

CRACKED CRICKET PITCH ANALYSIS (CCPA) USING IMAGE PROCESSING AND MACHINE LEARNING

KISHAN KANHAIYA^{*}, RAJAT GUPTA^{*}, ARPIT KUMAR SHARMA^{**}

ABSTRACT

Over the years, a number of technologies have been developed for assisting decision making involved in Cricket. To the best of our knowledge technology has not addressed the analysis of the Cricket pitch. We believe that a comprehensive analysis of the Cricket pitch if done is likely to be useful to accurately speculate winners/losers and also mitigating the need for manual pitch analysis. The process has been divided into three steps: Stage-I detects crack locations, Stage-II studies the shape of crack and Stage-III compute and analyze the effect of the depth of crack to the batsman/bowler.

INTRODUCTION

Cricket is one of the world's most popular game. The game of cricket is played on a carefully prepared piece of turf termed as the pitch.

It is on the pitch that the bowler projects the cricket ball. The impact produced due to striking of the ball on the pitch surface causes several variations in the velocity and trajectory of the ball after it pitches. The variations in speed and direction of ball after impact is a result of several factors such as pitch composition, air resistance, temperature etc. A thorough analysis of these variations can provide useful insights to both the stakeholders - batting and the bowling sides.

The movement of the ball is also directly dependent on the type of pitch.

For example,

1. Green Tops, these pitches have a thin layer of grass on the good length area which

causes the ball to seam and move after pitching. The grass will attract moisture which is needed for swing bowling. Thus, green pitches always favorswing bowling/fast bowling as the ball will deviate off the path and, in the air, as well. These wickets are unfavorable for batsmen as sometimes it is impossible for batsmen to judge the magnitude of the movement of the ball gets after pitching.

2. Dead Pitches, the most common wickets that are prepared these days are batsman friendly dead wickets. These pitches have no support whatsoever for the bowlers and batsmen love batting on them. These pitches are dark in color and have a solid feel about them. On this type of pitches, every single bit of the grass is rolled in and all the moisture is taken away. This is the most common types of pitch that are being used in a T20 or ODI matches.

^{*}BE, Computer Engineering, Netaji Subhas Institute of Technology, Delhi.

^{**}M.Tech, Computer Science, MDSU Ajmer.

Correspondence E-mail Id: er.aks31@gmail.com

 Dusty Pitches, these pitches are very common in the sub-continent. These pitches are soft and tend to crack as the clay is not rolled hard. These wickets are prepared mostly to assist spin bowlers. Spinners can turn the ball a lot more due to the loose surface as the ball grips a lot more. On such pitches the bounce of the ball is low.

Aspect	Description			
Composition	The materials used in pitch preparation also effect certain structural properties,			
	which in turn effect the ball's trajectory			
Location	Pitches in different parts of the world behave differently, owing to their exposure to			
	different climatic conditions			
Cracks	The cracks in the cricket pitch effect the trajectory and			
	speed of the ball after pitching on the surface			

Table 1.Pitch Properties Affecting Ball Motion
--

It clearly indicates that analysis of surface of the pitch plays a vital role in the game of Cricket. The Table1 lists some of the aspects of the cricket pitch and describes how each affects the game of cricket.

We in this paper have chosen to analyze the effect of cracks in the cricket pitch on the ball. The following example shows the importance of analysis of cracks on the pitch surface.

Example 1: Consider a cricket match (test) between two teams X and Y occurring from 1st Jan to 5th Jan. The game is to played at ABC Cricket stadium, the pitch at this stadium is reported to be hard and grassy during the pitch report. This type of pitch is expected to favour fast bowling.

Team X wins the toss and chooses to bat first. The game progresses as expected for the first 2 days with some cracks starting to evolve during Day2. However, on the third day of the match, Team Y started batting and into 45th over, we notice that a delivery deviated to an unexpectedly large extent. On checking the replay, it was found that the ball had pitched on an evolved crack which resulted in the unexpected deviation. Since, no analysis regarding this aspect was done beforehand, neither side is in the position to take advantage of the varying crack profile of the pitch. Therefore, this paper is focused on analysis of cracks on pitch and their effect on ball velocity.



