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Investigation into Tracking Football Players from Video Streams Produced by Cameras Set Up for TV Broadcasting

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ABSTRACT: *This paper describes a camera-based observation system for automatic analysis of football games. The algorithm runs on video streams produced by cameras set up for TV broadcasting. Our approach consisted of read video files, convert video files to frame, player detection using coupled object detection methods and training algorithms and tracking with Kalman filter. The result showed that the accuracy of player detection and tracking of the movies with low speed was more than high speed. Furthermore when the region of filed was nearly constant the accuracy of detection and tracking increased, because of training algorithm effects on detection. When the players run with constant speed, the accuracy of detection and tracking was very high. However Kalman filter coupled with training algorithm and object detection methods is efficient for detecting and tracking the football players very well.*

KEYWORDS: *Football game, Kalman filter, player detection, player tracking, training algorithm*

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I. INTRODUCTION

Motion detection and tracking of players estimates motion of players. Tracking of players from video is automatic method and it initializes player's position and corrects mistakes by observing position during tracking. Motion tracking of players is useful for broadcasters and sportsmen's at individual level of player so can improve quality of game. Coach can get information about team quality. Coach can give best development in game. Also coach can get hide movements of players due to the eyes through the camera. In broadcasting player's motion information can enhance using graphical analysis and movement can display on the screen to see for the viewers. Observation of movements of players is important to improve skill of player and team energy. Also it is useful to understanding the game. Tracking motions of players provide picturing of path in the game. Because of this the research is concentrating now a days to do analysis automatically or semi automatically using different data source like statistical data of game or manually labeling events of game. This task needs information of player movements. Motion trajectory data gives movement of players which is important in motion analysis. For many years analysis of motion of players have done by observation sheets. In 1980' video recording is developed for motion understanding. Motion analysis of players were done manually. It was time consuming and difficult task. Previous computer vision technology was slow due to computational abilities. But recently tracking process is growing to understand motion of players to do motion analysis of players. It is fast, time saving and easy technique to improve game for players. Moving object detection in computer vision involves identification of the presence of an object in consecutive frames where as it is used to monitor the movements with respect to the region of interest. Many technology and methods developed for player's motion trajectory [1]-[4].

The (semi-)automatic video analysis system of a soccer game typically comprises modules such as background/foreground segmentation, camera calibration and player detection. The acquisition is most commonly based on multiple fixed cameras around the stadium or sports hall, covering all the playfield [5]-[8]. With these topologies, the spatial segmentation task can be easily performed applying an approach based on background subtraction. On the other hand, simpler image acquisition architectures, such as with a single camera [4], [9] or using TV broadcasting sequences [10], [11] require more complex processing for the background/foreground segmentation, but also on the following stages, mainly on player detection and camera calibration. The most usual techniques for image segmentation range from background subtraction using a background model created from initial frames [8] to more complex dynamic model using a representation on a specific color space taking advantage of a dominant and homogeneous color field [5], [6], [10]. However, when background is neither static nor there is a dominant field color as in indoor sports, the basic methods presented above are not suitable for players' segmentation.

The relation between image coordinates and world coordinates is a fundamental task of the sports analysis problem, solved using the calibration of the camera with respect to the field. By knowing the camera parameters, it is possible to relate the position of the players in the image with their actual position on the field [5], [12]. When fixed cameras are used, this stage is trivially accomplished and can be performed manually; otherwise, when the camera moves, dynamic and automatic methods are required [13].

The detection of the players has been addressed with different techniques. Some of these methods rely on the extraction of features and posterior classification [9], [14]. However, if temporal tracking is not taken into account, false positives and missed detections are frequent. The dynamics of the players together with complex observation models are therefore also used to improve the detection and tracking of the players. In this sense, mean shift [15], Kalman Filters [16], and Particle Filters [17] are the most commonly adopted solutions. Therefore the goal of the presence study is to detect the players using coupled object detection methods, training algorithms and tracking with Kalman filter

II. FRAMEWORK OF PROPOSED SYSTEM

The proposed methodology, included of designed to automatically capture, process, and extract player and team performance statistics from some football video stream captured with an Uled Studio was used in this research. Only in the beginning of the processing, the system interactively queries the user to obtain initial information to support the automatic processing of the whole video. A block diagram of the main steps of the proposed methodology is presented in Fig. 1. The main stages of the framework are: read video files, convert video files to frame, player detection using coupled object detection methods and training algorithms and tracking with Kalman filter.

