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Estimation of Court Boundary and Showing of Player Trajectory using a Broadcast Handball Game Video

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Abstract

This study proposes a method for estimating court boundary for player tracking and showing of player trajectory for visualization in a broadcast handball video. The video captured by a camera shows approximately one-third of the court, and shifts from left to right to follow the players. Therefore, the camera direction is estimated for the player trajectory with a taken goal object position in the video, and the goal object is detected with the object detection algorithm YOLOv5. The court boundary is estimated in two ways: one is by using the goal object detection result, and the other is by using a feature of a red painted area on the court. The player is detected and classified to own team by YOLOv5 and uniform color, and its trajectory is shown on a top view of the court. We experimented with three videos to confirm the accuracy of the two proposed methods of the court boundary estimation. The results indicates that the estimation rates of the two methods were 59.2 % and 73.8 %, respectively.

Keywords: Computer Vision, Handball, Sports Analysis, Court Boundary Estimation, Player Trajectory Showing

1 Introduction

In ball sports, game analysis is a crucial role in defeating opponents, and its result of the analysis is utilized for pre-game meetings as well as adjusting strategies during the game. One method of analyzing a match is tagging which links an action of a player to the time. There are commercially available applications for tagging analysis, Data Volley [1] designed specifically for volleyball, and SPLYZA Teams [2] which allows an analyst to create customized tags. Although these tagging analysis applications capture the timing and location of the actions such as shots or passes on the court, they are not designed to record the player trajectory. Manually recording the player trajectory requires watching and recording the entire match video, which can be a burdensome task.

For basketball, there have been proposed methods for tracking players using ceiling-mounted cameras [3], as well as methods for capturing a player trajectory through the use of multiple cameras taken from different angles [4] [5]. Similarly, in handball, a method has been proposed for acquiring the player trajectory with multiple cameras [6]. However,

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these methods are limited by location of camera and cannot collect some match videos, and these methods cannot be used by the match video archived for broadcast that is shot with a single camera. Therefore, we focus on the method of analyzing the match video for broadcasting taken by the single camera.

A method for the analyzing the broadcast video of goal-based sports is introduced by Nie *et al.*, and it is for extracting the player trajectory with court boundary estimation [7]. This method relied on a deep learning technique, and high versatility as it can potentially estimate the court boundary by increasing the training data, even when there are lines of different colors on the court. One drawback of the deep learning technique is that its underlying learning model is not clear for solution of an issue, and making it challenging to pinpoint the cause of incorrect estimations. In other words, it remains unclear what type of data could enhance estimation accuracy. On the contrary, a rule-based technique is less flexible compared to the deep learning techniques however they offer transparency in the estimation process, that can contribute identification of the factors to misestimation. The rule-based technique can also be employed for the characteristic that have not been solved, by adding rules specific to other court characteristic. Therefore, in this study, we have employed for the rule-based technique.

This study proposes to estimate the court boundary for player tracking, and to show the player trajectory for visualization with the rule-base technique. The court boundary is estimated by goal line and sideline with the camera direction and a goal object position in the broadcast video. The player is classified to own team by uniform color information. The Section 2 provides a detailed explanation of the proposed method, and the Section 3 indicates evaluation its effectiveness. Finally, we conclude this paper, and the future works are written.

2 Proposed Method

2.1 Overview of the Proposed Method

The broadcasting handball game video is captured in a manner that shows approximately one-third of the court as shown in Fig. 1. The camera direction changes from left to right whenever there is a transition between offensive and defensive. The apparent inclination of the goal line and sideline are used by estimating of the court boundary along with the camera direction. Each team of the players is classified by the color of their uniforms after the court boundary is estimated. The trajectory of the classified player is shown for visualization.

