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OBTracker: Visual Analytics of Off-ball Movements in Basketball

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Abstract— In a basketball play, players who are not in possession of the ball (i.e., off-ball players) can still effectively contribute to the team's offense, such as making a sudden move to create scoring opportunities. Analyzing the movements of off-ball players can thus facilitate the development of effective strategies for coaches. However, common basketball statistics (e.g., points and assists) primarily focus on what happens around the ball and are mostly result-oriented, making it challenging to objectively assess and fully understand the contributions of off-ball movements. To address these challenges, we collaborate closely with domain experts and summarize the multi-level requirements for off-ball movement analysis in basketball. We first establish an assessment model to quantitatively evaluate the offensive contribution of an off-ball movement considering both the position of players and the team cooperation. Based on the model, we design and develop a visual analytics system called OBTracker to support the multifaceted analysis of off-ball movements. OBTracker enables users to identify the frequency and effectiveness of off-ball movement patterns and learn the performance of different off-ball players. A tailored visualization based on the Voronoi diagram is proposed to help users interpret the contribution of off-ball movements from a temporal perspective. We conduct two case studies based on the tracking data from NBA games and demonstrate the effectiveness and usability of OBTracker through expert feedback.

Index Terms—Sports visualization, basketball tracking data, off-ball movement analysis

1 INTRODUCTION

Basketball is a popular sport around the world. In a basketball game, when a team is on offense, the player that is in possession of the ball is regarded as the ball handler, and the other four players without the ball are regarded as off-ball players. Although off-ball players cannot directly control the ball, their movements can still effectively contribute to the offense [27]. For instance, they can make a sudden move to get rid of defenders and create an opportunity for an open shot. Hence, analyzing the off-ball movements can significantly facilitate the planning of basketball tactics and strategies.

Common basketball statistics (e.g., points and assists) primarily focus on what happens around the ball and are mostly result-oriented, making it challenging to objectively assess and fully understand the contributions of off-ball movements. To alleviate this problem, various models have been proposed to quantitatively evaluate the effectiveness of off-ball movements [14, 23, 57]. Although useful, models alone are still insufficient for the analysis, which is usually conducted in an exploratory manner. The experts need to tightly integrate game context information, such as score differences and remaining time, to understand how the off-ball movements contribute to the offense and why it is useful. This motivates us to propose a visual analytics approach to support interactive analysis of off-ball movements.

In this study, we propose a multi-level approach for the off-ball movement analysis and design a visual analytics system, OBTracker, to solve the problem. Users can first learn the patterns and effectiveness of off-ball movements under different game situations using the system. They can then select the interesting movements and learn the performance of different off-ball players in executing the movements. Users can finally inspect the detailed execution process and figure out why players can/cannot create opportunities for open shots. We encounter three major challenges during the implementation of this approach:

Assessing offensive contributions hidden in tracking data. The offensive contributions of off-ball movements are hard to detect [53, 57]. For example, even if an off-ball player manages to get into a good scoring position, it is not directly reflected in the match statistics such as points and assists. Quantifying such contributions requires a full investigation of the overwhelming on-court information from tracking data, in which both the valuable and valueless off-ball movements are recorded. To distinguish between the two types of off-ball movements, appropriate metrics should be established from positional data, such as space under control, to objectively evaluate their contributions.

Aggregating off-ball movements with game contexts integrated. In order to explore a vast number of off-ball movements, it is necessary to classify and aggregate them to reveal their general movement patterns. Game context of the movements (e.g., remaining game time and score differences), although providing essential analytical perspectives, is missing in the aggregation process. For example, coaches might want to learn how often a specific type of off-ball movement is used when the scores are close, and simple aggregation of movements cannot satisfy this requirement. Enabling effective integration of movement patterns and game contexts poses the second challenge.

Interpreting dynamic processes of off-ball movements. Existing on-ball basketball visualizations [10] focus on helping users evaluate and analyze ball handlers' actions under certain situations, which can be regarded as snapshot-based analysis. Off-ball basketball analysis, however, requires experts to track the progression of an off-ball movement to understand the continuous interactions between attackers and defenders on the court. Such a dynamic process can be interpreted from different perspectives, such as changes in the space under control or variations in the defensive structure. Furthermore, a detailed comparison is required to investigate the difference in player performance when executing the same type of off-ball movements. Appropriate designs should allow users to easily understand and interpret the off-ball moving process, which presents the third challenge.

For the first challenge, we develop an interpretable model that assesses the value of off-ball movements from the aspects of player positioning and team cooperation. The assessment result can be validated in the system. For the second challenge, we build an aggregation of typical off-ball movements and create a glyph-based design to present movement patterns and contextual information together. For the third challenge, we identify significant indicators for the interpretation and propose tailored visualizations to display the continuous offensive-defensive interactions during a movement.

In summary, the main contributions of this work are as follows:

- ◇ An extensible model that incorporates interpretable metrics to assess the value of off-ball movements.
- ◇ A visual analytics system to summarize typical off-ball movement patterns and interpret the dynamic off-ball moving process.
- ◇ Two case studies based on real-world basketball games.
- ◇ Expert interviews, design guidelines, and lessons learned derived through the design study.

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2 Related Work

In this section, we present relevant studies in two categories, namely, off-ball movement analysis and visual analytics in sports.

2.1 Off-ball Movement Analysis

As off-ball movement is a significant tactical term in team sports such as soccer [39] and basketball [27], it has been widely studied in sports analysis. Depending on the data used, existing studies can be broadly divided into two categories, namely, event-based and spatial-based.

Event-based. Studies based on event data mainly focus on the statistical analysis of off-ball movements [14, 30]. For instance, Conte et al. [14] analyzed tactical indicators to examine the frequency of off-ball movements used by winning and losing teams. Recently, the rise of machine learning methods has empowered researchers to conduct in-depth evaluations [6, 23, 57, 62]. Gómez et al. [23] built a decision tree that classifies the ball handler's actions after the screen and reflects the effectiveness of off-ball movements. Through a Markov chain, Stavropoulos et al. [57] modeled the sequence of basketball events to examine how off-ball movements can affect the finishing moves. However, the spatial patterns of off-ball movements are seldom considered in these studies due to the lack of space-related data. This may cause difficulties when evaluating an individual off-ball movement or interpreting the dynamics of a team's offensive behaviors. With the development of optical tracking systems [35, 56], fine-grained tracking data has shown promise for overcoming such limitations.

Spatial-based. Studies based on spatial data relate to various analysis tasks of off-ball movements, such as simulation [11, 24, 28] and aggregation [4, 41, 48, 70]. Miller et al. [41] and Andrienko et al. [4] both proposed novel techeniques to aggregate the player movements over different time periods. As for the evaluation task, Cervone et al. [9] and Fernandez et al. [19] quantified each off-ball player's on-court impact from the aspect of space ownership. Spearman [55] incorporated the scoring opportunities in different regions to assess the quality of off-ball positioning. However, these methods often discard the information about player's profile (e.g., shooting abilities) and team's collective behaviors (e.g., passing). To involve player representations, Sicilia et al. [53] proposed a deep learning solution, which used the change in expected scores to assess off-ball movements. Despite its usefulness, the value of an individual off-ball movement can be hard to reflect in the output score, as the model takes all players' movements as input and is not sufficiently interpretable. Therefore, we extend the previous work following advice from domain experts and develop an interpretable approach to assess the value of the off-ball movement in basketball.

In recent years, the coaching staff would use advanced statistical indicators [3] (e.g., screen outcomes) as well as retrieval systems for basketball plays [2, 37] to assist in the off-ball movement analysis.

