 2. Once the hue range for pitch is decided, the peak value of the soil is observed, and a number of pixels having a hue value equal to the soil peak are summed and used to identify the Pitch Pixel Ratio (PPR) [19]. If the PPR value is high, the keyframe is classified as a pitch view frame. Otherwise, it is classified as a non-pitch view frame. The algorithm for pitch view detection is shown below.

Algorithm 2. Pitch view detection

$I_{RGB} \leftarrow FieldFrame$

$I_{HSV} \leftarrow RGBtoHSV(I_{RGB})$

$PitchWindow \leftarrow InputPitchRange$

$P_{Peak} \leftarrow \ Max(PitchWindow_{Start}: PitchWindow_{End})$

$$PPR = \frac{Total\ number\ of\ pixel\ having\ hue = Ppeak}{Total\ number\ of\ pixels\ in\ the\ frame} \times 100$$

$If\ PPR > Th_{Pitch}\ then\ PitchFrame\ \leftarrow FieldFrame$

$Else\ NonPitchFrame \leftarrow FieldFrame$

2.1.3. Non-field view classification into Close-up and Crowd

It is perceived that all non-field views cover either a crowd or a close-up view of any person. Crowd shots generally display the audience or player's gathering and a close-up view spectacles zoomed-in view of a player [2]. Edge density is high in the crowd view compared to the close-up view. For the classification of non-field views into close-up and crowd views, we have used the edge detection method. Algorithm 3 displays the process for non-field view classification.

Algorithm 3. Non field view classification

$I_{RGB} \leftarrow NonFieldFrame$

$I_{Gray} \leftarrow RGBtoGay(I_{RGB})$

$I_{BW} \leftarrow CannyEdgeDetection(I_{Gray})$

$$EPR = \frac{Total\ number\ of\ edge\ pixels}{Total\ number\ of\ pixels\ in\ the\ frame} \times 100$$

$If\ EPR > Th_{Crowd}\ then\ CrowdFrame \leftarrow NonFieldFrame$

$Else\ CloseupFrame \leftarrow NonFieldFrame$

First, non-field view RGB frames are converted into Grayscale images. The canny edge detector is applied to a grayscale image. As close-up views have less edge concentration than crowd views, EPR is lesser for close-up views.

2.2 Score Detection

The text data presented in the scoreboard encompasses fruitful information for the event discovery. Events in cricket like four runs, six runs and wicket fall can be mined by checking the difference in run and wicket mentioned on the scoreboard. The following steps are usually taken to extract the information from the scoreboard. 1. Locate the interesting region of the scoreboard 2. Recognize the information of that region [20]. The style, dimension and position of the scoreboard are generally static for every frame of sports video. In the proposed work as illustrated in Algorithm 4 score and wicket caption regions are first located and segmented. As the size of this region is too small to perform the caption recognition task, the cropped image is enlarged. After enlarging the image, top-hat filter is applied. The image is then converted into black and white. Finally, OCR is applied to recognize the score and wicket caption.

Algorithm 4. Score Detection

$I_{RGB} \leftarrow KeyFrame$

$I_{SCR} \leftarrow ScoreCaptionRegion(I_{RGB})$

$I_{SCR} \leftarrow Enlarge(I_{SCR})$

$I_{TH} \leftarrow TopHatFilter(I_{SCR})$

$I_{BW} \leftarrow Binarization(I_{TH})$

$(Run, Separator, Wicket) \leftarrow OCR(I_{BW})$

Figure 2 illustrates the outcomes of the score detection process. Top hat filter followed by opening operation and binarization increases the accuracy of text recognition.