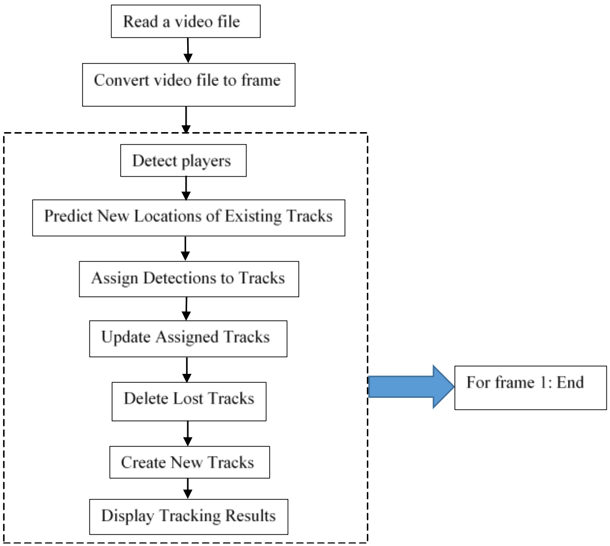


Fig. 1. Block diagram of the proposed methodology

The states of our player detection and tracking method are as bellow:

a) Create system objects used for reading video, detecting moving objects (players), and displaying the results.

b) Create System objects used for reading the video frames, detecting foreground objects (players and football field), and displaying results. Create a video file reader object. Create two video players, one to display the video, and one to display the foreground mask. Create system objects for foreground detection and blob analysis. The foreground detector is used to segment players from the background. It outputs a binary mask, where the pixel value of 1 corresponds to the foreground and the value of 0 corresponds to the background. Connected groups of foreground pixels are likely to correspond to players. The blob analysis system object is used to find such groups (called 'blobs' or 'connected components'), and compute their characteristics, such as area, centroid, and the bounding box.

c) Create an array of tracks, where each track is a structure representing a player in the video. The Kalman filter object used for motion-based tracking according to detected bounding box. The purpose of the structure is to maintain the state of a tracked object. The state consists of information used for detection to track assignment, track termination, and display. Noisy detections tend to result in short-lived tracks. For this reason, the program only displays a player after it was tracked for some number of frames. When no detections are associated with a track for several consecutive frames, the program assumes that the player has left the field of view and deletes the track. A track may also get deleted as noise if it was tracked for a short time, and marked invisible for most of the frames.

d) The color components (R, G and B) of each frame are extracted and using the G-color component, the football field is detected according to below code as illustrated in Fig. 2.

```
G=frame(:,:,2);
R=frame(:,:,1);
B=frame(:,:,3);
G= imadjust(G);
bwG=im2bw(G,graythresh(G));
bwG = imopen(bwG,
strel('rectangle', [30,30]));
bwG = imclose(bwG,
strel('rectangle',
[80,80]));
bwG = imfill(bwG,
'holes');
G1=immultiply(G,bwG);
R1=immultiply(R,bwG);
B1=immultiply(B,bwG);
fr=cat(3,R1,G1,B1);
```

Fig. 2. Detection the football field using G-color component

The detected field is then used to determine the moving players to return the centroids and the bounding boxes of the detected objects. It also returns the binary mask, which has the same size as the input frame. Pixels with a value of 1 correspond to the foreground, and pixels with a value of 0 correspond to the background. The program performs motion segmentation using the foreground detector. It then performs morphological operations on the resulting binary mask to remove noisy pixels and to fill the holes in the remaining blobs to find connected components as below code:

```
1- mask = obj.detector.step(fr);
2- mask = imopen(mask,strel('rectangle',[3,3]));
3- mask = imclose(mask,strel('rectangle',[10,10]));
4- mask = imfill(mask,'holes');
5- bw3=double(mask);
6- bw4=mask-bwareaopen(bw3,700);
7- mask=logical(bw4);
8- [~, centroids, bboxes] = obj.blobAnalyser.step(mask);
```

e) The Kalman filter is used to predict the centroid of each track in the current frame, and update its bounding box accordingly.TheKalman filter predicts the current location of the track and shifts the bounding box so that its center is at the predicted location.

