

iTTVis: Interactive Visualization of Table Tennis Data

Yingcai Wu, Ji Lan, Xinhuan Shu, Chenyang Ji, Kejian Zhao, Jiachen Wang, and Hui Zhang

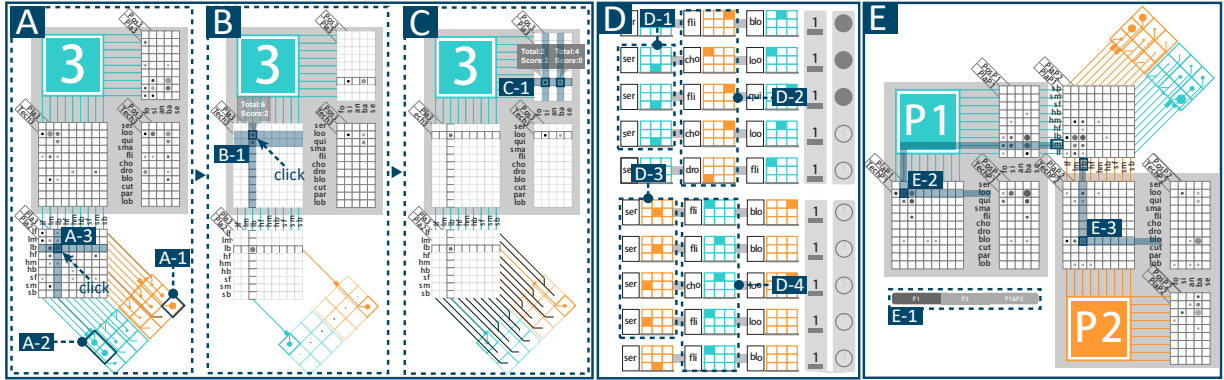


Fig. 1. Analysis pipeline of the case study discussed in Section 5.1.2. (A), (B), and (C) show different states of the intra-stroke matrices of Stroke 3, and the inter-stroke matrix of the stroke placement between Strokes 2 and 3. (A) shows the initial state. (B) shows the state change from (A) when a grid cell (A-3) of the inter-stroke matrix was selected. (C) shows the state change from (B) when the expert clicked on a grid cell (B-1) of the intra-stroke matrix representing the correlation of stroke techniques and stroke placements of Stroke 3. (D) shows the serve tactics in the end phases of rallies. The top five rows show the tactics of Player 1, while the remaining rows represent the tactics of Player 2. (E) shows the aggregated relationships of strokes after Stroke 5.

Abstract—The rapid development of information technology paved the way for the recording of fine-grained data, such as stroke techniques and stroke placements, during a table tennis match. This data recording creates opportunities to analyze and evaluate matches from new perspectives. Nevertheless, the increasingly complex data poses a significant challenge to make sense of and gain insights into. Analysts usually employ tedious and cumbersome methods which are limited to watching videos and reading statistical tables. However, existing sports visualization methods cannot be applied to visualizing table tennis competitions due to different competition rules and particular data attributes. In this work, we collaborate with data analysts to understand and characterize the sophisticated domain problem of analysis of table tennis data. We propose iTTVis, a novel interactive table tennis visualization system, which to our knowledge, is the first visual analysis system for analyzing and exploring table tennis data. iTTVis provides a holistic visualization of an entire match from three main perspectives, namely, time-oriented, statistical, and tactical analyses. The proposed system with several well-coordinated views not only supports correlation identification through statistics and pattern detection of tactics with a score timeline but also allows cross analysis to gain insights. Data analysts have obtained several new insights by using iTTVis. The effectiveness and usability of the proposed system are demonstrated with four case studies.

Index Terms—Sports visualization, visual knowledge discovery, sports analytics, visual knowledge representation

1 INTRODUCTION

Table tennis is one of the most popular sports around the world with more than 300 million active participants [5]. It elicited considerable attention in the Rio Olympics and was followed by 552 million television viewers [11]. The growing popularity of and fierce competitions in table tennis have resulted in the emergence of analysis methods to understand game tactics better and improve team performance. However, these methods are usually tedious and limited to watching videos and reading simple statistical tables. The rapid development of information technology has led to the acquisition of fine-grained data on table tennis matches for improved analysis and understanding [34]. The acquired data, characterized by dynamic, multivariate information on

stroke attributes, have an innate nature for analysis and help analysts explore tactics and evaluate the performance of players. Statistical analysis [21–23] and mathematical modeling [28, 33] have been used to analyze the fine-grained data. These approaches, however, are in a hard struggle, when dealing with fast-paced and highly dynamic sports with sophisticated stroke techniques and different playing tactics. This is because these approaches usually target one particular problem and cannot provide a quick and holistic view. Furthermore, these automatic methods based on clear rules or models are difficult to use in the detection of unusual or unexpected patterns. Interpreting and making sense of the analysis results present another obstacle. Thus, senior data analysts working for the Chinese national table tennis team approached us, seeking for a novel method to cope with table tennis data.

Visualization techniques are hence required to assist in presenting data intuitively, detecting trends and correlation patterns of tactics quickly, and understanding the identified patterns easily. However, comparatively little work in sports visualization has been conducted for table tennis; this domain has been dominated by soccer [17, 26], basketball [12, 14], tennis [30], and ice hockey [29]. The existing techniques cannot be directly applied in table tennis which has unique data characteristics and different design requirements. For instance, although tennis possesses the most similar structure as table tennis, the tennis visualization system TenniVis [30] aims at non-professional analysis based on general data like scores and service information. TenniVis does not support professional in-depth analysis (see Section 3.3) of

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fine-grained table tennis data (see Section 3.2), which contains detailed stroke attributes. These data attributes are not available in TenniVis.

A proper visualization system for table tennis that supports game narration, statistical exploration, and pattern detection for table tennis is yet to be proposed. Developing such a visualization system remains difficult due to two challenges. First, understanding and characterizing the sophisticated problem domain of analysis of table tennis data are difficult. Considering that the theoretical study of table tennis has been developing for decades, domain terminologies and mechanisms are abundant and complicated. Moreover, the domain experts, who worked for the Chinese national table tennis team, have been accustomed to traditional statistical analysis methods and are unfamiliar with visual analysis. Second, providing a comprehensive visual representation of complex table tennis data is non-trivial due to the time-varying, location-based, and stroke-interrelated features. These features restrict the establishment of a rational visualization design.

To address the first challenge, we have been working closely with domain experts for eight months. During the collaboration, we characterized the domain problems through several iterations of user-centric procedures, such as communicating, discussing, brainstorming, designing, and prototyping. To our knowledge, this study is the first attempt to systematically characterize the application domain problems. To address the second challenge, we developed and built *iTTVis*, an interactive system for the visual exploration of table tennis data. The system utilizes a score timeline to provide holistic narration and navigation by encoding various information, such as point outcome and rally length. Detailed stroke information is displayed on a representation of a table tennis table. Meanwhile, a statistical view enables users to gain insights into the intra-stroke relationships within a stroke and inter-stroke relationships between strokes. Frequent patterns of tactics can be extracted further to help analysts obtain insights. We evaluated the capability of *iTTVis* to capture and communicate valuable patterns through case studies with several domain experts and received encouraging feedback.

The major contributions of this study are as follows:

- ◇ A review of existing literature on the analysis and visualization of table tennis data and characterization of the domain problems in table tennis, for which a set of design considerations is derived.
- ◇ The first attempt—to the best of our knowledge—to establish a visualization for table tennis analysis by exploring from a match to a stroke progressively and interactively, and by providing crucial statistical data to discover patterns of tactics.
- ◇ Case studies with professional table tennis experts who incorporate visualization into their analyses and new valuable insights obtained for table tennis training and competition.

