Tac-Miner: Visual Tactic Mining for Multiple Table Tennis Matches

Jiachen Wang, Jiang Wu, Anqi Cao, Zheng Zhou, Hui Zhang, Yingcai Wu

Abstract—In table tennis, tactics specified by three consecutive strokes represent the high-level competition strategies in matches. Effective detection and analysis of tactics can reveal the playing styles of players, as well as their strengths and weaknesses. However, tactical analysis in table tennis is challenging as the analysts can often be overwhelmed by the large quantity and high dimension of the data. Statistical charts have been extensively used by researchers to explore and visualize table tennis data. However, these charts cannot support efficient comparative and correlation analysis of complicated tactic attributes. Besides, existing studies are limited to the analysis of one match. However, one player's strategy can change along with his/her opponents in different matches. Therefore, the data of multiple matches can support a more comprehensive tactical analysis. To address these issues, we introduced a visual analytics system called Tac-Miner to allow analysts to effectively analyze, explore, and compare tactics of multiple matches based on the advanced embedding and dimension reduction algorithms along with an interactive glyph. We evaluate our glyph's usability through a user study and demonstrate the system's usefulness through a case study with insights approved by coaches and domain experts.

Index Terms—table tennis, tactic, multiple matches, glyph.

1 Introduction

Table tennis is a swift, flexible, and highly-antagonistic sport with millions of participants worldwide. Recent years have witnessed an increasing interest in analyzing table tennis matches using data-driven methods [1], [2], [3]. Traditionally, analysts used statistical methods to analyze matches. For example, Zhang et al. [3] used scoring rates and usage rates to evaluate the technique effectiveness of players. These indicator-based methods mainly evaluate players' performance from technical aspects but fail to reveal the high-level competition strategies adopted by players. Thus, tactical analysis of table tennis is introduced to reveal players' playing styles, which indicate the competition strategies within matches.

In the table tennis field, a tactic is depicted by three consecutive strokes (a stroke means that a player hits the ball once), namely, the first stroke from a player, the second from his/her opponent, and the third from himself/herself again [4] (Fig. 2). Tactical analysis can help experts identify players' strategies of performing particular strokes. These strategies are critical for coaches to prepare future matches. However, tactical analysis is non-trivial due to the high dimension and large volume of the tactic data. Specifically, each match contains about 500 strokes, and each stroke is described by tens of attributes, resulting in a massive volume of tactics. Effectively exploring tactics and uncovering meaningful usage patterns have been challenging.

Existing methods of tactical analysis mainly focus on mathematical models. The widely-used three-phase method [4] evaluate players' performance according to statistics of technical indicators in three predefined match phases. Based on this method, many other studies [3], [5] further introduce new indicators and statistical models to improve the analysis results. Besides, researchers also use the Markov chain model [6] to simulate players' behaviors and predict match results. While these methods can help discover new insights, according to the domain experts, it is challenging for coaches to understand the complicated mathematical models, leading to distrust in the insights. Moreover, these models target at particular tasks, such as detecting key techniques. Thus, they may fail to deal with complex tasks and detect unusual patterns that are not predefined by rules.

To alleviate these issues, several visual analytics tools have been developed to allow intuitive data presentation and interactive match analysis. Wang et al. [2] introduces Tac-Simur to help visually explore and explain the model space when simulating tactics in table tennis matches. However, this system focuses on match simulation instead of in-depth tactic mining. Moreover, Wu et al. [1] developed iTTVis to visually summarize statistical correlations among stroke attributes in a set of linked inter- and intra-stroke matrices in the context of scores and tactics. However, this system focuses on the visualization of table tennis data at the stroke level instead of the tactic level. The tactical analysis of iTTVis is limited to presenting basic statistics of one match and does not support in-depth investigation of tactics of multiple matches. Analysis of multiple matches is significant for investigating players' tactics. According to the domain experts, a player often needs to employ different tactics to counter various opponents because the playing style varies from player to player [6]. For example, shake-hand players are quite different from pen-hold players due to the distinct ways to use the racket. Even for the same opponent, a player may change his/her playing style in different matches due to adjustment of the opponent's playing strategies. Therefore, to create a holistic view of a player's

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tactics, experts need to analyze multiple matches between the player and his/her various opponents. In summary, a visual analytics system is required to help analysts efficiently discover patterns of the tactics in multiple matches.

Developing such a visual analytics system encounters two major challenges. The first one is identifying the problem domain of tactical analysis in table tennis. Although domain experts have rich experience in tactical analysis, they often concentrate on solving specific problems. Therefore, they do not have a comprehensive characterization of the problem domain. The second challenge is facilitating investigations of massive multi-dimensional tactics. Each match involves hundreds of tactics, which poses challenges to identifying the overall tactic usage patterns. Moreover, each tactic contains dozens of attributes of three strokes, which hinders comparison and correlation among attributes within a tactic and among different tactics.

To address the first challenge, we worked extensively with domain experts to summarize their workflow for tactical analysis of table tennis. On the basis of the workflow, we characterized their requirements of tactical analysis. To address the second challenge, we integrated the domain knowledge with the advanced embedding and dimension reduction methods to plot a customized overview of massive tactics for exploration. In addition, we designed a glyph encoding five stroke attributes to facilitate the investigation of characteristics of tactics. We further developed Tac-Miner, a multi-scale visualization system for tactical analysis. The system consists of three main views, i.e., a steerable projection view for exploration, a glyph-based view for investigation, and a display view for tactic replay. The contributions are as follows:

- We identified the work flow and requirements of tactical analysis in table tennis.
- We introduced Tac-Miner, a visual analytics system where we applied the leading embedding and dimension reduction methods and designed a novel glyph for tactical analysis.
- We obtained valuable insights into the tactics of the top table tennis players from the case study.

2 Related Work

This section reviews related work on sports visualization and glyph-based visualization.

2.1 Sports Visualization

Sports visualization has garnered considerable attention from researchers in recent years [7], [8]. In soccer, studies mainly focus on visual analytics of game events [9], [10], [11], game statistics [12], [13], game videos [14], [15], and spatio-temporal patterns of teams and players [16], [17], [18]. In basketball, research topics involve movement analysis [19], [20], game presentation [21], [22], points prediction [23], and team performance evaluation [24], [25]. In addition, many significant works have also been conducted in other sports, such as tennis [26], [27], [28], badminton [29], baseball [30], [31], [32], [33], rugby [34], [35], ice hockey [36], and snooker [37]. However, these aforementioned works cannot be applied to tactical analysis of table tennis due to the different game rules and problem domain. In table tennis, Tac-Simur [2] supports visual exploration and interpretation of the match simulation. However, this work cannot enable complex tactic mining tasks. Moreover, Wu et al. introduced a visual analytics system called iTTVis to investigate table tennis data [1]. This system presents the statistics of stroke attributes in correlation matrices in the context of scores and tactics. However, it mainly supports the analysis at the stroke level instead of the tactic level. The tactic view in iTTVis consists only of basic statistics (i.e., scoring rates and frequencies) of tactics within one match. It does not allow experts to investigate tactics from multiple matches since its visualization is designed for one match. To address the issue, we developed Tac-Miner to support the multi-scale exploration and investigation of tactics.

