Journal of Robotics, Networking and Artificial Life
Vol. 11(3); March (2026), pp. 254-261
ISSN (Online): 2352-6386; ISSN (Print): 2405-9021
https://alife-robotics.org/jrnal.html

Research Article

# Research on Player Position Estimation from Various Views in Volleyball

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## ARTICLE INFO

*Article History*

Received 25 November 2024
Accepted 04 March 2026

*Keywords*

volleyball
player position
bird's-eye view
projective transformation

## ABSTRACT

In recent years, data-driven approaches have become increasingly important in sports analytics, particularly in the context of tactical analysis. In the domain of volleyball, the precise estimation of player positions is of paramount importance for the purpose of performance evaluation. Conventional methodologies are contingent on projective transformation employing fixed reference points; a process which restricts its applicability when considering variable viewpoints. This limitation assumes particular relevance in the context of broadcast footage. The present study proposes a robust system for estimating player positions from arbitrary camera angles, including legacy and zoomed-in footage. The proposed methodology utilizes the YOLOv9 model for player detection and employs manual identification of court lines and the net to define dynamic reference points for homography. The findings of Experiment 1 demonstrate that player positions can be estimated with an average error of 0.30 meters, which is sufficient for tactical use. Furthermore, experiment 2 introduces a dual-camera triangulation approach to address the challenge of estimating airborne players, where conventional ground-contact assumptions are inadequate. The synchronization of cameras and the utilization of calibration through the employment of chessboard patterns facilitate the computation of the three-dimensional position of jumping players, yielding an average error of 0.43 meters. This outcome underscores the method's aptitude for effectively managing real volleyball dynamics, incorporating in-air motion. Collectively, these methodologies furnish a versatile and precise instrument for volleyball analysis, thereby establishing a foundation for more extensive implementations within the domain of sports informatics.



## 1. Introduction

In recent years, Japan has launched its Third Basic Plan for Sports [1], a national strategy set to be implemented over five years from FY2022 to FY2026. A key pillar of this plan is the use of advanced technologies and digital transformation (DX) [2] to drive innovation in the field of sports. In line with this, significant efforts have been made to collect player positional data as a means of supporting tactical analysis in competitive sports [3], [4]. Among these efforts, there has been active use of YOLO [5], an object detection algorithm, to identify and track player positions in video footage. This approach is especially common in sports like soccer, volleyball, and basketball, where player positioning is closely linked to team strategy and scoring opportunities. In such sports, many teams employ not only coaches and managers but also dedicated analysts who track player movements in real time and perform detailed tactical evaluations.

In the sport of volleyball, which is typically played indoors, data analytics software such as DataVolley [6] is commonly used to support tactical decision-making. This software is widely adopted by professional teams and requires manual input of various details, including player positions, play types, and jersey numbers. By collecting and analyzing this information, the software can generate insights that assist coaches and analysts in developing strategies. However, because the data must be entered manually, the adoption of such systems has been limited among amateur teams, where staffing and resources may be insufficient. Recently, advancements in technology have enabled the estimation of player positions using camera images or other sensors, allowing for easier visualization of player movements. Typically, this involves creating a bird's-eye view and plotting player positions after estimating them from camera footage. Projective transformation, a commonly used method for this purpose, requires at least four reference points. In previous studies that aimed to visualize player positions in volleyball [7], [8], the transformation is typically computed using four fixed reference points—such as the corners of the court or points along the boundary lines—to project player positions onto a bird's-eye view. However, these methods are inherently constrained by the assumption of fixed camera viewpoints, since the transformation relies on static reference points. When the camera angle changes, manual recalibration is required: the reference points must be identified and input into the system anew for each perspective. This lack of adaptability presents a significant obstacle to applying such methods in situations with dynamic or variable camera conditions. Moreover, conventional approaches often depend on footage that captures the entire court, which limits their applicability. In particular, broadcast footage frequently involves dynamic camera movements that follow the ball or specific players, resulting in frequent shifts in viewpoint. Such changes necessitate constant redefinition of reference points, rendering the approach impractical for real-time or automated player tracking. In response to this issue, a recent study proposed a method for visualizing player positions in soccer by estimating a planar homography matrix using automatically identified correspondences between field lines and goalpost coordinates in match videos with moving viewpoints [9]. However, that method is specific to soccer and becomes difficult to apply when the goalposts are not visible in the frame. By contrast, volleyball matches typically include the net in the camera frame, providing a stable and consistent visual reference. This characteristic makes volleyball more suitable for automated projection-based methods, even under variable viewpoints.