f) Assigning player detections in the current frame to existing tracks is done by minimizing cost. The cost is defined as the negative log-likelihood of a detection corresponding to a track. The algorithm involves two steps; Step 1: Compute the cost of assigning every detection to each track using the distance method of the players detected by Kalman filter. The cost takes into account the Euclidean distance between the predicted centroid of the track and the centroid of the detection. It also includes the confidence of the prediction, which is maintained by the Kalman filter. The results are stored in an M×N matrix, where M is the number of tracks, and N is the number of detections. Step 2: Solve the assignment problem represented by the cost matrix using the “assignDetectionsToTracks” function. The function takes the cost matrix and the cost of not assigning any detections to a track. The value for the cost of not assigning a detection to a track depends on the range of values returned by the distance method of the objects detected by Kalmanfilter. This value must be tuned experimentally. Setting it too low increases the likelihood of creating a new track, and may result in track fragmentation. Setting it too high may result in a single track corresponding to a series of separate players. The “assignDetectionsToTracks” function uses the “Munkres” version of the Hungarian algorithm to compute an assignment which minimizes the total cost. It returns an M x 2 matrix containing the corresponding indices of assigned tracks and detections in its two columns. It also returns the indices of tracks and detections that remained unassigned.

g) The program updates each assigned track with the corresponding detection. It calls the “correct” method of Kalman filter to correct the location estimate. Next, it stores the new bounding box, and increases the age of the track and the total visible count by 1. Finally, the function sets the invisible count to 0.

h) The program deletes tracks that have been invisible for too many consecutive frames. It also deletes recently created tracks that have been invisible for too many frames overall.

i) Create new tracks from unassigned detections. Assume that any unassigned detection is a start of a new track. In practice, you can use other cues to eliminate noisy detections, such as size, location, or appearance.

j) The program draws a bounding box and label ID for each track on the video frame and the foreground mask. It then displays the frame and the mask in their respective video players.

This states created a motion-based system for detecting and tracking multiple moving players. In the following, we try using a different video clip of football games in deferent country with different field qualities, game speed, and camera systems to determine the program accuracy for analyzing the football game. We can modify the parameters for the detection, assignment, and deletion steps. The tracking in this research was solely based on motion with the assumption that all players move in a straight line with constant speed. When the motion of a player significantly deviates from this model, the program may produce tracking errors. The likelihood of tracking errors can be reduced by using a more complex motion model, such as constant acceleration, or by using multiple Kalman filters for every object. Also, you can incorporate other cues for associating detections over time, such as size, shape, and color.

III. RESULTS AND CONCLUSION

The algorithm tested with real and various data under static and dynamic environment. Implementation and motion estimation analysis is done and tested byMatlab software. Simulation is done in Matlab to give simulation of system. Motion estimation is done by calculating Euclidean distance between the predicted centroid of the track and the centroid of the previous detection using Kalman filter. The accuracy of our algorithm was tested by considering the program for games of Persepolis-ZobeAhan, Barcelona-Real Madrid, and ParisanGermain-Monaco (Fig. 3). The videos downloaded have different resolution and were acquired at different frames per second (fps). The sequences obtained have a duration between 10 seconds to 1 minute, and were selected with different situations, occasion, field color and so on to determine the algorithm suitability for different situation.

ParisanGermain-Monaco Barcelona-Real Madrid Persepolis-ZobeAhan

Fig. 3. The football games analyzed with our algorithm

3.1. Analysis of Barcelona-Real Madrid Football Game

The video streams weredownloaded from internet (90/ir) and after capturing, some parts of themwere cut and analyzed with our program. The 20 second captured clip was converted to 555 frame (25.5fps). The analysis of video streamwith our program showed that by increasing the frame numbers, the accuracy of our program to detect and track the players was increased. The detection and tracking was started at frame 10, then the detected players was increased as in frame 70, 8 players of 9 players was detected (Fig. 4).It was explained that the early frames until 100th frame were used to train the algorithm for true detecting the players and after that the program was justly using to detect and track the players without self-training, therefore by differing the region of game field, some miss detection were happen.As it is illustrated in Fig. 4, the field region was not differed and the accuracy of detection and tracking was increased. This was more verified among the frame 70-170 in Figs. 4 and 5. The field lines were caused some miss detections (Fig. 5, Frame 278), which increased false positive detections. In frames 360-380, there were not field lines in camera view and the accuracy of detection and tracking was increased.When the players moved acceleratory toward a goal, the region of filed differed and the accuracy of detection decreased (Fig. 5, Frame 429), furthermore after the players moved acceleratory, the tracking accuracy was decreased too, because we assume constant velocity for Kalman filter to track the players. In frame 518, the players had lateral movements and the filed region was constant, therefore the accuracy was increased, again. These processes were repeatedly happened during the clip. As it is illustrated in Figs. 4 and 5, the training frames of Barcelona-Real Madrid football game were captured from middle of football field, therefore the accuracy of detection and tracking the players in the middle of field was better than corners of field.