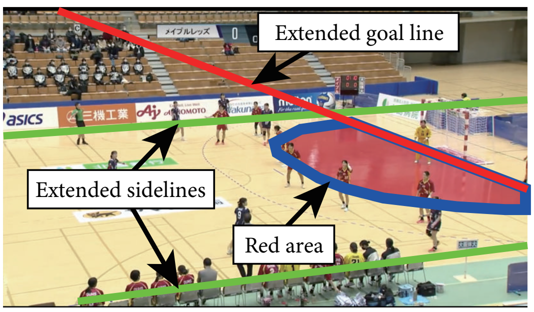


Figure 1: Extended goal line/side lines, and red area in broadcast handball video

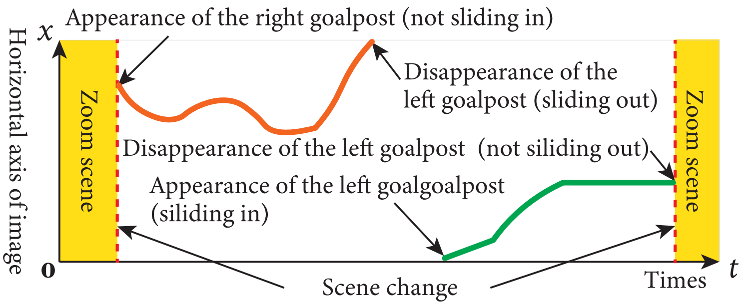


Figure 2: Schematic diagram of the change in coordinates of the goal object over time

2.2 Camera Direction Determination

The goal object may appear from the edge of the screen (slide-in) or disappear to the edge of the screen (slide-out) when the camera direction changes from left to right in the broadcast handball game video. Therefore, the camera direction is determined by the position of the goal object during slide-in/out states. The goal object is detected by YOLOv5 [8].

Fig. 2 illustrates a schematic diagram of the temporal change in coordinates of the detected goal object. The horizontal axis represents time t, and the vertical axis represents the horizontal axis x in the video frame. The figure shows the variation in x-coordinates of the center in the bounding box of the detected gaol object over time. The orange and green graph lines indicate the coordinates of the goal object on the right and left sides of the court, respectively. The camera direction is right if the slide-in/out occurs at the right edge of the screen (upper edge of Fig. 2). Conversely, the left case that it is occurs at the left edge of the screen (bottom edge of Fig. 2).

2.3 Court Boundary Estimation

The court boundary is constructed with the goal line and sideline, and we estimate the court boundary based on the extensions of both lines. We propose a method to estimate the extended goal line in Section 2.3.1, and propose two methods to estimate the extended sideline: (1) utilizing the bounding box of the goal object in Section 2.3.2 , and (2) utilizing the red area printed on the court in front of the right goal in Section 2.3.3.

2.3.1 Extended Goal Line Estimation

All line segments are detected using a probabilistic Hough transform at frame n where the camera direction has already been determined in Section 2.2. The number of line segments is counted when these extensions intersect the bounding box of the goal object (the specified range in Fig. 3). The coordinates of both ends (white points in Fig. 3) are calculated after detecting the line segments. Subsequently, a correlation coefficient is calculated between the x and y coordinates of the both ends of line segments in the video. We estimate the extended goal line that is an approximate straight line formed by the coordinates of both ends of the line segment if the calculated correlation coefficient is greater than T_1 or less than $-T_1$.

2.3.2 Extended Sideline Estimation using Goal Object

We describe a method for estimating extended sideline using the estimated extended goal line and the bounding box of the goal object. Firstly, the midpoint of the extended goal line (referred to as the lower goal line) as shown in Fig. 4(a). The θ_1 indicates the angle between

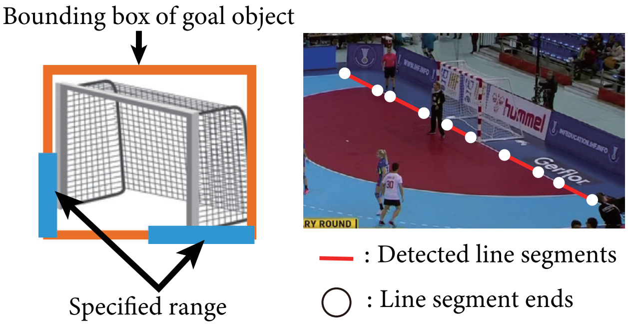


Figure 3: Specified range of bounding box and line segment's both ends

the extended goal line and the horizontal line to the x-axis, and θ_2 is between the extended goal line and the detected straight line. The i-th straight line of the frame is defined as the green line if $\theta_{2,i}$ satisfies $\theta_{2,i} = \theta_1 + T_2$. The distance d_1 is from the orange point to the midpoint point. The green line is defined as the extended sideline estimated in the upper part of frame n if d_1 is more than T_3 times the lower goal line.