2 RELATED WORK

This section presents two closely related research topics, namely, analysis and visualization for table tennis and sports visualization.

2.1 Analysis and Visualization for Table Tennis

Statistical analysis has been widely used in analyzing table tennis data. Loh et al. [22] computed game statistics, such as game duration and ball position, to compare competitive structures between junior and elite players. Lanzoni et al. [23] compared shot characteristics between Asian and European table tennis players by using the statistics of shot attributes. With multivariate data collection equipment, Leser and Baca [21] designed a type of qualitative performance analysis. However, these measures lack the consideration of game situations.

Mathematical modeling has also been adopted to analyze the game process. Pfeiffer et al. [28] utilized the Markov chain, a stochastic model based on transition matrices, to predict tactical effects. In this model, each game consists of a sequence of game situations regarded as transitions in discrete states. The model can calculate the performance relevance to tactical behavior patterns. Wenninger and Lames [33] also used the Markov chain to identify the impact of different tactical behaviors on winning probability in table tennis.

However, these standard methods lack visualization, leading to the difficulty in interpreting and understanding the results. Some work

also introduced visualization for its straightforward interface and convenient interaction. Websites and news reports have utilized simple charts, such as flow charts for outcome illustration [10], radar charts for the revelation of athlete capacity [2], and heat maps for ball position representation [9]. In practical training, a system based on video image processing technology was used to provide a dynamic histogram for each score [16]. The system was further extended to provide trajectory visualization [34]. Moreover, playing table tennis on a table with dashboards that support trajectory visualization in real time [3, 7] contributes to increasing the situation awareness of players. However, the system cannot be used in actual competitions and is unable to detect patterns of tactics. Although these visualizations can fulfill simple tasks like information representation, the technology used is rudimentary and unsuitable for pattern detection and comprehension, which are two of our major contributions.

2.2 Sports Visualization

Recent years have witnessed an increasing interest in sports visualization with numerous applications. MatchPad [20] provides a new interactive glyph-based visualization during rugby games for real-time sports performance analysis. Many studies focused on analyzing data after matches. SoccerStories [26] is a pioneering work in this direction; it presents a set of tailored techniques to explore soccer data. Several interesting and insightful designs, such as Director's Cut [32], Feature-Driven visualization [17], and A Table [27] have also been introduced to facilitate the soccer data analysis. These designs illustrate respectively game phases, tactics annotation, pattern identification, and ranking tables. NBA data have also been investigated in several valuable designs, such as CourtVision [15], Counterpoints [14], and GameFlow [12], which visualize seasons of NBA data and reveal heated confrontations. SnapShot [29] and StatCast [19] introduce new heatmaps for ice hockey and baseball visualization respectively. Baseball4D [13] is a new tool to reconstruct and visualize baseball games. These prior studies concentrated on multi-player sports visualization. Recently, Polk et al. [30] presented a novel sports visualization system, called TenniVis, with a focus on single-player sports for tennis data analysis. Furthermore, Parry et al. [24] introduced a new method called Video Storyboards and presented a case study on snooker video visualization.

However, a particular design for table tennis supporting game narration, statistical comparison, and pattern detection remains absent. We obtained insights from various related studies for each component of the system to realize an advantageous visualization system of table tennis. First, the score timeline is an indispensable component in sports visualization; in this timeline, scores evolve with the match time progressively. Viewers can map the game intervals on the timeline rapidly and acquire a glimpse of the match with time and score information. A standard design utilizes line and bar charts that encode the scores of the two teams or players [8]. Perin et al. [25] proposed a new method called Gap Charts to visualize the temporal evolution of scores to avoid overlaps. Glyphs, which better conform to real marks used in actual competitions, are applied to encoding critical points for indication. SoccerStories [26] places circles in different colors on the timeline to illustrate turning points.

Second, the visualization of structure information is essential. Tennis possesses similar structures as table tennis. Jin and Banks [18] proposed competition trees to organize and visualize the information of a tennis match. The game tree depicts point progression for selected games [1]. Polk et al. [30] used the Pie Meter view and the Fish Grid view to provide a visual summary of a match and that of a game, respectively. Stroke information possesses detailed attributes and is displayed on a visual representation of a real field, such as tracking ball trajectories in a 3D immersive tennis field [6].

Third, analysts think highly of the visualization of statistical analysis. Heatmaps are commonly used in sports visualization to demonstrate the frequency distribution of position information on the sports fields [14, 19, 29]. Standard visualizations, such as bar charts, are popular in information representation as well.

These studies on visualization shed light on our design. We derived initial system architectures that characterize the match evolution

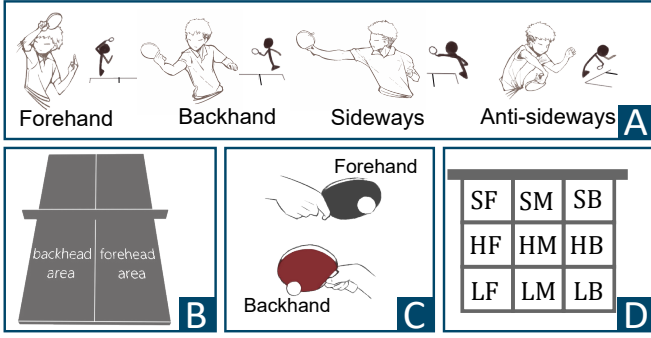


Fig. 2. Illustration of important concepts of table tennis: (A) four stroke positions, (B) backhand and forehand area, (C) backhand and forehand, and (D) nine stroke placements.

and support statistical analysis based on the abovementioned studies. However, most previous approaches are not designed for table tennis. Several essential aspects of data analysis for table tennis matches, such as correlation analysis of technical attributes between and within strokes, and pattern identification of tactics, are still missing. Our system is the first attempt to visually analyze table tennis data; it covers a wider range of important data properties.

3 BACKGROUND AND SYSTEM OVERVIEW

This section presents the background, data description, system overview, and a usage scenario of iTTVis.

3.1 Background

Table tennis involves two opposing players hitting a lightweight ball back and forth across a table using small bats. A table tennis **match** consists of the best 4 out of 7 **games**, where each game is awarded to the player who obtains 11 points first with at least a two-point margin. Each point is awarded to the player who wins the **rally**, which is defined as a period during which the ball is in play. A rally generally contains several to dozens of **strokes** from both players. A stroke means that the table tennis bat hits the ball once. And a serve is considered a special stroke and usually represents an advantage in a rally. Each player is asked to alternately serve two points. But when the competition score in a game reaches 10-10, each player takes turns serving one point instead of two.

3.2 Data Description

For a table tennis match with two players A and B, a data table with hundreds of strokes was collected. Specifically, our collaborators asked professional athletes to recognize and record the attributes of each stroke according to the video of the match. Each stroke, which corresponds to a row in the table, has a variety of attributes, namely, stroke attributes. The important attributes are described below.

Table 1. Data description

Game ID	The ID of the game to which this stroke belongs.
Rally ID	The ID of the rally to which this stroke belongs.
Stroke ID	The ID of this stroke within a rally.
Score A	The score of player A when this stroke takes place.
Score B	The score of player B when this stroke takes place.
Stroke player	The player who gives this stroke.
Stroke effect	The effect of a stroke reflecting the competition situation.
Stroke technique	The technique the player uses.
Stroke position	The position where the player gives the stroke.
Stroke placement	The drop point of the current stroke

- ♦ **Stroke effect:** The effect is recorded as an ordinal number marked by five levels. A small number indicates a good effect of the stroke for the stroke player. For example, the first level, as the smallest

one, means that the stroke directly leads to a point win for the stroke player and puts an end to the rally.

