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Exploration of Player Behaviors from Broadcast Badminton Videos

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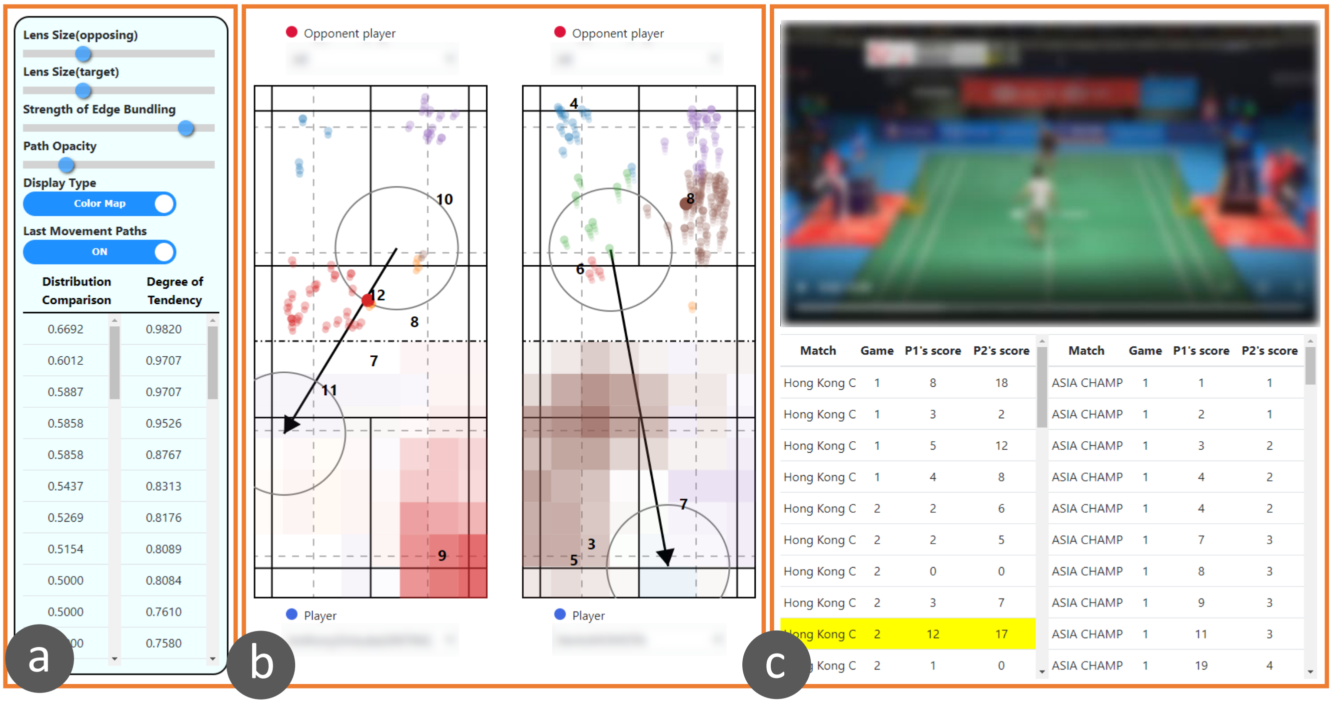

Figure 1: *The visual exploration interface of our system includes (a) a **distribution control** panel, (b) a **court view** panel, and (c) a **video view** panel that are linked mutually. The user can initially select a pair of two players to compare using the drop-down menus in (b), and the corresponding information will be linked to panels (a) and (c), respectively.*

Abstract

Understanding an opposing player's behaviors and weaknesses is often the key to winning a badminton game. This study presents a system to extract game data from broadcast badminton videos, and visualize the extracted data to help coaches and players develop effective tactics. Specifically, we apply state-of-the-art machine learning methods to partition a broadcast video into segments, in which each video segment shows a badminton rally. Next, we detect players' feet in each video frame and transform the player positions into the court coordinate system. Finally, we detect hit frames in each rally, in which the shuttle moves toward the opposite directions. By visualizing the extracted data, our system conveys when and where players hit the shuttle in historical games. Since players tend to smash or drop shuttles under a specific location, we provide users with interactive tools to filter data and focus on the distributions conditioned by player positions. This strategy also reduces visual clutter. Besides, our system plots the shuttle hitting distributions side-by-side, enabling visual comparison and analysis of player behaviors under different conditions. The results and the use cases demonstrate the feasibility of our system.

CCS Concepts

• ***Human-centered computing*** → ***Visualization systems and tools; Visual analytics;*** • ***Computing methodologies*** → *Machine learning;*

1. Introduction

Badminton has long been one of the most popular racket sports played within a standard court, and, for this reason, game broadcasts can be easily accessed via the Internet. Due to this convenient accessibility, coaches, analysts, professional players, and beginners can study, analyze, and learn techniques by repeatedly watching these video recordings. Although sponsor promotions and close-up replays are often inserted into these broadcasts, the recordings of badminton rallies exhibit a certain standard. In practice, rallies are often recorded via a fixed-view camera to capture the motions of players, as well as the movement of the shuttle. To quantify a rally, coaches and analysts usually classify and note down the key timestamps of hits and stroke types in a spreadsheet, which is achieved through a tedious slow-motion video watching procedure [CW07].

To scale up this traditional analytics methodology, we develop a system that facilitates effective visual analysis of trajectory data collected from broadcast video recordings [Fed20]. Practically, we incorporate machine learning techniques to extract meaningful statistical data that are often captured manually by analysts. We first partition a broadcast video into segments, in which each video segment shows a badminton rally. We then track players' feet in each video frame and transform the foot positions from the video coordinate system to the court coordinate system. In addition, we detect hit frames in each rally according to player poses. Since players have to move toward the shuttle and return the shuttle to their opponent when playing badminton, shuttle trajectories can be approximated by sequentially connecting players' foot positions in hit frames. It deserves noting that detecting hit frames based on players' poses is not a trivial task and demands a large amount of data for training. Since manually collecting hit frames is tedious, we utilize semi-supervised learning, in which a small amount of label data and many unlabeled data are utilized during training, to reduce the data collection load.

Our system allows users to analyze shuttle trajectories and investigate player behaviors visually. The goal is to examine shuttle hit distributions on the court under specified conditions. Specifically, users indicate a radius range where players hit shuttles in the previous and current shots (i.e., played by two different players) and our system displays where the shuttles will potentially land in the subsequent shot. Our designed interface contains two badminton courts, as shown in Figure 1 (b), such that coaches can compare shuttle hit distributions of players in historical games and develop effective tactics. Moreover, considering that the game tempo of badminton is high, and players have to travel and hit shuttles instantly, they exhibit a tendency to land shuttles at similar positions in certain situations. Consequently, our system conveys the relations between the positions in that players play the previous shots and the positions at which they will land shuttles. Finally, although our visualization system achieves interactive performance, users still have to specify various conditions and visually discover patterns of interest. To further conserve their time, our system retrieves the events in which behaviors of the compared players are considerably dissimilar, or a player's degree of tendency is high, for users to consider initially. We demonstrate that players' behaviors in their historical games are largely transparent under this view. In short, our primary contribution is an efficient visual analytics framework for summarizing and exploring badminton rally data. The framework uses machine learning to extract gaming statistics from broadcasts for analysis, and provides extensive data and interactive visualization. The use cases presented demonstrate its superiority over traditional tactic analysis methods.