2.2 Visual Analytics in Sports

Recently, visual analytics techniques have been extensively applied in various sports [8, 17, 45]. In racket sports, such as tennis and badminton, many studies proposed novel visual designs to explore spatio-temporal match data [15, 71, 74], capture tactical patterns [31, 47, 69], and perform simulative analysis [32, 66]. For example, CourtTime [46] presented a novel visual metaphor for identifying strategies from the player and ball movements in tennis games. In team sports such as soccer, SoccerStories [44] was one of the representative works, which designed an innovative visualization interface to explore player actions among different soccer phases. Moreover, a number of studies were based on tracking data to analyze soccer games from various aspects, such as searching for relevant game situations [50, 52, 60], investigating interesting game situations [49, 58, 59], and examining tactical behaviors [4, 72, 73]. In other sports, such as rugby [25, 33] and baseball [16, 29, 43], tracking data was also the primary focus of visual analysis.

However, existing studies in basketball were mainly based on box-score statistics and play-by-play data [67] rather than tracking data. With box-score statistics, PluMP [54] extended plus-minus plots to interpret the change in score differences. Utilizing play-by-play data, CourtVision [22] and Buckets [7] adopted a discrete heatmap to analyze shot performance. Other studies combined the two types of data to enrich the analysis process. For example, BKViz [36] facilitated the analysis of player performance through visual components at different levels of detail. Metoyer et al. [40] enhanced the storytelling of basketball games by coupling narrative text with visualizations. In addition, GameFlow [12] and GameViews [77] both provided comprehensive visual narrations to identify interesting game situations. As for tracking data, Sha et al. [51] proposed a chalkboard interface that allowed users to find similar basketball plays by drawing players' trajectories. POINTWISE [10] used tracking data from NBA games to evaluate the decision-making value of the ball handler. In contrast to the aforementioned studies, this work aims to provide a multifaceted evaluation of off-ball movements in basketball from a dynamic perspective. We incorporate an interpretable assessment model and propose tailored visualizations to help users perceive and evaluate the continuous interactions between attackers and defenders for off-ball movements.

3 Background and System Overview

In this section, we first present the background of off-ball movements in basketball. Then we summarize our interviews and user requirements. Finally, we provide a brief overview of the system components.

3.1 Background and Concepts

A basketball game is played between two teams on a rectangular court. Each team consists of 5 players whose goal is to score more points by putting the ball into the hoop during game time. A player without the ball in hand is called an **off-ball player**, while her/his action that promotes the team's attack is called an **off-ball movement**. Below are a few concepts related to the off-ball movement.

- ◇ **Cutter** is a typical type of off-ball player who moves strategically on the court to get rid of defenders and create easy scoring opportunities. The cutters' actions are the main focus of our study.
- ◇ **Ball handler** refers to a player in possession of the ball. The success of an off-ball movement also depends on if the ball handler can pass the ball successfully when the cutter is in a good scoring position.
- ◇ **Screener** is another type of off-ball player. They generally block the path of a teammate's defender to help the teammate get open space.
- ◇ **Possession** refers to a period of time that the offensive team controls the ball to score points.

Assumption. In this work, we assume that when a ball handler is possessing the ball, all off-ball players who are moving are regarded as cutters. When a cutter is moving, there might be a screener who blocks the path of defenders to help the cutter better move to create the scoring opportunity. It is noted that screeners do not necessarily exist during the off-ball movements. The role of a player is assumed to be consistent during a possession.

Definition of off-ball movements. Based on the assumption, we define an off-ball movement as the movement of a cutter, which is denoted as:

$$O = (S, \{p_t | t \in [T_{start}, T_{end}]\}),$$

where T_{start} and T_{end} are the time when the ball handler starts and loses possessing the ball. p_t is the position of the cutter at time t. Parameter S is the screener of the cutter ($S = NULL$ if not existing).

3.2 Interviews

We collaborated closely with four domain experts (EA, EB, EC, and ED) for one year to develop a visual analytics approach [68] for off-ball movements. EA is a professional basketball coach with many years of coaching experience in the national team. EB is a senior sports analyst who is familiar with data-driven methods for tactical analysis. EC and ED are two PhDs majoring in sports science.

To better understand the domain problem of off-ball movement analysis in basketball, we reviewed relevant literature and conducted a semi-structured interview with our experts. The interview lasted about one hour and focused on the challenges that the experts encountered when analyzing the off-ball movement. According to expert feedback, their current workflow relied on interactive video-based systems. For example, they would use Dartfish [1] to categorize game video clips and illustrate the tactical intent of each off-ball movement by drawing paths. Although effective, such a time-consuming manual labeling process made it difficult for them to summarize and analyze large-scale match data. Moreover, there is a lack of direct quantitative metrics in the system to assess the value of off-ball movements. These challenges

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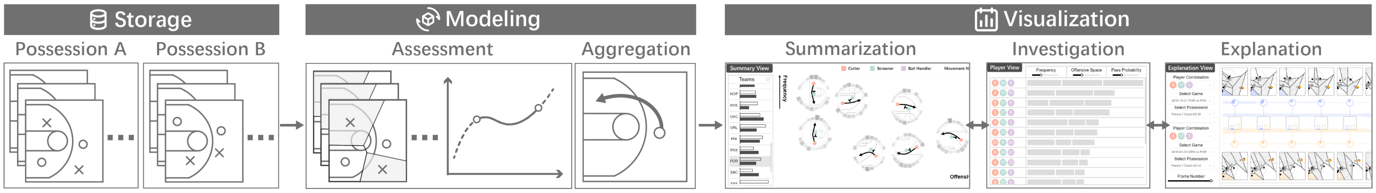

Fig. 1. The system overview. OBTracker consists of three components: a storage component, a modeling component, and a visualization component.

prompted us to design an efficient solution that summarizes the off-ball movement in large-scale games and quantifies the value of off-ball movement based on existing tracking data.

To improve the experts' trust in the assessment results, we discussed how to introduce interpretable metrics in the assessment method. The metrics included the change in expected scores, the impact on defense, and the movement speed and direction. We appreciated the change in expected scores during the discussion, as it could be properly validated by a comparison between the expected and actual scores in games. Although the impact on defense is a meaningful metric, there is a current lack of accepted methods for assessing the changes in defense, thus making it difficult to reasonably validate this metric. In addition, we focused more on player position than movement speed and direction, as each player has their preferred shooting zones, and the movement speed and direction may be closely related to these zones after tactical rehearsals. Based on the above discussion, we deconstructed the expected scores into two steps, namely, *how well the off-ball player is positioned* and *how likely the off-ball player is to receive the ball*.

Interview 2: VA system for the analysis. We conducted a second interview with experts to verify whether the model could fulfill their analytical goals. Although the model is useful, experts commented that they required additional information to obtain a more comprehensive insight beyond the performance score of each off-ball movement. EA and EB pointed out that evaluating the commonly used off-ball movements of each team could help them refine the strategic plans (**S1, S2**). For example, they could develop specialized defensive strategies for those valuable off-ball movements of the opposing team. In addition, for each type of off-ball movement, they desired to find the best performing players to improve the player arrangement (**I1, I2**). EC and ED hoped to explain why a particular off-ball movement was valuable (**E1, E2**). They believed it would be beneficial to the tactical training, such as guiding players to enhance their off-ball skills or teamwork.

3.3 Requirement Analysis

Based on the comments and feedback from our experts, we summarized six design requirements from three aspects to show how off-ball movement contributes to the offense and why it is useful.

Team-level Summarization can give experts an overall picture of a team's typical off-ball movement patterns.

S1 **Summarize the off-ball movement patterns of a team.** Every team uses various types of off-ball movements in their games. An overview of the typical off-ball movement patterns is thus required for experts to identify the tactical style of each team. The overview should present the players' movement paths, facilitating experts to quickly find and view the off-ball movements of interest.

S2 **Describe the characteristics of the off-ball movement.** Revealing the characteristics of a specific type of off-ball movement, such as its effectiveness, frequency of use, and related game contexts, can provide experts with a multifaceted evaluation of off-ball movements. For example, if two types of off-ball movements are equally effective, the one that is more often used at crucial moments (e.g., when the game is about to end) would be more valuable.