2.2 Glyph-based Visualization

Glyphs often perform better than other visualization techniques in detecting patterns involving multi-dimensional data [38], [39], [40]. They are effective in various disciplines. Ropinski et al. [41], [42] conducted several comprehensive surveys on glyph-based visualizations of medical data, and many valuable studies [43], [44], [45] have provided novel glyphs of diffusion tensors for medical application. Maguire et al. [46] proposed a systematic framework for glyph design and applied it to biological experiments where the need for multivariate analysis is pressing. Hlawatsch et al. [47] designed a metaphor-based glyph, flow radar glyph to visualize unsteady flow data. Other fields, such as audio or video visualization [48], [49], geo-information visualization [50], 3D visualization [51], [52], and diversity visualization [53] also use glyphs to enhance their efficiency and effectiveness. The same applies to the sports field. Matchpad [34] presents key events in a rugby match in real time with glyphs stemming from the local features of game events. Besides, Chung et al. [54], [55] proposed a conceptual framework for the design of sortable glyphs and developed a system for visualizing rugby matches. These studies have provided innovative and comprehensible glyphs in sports visualization and largely inspired our glyph design. The metaphoric glyph in iTTVis [1] illustrates tactics in table tennis effectively by encoding three attributes. However, given the larger data volume, higher data dimension, and sophisticated analysis tasks, this glyph is limited in efficiency and effectiveness; hence it cannot be directly applied to our system. Therefore, we redesigned a new glyph based on the design guidelines summarized by Borgo et al. [38].

3 Background and Requirement Analysis

This section introduces the original workflow of tactical analysis in table tennis and the requirements based on the workflow, along with the rules and concepts of table tennis.

3.1 Background

Table tennis is an antagonistic sport involving two (singles) or four (doubles) players who hit a ball across a table with rackets. In this work, we focused only on the analysis of singles (two players). A table tennis match is usually in the best-of-seven format, thus containing four to seven games.

The technical attributes

stroke placement	The position of the ball on the table before being hit.
stroke technique	The technique used to hit the ball.
stroke position	The position where a player hits the ball.
stroke spin	The rotation of the ball after being hit.
hit player	The player who hits the ball.

The contextual attributes

index	The identification of a stroke, including Match No., Game No., Rally No., and Stroke No.
score A / B	The score context at each stroke. If nobody scores before a stroke, they will not change, otherwise, one of them will be increased by one point.
action	The situation of the player when he/she gives a stroke, including serve, receive, offense, defense, stalemate, and control.
effect	The assessment of a stroke ranging from 1(best) to 7(worst).

Fig. 1. The description of the attributes in the data. The technical attributes depict the technical characteristics of a stroke. The contextual attributes display the match contexts of a stroke.

In each game, the player who first wins eleven rallies wins this game. In each rally, two players hit the ball by turns until one fails to hit it back, and the other wins the rally.

A stroke is an action wherein a player hits the ball back to the opponent by using the racket once. In our research, all strokes in a match are recorded along with multiple stroke attributes as the basic analysis unit of the match [6].

Tactics in table tennis reveal the playing strategies of players [5]. A tactic contains three consecutive strokes [4] (Fig. 2). Specifically, if a player wants to implement a tactic, he/she would hit the first stroke to induce his/her opponent to hit back with an expected stroke. If his/her opponent is induced, he/she can receive the ball using his/her prepared stroke in the third stroke to accomplish his/her tactic. At this point, if the third stroke directly results in a score, the tactic is successful. Otherwise, the third stroke induces the next tactic of the player. Therefore, the tactic attributes are composed of three series of stroke attributes (Fig. 2).

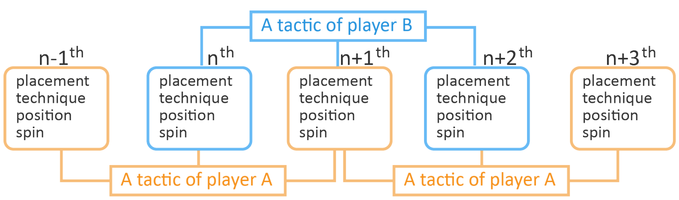


Fig. 2. The attribute structure and definition of a tactic in table tennis. A tactic consists of the attributes of three consecutive strokes. The five strokes compose three tactics of two players.

3.2 Data Description

Fine-grained table tennis data are manually collected from videos by the domain experts. A match is recorded by hundreds of strokes, and each stroke is depicted by approximately 20 attributes. Experts divide these attributes into two categories (i.e., technical ones and contextual ones (Fig. 1)). Technical attributes describe the technical characteristics of a stroke. Contextual attributes record the match contexts of a stroke. They are vital indicators for assessing the effect of a tactic. According to the definition of "tactic", we only considered the rallies containing more than two strokes.

3.3 Conventional Workflow

We cooperated with two domain experts, namely, a professor of physical education **(E1)** and his Ph.D. student **(E2)**, to identify the problem domain of tactical analysis. **E1** and **E2** have worked for the Chinese national table tennis team for 18 and 7 years, respectively. Both of them were professional table tennis players. We conducted semi-structured interviews with our domain experts twice a week. In the early interviews, we let them describe their workflow of tactical analysis, including the underlying difficulties and challenges. According to the experts, they used to conduct tactical analysis of multiple matches through Microsoft Excel. We summarized the workflow in four steps. At first, the experts filtered and sorted all tactics based on particular attributes and indicators to identify the tactics of interest. Then, they examined the specific attribute values including technical ones and contextual ones to evaluate the performance of the tactics. After that, they placed the tabular data of similar tactics and related strokes side by side to find the reasons for the performance of particular tactics. Finally, they replayed the corresponding videos manually to validate their analysis and clipped the videos for coaches to understand their insights. Experts indicated that this workflow was time-consuming and error-prone since they had to process the tabular data recorded by texts and numbers. With the workflow, we developed a pilot system. In the later interviews, we collected their feedback on the pilot system and summarized their analysis requirements.

3.4 Requirement

The requirements throughout the workflow are as follows.

R1: What are the key tactics? In the beginning of the analysis, experts need to identify the key tactics worth analyzing from all tactics, facilitating the analysis. They often need to examine summary indicators, such as the frequencies and scoring rates of tactics, which generally indicate whether a tactic is the key to the winning/losing of the players.

R2: How is the performance of a tactic? After selecting the tactics of interest, the experts need to assess the performance of these tactics in detail. They need to know whether the performance of a tactic is positive or negative, when a tactic is performed well/poorly, who performs a particular tactic better/worse.

R3: Why does a tactic work well/poorly? Tactics have different performance due to different attribute values and contexts. Therefore, experts need to determine the reasons for the positive or negative performance of a tactic to establish improved training plans and competition strategies and thus allow players to enhance their tactical performance.

R4: Where does a particular tactic exist in the video? To validate the analysis results, experts require the corresponding video clips of a tactic since raw videos contain raw data of matches. Moreover, experts often use videos to help them communicate their results to the coaches and players.

