Ball Localization and Player Tracking using Real Time Object Detection

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***Abstract* — In a fast-moving game like football, real time tracking is a challenging task. Although there are many CNN models for object detection and tracking, real time ball localization and player tracking, in a fast moving sequence such as football is associated with many bottlenecks. Specially in this type of application, the object of interest can be associated with diverse background scenarios at different time instances. For instance, the ball may be in the football pitch freely passing from player to player at one time frame, whereas it can be dribbling by a single player through the pitch in another time instance, or it may be inside the goalpost, or it may even be out of the pitch. Therefore, a single CNN model is not sufficient for the ball localization in this type of sporting event. Hence, in this research, several CNN models are trained and combined to get the best results of ball localization, which includes player tracking using customized deep SORT algorithm.**

Keywords — Ball Localization, Player Tracking, CNN, Deep SORT

I. Introduction

Football (soccer) is a fast-moving game, which is highly popular in Europe, backed by significant financial investments and a huge fan base. With the modern advancements in video technology, the football clubs, managers, coaches and broadcasters alike have taken steps to merge the technology with the football game to improve the player performance and the return revenues of the game. One of emerging domains of video technology research in football, is the player tracking and ball tracking [1],[2].

When extracting information from a football game video, it is a very important to localize the ball, because most of the information depends on the coordinates of the ball. In this research, the coordinates of the ball with respect to the video frame is identified and a player tracking method is utilized to re-initiate the ball tracking, when it disappears from the observed video frame. For this purpose, YOLO [3] and Deep Sort Algorithm [4] are employed as the backbone architectures, specifically for real time object detection and for player tracking respectively. Furthermore, several models generated using these two architectures are combined using conditional algorithm to generate a more accurate final output, i.e. ball tracking.

II. Objetives

The main objective of the research presented is to design an automated architecture to track and locate, the ball. In addition, the ball localization is improved using player tracking results. We focus only on these two features, as they are the key features of the game and they assist the stakeholders to analyses as well as to summaries the football game efficiently.

III. Methodology

The key outputs of the research revolve around the ball location. Hence, we have treated ball localization as our main task. To identify the ball in different occasions, several approaches are adopted, namely; Ball Localization when it is freely on the football pitch, Ball Localization when it is in the Goal Post, and Ball Localization when the ball is handled by a player.

Ball Localization when it is freely on the football pitch

This is the main module of our algorithm. When the ball is freely moving on the pitch, the ball is in a light green grass background. We have generated a custom database, with this particular background setting (i.e. when the ball is on a greenish grass backgrounds in Fig. 1) to train the main module.

Fig. 1. Annotating asample image in the database

It is noticed that at the 1st step of the training the moving average loss is about 104 while the learning rate is 0.00001. At the 14000 step the moving average loss is at 0.5. Immediately, the training is stopped, to avoid overfitting. The trained model is validated, by observing the performance at different number of steps. Further, step count of 10000 is selected as the optimal step count and the objects with precision level higher than 50% is selected as the ball candidates.

Ball Localization when it is in the Goal Post

A goal, one of the critical events in football is defined as the event when the ball crosses the goal posts. To assist the identification of this specific scenario, the goalpost is first localized and, then the ball is searched inside the goalpost contour to detect whether it has crossed the goalpost. Unlike the ball, the goalpost has special characteristics, such as the net with checkerboard pattern, and rectangle border of the post. Hence, the goalpost can be easily detected even without considering the color analysis. Therefore, to reduce the computational cost of the analysis, as a preprocessing step, thresholding is used to generate binary image as in Fig. 2. A new dataset is created using the preprocessed binary images, and another CNN model is trained for the goalpost detection task. It should note that the CNN models adopted in this research at each stage have different layered architectures. Yet, they are trained in a similar manner as explained earlier. At the testing stage, images with detection precision level higher than 60% are selected as the goalpost candidates.

The next step is to identify the coordinates of the ball in reference to the localized goalpost. For this purpose, the goalpost location is marked in the original frame, and a new YOLO model is trained to identify whether the ball has gone inside the goalpost, at each time instance. Fig. 3 presents a sample image of the annotated dataset used for goal detection.

