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Soccer Player Tracking System

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Abstract: In a game of soccer it is crucial to track multiple players to get some aspects of game. Challenges in tracking multiple players is to deal with rapid illumination changes in the background, occlusion among multiple players and similar look of players from distance. To detect the presence of players, adaptive Gaussian mixture model is used to extract moving foreground (players) and Histogram of oriented gradients learned using linear SVM. Among which GMM give best results. To identify tracking of players distance parameter is used till now, which give good result until the occlusion occurs among multiple players. In Occlusion this method can be failed to track the right player.
Keywords: Soccer game, Player Detection, Player Tracking, GMM player tracking, HOG player tracking

I. INTRODUCTION

Soccer is the world's most popular sport which is played by millions of people around the world. This much of popularity of the game lead us to work on soccer video analysis. Using Computer Vision we can reveal some aspect of game which is not obvious to the human eyes. Such features are distance cover by particular player/s, position of the player/s with respect to other players, movement speed and sprint counts of the players. This data used to evaluate technical performance analysis of the soccer player/s. Soccer Player Tracking system is the system which track multiple soccer players from the scene of a soccer video.

Accurate tracking of multiple soccer players in real time is the key issue in performance evaluation, and requires detecting players on video, finding their positions at regular intervals, and linking spatiotemporal data to extract trajectories. However, multiple-player tracking is a nontrivial task due to various challenges. Unlike vehicles or pedestrians, which have relatively predictable motion patterns, soccer players try to confuse each other with unpredictable changes in motion. Moreover, players look almost identical because of their jerseys and they are frequently involved in possession challenges and tackles, where they can be occluded by other players, resulting in tracking ambiguities. Environmental conditions can also negatively affect the process of player segmentation. Rapid changes in lighting during cloudy weather creates shadows on the pitch; in sunny weather, we find dark and long player shadows on the field; and in any weather, continuously blinking electronic billboards flash around the stadium make it difficult to track the players as a moving element.

J. Czyz ,J.B. Hayet, J. Verly,T. Mathes, J. Piater and B. Macq [1] presents a multi camera approach for sport broadcasting with modular system in which Image to model homography estimation performed by geographical module continuously for each video stream and Tracking of players in each view is based on the local features. They fuses the data provided by the tracking modules and by using zooming and rotating camera localize the players on the ground. Without using background modelling their system their local tracking of players can handle the occlusions. They present experimental results on raw TV-camera footage of a soccer game.

Sermetcan Baysal and Pınar Duygulu [2] represent tracking of soccer player in occlusion and rapid motion using particle filter approaches. They divide ground using particles that sampled at fixed positions instead of choosing particles on players. They globally evaluate players' likelihood of being on the model field particles using their combined appearance and motion model. That differentiate the interactions among the players in the state space model and track players in different types of occlusions. They describe the steps of the system and compute their methods on video data gathered from professional soccer league matches. It is mainly designed for the Sentioscope which is the soccer player tracking system. With experimental results they proved that their algorithm is more successful, compared with the previous methods, for multiple player tracking with similar appearances and random motion directions.

Panagiotis Petsas and Paris Kaimakis [3] In their paper they present a multi-target tracking system for estimating the position of multiple soccer players as they move around during a soccer game. With Static camera they record the silhouette observations, use 3D models and for predicting position of player they use particle filter method. They produce their dataset using Unity3D game engine which seems to be realistic. They build client-server architecture for their application.

Erikson Morais, Siome Goldenstein, Anselmo Ferreira and Anderson Rocha [4] explains an approach for the tracking of the indoor soccer players.They have used multiple stationary camera for taking their input. Using the input they want to build probablistic model for parameters of soccer players like motion. To build observation model they fuse input from each camera and configure it with actual measures of the court coordinates. And accordingly playes position can be projected on court coordinates. For the detection playes apperiance of the player is used as a key feature. By this approach skilled laboured work can be saved. Using this implementation they found error of tracking most of the players is 70 centimeters.

Haopeng Li and Markus Flierl [5] presents their approach using multi view cameras. Because it is advantageous in the occlusion condition as if playes seems occluded from one view point then we can seen them clearly separated using another view point. For the identification of players SIFT features are used. So 3D information can be build using this inter-view and inter-frame correlations. They showed that using multi view camera approach increase the tracking efficiency by 10% than the SIFT based tracking on static cameras.