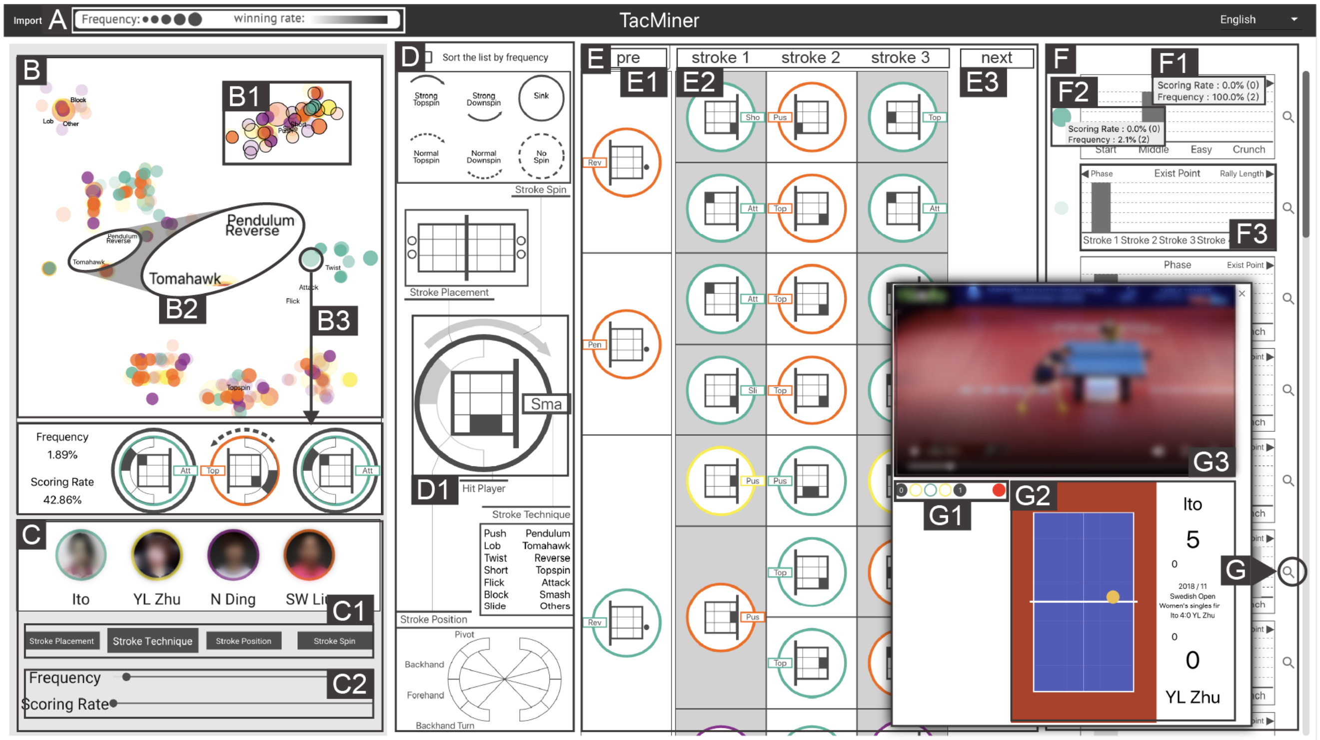


Fig. 3. Interface of Tac-Miner. (A) displays the encoding in (B). The system consists of three views, namely, a summary view (B, C), a detail view (D, E, F), and a display view (G). (B) displays the projection of all tactics featured by stroke technique (C1). (E, F) displays the attribute values and context information of the tactics selected in the projection plot (B1). (G) displays the video and other detailed information of a specific tactic.

4 Visual Design

This section introduces the design goals and illustrates the details of the visual design in Tac-Miner.

4.1 Design Goal

Based on the requirements, we established the design goals of the visual analytics system as follows.

G1: Steerable projection of all tactics. An overview is required to facilitate the identification of key tactics (R1). Generally, projection methods are used to provide an overview of massive high-dimension data. Moreover, to efficiently and comprehensively identify the key tactics, projections of all tactics from diverse perspectives are required. Therefore, the projection should be steerable for users to generate an on-demand layout.

G2: Effective glyphs of tactics. An effective glyph for multivariate tactic attributes is necessary for illustration and investigation of tactics (R2, R3). Experts are often overwhelmed when investigating the multi-dimensional attributes of multiple tactics (Fig. 2). A glyph can help solve this issue [38], [39], [40]. However, the glyph in previous work [1] cannot be scaled to more attributes and are not efficient enough when applied to analysis of massive tactic data. Therefore, a more scalable and effective glyph is required to facilitate an efficient and comprehensive analysis.

G3: Comparative analysis of different tactics. Experts can discover the differences of performances between tactics by comparing their effects in the matches (e.g., temporal change of scoring rates and using rates in the match) (R2). Moreover, through comparisons of particular tactic attributes, they can determine the reasons for the performance of specific tactics (R3) through comparisons. They need to know how a tactic differs from others in terms of technical and contextual attributes. These differences can be used to identify the key attributes that affect tactic performance.

G4: Correlation analysis of adjacent tactics. Correlation analysis is crucial for performance characterizing and reasoning (R2, R3). A tactic is highly related to the previous and subsequent tactics since it shares two strokes with each of them (Fig. 2). According to the experts, the subsequent and current tactics can help assess the performance of the current tactic, and the previous and current tactics can help interpret the performance of the current tactic (R3).

G5: Videos sessions of each tactic. Organizing the raw videos based on the tactic data can help experts efficiently examine the video contents they need. Since the analysis object is tactic, videos clipped based on tactics can help quickly validate the analysis results of particular tactics (R4).

4.2 System Overview

Tac-Miner is a web-based application. We processed the data with Python in the backend and visualized the data with React.js in the frontend. The whole system consists of a summary view (Fig. 3(B, C)), a detail view (Fig. 3(D, E, F)), and a display view (Fig. 3(G)). The summary view provides a steerable projection plot of all tactics (Fig. 3(B)) as navigation (*G1*). The detail view presents the tactic attributes encoded by glyphs (Fig. 3(E)) with context information (Fig. 3(F)) (*G2, G3, G4*). The display view provides real videos and the animation replay of a tactic (Fig. 3(G)) (*G5*). Analysts should first explore the summary view and choose the tactics of interest. Then they can examine the specific attributes of the chosen tactics for comparative and correlation analysis. Finally, they can check the display view to validate and communicate their insights to coaches and players.

4.3 Summary View

The summary view contains a steerable projection plot (Fig. 3(B)) and a control panel (Fig. 3(C)) (***G1***). In the projection plot, each tactic is embedded and projected as a point. For each point, we use color hue to encode different players since color hue is the most effective visual channel for categorical attributes besides spatial position [56]. The area of a point encodes the frequency, and the opacity encodes the scoring rate of a tactic (Fig. 3(E)). In this way, the mostly-used tactics with high scoring rates are represented by large points with high opacity, which can outstand these important tactics. We placed the shared attribute values on the plot as hints (Fig. 3(B2)). The widget below the plot displays the details of a particular tactic with glyphs (***G2***) (to be introduced in the detail view). Analysts can hover over the points to examine this information (Fig. 3(B3)). In the control panel, analysts can switch the projection layout by selecting the attributes they want to focus on (Fig. 3(C1)). In addition, analysts can filter the tactics in the plot according to the hit player, the frequency, and the scoring rate (Fig. 3(C2)).

