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Automated Goal Score Detection in Football Match Using Key Moments

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Abstract

Automated goal score detection in a football match is a comprehensive work and a challenging task as well. In this paper, we proposed a methodology for goal score detection using key moments of the match. Key moments in any sports are referred as actions that stimulate excitement or attraction of the audience. So, key moments can be identified using computer vision. Extracting one key moment involves many steps to happen at a time and it is necessary to integrate all the steps to identify it as a key moment. It is necessary to identify the goalpost region and track the ball to calculate the goal in football match. The proposed work analyses the various tracking algorithms and finalize MIL (Multiple Instance Learning) tracker technique to track the ball. So, the proposed work identifies the goal post region using sequence of image processing operations, tracks the ball using multiple instance learning tracker and confirms whether the goal has been occurred or not. The results of the proposed work have been shown.

Keywords: Key Moments, Computer Vision, Image Analysis, Line detection, Video Analysis, Object tracking.

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1. Introduction

Key moments play a prominent role to calculate a goal in football match. Key moments in any sports that can energize us, excite us and move us. Such kind of moments will be useful for automated goal detection. Football is the most popular game in the whole world with simple rules and playing around 90 minutes. It is the most popular game in number of participants and spectators. Penalty Kick is an example of a key moment. It is a method of restarting the play in which player is allowed to take a single shot on the goal while it's defended by the opposing team's goalkeeper. So, the main goal of this proposed work is to identify the key moments and detect the goal. "A key moment is a situation or event that exhibits a challenge and demands a response. How we respond to our key moments determines, to a large extent, our adequacy in dealing with life". In order to automate the Goal score calculation, the match video to be analyzed and important features to be extracted. Then key moments to be identified from the extracted features. In general, to know Goal score, Goal-mouth region to be identified and ball should be tracked properly to identify the goal. By integrating these two tasks the proposed work calculates the goal. Hence, the main objective of this proposed work is to identify goal in the football match using computer vision.

1.1 Scoring in Football

Scoring of football can appear to be unpredictable at first, yet truly there are just five different ways to score focuses in football:

- Touchdown (TD): A TD is scored when a player gets a go in the adversary's end zone or keeps running with the football into the end zone. A TD is worth 6 points.
- Two-Point Conversion: Upon scoring a touchdown, the scoring group can either endeavour to kick the ball through the objective posts for 1 additional point or can run/pass the football into the end zone for two additional focuses.
- Field Goal: A group may kick the football through the objective posts for 3 points.
- Wellbeing: When the guard handles a hostile player with the football in the hostile group's end zone. Security is worth 2 points.

Fig 1. Free and Penalty kicks

Currently, Automated goal score detection using key moments in Football, which is a challenging problem due to following reasons:

Although Football is a simple game that has simple rules played around 90 minutes, we would need to wait for a Goal to happen whether it's success or not. Extracting one key moment involves many steps to happen at a time and we have to integrate all such to make it as a key moment. It is a comprehensive work to extract all such key moments. The proposed work automated the process by extracting features and identifying the goal.

The rest of the paper is organized as; we have discussed the related work in section 2, Methodology in section 3 and Result Analysis in the section 4, Conclusion and future enhancement in section 5 and Acknowledgements in the section 6 which follows references at the end.

2. Literature Survey

The related work with Goal-mouth detection and automated goal score detection activities have been discussed in this section. Kongwah WAN et. al. (2003) [1], described a real-time working framework that detects goal-mouth appearances in football video, and fragments them into pixel coordinates. Pushkar Shukla et. al. (2018) [2], proposed a model for generating automatically sports highlights with a focus on cricket. This proposed model considers both event-based and excitement-based features to clip an event. This model showed that dividing whole cricket match into video shots and cues like replays, audio intensity, scoreboard, player celebration, player field scenarios so we could create high quality of clips without supervision. Burak Uzkent et. al. (2018) [3], have proposed an Ensemble of the Kernelized Correlation Filters and it is explicitly intended to address variations in scale and interpretation of moving objects. Long Chen et. al. (2018) [4], Real-time multiple object tracking has been done in this paper. Dealt with inconsistent detection by gathering applicants from yields from outputs of both tracking and detection. They have proposed an online different people framework which exploits latest deep neural networks.