Figure 1. Deviation due to cracks in pitch

There are many technological advance-ments in recent years which works as decision support or analysis for various games. Some of these tools are used in game of Cricket as well. Section 1.1 is presenting such tools which have been used for various decision support in modern day cricket.

TOOLS

Over the years many tools have been developed to aid accurate decision making in the game.

Some of these include Hawk Eye[1] , Snickometer[2] and Hotspot[3].

A brief review of these techniques is presented below.

Name	Approach	Use	Illustration
Hawk eye	Tracks ball trajectory using triangulation of images from various cameras.	Used to approximate the ball's path	MCGRATII SEAM MOVEMENT - BELL DISMISSAL • WIDRET DELIVERY • I PRALL HAD NOT BRANED
Snickometer	Uses the shape of the sound wave generated by various events to aid in decision makinges	Used to decide whether the bat stuck the ball or not, the sound of contact between bat and ball is sharp, and so is recognized easily among other "fat" waves	
Hot Spot	Uses infrared imagery to detect object interaction	Used to figure out whether the ball touched bat/pad in Ibw decisions	atwood Contraction

Table 2. Tools related Ball tracking and Decision making

RELATED WORK

A study of surface-ball impact is done by S.J Haake(1989)[4] ,who proposed a test and apparatus based method to measure the impact and implications of a golf ball pitching on the turf . Haake later teamed up with Carre, Baker and Newell to perform similar studies in cricket. They have published a series of papers dealing with the effect produced by various properties of the pitch on the ball motion. Their works include measurement of the impact of spinning balls (1998a)[5], analysis of cricket ball impacts using digital stroboscopic photography (1998b)[6] and The dynamic behavior of cricket balls during impact and variations due to grass and soil type(1999)[7]. In 2006 Ahmad, Prasad, Omkar, Rajan[8] studied quantitatively the impact of a cricket ball usingTIR imaging.

Although the above works cover many aspects of the surface, neither focuses on the role of cracks in the pitch and its effect on the ball's motion. In our study we have seen that the cracks do play an important role in the ball's motion. A survey of available literature shows that most of the works on crack detection has been done in the field of road/pavement construction and maintenance.

An automated pavement distress detection system was proposed by Cheng and Miyojim[9]. Their system detects the distresses on the road surface in three steps i.e. image enhancement. skeleton analysis and classification. Another method used for crack detection was introduced by Peggy Subiratset al.[10] uses a continuous wavelet transform. The coefficient maps of the mother wavelet are used for crack isolation.

Another method proposed by Sylvie Chambonet al.[11] introduced a 2D matched filter in order to define an adapted mother wavelet and then to use the result of this multiscale detection into a Markov Random Field (MRF) process to segment fine structures of the image. Fine structure extraction has many advantages in different domains of image processing. Cracks may be considered as pixels that are darker than the background. The procedure includes mainly three steps. First the fine structures can be extracted from the image using a 2D matched filter which defines an adaptive mother wavelet. After this some refinement operations can be done on the extracted image. So, the second step is segmentation of the connected components. Here the segmentation is done with Markov Random Fileds(MRF).Some post processing can be done to correct the errors that are stillpresent in the image. The final phase is

classification in which the images can be classified to different classes. The simplest classification is images with crack pixels and images without crack pixels. There may be hierarchical classification to detect different types of cracks (transverse, longitudinal).

The method introduced later in 2009 by Henrique Oliveria and Paulo Lobato Correia[12] proposed that the crack pixels in an image are identified using dynamic thresholding technique. This is a simple unsupervised system for the detection of cracks in road surveys and their classification into predefined set of crack classes.