- ♦ **Stroke technique:** The stroke technique records how the player gives the stroke. The domain experts define eleven important techniques: *serve, loop, quick attack, smash, flick, chop long, drop shot, block, cutting, parrel* and *lob*. More details can be found in a Wikipedia page [4].
- ♦ **Stroke position:** The stroke position records where the player gives the stroke. Each side of the table can be divided into the forehand area and the backhand area (Fig. 2B). The player can use forehand or backhand (Fig. 2C) in both areas. Four stroke positions are derived. The stroke position is defined as forehand when the player uses forehand in the forehand area. Similarly, backhand is defined as using backhand in the backhand area, sideways as using forehand in the backhand area, and anti-sideways as using backhand in the forehand area (Fig. 2A).
- ♦ **Stroke placement:** The stroke placement records the drop point of the stroke. The table tennis table is divided into 18 parts with nine parts at each side (Fig. 2D). All stroke placements are recorded as part names. That is, they are spontaneously classified into nine categories.

These attributes are deemed as a quantitative characterization of a fiercely competitive match, and imply the athletes' playing tactics and performance. We base our work on fine-grained data to provide a comprehensive analysis of an entire table tennis match.

3.3 Requirement Analysis

The concept of our system germinated eight months ago. Senior analysts working for the Chinese national table tennis team approached us, seeking for a novel method to address the bottlenecks they encountered when dealing with table tennis data. They had collected sufficient data on table tennis matches among the world's best players but lacked effective methods to cope with them. Their analysis was limited to the basic statistical methods provided by Microsoft Excel. Typically, they computed the occurrence rate of a certain attribute (e.g., stroke technique) and analyzed the overall relationship between the scoring rate and usage rate of various techniques [35]. However, the experts had been experiencing difficulty with these traditional methods for a long time. Detecting unusual patterns and gaining new insights had been a cumbersome trial-and-error process.

Therefore, our goal is to develop an advantageous visualization system that provides a new visual perspective with user-friendly interactions. We followed the nine-stage methodology framework [31] to conduct our study. Over the past eight months, we cooperated closely with domain experts. We held weekly meetings to characterize the sophisticated problem domain, discuss analytical requirements, present the prototype system, and collect feedback for further revision. The constant exchanges helped us design and refine our system iteratively. The major milestones of the design process are as follows.

Characterizing problem domains. We conducted multiple interviews with experts in the first two weeks to characterize the problem domain. Initial requirements were derived during the process of designing and presenting small views iteratively.

Designing an alpha prototype. We developed a prototype that supports a basic workflow of match narration and general statistical analysis. We deployed this alpha version for experts to use for half a month and collected their feedback regarding the system. They were satisfied with the basic workflow but required a more robust statistical analysis and a new method of identifying the underlying tactics.

Re-designing the beta system. We derived the updated requirements and redesigned the system (Beta 1.0). Our design in this phases concentrated on providing statistical exploration and detecting frequent patterns of tactics. We also allowed experts to use the Beta 1.0 version for a week and gathered their feedback. They liked the version much better and tried to work further on the system to detect new patterns.

Enhancing the beta version. The experts also offered new requirements to enrich and improve the system (e.g., providing smooth interactions and designing visual metaphors familiar to experts). We kept in touch with the experts for debugging in time and testing new functions.

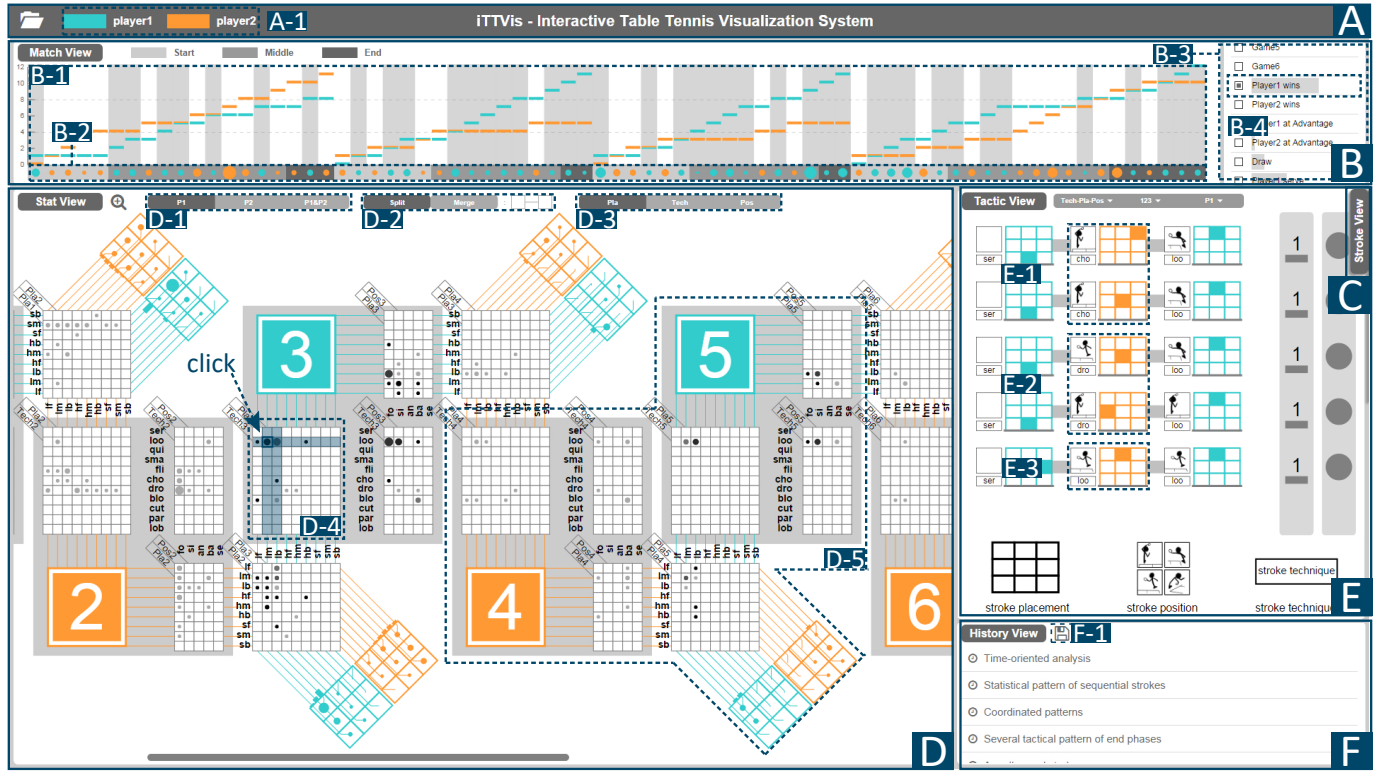


Fig. 3. Interface of iTTVis with a unified color encoding (A-1). The interface comprises five well-coordinated views: the match view (including a tailored step chart (B-1), a point outcome bar (B-2), and a selection panel (B-3)), the stroke view (collapsed and minimized in (C)), the stat view (D), the tactic view (E), and the history view (F).

At that point, we finally recognized their requirements after several iterative user-centric procedures, such as discussing, brainstorming, designing, and prototyping.

The requirements are condensed as follows.

T Time-oriented analysis of an entire table tennis match

T1 *How do the scores evolve over time through a match?* When analyzing table tennis matches, analysts attach great importance to score information, because it is inextricably associated with the game situation. The system should offer access to the exploration of the temporal evolution in scores and point outcomes (the winner of the rally), and provide an overall impression of the match.