Nima Najafzadeh, Mehran Fotouhi and Shohreh Kasaei [6] gives approach for tracking of multiple soccer players. For tracking multiple players Kalman filter is used.They divide tracking process in total four parts. First they determine state vector of multiple player by focussing on one player and other will be in retated position with him/her. Then they determine motion model of all of them for predicting position of all players. Then to detect soccer players they used observation method in which they divide player into 3 parts to increse efficiency in detection. Then they do correction in errors with the use of the result gain from motion model and observation model.

Section 2 shows related work, in which includes study of Modules and Approach of soccer player tracking system. That includes various camera configuration, Adaptive GMM and HOG are discussed for player detection. And in last Nearest Distance based tracking method is discussed. In Section 3 we discuss the approach that we use for tracking. Section 4 is about Implementation of the system. Section 5 is about the conclusion and Future work.

II. RELATED WORK

Related work can be shown in following modules.

1) Camera Configuration
2) Player Detection
3) Track Initiation

A. Camera Configuration

For Soccer Player tracking there are multiple choice for camera configuration selection based on tracking methods chosen. So, we need to study various aspect of different configurations.

In [7]– [13], broadcast footage captured by a pan-tilt-zoom camera is used, offering a relatively cheap and flexible solution to this issue because it is not necessary to physically set up cameras to track players in a game. However, such approaches must deal with continuous changes in view point. A more severe problem is that broadcast videos are usually zoomed to the region of action, and therefore, some players become not visible for tracking.

As a solution, studies in [14]– [17] place several static cameras to capture a single-view of the entire field. However, as it can be quite challenging for single-view tracking algorithms to resolve frequent and continuous occlusions of players. The methodologies proposed in [18]– [24] tackle the problem by pursuing a Multiview approach, in which the observations from four to eight static cameras are fused. Although the efforts of these Multiview approaches are laudable, considering the structure of sports arenas/stadiums, these systems introduce extra complications such as difficulties in camera setup, the Need to route data to a single processing node, and increased computational complexity, which makes them impractical and relatively expensive for real time applications.

B. Player Detection

Following methods of player detection has been studied.

1) *Foreground Extraction:* It is observed that in soccer game players are moving around on ground continuously. So, it will become easier to detect players using background Elimination, also known as foreground extraction. We have studied Adaptive Gaussian mixture model for the foreground extraction.

a) *Gaussian Mixture Model:* GMM build model for each pixels of the frame. Using this model it will decides whether it will be background or foreground pixels. For that it use many probability equations which will be worked as follow. In the parts of the frames in which their is no other objects have some regular behavior which is not changing much and we can build statistical model for that, knows as background. Result of the background subtraction is assigned to higher level module that learns the behavior of objects. so this objects can be tracks separately, which also help for background subtraction then.

As players are moves our from the frames and new players comes in the frames this model should decrease the influence of old data and after some frame discard it. So if player/s stay long at same position without movement it is consider as a part of background objects and it will be also give efficient result in case of sudden light changing. Selecting number of components for GMMl is based on [25,26]. GMM learns about the objects behavior without knowing about objects, known as unsupervised learning [John McGonagle, Vincent Tembo, Alex Chumbley].

2) *Observation Method:* For the detection of the object there are many methods available like template matching, SIFT, SURF, Using HAAR features. We have studied Histogram of Oriented Gradient in details.

a) *Histogram of Oriented Gradient:* HOG describe the features of the image/object. Means it provide short description about the objects by which we can recognize it. It generate description of the object as a whole, means that it doesn't create small small descriptor of objects as SIFT does. Method of Generation HOG feature of objects is described by the Dalal and Triggs[27]. These features can be used to classify the particular objects by training its feature using any machine learning algorithms. Mostly SVM is used for it. To classify humans several humans and non human images HOG features can be trained. Then to detect humans a detection window can be moved around the image and then it ask classification module that whether it contains human object or not [28].