In previous research, experiments were typically conducted using a single camera viewpoint, and high accuracy often relied on the assumption that players' feet were in contact with the ground. However, due to the nature of volleyball as a sport, players frequently perform actions while airborne. When such players are projected onto a bird's-eye view using projective transformation, significant errors can occur in position estimation.

To address these multiple challenges, this study conducts two experiments aimed at overcoming the limitations of existing approaches. First, we aim to enable robust player position estimation from various camera viewpoints, improving adaptability under dynamic conditions. Second, we utilize a dual-camera setup to capture the scene from two different angles and apply triangulation techniques to accurately estimate the positions of airborne players. By achieving these two objectives, the proposed approach seeks to expand the applicability of tactical analysis support in volleyball.

## 2. Methodology

### 2.1. *Methodology of Player Position Estimation from Various Views*

(Figure 1) presents an overview of the research pipeline in the form of a flow diagram. The system takes as input an image containing volleyball players and outputs a corresponding bird's-eye view representation. Initially, the input image is analyzed using YOLOv9 [10], a state-of-the-art object detection algorithm (hereafter referred to as YOLO)—to automatically detect and localize players within the scene.

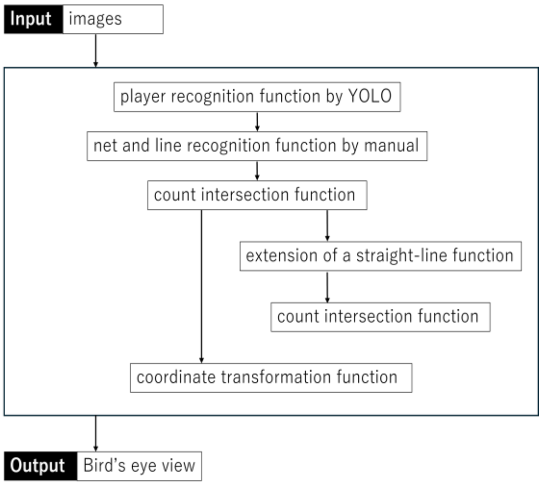


Figure 1 Flow diagram.

In parallel, the court lines and the net visible in the image are identified manually through visual inspection. Their coordinates are extracted by interactively tracing these elements using a mouse interface. Once the coordinates of the court lines and net are obtained, the number of intersections between lines is computed. Based on the detected number of intersections, appropriate reference points are selected for the purpose of projective transformation.

These reference points serve as the basis for computing a homography matrix, which is then used to geometrically transform the original image into a top-down (bird's-eye) perspective. This transformation aligns the court and player positions with a standardized court layout, facilitating spatial analysis.

In this framework, each player detected by YOLO is represented by a bounding box, as illustrated in (Figure 2). From each bounding box, the coordinates of the upper-left and lower-right corners are extracted. For determining the player's position within the image, the centroid of the bounding box is calculated. Specifically, assuming the upper-left corner of the image is defined as the origin (0,0), the center point of each bounding box is computed using Eq. (1), and this point is used to represent the player's location on the court within the transformed (bird's-eye) view.

$$\begin{cases} x = \dfrac{(x_{min} + x_{max})}{2} \\ y = y_{max} \end{cases} \tag{1}$$