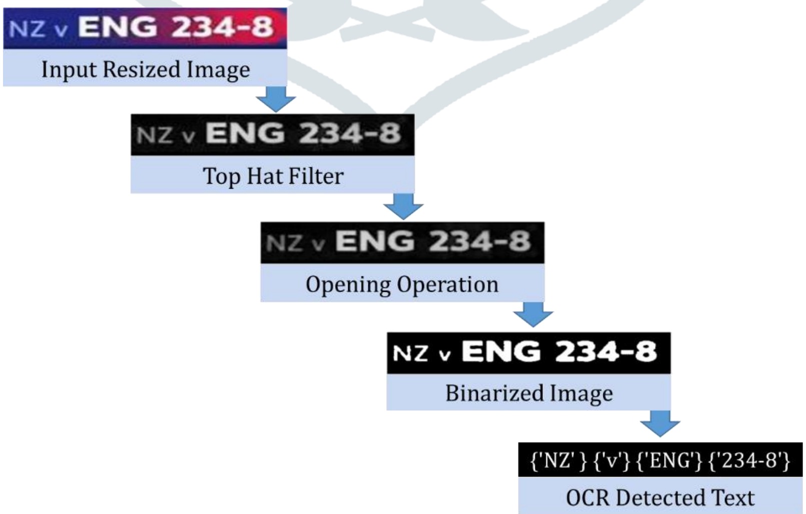

Figure. 2 Score detection process

2.3 Event detection framework

Once run and wicket information is extracted, we save the consecutive keyframes for which the run difference is 4 or 6 and the wicket difference is 1. Then we search for the pitch view from that keyframe in the reverse direction. Once we get a keyframe that shows a pitch view, we save that keyframe. The highlight is generated that starts from a pitch view and ends with either a close-up or a crowd view. In this manner highlight of exciting events are generated.

Algorithm 5. Event Detection

Load run and wicket information as RC and WC
If (RC(i+1)-RC(i) ==4 || 6) or (WC(i+1)-WC(i) ==1) then Last_frame=playframe(i+1)
For j=i+1; keyframe(j)!= pitch view; j=j-1;
First_frame=playframe(j)
Generate highlight from First_frame to Last_frame

The change in score is observed at keyframe 1805 in Figure 3. So that is marked as the end of the highlight segment and for checking the starting of bowl delivery, the pitch view is searched in the previous direction.

Figure. 3 Highlight segment

2.4 Wicket Fall Classification

In cricket, the following types of wicket falls are mainly observed: Caught, Bowled, Leg Before Wicket, Stumped and Run Out. We have proposed a method for the classification of wicket fall using text detection and recognition. It is observed that the type of wicket fall is displayed on the score bar after each wicket fall event. If we can extract that information automatically, then the classification of wicket fall type can be given without any training phase. Generally, researchers are adopting a specific approach to identify each kind of wicket fall. The proposed method can detect each type of wicket using a single process. Table 1 is presenting the text displayed on the scoreboard for each type of wicket fall.

Table 1: Scoreboard text indicating types of wicket fall

Wicket Fall Type	Text on Scoreboard
Caught	**c** PlayerName **b** PlayerName
Bowled	**b** PlayerName
Leg Before Wicket	**lbw b** PlayerName
Stumped	**st** PlayerName **b** PlayerName
Run out	**run out** PlayerName
Hit Wicket	**hit wicket** PlayerName

Steps for the wicket fall classification are shown below in Algorithm 6.

Algorithm 6. Wicket fall classification
If ($WC_{(i+1)}$-$WC_{(i)}$ ==1) then First_frame=playframe(i+1)
For j=playframe(i+1) ; j=j+50
Read frame(j), Crop ROI, Resize ROI, Black and White conversion, Apply OCR
*If OCR text contains any of pre-specified wicket types, assign that label to **wickettype.***
Assign wicket type label to generate highlight

As shown in Figure 4. From the keyframe where the difference between scores is observed, we start searching the frame for wicket fall information in the forward direction. In the proposed work region showing the detailed information of wicket fall is located and segmented. For text recognition from this region, the size of the region must be enlarged. Next, morphological operation opening is applied to the wicket information image. After applying the opening operation, the resulting image is converted into a black and white image. This binary image is fed to OCR for character recognition. Finally, string matching is applied to check whether OCR's output contains the information on wicket fall. If the OCR detected text matches any of the wicket fall types, the previously generated highlight segment is labeled with that particular type.

Figure. 4 Search segment for wicket fall detail

III. Results and Discussion

For cricket video summarization, there is no standard database available. The diverse dataset consists of 11 different cricket videos with various broadcasters is used to evaluate the performance of the proposed event detection system [17]. The details of the datasets are presented in Table 2.

No.	ID	Name of the Match	No. of Frames	Resolution	Frame Rate
1	Test19_WvE	West Indies vs England Test 2019	2836	1280×720	25 fps
2	NatWest11_IVE	India vs England NatWest 2011	2350	1280×720	25 fps
3	ODI14_IvN	India vs New Zealand One Day International 2014	4422	1280×720	25 fps
4	T2019_SvN	Sri Lanka vs New Zealand T20 2019	5875	1920×1080	25 fps
5	BBL11_HvS	Big Bash League 2011 Hobart Hurricanes and Melboume Stars	5551	1920×1080	25 fps
6	ICCWC19_NvE	New Zealand vs England ICC Cricket World Cup 2019	5983	1280×720	25 fps
7	ODI2022_IVB	India vs Banglades One Day International 2022	7500	1280×720	25 fps
8	AC22_IvS	India vs Shrilanka Asia Cup 2022	10218	1280×720	30 fps
9	Nidahas18_IvB	India vs Banglades Nidahas Trophy 2018	10241	1280×720	25 fps
10	RSWS_IvB	India vs Banglades RoadSafety World Series	15225	1280×720	25 fps
11	AC20_IvP	India vs Pakistan Asia Cup 2020	30969	1280×720	30 fps

To measure the performance of the proposed systems, the following evaluation metrics are used.

$$Precision = \frac{TP}{TP+FP} \quad Recall = \frac{TP}{TP+FN}$$

Where TP is true positive, FP is false positive and FN is false negative.