Another technique, detection and classification using anisotropy measure proposed by Tien Sy Nguyen et al.[13] introduced a method which detects not only small cracks but also joints and bridged ones.

Moreover the above methods require either expensive equipment (as in [4],[6]) or use physical models which are hard to construct due to strict constraints imposed on the spring's properties.

We believe that the cracks do play an important role in the ball's motion and therefore an analysis of their effect on the ball's velocity and trajectory would be beneficial to both stakeholders- the batting and the bowling side.

We are therefore motivated to propose a method to detect cracks in the pitch and analyze their effect on ball velocity.

LIMITATIONS OF RELATED WORKS

The studies in [4],[5],[6],[7]dealing with ball impact using physical spring mass models requiring physical setup and measurements on the pitch. These methods therefore are not suitable for automation.

The works [8], [9],[10],[11],[12] demonstrate the use of image processing techniques to

detect and analyze cracks in road/pavement scenario. Therefore, we propose an image processing based approach to estimate the effect of evolving cracks in cricket pitch with reference to the ball.

MOTIVATION

The limitations outlined above have motivated us to develop an automatic way to assess impact of the ball. Further the crack profile though being an important aspect has not been considered by any work in a comprehensive way.

CONTRIBUTION

We in this paper tried to analyze the effects of cracks in a cricket pitch on the ball speed using image processing and machine learning techniques.

THE CCPA FRAMEWORK

In this section we propose a new framework Cracked Cricket Pitch Analysis (CCPA), to analyze the effect of crack length and orientation on the rebound velocity of ball.

The framework proceeds by first extracting velocity and crack data from match videos and images. The data obtained is then used as input to a supervised learning algorithm which tries to capture quantitatively, the relationship between cracks parameters and ball velocity.

The process flow which consist of two parallel paths is outlined in the below figure and is described in detail in the following sections.

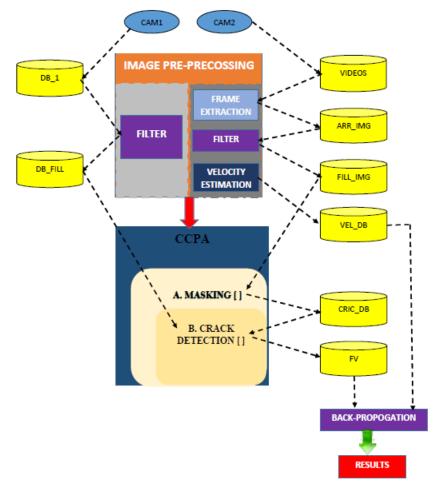


Figure 2. The process flow

Cracked Cricket Pitch Analysis (CCPA) using Image Processing and Machine Learning Kishan K et al.



Figure 3.Velocity Data Extraction

VELOCITY DATA EXTRACTION

This module aims at extracting the velocity data from the video of the playing session.

The video is first used to extract the frames, these frames are then filtered to remove any unneeded frames used along with the frame rate of the video to determine the initial and final ball velocities. A block diagram for this module is shown in Figure 3.

FRAME EXTRACTION

First the video is used to extract frames as per the following algorithm.

Algorithm 1 Frame Extraction
Input: video
Output: array_IMG
i:=1
repeat
for frames f in video do
array_IMG[i] =saveastiff(f)
f=nextframe()
i:=i+1
end for
untilf!=null



(a) Video

(b) Extracted Frame Figure 4.Frame Extraction

DESCRIPTION

The variable video represents the video of the playing session. The array array_IMG is a set of nof tiff images where nof is the no. of frames in the video. The function saveastiff() generates a

tiff image of the input frame and returns it. The function nextframe() is uses to go to the next frame in video, this function returns the next frame in video or null if no more frames remain to be processed.

DEMONSTRATION

FILTERING

showing the bowler running up are not required for our study.

The algorithm is presented below.