Implementation: We embedded each stroke within a tactic through the word2vec technique by a python package, gensim[1]. We trained four separate word2vec models for the four technical attributes, respectively. For example, during the training of the model for stroke technique, we take a stroke as a word and a tactic as a sentence. Each stroke only has the attribute of technique. In this way, we can embed the technical attributes separately so that we can enable users to change the projection layout by focusing on one of the four most important technical attributes (Fig. 3(C)). After training, each technical attribute is embedded into a bivariate vector, namely, $A_i = [x, y]$. Each stroke $S_j = [\lambda_1 A_1, \lambda_2 A_2, \lambda_3 A_3, \lambda_4 A_4]$, where λ is the weight for each attribute, and each tactic $T_k = [\omega_1 S_{j+1}, \omega_2 S_{j+2}, \omega_3 S_{j+3}]$, where ω is the weight for each tactic. Choosing one attribute (Fig. 3(C)) would set the chosen λ_i larger than other weights. In addition, the experts indicated that the first stroke of a tactic is the most important one because it is the provenance of a tactic. Therefore, we set ω_1 larger than ω_2 and ω_3. The magnification of λ and ω are given according to the reasonability of the projection layout evaluated by our experts.

After embedding, we flattened T_k into a 1×24 vector and used t-SNE implemented by scikit-learn [2] for projection. We used t-SNE due to its preservation of the data distribution and clear separation of clusters. We have tried other methods (e.g., MDS, PCA) for projection, but t-SNE outperforms the others in terms of the separability of different clusters.

4.4 Detail View

The detail view supports further analysis of the tactics selected in the summary view (Fig. 3(B1)). It consists of a glyph panel (Fig. 3(D)), a tactic list (Fig. 3(E)), and a context view (Fig. 3(F)).

1. https://radimrehurek.com/gensim/models/word2vec.html
2. https://scikit-learn.org/stable/modules/generated/sklearn.manifold.TSNE.html

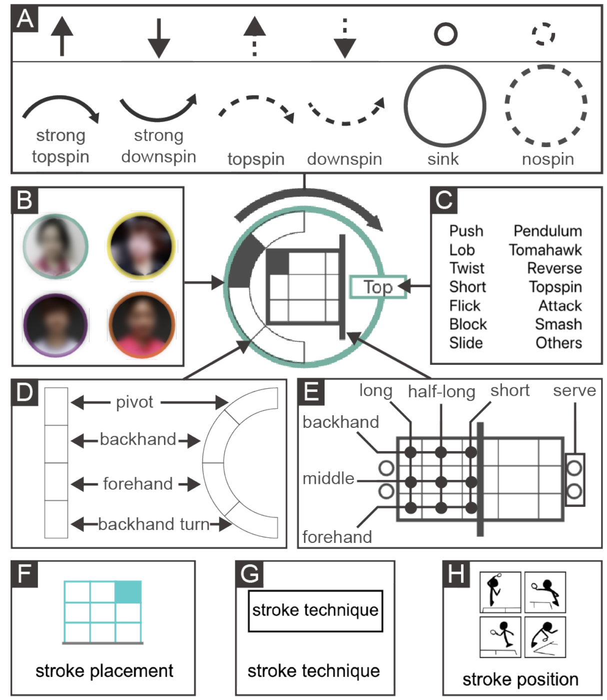


Fig. 4. The encodings of our glyph. (A), (B), (C), (D), and (E) are the encodings of stroke spin, stroke player, stroke technique, stroke position and stroke placement, respectively. (F), (G) and (H) are the three encodings in iTTVis.

Glyph panel. We used a novel glyph (Fig. 3(D1)) to encode a stroke and used three glyphs to represent a tactic (***G2***). Analysts can control the visibility of the attributes on the glyph. The glyph is designed to be circular to cater to the metaphor of the ball. The details are as follows.

- **Stroke placement (ball position)**: The experts preferred the table tennis table because it can present the placement of the ball clearly and vividly. Therefore, we used half of the table to encode the placement of a stroke. We divided the table into nine grids according to the actual scale of the table division introduced by the experts (Fig. 4(E)). The filled grid represents the placement of the ball on the table. Considering that the serve stroke is the first stroke of a rally and it does not have placement, we encoded the placements of two kinds of serve by two points beside the table. We placed the table horizontally and reversed it along with the hit player (Fig. 3(B3)). In this way, the metaphor of confrontation between two players is illustrated when a sequence of glyphs are placed side by side.
- **Stroke technique**: Encoding 14 techniques clearly by using identity channels [56] is difficult. We attempted to use hue, but it was challenging to recognize 14 different colors efficiently and accurately. Therefore, we encoded the techniques by using their abbreviation (Fig. 4(C)).
- **Stroke position (player position)**: The player is always around the table when hitting the ball. Therefore, we divided an arc into four parts to indicate four different stroke positions and placed it beside the half table (Fig. 4(D)). The filled part represents the player's position of current stroke.
- **Stroke player**: Players are generally distinguished by

their jerseys with different colors. Therefore, we encoded players by using different colors (Fig. 4(B)).
- **Stroke spin**: We designed six circular symbols and set them around the glyph to indicate the stroke spin so that the glyph is circular, similar to a ball. The symbols were designed according to the spin direction of the ball; thus, they can also be reversed along with half of the table (Fig. 4(A)).

Justification: The glyph in iTTVis [1] is the main alternative of our glyph. We improved our glyph based on five design guidelines (**DG**) summarized by Borgo et al. [38]. The rationality of our glyph is as follows.

- **Stroke placement**: The identical section on half of the table in iTTVis (Fig. 4(F)) can confuse analysts when investigating the differences in placement among multiple strokes. Therefore, according to **DG5** (redundant mapping of variables) and **DG6** (importance-based mapping) [38], we used double encoding, namely, position and shape to enhance the perception of different stroke placements because it is one of the most important attributes. We split half of the table into distinct grids based on the domain definition of different stroke placements (Fig. 4(E)).
- **Stroke position**: The icons of stroke position in iTTVis (Fig. 4(H)) are straightforward because they present the exact poses of the players while hitting the stroke. However, once placed in the glyph, their small size makes efficient and accurate identification of a particular position difficult. Therefore, according to **DG8** (simplicity and symmetry) [38], we simplified this encoding by using the position channel. First, we split a rectangle into four sections, and each section represents a stroke position value (Fig. 4(D) left). However, when multiple glyphs are juxtaposed vertically, the 1D position channel is not efficient enough. Therefore, we combined the position channel with the orientation channel (**DG5** (redundant mapping of variables) [38]), and encoded the stroke position with a divided arc (Fig. 4(D)).
- **Stroke player**: The encoding of players is combined with placement in iTTVis (Fig. 4(F)). To avoid the interference of color when examining other stroke attributes (**DG9** (orthogonality and normalization) [38]), we encoded players separately by using the color of the contours (Fig. 4(B)).
- **Stroke spin**: This attribute is newly added for tactical analysis. According to **DG10** (intuitive mapping based on semantics) [38], we adopted arrow-based symbols to encode stroke spin. We placed the symbols of each spin type (Fig. 4(A) top) at the bottom of the glyph. However, these symbols are too small to identify, and the layout breaks the visual balance. To solve these issues, we leveraged the metaphor of the spinning of the ball and placed arc-shaped arrows around the glyph (Fig. 4(A) bottom).