#### 2.1.1. *Method of reference points selection for various views*

First, the coordinates of the four reference points required for projective transformation are determined. In this study, the straight-line equations of the volleyball court lines are derived based on manually obtained points. Depending on the camera angle, only a portion of a given line may appear in the image; however, this does not pose a problem, as the lines are treated as infinitely extendable for computational purposes. When necessary, intersections are calculated by extrapolating the visible lines beyond the image boundaries. After identifying multiple court lines within the image, the system computes their pairwise intersections. In general, between zero and six intersection points can appear in each frame. When six intersections are detected, as shown in (Figure 3), it indicates that the full court is visible in the image. In such cases, the coordinates of the court's four corners can be directly obtained and used as reference points without further processing. If fewer than six intersections are found, the detected court lines are extended within the image plane, as illustrated by the dotted lines in (Figure 4), and additional intersections are sought. If a new intersection point is successfully identified—such as the blue dot shown in (Figure 4)—it is selected and included in the set of candidate reference points. Once all potential intersections are identified, the total number of usable points is assessed. If the number of intersections is fewer than four, as in (Figure 5), the image is deemed unsuitable for tactical analysis because too few players are likely to be visible. In such cases, the system outputs a prompt stating "Please change the angle of view" to notify the user. Reference points for the transformation are then selected based on the number and arrangement of intersection points. In this study, viewpoints that do not include the net, such as the examples within the blue frames in (Figure 3) are excluded from analysis, as the net is essential for spatial orientation on the court. When four or five intersections are detected, four key reference points are selected from among points labeled A, B, E, and F in (Figure 3). The selection follows a specific logic: point A is the intersection closest to the net line and located to its left, while point F is the closest point on the right. Point B is the nearest point to A that is not F, and point E is the closest to F that is not A. In cases where six intersections are found, A, B, E, and F are defined in the same manner. In addition, point C is defined as a point lying on the straight line between A and B, and point D as the remaining intersection not assigned to the previous labels.

### *2.1.2. Creating a Bird's-Eye View*

Using the court line intersections obtained in Section 2.1.1 as reference points, projective transformation is applied to convert the original image into a bird's-eye view, as illustrated in (Figure 6), for the purpose of estimating player positions. The transformation process follows the method described in [11]. Depending on the number of visible intersection points, three scenarios are considered: four, five, or six intersections.

- When four or five intersections are available, points A, B, E, and F in (Figure 3) are transformed into A', B', E', and F' in (Figure 6).
- When six intersections are detected, points A, C, D, and F in (Figure 3) are mapped to A', C', D', and F' in (Figure 6).

This approach ensures flexible application of projective transformation based on the available number of reference points.


Figure 2 Person detection with YOLO.


Figure 3 Taken image with virtual court line.

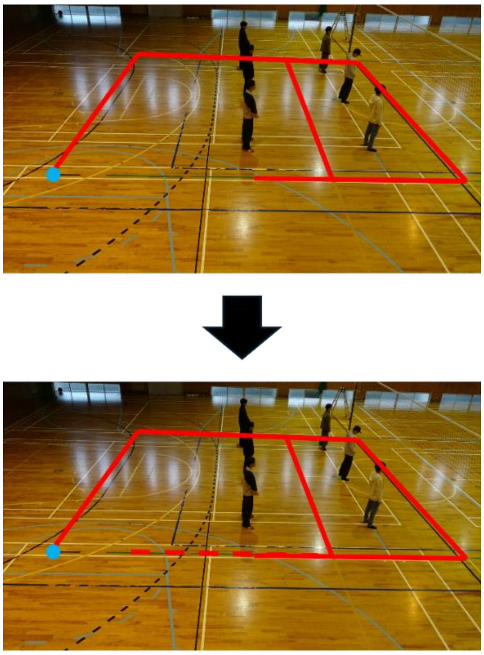

Figure 4 Creating intersection by extension.

