Tracking soccer players using the graph representation

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Abstract

In this project we consider the problem of tracking a soccer player using a static camera. The main goal is to find the position of players in the field at each instance of time to help them improve their game. The main difficulty in tracking the player is during occlusion or congestion. Tracking during occlusion can be done by splitting the segmented blobs using graph representation. Graph nodes correspond to the blobs obtained by image segmentation and edges represent the distance between the blobs.

1. Introduction:

In soccer scene analysis by image processing, robust tracking of the player is important, because it provides essential information on the events happening in the soccer game. Tracking player is mostly the base of soccer scene analysis. The movement of the soccer players on the field, as a function of time, is useful information that can contribute for improving the performance of players at different positions. The measured values may be associated to physiological variables as well as to technical and tactical information [2].

In this work, we propose a method for tracking soccer players using a static camera. As we will see elsewhere, occlusions and congestions are treated by splitting blobs containing two or more players using a simple player model and morphological filters.

Our work is the partial reproduction of Figueroa, P.et al. [1] which used multiple cameras to cover whole field and track individual players during the whole game.

One of the most difficult problems in tracking soccer players involves the occlusion and the player's congestions which occur. Iwase and Saito in [3] used 8 cameras covering the region of the goal in order to treat this problem. However, this kind of solution is expensive and the occlusion problems are not totally resolved. In our work we constructed a graph to handle occlusion and track players. Nodes in the graph represent blobs obtained from segmentation and the edges between them were established using spatial and temporal information of players in each frame.

The project is organized as follows: section 2 describes segmentation process we have followed, section 3 explains the tracking process, with the subsections provide blob color and graph representation and Section 4 shows some results of the method applied to real sequences and, finally, the last section gives some conclusions.

2. Segmentation of the players:

Background subtraction method is used to extract blobs from the images. Background subtraction is a simple and very common method used for segmenting moving objects with fixed background. Although updating background for each frame is an efficient method to handle illumination, shadows, background objects etc [4], using a fixed background for images also gives a pretty good result in our case. The background was obtained using median filtering [5] on the entire image frame obtained from the video.

The segmentation algorithm considered in this work consists of the following basic steps:

- Background extraction using median filtering
- Difference between the current frame and the extracted background
- Morphological filtering (opening and closing) to eliminate noise
- Image binarization
- Labeling of blobs using connected components

Fig. 1 shows the extracted background. Fig. 2 shows a region of the original image with labeled image.

3. Tracking of the players:

The main difficulty of the tracking process involves the temporal occlusions of the objects. The splitting of the blobs aiming at separating or isolating the players is an important step in identifying players. The splitting of the blobs is done considering spatio-temporal information of the image sequences. The spatial information is obtained through shape, size and color of the blobs and the temporal information explores the relation between blobs in different images.

Fig. 1: Background image

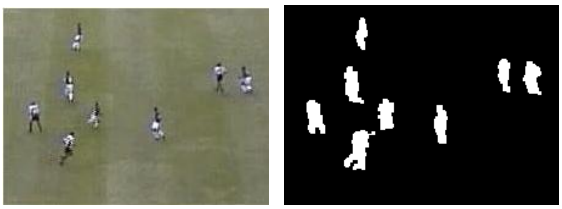

Fig. 2: Original and Labeled Image

A graph is constructed from the blobs obtained from segmentation. The blobs represent the nodes in the graph and the edges represent distance between the blobs. The edges help us splitting the blob and track them along the image sequences. The correct determination of the number of players in a single blob helps us splitting the blob hence tracking the players efficiently.

3.2. Defining blob color

Each team has been distinguished by different colors. In soccer, teams have different uniform and we have used this information define color for each team. Histogram is an efficient method to model the players in either of two categories. The model of player has been divided into multiple regions according to their team's uniform i.e. t-shirt, short and socks etc. In our case we used intensity histogram to create two models.

3.3 Splitting the blobs

Sometimes objects can get grouped into one blob during segmentation either due to the small distance between them or by effects such as shadows and noises.