Player-level Investigation can help experts assess and compare the performance of different players in a specific type of off-ball movement.

I1 **Present the players involved in the off-ball movement.** An off-ball movement usually involves multiple players, such as the cutter, the screener, and the ball handler. This leads to various combinations of players for one type of off-ball movement. For instance, a player may act as a cutter or screener in the same type of off-ball movement. Therefore, experts need to know the player information when investigating a specific type of off-ball movement.

Table 1. Basketball Data Description

Tracking Data	
T_{ball}	3D trajectory of the ball, which is a sequence of timestamps and locations.
T^i_{player}	2D trajectory of the i-th player, which is a sequence of timestamps and locations.
Event Data	
Team A / B Scores	Scores made by Team A / B.
Possession Description	Outcome of the possession (*i.e., field goal made, foul, and turnover*).
Possession Timestamp	Time when the possession ends.

I2 **Reveal the player's performance in an off-ball movement.** For a specific type of off-ball movement, experts want to find the best performing combinations of players. The player performance can be measured by multiple criteria, such as how well the cutter is positioned and how likely the ball handler is to give the pass. Hence, visualizations that support multivariate rankings of player combinations can assist experts in multi-criteria analysis.

Action-level Explanation can help experts explore the detailed process of an off-ball movement and understand the difference in how players execute the off-ball movement.

E1 **Interpret the dynamic process of an off-ball movement.** When experts focus on a specific off-ball movement, its exact process should be outlined to reveal the continuous interactions between attackers and defenders on the court. For instance, showing changes in the defenders' positions enables an analysis of how this off-ball movement can impact the opponent's defensive structure.

E2 **Compare the performance of different players when executing the same off-ball movement.** Experts require a comprehensive comparison to uncover the reason why some players can perform better than others in the same type of off-ball movement. Besides the player positions, key indicators, such as the space controlled by the cutter and the probability of receiving the ball, can promote the understanding and comparison of the off-ball moving process.

3.4 Data Preprocessing

We use a public dataset from STATS SportVU [35] for the study. It includes 631 NBA games in a regular season. Each game is stored as a list of possessions, and each possession contains the tracking data and event data. The attributes of each possession are shown in Table 1. The spatial locations are recorded at 25 frames per second, while there are about 1.32×10^8 frames in total.

We process the data in three steps to extract off-ball movements from the raw tracking data. 1) **Identify ball handlers.** For each frame, the ball handler is assigned to the offensive player closest to the ball at a distance of less than 3 feet. We randomly sample 2000 frames from the data and verify that 99.2% of frames are correct based on the video. 2) **Extract cutters' trajectories.** We first extract the trajectory of the 4 off-ball players during each possession and obtain about 6.10×10^5 trajectories in total. Then, the trajectories produced by slow-moving players (i.e., average speed less than 6 feet per second) or players not in the offensive half court are removed since they did not perform the cutting behavior at that time. After filtering, about 2.57×10^5 (42.1%) trajectories are retained. The players corresponding to these trajectories are regarded as cutters. 3) **Identify the screener.** For each cutter's trajectory, we detect whether a screener is involved. If an off-ball player remains stationary while the cutter moves past (i.e., less than 3

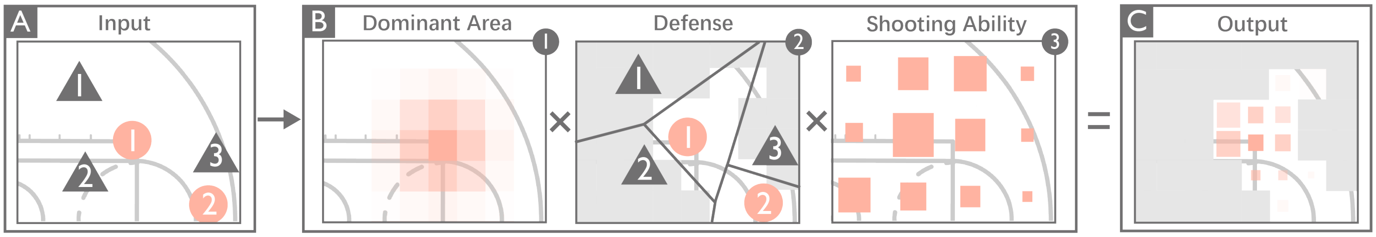

Fig. 2. The process of calculating the shooting expectation. (A) shows an example input of players' positions at time T, where circles indicate attackers and triangles indicate defenders. (B) visualizes the matrices generated based on three considerations. (C) visualizes the output matrix.

feet away), we will identify such a player as the screener. We obtain about 6.61×10^4 off-ball movements with a screener involved. We have sampled 1000 movements and invited experts to verify whether the screener is correctly identified by watching the corresponding video clips. The accuracy is 79.4%, and most errors come from situations where players simply stand nearby rather than block defenders. The time for the entire processing flow is approximately 21 hours on a PC with 32GB RAM and a Ryzen 3600 X CPU.

3.5 System Overview

Guided by the above requirements, we propose OBTracker, a visual analytics system for off-ball movement analysis. The system comprises three components: a storage component, a modeling component, and a visualization component (Fig. 1). The storage component indexes raw tracking data by the possession information of each game. The modeling component takes the tracking data as input, calculates the offensive contribution of each off-ball movement, and aggregates the typical off-ball movements for each team (**S1**). The visualization component consists of three views for multi-level analysis (**S2, E1, E2**).

4 MODEL

In this section, we introduce the interpretable modeling of off-ball movements and evaluate the model through a quantitative assessment.

4.1 Off-ball Movement Assessment

To accurately assess the value of off-ball movements, we need to fully consider the on-court spatial information and interactions between players. Sicilia et al. [53] used a deep learning solution for this problem, yet the computed score of the off-ball movement is hard to explain due to the black-box model. To this end, we adopt an interpretable model to characterize the contribution of off-ball movement.

Definition of the contribution. The goal of an off-ball movement is to reach a position where the player could have a better chance of scoring. Therefore, we adopt scoring expectations to evaluate the changes in the scoring chance of off-ball movements. Statistically, scoring expectation can be represented with the following formula:

$$E(s) = E(s|ball\_received = true) \cdot P(ball\_received = true). \quad (1)$$

For the rest of this paper, we will denote $E(s|ball\_received = true)$ as **shooting expectation** and $P(ball\_received = true)$ as **passing probability** for simplicity.

Off-ball movement is a dynamic process, in which the off-ball player and defenders continuously change their positions on the court. Such changes in an off-ball movement may lead to an increase or decrease in scoring expectations. For example, the defender may lose a few steps and give the off-ball player an open space to receive the pass. Hence, we assess the offensive contribution of the entire off-ball movement with the change in scoring expectations, which is defined as follows:

$$Contribution(P_i) = E(s, P_i, T_{end}) - E(s, P_i, T_{start}), \quad (2)$$

where P_i denotes the i-th off-ball player and T_{start}, T_{end} represent the start and end times of the off-ball movement, respectively.

4.1.1 Shooting Expectation

The shooting expectation is used to estimate an off-ball player's scoring expectation assuming she/he receives the ball at the current time. It is calculated based on three considerations: dominant area, defense, and shooting ability (Fig. 2(B)). The first two are used to assess the ability of an off-ball player to control the surrounding region. We take them into account since the more control the player has, the less interference she/he will suffer when taking a shot. The last one is used to examine the off-ball player's shot performance in the current region. We add it since a player's scoring expectation in a region also depends on her/his shooting ability. For example, a player who generally shoots under the basket may perform poorly outside the three point line.