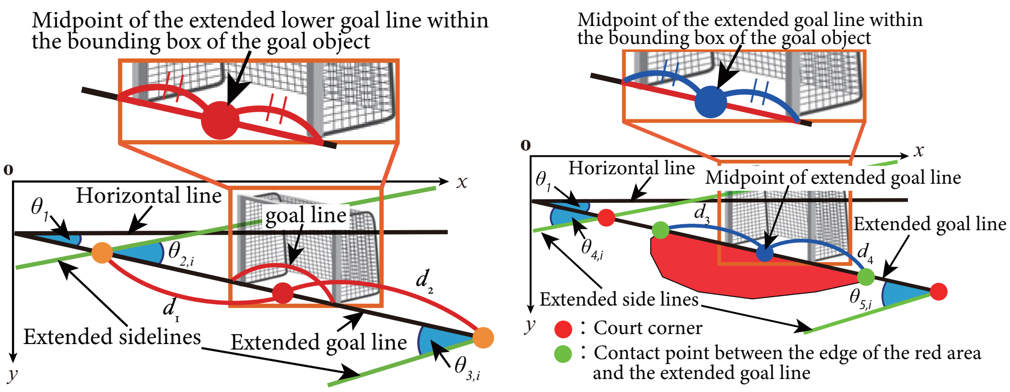
Next, the angle θ_3 is calculated, and the green line is extracted if satisfies $\theta_{2,i} < \theta_{3,i}$. A distance d_2 from the orange points to the midpoint point. The detected straight line is defined as the extended sideline estimated in the bottom of frame n if d_2 is more than d_1.

Once the two extended sideline is estimated, and the intersection point is utilized as the corner of the court that the extended goal line and the two extended sidelines. These intersection points serve as the basis for estimating the court boundary of the handball.

2.3.3 *Extended Sideline Estimation using Red Area*

We describe a method for estimating extended sideline using the estimated extended goal line and a red area printed on the court. Firstly, goal line passes through the bounding box of the detected goal object, and the midpoint of the extended is calculated as shown in the upper part of Fig. 4(b). Additionally, a contact point on the extended goal line with the edge of the red area is determined, and the distances between the midpoint and the green point are calculated by d_3 and d_4. The red points are the corners of the court that d_3 and d_4 multiplied by T_4.

Straight lines are detected if the angle θ_5 satisfies $\theta_{4,i} > \theta_1 + T_4$, or the angle $\theta_{5,i}$ satisfies $\theta_{4,i} < \theta_{5,i}$. The green line is estimated as upper and lower extended sideline of frame n, and a crossing with the extended goalline is closest to a corner of the court in the detected



(a) Method using bounding box (b) Method using Red Area

Figure 4: Schematic of extended sideline estimation

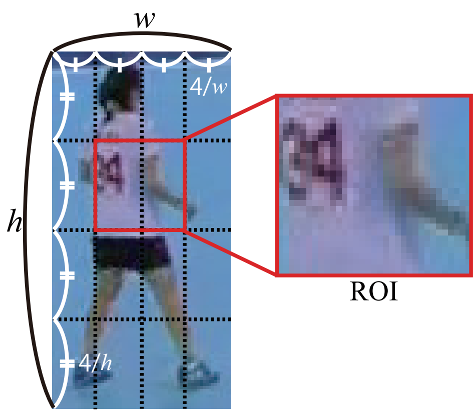


Figure 5: Player ROI

straight line. The intersections of the extended goal line with the two extended sidelines are defined as the corners of the court, as described in the Section 2.3.2. Finally, the court boundary of the handball court are determined by finding the intersections of the extended goal line with the two extended sidelines.

2.4 Team Classification of Players

We describe a method to obtain the representative colors that serve as the basis for team classification. A red rectangle in Fig. 5 is extracted as the player ROI that the h and w of the player bounding box are each divided into four parts after person detection using YOLOv5. Since the extracted ROI is in a RGB color system, and is not in the Cartesian coordinate system. Therefore, the distance intervals between colors are different. They are converted to a L*u*v* color system from the RGB one. The distance intervals between colors are equal, and the the pixel values in L*u*v* system is clustered by the k-means method.