In this step all those frames are removed which are not needed for our study, for eg.- frames

Algorithm 2 Frame Selection
Input: array_IMG
Output: fil_IMG
i:=1
repeat
for frames f in array_IMGdo
if (req_frame(f)==true) then
fil_IMG[i]=f
end if
f=nextframe()
i:=i+1
end for
until f!=null

DESCRIPTION

The function req_frame() is used as a basis for filtering images in array_IMG. The function returns true if the pitch is visible and ball is free. Thus the image array fil_image has only those images which are needed.

The frames obtained are then used to estimate velocity using the following algorithm.

VELOCITY ESTIMATION

Algorithm 3 Velocity Estimation				
Input: array_FV,Video				
Output: Vel_DB				
fr = getframerate(Video)				
repeat				
for each ball b do				
m = getinitframecount(b)				
n = getfinalframecount(b)				
u = calcinitvel(fr,m)				
v =calcfinalval(fr,n)				
k= v/u				
vel_DB.save(v,u,k)				
b= nextball()				
end for				
untilb!=null				

DESCRIPTION

The video's frame rate (fr) is first obtained using getframerate(), next two helper functions (implemented manually) are used to obtain m and n which are used in the velocity calculation functions to obtain the pre collision velocity u and the post impact velocity v. These calculations are made as per the following formulae:

 $u = \frac{l_1 * f_r}{m}$ where m is the no. of frames from ball release to ball pitching and l_1 is the distance from bowlers end to the point where the ball pitches and $v = \frac{l_2 * fr}{n}$ where n is the no. of frames from the ball pitching to the ball reaching the batting crease and l_2 the distance from point of impact to batting crease. Also $l_2 = 17 - l_1$

EXTRACTING CRACK DATA

This module extracts crack data from the pitch using images of the pitch surfaces taken at regular intervals during game play.

The process involves filtering frames to remove any unwanted elements by extracting only the pitch section and then using Canny Edge Detector on the resulting frames.

PITCH EXTRACTION

The pitch sections are extracted from the images obtained from Cam2 to remove any unwanted elements using a Delta Entropy based segmentation technique.

The algorithm is presented below:

Algorithm 4 Pitch Extraction
Input: fil_IMG
Output: Crick_DB
i:=1
repeat
for images f in input Set do
Crick_DB[i] =extract_pitch(f)
f=nextframe()
i:=i+1
end for
untilf!=null

DESCRIPTION

The function extract_pitch() masks everything except the pitch in the selection and returns an image containing the pitch surface only. This function has been implemented using Delta Entropy separation and colour segmentation techniques. A small area containing the pitch is selected manually, the algorithm then performs colour matching to isolate the pitch surface.

CRACK DETECTION

The pitch frames obtained from Algorithm 3 and 4 are passed to the Canny Edge Detection Algorithm. Canny was chosen because of its non-maximal suppression and double thresholding properties and also because it gave the best results with our dataset.

Algorithm 5 Crack Detection
Input:Crick_DB
Output:array_FV
i=1;
repeat
for frames f in Cricado
crack_data = detect_Crack(f)
array_FV.append(i,crack_data)
f= nextframe()
i:=i+1
end for
untilf!=null

DESCRIPTION

The function detect_crack() uses the Canny Edge Detection Algorithm to detect cracks in the pitch surface, the data thus collected is stored in the array array_FV along with the frame no. The info obtained from fetect_crack() includes coordinates of crack segment end points. Using the length and orientation are computed as:

Length =
$$\sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

$$\Theta = \arctan\left(\frac{\mathbf{y}_2 - \mathbf{y}_1}{\mathbf{x}_2 - \mathbf{x}_1}\right)$$

SUPERVISED LEARNING

The Crack Data and Velocity Data obtained are given as inputs to the backpropagation algorithm which gives a best fit curve for the data thereby relating the crack parameters and initial velocities with the final velocities.