III. Our Approach

A. Camera Configuration

We have chosen dataset which is created using static camera. It took 6 cameras to cover whole ground, 3 on right side of ground and 3 on the left side of the ground. So using this dataset we can analyze the performance of players which are in the focus of that camera at a time[29]. We choose static camera's dataset because from it we can track player/s for longer time using single video source, and also height and width parameter do not change drastically as in rotating and zooming cameras.

B. Player Detection

For detection of the players we have compared two different approach.

1) *Gaussian Mixture Model:* As we discussed about the features of this model this give accurate result if we apply few operations on it. i.e. After applying adaptive GMM we apply Morphological open and dilation with 3x3 and 50x50 cell element. Which removes noise and fill gap if any in players element. Still some small group of pixels remain, which we removed by setting up height and width ratio that is minimum needed for human. So, using it we got 100% accuracy in the detection of soccer players. False alarm in this are the sign board which appears in the video is some time because it is blinking and its height width ratio nearer to humans.
2) *Histograms of Oriented Gradients:* As we discussed about this method it learns about human and non-human objects in the images. As soccer playe's gesture, position changing continuously during the play time of game, other methods which learns about local features of the object will fail to give accurate results. In the case of HOG also some time it happens that due to varied posture of the human which is not trained as a human cannot be detected.
3) *Tracking:* To track soccer player first we detect soccer players from the frame, then select any one of them to start tracking for him/her and also save their location. Then in next frame we detect all player again and to track the player that we have selected in previous frame we calculate its distance with all player's location that have been detected currently. Then we assume that the minimum should be of the same player as in single frame players are not moved so far.

IV. IMPLEMENTATION AND RESULT

A. System configuration and Dataset

We have used opencv(3.1.0) with python(3.5.3) on Ubuntu 16.04 system for the implementation of soccer player tracking system. We use opencv because it is open source and provide real time image processing capabilities. We use ISSIA soccer dataset[29] for our experimental result. It consists of 6 camera views of the playfield at 25 frames per second with a resolution of 1920 x 1080 pixels. Details of pother packages used is shown in Fig. 1.

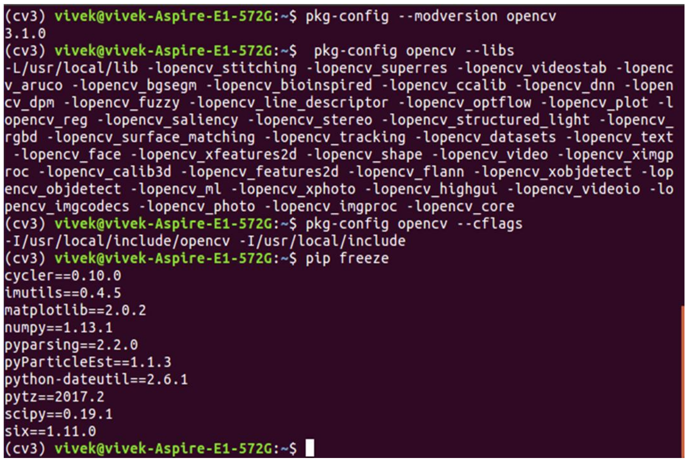

Fig. 1 Software and package install for the system Configuration

Fig. 2 Extracted Frame from the input Video

B. Extracting Video Frames from the Soccer Video

As we are working on videos we have to extract all frames from it. We are extracting it on run time and then process in every frame. Sample of such frame is shown in Fig. 2.

C. Improved adaptive Gaussian mixture model for Foreground Extraction

We use Adaptive GMM to detected moving objects which are humans and football. We have used adaptive GMM because it selects number of components by its own to adjust to the sudden illumination changes. Fig. 3 shows the output off the applying of the GMM on the video frame of Fig. 2.

D. Morphological Open Operation

To remove extra small dots from the frame we use morphological open operation. Because of the changing in the lights and shadows scattered pixels also detected as a changing set. Fig. 4 shows result of applying Morphological Open Operation.

E. Morphological Dilation Operation

After applying Open operation there will be removal of border pixels in the set of detected players. To fill that gap we apply morphological Dilation operation. Result of which is shown in Fig. 5.