Dominant area. Many studies [9,19,55] have introduced the concept of dominant area to quantitatively assess a player's capacity to occupy the court. Similar to these ideas, we make a reasonable assumption that the closer a player is to a region, the better she/he can control it. Based on the assumption, we first divide the basketball half court into grids of equal size. Then, we use a bivariate normal distribution to estimate how well an off-ball player can control the region in each grid cell, while the mean of the distribution is the region that the off-ball player stands at. Therefore, we define the value of the dominant area for the grid cell in row x and column y in the following form:

$$M_{dominant}(x,y) = \frac{1}{2\pi} exp\left[-\frac{(x-x_{player})^2+(y-y_{player})^2}{2}\right], \quad (3)$$

where $M_{dominant}$ denotes a matrix that records the value in each grid cell, x_{player} and y_{player} represent the row and column numbers where the off-ball player is located. An example of $M_{dominant}$ is visualized in Fig. 2(B1), reflecting how Attacker 1 can control the region around her/him in the input image. The higher the opacity of a grid cell, the better the player can control the region.

Defense. Besides the distance, defense is another factor affecting a player's dominant area. As the Voronoi diagram is a common tool for modeling defensive positioning [9, 20], we use it to involve the influence of defense. Specifically, we build a matrix based on Voronoi partitions, which serves as a mask for $M_{dominant}$:

$$M_{defense}(x,y) = \begin{cases} 1, & cell(x,y) \notin Voronoi(Def) \\ 0, & cell(x,y) \in Voronoi(Def) \end{cases}, \quad (4)$$

where $M_{defense}$ is the generated matrix, $cell(x,y)$ is a grid cell in row x and column y, and $Voronoi(Def)$ represents the Voronoi cells of all defenders. An example of $M_{defense}$ is visualized in Fig. 2(B2), where the gray cell indicates that the value of the matrix entry there is 0.

Shooting ability. Differences in players' shooting ability can lead to their different scoring expectations in the same region. We thus take the shooting ability into account by using each player's shot data from all games. Notably, we increase the size of the grid cells to avoid having too many cells that do not contain any shot records. Based on these shot records, we construct a matrix for each player:

$$M_{shooting}(x,y) = Freq(x,y) \cdot AvgScore(x,y), \quad (5)$$

where $Freq(x,y)$ denotes shooting frequency, which is the number of a player's shots in $cell_{x,y}$ divided by her/his total number of shots, and $AvgScore(x,y)$ denotes average scores per shot, which is the player's total scores in $cell_{x,y}$ divided by the number of shots. An example of $M_{shooting}$ for Attacker 1 is shown in Fig. 2(B3), where the square size indicates the value of the matrix entry. Finally, we upsample the matrix to adapt to the size of $M_{dominant}$ and $M_{defense}$, thereby obtaining

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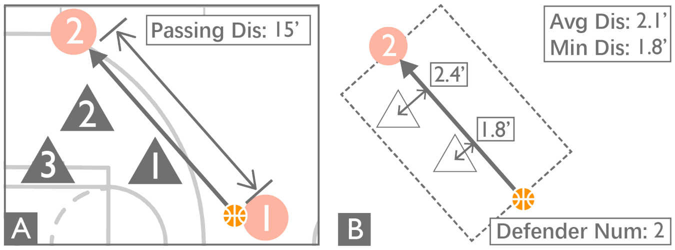

Fig. 3. The input features for linear regression. (A) shows the feature of *passing distance*. (B) shows how we calculate interference from the defender, such as counting *the number of defenders near the pass path*.

$M_{shooting}$. The shooting expectation is computed by the sum of element-wise matrix multiplication of the three matrices (Fig. 2(C)).

4.1.2 Passing Probability

The passing probability, $P(P_i,T)$, denotes the probability of the i-th player receiving the ball from the ball handler at time T. We use a linear regression model to estimate the passing probability from four essential features, including *the passing distance* (Fig. 3(A)), *the number of defenders near the pass path, the average and minimum distance from these defenders to the pass path* (Fig. 3(B)).

Regression Model. To train the model, we first extract a total of 32297 moments from the dataset when the ball handler is about to give a pass. We then split these moments into two parts, 50% for the training and 50% for the testing. For each off-ball player at such a moment, we create a sample and set its dependent variable to 1 or 0 depending on whether the player actually receives the pass or not. The regression equation is as follows:

$$P(P_i,T) = c_0 + \sum_j^{[1,4]} c_j \cdot F_j. \tag{6}$$

F_j ($j \in [1,4]$) denote the aforementioned features, while c_j ($j \in [0,4]$) denote the constant term and coefficients. The values of $c_0 - c_4$ are 0.937, -0.017, -0.090, -0.052, and 0.055, respectively. All input features have small p-values ($p < 0.05$), which confirms the association between the input features and passing probability. In addition, the F-value of this model is 4260, and the R-squared value is 0.348.

Validation. To assess the effectiveness of the regression model, we test the model with a prediction task. For each extracted moment in the testing set, we calculate the passing probability for all four off-ball players. The testing metric is based on whether the player who actually receives the pass appears in the top-1, top-2, and top-3 results, and the test results are 68.7%, 89.1%, and 96.7%, respectively. This is consistent with the observation that players are usually unwilling to conduct a difficult pass to avoid turnovers as much as possible.

4.2 Model Evaluation

The contribution of an off-ball movement is assessed by scoring expectations. Thus, we evaluate the effectiveness of scoring expectations to validate our method. Scoring expectation reflects how likely an off-ball player is to score points. In other words, if a higher scoring expectation occurs in a particular possession, the offensive team is supposed to score more points in that possession. Under this assumption, we randomly select 10% of the games as the testing set, and use the rest as the training set. For each possession, we calculate the scoring expectations at each time frame and select the highest one as the scoring expectation of the possession. Finally, we calculate the average scores for all possessions, the top-5% possessions, and the bottom-5% possessions (free throw points are not involved as they may not come directly from the attack). The evaluation result is presented in Table 2. From this table, we find the points scored in a possession are positively correlated with the highest scoring expectation occurring in that possession, thus verifying our assumption. Notably, there is not a big gap between the actual scores in the top 5% and bottom 5% possessions. The reasons for this phenomenon can be complex, considering that basketball is a highly dynamic sport. For example, some off-ball players control the ball themselves to attack rather than take a shot immediately after

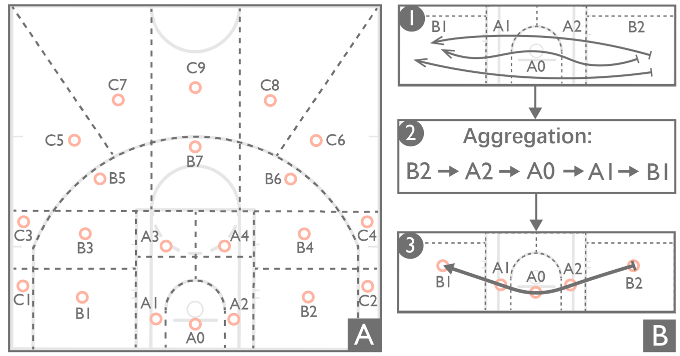

Fig. 4. The illustration of the aggregation. (A) displays the functional divisions and their center points on the basketball court. (B) shows an example of the trajectory aggregation process.

receiving the ball. Hence, the expectations currently calculated by the model only somewhat reflect actual scoring trends.

In this work, shooting expectation and passing probability are computed from player positions. Additional features such as movement speeds and directions might also affect the metric values. Future studies can investigate how these features correlate to player positions and consider extending the models with additional interpretable variables.

Table 2. Experimental Result of Model Evaluation

Possessions	All	Top-5%	Bottom-5%
Average Scores	0.762 pts	**0.801 pts**	0.719 pts

5 Aggregation of Off-Ball Movements

In this section, we introduce our aggregation method that summarizes the frequently used off-ball movements for each team.