The color information of each cluster by the k-means method is obtained as the representative color for each team. The clusters of representative colors are compared with all the pixels in the ROI, and the cluster with the smallest sum of distances is used to determine the team with cluster color.

2.5 Player Trajectory Showing

We show the player trajectory using the court boundary estimated in Section 2.3, and the player teams are determined in Section 2.4. The estimated court boundary is transformed into a top view by a projective transformation. The person in Fig. 6 is detected and tracked using DeepSort [9]. The upper left coordinate (x, y) is obtained with width w and h, the foot coordinate of the player j shown in Fig. 6 is calculated. Since the tracked persons include bench players and spectators, and the players are identified based on the criterion that their foot coordinates fall within the court boundary.

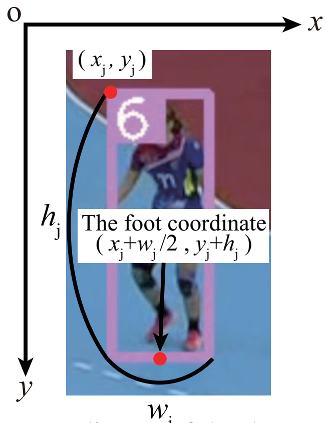


Figure 6: The coordinates of the detected players' feet

Table 1: Result of judging the camera direction

Games	Total frames	Positive (%)	Negative (%)
1	216	212 (99.1)	4 (0.9)
2	159	154 (96.9)	5 (3.1)
3	151	147 (97.3)	4 (2.7)
Total	526	513 (97.5)	13 (2.5)

3 Experiment and Discussion

3.1 Result of Camera Direction

In this Section, we conducted an evaluation experiment using the proposed method on three broadcast handball game videos each of them in game 1–3 [1,2,3].

The camera direction was considered to be correctly identified when the camera direction of the proposed method coincides with that of the visual check. The camera direction is incorrectly identified when they were different. The results of the camera direction experiment are shown in Tbl. 1. The correct decision rates were 99.1% for game 1, 96.9% for game 2, and 97.3% for game 3. In addition, a case of misjudgment was observed where there was no slide-in/out of the goal object as shown in Fig. 7. A future method is considered to determine the camera direction using time-series data, such as the camera direction in the before and after images in this case.

3.2 Result of Court Boundary Estimation

We describe the court boundary estimation results. The parameters are T_1=0.999, $5 \leqq T_2 \leqq 7$, T_3=1.5, and T_4=4 which gave the highest estimation accuracy in game 1. The court boundary was correctly identified when it aligned with the goal line and sidelines, and was incorrectly identified when they were different.

The results of the experiment are shown in Tbl. 2, where the method 1 is the court estimation method using the bounding box of the goal object, and the method 2 is the court

[1] Women's World Championship 2019 Russia vs. China

[2] 72nd Japan Handball Championship (Women's Division) Maple Reds vs. Osaka University of Health and Sport Science