Hossam M. Zawbaa et. al. (2012) [5], This paper shows an AI (ML) based Event detection outline framework for summarizing imperative occasions amid soccer matches. The proposed framework performs great as its investigation results accomplish high exactness. It has been proved that utilizing the SVM classifier is more suitable for football recordings synopsis than ANN classifier. Marco Godi et. al. (2017) [6], In this paper, they have been used reverse paradigm: Basis the audience behaviour and what could be the excitement, they have been detected the events happening in the game and proposed a technique to transiently find features in a game occasion by breaking down exclusively the gathering of people conduct. Also, they proposed to utilize a deep 3D CNN on cuboid video tests to separate between various fervor of the spectators. Samuel F. de Sousa et. al. (2011) [7], In this paper, they had been given order of hierarchy and arranged approaches into this chain of importance depending on their investigation level, i.e., low, middle, and high states. An outline of football occasion distinguishing proof has been introduced and examined general issues identified with it so as to give applicable data about what has been done on soccer video processing.

Mahesh kumar H. Kolekar et. al. (2008) [8], The main purpose of this paper is to naturally generate highlights of the game sequences so that choices of occasions can be found and played back. Caption acknowledgement has been done utilizing the sum of total difference-based caption recognition model. In this paper, they have proposed extraction of excitement highlight depends on audio features and discovery of the occasions of excitement highlights depends on caption content analysis. The highlights are utilized to produce automated clip for cricket video. Heng Fan et. al. (2018) [9], In this paper, they have presented LaSOT, a great benchmark for Large-scale Single Object Tracking. By releasing LaSOT, they had a hope to give the network an extensive scale devoted benchmark with high caliber for both the training of deep trackers and the veritable assessment of tracking algorithms. LaSOT gives lingual annotations to each grouping, intending to empower the investigation on coordinating visual and lingual highlights for strong tracking. Qiang Wang et. al. (2017) [10], In this paper, they have been presented an end to end lightweight system architecture, specifically DCFNet, to get familiar with the convolutional features and play out the correlation tracking procedure all the while. They have been exhibited how they can prepare a lightweight system in an end-to-end design to consequently become familiar with the features best fitting DCF based tracking. The component extraction in the normal DCF based trackers can be substituted by utilizing trained convolutional features, permitting our tracker to accomplish a noteworthy accuracy gain contrasted and these utilizing HoGs.

Jan Issac et. al. (2016) [11], In this paper, they have applied a Gaussian Filter to the issue of 3D object tracking from depth images. There are basically 2 hindrances while applying Gaussian filter to this issue as GF is non-strong to outliers and the same has been addressed by applying robustification technique. The other one is intricacy of GF is restrictive to high dimensional estimations got from depth of camera. The proposed update is qualified for parallelization since the data originating from every pixel is handled independently. The test results represent the upside of GF based strategies over PF-based techniques. Di Wu et. al. (2017) [12], A novel kernelized multi resolution convnet tracking algorithm has been proposed that uses the middle of the road reaction maps from the kernelized correlation filter outputs. The multi-goals convnet learns the indirect translational output precisely and later a versatile learning plan is received for model update. The learning paradigm can generalise over different data sets without change of hyperparameters. Also, it opens the door on the end-to-end deep learning. Mathieu Garon et. al. (2018) [13], In this paper, they have given advancement in 6-DOF tracking execution on a data set containing genuine data and all the more testing situations, which they expect will spur further research in the field. The successions are assembled into 3 situations: stability, occlusion, and interaction. Furthermore, the architecture takes into consideration training on numerous objects and test on various objects it has never found in training.