As stated in the design requirements (Sect. 3.4), the experts desire to examine the off-ball movement patterns of each team. However, it can be hard for them to deal with an overwhelming number of off-ball movements due to the large volume of tracking data. The aggregation method is thus necessary to categorize off-ball movements by spatial patterns and present typical movement patterns of each team. Considering that trajectory data can be simplified and aggregated into a sequence of spatial divisions [5,34,63], we follow the same idea in our analysis tasks. In particular, we should not simply divide the court into equal-sized grids as most regions are not completely equivalent. For example, in NBA games, players cannot stay for more than three consecutive seconds in an area near the basket, while there is no such restriction in other regions. Thus, we refer to [42] and obtain 21 functional divisions of a basketball half court. As the division-based simplification method can preserve the overall movement pattern of large-scale trajectory data [38,61,64,76], we perform the aggregation based on the divisions. For a trajectory: $Tr = \{(x_0,y_0),(x_1,y_1),...,(x_m,y_m)\}$, we transform it into a sequence of functional divisions: $Seq = \{D_0 \rightarrow D_1 \rightarrow ... \rightarrow D_m\}$, where $(x_i,y_i) \in D_i$. We then remove consecutive identical labels and denote Tr as an aggregated trajectory: $Seq' = \{D'_0 \rightarrow D'_1 \rightarrow ... \rightarrow D'_n\}$, where $D'_i \neq D'_{i+1}$. An example of the aggregation is shown in Fig. 4(B1, B2). To visualize the movement pattern of the aggregated trajectories, we set a center point for each of the divisions (Fig. 4(A)). The aggregation result is then described by a smooth curve through the center points of the divisions, such as the one in Fig. 4(B3). In addition, we aggregate the off-ball movements of different teams separately and sort them in descending order of frequency. This helps to summarize each team's typical off-ball movement patterns (**S1**).

6 Visual Design

We propose OBTracker to fulfill the requirements in Sect. 3.4. OBTracker contains three views: summary view (**S1, S2**), player view (**I1, I2**), and explanation view (**E1, E2**). Users can first view essential statistics for each team in the summary view (Fig. 5(A)) and select a team of interest in the *team list* (Fig. 5(A1)). The aggregated off-ball movements of the team are shown in the *movement overview* (Fig. 5(A2)). Users can compare the frequency and effectiveness of off-ball movements and observe their spatial patterns as well as context information.

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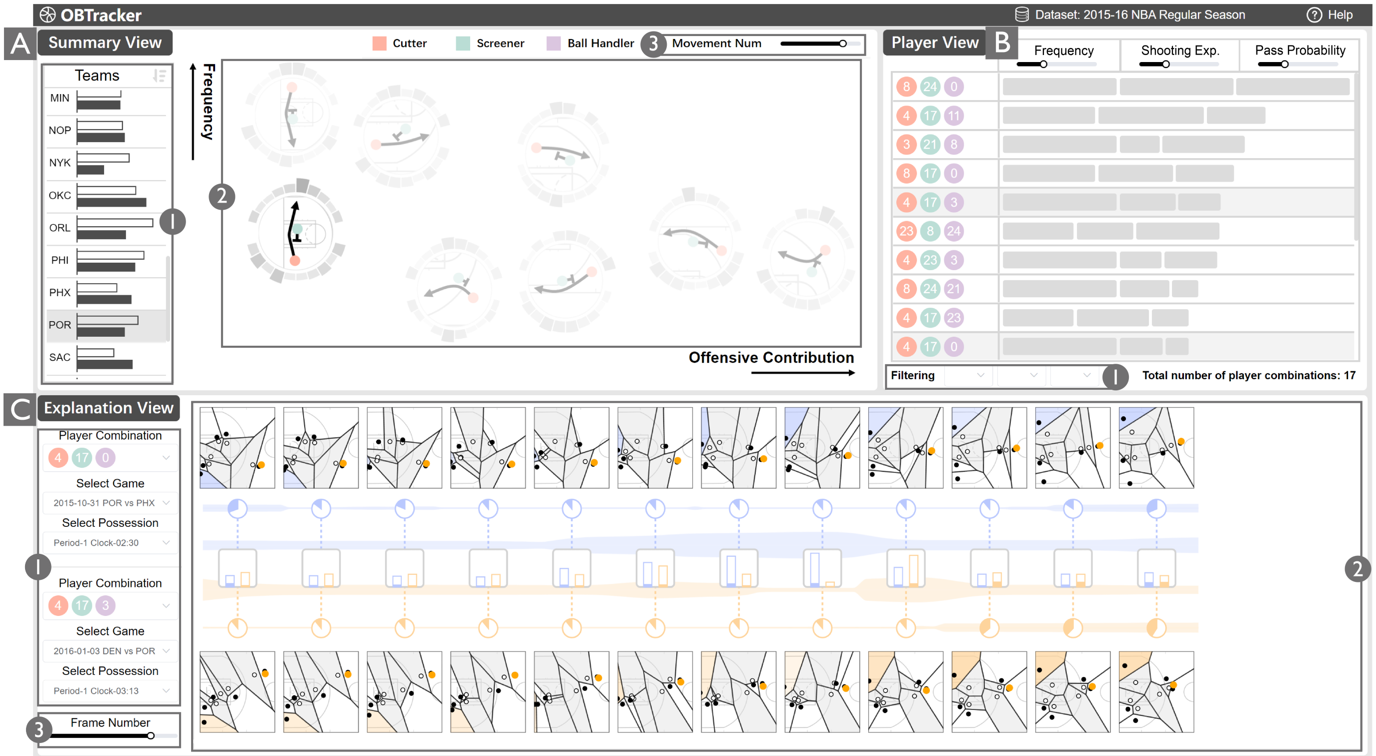

Fig. 5. The system interface of OBTracker. (A) The summary view provides navigation of basketball teams and presents a team's typical off-ball movement patterns. (B) The player view shows a list of player combinations and their performance when executing a specific type of off-ball movement. (C) The explanation view illustrates why an off-ball movement is effective from the aspects of player positioning and team cooperation.

By choosing a type of off-ball movement, users can learn the players involved and their performance in the player view (Fig. 5(B)). After selecting a group of players, the explanation view (Fig. 5(C)) will be shown to help users understand why some players perform well.

6.1 Summary View

The summary view (Fig. 5(A)) contains two parts: (1) the *team list* allows the selection of a team for further investigation (**S1**); (2) the *movement overview* summarizes the characteristics of the commonly used off-ball movements for the selected team (**S1, S2**).

Team list (Fig. 5(A1)). This part presents a list of basketball teams. In each row, the white bar indicates the number of off-ball movements used by the team, while the black bar indicates the average offensive contribution from the team's off-ball movements. A sort button is placed in the top right corner, enabling users to sort the teams by the two different attributes. Such a list can help users obtain a quick overview of the tactical style of each team.

Movement overview (Fig. 5(A2)). This part aims to provide a summary of the off-ball movements for the selected team (**S1, S2**). Each movement glyph represents a type of off-ball movement used by the selected team (i.e., a sequence of functional divisions described in Sect. 5). For each glyph, the x-coordinate represents the offensive contribution, and the y-coordinate represents the frequency of the off-ball movement. We use such a scatterplot layout rather than a list to show the most common off-ball movements since it is more efficient when simultaneously comparing two different measures. For example, users may quickly find off-ball movements with high frequencies and offensive contributions by looking at the movement glyph in the top right. We manage to avoid the overlap issue by following the way in [18].