[3] 45th Japan Handball League Men's Siegster Tokyo vs. Toyoda Gosei

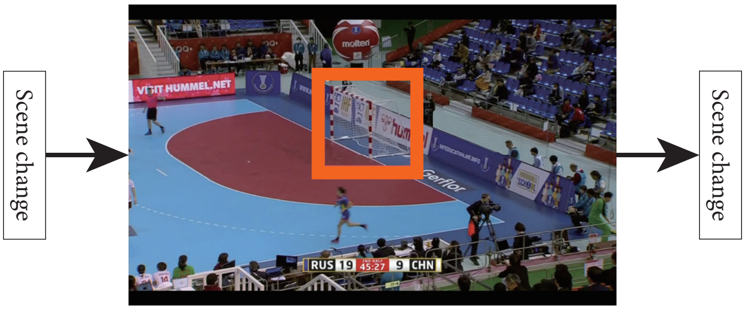


Figure 7: Scenes without slide in and slide out

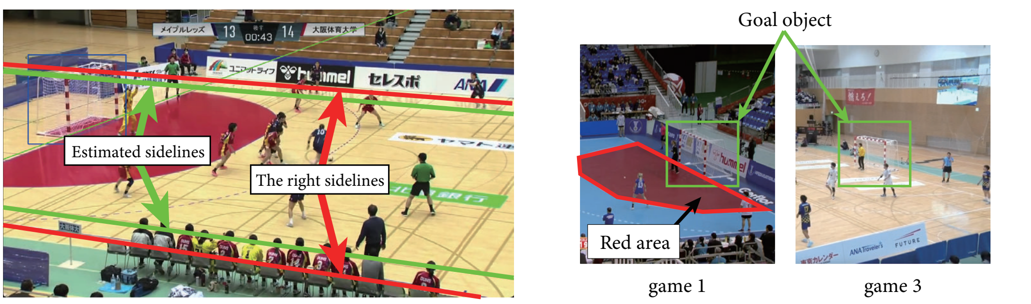
Table 2: Result of estimating the court boundary

	Method 1		Method 2	
Games	Positive (%)	Negative (%)	Positive (%)	Negative (%)
1	45,616 (93.7)	3,079 (6.3)	46,762 (96.0)	1,933 (4.0)
2	27,275 (50.8)	26,416 (49.2)	39,635 (73.8)	14,056 (26.2)
3	34,404 (68.1)	16,084(31.9)	- (-)	- (-)
Total	61,679 (59.2)	42,500 (40.8)	39,635 (73.8)	14,056 (26.2)

The used parameter in game 2 and 3 is tuned in game 1.
The total is the sum of Game 2 and 3.

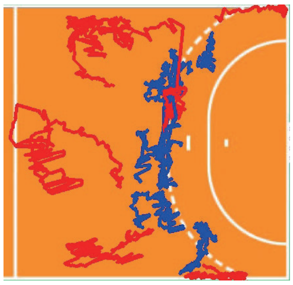
estimation method using the red area. The game 1 was used to determine the threshold. Both methods 1 and 2 estimated the court boundary with high accuracy. The method 2 having a higher court boundary estimation rate than the method 1. The estimated results are higher accuracy than the method 1 as in the game 1 in the game 2. There was no red area on the court, and only the method 1 was used in the experiment in the game 3.

The correct estimation rate of the method 1 is lower than that of the method 2 of game2. The reason is the printed lines on the court other than the handball lines as shown in Fig. 8(a), and it was confirmed that the lines were estimated inside the appropriate sideline. The correct estimation rate of the method 1 was 68.1% in game 3. The reason is no red area in front of the goal object as shown in Fig. 8(b). It reduces the accuracy of line segment detection by the Hough transform and prevents estimation of the extended goal line. A study of methods using other features than the bounding box of the goal object and red area can be mentioned.



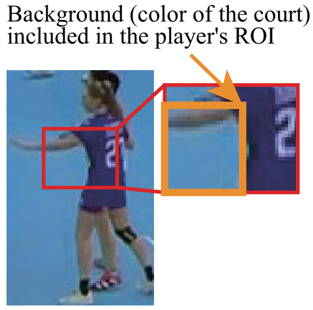
(a) Estimated sidelines for game 2 (b) Extended misjudgment of the goal line

Figure 8: Example of court boundary mis-estimation



Red Lines : Trajectory of attacking players
Bule Lines : Trajectory of defensive players

(a) Results of player trajectory display for each team



(b) team misjudgment

Figure 9: Player movement trajectory display results and team misjudgment

3.3 Showing of Player Trajectory for Each Team

The court boundary estimated using the method 2 were utilized for the game 1 in our experiments. Fig. 9 (a) shows some of the results of the player trajectory showing for each team. The player trajectory could be paited for each team. On the other hand, when the player's ROI included the color of the court, the team was misjudged. Therefore, a future method is considered to remove the background of players by estimating the color of the court and judging the team.

4 Conclusion

This paper introduced a method for estimating court boundary and showing player trajectory in the broadcast handball video. The experimental results are more accurate than the method 1 with 59.2% and 73.8% correct estimation rates for the method 1 and 2, respectively. The shown player trajectory included the trajectory paths of each player on both teams. Our focus will be on enhancing the accuracy of court boundary estimation and team identification methods in future research. Additionally, we aim to apply this methodology to develop strategies that incorporate the player trajectory of attacking and defensive players.

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