Frame 1

Frame 10

Frame 70

Fig. 4. Increasing accuracy of the player detection and tracking by increasing the movie frames until 100th frame in Barcelona-Real Madrid game

Frame 170

Frame 278

Frame 429

Frame 518

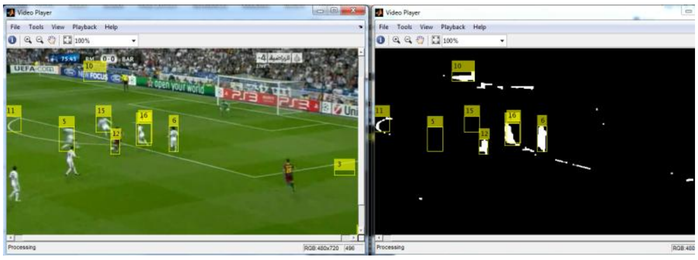


Fig. 5. Detection and tracking the players after frame of 100in Barcelona-Real Madrid game

3.2. Analysis of ParisanGermain-Monaco Football Game

Ten (s) captured video streamofParisanGermain-Monaco football game was converted to 250 frame (25 fps). As it is illustrated in Fig. 6, the quality of filed and field color of this game was different from Barcelona-Real Madrid football game, furthermore distance of audience and field was different. With increasing frame number until frame 100 the accuracy increased. The analysis of video streams of ParisanGermain-Monaco and Barcelona-Real Madrid games showed that in the filed which its color was very different with its edge, the accuracy of detection and tracking was increased. The detection and tracking was started at frame 10, then the detected players was increased as in frame 39, all players was detected and tracked (Fig. 6). As it is shown in Figs. 6 and 7 the accuracy of detection and tracking increased until the frame number reach to 100^{th} frame then by changing the camera the detection was lost and the bounding box just showed some estimating players with Kalman filter which in the following these estimation was lost, too.

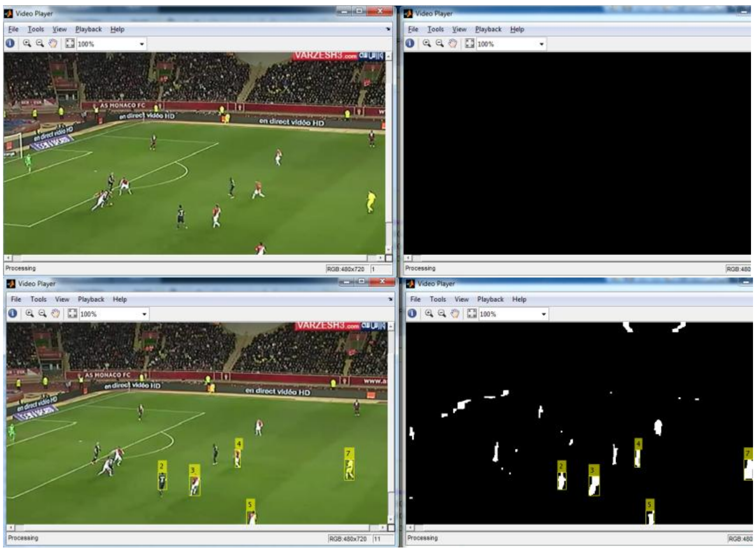
The best detection and tracking in this video stream was acquire in the frames of 39-70. The accuracy in this frame was 100%, although some false positive detection existed. The effect of field lines on miss detection in this game was lower than Barcelona-Real Madrid football game. When the players moved acceleratory toward a goal, the region of filed differed and the accuracy of detection decreased (Fig. 7, Frame 108-158), because of its players acceleration which was not assumed for Kalman filter. These processes were done for all frame.