Glyph design (Fig. 6). According to the experts' advice, game context (i.e., score differences and remaining game time) can provide meaningful insights for off-ball movements (**S2**). Therefore, we integrate context information into the movement patterns using the glyph technique, which is efficient for encoding multidimensional data [13, 75]. The red and green circles (Fig. 6(A)) represent the cutter and screener. The cutter's path comes from the aggregation result of multiple trajectories (Sect. 5), which is a smooth curve through the center points

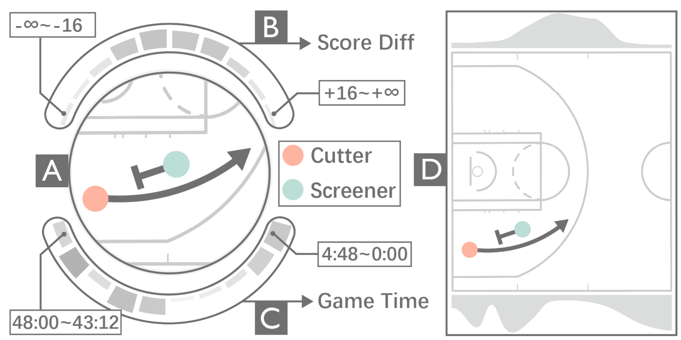

Fig. 6. The glyph design for visualizing a type of off-ball movement. (A) depicts the movement path. (B) and (C) show the distribution of off-ball movements over the score difference and the remaining game time, respectively. (D) is an alternative to this glyph design.

of several divisions. The screener's path records her/his average positions where she/he sets the screen. The outer circle (Fig. 6(A)) serves as a lens to help users focus on the off-ball movement paths and remove the blank background on the basketball court. For the context information, we use two modified histograms to show how this type of off-ball movement distributes over the score difference (Fig. 6(B)) and the remaining game time (Fig. 6(C)). From left to right, the score difference represented by each interval is from falling behind to leading ahead, while the remaining game time is from more to less. The higher the frequency in a given interval, the longer the bar and the darker the color. For example, the histogram in Fig. 6(B) suggests that this type of off-ball movement is often used when the score is close, while the one in Fig. 6(C) means that it is often used in the first half of the game and the final moments.

Design alternative (Fig. 6(D)). We offer a rectangular alternative to the glyph design, where trajectories are plotted on a complete court. Although effective, when multiple such alternatives are placed in the overview, their size becomes so small that it will be hard for users to discern them. To address the issue, we choose a circular layout and

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regard it as a metaphor of a lens to magnify the trajectories and help experts focus on movement patterns. The circular layout combining trajectory and context has proven effective in the visualization application [26, 78]. However, compared to the rectangular layout, the circular one compromises some visual efficiency since the bar lengths can not be compared on the same reference line. To compensate for this, we use two visual channels (both the length and luminance) to enhance users' perception of the distribution. Moreover, a rectangular histogram layout can avoid confusion with cyclic attributes such as movement directions. We thus include it as an option for our system design.

Interactions. The interactions of this view are described below.

- **Select a team.** As a starting point for analysis, users can click on a team in the *team list* to view the team's most common off-ball movements in the *movement overview*.
- **Adjust the number of off-ball movements.** Users can use the slider (Fig. 5(A3)) to control the number of off-ball movements shown in the *movement overview*.
- **Select an off-ball movement.** By clicking a movement glyph in the *movement overview*, users can investigate which players have executed such a type of off-ball movement via the player view.

6.2 Player View

After selecting the off-ball movement in the summary view, the player view (Fig. 5(B)) visualizes the relevant player combinations (**I1, I2**). We list the player combinations with essential performance indicators. The leftmost column shows the involved players. Each circle represents a player with his/her jersey number. The other columns display three performance indicators: frequency, shooting expectation, and passing probability. We normalize each indicator and encode it with the bar. Rows are ranked by the weighted sum of the performance indicators by default. Hence, the top player combinations are supposed to perform well when executing the selected type of off-ball movement.

Interactions. The main interactions of the player view are as follows.

- **Show player information.** Users can hover on the circle in the leftmost column to see a player's name and playing position.
- **Adjust indicator weights.** As users may place more importance on a specific performance indicator, we set a slider in each column header to enable users to adjust the associated weight. When the weight is modified, the ranking in the table changes accordingly.
- **Rank by an indicator.** Users can also click on the column header to directly rank the player combinations by a particular indicator.
- **Filter by players**. Users can click the dropdown lists (Fig. 5(B1)) to filter the player combinations. The three lists from left to right represent the cutter, screener, and ball handler, respectively.

6.3 Explanation View

The explanation view (Fig. 5(C)) displays the detailed process of the off-ball movement and illustrates its effectiveness from the perspective of player positioning and team cooperation (**E1**). We juxtapose the two off-ball moving processes for comparison (**E2**).

Select panel (Fig. 5(C1)). This part displays the information necessary for locating a particular off-ball movement, including the player combination, the game and possession profile. We place this panel so that users can further select and examine the off-ball moving process performed by the player combination they are interested in.

Movement flow (Fig. 5(C2)). This part displays two off-ball moving processes (**E1, E2**). We use colors to distinguish them. As the entire moving process may contain hundreds of frames, we uniformly sample key frames to reduce data complexity. For each key frame, we adopt a Voronoi-based visualization [65] to show the game situation (Fig. 7(A)). Orange dots represent the ball, while the other solid and hollow dots represent attackers and defenders, respectively. The defenders' cells are filled with gray. The cutters' cells are colored differently, with luminance indicating the scoring expectation. We arrange the Voronoi diagrams in chronological order from left to right (Fig. 5(C2)). The vertically aligned Voronoi diagrams reflect the game situations of the two moving processes at similar times. This can help users examine the continuous interactions between attackers and defenders.

We show the assessment results of the off-ball moving process for the evaluation and explanation (**E1**). The pie chart (Fig. 7(B)) shows the passing probability for the corresponding Voronoi diagram. For the

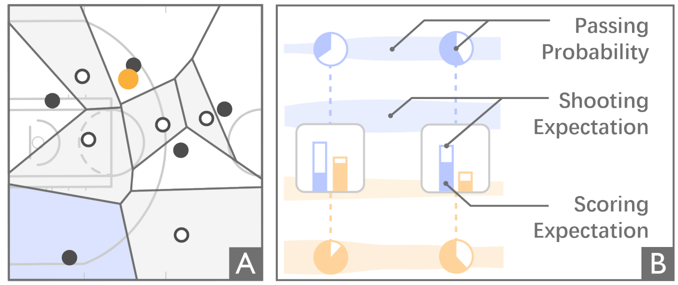

Fig. 7. The visual design for visualizing the detailed process of the off-ball movement. (A) is based on the Voronoi diagram and shows the player and ball positions at a specific time. (B) visualizes the metrics for quantifying the offensive contribution of the off-ball movement.

bar chart in the center, the outer bar denotes the shooting expectation. The inner bar encodes the scoring expectation, which is also the product of the two aforementioned indicators (Sect. 4.1). We juxtapose these assessment results for the comparative analysis (**E2**). During the design process, we have also considered superposition and explicit encoding for comparative visualizations [21]. However, the superposition may raise overlapping issues. The explicit encoding may be insufficient as users need the absolute value to analyze a single off-ball moving process. We thus adopt the juxtaposition to support the analytical task. We use two flows to show the trend of passing probability and shooting expectation during the moving process (Fig. 7(B)). The width of the flow reflects the values of the two indicators, and it presents the information of all frames in a complete off-ball moving process.

Interactions. The main interactions in this view are presented below.

- **Select an off-ball movement.** Users can select an off-ball movement through the dropdown list in the *select panel*. Then they will see the detailed process displayed in the *movement flow*.
- **Adjust the number of key frames.** To view the movement at different levels of detail, users can drag the slider (Fig. 5(C3)) to adjust the number of key frames displayed in the *movement flow*.

7 Case Studies

In this section, we evaluate the effectiveness and usability of OBTracker with two case studies conducted by four senior experts (EA, EB, EC, and ED). We further collected their feedback for future improvements.

7.1 Case 1: Investigating the high efficiency of Team LAC.

The first case is about investigating the efficiency of a team in executing off-ball movements. We invited EA and EB to perform such an analysis. At first, the experts clicked the sort button in the *team list* and found the longest black bar showing in Team LAC (Fig. 8(A1)). This implied that Team LAC owned the highest average off-ball efficiency. Hence, the experts selected LAC to examine their frequently used movements.

