TIVEE: Visual Exploration and Explanation of Badminton Tactics in Immersive Visualizations

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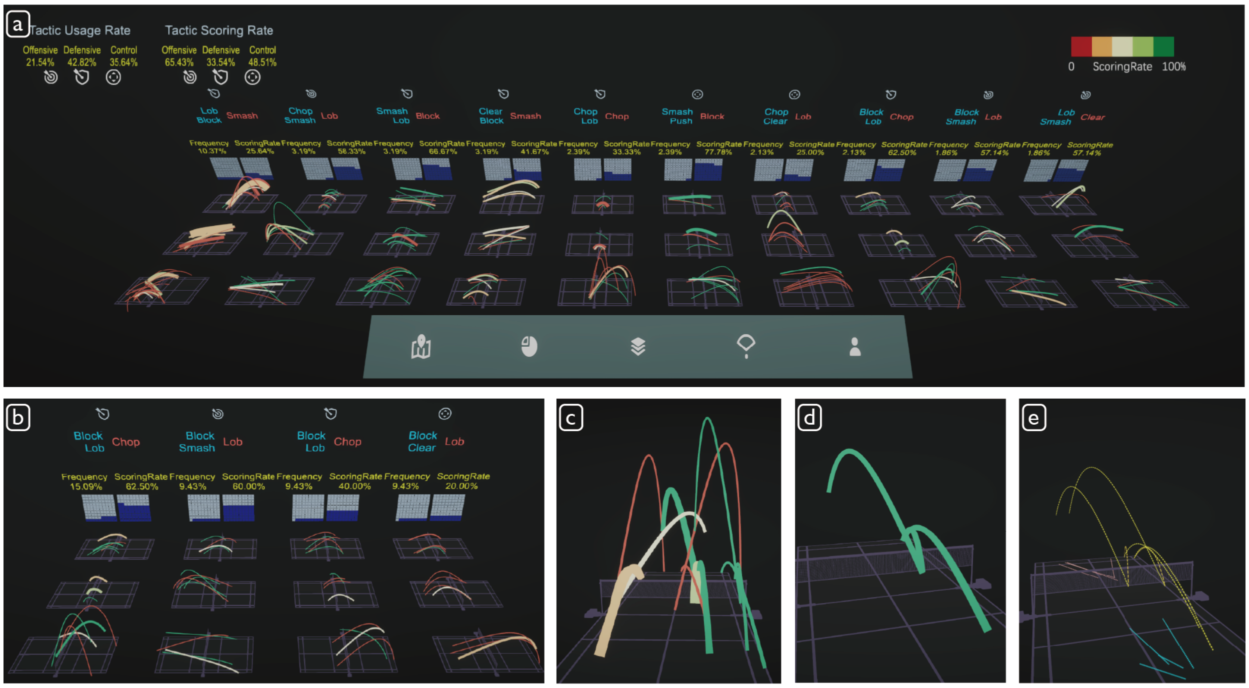

Fig. 1. System Interface. TIVEE is used to analyze badminton tactics in an immersive environment. Users can first obtain an overview (a) of commonly used tactics of Chen Long. The overview shows aggregated trajectories and statistical information (i.e., R_{usage} and $R_{scoring}$) of each tactic group. Users can set a specific game scenario with the menu and the overview will be updated to show the corresponding tactics (b). Users can further inspect a tactic group (c), a tactic (d), and the origin trajectories of the selected tactic (e).

Abstract— Tactic analysis is a major issue in badminton as the effective usage of tactics is the key to win. The tactic in badminton is defined as a sequence of consecutive strokes. Most existing methods use statistical models to find sequential patterns of strokes and apply 2D visualizations such as glyphs and statistical charts to explore and analyze the discovered patterns. However, in badminton, spatial information like the shuttle trajectory, which is inherently 3D, is the core of a tactic. The lack of sufficient spatial awareness in 2D visualizations largely limited the tactic analysis of badminton. In this work, we collaborate with domain experts to study the tactic analysis of badminton in a 3D environment and propose an immersive visual analytics system, TIVEE, to assist users in exploring and explaining badminton tactics from multi-levels. Users can first explore various tactics from the third-person perspective using an unfolded visual presentation of stroke sequences. By selecting a tactic of interest, users can turn to the first-person perspective to perceive the detailed kinematic characteristics and explain its effects on the game result. The effectiveness and usefulness of TIVEE are demonstrated by case studies and an expert interview.

Index Terms—Tactic analysis, stroke sequence visualization, immersive visualization

1 Introduction

Tactic analysis is a core subject of sports data research. It helps coaches develop effective winning strategies by identifying the key attributes from the event sequence [20,51] and explore athletes' characteristics by visualizing the sequence of playing actions [32,54,61]. In the field of badminton, important tactic insights are implied in the sequence of consecutive strokes that players on each side alternatively perform until one wins the score [12]. Advances in sequential pattern mining have shown great potential in finding valuable subsequences using statistics [31] or machine learning algorithms [17,29]. These approaches attempt to extract the subsequences with high frequency or have a strong relationship between them and their outcomes. Visualization methods (e.g., small multiples [24,38,62], flow diagrams [18,59], glyphs [25,53], and

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scatterplot [26, 40]) can further support experts to evaluate the player tactics by showing the patterns such as the sequence of key attributes (e.g., ball placement and stroke position) in each stroke.

However, effective evaluation for the tactic of stroke sequences can be hindered due to the lack of three-dimensional perception of stroke attributes. For instance, experts are interested in observing the correlation of different attributes between adjacent strokes (e.g., height and distance from the net) to estimate the effectiveness of the tactic. These attributes are inherently three dimensions. Introducing abstract visual glyphs or statistical charts to reveal the pattern can lose the context information, which causes difficulties for the cognition of the situation on the court. Therefore, experts have to replay videos multiple times and repeatedly compare between videos to justify the correctness of identified patterns, as videos can clearly tell what happened [8,11,43]. However, it is laborious and time-consuming.

In this work, we aim at assisting experts in evaluating badminton tactics by exploring and understanding sequential stroke trajectories in virtual reality. Attributes in each stroke can be naturally represented by 3D trajectories in an immersive environment [57]. Recent advances in immersive trajectory visualizations show that visualizing trajectories in their actual form and designing filtering interactions can help users perceive the trajectory characteristics and find interesting subsets effectively [19, 57]. However, these studies consider the trajectory independently, thus failing to unveil the correlation between the consecutive strokes. Furthermore, since adjacent trajectories run in the opposite direction, placing them in the same context can easily lead to overlapping and interweaving the key features.

We cooperated closely with five domain experts, including a professor, students and an athlete in badminton, to collect and refine requirements for the tactic analysis of badminton. Based on the requirements, we propose TIVEE, a **T**actic analytics system using **I**mmersive **V**isualization to **E**xplore and **E**xplain the badminton tactics. We first present a tactic overview to help experts explore different tactics from a third-person perspective. In order to reduce visual clutter while visualizing the correlation of adjacent strokes, trajectories are separated according to their stroke orders and placed in their real form on individual courts. We layout courts based on their stroke orders and statistical importance to easily help experts focus on interesting tactics. To better tailor strategies, we also provide tactic customization with an extra badminton court for the experts to identify specific game scenarios. We then design the detailed court view to support experts in inspecting and explaining the common causes of a class of tactics that lead to wins and losses. After experts select one interesting tactic, our approach places the trajectories on the same court and supports experts to explore from a first-person perspective. We present two case studies using the real-world dataset of **ten** professional badminton players to illustrate the usefulness of TIVEE. The system is capable of assisting experts in finding exciting patterns of players' commonly used tactics easily. Detailed observation for a tactic provides the experts with an explanation of tactical feasibility. We further gather feedback through the post-study interview with our experts to validate the usability and effectiveness of our system.