3.3. Analysis of Persepolis-ZobeAhanFootball Game

Its video stream was downloaded, captured, and cut for analyzing with our program. The 10 second captured clip was converted to 190 frame (19fps). The analysis of clip with our program showed that by increasing the frame numbers, the accuracy of our program was increased similar to previous analyses. The detection and tracking was started at frame 27, then the detected players was increased as in frame 51, 7 players of 8 players was detected (87.5%) illustrated in Fig. 8.

Frame 1

Frame 10



Frame 39

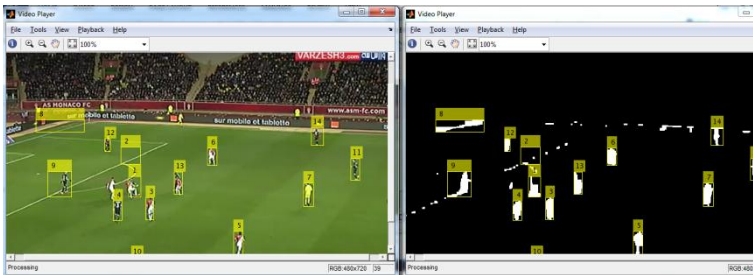


Fig. 6. Increasing accuracy of the player detection and tracking by increasing the movie frames in ParisanGermain-Monaco game

Frame 70

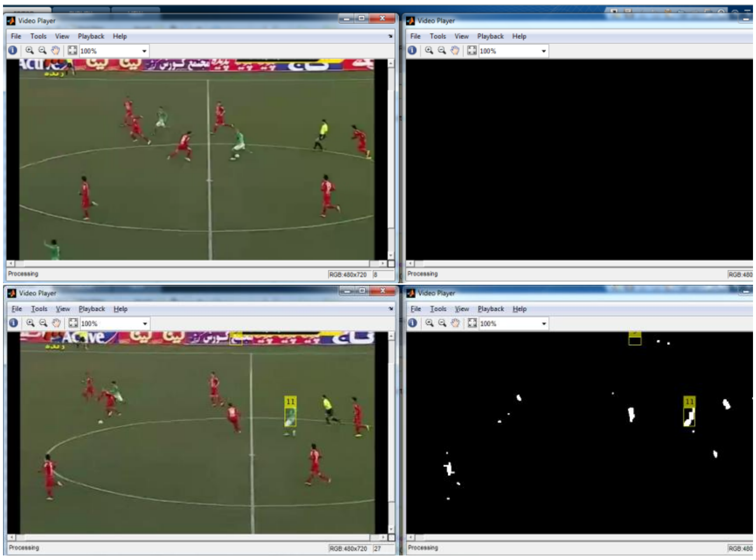
Frame 101

Frame 158

Fig. 7. Detection and tracking the players after frame of 39in ParisanGermain-Monaco game

Frame 1

Frame 27



Frame 51

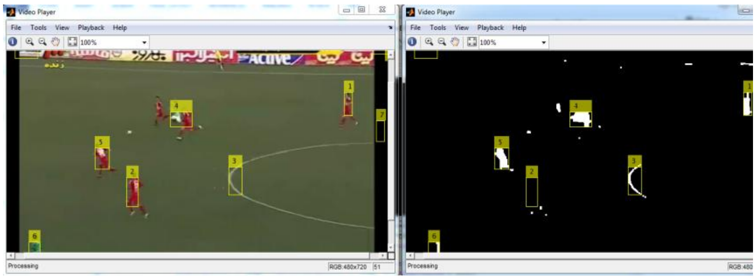


Fig. 8. Increasing accuracy of the player detection and tracking after increasing the movie frames in Persepolis-ZobeAhan game

Although the players were acceleratory moved toward a goal, the accuracy of detection and tracking of frame 51-150 was very high because of low speed of movie. The frame per second of this clip was lower than other clip, which approve the movie speed was lower than the others. This caused to increase the accuracy of detection and tracking, however the quality of cameras was lower. On the other hand the close up of cameras used in Persepolis-ZobeAhan football game was smaller than the other games.