3.1 Performance of event detection and classification

Table 3 shows the results of event detection and wicket fall classification method. From the outcome, it is observed that key events are identified effectively by the proposed method.

Table 3: Results of Event Detection

Type of Event	No. of Events	Detected Events				
		TP	FP	FN	Precision	Recall
Boundary	12	12	0	0	1.00	1.00
Six	12	11	0	1	1.00	0.92
Wicket	16	16	0	0	1.00	1.00
Wicket Classification	14	13	0	1	1.00	0.93

The proposed system's performance is compared with present event detection techniques and shown in Table 4.

Table 4: Comparison of proposed method with existing event detection techniques

Techniques	Boundary		Six		Wicket	
	Precision	Recall	Precision	Recall	Precision	Recall
Ali Javed et al. [21]	94.79	89.65	90.41	88.00	88.09	90.24
Pushkar Shukla et al. [10]	89.23		86.79		92.68	
N. Harikrishna et al. [22]	92.00	90.00	25.00	25.00	92.00	85.00
A. Bhall et al. [11]	86.74		89.12		92.45	
Proposed Method	100	100	100	92.00	100	100

Wicket fall classification is yet to get much attention from researchers. So we have compared the proposed system's performance with available wicket fall classification techniques and shown in Figure 5. The approach presented by Qamber Abbas and Youmeng Li [23] is working with image sequence and using HOG and LBP features and SVM classifier to predict wicket fall type. It can identify four different categories Bowled, Caught Behind, Catch Out and LBW. Whereas our approach is modest text detection and recognition based approach. It needs to localize the region of the score bar where wicket fall information is displayed. Before applying OCR preprocessing to score bar image is essentially required. Our approach can accurately classify Caught, Bowled, Leg Before Wicket, Stumped, Run out and Hit Wicket types of wicket.

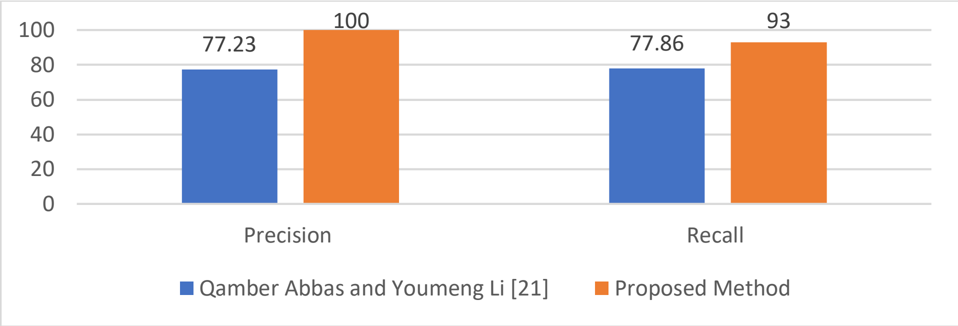

Figure. 5 Performance comparison of wicket fall classification

Once interesting events are detected using run and wicket difference value, highlight is built using the method shown in Algorithm 5. According to this method, the highlight segment is started from the pitch view which is the mark of delivery of the new ball. If the pitch view corresponding to the current event is classified, then our approach will search for the pitch view in a backward direction and may include the previous ball delivery segment of the video in the current interesting event video summary. Which probably reduces the attention of the viewer. The other possibility is if some other view is missed and classified as a pitch view then the summary will start from that wrongly classified view. So the accuracy of shot boundary detection, replay detection and view classification affects the outcome of video summary preparation.

IV. Conclusion

A system for event detection and classification is proposed in this paper. We have efficiently used visual features. The shot view classification is based on traditional feature extraction methods. Shots are classified into field view, pitch view, close-up view and audience view. The event detection and classification method can detect four, six and wicket fall events accurately. The wicket classification technique using text detection and recognition is a novel contribution that achieves 100% precision and 93% recall. The results show the effectiveness of our approach. When final summaries are generated if the pitch view at the start of the current event is not recognized then the pitch view belonging to the previous bowling will be selected as the start highlight. Thus highlight duration will increase and it may cover the same uninteresting segments of video with actual exciting events.

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