3. Proposed Methodology

The proposed methodology is basically focused on football. As football sport has been taken into the consideration, this work follows detecting key moments in the football game. There are so many key moments in the football game like Goal, foul, audience behavior during winning of the match and cheering etc. Out of all those, Goal score is detected with the help of key moments. In order to detect the goal score, we would need to do Goal-mouth detection as well as ball tracking. Hence, the block diagram of the proposed work is shown as in Fig (2).

3.1 Block Diagram

Figure 2: Block Diagram of Automated Goal Score Detection

Here football match video has taken into the consideration to figure out the key moments for a goal score detection. So, the proposed work detects the goal score by tracking the ball, confirms the ball falls in the Goal-mouth region.

3.2 Goal Score detection

Goal score detection is the combination of Goal-mouth detection and Ball tacking. When these two actions have been combined together or happened at a time, we can figure it out this as a goal score. This can be detected using a few Image processing operations with MIL (Multiple Instance Learning) tracking technique. Hence, the proposed goal score detection technique has two submodules (i) Goal-mouth detection (ii) Ball tracking and they have been discussed in detail below.

3.2.1 Goal-mouth detection

The area which is directly in front of the goal, as in soccer or football is called goal-mouth. Association of a football or soccer is a football game in which two teams of eleven players try to kick or head a ball into the opponents' goal. If we detect where goal is happening or the area of the goal then we could detect goal mouth and it is known as Goal-mouth detection. For Goal-mouth detection, Image processing operations have been performed. Goal-mouth detection has been done as follows and steps involved in it will be given as below. Dominant green colour area detection has been done using RGB colour model. The G component of RGB Colour model has been considered to detect the green colour in the goalpost image. The threshold value 50 of G component has been chosen using trial and error method with various football videos and pixels with G value > 50 are considered as dominant green colour. As a result of this step, the proposed work identified the region in which the goal score calculation to be done.

RGB image has been converted into gray colour image in order to do further image processing operations. Noise in the image has been reduced using low pass filter. Canny edge detection algorithm is used to detect the edges in the image for identifying the goal post region. The goal post region is obtained by applying masking on edge detected image, the masking is derived by mapping the edge detected image with the dominant green colour image. The horizontal and vertical lines are identified to find the goal-mouth in the region of interest using Hough transform.

Hough transform is a feature extraction technique used in image analysis, computer vision and digital image processing. We would need to find aligned points in images that create lines. Then we will get edges of the image. Further, we have to apply hough transform in order to detect points in images. Hence, it is used to detect goal-mouth.

3.2.2 Ball Tracking

Tracking is the process of finding an object in successive frames of a video and it is a well-studied problem within the area of image processing. The performance of the object tracking algorithms have been improved in the most recent decades. But still, it is as yet considered as a complex problem to solve. Tracking is faster than detection but detection will take a lot of time. To detect an object, the annotation for each and every frame of a particular video has to be done. It will take a lot of time but for tracking just one object will be selected while running the video, that will be tracked for next subsequent frames of the video.

The main aim of an object tracking algorithm is to keep track of an object in a sequence of frames in a video. A tracking algorithm initializes a frame from a video sequence with a bounding box to indicate the location of the object in that frame that we are interested in tracking. The tracking algorithm outputs a bounding box around that object for all subsequent frames. If we encounter the ball is in the goalpost then we can identify that one as goal. By integrating goal-mouth detection and Ball tracking can be considered as Goal Score. The significance of the ball tracking is to detect the key moment in football sport. So, there is a requirement of an efficient object tracking algorithm. The movement of the ball in goalpost region should be tracked properly to detect the goal score. So, it is necessary to identify an efficient object tracking algorithm for the scenario. Hence, the proposed work have analysed using all seven correlation tracking algorithms like Boosting Tracker, Multiple Instance Learning tracker, Kernelized Correlation Filters tracker, Tracking, Learning and Detection tracker, MEDIANFLOW tracker, MOSSE tracker, Correlation Filter with Channel and Spatial Re-liability Tracker (CSRT) trackers to find the efficient ball tracking technique for the accurate goal detection.