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

- An immersive analytics system that supports experts in exploring badminton tactics in numerous sequential stroke trajectories.
- Case studies with professional badminton experts, interviews that reveal the usability of the visualization design and the effectiveness of the system, and valuable tactical guidance for players.

2 Related Work

2.1 Racquet Sports Analysis with 2D Visualization

Racquet sports visualization has received considerable attention in recent years, as seen in studies on tennis [34, 35], table tennis [47–49, 52], and badminton [57]. Moreover, Wu et al. [51] introduced a visual analytics framework of event sequence data in racket sports.

In racquet sports, three consecutive strokes are often studied together as they indicate a player's tactical behavior. The tactic view in iTTVis [52] presents the usage and scoring rates of different tactics to help analysts evaluate players' performances. Tac-Simur [49] proposes a second-order Markov chain model to simulate the tactical correlations. Inspired by the previous studies, this study examines the three-stroke tactics in badminton and chooses to present the usage and scoring rates of tactics to help analysts evaluate their effectiveness.

Racquet sports have innate spatial-temporal features. The stroke view in iTTVis [52] presents the spatial-temporal distribution of strokes in multiple table tennis tables. CourtTime [34] employs multiple 1D spatial-temporal charts to help analysts explore multiple movement patterns of the player and ball in a tennis rally. However, these methods discard the 3D nature of the trajectories. Therefore, we develop TIVEE to assist badminton experts to intuitively understand and discover tactic insights with immersive visualizations.

2.2 Immersive Visualization in Sports Science

Immersive visualizations have been widely studied for the exploration and analysis of common types of data, including spatial trajectories [7, 19, 57], abstract data [6, 23, 55], and multidimensional data [2, 5, 10]. By leveraging the sense of presence and the embodied interaction [13], previous research has successfully developed immersive technologies for corresponding data to improve the user performance in both physical data and abstract data. For example, FibeyClay [19] allows users to select, rotate, and scale the 3D physical trajectories directly to expedite pattern searching with VR equipment. Liu et al. [30] used a shelf metaphor to flexibly layout multiple charts in an immersive space, allowing users to effectively compare and analyze trend of data of various scales under different layouts.

Sports data shares many of these data types, such as the trajectories of athlete movements and the location distribution of key events. Several toolkits such as DXR [42] and IATK [9] are able to rapidly prototype and explore these common types in an immersive environment using concise programming grammar and graphic user interface. However, general immersive technology falls short in the situated decision-making provided for sports experts and the intuitive analysis of complex heterogeneous data [28]. Lin et al. [27] designed a situated AR visualization with immediate visual feedback of shooting trajectory for basketball free throws training. Tsai et al. [46] immersed the basketball tactical execution in VR with multiple perspectives to intuitively express complex offensive tactics. However, these works tend to present a small number of cases with concise visualization instead of analyzing and discovering patterns from a large scale of data. Ye et al. [57] explored the patterns of the 3D badminton shuttle trajectory using a VR visualization system called ShuttleSpace. It clusters the trajectory into multiple categories and applies peripheral vision and stroke metaphor to explore the trajectory from the first perspective intuitively. While successful for technique performance analyzing, Shuttlespace does not consider the tactic insights that hid in the sequence of stroke techniques. To address the issue, we distribute stroke trajectories in multiple courts and allow experts progressively analyze tactics from the third and first perspectives.

2.3 Immersive Visualization for 3D Trajectory

3D trajectory implies important research value across different domains, like geographic traffic [1, 3, 16, 44], neuroscience [36, 50], and sports [4, 15, 21]. Tominski et al. [45] proposed a hybrid 2D/3D trajectory wall to visualize attributes related to each point within the trajectories superposition of 2D trajectories in 3D space. Space-Time Cube (STC) is a typical visualization design for time-geography datasets [14, 22]. It was first introduced to connect time and space for time-geography movement. Yang et al. [56] found that adding the third dimension of height with reasonable encoding design can reduce the impact of overlapping in flow map. Although these trajectories are presented in three dimensions, the trajectory itself has only two-dimensional features, which does not conform to the nature of badminton trajectories.

LucentVision [33] generates a 3D virtual visualization for serves, which is of great significance in tennis games. ShuttleSpace [57] visualizes 3D trajectories with clustered and raw trajectory data in a real badminton court and provides a first-person view for exploring the data from the user's perspective. However, visualizing the trajectories

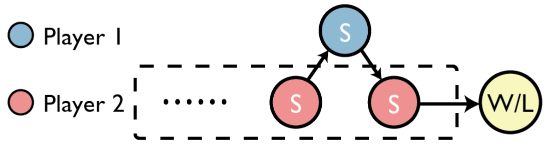

Fig. 2. The structure of a badminton tactic. A tactic of a player (pink) is comprised of multiple consecutive strokes and should contain at least two of his/her strokes.

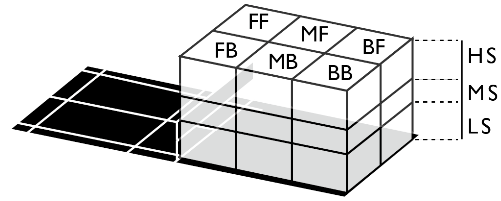

Fig. 3. Illustration of court division basis.

of stroke sequences containing multiple techniques directly according to their physical location will cause large occlusion. To reduce such clutter while maintaining the connections between strokes, we carefully design a multi-court layout to arrange the trajectories by their categories and importance, which allows experts to gradually classify and filter the trajectory sequence.

3 Background And Design Requirements

In this section, we first introduce the concepts of badminton and the data description. Then we provide an interview study that derives requirements for the tactical analysis of badminton in VR environments. Finally, we present the system overview.

3.1 Background

Badminton is one of the major racket sports. In badminton, two opposing sides of players hit a shuttlecock back and forth. A professional badminton match usually consists of the best 2 out of 3 games, where each game is awarded to the player who wins 21 rallies first. The major concepts are as follows.

- ◇ A **stroke** is an action of hitting the shuttle using a racket. It is the basic unit in a game and can be characterized by various attributes, such as the stroke technique and the hit point. The detail of the stroke attributes can be found in Sec. 3.2.
- ◇ A **rally** is the process of scoring one point in a game. It contains a list of consecutive strokes of two players.
- ◇ A **tactic** is how players organize and perform strokes in a rally to achieve a higher winning rate. A player's tactic (Fig. 2) is defined as a combination of consecutive strokes (contain at least two of his/her strokes) [58]. For example, a representative tactic is to use a technique of *lob* first and *smash* later to force the opponent to make mistakes.

The usage of tactics is the key to a badminton game. Hence, analysts are keen to understand when and how players use certain tactics and the effect of each tactic. This is traditionally accomplished by conducting statistical analysis. 2D Visualizations [49, 52] have been applied to reduce the cognitive load when conducting the tactical analysis in racket sports. However, the analysis of badminton tactics highly requires the presentation of 3D features of the stroke trajectory. For example, the height of the hit point in a tactic can largely influence the effect of this tactic. Even if two players use the same tactic *lob and smash*, a higher hit point of *smash* may lead to a better effect. This motivates us to design a visual analytics approach in VR environments to facilitate the tactical analysis of badminton.

3.2 Data Description

The data of each badminton game is provided as hundreds of strokes. Each stroke has a variety of attributes. The detailed explanation of each stroke attribute is as follows.