The encodings of stroke placement, stroke position, and stroke spin are reversed according to the stroke player to strengthen the relationships between adjacent glyphs (**DG10**(intuitive mapping based on semantics) [38]), emphasizing the concept of tactic.

Tactic list. The tactic list illustrates the most details of the selected tactics with glyphs in structure-driven placement [38] (Fig. 3(E)) for comparative (***G3***) and correlation analyses (***G4***). As mentioned before, the first stroke of a tactic is the provenance of the tactic and reflects the intention of the player. Therefore, we used the hierarchical structure and selected the first, second, and third strokes as the root of the structure, the child of the root, and the leaf, respectively. All tactics were sorted by the frequencies of particular attributes at each level because experts are generally interested in the frequently-used tactics. We also provided the previous and subsequent strokes of each tactic (Fig. 3(E1)) for correlation analysis (G3) of the reciprocal relation between tactics of the two players. According to the definition (Fig. 2), with the previous stroke, analysts can determine the relationships between the current tactic (Fig. 3(E2)) and the previous tactic (Fig. 3(E1)). With the subsequent stroke, they can investigate the relationships between the current tactic (Fig. 3(E2)) and the next tactic (Fig. 3(E3)).

Context information. We provided context information (***G5***) to facilitate comparative and correlation analyses (***G3*** and ***G4***). The point beside each tactic encodes the frequency and scoring rate by its area and transparency, respectively (Fig. 3(F2)). Additionally, we displayed the distribution of the frequency and scoring rate of a tactic in different conditions defined by the domain experts (Fig. 3(F)). The frequency and scoring rate were encoded using the height and luminance of the bar, respectively.

Interaction: The interaction in detail view is as follows:
- **Switching attribute:** The selected tactics are displayed in the tactic list, with stroke player and the selected attribute for projection visible by default (Fig. 3(D1)). Analysts can hide or display the attributes by clicking on their corresponding encodings on the glyph. If an attribute is hidden or displayed, the tactic list will be reorganized.
- **Unfolding strokes:** Analysts can click the button in Fig. 3(E1, E3) to unfold the adjacent strokes.
- **Switching context:** Analysts can switch the context information by clicking the arrow at the top of Fig. 3(F3).
- **Hovering:** Analysts can hover on the point and the bar chart (Fig. 3(F1)) and to examine the specific values.

4.5 Display View

The display view provides a replay of each tactic for validation and further investigation (***G5***). Analysts can click on the button (Fig. 3(G)) near the context information to unfold the display view, which includes the video clips and animation of a particular tactic. The display view mainly includes a rally list, a display table, and a video widget.

Rally list. In the display view, all rallies containing the selected tactic are shown in a list. Each row of the list presents a rally (Fig. 3(G1)), and the unfilled circles represent the three strokes in the tactic and filled circles with numbers on them display the other strokes. Analysts can click on the rally to display the animation and the videos of this rally. The videos are clipped based on the time stamps recorded during data collection.

Display table. We replayed the selected rally by dynamically displaying a yellow ball on the table according to the placement of each stroke (Fig. 3(G2)). We also placed some context information as a reference for analysis.

Video widget. The starting and ending times of a rally is recorded manually by experts when collecting the technical and contextual attributes of strokes. The system can provide the accurate video clips of the rallies containing the selected tactic in the display view (Fig. 3(G3)). The video clips would repeat the chosen rally by default.

5 System Evaluation

We evaluate our system from two aspects, namely, visual design and usability. The most complicated visual design in our system is the projection plot and the glyph. While the concept of projection is hard to understand for general users, our experts can understand it since they have rich experience of data analysis and are familiar with the underlying embedding and projection algorithms. Therefore, we conduct a user study to focus on evaluating the design of the glyph by comparing it with that of iTTVis. To evaluate the usability of our system, we conducted a case study with five insights found in two cases.

5.1 user study

We conducted a controlled user study to evaluate the performance of our glyph. We selected the glyph of iTTVis as the baseline. We introduce the hypotheses and experiments of the study then present the results and user feedback we collect through post-study interviews.

5.1.1 Hypotheses

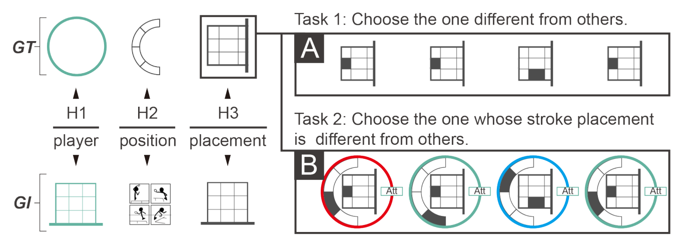
The existing work, iTTVis, has provided an intuitive glyph (**GI**) [1]. However, this glyph is not efficient enough when applied to the analysis of massive high-dimensional tactic data. We designed a new glyph (**GT**) for our system based on the design guidelines [38]. Compared to **GI**, **GT** improves the encodings of three attributes, namely, stroke player, stroke position, and stroke placement. Therefore, we hypothesize that **GT** performs better than **GI** as follows.

- **H1:** Users can perceive the values of stroke player more quickly by using **GT** rather than **GI**.
- **H2:** Users can perceive the values of stroke position more quickly by using **GT** rather than **GI**.
- **H3:** Users can perceive the values of stroke placement more quickly by using **GT** rather than **GI**.

5.1.2 Experiment Design

We designed a within-subjects experiment to compare the performance of the two glyphs, **GT** and **GI**. As shown in Fig. 5, we tested the encodings of stroke player (**H1**), stroke position (**H2**), and stroke placement (**H3**). We excluded the encoding of stroke spin due to the lack of stroke spin in **GI**.

Users primarily used Tac-Miner to identify the differences between glyphs when conducting comparative and correlation analyses. Therefore, the tasks in the study were to spot the outlier, simplified from the analysis process. During analysis, users could opt to display one or multiple attributes in the glyph. Therefore, for the encoding of each attribute, we designed two types of tasks to test the performance under the two conditions. For example, Fig. 5(A, B) displays the two types of tasks used to test the encoding of stroke placement in **GT** (the system display 1-7 glyphs vertically, therefore, we chose the average, 4, as the number of options). Specifically, in Task 1, four glyphs were provided for the subjects, and each glyph only displayed the encoding of one attribute (Fig. 5(A)). Subjects required to find the glyph different from the others. This task mainly tested the performance of the encoding of each attribute independently without any interference. In Task 2, four glyphs were provided, and the encodings of the other attributes were also displayed as interference (Fig. 5(B)). The values of the other attributes were randomly applied. Subjects required to find the glyph whose specific attribute (told to the subjects in each question) was different from the others. This task tested the performance under the interference of other encodings. We repeated each kind of task 8 times in the encoding of each attribute. Thus, each subject required to complete 96 questions, and totally, we collected 1,152 samples (Fig. 5).



Task	Glyph	Attribute	Repetition	Subject	Total
2	2	3	8	12	1152

Fig. 5. The experiment design of the user study. (A) and (B) are the two kinds of tasks used to test the encoding of position in **GT**. The table in the bottom presents the detailed experiment setup.