Out of those only three have been chosen for the proposed goal score detection that was successful when used Boosting tracker, MIL (Multiple Instance Learning) tracker and CSR tracker, we could see the performance while using these trackers.

3.2.2.1 Object Tracking Algorithms

The description and analysis of the seven tracking algorithms are given as below.

3.2.2.1.1 Boosting Tracker

Boosting tracker depends on an online variant of AdaBoost - the calculation of the HAAR based face identifier utilizes inside. This HAAR classifier should be prepared at runtime with negative and positive instances. The bounding box provided by the user is taken as the positive case and many picture fixes outside the bounding box are treated as the foundation. Given another edge, the classifier is kept running on each pixel in the area of the past area and the score of the classifier is recorded. The new area of the item is where the score is greatest. So, we have one increasingly positive case for the classifier and when more casings come in, the classifier is refreshed with this extra information. Tracking execution is fair but it doesn’t dependably realize when following has fizzled.

3.2.2.1.2 MIL (Multiple Instance Learning) Tracker

The MIL tracker doesn't determine positive and negative models, however positive and negative "packs". The gathering of pictures in the positive pack are not every single positive model. Rather, only a single picture in the positive pack should be a positive model. In MIL, a positive pack contains the fix focused on the present area of the item and furthermore fixes in a little neighbourhood around it. Regardless of whether the present area of the followed item isn't precise, when tests from the area of the present area are placed in the positive pack, there is a decent shot that this pack contains no less than one picture in which the area is pleasantly focused. The advantage of this tracker execution is entirely great. It doesn't float as much as the BOOSTING tracker and it completes a sensible occupation under incomplete impediment.

3.2.2.1.3 KCF (Kernelized Correlation Filters) Tracker

KCF represents Kernelized Correlation Filters. This tracker expands on the thoughts displayed in the past two trackers. It uses the reality of different positive examples utilized in the MIL tracker that have huge covering areas. This covering information prompts some pleasant scientific properties that is misused by this tracker to make following quicker and progressively exact in the meantime. The advantage of this tracker is the accuracy and speed. However, it does not recuperate from full impediment. Not actualized in OpenCV also.

3.2.2.1.4 TLD (Tracking, learning and detection) Tracker

TLD tracker disintegrates the long-haul following errand into three parts following, learning, and identification. "The tracker pursues the area from casing to outline. The locator confines all appearances that have been watched up until now and redresses the tracker if important. The learning gauges indicator's mistakes and updates it to evade these blunders later on." On the positive side, this tracker seems to follow an object over a bigger scale, movement, and impediment. In the event of video grouping where the item is taken cover behind another object, this TLD tracker might be a decent decision. This tracker is scalar invariant and it works best under impediment over different edges but lot of false positives making it practically unusable.

3.2.2.1.5 MEDIANFLOW Tracker

MEDIANFLOW tracker tracks both backward and forward ways in time and measures the errors between these two directions. Limiting this forward backward blunder empowers them to dependably distinguish following disappointments and selects solid directions in video groupings. This Median Flow tracker works best when the movement is little and there is no impediment but fails under extensive movement.

3.2.2.1.6 Minimum Output Sum of Squared Error (MOSSE) Tracker

This MOSSE tracker utilizes versatile relationship for item following which produces stable connection channels when instated utilizing a solitary casing. It is generous to varieties in lighting, scale, present, and non-rigid deformations. It identifies impediment dependent on the crest to-sidelobe proportion, which empowers the tracker to resume where it left off when the object returns. MOSSE tracker works at a higher fps (450 fps and significantly more). But in an execution scale, it falls behind the profound learning-based trackers.

3.2.2.1.7 Discriminative Correlation Filter with Channel and Spatial Reliability Tracker (DCF_CSRT)

This DCF_CSRT utilizes the spatial unwavering quality guide for modifying the channel backing to the piece of the chosen area from the casing for following. It guarantees expanding and confinement of the chosen area and improved following of the non-rectangular areas. It works at a nearly lower fps (25 fps) and gives higher precision for object tracking. It utilizes 2 standard features (i) Histogram of Gradients and (ii) Colour names and it is slower than the KCF tracker.