2. Related Work

2.1. Sports Data Visualization

Visual analytics of movements and trajectories provides an intuitive form of understanding the underlying patterns hidden in datasets [AAB*13]. This not only allows sports analysts and coaches to study collective movement behaviors, but also facilitates their ability to identify the habits, styles, strengths, and weaknesses of a certain player. In 2018, Perin et al. [PVS*18] proposed a taxonomy in sports data visualization to guide follow-up scientists regarding how existing approaches are designed to handle score data, tracking data, and metadata. Recently, Du and Yuan [DY20] revisited this taxonomy on competitive sports data beyond data types, and took task categories and visualization techniques into consideration. Visual analytics have been introduced in different sports, such as basketball [LTB16], soccer [JSS*14, SJL*18], tennis [PYHZ14, PJHY20], and table tennis [WLS*18, WZD*20].

Among the collected sports data, trajectories play an essential role because visualizing players' movements from a top view can provide an overview of a game. Aggregation techniques, such as glyph-based visual abstraction [AAA*19] or classical clustering algorithms [LTB16, SAMS*17], are frequently utilized to eliminate unwanted spatial or temporal visual complexity. In addition, Janetzko et al. [JSS*14] proposed a multi-faceted view to assist analysts in finding essential events in a game. Losada et al. [LTB16] introduced coordinated views and linked video sequences to actions to illustrate the relationship between collected data and video clips intuitively. With these techniques, however, analysts still need to collect data on a game manually, and the amount of requested time is highly correlated to the number of labels (e.g., lob, drop, smash, etc.) predefined in the data spreadsheet.

2.2. Game Data Acquisition

To extract massive amounts of data efficiently, Therón and Casares [TC10] utilized GPS devices to record players' positions in basketball games. Later, approaches were investigated to automatically build court scenes from videos to map events to a standard top-view representation. Wen et al. [WCW*16] used a camera calibration technique to extract a panoramic court from a video and map it to a standard court in basketball games. Stein et al. [SJL*18] integrated and overlaid recorded soccer videos with abstract visualization to accelerate advanced collaborative movement analysis. Wu et al. [WXW*19] developed a system that allows users to semi-automatically track and collect positions of soccer players from recorded videos using machine learning techniques [RDGF16] and summarized the corresponding team formation.

Classical works were also performed to extract badminton game data from video frames [CW07] or sensors [TTL16]. Chu and Situmeang [CS17] presented a report that detects badminton courts in broadcast videos by extracting court lines. They further proposed a taxonomy of badminton strokes and players' strategies using mathematical model. Hsu et al. [HCJ*19] proposed a badminton analysis and training pipeline, which incorporates object tracking with hardware devices, such as smart badminton rackets or smart gloves [SPHL20], to allow machines to interact with players and perform training in various tactics. Ghosh et al. [GSJ18] developed a video annotation approach to detect players' positions and their corresponding actions. Deng et al. [DWW*21] introduced a multiple-level video annotation approach for sports videos, such as table tennis content exploration. The above-mentioned approaches concentrated on video annotation, and did not integrate with a visual analytics pipeline for data exploration.

2.3. Visual Analytics in Net-separated Confrontation Sports

Different from team sports described previously, badminton players hit the shuttle across a net to win points. The shuttle speed, the move, the strength, and how to receive such a shuttle require proper training and techniques [OM06]. To visualize such net-separated sports, Wu et al. [WLS*18] proposed *iTTVis*, a pioneering visual analysis system for table tennis. The system consists of statistics and pattern detection models that facilitate the cross-analysis of underlying data. Their team also visualized consecutive usages of tactics and the corresponding winning rates for coaches to analyze a player's strengths and weaknesses [WGW*20, WLG*21]. In addition to tactics, visualizations in 3D or beyond 3D have also been investigated. Ye et al. [YCC*20] and Chu et al. [CXY*21] introduced an immersive analytics scheme using VR headsets, which allows experts to analyze 3D badminton trajectory data from the first-person perspective.

Although several systems have been presented to visualize net-separated confrontation sports, they were not designed to depict massive amounts of shuttle hitting positions extracted from broadcast videos. They either demand experts to label event sequences [WLS*18, WGW*20, WLG*21] or aim to provide users with an immersive analytics environment [YCC*20, CXY*21]. In other words, the datasets the previous works visualize are not massive, and they do not have to handle the caused visual clutter. In addition, our system can map each shuttle trajectory to the corresponding court-view shot video since the trajectories are automatically extracted. Enabling users to watch the video if they are curious about a specific shot is needed since videos contain the most information in games.

3. Background and Design Principles

3.1. Introduction of Badminton

Badminton is a racket sport in which a single player or two players per side aim to land a shuttle across a net to the other half-court of the opponent(s) [AAB*13]. A player needs to gain 21 points to win a game, and win two games to get the series [Per15]. A point in a game is obtained through a process called a *rally*, in which the opposing players strike the shuttle toward each side of the court until the shuttle lands to win a point. A *stroke* or a *shot* is an action to strike the shuttle with the racket. A good combination of strokes usually leads players toward a winning position. In addition, a *tactic* aims to find the most effective stroke patterns against the opponent. This requires badminton coaches to collect and analyze data to obtain statistical knowledge of the players and the opponents, and transfer this knowledge to the players. Such knowledge relies on the coach's experience, and it is often gained through massive data analysis.

3.2. Requirements for Badminton Analysis

To understand the traditional badminton analytics pipeline, we organized regular meetings with several badminton experts. One is a professor who specializes in badminton coaching and education at our university. Another expert is the President of the Chinese Taipei Badminton Association (CTBA). We also consulted one professional player. Together with the domain experts, we organized a creative visualization opportunities (CVO) workshop [KGD*19] to clarify challenges and expectations in the field. In the workshop, the experts first shared the scenario they collected data from game videos and how they designed badminton tactics. The coaches also explained to us a record sheet that they used to label shot landing positions manually. Generally, they all point out that data collection is labor intensive such that they can only collect data with low precision through limited human resources. In practice, the experts partitioned a half badminton court into six regions based on the short service line, long service line, and the center line, and asked annotators to label the region in which each shuttle would land (similarly to Figure 1(b)). Although the left and right service courts much larger than the other regions is reasonable (i.e., players would move to the center court after they play a shot), the quantization of the court is still problematic since shuttles could land at positions close to service lines. Hence, we summarized the approach goals (G) and requirements (R) after the workshop and showed them as follows:

Approach Goals (G). We collected three main objectives that the experts expect the software to achieve.

- **G1** A system that can process broadcast videos to extract badminton game data for visual analytics.
- **G2** An integrated visualization that shows statistical analysis and allows intuitive communication with players, especially through coordinated views and video clips.
- **G3** A systematic rally summary that can enable historical behavior comparison and strategy development.

Approach Requirements (R). We focus on revealing where players would land shuttles in historical games. For this reason, we summarize the approach requirement as follows:

- **R1** *Data preprocessing.* The analysts are not interested in advertisements, close-ups, or replays in broadcast videos. Irrelevant video clips should be filtered out automatically. Moreover, the system has to automatically extract game data, such as shuttle trajectories and player positions, from the court view shots.
- **R2** *Correlation of potential shot types (e.g., lob, drop, smash, etc.), player positions, and shuttle trajectory and speed.* A system that allows users to implicitly understand shot types by analyzing player positions, shuttle trajectories, and shuttle speeds.

(a) (b) (c) (d) (e)

Figure 2: *Our system workflow, including (a) input online video recordings, (b) automatic rally video clip segmentation, (c) shuttle trajectory extraction in rallies, (d) coordinate system transformation, and finally (e) a coordinated visual analytics system.*

R3 *A direct visual design for data exploration.* Although several visualization examples were discussed throughout the CVO workshop, using classical court diagrams in 2D is anticipated by the analysts. The visual elements should be commonly used and easy to interpret since the target users of our system are coaches and players. We also explored 3D and mixed reality techniques, yet our experts assert that 2D plots function most intuitively for large data analysis.