5.1.3 Participants

We recruited 12 subjects (4 females, 8 males, age: 22-35) for the user study. To yield comprehensive insights into the visual design and the domain, we recruited students from both the department of computer science (CS) and the department of sports science (SS). Among the subjects, 6 postgraduates (2 females, 4 males) were from CS, and majored in information visualization. All of them could play table tennis and were familiar with the rules. The other 6 postgraduates (2 females, 4 males) were from SS and their research fields were related to the analysis of table tennis matches. All of the subjects had experience in visualization and had not used iTTVis and Tac-Miner before. The tasks were completed on a 15-inch tablet (with Intel Core 17-8650U, 16GB memory, and a 3240×2160 display).

5.1.4 Procedure & Results

The study followed the procedure including a 5-min tutorial session, 5-min training session, 10-min formal session, and a follow-up interview. In the tutorial, we introduced the visual encodings of two glyphs, **GT** and **GI**, and explained the study tasks that subjects were required to identify the different glyph with or without the influence of other encodings. Then each subject was given a training session where we tailored 12 questions based on the study tasks to ensure that subjects fully understood the encodings and the tasks.

In the formal session, we asked subjects to complete two individual parts for **GT** and **GI**. The order of questions within each part was randomized, and the order of these two parts was counterbalanced for each subject. After they finished the tasks, we conducted interviews to collect feedback.

Apart from the answers, we also recorded the response time of each question. We used a student's t-test (significance level: 0.05) to measure the difference in the performance of the two glyphs. The corresponding means, confidence intervals, and the p values are shown in Fig. 6.

Efficiency. The efficiency result is reported in Fig. 6(A, B). Although the encoding of stroke player in **GT** performs better than that of **GI**, the improvement is not significant in Task 1 ($T(11) = 0.489$, $p = 0.63$) and Task 2 ($T(11) = 0.34$, $p = 0.74$). Thus, **H1** is rejected. As for the encoding of stroke position, **GT** performs significantly better than **GI** in Task 1 ($T(11) = 3.776$, $p < 0.05$) and Task 2 ($T(11) = 2.939$, $p < 0.05$). Thus, **H2** is supported. However, the encoding of stroke placement of **GT** performs slightly worse than that of **GI** in Task 1 ($T(11) = -0.886$, $p = 0.385$) and Task 2 ($T(11) = -0.908$, $p = 0.374$). Thus, **H3** is rejected.

Accuracy. Although the accuracy is not in the hypotheses, we still reported it for completeness. As we expected, the accuracies of the two glyphs are almost the same (Fig. 6(C, D)). We thought it is because of the ceiling effect caused by the tasks. Both tasks were not difficult enough to reveal the significant differences between the two glyphs.

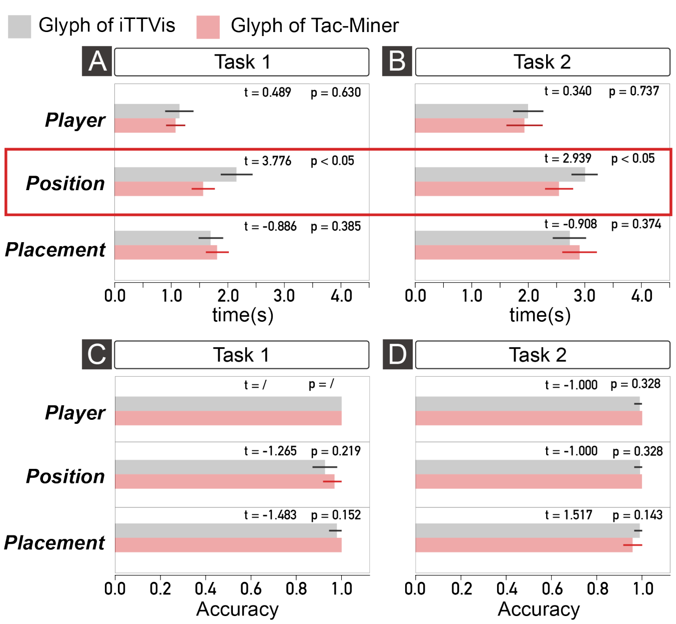


Fig. 6. The result of the user study. We conducted students' t-test to measure the accuracy and response time of the tasks with the two glyphs. **GT** performs better than **GI** in the encoding of stroke position.

5.1.5 *Subject Feedback*

After the test, we asked the subjects about their opinions on the pros and cons of **GT** compared with **GI**. Eight subjects (4 CS and 4 SS) preferred **GT** to **GI** whereas three subjects (1 CS and 2 SS) preferred the opposite. One subject thought both glyphs had pros and cons.

Pros. Subjects reached the consensus that the encoding of stroke position of **GT** was better than that of **GI**. They stated that the divided arc in **GT** (Fig. 4(D)) was more perceptible than the icons in **GI** (Fig. 4(H)), which conformed to **H2**. Moreover, several subjects thought that the independent encoding of stroke player in **GT** (Fig. 4(B)) could help avoid interference when recognizing stroke placement, but the effect was not significant. This condition may explain why **H1** was rejected. Moreover, the four subjects from SS preferred **GT** because they thought that the encodings of stroke position and stroke placement in **GT** coordinated with each other better and more vividly depicted the scene where a player hit a stroke.

Cons. One subject (CS) commented that the unequal division of the table ((Fig. 4(E))) in **GT** could cause perception inequality. The larger parts on the table were always more distinct than the other parts, and this led to longer time spent on particular questions. Additionally, three other subjects (1 CS and 2 SS) said, the encodings of stroke position (Fig. 4(D)) and stroke placement (Fig. 4(E)) in **GT** looked like a whole. Therefore, when comparing the stroke placement in Task 2, they often spent more time in **GT** than in **GI** to exclude the interference of stroke position. We thought this phenomenon might be caused by the use of the same channel, position, in the two encodings and the close placement of the two encodings. These factors may explain the rejection of **H3**.

In conclusion, our glyph, **GT**, improves the performance during analysis compared with **GI**, especially in perception of stroke position. However, there is still some room for improvement (e.g., the repetition of the position channel).

5.1.6 *Result Discussion*

The performance comparison between the two glyphs can be summarized into two conditions according to the results of the user study. In tasks related to stroke position, **GT** outperforms **GI** in efficiency and accuracy since the encoding is simplified, and the changes of values are more perceptible in **GT** than in **GI**. In the tasks related to stroke player and stroke placement, both glyphs perform similarly in efficiency and accuracy. However, sometimes, users may prefer **GT** due to its orthogonality and normalization in encoding stroke players, and sometimes, users may prefer **GI** due to its perception equality in encoding stroke placement. Users' preference matters much in such tasks. A switch between **GT** and **GI** may be preferred by users in such tasks. Therefore, in summary, **GT** does improve the glyph-based visualization methods for technical attributes in table tennis, while **GT** still faces some limits. In the future, we will further examine the performance difference between **GT** and **GI**. We plan to provide both glyphs in our system for more analysts to test their performances in real analysis scenarios. We will further improve **GT** in the future.

5.2 Case Study & Expert Feedback

We invited our domain experts, (**E1**) and (**E2**), to conduct the case study with us. The cases were conducted on a PC (with Intel Core i7-4790K, 8GB of memory, and a 1920×1080 display) using Google Chrome. We first introduced the visual encodings and interactions to the experts. After they got familiar with the system, they analyzed the matches together. We collected their feedback after the case study.