Fig. 2. Thresholded, binary image for Localized Goalpost

Fig. 3. Annotated image with the ball inside the goalpost

Player Tracking

The player tracking is used in the proposed system, mainly to analyze the player moments and the behavior around the ball's trajectory. Also, the player movement is used to assist the ball tracking in scenarios where the model presented earlier fails to detect the ball position. When the earlier system fails to detect the ball, the nearest neighboring player to the last location of the ball is discovered. Thereafter, the particular player's track is used as the temporary track of the ballwith the assumption that ball is with this particular player. The architecture of the tracking algorithm is developed using the DEEPSORT algorithm. Since the DEEPSORT uses linear algorithms: Kalman and Hungarian algorithms to track the player path, the non-linear behavior of the player will cause disruption in individual player tracking. In the proposed system, two methods are implemented to address this problem. They are,

1. Track the two teams separately: When players are involved in one-on-one defending proximity of the two players are very narrow. Hence, there is a high probability for individual tracking ID to be falsely changed between the two players when they cross over. This can be reduced by following two detection sets separately for each team based on jersey colour of individual team.

2. Analysis of tracking ID: Due to the random movement of the players and the change of the camera angle, system may mistakenly detect the same player as two different players in neighbouring time instances. To overcome this issue, the characteristics of each track and its ID are monitored and once similarity level between two adjacent IDs increase, they are linked together using tracking interruption commands.

Using, above fine-tuning methods, the proposed player tracking method is optimized. Further, the player tracking is used to assist the ball tracking when the system fails to detect the ball, as follows.

1. The Euclidian distance of each player to the ball is estimated and stored along with the player tracking ID when the ball disappears from the tracking system.

2. The Euclidian distance of each player to the ball is estimated and stored along with the player tracking ID when the ball re-appears.

3. Select the trajectory of the player with the smallest average Euclidian distance in the above two cases as the best trajectory of the ball during the missing interval.

The overall structure of the proposed algorithm for ball localization and tracking is presented in Fig. 4.

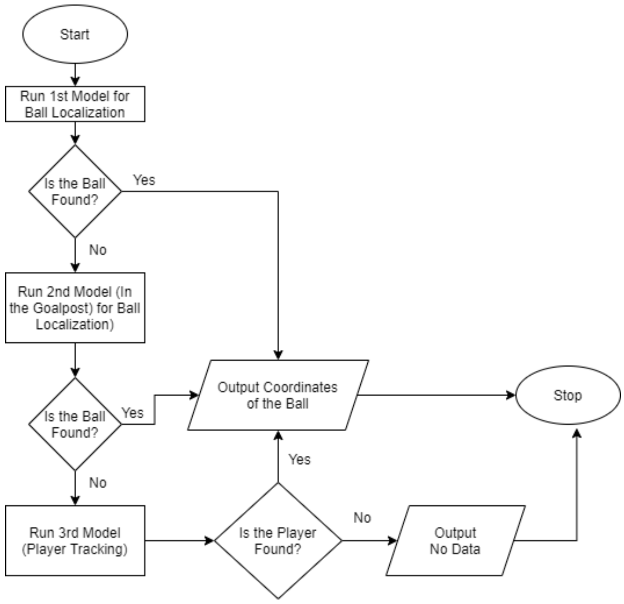

Fig. 4. Proposed Ball Tracking and Localisation Algorithm

IV. RESULTS AND DISCUSSION

As presented in Fig. 5, the developed ball tracking model is able to successfully locate and track the ball with 80% accuracy. Yet, in this model, the tracking becomes challenging when the ball is shadowed by players. The output of the goalpost localization algorithm is presented in Fig 6. In average the model is able to detect the goalpost with 95% accuracy. Fig. 7 presents the goal detection through ball and goalpost location identification. When searching the ball inside the goalpost, the optimal number of step size is selected as 7500 steps while the threshold value is lowered to 0.4 and only the contour which has the highest accuracy is selected as the final trajectory of the ball. Furthermore, the trained model performed with 65% of accuracy. If the system is unable to locate the ball using above 2 algorithms, then the player tracking algorithm is initiated. The tracking of players of each team separately is presented in Fig. 8 along with ball positioning in color yellow. Furthermore, it illustrates a time instance just before the ball localization failed.