- ◇ S_{player}: The player giving the stroke.
- ◇ $S_{technique}$: The technique used by the player to give the stroke. According to kinematic features, stroke techniques can be divided into three categories [60]: 1) offensive technique (including *smash*, *net shot*, and *cut smash*), 2) control technique (including *clear*, *drop*, *chop*, *push*, *hook shot*, and *drive*), and 3) defensive technique (including *lob* and *block*).
- ◇ T_{player}: The 2D movement trajectory of the player. For each stroke, we record two 2D positions of the player — the one when the opponent hit the shuttle at the previous stroke (P_{start}) and the one when he/she hit the shuttle at the current stroke (P_{end}) — to reveal his/her movement to return the shuttle.
- ◇ $T_{shuttle}$: The 3D flying trajectory of the shuttle. For each stroke, we record three key points of the shuttle's flying trajectory — the start position (P_{start}), the highest position ($P_{highest}$), and the end position (P_{end}) — to reconstruct the whole trajectory based on the shuttle's kinematic features [41].
- ◇ T_{field}: The fields where the shuttle comes from and falls into. Instead of analyzing the exact 3D positions, experts tend to divide the 3D court space into multiple fields and analyze the fields of the start/end position of the shuttle [37]. Following experts' requirements, we divide a half-court into $3 \times 2 \times 3$ fields (Fig. 3). According to the distance to the net, the court can be divided into fore-court, middle-court, and back-court. The player can hit the shuttle in their forehand area or backhand area. The height can be divided into three levels: low-space (0-1.55m), middle-space (1.55-2.5m), and high-space (2.5-4m).

According to the category of the technique used in the last stroke, we further consider three types of tactics: the offensive tactics, the control tactics, and the defensive tactics [58].

3.3 Requirement Analysis

We have collaborated closely with domain experts in the past year to develop a visual analytics approach in VR environment to facilitate tactical analysis in badminton. The experts included a badminton professor who works for one of the top national badminton teams, a badminton player of the national level, and three postgraduate students from the Department of Physical Education. We held weekly meetings to characterize problem domains, discuss analytics requirements, and collect feedback to develop and refine the visual analytics approach. The detailed milestones are as follows.

- ◇ **Characterizing problem domains.** We designed a simple prototype to facilitate the understanding of problem domains during the discussion process. After multiple rounds of discussion, we came up with basic analysis requirements.
- ◇ **Designing visualizations for 3D sequential strokes.** Considering that our analysis for the tactic of badminton requires a 3D environment, we tried several commonly used methods to visualizing the multiple trajectories, including clustering and bundling. It turned out that these methods cannot address the problem of occlusion caused by multiple sequential trajectories. So we came up with a new representation.
- ◇ **Designing interactions and visualizations for analysis.** When the design for the representation of sequential strokes was done, we started designing visualizations and interactions according to analysis requirements. We designed the initial system and continuously refined the design based on expert feedback.
- ◇ **Developing the immersive analytics system.** We developed a prototype that supports the analysis. A workflow was first proposed for the connection of the whole system. Through continuous iteration, TIVEE has been improved to support an overview and detailed observation of tactics.

We collected the requirements from the experts for analyzing tactics in badminton. The detailed requirements are as follows.

R1: Summarizing the usage of tactics. Badminton tactics are diverse, and a player will use various tactics in a match. Experts are interested in analyzing a player's commonly used tactics, which helps to outline his/her playing style. In addition, knowing the scoring rates of different tactics helps to deepen the understand-

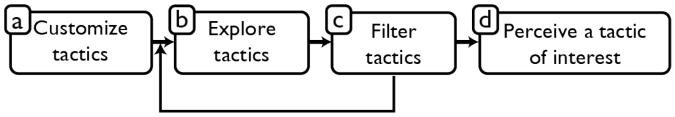

Fig. 4. System workflow of tactic exploration and explanation in immersive visualizations.

ing of the player's strength and provides clear guidance for the following analysis.

R2: Presenting the similarity between tactics. Although tactics are different in terms of the kinematic features, such as the 3D position of the hit point and the technique used, a set of tactics would be considered as similar to each other due to the similar tactical aim (e.g., playing defensive tactics to wait for mistakes). Showing a category of tactics can help the experts learn different offensive/defensive tactics and conduct a detailed analysis.

R3: Identifying the relation between tactics and game situations. After obtaining an overall picture of a player's tactics, the experts need to know how the player uses different tactics to cope with different game situations. Correctly applying a tactic in an appropriate situation is the key to increase the winning rate. Hence, knowing the usage of tactics under different situations can help players identify valuable usages and existing weaknesses.

R4: Revealing the characteristics of a tactic. When focusing on analyzing a specific tactic, experts will develop an interest in how the player performs such a tactic with strokes. Different execution styles can reflect the athletic or physiological characteristics of the player; for example, different players may have various distributions of height at the hit point when performing the tactic of *lob-smash* due to height issues. Revealing these details can help experts understand the efficient way of performing a tactic and establish corresponding coping tactics.

R5: Explaining the effect of a tactic. The effectiveness of a tactic is determined by multiple factors, including how the player deploys this tactic and how the opponent responds to this tactic. The success of this tactic may be because the player found the opponent's gap or the player forced the opponent, whose weakness is a backhand catch, to return the ball backhand. Therefore, the system should support the correlation analysis of different attributes and assist experts in finding the key to success.

3.4 System Overview

Figure 4 shows the workflow of TIVEE. First, users customize the targeted tactic (Fig. 4a) by specifying the players to use the tactics and the stroke number of forming a tactic. Then, TIVEE automatically extracts tactics from the match data and visualizes the summarization of tactics on multiple 3D courts (R1, R2), which are listed according to the ranking score (Fig. 4b). Users can explore the overall tactics with statistical information and iteratively select an interesting subset (R3) by the game scenario setting (Fig. 4c). Finally (Fig. 4d), TIVEE restores the strokes of the tactic of interest on one court to reveal the relationship between various tactic attributes (R4). Users can intuitively perceive the stroke sequence and explain the effect of the tactic in a first-person perspective (R5).

TIVEE is a VR-based program. Equipped with HTC Vive Pro settings, the users are allowed to analyze in a 4 m^2 space (2 m $\times$ 2 m). The whole system was implemented using Unity with C#. Deployed in a PC with an Nvidia GeForce GTX 1660 SUPER GPU and a 3.90GHz AMD Ryzen 7 3800X CPU, TIVEE can get over 100 fps.

4 System Design

In this section, we first introduce a brief usage scenario to clarify how TIVEE can be used to achieve the analysis. We then describe three major components of TIVEE, i.e., tactic overview, tactic customization, and tactic explanation in detail.

4.1 Usage Scenario

Tom is a coach of one of the world's top badminton players, Adam. Adam will have a match with another top-level player Ben in a few days. With the aid of TIVEE, Tom wants to know the strengths and weaknesses of both players to provide Adam with tactical guidance. From the tactic overview, Tom noticed that Ben uses offensive tactics the most (R1, R2), and the scoring rate of them is only around 50%. Among these offensive tactics, owning the lowest scoring rate is *lob-smash* against the opponent's clear. Tom wants to know how Ben carries out this tactic so that the scoring rate is so low. He selects the tactic for detailed observation and turn to the first-person perspective. By viewing the origin trajectories of this tactic through animation, Tom concludes that Ben has a weak control in the back-court offensive tactics, which makes it easy to get out of bounds (R4, R5). Knowing Ben's weaknesses, Tom switch to the data of Adam to find out ways of winning Ben. Through iterative explorations, Tom learns that Adam is good at using *clear*, which can force the opponent to return the ball in the back-court. This provides opportunities to win Ben. To better use a *clear*, Tom customizes the game situation and identifies the suitable situation for Adam to use *clear* (R3).