R4 *An interface for discovering players' tendencies and behavior comparison.* Players would feel confident if they knew where the opposing players tend to land shuttles under specific conditions. This information is also essential for coaches to elucidate the weaknesses of the players. In addition, the coach requests side-by-side panels for player comparison because they can design tactics based on the strengths of the players on his or her side and the weaknesses of the opposing players.

R5 *Integrated coordinated views with a user interface to assess analytical results.* Panels, such as a heatmap view for managing statistical results, show the selected data, and corresponding videos are requested. This enables analysts to explain and communicate with the team optimally.

3.3. System Pipeline

We designed our system based on the aforementioned requirements. Figure 2 presents an overview of our approach, which includes (a) input online video recordings, (b) automatic rally video clip segmentation, (c) shuttle trajectory extraction in rallies, (d) coordinate system transformation, and most importantly (e) a coordinated visual analytics system. Each component will be detailed in Sections 4 and 5, respectively. Our goal is to develop a novel visual analytics system that allows badminton coaches, professional players, and naive players to investigate and compare patterns and habits in a series of games. We begin with data acquisition. Our setting is inspired by the traditional analytics pipeline, in which analysts need to manually collect data by watching game videos (Figure 2(a)). We replaced this laborious process with state-of-the-art machine learning techniques (**R1**). As shown in Figure 2(b), we first train a neural network to remove unnecessary clips, such as advertisements and close-up replays. Then we extract the shuttle trajectory in a rally, by tracking players and detecting hit frames to identify the hit positions of the shuttle (Figure 2(c)) (**R2**). Based on the aforementioned information, we can transform the perspective court view in the video to a standard top-view court coordinate system and avoid the influence of depth perception in the video (**R3**). Figure 2(d) presents a conceptual diagram of this step. Finally, we record all information in a database, so that the information present in the coordinated views is mutually linked for visual exploration (Figure 2(e)) (**R4**, **R5**).

4. Game Data Acquisition

We apply computer vision techniques to collect game data from broadcast badminton videos for visual analysis. Specifically, the goal is to obtain shuttle trajectories from historical games, and show data on the screen to reveal player behaviors. The overall process can be divided into the following steps: (1) rally video clip segmentation (**R1**) and (2) rough shuttle trajectory extraction (**R2**).

4.1. Rally Video Clip Segmentation

Broadcast badminton videos contain not only long-shot court views, but also advertisements and close-up replays, which are not useful for data analysis. For this reason, we train a neural network on our collected dataset to classify each video frame into court and non-court views. The backbone of the neural network is ResNet-18 [HZRS16]. The dataset contains 4268 and 3714 court view and non-court view frames, respectively. We downsample each video frame to the resolution of 64×64. We also augment the collected dataset by horizontally flipping the original video frames for training. In fact, training the classifier is not difficult because the badminton court contains clear and unique visual features. After network training, we classify each video frame into the court view and the non-court view categories. The long broadcast video is then segmented into short clips according to temporal adjacency and the assigned labels. Since a badminton rally or an advertisement lasts for at least a specific period of time, we flip the label of a video clip if it is shorter than 60 frames (1 second) to improve segmentation accuracy further.

4.2. Shuttle Trajectory in a Rally

Tracking shuttle movements is challenging because shuttles are small and move fast in badminton videos. In addition, the tracked 2D shuttle positions are in the video coordinate system. The lack of depth information also makes the transformation of shuttles

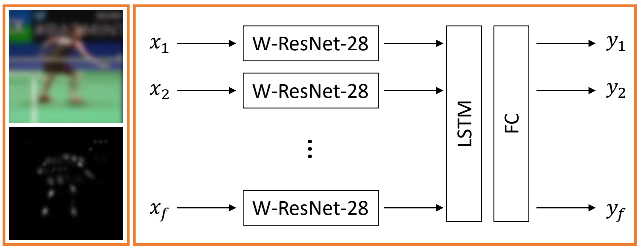

Figure 3: *(Left) The network takes the RGB image and the corresponding joint heat map to detect whether the player strikes the shuttle. (Right) The network architecture.*

from the video coordinate system to the court coordinate system for future analysis challenging. Considering that players' feet are (mostly) on the ground and they have to run toward the shuttle to return it, we instead track player positions on the court and detect their hit poses to obtain shuttle hitting positions. The coplanarity with the court enables the transformation of the coordinate system. By consecutively connecting foot positions when players hit the shuttles, we obtain approximate shuttle trajectories. We also compute each hit's mean shuttle speed based on the moving distance and the number of frames between hits. Users will use our system to visually analyze these extracted shuttle trajectories and examine players' behaviors.

Player tracking. We apply a pre-trained neural network – YOLO-v3 [RF18] to locate player positions in each video frame. Specifically, given an image, it returns bounding boxes that tightly crop the players. We then apply the OpenPose model [CHS*18] to detect the player's pose in each sub-image. Since our goal is to analyze where players hit the shuttle, we consider only the two feet' joint positions and transform the mean to the court coordinate system. Since YOLO-v3 [RF18] and OpenPose [CHS*18] were pretrained on pedestrians, they did not always correctly locate badminton players and detect their poses. The failure cases often occur at top-side players because of low video resolution and net occlusion. We thus fine-tune the networks according to our collected datasets. Particularly, we first collected 3000 failure samples of the original OpenPose model, fixed the joint labels, and then used the corrected samples to fine-tune the model.

Analyzing positions in the video coordinate system is meaningless because broadcast videos are often captured by cameras with different positions and orientations. The coordinate system also suffers from distortions caused by perspective projection. Because of the fixed camera motion throughout a badminton game, we manually label the four corners of the court in the first frame of a broadcast video, although several approaches have been presented to detect court corners [CS17]. Since the court, in reality, is a plane and its width and height are predefined, we apply homography to transform player positions (i.e., mean of the feet joint positions) from the video coordinate system to the court coordinate system for further analysis. It is worth noting that the court coordinate system can be rotated by 180 degrees to align data for analysis.

Hit frame detection. Detecting hit frames in a rally video is essential for generating shuttle trajectories. To achieve this goal, we train a classifier that can determine whether the player hits the shuttle. The input of the classifier is player sub-images cropped by YOLO-v3 [RF18] from video frames and the corresponding joint heat maps (Figure 3 left) extracted by the OpenPose [CHS*18] model. The concatenation is then scaled to the resolution of $w \times h \times c$ tensor x. In our implementation, $w = h = 96$, and $c = 4$ because of the RGB channel and the 1D heat map. The output is a label y^* indicating whether the frame is a hit frame. Figure 3 right shows the network architecture. The backbone of the image encoder is W-ResNet-28 [ZK16], and the long short-term memory network (LSTM) [HS97] contains 64 hidden units. In other words, the classifier first extracts visual features from spatial images and then feeds the features into the LSTM for learning temporal feature correlations. The fully connected layer on the back determines whether the frame is a hit frame.