Fig. 3 shows one approach to tackle this problem by isolating players which are linked by short connections. The short connections can be eliminated by considering the blobs as regions of the original images and applying a series of morphological operations for post-processing and splitting of these blobs. The original image is first eroded vertically *n* times, where *n* is dependent on position of player on the field. The result is shown in Fig. 4.

Fig. 3. Some cases of occlusion

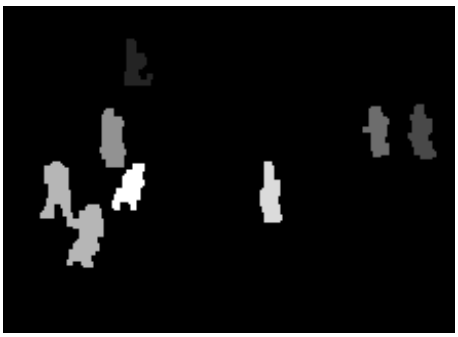

Fig. 4. After splitting by segmentation

Blobs can also be split by constructing a graph and model of the blobs. The splitting of a blob in the current frame in two or more blobs depends on the number of components of the corresponding node in the graph and on its configuration in the previous frame.

The model of each blob is taken from the isolated blobs (before the occlusion) and these are fitted in the joined blob to search for the best match. One blob can be split vertically or horizontally depending on the position of the related blobs in the previous frame and the number of its components. As the splitting of more than three players becomes more complex, here we consider only two or three player splitting at same time. If the size of the blobs is not big enough to split horizontally or vertically then the objects are considered to be in total occlusion and they share the same position. Fig. 5 and 6 illustrate the splitting by model method and the corresponding graph with the number of components in each node.

Fig. 5. The graph representation

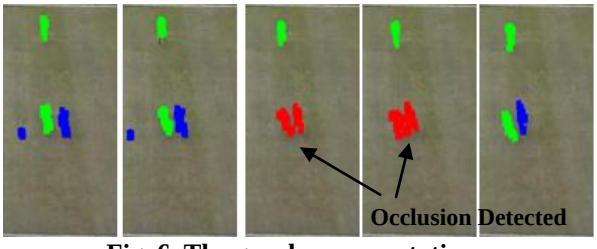

Fig. 6. The graph representation

3.4 Tracking every Player

To track a player, its initial blob is defined and the corresponding node is found in the graph. At each step, the graph is traversed by considering a minimal path, using the distance between the blobs. As there is only one edge at each step to be considered, this method is an easy way to track isolated players. In case of contact or occlusions by other players, tracking of the players becomes more difficult, a problem which blob-splitting cannot eliminate entirely since one node may contain more than one player.

In this implementation, mainly cases of short temporal occlusions or contacts of more than two players were considered. However, attention has been given to two player occlusions since it is one of the most common situations in soccer. Tracking in such cases is done is performed by considering same trajectory for both players. To maintain the right path of the players during the tracking, when players separate after occlusions, the color of the blob along with the distance information between blobs conveyed by the graph is considered. During an occlusion of two players, the direction of their trajectory is also considered in order to decide the correct paths, specially, in the case when players in contact belong to the same team.

4. Results and Applications

To illustrate the method a video of a soccer game was captured using an average camera. The code was implemented on the video to observe the results. Figure 7 and Figure 8 are sequence of four images chosen to demonstrate the results obtained.

As shown in Fig. 7, when there was no occlusion players were identified with respect to their team. The team with black shirt, white shorts and white socks were identified using the intensity histogram and the corresponding pixels were given blue color and the other team color was chosen as green. One can also see that the identified blobs also have a small tail at the bottom. The reason behind that tail is that during segmentation player's shadow was also captured and there was no particular way identified to get rid of it. The results came out to be very good and for most of the part the team players were identified correctly, apart when they were really far from the camera.