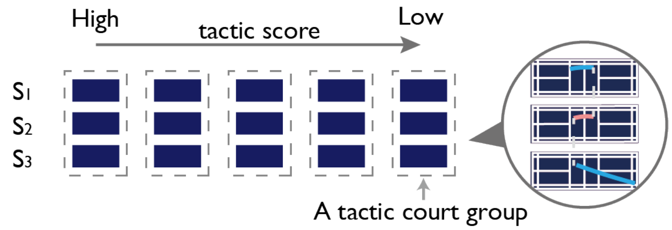

Fig. 5. Layout for multiple courts from a top-down view. The stroke trajectories in the same row of the court have the same stroke sequence (from S_1 to S_3 in this example). The stroke trajectories in each column belong to the same tactic group, further sorted by the tactic score. Different colors indicate the players on both sides.

4.2 Tactic Overview

The tactic overview is provided to show the corresponding statistical data of badminton tactics and the relation between consecutive stroke sequences in tactics (R1, R2). Users are able to explore the scene in a third-person perspective with flying navigation mode. Considering the effectiveness of small multiples in VR environments [30], We design a multi-court layout (Fig. 5) to visually summarize the tactics and prevent the issue of visual overwhelming when the tactic number grows. Each column in the layout (Fig. 5) represents a tactic group that consists of multiple similar tactics. Each row (Fig. 5) in a group shows the strokes of tactics in this group using a virtual court. We rank the tactic group from left to right (Fig. 5) according to the tactic score (i.e., a summarization of the usage rate and the scoring rate of each tactic group). This can help users focus on the analysis of important tactics.

Visualization of a tactic group. According to Figure 2, a tactic is characterized by a sequence of consecutive strokes. Hence, the number of tactics could be large and it is hard to present all the tactics in the VR environment. To address this issue, we aggregate similar tactics into groups to reduce the number of visual items. Two tactics will be aggregated into one group if they have the same sequence of $S_{technique}$. In each tactic group, we use $2n-1$ courts to visualize the strokes of tactics as well as the reaction strokes of opponents where n is the tactic length (n = 2 in Fig. 5). The first stroke of tactics is placed at the top court and the last stroke is placed at the bottom court (Fig. 5). Each court serves as a small multiple in three dimensions that displays the shuttle trajectories with the same stroke ordinal in one tactic. The thickness of strokes encodes the usage rate of the corresponding tactic (R_{usage}) and the color encodes the scoring rate ($R_{scoring}$) of the corresponding tactic. R_{usage} is computed as the ratio of the number of rallies with this tactic to the number of all rallies. $R_{scoring}$ is computed as the ratio of the number of winning rallies with this tactic to the number of all rallies with this tactic. We use a discrete palette to encode the scoring rate of the strokes (Fig. 1a). Similar to R_{usage} and $R_{scoring}$, we further compute the usage rate and the scoring rate of each tactic group and use waffle charts at the top-back of each tactic group (Fig. 1a) to encode the two indicators. The left waffle chart shows the usage rate while the right one shows the scoring rate. Users can

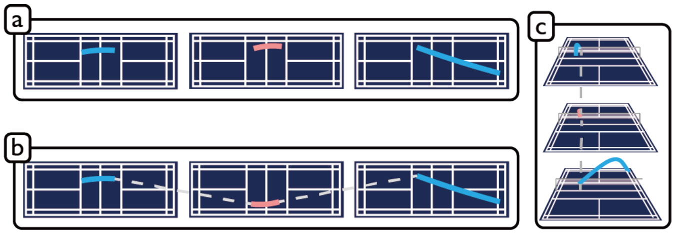

Fig. 6. Alternatives for court alignments. a) align the court according to its long side. b) Rotate 180° from the origin position of the second stroke to keep the shuttle trajectories in the same direction. c) align the court in the vertical direction.

learn the accurate data value through the number of presented grids in waffle charts. Here we use waffle charts but not barcharts to encode the statistical data since users may face perceptual errors of the data when using barcharts due to the perspective effect in VR environments [39]. The filling direction of the two waffle charts (i.e., usage rates and scoring rates) is also different. This can ensure the symmetry of the two waffle charts, which is helpful for forming a special shape. This shape can be regarded as visual patterns of the combination of usage rates and scoring rates (e.g., the shape of high usage&low scoring is different from low usage&high scoring) and therefore facilitate the analysis.

According to experts' suggestions, we further compute a tactic score for each tactic group to reveal its importance by considering both the usage rate and the scoring rate. The tactic score is a weighted average of the usage rate and the scoring rate. This can help experts find interesting tactics for tactical guidance.

Interactions. Interactions in the tactic overview are as follows.

- *Changing the viewing angle of small multiples.* Experts can use the trackpad of the controller to get close to the tactic they are interested in or fly far away to observe as many tactics as possible at the same time.
- *Adjusting the order of small multiples.* Experts can click the virtual function menu to see the slider of the weight of usage rates and scoring rates. They can further use raycasting to change the weights to recompute the tactic score and the order of small multiples (tactic groups) will be changed accordingly.
- *Decomposing a tactic group.* Experts can use the trackpad to select a tactic group and decompose the tactic group into multiple subgroups according to the hit point and the drop point. For example, when using the hit point to decompose the tactic group, the tactic overview will be updated to show the subgroups and strokes in a subgroup will share the same field of the hit point.

Design alternatives of the multi-court layout. Though stroke trajectories are happened in the same court during one game, unfolding and distributing them to different courts for visualizing is necessary due to the visual clutter and the overlapping of the T_{field}. During the collaboration with our experts, we conclude that the layout of the multiple courts should intuitively reveal 1) the sequence of continuous stroke features, and 2) the distribution of the features in different tactics. We fulfill the first consideration by aligning the T_{field} from each court in the tactic court group since the features are perceived and analyzed according to the granularity of a court field rather than its actual position. According to the Gestalt law of proximity, we further set the courts as close as possible without overlapping to show the relations between T_{field} of the continuous strokes. In particular, we align the field according to its short side (fig. 5) rather than the long side (fig. 6ab) and vertical direction (fig. 6c) since the distance between the same area in adjacent courts is the shortest without occlusion. Moreover, we keep the original direction of the court instead of making all stroke trajectories in the same direction to achieve the effect that the T_{field} in adjacent courts appeared in the same relative position.

4.3 Tactic Customization

In addition to having an overview of general tactics, the expert wants to identify tactics that the player commonly uses in specific game situations to better tailor strategies (R3). Users can use the virtual menu to jump to the tactic customization and set the context game scenario.

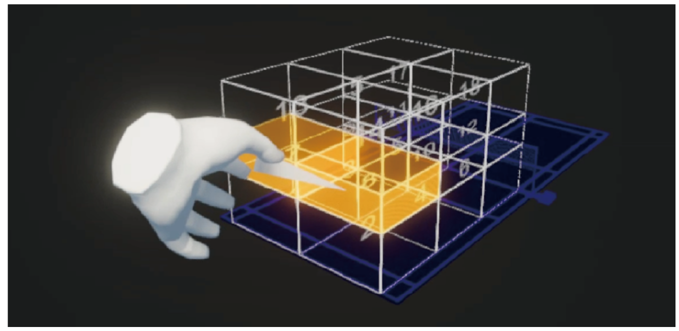

Fig. 7. Illustration for tactic customization. The user can use the VR controller to point out one or several fields of P_{start} and P_{end} in the court to extract corresponding tactics.

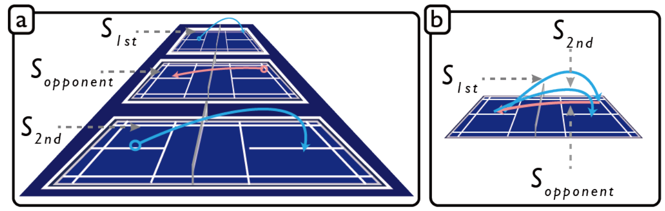

Fig. 8. Illustration of unfolding and folding adjacent strokes of a tactic. Unfolded adjacent strokes are listed in different courts in a line according to the stroke ordinal. Folded strokes are placed in the same court and connected through the drop point of each stroke and hit the point of the next stroke.