T2 *How can analysts navigate into key rallies on the match timeline and explore the transformations of strokes within rallies?* Not all rallies weigh equally in a match. Analysts are interested in key rallies that exert impact on the match. The system should allow analysts to locate these key rallies on the timeline according to indications proposed by experts, such as rally lengths and point outcomes. Analysts also intend to unfold these rallies to explore more features of strokes.

S Statistical analysis of three essential attributes, namely, stroke placements, stroke positions, and stroke techniques, recognized commonly by experts

S1 *How do stroke attributes intra-relate within a stroke?* Different strokes exhibit distinct characteristics of frequency distribution and scoring rates on three attributes. These attributes may also possess interesting intra-stroke relationships. For example, a certain stroke technique is likely to be used with a particular stroke placement, accompanying a high scoring rate. Analysts intend to compare the distribution between strokes and explore the intra-stroke relationships. Thus, the system should provide a statistical analysis of the three attributes of each stroke.

S2 *How do stroke attributes inter-relate between adjacent strokes?* Experts indicate that stroke attributes inter-relate between adjacent strokes. That is, a player gives a stroke with a particular technique and the other player is likely to utilize this technique on the next stroke for hitting the ball back. Analysts wish to examine and analyze detailed inter-stroke relationships and scoring features between adjacent strokes.

C Cross-analysis between the timeline and statistics

C1 *How do the timeline and statistics relate to each other?* Analysts want to brush multiple rallies on the timeline and examine the states of statistics and tactics. Analysts also intend to filter information from the statistics and display the corresponding tactics. The system thus should support cross-analysis and comparisons.

P Pattern mining of tactics in table tennis matches

P1 *What are the frequent patterns of tactics?* What are the scoring rates of tactics? The combination of the stroke attributes of three strokes is considered as a tactic. Players tend to exhibit frequent patterns of tactics in table tennis matches. The system should assist analysts in detecting frequent patterns of tactics with high scoring rates.

Other requirements, such as offering access to recording historical exploration with user annotations, are satisfied to the best of our ability.

3.4 System Overview

We designed and developed iTTVis to analyze the data on a match from three perspectives: the time-varying process of score information with the *match view*, the statistics of inter- and intra-stroke relationships of stroke attributes with the *stat view*, and the frequent tactic patterns with the *tactic view*. The system includes two additional views, namely, the *history view* and *stroke view*. The history view allows users to view, add, remove, and annotate the exploration history. The stroke view displays the detailed attributes of selected strokes on table tennis tables.

We provided a brief usage scenario to demonstrate how an analyst can use the system. The user recognizes the unified color encodings on the top (Fig. 3A-1) before exploration. She looks through the match view (Fig. 3B) and sees the score evolution instantly from the tailed step chart (Fig. 3B-1). She then explores the horizontal bar (Fig. 3B-2) and selects a rally of interest. The stroke view (Fig. 3C) slides in and displays all the strokes of the rally (Fig. 4). She can also brush multiple rallies on the tailed step chart (Fig. 3B-1) or from the selection panel on the right (Fig. 3B-3). The stat view (Fig. 3D) and tactic view (Fig. 3E) update the contents in the light of the selected rallies on the tailed step chart. By default, these two views display the information on all the rallies of the match. Afterward, the user interactively explores intra-stroke relationships within a stroke and inter-stroke relationships between strokes on the stat view. She discovers tactics with high frequency or high scoring rates on the tactic view (Fig. 3E). The current states can be saved with simple annotations on the history view (Fig. 3F) when she wants to put an end this time but hopes to review and re-explore next time.

The entire system is a web application with two parts, namely, data preprocessing as the backend and interactive visualization as the frontend. Node.js was employed to build the backend, which extracts necessary information, such as the score and attribute of each stroke, from CSV files according to the requests from the frontend. AngularJS was used as the front-end framework. D3.js was used as the visualization library to develop the interactive visualization views.

4 VISUAL DESIGN

We followed the three design rationales below to design iTTVis.

Use familiar visual metaphors. Domain experts lack experience on working with advanced visualization systems. They prefer an interface with intuitive and familiar metaphors, such as icons, lines, and tables, thus requiring us to make careful design choices.

Support smooth interactions. The system should allow users to explore data interactively, thus providing an engaging experience and enabling experts to integrate their expertise into the analysis process.

Connect abstract data to the physical context. Abstract data analysis leads to the difficulty in comprehending and interpreting the results. Therefore, establishing a connection between abstract data and the physical context of table tennis is important. We related the designs with table tennis (e.g., encoding on a table tennis table).

The detailed designs and interactions are presented below. For a unified color encoding, we used cyan and orange to represent two players respectively in the entire system (Fig. 3A-1).

4.1 Match View

Analysts require a timeline view that provides an overview of the score information of a match and supports multi-option navigations into key rallies (T1 and T2). We created a concise and vivid match view (Fig. 3B) to deliver an overview of the time-varying process and enable multi-level exploration.

Description: In the match view, we employed a **tailored step chart** (Fig. 3B-1), which is a familiar metaphor for the score timeline, to show the time-varying score information (T1). A **point outcome bar** (Fig. 3B-2), which shows additional information on each rally, including, point outcome, rally length, and phase (T1), was further used to substitute for the horizontal axis of the step chart. Brushing multiple rallies are supported in the chart for further analysis. A **selection panel** (Fig. 3B-3) was also used to facilitate the selection of rallies. The detailed encodings are illustrated as follows.

Tailored step chart. We encoded the score information of two players at all rallies of a match as two tailored step lines in corresponding colors (Fig. 3B-1). Each tailored step line comprises a series of small boxes. Each box corresponds to a rally. The y-coordinate of each box represents the point of the corresponding player (distinguished by color) at the end of the rally. The fall of the step lines indicates the beginning of a game, where the scores of two players return to zero. The selected rallies are highlighted with gray bars on the chart.

Justification: We first considered the line chart, which is commonly used to visualize the time-varying score [6, 11]. However, the line

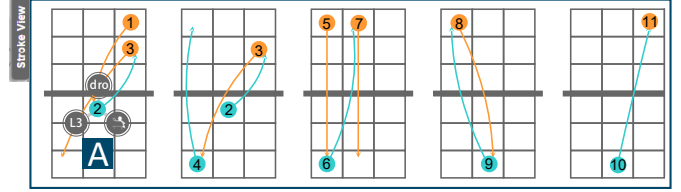


Fig. 4. The stroke view displays a series of tables with detailed information of each stroke. The stroke technique, position, and effect are displayed when hovering on the ball (A).

changes continuously, leading to a misunderstanding that the score is varying all the time instead of at the end of each rally. The regular step chart illustrates that the score changes one by one. To make the stepped lines clear, we removed the useless vertical lines and used color to maintain the continuity.

Point outcome bar. The point outcome bar, which is composed of a horizontal bar with a series of balls on it (Fig. 3B-2), encodes the phase length and additional information of rallies. Each ball represents a rally (Fig. 3B-2). The color of the ball indicates the winning player of the rally, and the area of the ball encodes the length of the rally. The luminance of the bar encodes the phase information. Each table tennis game consists of three phases, namely, a start phase (ends when a player scores four points), a middle phase (ends when a player scores eight points), and an end phase (ending with the game). Different phases appear orderly in a game with varying degrees of tension. Thus, the bar has three types of luminance in each game.