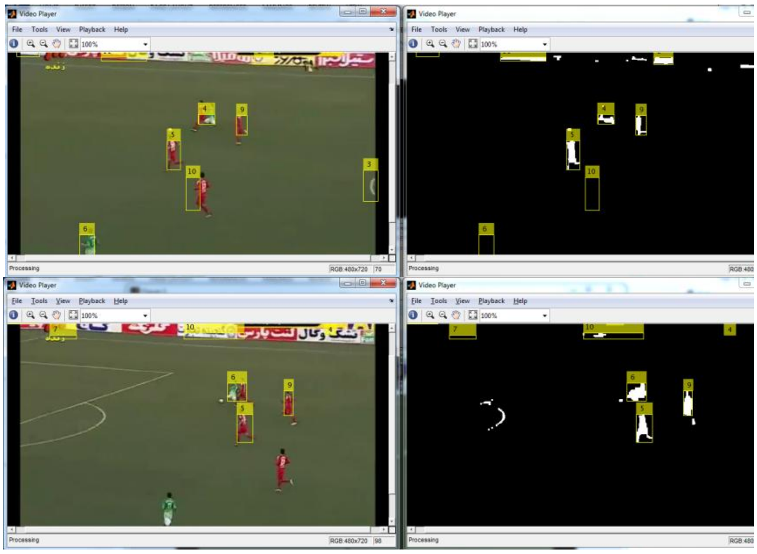
As it is illustrated in Fig. 9, by differing the region of game field, some miss detections were happen, but they were lower than the other researched video streams. This was more verified among the frame 51-136 in Figs. 8 and 9. The field lines were caused some miss detections (Fig. 8, Frame 51; Fig. 9, Frames 136 and 170), which increased false positive detections, especially in frame 170.

As it is shown in the Figs. 4-9, some different problems need to be solving while tracking players such as occlusion between player, size of players in pixels and players shape and colors. However Kalman filter coupled with training algorithm is efficient for this solution in visual tracking. It handles uncertainty and provides better result in complex background. It increases robustness and accuracy.

A number of observation systems for football games and sport games have been developed, most of them in the sport sciences and some of them even commercially. Those systems are typically characterized by their requirements for extensive manual data entry by operators. Intille and Bobick [17], [18] have developed a seminal visual observation system for American Football and their results were close to ours. Differences are caused by the different natures of the game. American football is structured into modular, preplanned plays with failed actions (interceptions and turnovers) being exceptions, players having very specific roles in plays, and the ball being held most of the time. In the real football these characteristics are not met and complicate the visual observation drastically. Another difference is our emphasis on accurate estimation of player positions using Kalman filter which is the key for the recognition of game situations such as scoring opportunities, players being under pressure, passing opportunities, etc.The research work in computer vision that is applicable to game observation is too big to be discussed in detail.

Frame 70

Frame 98



Frame 136

Frame 170

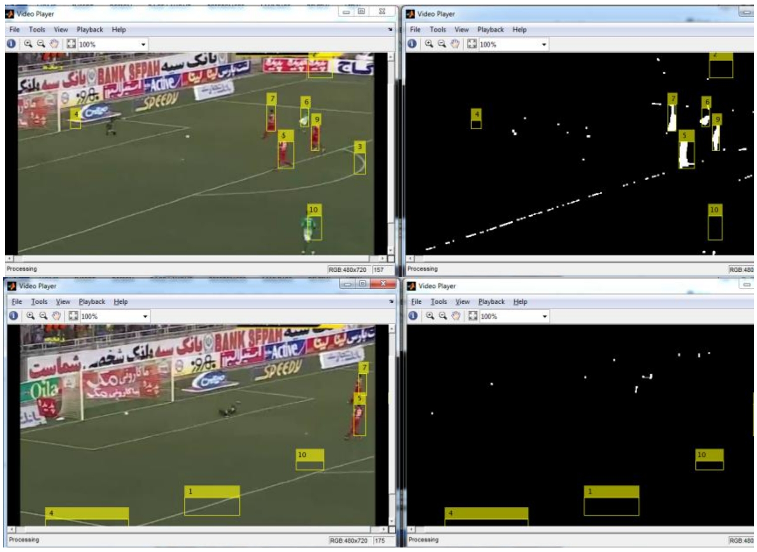


Fig. 9. Detection and tracking the players after frame of 51in Persepolis-ZobeAhan game

IV. CONCLUSIONS

In this research we presented a new approach to automatically analyze a football game, yielding valuable information about individual and collective performance. Motion analysis of sport players is now a demanding concept for study and understands improvement in game in which movement of players is estimated by using coupled training algorithm and Kalman filter. It handles uncertainty and provides better result in complex background.This is robust and effective tracking method for players.

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