Game scenario setting. To simplify the work of context setting, the expert only needs to selectively set three major elements of the previous stroke: $S_{technique}$, T_{field} of the P_{start} and P_{end} of the stroke. We provide an extra scaled-down badminton court for customizing tactics based on the real scene (Fig. 7). After determining the stroke technique used in the previous stroke, the expert can use the VR controller to select the T_{field} in the real court to mark the start and end of the stroke according to his analysis interest. The tactic data whose previous stroke meets the filter condition will be extracted. The tactic overview will be updated to show the tactic groups of the filtered data.

4.4 Tactic Explanation

After rounds of decomposition of tactic groups in the tactic overview, users can select a tactic of interest and jump to the tactic explanation to perceive the tactic from a first-person perspective. With the first-person perspective, users can watch the animation of the selected tactic to replicate the real scenario. This can help users more clearly see the detailed kinematic characteristics of the tactic (which is important for justifying the performance) and more easily learn the tactical purpose (R4, R5). Specifically, a tactic can be summarized and demonstrated by many use cases that appeared in real games. Here we present the summary of a tactic and allow users to use several forms of visualizations to explain the tactic's practicality.

Summary of a tactic. A tactic in badminton refers to how a player performs several consecutive strokes (Fig. 2). Considering the similarity of kinematic characteristics of the same stroke technique, we refine the data according to the stroke technique and spatial area of key attributes (i.e., hit point and drop point) to get different tactics. We use stroke sequence to represent the tactics (Fig. 8a). The complete sequence of a $n-stroke$ ($n=2$ in Fig. 8b) tactic contains $2n-1$ adjacent strokes, including n strokes of the player himself and $n-1$ stroke of the opponent. For representing the feature of a stroke within a tactic, we follow the work [57] to aggregate the origin trajectories. Based on the position, velocity, and angle of the hit point of the original data, the average values are derived and used to simulate the summarized trajectories.

We present a tactic in a single court for detailed observation from a first-person perspective (Fig. 9a). Adjacent strokes are connected by the drop point (i.e. the hit point of the next stroke in the same court)

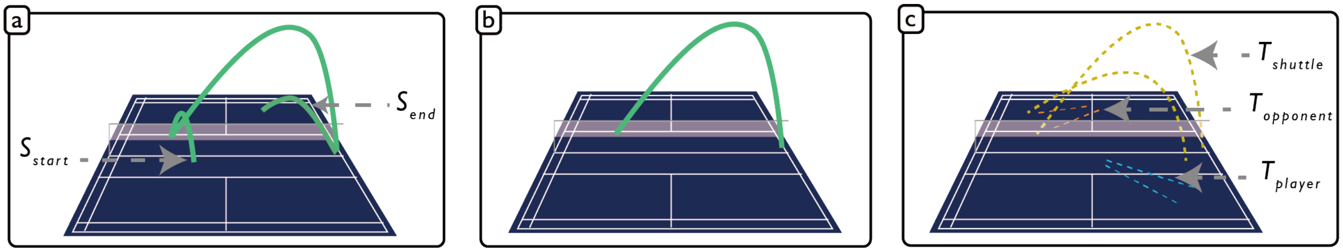

Fig. 9. Three visualizations of a tactic for detailed observation shown from the player's perspective. a) Origin sequential strokes within the selected tactic. b) A single summarized stroke within the tactic. c) All origin trajectories, including player's and the opponent's movement, the shuttle trajectory.

to restore the actual reality, in which the shuttle flies inside the same court. The correlation between strokes is reflected, and continuity of the tactic is kept. Considering the visual clutter which would be caused by a growing stroke number of selected tactic, we allow the expert to focus on an individual stroke and set other strokes invisible (Fig. 9b).

Different forms to show the actual usage of a tactic. Considering the diversity of the original data within a tactic, simply displaying the summarized trajectories will lose the versatility of the tactic in actual use. Showing all origin trajectories of this tactic (Fig. 9c) helps the expert observe the execution of each usage. To demonstrate the real scene of how a tactic is executed, we provide animation of actual execution from first-person perspective. The synchronized animation shows the shuttle flight trajectories and the player's movement trajectories changing over time. It helps the expert understand the ease of implementation of this tactic. The expert provides feedback that the animation with origin speed is too fast to understand the tactic. We allow the expert to change the animation speed to fit his analysis process.

Interactions. Interactions for the observation of a tactic are as follows.

- *Changing the viewing angle of the court.* Users can walk in the virtual court to get a detailed observation from the first-person view of the selected tactic. They are allowed to walk in the court through physical movements based on head tracking and hand movements on controller's trackpad.
- *Fold mode switch.* The expert can switch between unfold and folded modes of adjacent strokes by clicking the trigger.
- *Visualization switch.* We use a menu to provide three tactic visualizations (Fig. 9) for the expert to choose. The expert presses the menu button to activate the menu and uses the trackpad as up and down keys to switch between the visualizations.
- *Animation setting.* A slider is provided to help the expert adjust the animation speed.

5 Evaluation

In this section, we evaluate the effectiveness of TIVEE through two case studies and an interview with domain experts.

5.1 Experiment Settings

Dataset. Our dataset contains 32 national badminton players' singles matches (i.e., *Badminton World Federation World Tour* of 2018 and 2019 seasons), involving the top 10 men's singles players in the world by 2020. To better demonstrate the effectiveness of the tactic usage, we extracted the tactics that directly lead to win/lose for the analysis (i.e., the last two strokes of the winner in a rally). We provide the experts with selections of players and the stroke number of tactics to analyze. Rallies without enough stroke numbers of tactics were automatically filtered. Finally, we obtained 29532 rallies and 59064 tactic records for the detailed analysis. Each row of the dataset contains the information about S_{player}, $S_{technique}$, key attributes of player movement T_{player} and shuttle trajectory $T_{shuttle}$, and the result of this stroke (i.e., win, lose, or continue, which helps to determine a rally). We have classified each set of records according to the tactic definition introduced in Sec.3.2 to obtain different tactics.

Participants and procedure. We invited three domain experts to conduct the case studies and the interview. Expert A is a badminton player at the national level. Expert B is a senior data analyst for over five years in badminton. Expert C is a postdoctoral fellow majoring in performance analysis in the Department of Physical Education. We have collaborated with these experts for the prior prototype. However, they had not been exposed to the dataset used in case studies. Before the case studies, we introduced our system to the experts with a short demo to demonstrate the system usage. After they got familiar with our system, we assisted them in wearing the VR headset. We began the studies once they were comfortable with the virtual environment. Each case lasted 20 minutes and could be stopped at any time according to the user's physiological needs. After case studies, we organized an interview to collect their usage feedback. Here we present two representative case studies to evaluate the system.

5.2 Case Studies

5.2.1 Case 1: What makes Kento MOMOTA's world No.1?

This case is to analyze Kento Momota to know his playing style and obtain insights into why he can dominate the current men's singles. We invited expert A to do the analysis. Kento Momota is the top-ranked badminton player of men's singles. Surprised by his stable performance, the domain expert is eager to determine the reason behind the success.