Selection panel. Rallies can be selected in the selection panel. For example, when users select “Player1 wins”, all rallies that Player 1 won will be highlighted in the tailored step chart (Fig. 3B-1). All selections were developed with experts, and provide easy navigation into key rallies (T2). The gray bar behind each selection encodes the number of rallies that match this selection (Fig. 3B-4).

4.2 Stroke View

When analysts click on a ball in the point outcome bar, the stroke view (Fig. 4) slides in to illustrate detailed information, including placement, technique, position, and effect of each stroke in the rally (T2). We used a ball with a directed curve as a stroke, and a table tennis table as the background. The number shown on the ball indicates the sequence number of the stroke, and the position of the ball on the table illustrates the stroke placement. The stroke technique, position, and effect are displayed when hovering on the ball (Fig. 4A). All the strokes were divided according to the instructions of experts who required that the first to third, and the second to fourth strokes should be arranged in the same table, respectively. The remaining strokes were divided in the light of the stroke direction.

4.3 Stat View

Three stroke attributes both intra-relate within a stroke and inter-relate between adjacent strokes within rallies selected on the tailored step chart. Thus, complex sequential intra-stroke and inter-stroke relationships are generated. Creating an informative and discernible visual representation of these relationships poses great challenges.

We used the pairwise correlations among the three attributes in a stroke to measure intra-stroke relationships, and used correlations between the same attributes of two adjacent strokes to measure inter-stroke relationships. Specifically, the correlations between two attributes denote the occurrence frequency and scoring rate of the combination of each value of the two attributes in all selected rallies.

Description: We employed a sequence of aligned matrix views to present the correlations sequentially in the stat view (Fig. 3D). The layout and encodings are briefly described as follows. First, we used a gray block to represent a stroke. The blocks were arranged according to the stroke sequence. Second, between any two adjacent blocks, we used a matrix to represent correlations between the two strokes in a certain

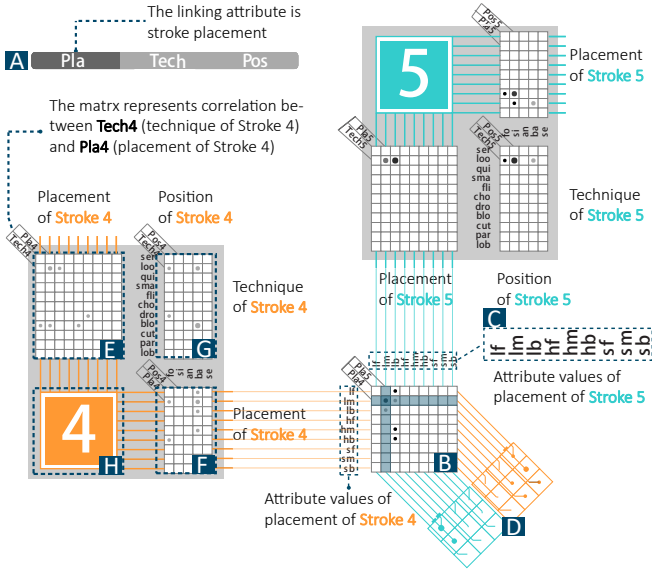


Fig. 5. Illustration of the visual encodings used in Fig. 3D-5. (A) shows the linking stroke attribute, namely, stroke placement. (B) shows an inter-stroke matrix. (C) shows the abbreviations of the attribute values of the stroke placement. (D) shows the table tennis table. (E), (F) and (G) show three intra-stroke matrices. (H) shows the sequence number card.

stroke attribute (Fig. 5B). We call the matrix the **inter-stroke matrix**, and we call the certain stroke attribute the **linking stroke attribute** (Fig. 5A). Furthermore, we placed three matrices in each stroke block to represent pairwise correlations among the three attributes (Fig. 5E, F, G). We call these three matrices **intra-stroke matrices**. Generally, the inter-stroke and intra-stroke matrices are aligned with each other, thus creating a neat and symmetrical view to allow multi-facet correlation analysis among a sequence of strokes.

Inter-stroke matrix: The inter-stroke matrix represents correlations between two adjacent strokes in the linking stroke attribute. As shown in Fig. 5B, it is a square matrix linking with the two stroke blocks by guidelines (i.e., the solid orange/cyan lines).

We used an example to explain how the matrix works when the stroke placement is selected as the linking stroke attribute (Fig. 5A). The inter-stroke matrix (Fig. 5B) shows the correlation between the stroke placements of Strokes 4 and 5. Each row corresponds to an attribute value of the stroke placement of Stroke 4, while each column corresponds to that of Stroke 5. The circle in a matrix entry represents the combination of the two associated attribute values within the selected rallies. The area of the circle encodes the occurrence frequency, and its luminance encodes the scoring rate of the combination. For instance, the circle highlighted in Fig. 5B encodes the occurrence frequency and the scoring rate of the combination of lm (long middle) of Stroke 4 and lm of Stroke 5. The abbreviations of the attribute values improve the matrix readability (Fig. 5C).

When the stroke placement is selected as the linking attribute, a table tennis table with 18 grid cells is then employed to illustrate stroke placements intuitively as shown in Fig. 5D. The area of the circle in the grid cell encodes the frequency of the stroke placement.

Intra-stroke matrix: In the gray stroke block, three matrices respectively represent pairwise correlations among the three attributes, namely, stroke placement and stroke technique (Fig. 5E), stroke placement and stroke position (Fig. 5F), and stroke technique and stroke position (Fig. 5G). The encodings, namely, the circles and matrix entries, of the intra-stroke matrices are similar to those of the inter-stroke matrix. The arrangement of intra-stroke matrices is detailed as follows.

Description: First, we placed the two intra-stroke matrices, whose columns or rows represent the linking stroke attribute (the stroke placement shown in Fig. 5A), as shown in Fig. 5E and 5F. The blue and

orange guidelines are used to link the columns or rows, which represent the linking stroke attribute, of the inter-stroke matrix and intra-stroke matrices. Furthermore, the columns and rows of the third intra-stroke matrix (Fig. 5G) do not represent the linking stroke attribute. The matrix is then placed in the right angle of the stroke block with its columns and rows aligning with those of the first two matrices (Fig. 5E, F). A sequence number card is further added to the stroke block (Fig. 5H).

Justification: We followed three rules in the process of arranging the matrices. First, the columns or rows of intra-stroke matrices representing the same stroke attribute should be aligned correspondingly. In this manner, the three intra-stroke matrices are consistent and related. Second, the columns or rows of intra-stroke matrices representing the linking stroke attribute should be aligned with the corresponding columns or rows of the inter-stroke matrices before or behind the stroke block. In this manner, matrices within a stroke and between strokes are consistent and related. Third, subsequent strokes can be continuously added in one direction. The arrangement possesses good expandability.

Interaction: The view supports a set of useful interactions as follows.