F. Contours for the Detected Regions Using Adaptive GMM

Now to see how many players are detected we need to draw bounding box around the detection of the players. Before drawing of bounding box we need to find relevant contours. Here we want to detect player candidates only so we apply height and width condition which is minimum require to be a player candidate according our video frames. Fig. 6 shows the result of bounding box without applying of condition and Fig. 7 shows result of applying condition to detect only human candidate according to height and width ratio.

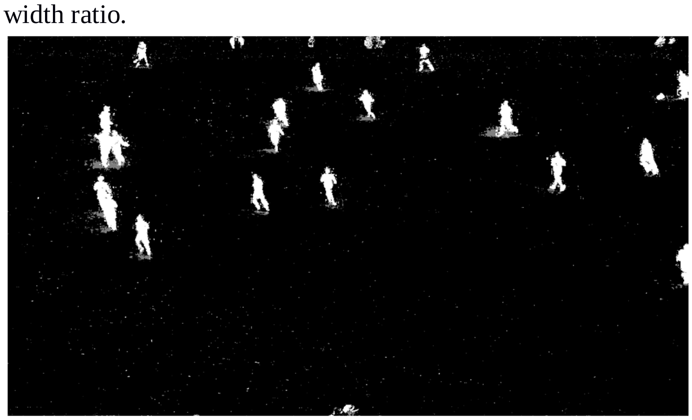

Fig. 3 Adaptive GMM with History parameter as 1000

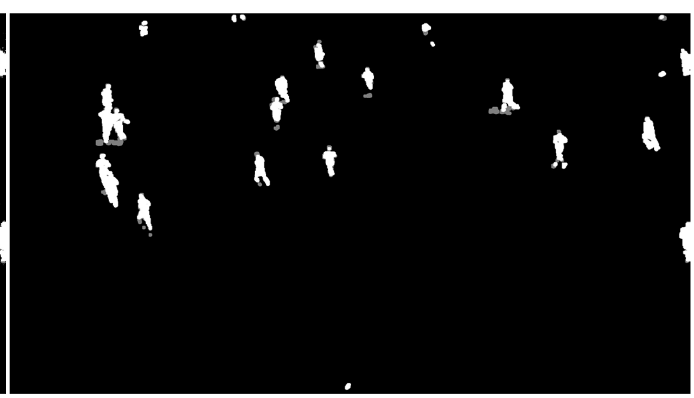

Fig. 4 Morphological Open Operation with 3x3 cell element

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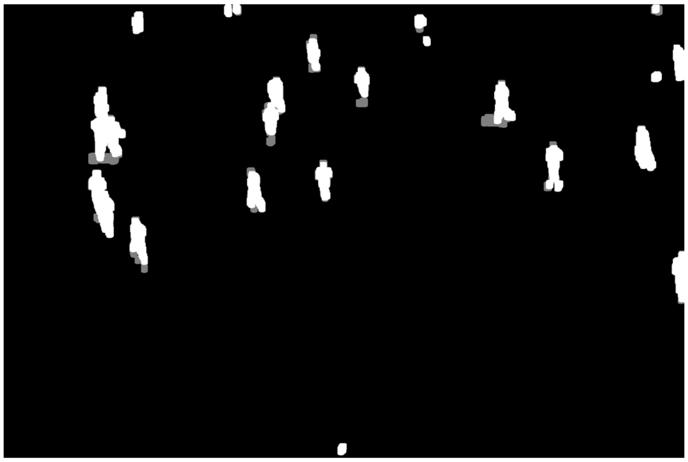