Unlike the court view classification task, detecting the hit frame is challenging because of the ambiguity between running and hitting poses. A large number of training samples are needed. To reduce the manual labeling work, we train the classifier on a small amount of labeled data and a large amount of unlabeled data using a semi-supervised approach. Similar to supervised learning, the classifier is trained on the labeled data L by minimizing the cross-entropy loss. Regarding the unlabeled data U, the consistency loss was minimized. Specifically, for an input sample x, we randomly augment the sample by horizontal flipping or a limited degree of rotation $q(\cdot)$, denoted as $\hat{x}$, and expect the classifier to output the same label for these two samples $\mathbf{x}$ and $\mathbf{x}'$. Formally, we train the classifier by minimizing

$$\begin{aligned} arg\min_{\theta} J(\theta) = & \ \mathbb{E}_{(x,y^*)\in L}[-log p_{\theta}(y^*|x)] \\ & + \lambda \mathbb{E}_{x\in U} \mathbb{E}_{\hat{x}\sim q(\hat{x}|x)}[\mathcal{D}_{KL}(p_{\theta}(y|x)||p_{\theta}(y|\hat{x}))], \end{aligned} \quad (1)$$

where θ indicates the network parameters, p is the probability function, $\mathcal{D}_{KL}$ denotes the Kullback-Leibler divergence that measures the similarity of two distributions, and λ is the parameter used to balance the loss between the labeled and the unlabeled data. In our implementation, we train the classifier on 1085 labeled (hit : non-hit frames = 1:9) and 11441 unlabeled samples. Each sample contains 50 frames and the corresponding 50 labels. This is clearly an imbalanced problem because non-hit frames are much more than hit frames. We use the focal loss [LGG*17] to prevent the classifier from always guessing the non-hit label. We also apply the training signal annealing strategy to prevent the classifier from overfitting the labeled data. Specifically, when the predicted probability of a correct label is larger than a threshold n_t, the loss of that sample is not counted. The threshold $n_t = \alpha_t \times (1 - \frac{1}{k}) + \frac{1}{k}$, where $\alpha_t = \frac{t}{T}$, t and T are the current and the total numbers of the iteration, respectively, and K is the number of classes. Intuitively, n_t increases from $\frac{1}{k}$ to 1 as the number of iteration t increases.

5. User Interface

Figure 1 shows our exploration interface consisting of (a) a *distribution control* panel, (b) a *court view* panel, and (c) a *video view* panel. Users can interact with functions in each panel, and the data will be linked in a coordinated manner [WBWK00, Rob07].

The middle *court view* panel (**R3**) is the primary panel in our visualization, in which sample dots or heat maps are displayed to reveal players' behaviors on the court. There are two courts displayed in this view, and users can select players to be analyzed via drop-down menus. In practice, users can compare how the two players behave on the court by visual analysis. Since badminton is a two-player game, by default, our system considers the bottom-side player to be the *target player*, whose behaviors will be examined by users. Accordingly, the top-side player is the opponent of the target player, and is denoted as the *opposing player*. We will use the opposing player and target player to indicate the top-side and the bottom-side players, respectively, in later paragraphs. Note that we align player positions initially on the top-side and bottom-side courts by rotation in order to study players' behaviors in the same coordinate system. The *distribution control* panel (**R4**) lets users set parameters when using our system, such as resizing the filtering lens, adjusting the point opacity, and modifying the tightness of edge bundling [Hol06] during the investigation. We will provide corresponding details in the subsequent paragraph. Finally, in the *video view* panel, we include video recordings for fast inspection. When users click on a stroke in the *court view* panel, the corresponding recordings will be played automatically (**R5**). We also show the statistics of each shot, such as the name of the competition, the game of the shot, and the points that players have gained, at the bottom of the *video view* panel for users to understand the game situation.

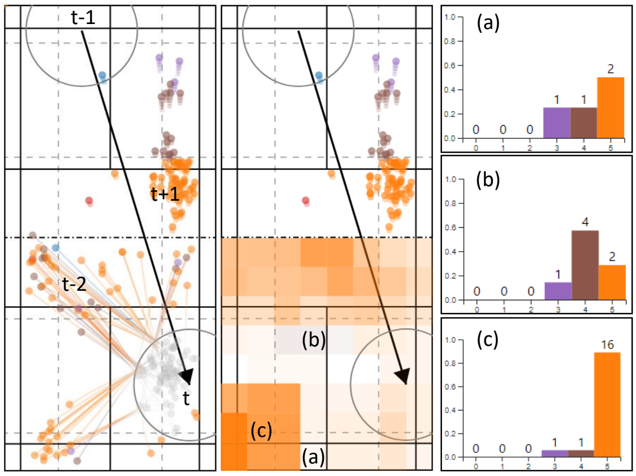

Figure 4: *Left and middle sides are the sample dot distribution and the heat map used to reveal a player's behavioral tendency. Shots from $t-2$ to $t+1$ are marked on the left. The bar charts (a) - (c) show the statistics of the three corresponding regions in the heat map, respectively. The horizontal and vertical axes represent the court sector index and the corresponding shuttle hitting probability, respectively. We also show the number of shuttles on the top of each bar for users to consider. The visualization indicates that the target player tends to play a parallel drop shot when traveling from the bottom-left court (c) to the right court to return shuttles.*

5.1. Sample Dot Distributions

One of the keys to understanding a player's behavior is observing where he or she will land shuttles on the opposing court. Since drawing trajectories on the court would introduce visual clutter, we present a 'time-to-space' representation based on the assumption that player behaviors depend on only recent shots. For example, analysts can examine shots $t-2$, $t-1$, and t to forecast the shuttle hitting position at shot $t+1$. Accordingly, we transform each shot trajectory into multiple and overlapping segments, in which each segment contains four consecutive shots. The time points of the four shots are $t-2$, $t-1$, t, and $t+1$, respectively. We then visualize the segments rather than the whole trajectories for users to analyze player behaviors. In this study, we provide users with two *filtering lenses* [BC87, TGK*17, KTW*13, KKE16], which are represented by black circles, for them to study data under the condition in which players are in the lenses. This strategy can reduce visual clutter [AMST11] because the system only shows partial data on the screen. Users interact with the system by moving the filtering lenses and adjusting their radius individually. Our system updates the shuttle hitting distributions immediately. In Figure 4 (left and middle), the arrow shows the condition in which the opposing player strikes the shuttle toward the bottom side from shot $t-1$ to shot t, respectively. The goal is to reveal where the target player will return shuttles under such a condition. Therefore, we display sample dots on the top side court to indicate the shuttle hitting positions at shot $t+1$. Each dot is attached with a tail indicating the mean shuttle velocity. A longer tail means a higher velocity.

We partition a half badminton court into six sectors based on the observation of hit distributions (Figure 5). The dots in the six sectors of the top court are in six distinct colors. We use the colors to depict further how the target player reacts when he or she moves from different parts of the court to hit shuttles. We first clarify that the order of shots from $t-2$ to $t+1$ in the central view are dots on the bottom court, the filtering lens on the top court, the lens on the bottom court, and dots on the top court, respectively. Marks in Figure 4 left illustrate the shot order. This means that the target player plays shot $t-2$ at a specific position and then moves toward the bottom-side circle to play shot t. The goal is to reveal the relations of hit positions between shot $t-2$ and shot $t+1$. Specifically, our system depicts the target player's positions at shots t and $t-2$ using gray and color dots, respectively, and connects the two shots to indicate the player's movement. The dot colors on the two sides of the court correspond to each other. For example, players move from the orange dots at shot $t-2$ toward the lens area to play shot t would land shuttles at the front left court (Figure 4 left). We also bundle the connecting lines [Hol06] to reduce visual clutter.