Ball tracking of football match has been done using seven different correlation tracking algorithms and the results are analysed. However, out of those seven correlation tracking algorithms only three have been chosen based on the tracking result report. They are Boosting tracker, Multiple Instance Learning tracker, CSRT tracker.

Hence, Ball tracking has been done using these three correlation tracking algorithms and their performance analysis have been done based on the time taken to process the frames. Since the goal score calculation has to be done in real-time, so the time taken to process the frames in the input video is considered as a metric to choose the best tracking algorithm. The tracking speed of the three algorithms have been given in the table 1 and shown it in a graph in Fig 6.

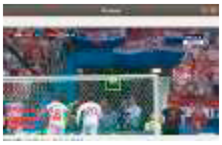

Fig 03: Object Tracking using MIL Tracker

Fig 04: Object Tracking using Boosting Tracker

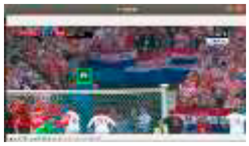

Fig 05: Object Tracking using CSRT Tracker

Table 1. Tracking Speed of Algorithms.

Correlation Trackers (X)	Y (FPS)	Success
MIL Tracker	21.44	Yes
CSRT Tracker	40.51	Yes
Boosting tracker	45.77	Yes

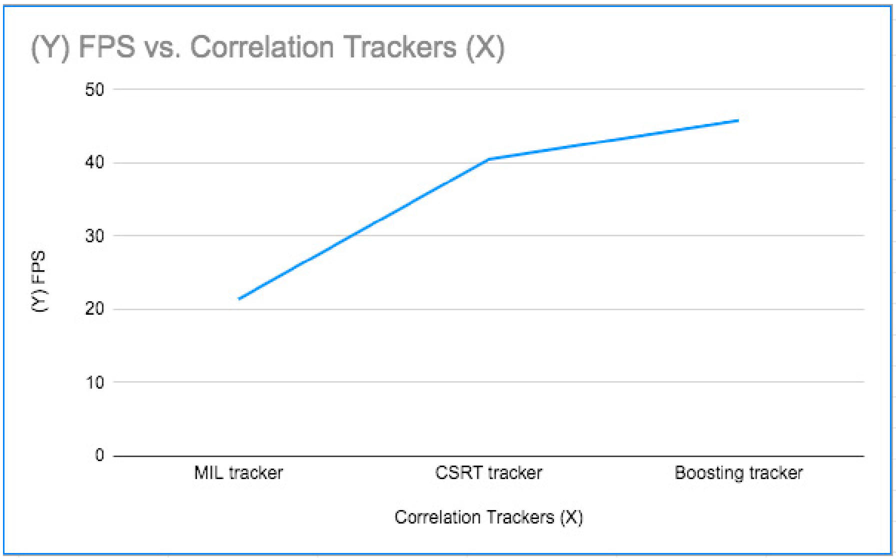

Fig 6. Performance Evaluation of Object Tracking Algorithms

Table 1 illustrates the number of frames per sec processed by different correlation tracking algorithms Boosting tracker, MIL tracker and CSRT tracker and the Fig 6 shows the same in a graphical representation. Since the speed of the input video matches with the processing speed of the MIL tracker algorithm, MIL is chosen. Hence, it will be considered as the best tracking algorithm for the proposed work for this input video.

By combining Goal-mouth detection and ball tracking can be considered as a key moment of Goal in football match. Once the ball is reaching towards goal mouth and it’s in between both horizontal and vertical lines of Goal-mouth can be considered as a Goal. So, If the ball has been tracked in the region of interest of the goal mouth then Goal score detection is done by identifying it as a Goal.