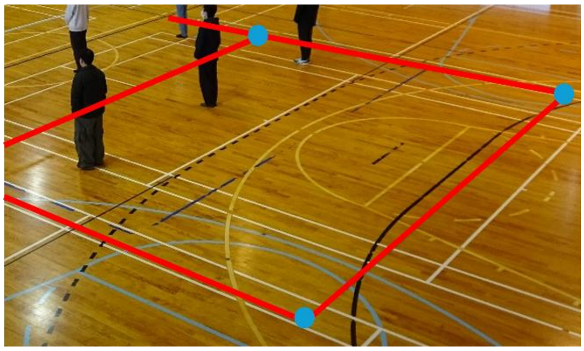

Figure 5 Example with 4 or less intersections.

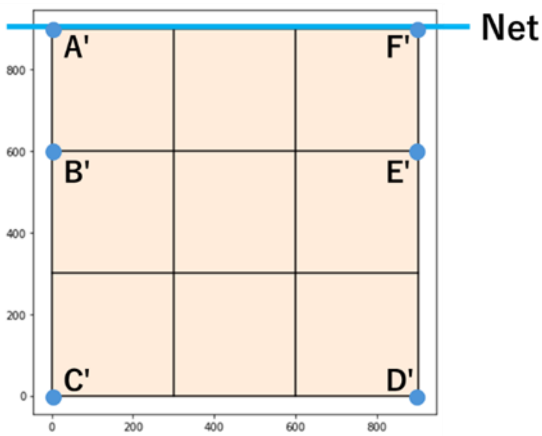


Figure 6 Bird's-eye view.

### 2.2. *Methodology of Estimation of Airborne Players*

This section describes the improvement of accuracy in estimating the positions of airborne players. To precisely estimate the 3D positions of players, this experiment utilizes two cameras with different viewpoints, synchronized in time. To reduce the positional error caused by internal camera parameters, camera calibration is performed using a chessboard pattern. The calibration process follows standard methods provided in OpenCV, where distortion parameters and other intrinsic properties are precomputed and later used during position estimation.

Time synchronization of the two camera views is conducted based on a method referenced in previous research [12], allowing the video frames from both cameras to be aligned temporally.

The player stood at the positions marked with light green dots and performed vertical jumps. The 3D positions during these airborne moments were then estimated.

The recorded video is converted into images at 30 frames per second and fed into the system. To determine the relative positions of the cameras, the coordinates of the four corners of the court are manually extracted from both camera views. Simultaneously, players are detected in each image using YOLO, and their coordinates on the image plane are obtained. Using the positions of the two cameras and the detected player positions from both viewpoints, the 3D positions of the players are estimated via triangulation. The triangulation method employed in this study uses the function provided by OpenCV.

## 3. **Experimental Details**

This research involved two experiments conducted with data collected in the gymnasium at Komatsu University's Awazu campus. The first experiment estimated player positions from multiple angles. The second experiment estimated player positions during jumps.

In the first experiment, a variety of images were captured from multiple viewpoints using several cameras (Figure 7). Representative examples of the images taken from each angle are shown in (Figure 8). In this experiment, although videos are commonly used for estimating player positions, still images were employed to evaluate positional accuracy. The ground truth positions of the players on the court were measured manually using a tape measure and were defined as the correct positions. The spatial arrangement of the players during the experiment is illustrated in (Figure 9). The estimation error was calculated by comparing the player positions obtained by the proposed system with the ground truth positions and was used as the evaluation metric. In the second experiment, the setup of camera positions and player locations is illustrated in (Figure 10). To further assess the method's generalizability, we conducted two recording sessions, each using two cameras. In the first session, the cameras were placed at the positions shown in yellow in (Figure 10); in the second session, they were placed at the red positions. As in Experiment 1, the ground-truth player positions were measured in advance using a tape measure.