Fig. 5 Morphological Dilation Operation with 50x50 cell element

Fig. 6 Drawing of Bounding Box without any condition

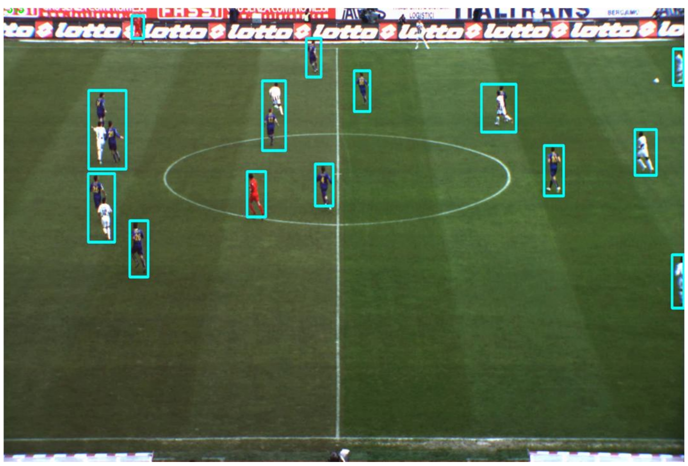

Fig. 7 Drawing of Bounding Box with condition of Humans aspect ratio

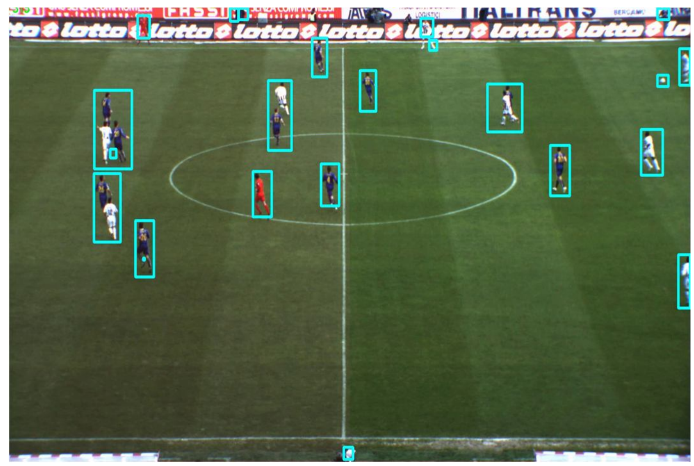

Fig. 8 Detection of Players using HOG learnt using linear SVM

G. HOG learnt using linear SVM

Fig. 8 shows the result of the applying the overlapping windows of the frame with its HOG features to detect that whether that window contains humans or not. From the result it is clearly seen that some players cannot be identified as a human as their gestures are in different positions during the game of soccer.

H. Track Players Using Distance Parameter

As GMM can detect all player candidate and HOG learnt using linear SVM is slower to process for the big frame, we use GMM with Distance parameter to track the players. First we find the contours which have players in it. Then we find out their positions in a set of array and assign them label of numbers which is starting from number 0. Then in next frame we do the same and assign same number label to a player which is at the most near by location compared to previous frame. If near by player location is greater than threshold distance then we assume that player is not available because we track players from a video frame which covers only limited portion of the soccer ground so it might happen that players are no longer available in the scene. Tracking of multiple soccer player's is as shown in Fig. 9. In the condition of occlusion this method cannot track occluded player separately, and after occlusion it may or may not be assigned to its correct label based on their position after the occlusion.

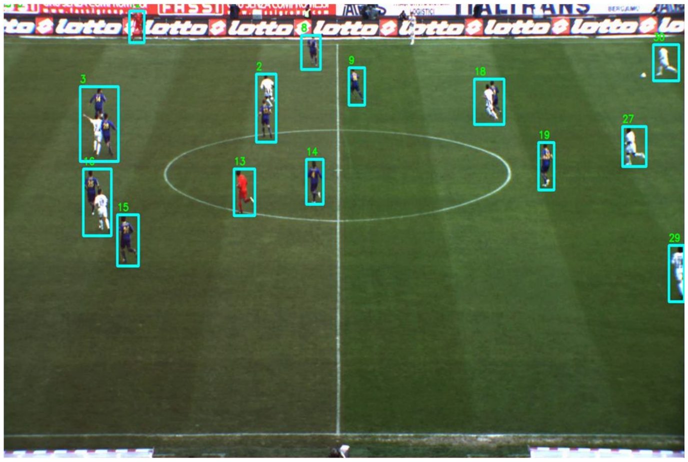

Fig. 9 Tracking of Multiple players using GMM and Nearest Tracking Location

V. CONCLUSIONS AND FUTURE WORK

Here, we conclude that tracking of soccer player is not as easy as tracking of objects and pedestrians because of frequently changing of the position and gesture of the players. So to track them we compare two efficient approach of GMM and HOG , among which we find GMM best to track with.

Our approach for tracking multiple soccer players fails in occlusion. So in future we would like to work on tracking in occlusion condition too.

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