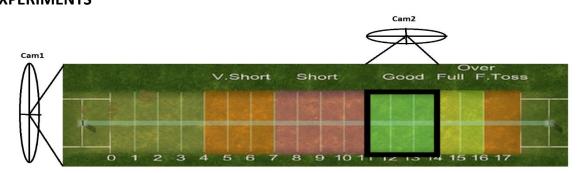


Figure 5.Experimental Setup

SETUP

The experimental setup used to prepare the data set has been illustrated below:

Two cameras were setup as shown above, Cam2 is positioned at the good length, and records the pitch surface continuously to facilitate crack detection, Cam1 is positioned behind the bowler end and records the ball trajectory. This video is used for velocity estimation.

The good length was chosen as most balls were noted to pitch around 12m from the bowling end.

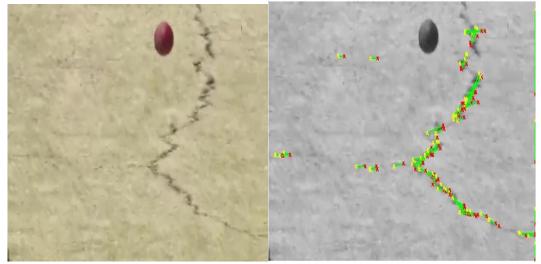
We thus assume I1=12m and I2=5m for velocity estimation.

EXPERIMENTS

EXPERIMENT PROCEDURE

The input video from Cam1 is first processed using the preprocessing stage. The frames of

the video are first extracted, each frame is examined for pitch visibility, for frames in which the pitch is visible, the pitch is segmented out using a Delta Entropy technique (figure 3)



(a) Original Image (b) Figure 6.Crack Detection

(b) Crack Detection

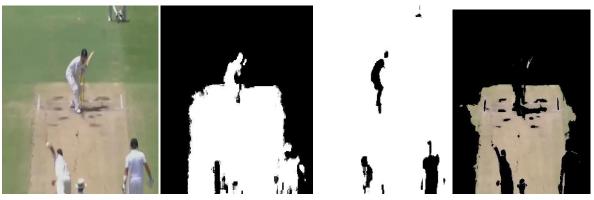


Figure 7.Pitch Extraction

The video from Cam1 are also used in the velocity estimation module to calculate velocities of striking and rebound velocities of the balls at different times as specified in Algorithm 5.

The velocity data obtained for one video with fr = 25 is tabulated below. Now the Crick_DB database obtained form Cam2's video is used to identify cracks using the Canny algorithm (Figure 8) Cracks are noted for the same intervals for which velocity was estimated. The Crack data obtained is tabulated below.

From table 3 and 4, it is evident that k changes abruptly when there is a change in crack length and orientation, this suggests a correlation between crack properties and the value of k.

Thus we next use the backpropagation algorithm to extract this correlation into the crack proportionality factor k'.

S. No.	Day	Team	Over No.	Number of Cracks	Mean Crack length
1	1	1	20	0	0
2	1	1	40	5	1.5
3	1	1	60	15	4.5
4	2	1	80	35	10.5
5	2	1	100	40	12
6	2	1	120	60	18
7	2	1	140	65	19.5
8	2	2	160	67	20.1
9	3	2	180/10	70	21
10	3	2	200/30	75	22.5
11	3	2	220/50	85	25.5
12	3	2	240/70	88	26.7138
13	4	2	260/90	92	27.6
14	4	2	280/110	102	30.6
15	4	1	300/10	110	33

Table 4.Crack Data (capturing crack details)

Inning No: 1 – Team 1, 230 all out in 170 overs

Inning No: 2 – Team 2, 187 all out in 120 overs

Table 5.Crack Data (feature vectors)

S. No.	Point1_1	Point1_2	Point2_1	Point2_2	thetha	length
1	640	12	640	130	0	118
2	640	167	640	224	0	57
3	640	289	640	310	0	21
4	640	337	640	360	0	23
5	414	255	435	263	-67	22.4772050542
6	530	304	553	313	-67	24.6981780705
7	395	254	426	265	-70	32.8937684068
8	531	304	545	309	-70	14.8660687473
9	37	211	52	214	-79	15.2970585408
10	458 rd	293	483	297	-79	25.3179778023