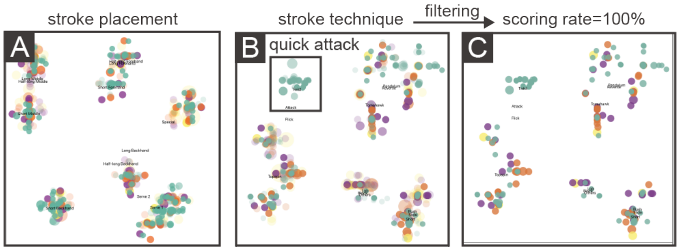


Fig. 7. Analysis process of insight 1. (A) present the projection layouts dominated by stroke placement. (B) present the projection layouts dominated by stroke technique and (C) presents the tactics whose scoring rates are 100 percent based on (B).

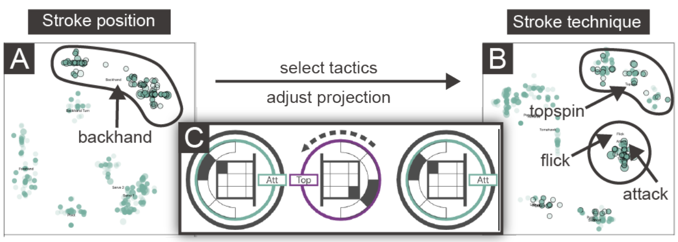


Fig. 8. Analysis process of insight 2. (A) and (B) display the projection layouts of Ito's tactics which dominated by stroke position and stroke technique respectively. (C) displays the detailed attributes of one of the tactics the experts hovered in (A).

5.2.1 Case 1

The first case focused on the three matches from the *Seamaster 2018 ITTF World Tour Swedish Open* where Ito Mima played against Liu Shiwen, Ding Ning, and Zhu Yuling. Ito won all of the three matches. The experts wanted to analyze the reasons for Ito's winning streak.

Insight 1: Ito's quick attack was dominant. The experts examined the summary view with the projection dominated by stroke placement (Fig. 7(A)). They found that all of the players' tactics were scattered similarly. Therefore, they clicked the "Stroke Technique" button (Fig. 3(C1)) and observed that the cyan points had one more cluster than the points in other colors (Fig. 7(B)). By hovering the points, they found that the technique of these tactics was quick attack. This phenomenon indicated that Ito's technique, quick attack made her tactics more diverse than those of other players. The experts further filtered the tactics to only show those with high scoring rates. They found that Ito's tactics with quick attack remained a lot (Fig. 7(C)). The experts explained that Ito's tactics with quick attack, which were not used by others were her main strength. This conclusion agreed with their empirical knowledge.

Insight 2: Ito's backhand was dominant. For further insights, the experts focused on Ito's tactics. They switched the projection to the one dominated by stroke position (Fig. 3(C1)). The experts observed that most of Ito's tactics stemmed from strokes given in backhand (Fig. 8(A)) except for the serve strokes. According to the experts, it means that Ito's opponents tended to defeat her by hitting many strokes to her backhand. However, most of the points of this type of tactic were dark (Fig. 8(A)), which means Ito achieved a high scoring rate by utilizing this type of tactic and her opponents' strategies fail. The experts further examined the technical details of several points (Fig. 8(C)) and found that most of the tactics included offensive techniques like quick attack. The experts speculated that these tactics were Ito's primary methods for offense. They further selected these points and clicked the "Stroke Technique" button (Fig. 3(C1)) to investigate the techniques of these tactics. As Fig. 8(B) shows, indeed, the first strokes of this type of tactic were mainly given through offensive techniques including topspin, flick, twist, and quick attack. The experts explained that tactics beginning with strokes given through offensive techniques were offensive tactics. With such offensive tactics, Ito could take the initiative to score points. Therefore, the tactics beginning with strokes given in backhand was Ito's major strength during these matches.

Insight 3: Consecutive quick attack in backhand was dominant. The experts continued to investigate the tactics (Fig. 8(A), the black contour) in the detail view. They found that regardless of the opponents (contour color), Ito was most likely to give the third stroke in the same position, backhand, as that of the first stroke (Fig. 9(step 1)). They further hid the encoding of hit player (Fig. 9(step 2)) and realized that this type of tactic generally had high frequencies and scoring rates. Inspired by **Insight 2**, the experts deduced that the technique of the first and the third strokes in this type of tactic was probably quick attack. They switched on the encoding of stroke technique (Fig. 9(step 3)) and found the majority of this type of tactic included quick attack in the first and third strokes. Therefore, Ito's tactics with two consecutive strokes given by quick attack in backhand were the key factors for her victory.

The experts further unfolded the next stroke of the tactics whose first stroke was given by quick attack in backhand to determine the reasons for the high frequencies and scoring rates of these tactics (Fig. 9(step 4)). They found that Ito's opponents mostly used strokes given by block, topspin, and other when countering Ito's consecutive quick attack in backhand (Fig. 9(step 4)). Under such conditions, Ito scored more points. The experts explained that the three techniques were disadvantageous for Ito's opponents in such conditions. The experts further checked the corresponding video clips and validated their explanation.

Afterward, the experts examined the stroke placement. They enabled the encoding of stroke placement (Fig. 9(step 5)). For convenience, they re-ranked the tactic list in descending order (Fig. 3(F1)) and immediately found that at the top of the list, three strokes were given by the techniques mentioned above (i.e., block, topspin, and other). The values of stroke placement of the three types of strokes were extremely different (middle, backhand, and forehand), which indicated that Ito's tactics with two consecutive strokes given by quick attack in backhand tended to vary the stroke placement frequently, leading to her opponents' barely adopting effective strategies in time.

Insight 4: Ito tended to dominate the match as soon as possible. The experts hoped to further their investigation. Thus, they hid the next stroke and the encoding of placement. According to the context information, the experts discovered that Ito mainly adopted the tactics with consecutive strokes given by quick attack in backhand during the start phase and middle phase of a match (Fig. 10(A)). Moreover, almost all of the rallies where this type of tactic occurred