The filtering lens was designed as a circular shape to allow users to filter data based on players' positions. Since the points scored by badminton players are independent of their position on their own court. there is no need to provide users with lenses of different shapes. The default radius is 1.5m, which represents a player's defend zone, where they can only move a little to return the shuttle. Users have the option to adjust the lens size to match the height and speed of the players. It's important to find a suitable size, as a too-large lens may lead to general behavior not relevant to the player's position, while a too-small lens may result in limited data and bi-

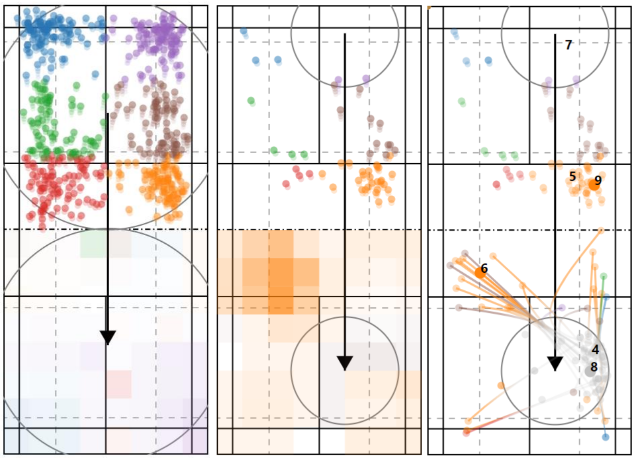

Figure 5: *(Left) We set the filtering lenses to the maximum radius, and observe the overall shuttle hitting distribution played by a player. (Middle) The heat map shows that the player tends to play parallel drop shots when he or she moves from the front-left court to the middle-right court for returning shuttles. (Right) Users can investigate the shuttle trajectory in the dot sample distribution and realize how the rally was played.*

ased observations. The lens size depends on the purpose and player statistics. For instance, users can set a maximum radius to study a player's overall behavior (Figure 5 left). Note that increasing the lens radius to cover the entire court does not result in misselection as almost all shuttle hitting positions are within the court.

When using a large filtering lens, visual clutter can occur due to the simultaneous display of dots from shots $t-2$ and t in the bottom side court. To alleviate this, we provide users with the option to turn off the dots from shot $t-2$ by clicking a button in the *distribution control panel*. With this setting, player positions from shot t are displayed as colored dots, with colors corresponding to the top-side court sectors. Since the change only affects the color scheme of shot t, users can still understand whether shot $t-2$ is on or off by focusing on the central view, minimizing the impact on the user experience.

5.2. Heat Maps

Our system allows users to switch sample dot distributions to heat maps, which also reveals where players will land shuttles if they travel from the position at shot $t-2$ to receive shuttles at shot t. The heat map summarizes the dots and connecting lines at the bottom court and can avoid visual clutter when a large amount of data are presented. Specifically, we partition the bottom-side court into an 8×8 regular grid and denote each local quad by $q_{i,j}$, where i and j are the row and column indexes, respectively. For each quad $q_{i,j}$, we fill a color to represent where players will land shuttles at shot $t+1$ if they move from $q_{i,j}$ at shot $t-2$ to the filtering lens (at shot t) for returning shuttles. The color corresponds to the six sectors on the top court, and a high saturation color indicates the high degree of tendency (Figure 4).

To determine the color of each quad $q_{i,j}$, we compute $p^s_{i,j}$ to represent the probability of the hitting sector s that the target player would land shuttles if he or she plays shot $t-2$ at quad $q_{i,j}$, where $\sum_s p^s_{i,j} = 1$. Since each court sector s has its own color C^s, we colorize the quad using C^s if $p^s_{i,j}$ is apparently higher than $p^r_{i,j}, \forall r \neq s$. In this study, we consider that a high degree of tendency is supported by more samples and lower entropy of probability $p^s_{i,j}$ in the dataset. This idea can be implemented using the weighted entropy and formulated as

$$F_{i,j} = S\left(\frac{k-b}{a}\right) \times \left(H_{max} - H(P_{i,j})\right), \tag{2}$$

where S is the Sigmoid function, H is the Shannon entropy, $P_{i,j} = \{p^0_{i,j}, p^1_{i,j}, \ldots, p^5_{i,j}\}$, k is the number of samples at quad $q_{i,j}$, and a and b are the user-specified parameters. The larger values of a and b imply that high reliability demands more samples. We set $a=2$ and $b=4$ in our implementation. The low entropy $H(P_{i,j})$ indicates that one of the hitting probabilities $p^s_{i,j}$ is high, and the others are low. We also consider the one-hop neighbors of quad $q_{i,j}$ when computing $F_{i,j}$ to reduce the zone effects caused by the spatial partition. Apparently, the large value of $F_{i,j}$ implies a high degree of behavioral tendency because: (1) there are many samples around $q_{i,j}$, and (2) the shuttle hitting positions at shot $t+1$ gather at a certain court sector. As a consequence, we colorize each quad $q_{i,j}$ using

$$C_{i,j} = \alpha C^m + (1-\alpha)W, \quad \text{where} \quad \alpha = \frac{F_{i,j}}{H_{max}}, \tag{3}$$

m is the sector with the highest $p^s_{i,j}$, and W is the white color. In other words, the heat map only highlights a high degree of behavioral tendencies, and no false color composite would occur. Users are also allowed to right-click the quad to observe detailed statistics. Our system shows the number of shuttles hitting on the six court sectors using a bar chart, as demonstrated in Figure 4.

5.3. Highlighting Players' Behaviors

Users move the filtering lenses and examine shuttle hit distributions on the badminton courts to visually analyze players' behaviors when using our system. To reduce their manual load, we retrieve and highlight two types of events that deserve further investigation: (1) dissimilar players' behaviors under the same condition, and (2) the condition that causes tendentious shuttle hitting positions. We describe the corresponding details as follows.

Dissimilar players' behaviors under the same condition. The coach at our university pointed out that comparing players' behaviors is essential for them to develop effective tactics. Therefore, after users select players for comparison, our system finds the conditions in which the players' behaviors are the most dissimilar. Specifically, the system moves the lenses and computes the dissimilarity of the shuttle hit distributions. It then sorts the conditions according to the dissimilarity values in descending order and shows the values in the *Distribution Comparison* panel (Figure 1 (a)). Users can observe the conditions in which players' behaviors are considerably different by clicking the large dissimilarity values.

Note that the retrieved conditions depend on the radius of the filtering lenses. We let users specify the lens radius (via the distribution panel) since setting the parameter requires domain knowledge.

Condition that causes tendentious shuttle hitting positions. Knowing where shuttles will land is particularly beneficial to players because they can travel in the optimal directions at their pace. Consequently, we highlight the condition in which one of the six court sectors has the highest hitting probability. Recall that $p^s_{i,j}$ is the hitting probability of sector s if the target player hits the shuttle around quad $q_{i,j}$ at shot $t-2$. To achieve the goal, given the specified players and the radius of the filtering lenses, the system moves the lenses and determines the highest $p^s_{i,j}$ at each condition. Then, it sorts the conditions according to the corresponding highest $p^s_{i,j}$. Similar to the highlights of dissimilar players' behaviors, we show conditions with the highest $F_{i,j}$ in descending order in the *Degree of Tendency* panel. Users can click the values and examine the target player's tendencies before they play games.

6. Results and System Evaluation

We implemented the presented method and ran the system on a desktop PC with Quad-Core Intel Xeon CPUs and 12GB RAM. The graphics interface is written in JavaScript using the D3 library [BOH11]. The neural networks used to collect badminton game data were implemented using Python and Pytorch. Overall, the network training takes a couple of hours to a day. It depends on the complexity of the task and the amount of data. The training time, however, is not a big issue because the networks can be trained once and then used to process all broadcast videos. We used the models to process broadcast badminton videos and stored the extracted game data in the database. Then, coaches can use our system to explore player behaviors and develop tactics that could beat the target opponent.

Figure 5 left shows an overall view of the shuttle hitting distribution played by a professional player. Recall that this target player is at the bottom side and returns the shuttle at shot t. The dots on the top-side court indicate where the shuttle would land at shot $t+1$. We set the two filtering lenses to the maximum radius to reveal data played at all positions on the court. One can easily observe that most of the dots are close to the periphery of the court. This is reasonable because players, by default, would defend at the middle court to reach the shuttle sent by the opponent with the minimum distance. The middle court is the opponent's comfort zone. Notice that the dots can be roughly partitioned into six groups according to their positions. Furthermore, the dot distribution shows that smashes are primarily located at the regions close to the sidelines and between short and long service lines (i.e., top-side court) because dots around the region have long tails. *Clears* and *drops* are located at the back- and front- courts, respectively, and their mean speeds are often slow. Finally, the heat map shows that the player exhibits no obvious tendency to land shuttles at a specific position under this loose condition.