Fig. 5. Results of ball Identificaton, when it is on the football pitch

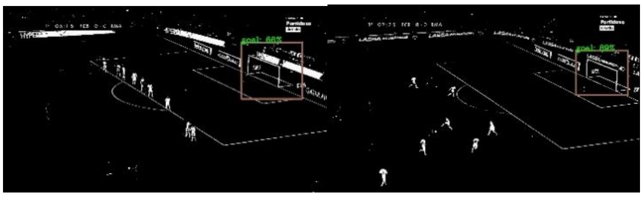

Fig. 6. Results of Goalpost Localization

Fig. 7. Results of ball Identification, inside the goalpost

Fig. 8. Player tracking of team with Red and White Jerseys

Fig. 9. Ball tracking using player movements

Since the ball is closer to the payer 1 in Red team (using information before and after the ball disapearence), the location of the ball is tracked using the player 1's location of the Red team as in Fig 9. Note that in Fig 9 it is hard to get a clear picture of the ball as it is shadowed by the player movements. A summary of the performance of each individual sub-module in our propsed system is tabulated in Table 1.

Table 1. Performance of each sub module in the proposed system.

Model	Accuracy
Ball Localization when it is freely on the football pitch	80%
Goal Post Localization	95%
Ball Localization when it is in the Goal Post	65%
Player Tracking	undefined

V. Conclusion

In our research, the ball localization is successfully carried out using several sub modules to overcome the limitation of using one fixed model. Hence, we present an optimized ensemble algorithm for effective and efficient ball tracking. The main module in our proposed design localizes the ball, when it is freely moving on the football pitch with a higher accuracy. If the main module fails to obtain a positive track, the algorithm searches for the prominent nearest object (player or goalpost) in the current frame. If the nearest object is the goalpost, our algorithm searches the ball inside the goalpost. If the nearest object is a player, our algorithm tracks the nearest player to the ball before and after the ball tracking algorithm failed and reinitiate the process with the assumption that ball is shadowed by the player. Therefore, our research addresses the ball localization, when it is not even possible to identify the object of interest through the visual inspection by a human observer.

References

[1] Speck, D., Barros, P., Weber, C., & Wermter, S. (2017). “Ball Localization for Robocup Soccer Using Convolutional Neural Networks,” *Lecture Notes in Computer Science,* 19–30,doi: 10.1007/978-3-319-68792-6_2

[2] Barry, D., Shah, M., Keijsers, M., Khan, H., & Hopman, B. (2019). “xYOLO: A Model For Real-Time Object Detection In Humanoid Soccer On Low-End Hardware,” *2019 International Conference on Image and Vision Computing New Zealand (IVCNZ)*,Dunedin, New Zealand, 2019, pp. 1-6, doi: 10.1109/IVCNZ48456.2019.8960963

[3] J. Redmon, S. Divvala, R. Girshick and A. Farhadi, "You Only Look Once: Unified, Real-Time Object Detection," 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, 2016, pp. 779-788, doi: 10.1109/CVPR.2016.91.

[4] N. Wojke, A. Bewley and D. Paulus, "Simple online and realtime tracking with a deep association metric," *2017 IEEE International Conference on Image Processing (ICIP)*, Beijing, 2017, pp. 3645-3649, doi: 10.1109/ICIP.2017.8296962.

[5] TONG, X., WANG, T., LI, W., & ZHANG, Y. (2010). “A NOVEL ALGORITHM FOR EFFECTIVE BALL TRACKING,” *International Journal of Pattern Recognition and Artificial Intelligence, 24(03), 359–379.* doi: 10.1142/S0218001410007993

[6] Lu, Chun-Wei & Lin, Chih-Yang & Hsu, Chao-Yong & Weng, Ming-Fang & Kang, Li-Wei & Liao, Hong-yuan. (2013). “Identification and tracking of players in sport videos”. *ACM International Conference Proceeding Series*. 113-116. doi: 10.1145/2499788.2499842.

[7] Maryam Babaee, Zimu Li, Gerhard Rigoll,“A dual CNN–RNN for multiple people tracking”,*Neurocomputing*,Volume 368,2019,Pages 69-83,ISSN 0925-2312, doi: 10.1016/j.neucom.2019.08.008.