Insight 1: Team LAC excels at off-ball movements outside the three point line. The experts quickly noticed the glyph in the top right corner (Fig. 8(A)). According to the paths (Fig. 8(A2)), they identified that the most frequent and efficient off-ball movement for Team LAC was outside the three point line and ended at the left wing (i.e., the bottom left corner of the court). Moreover, they inferred that such a type of off-ball movement was used more frequently when the score was close, as the middle bars of the histogram above the glyph were slightly longer. EA also found that the three off-ball movements appearing on the far right were all outside the three point line (Fig. 8(A2, A3)). In contrast, the two appearing on the far left (Fig. 8(A4)) both ended at the low right post (i.e., the right area near the basket). Based on these findings, EA stated, *"Team LAC can work well for off-ball movements outside the three point line, but sometimes struggles in the inside area."* EB added, *"Defensive rotations outside the three point line will be a key point when establishing a defensive strategy against Team LAC."*

Insight 2: Stephenson is skilled at creating scoring chances in baseline cuts. The experts noted that two baseline cuts (i.e., an off-ball player runs along the line behind the basket) appeared in the middle part (Fig. 8(A5, A6)). From the histograms, they inferred that both cuts were commonly used when scores fall behind (Fig. 8(A5)). To investigate potential improvements in the baseline cuts, the experts clicked the

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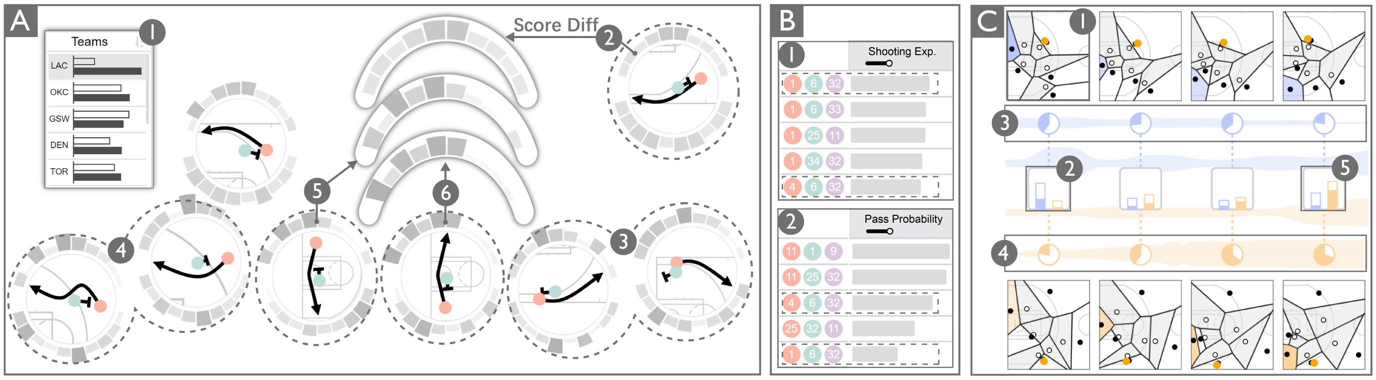

Fig. 8. The pipeline for the first case. (A) presents the *movement overview* for Team LAC. (B) shows several combinations of players who have executed the baseline cut. (C) compares the off-ball moving processes of two cutters.

right-to-left cut and turned to the player view (Fig. 8(B)). When the items were ranked by shooting expectation, the cutter with #1 jersey (Lance Stephenson) appeared in four of the top five well-performing player combinations (Fig. 8(B1)). However, when the table was ranked by the passing probability, Stephenson only appeared once (Fig. 8(B2)). EA deduced, *"Stephenson is skilled at creating open space through his running. However, these opportunities may rarely lead to direct scores as there are usually not good enough chances for him to receive the ball."* In addition, the ball handler with #32 jersey appeared multiple times (6/10), indicating that Blake Griffin could be the primary ball handler for such a baseline cut (Fig. 8(B1, B2)). Meanwhile, the screener with #6 jersey (i.e., DeAndre Jordan) was probably the primary screener as he appeared five times in these combinations.

Insight 3: The strong side is not a good starting point for baseline cuts. In the player view, the experts found an interesting player combination (cutter-#4, screener-#6, ball handler-#32). This combination was only slightly behind another combination (cutter-#1, screener-#6, ball handler-#32) in terms of shooting expectation (Fig. 8(B1)) but much ahead in terms of passing probability (Fig. 8(B2)). As only the cutter varied between the two combinations, the experts went to the explanation view to examine why the #4 cutter (i.e., JJ Redick) could perform better than Stephenson. After setting relevant information in the *select panel*, the experts could see two off-ball moving processes (Fig. 8(C)). The blue was for Stephenson, and the yellow was for Redick. Through the Voronoi diagrams, the experts found the two cutters moved in a nearly identical path, while Stephenson started from the strong side (i.e., the side of the court where the ball is) and Redick started from the weak side (i.e., the other side where the ball is not). When Stephenson was under the basket (Fig. 8(C1)), the lower blue flow for the shooting expectation reached its widest. Meanwhile, the yellow outer bar was much shorter than the blue one (Fig. 8(C2)), which implied that Stephenson had a better offensive performance under the basket than Redick. However, according to the blue pie chart and the background flow (Fig. 8(C3)), the passing probability for Stephenson was always less than half and gradually decreased when moving from the strong side to the weak side. In contrast, the passing probability for Redick was gradually increasing (Fig. 8(C4)), and his scoring expectation reached the highest (Fig. 8(C5)) when he finally arrived at the same side of the ball handler. Based on these findings, EA concluded, *"Starting the baseline cut from the strong side is not a good option as there may be many defenders interfering in the pass path."* EB also commented, *"If Stephenson can adjust his moving path according to the ball handler's location, he can further improve his offensive efficiency."*

7.2 Case 2: Investigating the inefficiency of Team NYK.

We invited EC and ED for the analysis. EC also began with the *team list*, in which the shortest black bar indicated that Team NYK was the least efficient in executing off-ball movements (Fig. 9(A1)). EC then clicked Team NYK for further exploration.

Insight 1: Team NYK excels at baseline cuts but struggles with off-ball movements near the three point line. With *movement overview*, EC noted two baseline cuts on the right side (Fig. 9(A2, A3)), which represented two efficient off-ball movements of Team NYK. The

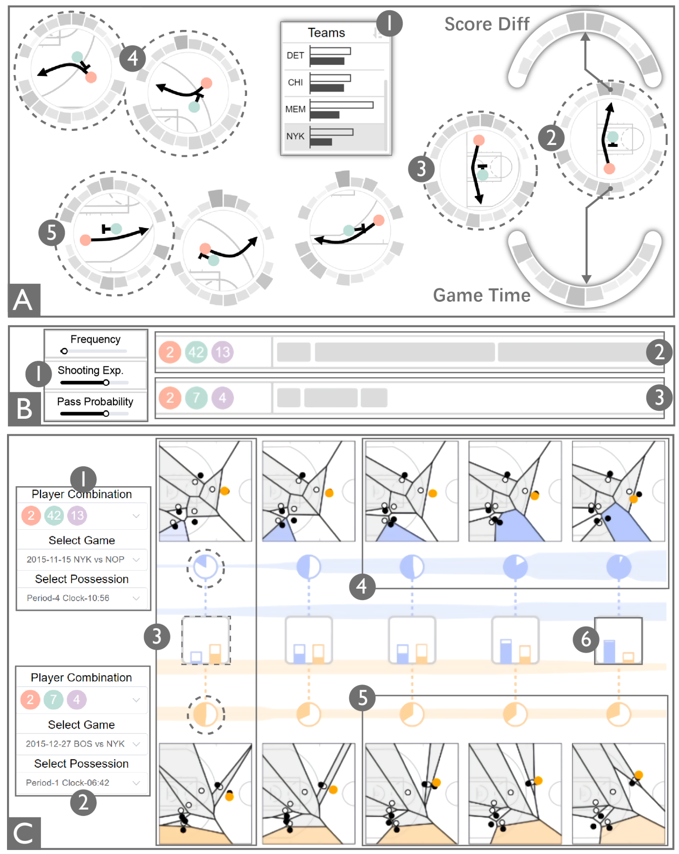

Fig. 9. The pipeline for the second case. (A) presents the *movement overview* for Team NYK. (B) shows two player combinations for the curl cut. (C) compares the off-ball moving processes of the two combinations.

histogram above the left-to-right baseline cut (Fig. 9(A2)) indicated it was often used when the score was close or in a big lead. Meanwhile, the one below suggested it was used more in the first half than in the second half of the game. Despite the efficiency of baseline cuts, ED pointed out that there were two off-ball movements near the three point line in the top left corner (Fig. 9(A4)). This meant that the most frequent off-ball movements used by Team NYK were very inefficient on offense. EC stated, *"Such phenomena may explain why Team NYK's overall offensive performance of off-ball movements is poor."* Moreover, both experts noticed that Team NYK was almost the least efficient at a commonly used basketball cut (Fig. 9(A5)), the curl cut (i.e., an off-ball player curls around a screener to receive the ball). EC then clicked it to see which players had executed such an off-ball movement.