Day3, 70th Over, 2nd Inning

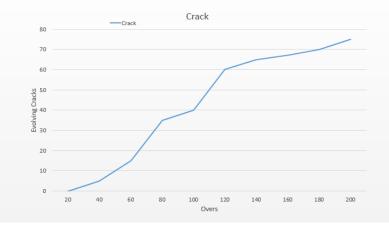


Figure 8.Curve Obtained from Backpropagation

RESULTS AND VALIDATION

In this paper we have extracted cracks from the pitch, estimated ball velocity from the video of playing sessions as outlined in Algorithm and have established a link between both these parameters. The plot above clearly indicates a correlation between velocity and mean crack length and orientation. We have further validated our findings using a bowling machine and speed gun. The bowling machine was used to pitch balls with the same initial velocity on cracked parts of the pitch and also on regions without cracks and the recoil velocities were noted using speed gun.

The results thus obtained are tabulated in table 6.

S. No.	Without Crack (km/hr)	With Crack (km/hr)
1	110	114
2	90	88
3	100	105
4	110	112
5	120	117

Table 6.Validating using Bowling Machine and Speed Gun

CONCLUSION

In this thesis we studied the impact of cracks present in the cricket pitch. In order to do this, we developed a dataset as outlined in Section 4.1.

Experiments were carried out based on the dataset, as per the section 4.2 using algorithms presented in Section 3.

The results obtained were encouraging as we were able to show a relationship between cracks in a cricket pitch and the ball's rebound velocity.

Our findings have also been validated using a bowling machine and a speed gun.

FUTURE WORK

Some limitations of the work include some degree of manual intervention, which we will try to overcome in our future work.

The concept of crack detection can also be applied to a variety of other scenarios such as drought areas. Further works can be done to explore such applications.

REFERENCES

- [1]. https://en.wikipedia.org/wiki/Hawk-Eye.
- [2]. https://en.wikipedia.org/wiki/Snickomete r.
- [3]. https://en.wikipedia.org/wiki/Hot_Spot_(cricket).
- [4]. https://www.jstage.jst.go.jp/article/kikaic 1979/64/623/64_623_2318/_article.
- [5]. https://www.jstage.jst.go.jp/article/kikaic 1979/64/623/64_623_2318/_article.
- [6]. https://www.researchgate.net/publicatio n/229920468_The_dynamic_behaviour_o f_cricket_balls_during_impact_and_varia tions_due_to_grass_and_soil_type.
- [7]. https://www.researchgate.net/publicatio n/229920468_The_dynamic_behaviour_o f_cricket_balls_during_impact_and_varia tions_due_to_grass_and_soil_type.
- [8]. https://www.researchgate.net/publicatio n/4215180_Hebbian_learning_based_FIR _filter_for_image_restoration.
- [9]. https://www.researchgate.net/publicatio n/223423390_Novel_System_for_Autom atic_Pavement_Distress_Detection.
- [10]. https://www.researchgate.net/publicatio n/235420460_A_Combined_wavelet-

based_Image_processing_method_for_e
mergent_crack_detection_on_Pavement
_surface_images.

- [11]. https://www.researchgate.net/publicatio n/252096911_Introduction_of_a_wavelet _transform_based_on_2D_matched_filte r_in_a_Markov_Random_Field_for_fine_ structure_extraction_Application_on_roa d_crack_detection.
- [12]. https://www.researchgate.net/publicatio n/221906399_Supervised_Crack_Detecti on_and_Classification_in_Images_of_Roa d_Pavement_Flexible_Surfaces.
- [13]. https://www.researchgate.net/publicatio n/278805713_Automatic_Detection_and _Classification_of_Defect_on_Road_Pave ment_using_Anisotropy_Measure.