The expert first used the controller in the right hand to choose the data of Momota from the menu and set the stroke number of tactics as 2 through a slider. There are a total of 1283 records that meet the conditions. Then, he had an overview of Momota's commonly used tactics (Fig. 10). These tactics are initially grouped by the combination of techniques, and the tactic groups are sorted by R_{usage} and are arranged from left to right in descending order. Above the displayed tactics, there are two waffle charts showing R_{usage} and $R_{scoring}$ for each tactic. The expert immediately noticed that the most frequent tactics of Momota are control tactics, while the usage of his offensive tactic is relatively low but with a high scoring rate. The expert explained that Momota's playing style has changed from relying on offensive scoring to relying on ball control since he was reinstated in 2017. His shift of playing style has allowed him to retain high $R_{scoring}$ on offensive tactics along with the intrinsic aggressive feature and high R_{usage} on his control tactics with a decent $R_{scoring}$.

Attracted by the usage situation of control tactics, the expert decided to select control tactics for further exploration. He selected control tactics by using the raycasting to target the bar of control tactics. TIVEE then did a filter to get control tactics and aligned them according to the previous layout (Fig. 10b). Through unrestricted navigation for observing the displayed tactics, the expert found that $R_{scoring}$ of the tactics ended with a technique *clear* is lower than others. There are far more *straight clears* than *slashes* among them. What's more, $R_{scoring}$ of *straight clears* from Momota's left-hand area is higher than that from the right-hand area. It meets the expert's expectations about his playing style. The expert explained that Momota is the only left-handed top player in men's singles today. The advantages and weaknesses of him for being a left-handed player can be fully reflected in the tactic group of *lob-clear* with opponents' *clear*, which is one of the lowest $R_{scoring}$ tactic groups. This tactic group could be clearly divided into several tactics according to the division basis (i.e., hit point area and drop area) of the final stroke (i.e., clear). The $R_{scoring}$ and R_{usage} of each tactic within this tactic group also clearly differs.

For a detailed observation, the expert activated the tactic group and turned to the tactic explanation view (Fig. 10d). The expert then

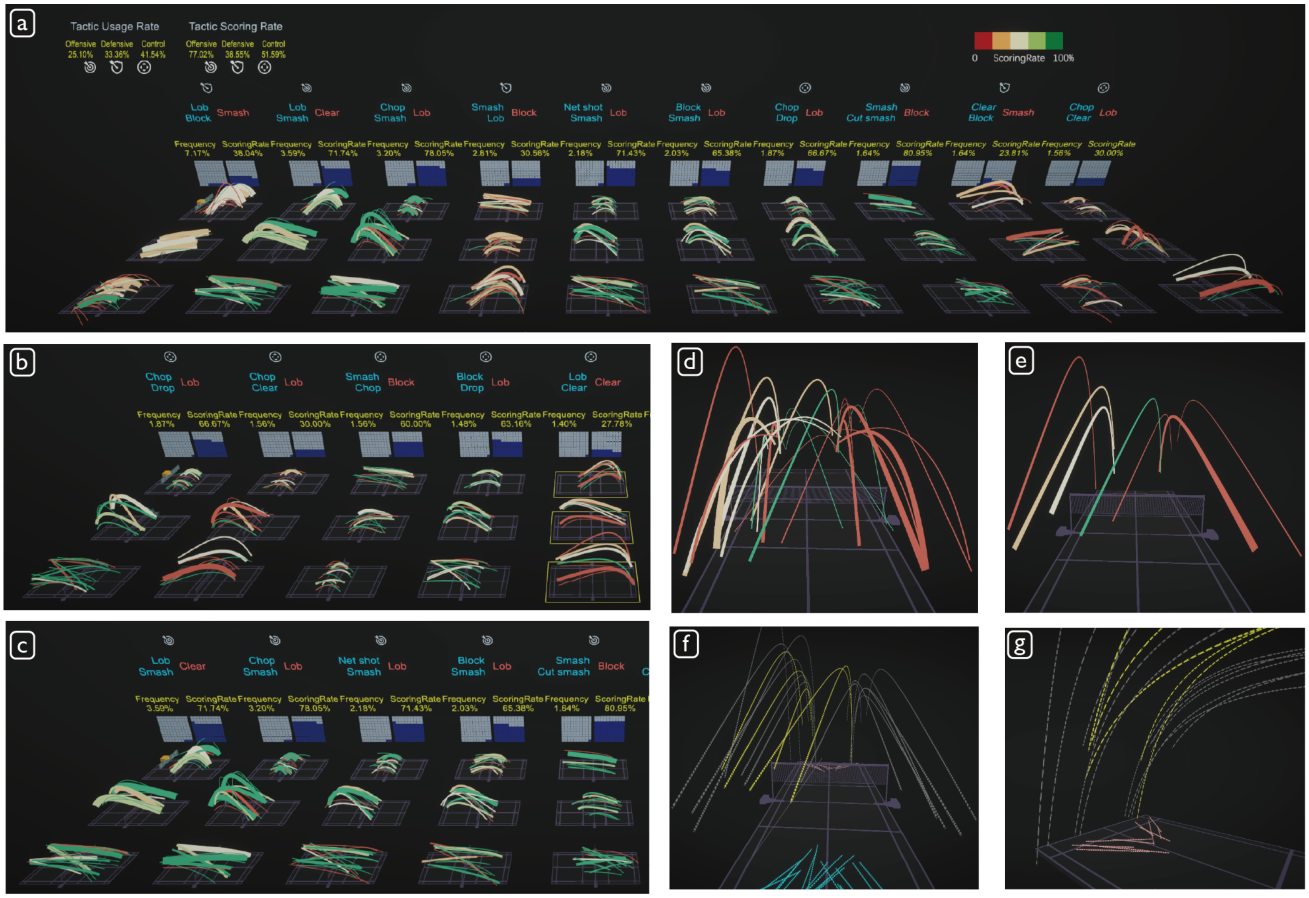

Fig. 10. a) Commonly used tactics of Kento Momota from the third-person perspective. b) Commonly used control tactics and c) offensive tactics of Momota. d) Strokes within the tactic group of *lob-clear* with the opponents' clear from the first-person perspective. e) The last strokes within each tactic. The color of each stroke represents the $R_{scoring}$ of this tactic, the thickness of the stroke represents the R_{usage} of the tactic. f) Origin trajectories of these tactics, including shuttle's trajectory, the player's movement, and the opponent. g) End points of each trajectory. Most of the end points with a result of losing drop out of the bounds.

unfolded these tactics according to the stroke order and focused on the last stroke (Fig. 10e). The *clears* could be divided into three parts, i.e., *straight clears* from Momota's left and right hand area, and *slash clears* from his left hand area to the opponents' left hand area. Based on the color of each tactic, the expert found the *straight clears* from Momota's right-hand area all end in failures, and *straight clears* from his left-hand area have a higher $R_{scoring}$. What's more, the $R_{scoring}$ of the *slash clear* reached 80%-100%, but there only exists *clears* from Momota's left-hand area to the opponents' left-hand area and the usage rate of *straight* from his right-hand area is lower than those from his left-hand area according to the trajectory thickness. Considering the dominant hand advantages, the expert explained that Momota has better control of the shuttle in his left-hand area. Combined with the nature of the *clear* technique, a *clear* will make the opponent run back and forth on the baseline, resulting in great energy consumption and a low-quality return. The opponents were hard to return when facing a *clear*. The expert further explained that the high scoring rate of *slash clear* is caused by the opponents' weakness in their left-hand area, which strengthens the difficulty of return.

Expert wondered why his winning rate in his backhand area was so low. The expert chose to view the origin trajectories of displayed tactics (Fig. 10f). Using the teleportation based on the trackpad, the expert came to the opponents' half-court (Fig. 10g). As soon as he saw the distribution of drop points, he understood why the difference in $R_{scoring}$ between backhand and forehand usage and reinforced their insight that *left-handedness contributes to Momota's success*. The *straight clears* from Momota's right-hand area all landed out of bounds, resulting in missing points. While some of the *straight clears* from his left-hand area still stayed in bounds, it is hard for the opponents to return.