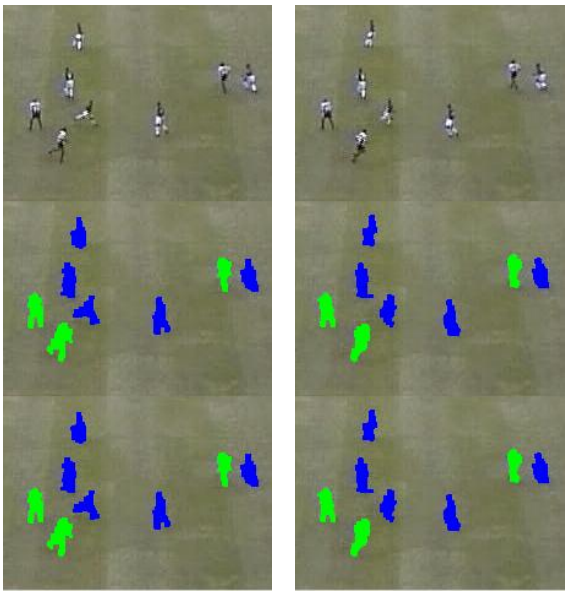

Fig 7. Sequences with no occlusion

With the help of graph representation a feedback memory was given about the position of each player from the previous image. This knowledge was very helpful to identify the occlusion and congestion. Fig. 8(a) shows the result of correct identification of occlusion and Fig. 8(b) shows the correct

identification of congestion; both were marked in red when identified.

The graph representation was also helpful to compute the number of players during congestion and with its help the blob was divided for different players. A best fit model was used to give the final division.

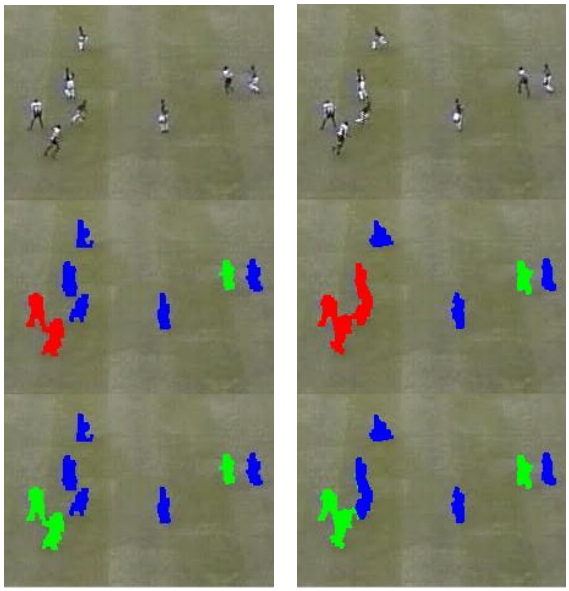

Fig 8. (a)With occlusion (b) With congestion

The two application which we can think of top of our head is that we can use this system to improve the performance of the soccer player by letting them know about their position and distance from other players in the field at any instant of time and secondly, this can be also helpful for improving the performance of sideline referee. The line referee is supposed to keep track of the last player on his side and should also stand behind him. This is done to keep track of off-side calls. If at any movement he is not doing his job correctly, with the help of this method, he can be notified at the end of the game. These are some of the application in which this method can be very useful.

5. Conclusion

In our work we have demonstrated a method to track soccer player using a single static video camera. The tracking algorithm used here is searching path in a graph and occlusion is treated by splitting the blobs. To distinguish players in each team we used intensity histogram to define color for them. The quality of image is important in our solution. When the player is farther, it is difficult to recognize. In our future work we would like to consider color histogram to obtain better result in color definition. The results were also not satisfactory when two players cross each other. Due to the lack of information, the method is not able to predict correctly about the position of each player in the single blob at each instant of time during occlusion. However, the obtained results show efficient tracking in the situations of short occlusion and congestion. These methods can be used to track all players during a whole game using multiple static cameras which cover the whole field. This would help the players to study and improve their positions in the entire game.

6. References

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