The player's behavioral tendency appears when users scale down the filtering lenses (Figure 5 middle). This target player was used to playing parallel drop shots when he or she moved from the front-left court to the middle-right court for returning shuttles. By switching the heat map to the sample dot distribution and clicking a dot on the court, users can investigate the original (partial) shuttle trajectory under the specified condition. In Figure 5 right, the numbers adjacent to dots indicate the shot orders. As can be seen, the target player hit the shuttle at the position with 6. After the opposing player returned the shuttle from the position with 7 to the position with 8, the target player moved toward the right sideline and returned the shuttle to the position close to the short service line.

	Accuracy	Precision	Recall	F1
Court-view	97%	100%	94.6%	97.2%
Hit-frame	91%	87%	81%	84.3%

Table 1: *This table shows the performance of our court-view detection and hit-frame detection methods on the testing sets.*

6.1. Design Decisions

Segments vs. Trajectories. The badminton trajectory data was divided into small segments and displayed to show the distribution of shuttle landing locations based on player positions from the previous shots. This design was chosen for two reasons: (1) player behavior is only dependent on recent shots due to the fast pace of badminton games, and players are unable to make decisions based on distant shot situations; (2) player behavior is uncertain, and it's important to display a sufficient amount of data to avoid presenting biased information. While complete shuttle trajectories provide all the information, overlapping lines can make it difficult for users to identify insights. Therefore, we allow users to focus on the data of consecutive shots when analyzing player behavior.

Heat maps vs. Dot Distributions. Our heat maps and sample dot distributions complement each other. The heat map allows users to quickly spot the high degree of a player's behavioral tendency, whereas the sample dot distribution reveals exact shuttle hit positions. Specifically, when observing the bottom left court of Figure 4 (left) at first glance, users do not have an impression that the target player would land shuttles in front of the short service line because of the purple and brown dots. However, the heat map and the corresponding histogram (Figure 4 middle and right) reveal a high degree of behavioral tendency since they clearly indicate the probability is about 80%. On the other hand, the dot distribution view shows exact shuttle hit positions and partial trajectories of a game (Figure 5), which allows users to realize why players land shuttles at certain positions. In short, switching the two views back and forth helps users examine players' data efficiently. Users can discover events of interest from heat maps and then examine details in sample dot distributions.

6.2. Effectiveness of Automatic Data Extraction

We evaluate the court view classifier by dividing the dataset (consisting of 4268 court view frames and 3714 non-court view frames) into 8:1:1 training, validation, and testing sets. The neural network was trained using the training set, and the training was terminated when the validation loss stopped decreasing for 50 iterations. The hit frame detection model was similarly evaluated. The dataset consisted of 1085 labeled and 11441 unlabeled samples, with a hit to

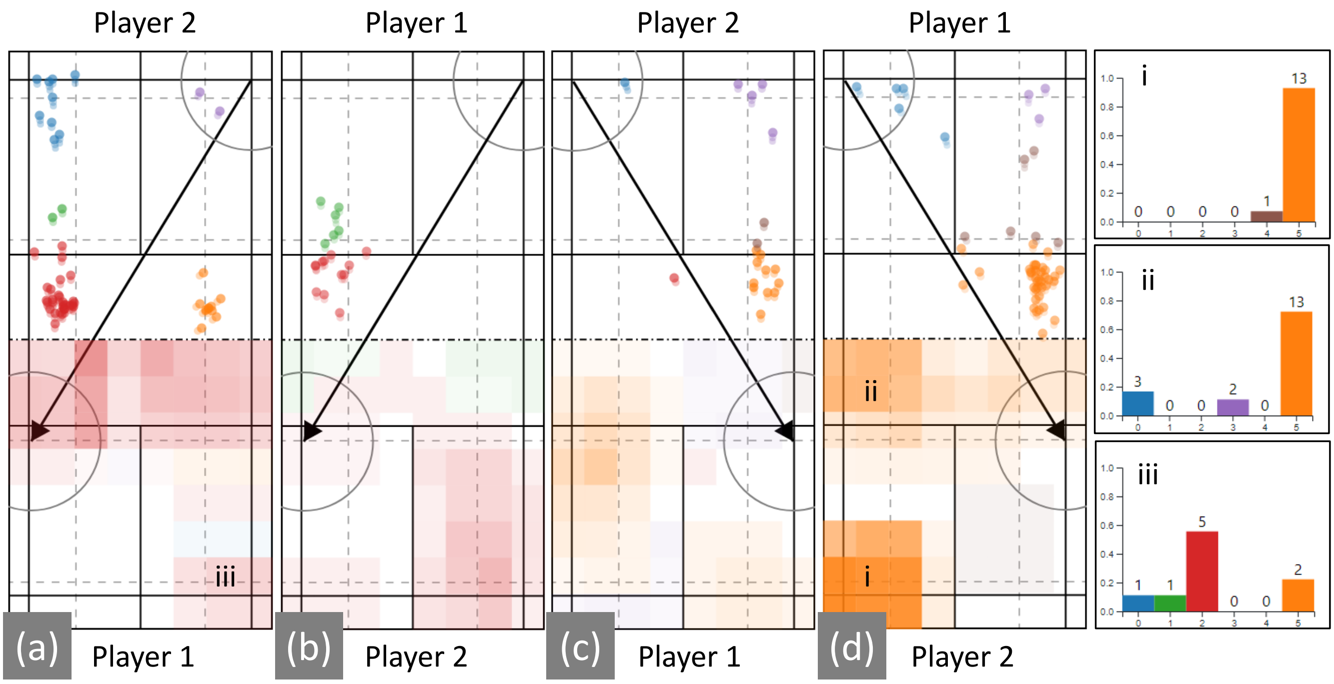

Figure 6: *The dot distributions show the different playing styles when the shuttle was sent from the backcourt to the frontcourt. As indicated,* Player 1 *and* Player 2 *exhibited markedly different behaviors when handling diagonal shots from the right side of the backcourt to the left side of the frontcourt (a) and (b). However, they behaved similarly when left and right were flipped (c) and (d). The heat map and the bar charts also show that* Player 2 *tends to play a parallel drop shot when he or she travels from the back-left side to the front-right side of the court to return shuttles.*

non-hit frame ratio of approximately 0.1 among the labeled samples. We display the performance of both algorithms in Table 1.

Regarding player positions on the court, accurately measuring the error (Figure 2d) is almost impossible since only broadcast videos are available. Specifically, from Figure 2 (c) to (d), errors could occur because of the imperfect player localization (YOLO-v3 [RF18]) and pose detection (OpenPose [CHS*18]) and numerical inaccuracy of the homography transformation. Since exact player positions are unavailable, we could only measure the deviation of player positions on the court caused by imperfect foot tracking. In other words, we first transformed the detected and manually annotated feet positions from the video coordinate system to the court coordinate system and then measured the distance. The root mean square error is approximately 30 cm. We have discussed this error with our expert. He mentioned that the error is acceptable since players are normally higher than 160 cm. The statistics mentioned above indicate that our system can extract reliable game data from broadcast badminton videos. Note that the feet could be blurred because of high moving speeds and occlusions by the net (i.e., the top side player).

Automatic methods can be imperfect. Specifically, our court view detector could make mistakes. When a court view shot is misclassified as an advertisement, we miss the data that can be collected for visualization. On the other hand, when an advertisement is misclassified as a court-view shot, the player detector (YOLO-v3) fails to locate player positions. Users may need to investigate the error when no players are detected. Regarding the hit frame detector, when it misclassifies hit and non-hit frames, the extracted shuttle hitting positions would be wrong, and visualizing the connected shuttle trajectories could mislead users. Since each method takes the result of the previous method as input in the data collection pipeline, we let users manually correct the results at each stage to prevent misleading situations.