To further demonstrate the advantage of his left-handedness, the expert turned to offensive tactics (Fig. 10c). He found that the top-ranked tactic groups are mainly ended with *smash* to return opponents' *lob*. $R_{scoring}$ of tactics from Momota's left-hand area are lower than those from the right-hand area. The expert was initially puzzled because the insights about left-handed advantages obtained above seemed not to apply well here. To explain this phenomenon, he looked at the strokes before the last smash. He found that these tactics are mainly started with a fore-court technique (e.g., *chop, net shot*). Combined with other tactics started with fore-court techniques, the expert concluded that Momota is good at using fore-court techniques. The expert explained the difficulty of returning a *fore-court* technique. Due to the distance between the hit point and the net, the opponent must have a quick movement to hit the shuttle, or he has to return the shuttle passively. As long as the opponent uses these two techniques, Momota has the opportunity to use *smash* to make the opponent hard to return. Why *smashes* from Momota's left-hand area have lower $R_{scoring}$ is still related to his left-handedness. Once he smashes the shuttle to the opponents' right-hand area (i.e., the opponents' dominant hand area), it is harder for his opponents to defend.

This case shows Kento Momota's playing style based on tactics. Despite his domination of the men's singles in the world, the expert has come up with several tactics to beat him through the analysis of his defensive and control tactics. For example, we can take advantage of his weaknesses in the backhand area and make Momota use *straight clear* from his right-hand area.

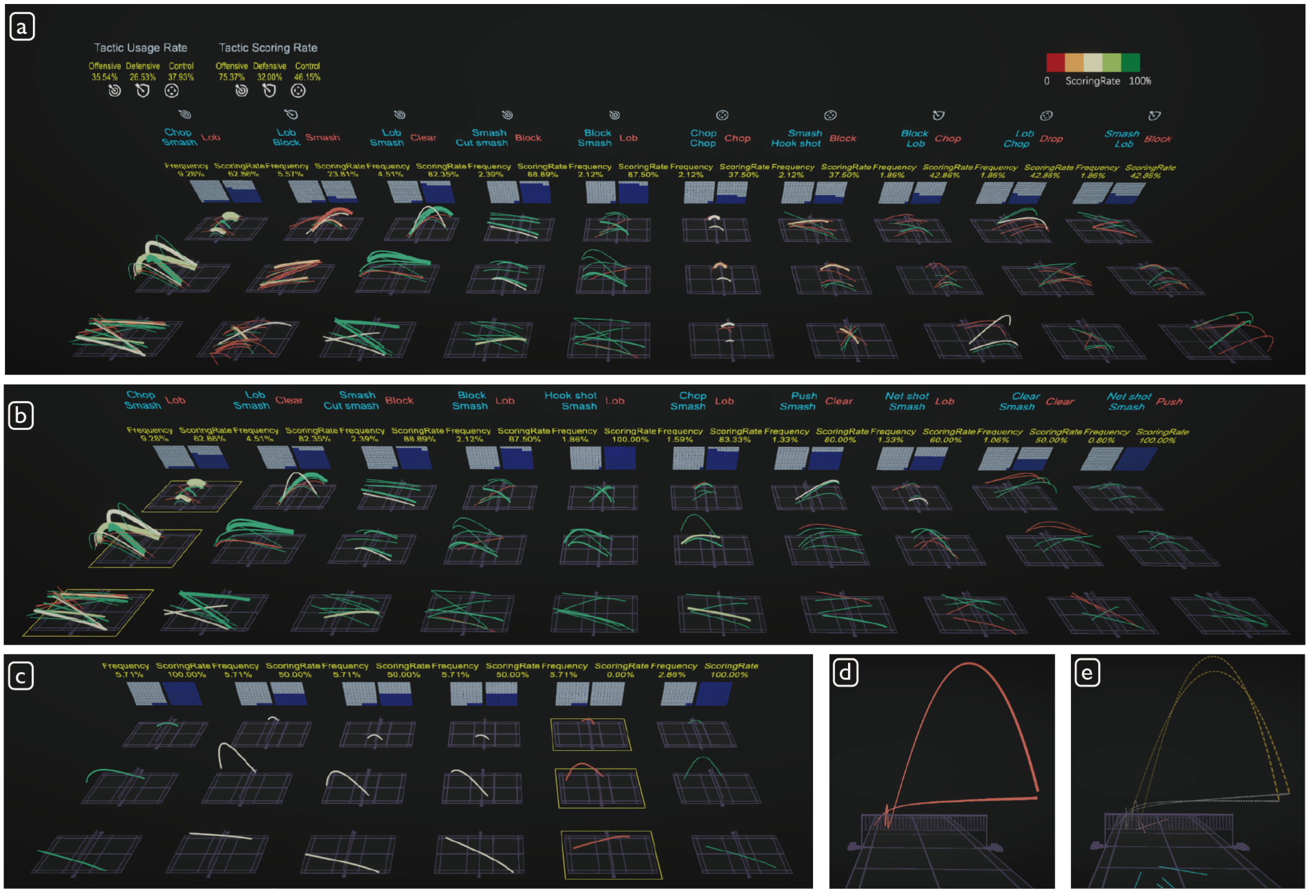

Fig. 11. Tactic analysis of Axelsen. a) Overview of commonly used tactics. Axelsen is a player whose offensive tactics dominate. b) Most commonly used offensive tactics. The last strokes of tactics started from Axelsen's forehand area have a lower $R_{scoring}$ compared to those started from the backhand area. c) Tactics subdivided according to P_{start} and P_{end}. d) The tactic with a $R_{scoring}$ of 0%. e) Origin trajectories of the selected tactic.

5.2.2 Case 2: Develop tactics for Chen Long to deal with Viktor Axelsen.

We invited expert B to do this case of tactic development for Chen Long against Viktor Axelsen. They are both tall players with heights over 1.85m and have very different playing styles. At first, the expert set the dataset to the 6 matches between Axelsen and Chen Long with 753 records (377 for Axelsen and 376 for Chen). The expert decided to analyze Axelsen first and set the stroke number as two to get an overview of his tactic usage situation (Fig. 11a). He found Axelsen's offensive tactics had a high usage rate of 35.54% which is quite different from other players. Through observing the displayed tactics, the expert found that commonly used tactic groups are mainly offensive, which confirms the playing style of Axelsen. He noticed that tactics with high $R_{scoring}$ (over 50%) were all offensive tactics and came from Axelsen's back-court. In contrast, the tactics used in fore-court had a lower $R_{scoring}$, and the tactics *lob-block* to defend Chen's smashes had the lowest $R_{scoring}$ of only 23.81%. The expert got an initial insight *Axelsen's defensive ability is relatively weak but has a solid offensive ability in the back-court*.

Knowing the basic playing style of Axelsen, the expert decided to analyze offensive tactics to discover the characteristics of Axelsen's attacks (Fig. 11b) and tried to find weaknesses of Axelsen's tactic usages. Observing the strokes before the last *smashes*, the expert found Axelsen would use *smashes* when Chen did not use offensive tactics to hit the shuttle to his back-court or middle-court. To make his tactics work, Axelsen would first find chances to force Chen to send the shuttle to his back-court or middle-court. One of his commonly used strategies was to use *chop* to force the opponent to defend with a *lob*. No matter which direction the shuttle flies, he would use *smash* to return the ball regardless of other control techniques, such as *lob* or *clear*, which are commonly used for other players. The expert explained this was related to his youth, *Axelsen had sufficient physical strength to carry out continuous attacks*, which was impossible for other older athletes.