- ◆ **Change the linking stroke attribute.** Users can change the linking stroke attribute encoded in inter-stroke matrices. Three attributes, namely, stroke placement, stroke technology, and stroke position, can be selected as the linking stroke attribute (Fig. 3D-3).
- ◆ **Switch the matrix mode.** The view provides three modes: Player 1 serves, Player 2 serves, and mixed (Fig. 3D-1). When a user switches to the player 1 serves mode, the rallies where Player 1 serves in selected rallies are used as the data source. The numbers of the server's strokes are always odd, and the numbers of receiver's strokes are always even. Thus, all strokes with odd stroke numbers are in the color of Player 1, while all strokes with even numbers are in the color of Player 2 (Fig. 3D). When the player 2 serves mode is selected, the selection of data sources and encodings are similar. When the mixed mode is selected, the data source includes all selected rallies, and all strokes are colored in gray, because each stroke can be struck by Player 1 or Player 2.
- ◆ **Slide to show more strokes.** The view provides a sliding bar on the bottom of the view to support browsing for all strokes.
- ◆ **Hover and click to show additional information.** When users hover on a grid cell of a matrix (Fig. 5B) or a table (Fig. 5D), the corresponding rows and columns are highlighted (Fig. 1A,B,C). All matrices are updated simultaneously, and other rallies that exclude the values of the grid cell are filtered out. This interaction enables a flexible filtering ability that helps users interactively explore correlations within a stroke and between several strokes. Moreover, the results filtered can be fixed by clicking on the cell. Users can continue to hover or click to explore data on this basis.
- ◆ **Merge multiple strokes.** The view allows users to merge several strokes such that the intra-stroke and inter-stroke matrices of the strokes are aggregated. When users input the sequence numbers of strokes and click the merge button (Fig. 3D-2), all selected strokes are aggregated into two stroke blocks with one inter-stroke matrix between them (Fig. 1E). Three selections, namely, p1-to-p2, p2-to-p1, and mixed, are further provided (Fig. 1E-1). When p1-to-p2 is selected, the first block represents the aggregated intra-stroke matrices of the strokes of Player 1 while the second block represents aggregated intra-stroke matrices of strokes of Player 2 (Fig. 1E). The inter-stroke matrix between the two strokes shows the aggregated information of inter-stroke matrices from strokes of Player 1 to Player 2. When p2-to-p1 is selected, the encodings are similar except that the order of the two players is reversed. When mixed is selected, the matrices encode the correlations between two successive strokes without considering the order of the two players.

Justification: The correlations can be regarded as many-to-many relationships. Commonly, matrix views and many-to-many lines are used to arrange many-to-many relationships in space. We used many-to-many lines initially, for they are straightforward and easy to understand. However, considering that many correlations needs to be encoded, many-to-many lines would result in unavoidable overlays and visual clutter. On the contrary, matrix views possess high information density and clutter-free features that match our desire for a clear and all-round

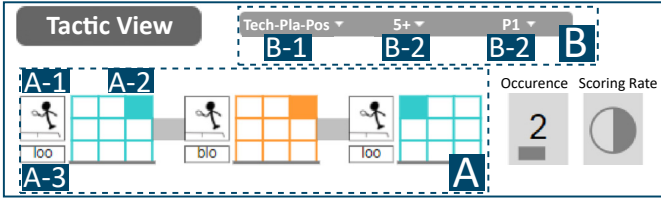


Fig. 6. (A) shows a tactic in which the attributes of each stroke are visually encoded by three glyphs. For instance, the attributes of the first stroke of the tactic are represented by three glyphs, namely, (A-1) for the stroke position, (A-2) for the stroke placement, and (A-3) for the stroke technique. (B) shows three types of configurations of the tactic.

presentation of correlations. Another point is that the matrix is a **familiar metaphor** for the experts who are accustomed to analyzing data in a tabular format.

4.4 Tactic View

This view visualizes the tactics used in the selected rallies. According to the experts, the combination of the stroke attributes of three consecutive strokes is regarded as a tactic in the domain. The tactic view (Fig. 6) automatically detects all the tactics in the selected rallies and lists them in order of frequency (P1).

Description: We designed three compact and discernable glyphs for the representations of three stroke attributes in tactics as follows.

- ◇ **Stroke position.** We also designed four icons to illustrate four different stroke positions (Fig. 6A-1). The icons are created by simplifying the figures in Fig. 2A, and are **familiar and intuitive**.
- ◇ **Stroke placement.** Half of the table tennis table is divided into nine grid cells, and the filled grid indicates the stroke placement (Fig. 6A-2). This design **connects the abstract data to the physical context** of table tennis.
- ◇ **Stroke technique.** The 11 stroke techniques cannot be easily encoded by color or other visual channels. Thus, the stroke techniques are shown in abbreviations to obtain a balance between readability and separability (Fig. 6A-3).

In short, these designs can significantly help browse and compare tactics quickly. Further, on the right of each tactic, the occurrence frequency and scoring rates are encoded by bar chart and pie charts, respectively.

Interaction: The tactics can be displayed with one, two, or three kinds of stroke glyphs by selecting the desired option in a drop-down list (Fig. 6B-1). For example, Fig. 6B-1 shows the tactics encoded by three kinds of glyphs. Users can change the kind of tactic as well. In the Fig. 6B-2, 1-3 means the serve tactic containing the first, second, and third strokes; 2-4 means the receive tactic containing the second, third, and fourth strokes; and 5+ means the tactic containing any three consecutive strokes after the fifth stroke. Users can filter the tactics by players (Fig. 6B-3). The player who strikes the first stroke of a tactic is considered to employ the tactic.

Justification: We considered and tried several design choices. Initially, we used text to describe the stroke attributes of tactics, such that the tactics are easy to read and understand. However, the tactics appeared lengthy and could not be browsed and compared easily. We further resorted to category marks, such as A, B, and C or 1, 2, and 3 to encode the stroke attributes. Although these encodings were concise and easy to compare, the readability was poor.

4.5 History View

The history view offers access to recording and replaying the patterns detected during exploration. The view consists of a table with multiple records (Fig. 3F). When users detect useful patterns or find communicative visual evidence during exploration, they can save the current states of all views as a record with simple annotations (Fig. 3F-1). Moreover, the saved states of views will replay after selecting a record, which allows analysts to review and re-explore the patterns.

4.6 Cross-view Interaction

To allow users to fulfill cross-analysis requirements (C1), iTTVis provides a set of cross-view interactions to help users explore table tennis data smoothly (D2) and gain deeper insights.

- ◇ **Match View to Stroke View:** When users click on a rally in the match view, the stroke view illustrating the detailed information of the rally slides in from the right side of the interface.
- ◇ **Match View to Stat View/Tactic View:** When users brush several rallies or click on selections in the selection panel to select the rallies in the match view, all matrices in the stat view are updated to display the correlations within these selected rallies accordingly. Only tactics used in the rallies are ranked in the tactic view.
- ◇ **Stat View to Tactic View:** When a matrix entry is clicked on the stat view, only the tactics with the stroke attributes of the corresponding strokes remain in the tactic view. The others are removed.

5 CASE STUDIES AND DISCUSSION

This section presents four case studies and a user study. The studies were conducted on the Google Chrome browser on a PC (equipped with Intel Xeon E3, 32GB of memory, and a 1920*1080 display).

We deployed iTTVis on the web and invited three domain experts (A, B and C) to use the system for three weeks and to provide feedback afterward. The experts were data analysts with a focus on the analysis of techniques and tactics of players. The most senior expert (A) worked for the Chinese national table tennis team. B was a PhD student majoring sports science supervised by A. C was an undergraduate student majoring computer science who was also a professional table tennis athlete. Before they used the online system, we gave an offline tutorial by showing them how to use the system. We also answered their questions about the system when they used the system.

5.1 Case Studies

All domain experts found many interesting patterns and gained valuable insights with iTTVis. Due to the limited space, we only asked the expert B to summarize his findings and wrote several short articles. We worked with him to discuss the insights and figure out how he used the system to discover patterns. The results are summarized as four case studies.