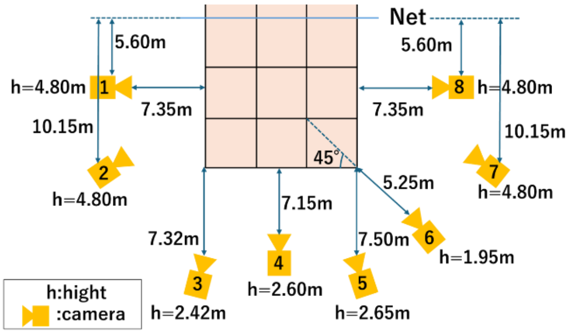


Figure 7 Shooting method at Experiment 1.

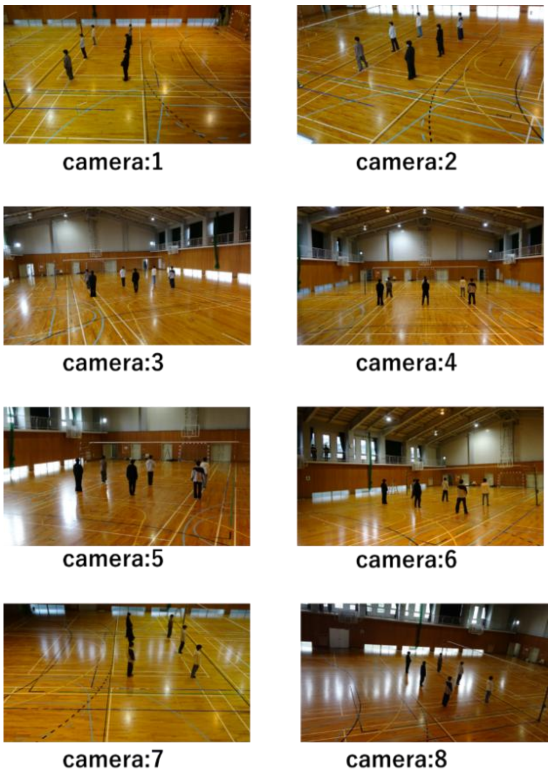


Figure 8 Images taken from each camera angle of view.

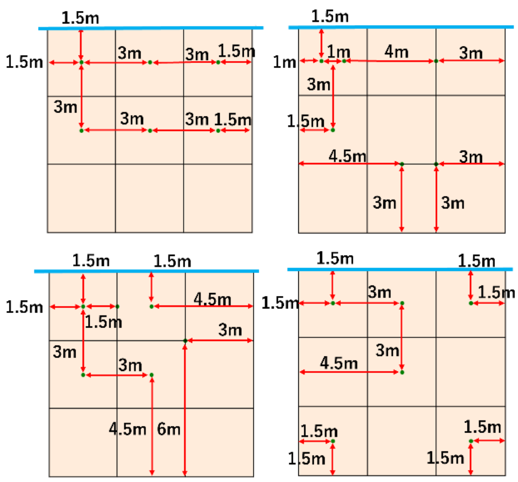


Figure 9 All positions pattern.

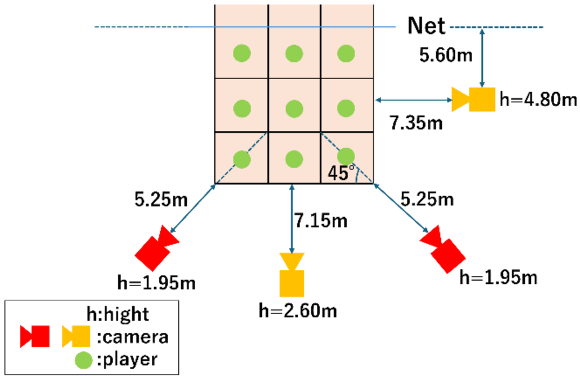


Figure 10 Shooting method at Experiment 2.