4. Result Analysis

The proposed Goal score detection has been implemented using Open-CV 3.0 on ubuntu 16. 04. 6 system. The proposed work has been tested with the FIFA.mp4 data set that has been provided by Nanoyotta Technologies Pvt Ltd. The results of the goal score calculation in football match have been shown from figure 6 to 13 as step by step from reading the input frame to goal score calculation. The Goal score calculation has been done as two modules (i) Goal-mouth detection and (ii) Ball tracking. Finally, when the ball is tracked in goalpost region, it is considered as a Goal. Hence, each step of this entire process is as shown with the help of images.

4.1 Input Frame

This is the frame (Fig 7) that has been taken from the data set FIFA.mp4 as an input image.





Fig (7) **Fig (8)** **Fig (9)** **Fig (10)** **Fig (11)**




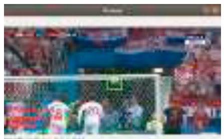

Fig (12) **Fig (13)** **Fig (14)** **Fig (15)**

Fig 7: Sample Goalpost Image **Fig 8**: Dominant Green detection **Fig 9**: RGB to Gray Colour Image **Fig 10**: Smoothened Image **Fig 11**: Canny Edge detection **Fig 12**: Region of Interest **Fig 13**: Horizontal Line detection **Fig 14**: Vertical Line detection **Fig 15**: Object Tracking using MIL Tracker

4.2. Dominant Green detection

The dominant green colour has been detected and shown the resultant image in Fig 8. This initialization stage computes the key statistics like dominant green and goal-line. It's a binarized result of the original image of sample goalpost and shadowy effect. As a result, the pixels binarized as green and displayed as original green colour.

4.3. RGB to Gray Colour Image

The sample goalpost image to be converted from RGB to gray scale image for region of interest calculation along with dominant green detected image. The decimal code for Red is (255,0,0), Green is (0,255,0), Blue is (0,0,255) and Gray is (128,128,128). The resultant output of RGB to Gray colour image has been shown in the Fig 9.

4.4. Smoothened Image

The Gray scale converted image is smoothened using low pass filter to reduce noise within the image. Fig 10 shows, the output of smoothened image.

4.5. Canny Edge detection

The horizontal and vertical lines have been detected by applying canny edge detection on smoothened image to identify the goal post region and the output image is shown in Fig 11. Since canny edge detection is a proven edge detection algorithm, this approach has been used in this proposed work.

4.6. Region of Interest

Region of interest is a portion of an image it would be useful to perform a few operations on that particular area. We can filter that region and do required operations. The region of interest on the edge detected image (Fig 11) is calculated by applying mask based on dominant green colour image (Fig 7) and the output image has shown in Fig 9. Hence, the goalpost alone would be visible to perform specific operations of line detection and it is shown in the Fig 12. This helps to perform Goal score calculation on Goalpost region.

4.7. Horizontal Line detection and Vertical line detection

It is necessary to identify the horizontal and vertical lines in the region of interest (goalpost region) once the region of interest is identified. Horizontal and vertical lines have been identified by applying hough transform in the goalpost region. The output images of the horizontal and vertical line detection have been mapped with input frame and shown in Fig 13 and 14. Now, the region of interest is identified and obtained the goalpost location in the region of interest image for calculating the goal of the ball. So, it is necessary to track and identify the ball whether it falls in the region for goal score calculation.

4.8. Ball Tracking

The second module of the proposed algorithm is analysis of the various object tracking approach and finalise the best tracking algorithm for goal score calculation in Football Match. The ball has been tracked using MIL and it can be seen that it is in goal-mouth region in Fig 12. Finally, the key moment of goal score detection has been done using goal post region identification along with tracking of ball locations using MIL. Thus, the proposed work calculated goal as one since the ball is in the region of interest in Fig 03 and the goal is zero since the ball is out of the region of interest in Fig 04.

5. Conclusion and Future Enhancement

In this paper, we have proposed the automated goal score detection technique for a football match. Based on the insights and observations from the data, the proposed technique has analyzed football match video, identified key moments and calculated the goal using identified key moments. In future, the work can be extended for real-time processing.

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