5.1.1 Grit Prevails

Wang Hao (cyan) and Oh Sang-eun (orange) on April 6, 2007. The expert browsed the tailored step chart and the point outcome bar (Fig. 7A). He quickly detected the large score gaps in Games 3 and 4 (Fig. 7A-3 and 6A-4). He deduced that Wang and Oh were not in their best form in Games 3 and 4, respectively. Further, he was attracted by the relatively long end phase in the last game on the point outcome bar (Fig. 7A-2). In such a long end phase, the players tried their best to break the ice. He then looked at the corresponding step chart to track the varying scores. Wang lagged behind Oh initially. After the score of Oh reached 10 (the game point), the score of Wang continually rose and finally surpassed that of Oh. The expert illustrated that Wang lagged far behind at the beginning of the end phase, but Wang kept pursuing and finally won the game. Wang's success was a tribute to his perseverance and stress tolerance under the disadvantageous conditions.

Kalinikos Kreanga (cyan) and Wang Hao (orange) on May 19, 2008. The expert selected all rallies with equal scores indicating fierce competitions. He then noticed that these rallies appeared in Game 1 frequently (Fig. 7B). He deduced that both players were eager to win the first game, leading to the comparatively fierce game. He selected a long rally (denoted by the largest ball on the point outcome bar) of Game 1 to see the details in the stroke view (Fig. 7C). He noticed that the second stroke struck a half-long ball (Fig. 7C-1). It caused a disadvantage to the stroke player, for it did not control the ball within the short area. He hovered on the second stroke and found its technique was drop short (Fig. 7C-1). The expert then explained that Kreanga struck the second stroke with a low-quality drop short, thus leading to the advantage of Wang in the beginning. However, Kreanga struck the ball towards different directions alternatively (Fig. 7C-2) when he browsed the last three tables, thus making Wang run back and forth to return the ball and finally lose this rally.

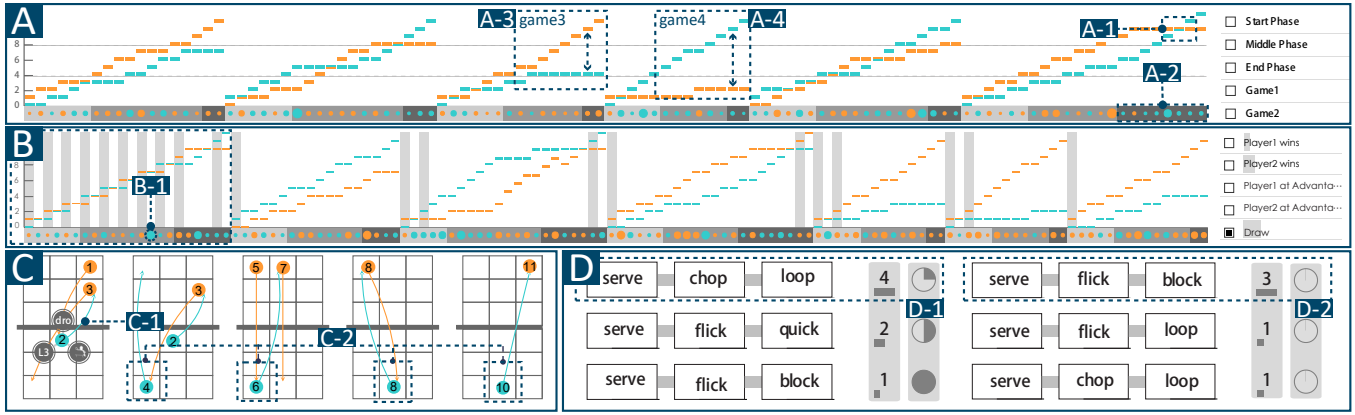


Fig. 7. (A) shows the score information of Wang Hao (cyan) and Oh Sang-eun (orange) on April 6, 2007. (B) shows the match view of Kalinikos Kreanga (cyan) and Wang Hao (orange) on May 19, 2008. (C) shows the detailed stroke information of a long rally selected by an expert. (D) shows the serve tactics of Wang Hao (D-1) and Oh Sang-eun (D-2) in the end phases of rallies.

The match and stroke views allowed the expert to quickly summarize the match, locate the key rallies, and detect the key features of a rally.

5.1.2 Accurate Use of Stroke Position Wins Admiration

Wang Hao (cyan) and Oh Sang-eun (orange) on April 6, 2007. The expert selected the player 1 serves mode from the selection panel to browse the statistics of serving rallies of Wang. The expert knew that the combinations of stroke placements between the second and third stroke would change frequently. Therefore, he paid particular attention to the inter-stroke matrix between the second stroke and the third stroke and the corresponding table tennis table (Fig. 1A). Firstly, he noticed from the table that Oh struck the ball to long backhand most in the second stroke (Fig. 1A-1) and Wang struck the ball to long backhand and long middle most (Fig. 1A-2). The expert then focused on the largest circle in the inter-stroke matrix of the stroke placement (Fig. 1A-3) which stands for the combination of lb (long backhand) of the second and third stroke. The expert recognized that both players were likely to strike the ball to the backhand area of the opponent. He further explained that the forehand attack in the forehand area of male players shows dominant advantages compared with the backhand attack in the backhand area. To explore which stroke techniques Wang employed in the third stroke to return the long backhand ball to long backhand, the expert clicked on the grid cell of the largest circle. He then browsed the intra-stroke matrix (Fig. 1B-1) that represents the correlation between stroke placement and stroke technique of the third stroke.

The expert found that Wang was likely to return the long backhand ball with loop (loo) and quick attack (qui) in the third stroke (Fig. 1B-1). The expert was interested in the strokes with loop. He further clicked on the grid cell of loop and long backhand to view Wang's statistics about stroke position when Wang struck the ball to the long backhand area with loop. As shown in Fig. 1C-1, Wang struck and scored twice with sideways, but struck and lost four times with backhand. Thus, the expert deduced that it was easier for the player to exert force with sideways to strike the ball using loop, compared with backhand. However, despite the advantages with sideways, the player would be likely to lose, if the stroke did not lead directly to points and there was not enough time for the player to return the next stroke. Thus, Wang won admirations, for he made the right decision to strike less with sideways but seize the opportunity to score with sideways simultaneously.

Finally, the expert mentioned that players would employ limited techniques after the fifth stroke. Therefore, he further merged all strokes after the fifth stroke and browsed the aggregated inter-stroke and intra-stroke relationships. As shown in Fig. 1E, Wang mostly struck the ball to long middlehand with loop (Fig. 1E-2) and Oh mostly returned Wang's ball to long middlehand with block (Fig. 1E-3).

With the stat view, the expert quickly identified the interesting and insightful patterns of inter-stroke and intra-stroke relationships and then tracked the relevant patterns.

5.1.3 The Deficiency in Receiving Leads to Failures

Wang Hao (cyan) and Patrick Baum (orange) on April 6, 2007. The experts selected all the rallies Wang won on the match view (Fig. 3B-4). He then chose the player 1 serves mode in the selection panel to see how Wang won his serving rallies (Fig. 3D-1). The expert focused on the matrix (Fig. 3D-4), which represented the correlations between the stroke technique and stroke placement of the third stroke, for its interesting pattern. He found two outstanding points: the intersection of long backhand and loop, and that of long middle and loop (Fig. 3D-4). The expert commented that among the rallies where Wang served and won, Wang often struck the third stroke with loop to long backhand or long middle and mostly scored.