7. Qualitative Evaluation

7.1. Use Cases

We present three use cases of the proposed approach. In order to maintain the anonymity of the players, we do not use their real names. Instead, we refer to them as *Player 1* and *Player 2* to demonstrate the insights gained from previous badminton matches. Note that a basic understanding of badminton games is required to fully comprehend the results.

Case 1: playing style. Figure 6 shows how the two professional players played games in previous contests. The scattered dots on the courts of (a) and (b) show that *Player 1* returned the shuttle back to various corners, whereas *Player 2* did not when the opponent sent the shuttle from the right side of the backcourt to the left

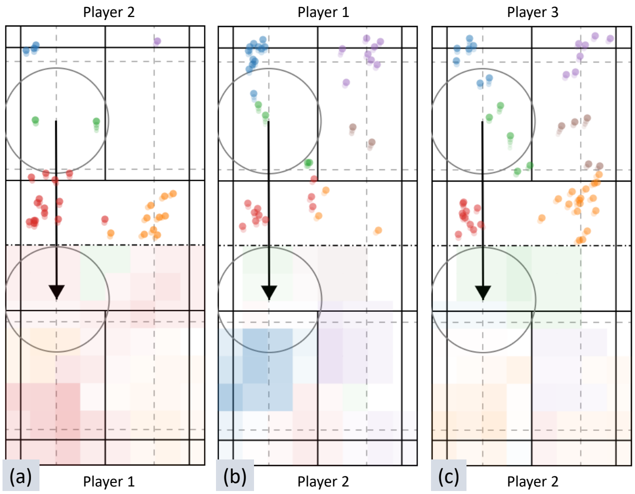

Figure 7: *The dot distributions show how the players handled diagonal* drop *shots in contests.* Player 2 *adopted different tactics when playing with* Player 1 *and* Player 3.

side of the frontcourt. However, by horizontally flipping the filtering lenses, we observed that the two players behaved similarly, as indicated in (c) and (d). We showed the results to the badminton coach at our university during the user study. He pointed out that *Player 1*'s tactic was to consume the opponent's physical energy by forcing him or her to move around the court. In contrast, *Player 2* is left-handed. The player played forehand on the left court and was aggressive to drop shuttles at the frontcourt. This strategy forced *Player 1* to return a *high shot* because *Player 1* had to travel from the backcourt to return the shuttle. As a result, *Player 2* could smash the shuttle in the next strike. The coach also mentioned that, in (a), *Player 1* occasionally sent shuttles to the right side of the court because *Player 2* is left-handed, although *Player 1*'s playing style is consuming the opponent's physical energy.

The heat map reveals that *Player 2* tends to play parallel drop shots when he or she travels from the left court to the right court to return shuttles (d). By contrast, *Player 1* has a low tendency to play parallel drop shots when traveling from the right court to the left court, as indicated in (a).

Case 2: tactics for different opponents. In badminton, a diagonal *drop* shot is an effective strategy if the two players are on the same side of the court because it forces the opponent to travel a longer distance than a parallel *drop* shot to hit the shuttle. However, the strategy also is risky because the opponent gets a comfortable shot if he or she reaches the shuttle in time. The opponent can decide whether to send the shuttle parallel close to the frontcourt or the backcourt. Both two positions are effective. Figure 7 (a) shows that *Player 1* tends to play *drop* shots when receiving a parallel *drop* shot at the left side of the frontcourt (i.e., most shuttles land in front of the short service line), and approximately half of them are diagonal. In contrast, in (b), *Player 2* seemed more conservative and seldom played diagonal *drop* shots when competing with *Player 1* because there are only three orange dots on the court, and

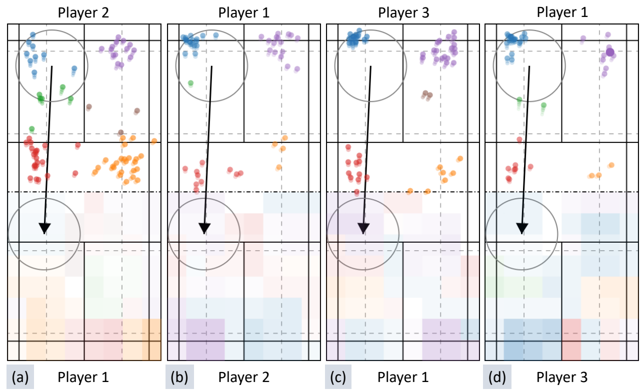

Figure 8: *The heat maps at the bottom-side show how the players handled a* drop *shot when they traveled from different positions.*

two of them are quite close to the center line. Instead, the player frequently sent shuttles close to the back service line. However, after changing the opponent of *Player 2* to *Player 3*, we found that *Player 2* was not as conservative as when competing with *Player 1*, as indicated by many orange dots in (c). This means that sending diagonal *drop* shots to *Player 3* can be an effective strategy.

Case 3: game tempo. Figure 8 shows a condition that opposing players hit shuttles from the backcourt to the frontcourt. The shuttle hitting distributions do not reveal substantial information because most sample dots are around four court corners. The only useful information could be that *Player 2*, and *Player 3* occasionally played diagonal *drop* shots when they competed with *Player 1* (i.e., a few orange dots in (a) and (c)). However, by further examining heat maps at the bottom side, one can see that shuttle hitting positions correlated to where the target player traveled from to return shuttles. Recall that the colors of the bottom side quads and the top side dots correspond. Hence, the blue and purple quads and the corresponding dots in (b-d) show that, when target players moved from the backcourt to the frontcourt to return shuttles, they often played a *clear*. This is a defense strategy because *clear* shots are slow, and players could gain some time to play the next shot. However, in (a), since the bottom side quads are close to red and orange, the heat map reveals that *Player 1* frequently dropped shuttles at the frontcourt. The strategy forced the opponent to travel but also increased the game tempo. In other words, *Player 1* must be aggressive and confident in his or her spontaneous response.

The heat maps also reveal that *Player 2* tended to play diagonal shots when he or she traveled parallel from backcourt to frontcourt to receive left *drop* shots. On the other hand, *Player 1* and *Player 3* tended to play parallel shots under this condition.

7.2. Expert Interview Feedback

To demonstrate our approach's usability and its potential improvement, we interviewed a badminton coach, who has regularly analyzed badminton data for more than 10 years to instruct teams. We also interviewed two varsity badminton players, who won several national badminton competitions. The goal is to determine whether our system helps them discover the opponent's behaviors and develop tactics **(G1-G3)** and realization of requirements **(R1-R5)** in Section 3.

7.2.1. Study Procedure

The interviews for the coach and the players were separate, but the study procedures were the same. In the beginning, we introduced our system to the participants, taught them how to interpret the visual elements and how to interact with the system, and then showed them several cases that we found during the exploration procedure. Case 1 in Section 7.1 was one of the cases. We showed the participants the cases for the following two reasons: (1) we wanted to demonstrate an example that shows the feasibility of our system, and (2) we were interested in the cases and wanted to study their corresponding insights. The instruction was not a single direction. The participants also told us what they additionally observed in our visualization according to their badminton knowledge. As a second step, we let the participants freely explore the collected data by using our system and assisted them if they encountered operation problems. We explicitly asked the participants to find at least one exciting event before entering the discussion phase. Case 2 and Case 3 were discovered by the coach and one of the players, respectively. Overall, each interview was conducted and recorded for approximately an hour.