## 4. Results and Discussions

### 4.1. *Results of Experiment 1*

The findings of this study are summarized in (Table 1), which displays a subset of the dataset containing the coordinates and ground truth positions for 351 successful data points. (Figure 11) illustrates an example of the resulting bird's-eye view output. The mean positional error was 0.18 m along the x-axis (parallel to the net) and 0.21 m along the y-axis (perpendicular to the net), yielding a mean overall error distance of 0.30 m. Given that the average shoulder width of an adult male ranges from 0.4 to 0.45 meters, this level of accuracy is deemed sufficient for tactical analysis. As shown in (Figure 12), the bounding box generated by the YOLO detection algorithm effectively encloses the subject within the frame. In cases where the bounding box appears too large, the observed error is attributed to the misalignment between the actual frame and the detection output.

(Table 2) compiles the accuracies by camera viewpoint. Footage from cameras 3, 4, and 5—mounted near the rear of the courts showed larger mean errors along the y-axis than along the x-axis over the court area. In our image plane, the x-axis corresponds to real-world depth; with monocular position estimation, the y-axis error tends to exceed the x-axis error. Among these, camera 4, which views the court straight from behind, produced the largest error, likely because estimating positions along the y-axis from this angle is particularly difficult. Accuracy improved as the viewpoint approached a top-down perspective (cameras 1 and 2). By contrast, camera 8, despite being installed at roughly the same height as cameras 1 and 2, did not achieve comparable accuracy.

(Figure 13) shows a frame from camera 8 with players detected by the YOLO algorithm, and (Figure 14) depicts the simultaneous bird's-eye projection. Small differences in field of view were observed; for instance, camera 1 captured the feet of partially occluded players, enabling precise localization, whereas camera 8 did not record the feet of the player positioned near the center of the left column in (Fig. 13).  The lower edge of the bounding box sat around the waist instead. Had the feet been included within the box, the player's position could have been estimated more accurately, which likely explains the higher error for camera 8.

In this experiment, we used YOLO, a model trained using COCO data, which is publicly available without fine-tuning YOLO on domain-specific datasets. In general, YOLO can improve the accuracy of recognition and more accurately surround the bounding box by learning to match the environment in which it is used. In this research, a training model using images of volleyball players is expected to improve player recognition accuracy. However, in sports like volleyball, where frequent occlusion occurs due to overlapping players, image-based methods alone may not be sufficient to achieve high recognition performance. To address such occlusion-related challenges, multi-view tracking that leverages multiple camera angles is considered to be an effective approach.

Table 1 Error with the correct position

| | x1 | y1 | x2 | y2 | dx | dy | distance |
|---|---|---|---|---|---|---|---|
| 1 | 359 | 209 | 349 | 190 | 0.13 | 0.34 | 0.36 |
| 2 | 677 | 219 | 676 | 191 | 0.02 | 0.50 | 0.50 |
| : | : | : | : | : | : | : | : |
| Avg. | | | | | 0.21 | 0.21 | 0.30 |

unit: x1, y1, x2, y2(px)  dx, dy, distance(meter)

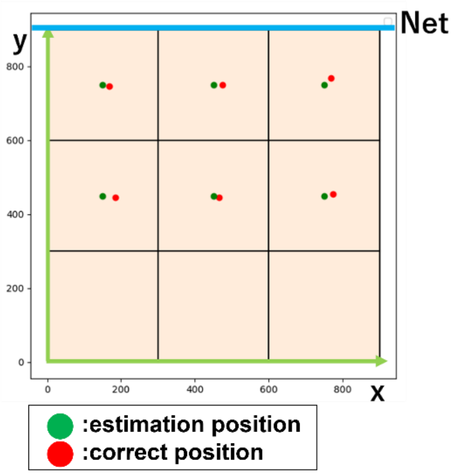


Figure 11 Example of a bird's-eye view.

Figure 12 Example of people detection.