Furthermore, the expert clicked on the intersection of loo and lm, and chose Wang's serve tactics in the tactic view. Then the all serve tactics of Wang that contained combinations of loop and long middle at the third stroke would be displayed on the tactic view. As shown in Fig. 3E, Wang employed five kinds of serve tactics. In two of the tactics, Baum struck the second stroke with chop long (Fig. 3E-1), and in another two tactics, Baum struck the second stroke with drop short (Fig. 3E-2). The expert explained that male athletes are not inspired to strike the ball with chop long in the second stroke, for it would offer access to the opponent to attacking first. The expert deduced that Baum might be weak in receiving the serve Wang struck. Besides, Baum struck the ball with drop short to the half-long area instead of the short area. The expert believed that Baum did not play well with this technique. Based on these findings and conclusions, the expert deduced the reason why Wang scored at the third stroke with loop to the long middle area during rallies might be that Baum was not good at receiving Wang's serve. In the last tactic, Wang served the ball to the half-long area. The expert identified it was not a good serve. And Baum then returned with loop successfully (Fig. 3E-3). However, Wang returned with loop and won finally. The expert speculated that Baum did not employ a high-quality loop in this tactic and finally lost his initial advantage.

The study demonstrated that the expert could quickly identify the interesting statistic patterns and relevant tactical patterns in key rallies with the coordinated views.

5.1.4 Offensive Awareness Works

Wang Hao (cyan) and Oh Sang-eun (orange) on April 6, 2007. The expert selected all end phases, when both players are under great pressure, on the match view and browsed serve tactics, namely the tactics for strokes 1-3. Initially, the expert selected only the stroke techniques of strokes 1-3 to analyze the tactics. He found that the most frequent serve tactic of Wang was that Oh struck the ball with chop long after Wang served, and Wang returned the ball with loop at the third stroke (Fig. 7D-1). The expert said that Oh gave the second stroke with chop long indicating a disadvantage, which created a chance for the opponent to attack first. Indeed, the expert found that Wang successfully scored

once (Fig. 7D-1) with this serve tactic. As for Oh, the most frequent tactics were that Wang struck the ball with flick after Oh served, and Oh returned the ball with block at the third stroke (Fig. 7D-2). The expert deduced that Wang was at an advantage at the second stroke, for possessing a chance to attack first but Oh was forced to return with block without a chance to score at the third stroke.

Furthermore, the expert added the stroke placement attribute to the tactics. He found that Wang served with short ball many times (Fig. 1D-1). Serving with short ball was considered high-quality in the domain. He guessed that this could explain why Oh was often forced to return with chop long, leading to the disadvantage of Oh. Meanwhile, Oh often served with half long ball (Fig. 1D-3), and it gave the opponent a good chance to attack. The expert also found that Wang often returned the serve with flick decisively (Fig. 1D-4) whereas Oh did not always return with attacking techniques (Fig. 1D-2). He then summarized the patterns of the tactics the two players used in the end phase: Wang served with high quality and grasped chances to attack first. Oh, however, served with relatively low quality and hesitated to attack at the second stroke, thus losing chances to score. From the exploration of the end phases, the expert believed that Wang possessed a better mindset than Oh, considering that Wang made decisions decisively and grasped chances under great pressure.

The case study demonstrated that the expert could quickly browse and summarize the tactical patterns with the tactic view.

5.1.5 Domain Expert Feedback

We collected the feedback from the three experts. Overall, they were quite satisfied with our system, due to its straightforward visualizations and strong analytical abilities. Specifically, three aspects of our system that the experts approved heartily are as follows. First, the experts were deeply impressed by the stat view, because it provided quick access to finding the correlations within a stroke and between several strokes. They particularly appreciated the way the stat view displayed the data. They thought the matrices are informative and not hard to understand. They also commented that the matrices were similar to Excel tables they usually worked with. Second, the experts also confirmed its usefulness for flexible cross-view filtering and selections. They commented that this function could support multi-step and multi-perspective analysis. Third, the glyphs in the tactic view and the table icons in the stat view were also well received. The experts pointed out that these elements enhanced the intuitiveness of the system. The expert A, who had been working with us all along, commented, “The system has been drastically improved compared to the initial prototype. I believe that it is one of the best table tennis analytics systems with many intuitive visual designs that greatly supports for much deeper analysis.” Two suggestions were further proposed by the experts. First, the system should be further enhanced with integration of probability prediction and other statistical models. Second, the rules of playing doubles are a bit different from those of playing singles in table tennis. The system should be improved to support analysis of table tennis doubles.

5.2 Discussion

Lessons Learned. The entire design process has been invaluable for teaching us a great deal about how to develop an interactive table tennis visualization system and cooperate with domain experts. First, the encodings of abstract data need to be connected with the physical contexts of the application domain. This connection can deepen our understandings of data, thus enabling us to identify interesting patterns with practical significance. For example, stroke placements correspond to the positions on the table tennis table one by one. Thus, it is suitable to encode the attribute on the table. Moreover, stroke positions display obvious features on the positions of players and the actions of the hands. Designing icons with particular features is beneficial.

Second, the data representations at different perspectives produced different results. The final decision about how to display data was made through multiple user-centered designs with experts. For example, we attempted to display the statistics of stroke attributes computed in the light of each rally. A stream graph was initially employed to illustrate the frequencies of stroke attributes at different rallies. However, the

distributions of attributes at different rallies change irregularly. The results obtained from the graph are disordered with low consistency and relevance between rallies. But when we decided to display these statistics in the stroke sequence, the interesting patterns were identified. Frequent patterns of combinations of the three stroke attributes at each stroke and close relations between adjacent strokes were observed.

Finally, the iterative user-centered approach plays a crucial role in cooperating with domain experts who are unfamiliar with visualizations. They cannot express their requirements adequately and have a fuzzy understanding of what visualizations can achieve. Feedback and prototype enhancements were necessary in the process.

Limitations. Although iTTVis demonstrates a potential to analyze table tennis data, it still has several limitations. First, our system is designed for only one match. It does not support visual comparison of multiple matches, let alone the analysis and tracking of the dynamic change in playing behavior of a player in different matches over a long time. We plan to introduce a new method to enable the comparative visualization of multiple matches at multiple levels of details. We will also explore new temporal visualizations for detecting and understanding the changes in playing behavior of a player. Second, our system supports the analysis of frequency and scoring rates, but lacks the support for predictive analysis. The integration of the capability of probability predication [28, 33] into the system is worth a further study.

General Applicability. Although iTTVis was developed to analyze table tennis data, the overall framework may be applicable to other single-player sports with similar rules and data structures such as tennis, snooker, and badminton. Before applying the system to other sports, we suggest that visualization practitioners obtain initial data and refine the definitions of match, game, rally, and stroke.

6 CONCLUSION

This work investigated the problem of visual analysis of table tennis data. We worked with the domain experts to identify the problems in the analysis of table tennis data and integrated a visualization system into the analysis process as a favor. We conducted case studies and a task-based evaluation to demonstrate the effectiveness and usefulness of the developed system. This work has three implications.

First, to the best of our knowledge, this study is the first attempt to comprehensively characterize the domain problems about the visual analysis of table tennis data. Given that only a few designs are available to visually analyze table tennis data, we hope this work can shed light on table tennis analysis and inspire further visualization work in this domain. Second, our system allows experts to obtain new insights. Compared to traditional methods, such as watching lengthy videos and reading statistical tables, our system offers new perspectives for the domain experts to integrate visualizations into the analysis of table tennis data. They, indeed, detected some new and significant patterns through the system, which convinced them the novelty and effectiveness of iTTVis. Third, we encountered a problem on visualizing many-to-many relationships within a stroke and between two successive strokes, during the process of visualizing the time-varying and stroke-interrelated table tennis data. This problem may arise in other sports visualization areas, like tennis and badminton. It may also emerge when dealing with general time-varying data with similar features. However, this problem, to our knowledge, has not been systematically studied. We hope our work would encourage other researchers to study this problem. In the future, we plan to integrate the analysis and comparison of multiple table tennis matches into iTTVis.

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