Insight 2: The inefficiency of Team NYK comes from ineffective teamwork. In order to better distinguish the performance of different player combinations, EC lowered the weight of frequency and increased the weight of the other two attributes (Fig. 9(B1)). While browsing the table, the experts found two interesting combinations of players. The first combination ranked top and performed well in both the shooting expectation and passing probability (Fig. 9(B2)). The second combination was ranked at the bottom, and its performance in the passing probability was lower than the shooting expectation (Fig. 9(B3)). The cutter in both combinations was the #2 player (i.e., Langston Galloway).

The experts were curious why the same cutter performed so differently in such a curl cut. They then selected two off-ball moving processes with the *select panel* (Fig. 9(C1, C2)) for comparative analysis. At the beginning of the two off-ball moving processes, the cutter and the ball handler stood in almost the same positions (Fig. 9(C3)). Through the bar chart and pie charts, EC found that the lower combination was even better than the upper one in terms of shooting expectation and passing probability at that time. However, as the moving processes continued, the blue flow became gradually wider, and the yellow flow became gradually narrower. This implied that the upper combination overtook the lower one in both indicators during the movement. EC thus looked closely at the two series of Voronoi diagrams to find out the reason. From the blue diagrams (Fig. 9(C4)), EC stated that the screener had successfully blocked the cutter's defender, thus providing him with open space to receive the ball and shoot. As for the yellow diagrams (Fig. 9(C5)), EC thought the screener had failed to block the defender. The ball handler even moved in the other direction, making it difficult for the cutter to receive the ball. These differences in teamwork eventually led to a significant gap in the scoring expectations of the two movements (Fig. 9(C6)). EC concluded, *"If Team NYK want to improve their performance in off-ball offense, they need to avoid making too many mistakes in teamwork as much as possible."*

7.3 Expert Interview

After the case studies, we conducted one-on-one interviews with the experts and collected their feedback. Overall, all the experts thought highly of the usability of OBTracker. They confirmed that the system could help them perform off-ball movement analysis in basketball for three main reasons. First, the analysis workflow of OBTracker can reduce the burden of traditional video analysis methods. EB mentioned, *"I need to watch a lot of game videos to figure out a team's tactical style in off-ball movements. However, I can now use the overview in the system to quickly assess a team's typical off-ball movements."* Moreover, EC also stated, *"This way of summarizing the off-ball movements can save me a lot of time recording and collating data."* Second, the player view provides new insights into the player arrangement for off-ball strategies. EA commented, *"The table of player combinations is useful. The rankings can help us assign the most suitable player for each offensive tactic."* Third, the details and variations during an off-ball moving process can help verify the experts' conclusions. EC stated, *"When investigating the concrete off-ball moving process, I saw a series of charts clearly showing the changes in game situations. I can also verify the rationality of the player rankings through these charts."*

Suggestions. The experts also shared their thoughts to further improve the usability of OBTracker. EA suggested some aggregation methods could be added to the table in the player view. *"For a commonly used type of off-ball movement, I will see a bit too many combinations of players on the table. This may be a considerable disadvantage when I want to focus on a particular off-ball player."* Meanwhile, EB thought the off-ball movements in the *movement overview* could be further categorized by the defense. *"The same off-ball strategy may work quite differently against different defensive systems. Therefore, in addition to the player's running path, I think the opponent's defensive strategy is also a significant classification basis."*

8 Discussion

Extensibility. The extensibility of OBTracker stems from two aspects. First, with reasonable adaptations, our analytical framework can be extended to other similar team sports (e.g., soccer and rugby), where movement is also important. For example, the multi-level analytical requirements are generic, including the aggregation of large-scale trajectories to summarize the movement patterns or the interpretation of individual movement processes. Second, the assessment model can easily introduce additional metrics to further enhance the performance. The basic idea of the model is to quantitatively represent independent factors by discretizing the basketball court, and to integrate the effects of multiple factors by element-wise matrix multiplication. The model thus allows to include additional factors that are not currently covered, once they can be spatially discretized and finely modeled in the future, such as defensive pressure on basketball players from the Z-axis.

Lessons Learned. We have learned lessons from our cooperation with domain experts and model development. First, domain-driven visual representations serve as an intuitive language for requirement communication. At an early stage of the expert interview, we presented the potential metrics with mathematics formulas and visualized the trend across time with line charts. We discovered that the experts had a hard time understanding the metrics and told if the metrics were effective. To better show the metrics, we visualize the value changes side-by-side with the trajectories on the court. We also used animation to show how value reaches the peak and provided efficient interactions for exploration. Follow-up studies with domain experts can consider using domain-driven visual representations to improve communication efficiency. Second, model explainability costs. In this work, we focus on developing an explainable model for off-ball movement evaluation and interpretation. To ensure explainability, we do not consider deep learning-based methods. In fact, deep neural networks are powerful in fitting data points with non-linearity. Future studies could consider how to balance the explainability and model performance and improve the effectiveness of visual analytics. For example, we could introduce deep learning to detect player roles during data preprocessing and use explainable models for the core component, i.e., evaluating off-ball movement contributions.

Limitations. We have observed three limitations in this study. First, the system provides inadequate information about defense at the level of team summarization. According to our experts, they are interested in understanding the general effects of a specific type of off-ball movement, such as its impact on the defensive system. Nevertheless, visual clutter is almost inevitable when aggregating the trajectories of multiple defensive players. Considering that the five defenders typically follow a holistic defensive strategy (e.g., zone defense), how to detect and aggregate defensive information remains to be resolved. Second, the assessment model cannot explicitly describe the offensive contribution of screeners. In an off-ball movement, the screener generally takes on a different role than the cutter. Their primary goal is to create open space for other teammates rather than score points directly by themselves. Hence, we will further investigate how other tactical indicators can be used to evaluate the contribution of such behaviors more accurately. Third, it requires more fine-grained modeling of player behaviors. Currently, we assume that a player's role (e.g., cutter or screener) is consistent during a possession, but actual cases would be more complex that a player might act as a screener and then become a cutter (e.g., Spain Pick&Roll). Future work can investigate the detection of player roles with deep learning models and reconstruct the process of multiple-player cooperation.

9 Conclusion

In this work, we explored the creation of an advisory tool for basketball coaches to analyze off-ball movements and improve strategic plans. At first, we collaborated closely with domain experts and established an interpretable model for assessing and understanding the effectiveness of an off-ball movement. On the basis of the model, we further presented OBTracker, an interactive visualization system that supports multi-level analysis of off-ball movements, including team-level summarization, player-level investigation, and action-level explanation. Finally, we conducted two case studies and collected expert feedback to demonstrate the effectiveness and usability of OBTracker.

In the future, we aim to adapt our assessment model to other team sports (e.g., soccer). Moreover, we plan to extend OBTracker to present the actions of off-ball screeners and uncover their contributions. This can facilitate coaches to better understand and build team tactics.

Acknowledgments

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