Table 2 Error of each camera angle of view (meters)

| camera's No. | dx | dy | distance |
|---|---|---|---|
| 1 | 0.19 | 0.10 | 0.21 |
| 2 | 0.11 | 0.20 | 0.23 |
| 3 | 0.08 | 0.21 | 0.22 |
| 4 | 0.08 | 0.40 | 0.41 |
| 5 | 0.22 | 0.31 | 0.38 |
| 6 | 0.14 | 0.22 | 0.26 |
| 7 | 0.25 | 0.08 | 0.26 |
| 8 | 0.35 | 0.16 | 0.38 |

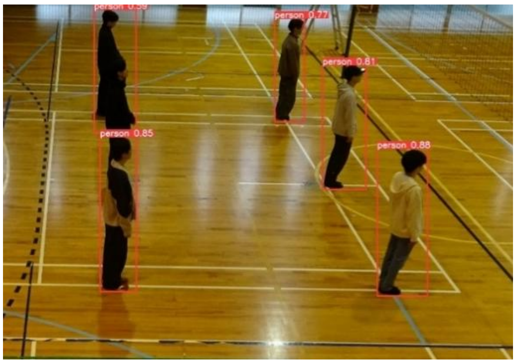

Figure 13 Player Occlusion.

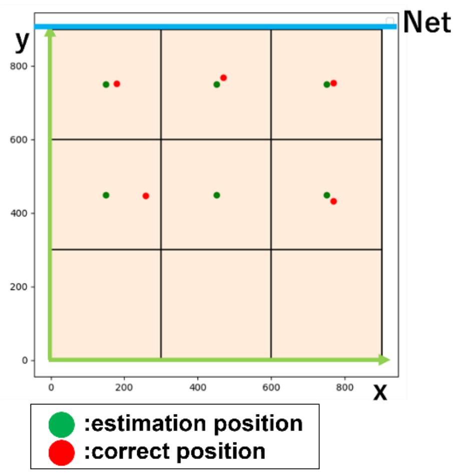


Figure 14 Estimation of player position at occlusion.

Table 3 Difference in reference points and error (meter)

| Reference point for the perspective transformation | dx | dy | distance |
|---|---|---|---|
| A, B, E, F | 0.21 | 0.24 | 0.32 |
| A, C, D, F | 0.21 | 0.15 | 0.26 |

This reduction in YOLO's detection accuracy caused by player occlusion likely contributed to the overall decrease in experimental accuracy. However, when examining images from Camera 4's field of view at the same moment, the two players occluded in Camera 8's field of view were successfully enclosed by bounding boxes. These findings suggest that leveraging multiple fields of view could enable the creation of a system more robust to occlusions.

In this research, player position estimation was performed from a single viewpoint, but it is difficult to accurately acquire 3D information from a single viewpoint. Therefore, it is necessary to construct a system that integrates multiple viewpoints in the future. Considering the installation of multiple cameras, there is a possibility that there is an angle of view where occlusion is not confirmed, and we believe that this problem will be solved.

Next, we analyzed performance as a function of the number and configuration of detected court-line intersections. (Table 3) reports the mean localization error for two homography configurations: one using A–B–E–F as control points and another using A–C–D–F. The discrepancy is most pronounced along the image y-axis. Because YOLO detections are held fixed in this comparison, the residual error is attributable to the homography estimation and warping stage. From projective geometry, accuracy generally improves as the quadrilateral spanned by the control points covers a larger image area, and points lying inside that quadrilateral are mapped more faithfully than points outside it. These properties plausibly account for the observed differences in accuracy between the two configurations.

### *4.2. Results of Experiment 2*

The results of experiment 2 which focused on the estimation of the 3D positions of airborne players, are outlined in (Table 4). In this context, the coordinates are defined such that the bottom-left corner of the court is set as the origin (0, 0). The primary objective of this study is to project player positions onto a bird's-eye view; estimation along the z-axis (height) is not evaluated herein. As demonstrated in (Table 4), a segment of the dataset collected during the present experiment is presented. The mean estimation error was found to be 0.43 meters. Although this is slightly larger than the error observed in Experiment 1, it is within the range of a player's shoulder width and thus considered acceptable for practical applications.