7.2.2. Questions in the Interviews

We classified our questions into three topics, followed by an open comment and suggestion question. In each topic, we began with our initial questions to trigger the discussion. The coach and the players first answered our questions and then provided their supplementary opinions. We summarized the content below.

Full automatic analytics framework – needs and demands. We are interested in experts' level of acceptability and comments in terms of using the visual analytics framework in their daily work. Our initial questions are as follows:

Q1 Do you agree that an automatic system that extracts features, such as shuttle position, speed, and type, is helpful in comparison to manual annotation? If yes, why?
Q2 Do you trust the results annotated by the computers? What is your expected level of accuracy? Do you think that manual annotation can still achieve better results than computers?
Q3 What do you think are the limitations of an automatic annotation approach?

The coach expressed his strong interest in the machine-assisted visual analytics framework due to the increasing amount of data and limited human resources. He stated, *"Usually, I need to spare* $3-10$ *hours to annotate a video,* $2-3$ *hours to perform analysis, and* $3-4$ *hours to discuss it with the player."*. Therefore, he especially appreciates that the present approach can collect data automatically, which improves and accelerates the traditional analytics pipeline (**G1, R1**). With visualization, the data are shown clearly, which allows the coach to investigate and compare individual players in a short period of time. *"It is a clear improvement from the traditional analytics approach"*, the coach stated (**R3**). The coach expected the annotation accuracy to be higher than 80%, and he was satisfied with our current system because even manual annotation can contain certain errors. One of the players said, *"In the beginning, I didn't know that the data were automatically collected. The dot distributions and the revealed information look realistic."* This shows that the integration of data-driven analytics and visualization **(G1-G2)** markedly improved the traditional analysis procedure. However, although the modern machine learning approach can detect player positions, stroke positions, and speed with high accuracy, some data types still require human judgment. For example, the intention of a player when performing a technique, the variants of a technique accomplished by a player, or if a player is in an active or passive situation. Such data necessitate observation of players' facial expressions and slight body movement changes, which cannot yet be well detected using modern learning techniques. Since our approach has fulfilled most of their requirements, more advanced techniques for such challenges are reasonably anticipated.

Shuttle hitting distribution – the requirements and open possibility. The analysis of shuttle hitting distribution is a relatively new methodology, and we summarized the needs and the strengths of using our system.

Q4 Does our system successfully support finding essential stroke patterns? Could you give us a few examples after experiencing the system?
Q5 What patterns did you identify by investigating the temporal aspect of shuttle trajectory using the system?

As described previously, directly extracting a player's intention from a video is technically challenging. The present system performs an analysis of stroke types based on shuttle speed and shuttle hitting positions. This allows experts to identify such intention in a rally implicitly. For example, if a player is in an active position, he or she can be aggressive and often smash a shuttle in the present rally. This can be detected and classified by the system through speed and position detection. However, detailed stroke patterns, which require observation of the player's body pose and movement (e.g., movement of arms, rotation of wrists, etc.), are still challenging. Alternatively, if the player is not in an aggressive situation, he or she may perform a *clear* to force the opponent to run across the court. *"With the current system, I can see the shuttle distribution, order, speed, and distance of a series of strokes in the visualization, which allows me to identify which stroke pattern the player is aiming at."*, explained by the coach (**R2**). A player said, *"A smash can be slow but sharp. It forces the opponent to return a high shot for the player to smash again. Without observing the spatial temporal pattern, users may not understand why the player did not play a fast straight."*

Potentiality – collaborative discussions and education. In this topic, we investigate the appropriateness of using our system in communication and education. Our questions are:

Q6 Do you think that our interactive visualization can present better information during the discussion in comparison to your traditional procedure? If yes, in what aspects?
Q7 Do you think that such a system can be used for educational purposes, such as educating junior players?

The coach expressed the convenience of using our system. *"I can use the interface to search the shuttle speed according to the player's position. I also can visually compare our player with his or her opponents or the difference between two opponents simultaneously."*, described by the coach (**R4**). The coach highly appreciated the interactivity of our system since it can be used to present the core findings that he observed and can quickly switch the content if a player has concerns or questions (**G3, R5**). *"The system is capable of showing the stroke patterns and behaviors of professional players, so I can use it to explain and educate the junior players visually."*, recommended by the coach. However, the coach stated *"The court view panel shows the shots at different time points. I have to explain how to interpret the view when I discuss with new users."* The players agreed that the system could be effectively used for education. A player remarked, *"Novice players do not need the visualization because they frequently make mistakes in a game. However, when the players practice and overcome this problem, they need to seek opportunities to get points. They can use the tool to find a better strategy."*

Open comments and suggestions. We also asked the coach to provide open comments about the current system, by explicitly asking the following questions.

Q8 Do you have any comments or suggestions about our system? What interface would you like to add?

Q9 Do you like the system to recommend interesting data patterns to you, as shown in Figure 1 (a), or do you prefer to search for data patterns by yourself actively?

The coach stated definitively, *"The system is fully functional. It provides me with the essential functionality that I like to perform."* The only suggestion that the coach offered was to include some external values, such as the total number of hits, in the *distribution comparison* panel, although he also mentioned that this is not mandatory. He said that he liked the *distribution control* panel, which allows him to select interesting patterns, as suggested by the system.

7.3. Generalization to Other Net Games

Our data extraction technique has the potential to generalize to other net games, such as tennis, since the broadcast videos of these two sports have similar forms. Specifically, they both contain court-view shots, in which camera positions and orientations are fixed. In addition, analyzing where players hit balls should also be beneficial to tactics design. However, considering different rules and tactics in sports, our current visualization design may be insufficient to visualize data from other net games. Consulting domain experts before using our system to visualize such data is needed.

7.4. Limitations

We track player positions and hit frames in broadcast badminton videos to extract approximate shuttle trajectories. The main shortcoming is the unknown shuttle position when players do not hit the shuttle. Although the amount of missing data is about 10% (i.e., the average length of a rally is approximately 10 shots), this prevents users from analyzing how players lose points and whether a tactic is effective by using our system. We note that obtaining the landing position of a shuttle under such a circumstance demands high-quality shuttle tracking and 3D trajectory reconstruction techniques. While automation is challenging, a possible approach to overcome this problem is to annotate the positions by leveraging human resources [DWW*21]. Second, our automatic data extraction is imperfect. Users have to correct the extracted data manually if the automation makes mistakes. Providing them with an intuitive interface that can examine the correctness of data efficiently is demanded. Finally, we currently focus on visualizing shuttle distributions under specific player positions. Considering that players' physical and mental conditions are also essential factors in a badminton competition, we plan to visualize the change in player behaviors/statistics throughout a game.

8. Conclusion

We have presented a system to extract badminton game data from broadcast videos and visualize historical data for coaches to explore player behaviors. Compared to the traditional approach, where coaches have to spend hours watching videos and analyzing statistics, our system provides them with an integrated interface to thoroughly and objectively study game data. By moving the filtering lenses and observing dot distributions and heat maps, coaches can rapidly determine the opponent players' weaknesses and develop effective tactics. The system was developed with a badminton coach at our university and has been demonstrated to a nationally recognized athlete player and several junior players. They agreed that our system was highly useful and wanted to utilize it to study opponent players' data.

In the future, there could be multiple extensions of our work. First, we plan to reconstruct 3D shuttle trajectories from broadcast videos. The benefits of the 3D trajectories are two folds. (1) True shuttle landing positions can be determined, particularly when players fail to return shuttles. (2) Shuttles hit above or below the net is an important cue for classifying a shot as offense or defense. Given 3D trajectories, we will also design novel views for further examining players' behaviors. In addition, our current system visualizes extensive amounts of historical game data to reveal player behaviors. It could be interesting to extend the system for in-situ sports analytics in the future.

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