The expert then found a scoring bias on the last stroke within the tactic usage of Axelsen. *Smashes* whose end points were near the sidelines had an extremely low $R_{scoring}$. However, those away from the sidelines were high. It was evident in the most commonly used offensive tactics (Fig. 11b). The expert explained that Axelsen is particularly prone to smash the shuttle out of bounds. The expert concluded *Axelsen has poor control of shuttle near the sideline*. To find out how Axelsen would perform *smashes* into the opponents' sidelines, the expert chose the first tactic group *chop-smash* with the opponents' *lob* for further exploration.

Splitting the tactics within the tactic group according to the T_{field} of P_{start} and P_{end} of each stroke, the expert got small multiples with more detailed tactics (Fig. 11c). Based on the trajectory color, the expert found the fifth tactic had the lowest $R_{scoring}$ of 0%. To better describe the tactic, the expert activated it and entered the explanation view. This tactic started with Axelsen's chop from his backhand area in the fore-court into the opponent's forehand area in the fore-court (Fig. 11d). The opponents returned with a high lob to Axelsen's forehand area in the back-court, and Axelsen hit the shuttle in a slash smash. Through observing the origin trajectories of the movement of players (Fig. 11e) and viewing the execution's animation of the tactic, the expert found Axelsen would make such a decision was because he was picked a gap. It was difficult for him to make an active smash and this slash smash was a forced return. The expert concluded *Axelsen has difficulty coping with the tactics of being picked in the back-court.*

To provide Chen Long with useful and actionable tactical guidance against Axelsen, the expert then chose the data of Chen Long and turned to another view of him (Fig. 1a). From this view, the expert concluded *Chen is a defensive player* whose defensive tactics dominated his performance. It also proved the difference between their playing styles. Considering Axelsen's advantages in offensive tactics, the expert turned to the tactic customization view to learn Chen's tactics when facing offenses. Setting Axelsen's stroke with the technique of *smash*, the expert found that Chen always used *block* for the defense, but the $R_{scoring}$ was low (Fig. 1b). From the selected tactics, the expert speculated an effective way to defeat Axelsen is to use the tactic *block-lob* against Axelsen's *hook shot* and to use *block-lob* against Axelsen's *chop*. The expert proposed a suggestion, *seek for as many gaps in Axelsen's back-court as possible*. He further selected the tactic with the highest R_{usage} for detailed observation. The movements of the two players and the tactic animation verified the rationality of his suggestion (Fig. 1c-e).

5.3 Domain Expert Interview

After case studies, we conducted one-to-one interviews with experts respectively. Due to the limited space, in previous sections we did not present the case of Expert C, which is about analyzing the playing style of *Anthony Ginting*. Nevertheless, Expert C provided valuable feedback about the system and we summarized all the feedback from the three experts as follows.

Visual Design and Interactions. Overall, the experts appreciated our system. Compared to traditional tactic analysis methods with 2D visualizations of abstract data, the experts can perceive the tactic characteristics in a tangible form through viewing the summarized 3D trajectories as the representation of tactics. It helps reduce the experts' cognitive load. They also appreciated the structure design of a tactic as it supports the analysis of a single tactic. It maintains the spatio-temporal information between strokes. The analysis of multiple tactics is also practical. It reduces the visual clutter by unfolding the strokes and the alignment layout. They could obtain valuable insights about players' playing styles based on the overview. With a combination of the third-person perspective for the overview and the first-person perspective for the detailed observation, the experts appreciated the intuition and authenticity of our system. Expert B thought that the animation to restore the tactic's execution is more convenient than traditional video replays and reduced the time for watching multiple videos. Through navigating in the virtual environment, the experts commented they could observe comprehensive information in the scene through the interaction of teleportation. The experts preferred using VR controllers to the traditional desktop mouse click as the VR controller provided them with better perceptions.

Suggestions. The experts proposed two suggestions to TIVEE. First, expert C commented a direct tactical match between two players would enhance the usability of the system. He hoped the system could directly provide a player's tactics that can easily overcome the weaknesses of a designed opponent. Second, simplified movements in the virtual environment are needed. Expert A pointed out physical sicknesses occurred during the case study due to too many movements in the VR, especially the navigation in the sky. The system should provide more simple navigation for the scene observation.

6 Discussion

In this section, we discuss the significance, lessons learned, generalizability, and limitations and future work of TIVEE.

Novelty/Significance. Previous immersive visualization methods such as Shuttlespace cannot be applied to the tactical analysis of badminton since they break a series of consecutive stroke sequences into individual instances and regard the problem as visualizing and summarizing a set of 3D trajectories, thereby discarding the important tactical relations. By considering consecutive strokes as a unit, this work transforms the problem to visualizing relations between 3D stroke trajectories, which is the major difference compared to current analysis tools and processes. An immersive visual analytics approach, including the tactic overview, tactic customization, and tactic explanation, is therefore proposed to help users more easily explore and explain badminton tactics, contributing to both visual sports analytics and related trajectory immersive visualizations.

Lessons learned. We have learned two lessons through this study. First, splitting large scale spatio-temporal trajectories into different spaces can be useful in reducing the exploring difficulties. The 3D consecutive trajectory segments appearing on the same court are inevitably intertwined, which creates significant difficulties for analyzing the relations between them. In the overview phase, we employ a multi-court layout that distributes trajectory segments to small multiples, which allows users to effectively find interesting stroke sequences to drill down for detailed exploration. Second, for non-visual experts to analyze the relation of 3D trajectories, the design complexity of visualization should be limited. Initially, we proposed several visual designs to assist them in understanding the correlation between strokes in the same tactic, such as the combination of 3D parallel coordinate plots and matrix. However, such design coupled with the 3D trajectories confused experts and commented that watching an animation showing how the tactics are executed is more preferred. Therefore, we simply provided trajectory animation with the first-person view in the tactic explanation phase.

Generalizability. TIVEE provides the opportunity for the 3D spatial characteristics observation and therefore can be extended to other racket sports like tennis and table tennis, in which the spatio-temporal information contained in the stroke sequence is significantly important. Moreover, the pipeline can be adapted to analyze volleyball which emphasizes the relation between the consecutive touches. However, it can hardly be adapted to the non-racket sports (e.g. soccer and basketball) since they have different definition of tactic.

Future work. First, interactions using planar graphic user interface such as checkbox and slider, are inconvenient in VR with a controller. The user is likely to shake his/her hand when using the controller in air, which will cause the controller to shift and deviate from the visual target to be interacted with. More stable interaction design (voice interaction) needs to be proposed. Second, considering the accuracy and the reliability of the analysis, the system requires experts to manually setup a set of parameters. Reducing manual operations can largely improve the usability of this work. In the future, we will incorporate template-based configurations and automatic recommendation techniques into the system to reduce the manual operations and improve the system usability. Third, the available records after user customization may be limited, resulting in poor verification of the tactic effectiveness. In the future, we plan to add a simulation component into the system to help users more easily verify the effectiveness of a tactic.

7 Conclusion

In this work, we propose an immersive analytics system, **TIVEE**, to help badminton coaches explore and explain commonly used and exciting tactics, and discover the strengths and weaknesses of a player. This study is the first work to analyze badminton tactics in a 3D environment. We closely collaborate with domain experts to characterize the problems of tactic analysis and obtain analytical requirements to derive designs. To visualize a set of tactics, we design a multi-court layout of the stroke trajectory to characterize the kinematic features and maintain the spatial and temporal correlation between adjacent strokes involved in tactics. For explaining a tactic's effectiveness, we provide several visualizations for an individual tactic, including the summary of origin data, folding/unfolding of sequential strokes, and animation for the users to observe the actual execution of player and shuttle movements. We conduct two case studies and an expert interview to demonstrate the effectiveness of our work. In the future, we plan to integrate automatic recommendation techniques and simulation models to improve the usability of the system.

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