It is hypothesized that the elevated error rate observed in Experiment 2 may be attributable to several factors. Initially, the relative positions of the cameras were determined by manually extracting the four corners of the court from the images. It has been demonstrated that even minor deviations of a few pixels during this process can result in a discrepancy of several centimeters – or even tens of centimeters – in camera positioning. This, in turn, has a detrimental effect on the accuracy of player position estimation. Secondly, the additional processing step of triangulation itself may introduce further error; as the number of steps increases, so does the potential for accuracy degradation.

Moreover, as in Experiment 1, there were instances in which player positions could not be estimated due to occlusion, as illustrated in (Figure 15). As demonstrated in (Figure 15), despite the presence of three players, only two bounding boxes are detected due to occlusion. The present system is predicated on player detection by YOLO, which precludes the estimation of positions for undetected players. Consequently, in a manner analogous to Experiment 1, this limitation persists as a domain for prospective enhancement.

Table 4 Error with correct position(meter)

| No. | x | y | z | dx | dy | distance |
|---|---|---|---|---|---|---|
| 1 | 2.02 | 6.93 | 0.56 | 0.52 | 0.57 | 0.77 |
| 2 | 4.53 | 7.35 | 0.79 | 0.03 | 0.15 | 0.15 |
| 3 | 6.99 | 7.64 | 0.25 | 0.51 | 0.14 | 0.53 |
| : | : | : | : | : | : | : |
| Avg. | | | | 0.16 | 0.14 | 0.43 |

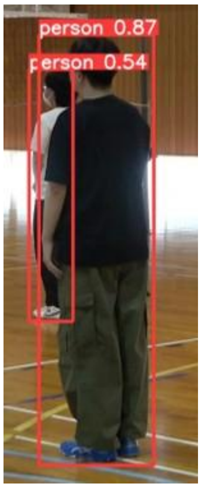


Figure 15 Occlusion.

## 5. Conclusion

This research extends tactical analysis by estimating player locations from multiple camera viewpoints rather than relying on a single fixed perspective. As reported in Section 4, the mean positional error was 0.18 m along the x-axis (parallel to the net) and 0.21 m along the y-axis (perpendicular to the net), yielding a mean overall error distance of 0.30 m. While the error varies across viewpoints by approximately 0.20 m, the method still reconstructs a bird's-eye representation from imagery acquired at arbitrary viewing angles.

This result indicates that player position estimation can be performed without being constrained by the shooting environment, enabling its application in a variety of settings. Furthermore, it suggests the possibility of utilizing previously recorded footage for tactical analysis.

Moreover, experiment 2 demonstrated that even for airborne players, their positions could be projected onto a bird's-eye view with a small average error of 0.43 meters. This result suggests that the proposed system is capable of accurately estimating player positions regardless of their state during the match.

However, certain viewing angles may result in player occlusion, which can impede accurate player detection by YOLO. Such advancements would significantly improve the system's applicability for tactical analysis across a broader range of scenarios. Currently, experiments 1 and 2 have been conducted independently. By integrating the systems developed in each experiment, it is expected that the positions of all players in the image can be estimated accurately under various environmental conditions. Then, the detection of lines and nets is performed by an object recognition algorithm, aiming for full automation. While this research established the feasibility of position estimation in volleyball, such capabilities are equally valuable for sports like soccer and basketball. Consequently, our future research will focus on developing a generalized framework applicable to other sporting domains. Unlike volleyball, these sports present unique challenges, such as the simultaneous presence of opposing teams on the same field and fluctuating outdoor lighting conditions that may affect player visibility. To address these factors, we aim to design a robust system capable of adapting to sport-specific characteristics and complex environmental variables.

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