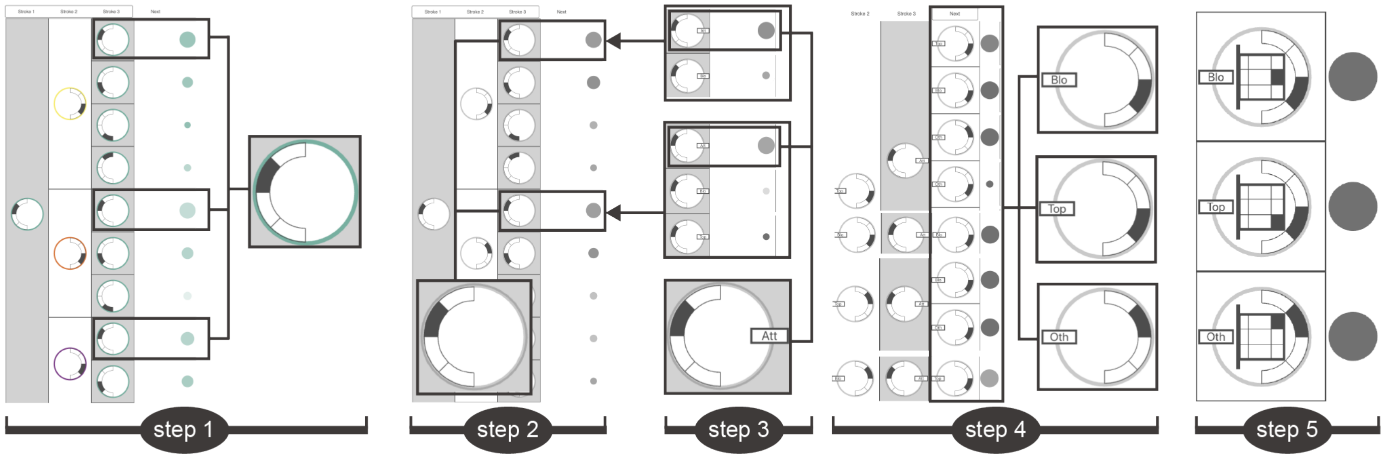


Fig. 9. Analysis process of insight 3. At step 1, the experts investigated the stroke position with stroke player. At step 2, they hid the stroke player. At step 3, they displayed the stroke technique. At step 4, they unfolded the next stroke of each tactic. At step 5, they displayed the stroke placement.

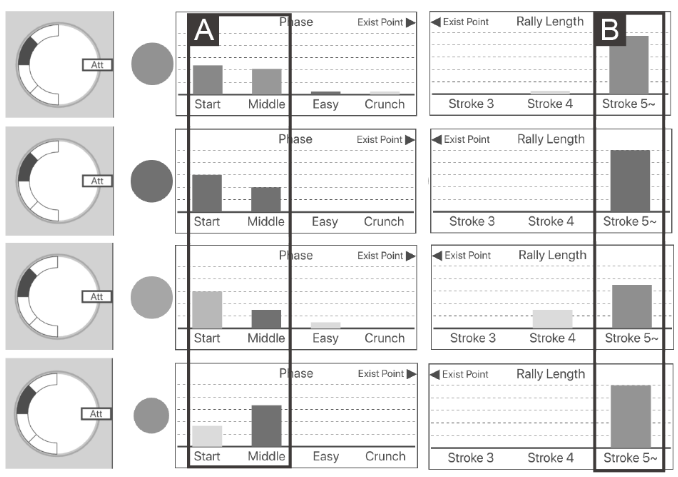


Fig. 10. Analysis process of insight 4. (A) illustrates the distribution of Ito's tactics with two consecutive quick attack given in backhand. (B) illustrates the rally length of the corresponding tactics.

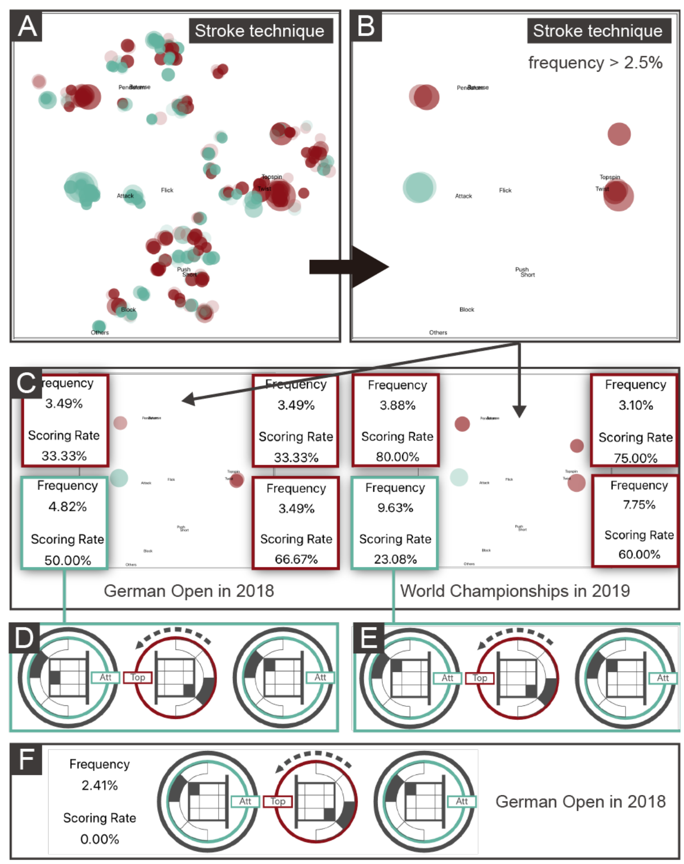


Fig. 11. Analysis process of insight 5. (A) illustrates the projection layouts dominated by stroke technique. (B) presents the frequent tactics in the two matches. (C) illustrates the frequencies and scoring rates of the frequent tactics in the two matches separately. (D) and (E) are the details of the corresponding tactics in (B). (F) presents the performance of the same tactic as (D) displayed in German Open in 2018

were long ones (more than five strokes) (Fig. 10(B)). Therefore, they deduced that Ito's match strategy focused on consecutive offense during stalemate, and she dominated the game at the start and middle phase as soon as possible. In this way, she could increase the pressure on her opponents and win the match more easily.

5.2.2 Case 2

The second case focused on two matches of two players, Ito Mima and Sun Yingsha. One was from *Seamaster 2018 ITTF World Tour German Open* and the other was from *Liebherr 2019 ITTF World Table Tennis Championships*. Ito lost in both of these two matches and her performance in the latter match was much worse than that in the former one. The experts hoped to figure out the reason.

Insight 5: Ito was easily suppressed by the stroke hit to her long backhand by Sun. The experts examined the projection layout dominated by stroke technique. They found that there were several large points (frequently-used tactics) in cyan (Ito's tactics) and red (Sun's tactics)(Fig. 11(A)). Therefore, the experts filtered out the tactics whose frequencies were lower than 2.5% (Fig. 11(B)). They found that Sun's frequent tactics were diverse and mainly featured pendulum, reverse, topspin and twist. In contrast, Ito's frequent tactics only featured quick attack, which was expected by the experts. The experts further examined the details of the points. As Fig. 11(C) shows, in German Open in 2018, the average scoring rates of the two players' frequent tactics were close to each other. However, in World Championships in 2019, Sun's average scoring rate was much higher than Ito's, which verified the worse performance of Ito in this match. By comparing Ito's frequent tactics in the two matches, the experts found the two tactics were almost the same except the stroke placement of the first stroke ((Fig. 11(D, E))). In the former match, Ito often launched the tactic by receiving the stroke hit to her long middle hand, whereas, in the latter match, she often launched the tactic by receiving stroke hit to her long backhand. Therefore, the experts deduced that the reason for the worse performance of the latter tactic is that Ito was suppressed by the stroke hit to her long backhand. They loosened the filtering condition in the former match and found the latter tactic in the former match (Fig. 11(F)). Indeed, the performance of the latter tactic was also poor in the former match. The experts further explained that Ito was easily suppressed by long backhand because Sun was better at hitting the stroke to the opponents' long backhand than other players. Sun's strokes to long backhand were more powerful and swift. Although Ito's consecutive quick attack in backhand was dominant when against other players (**Insight 3**), it lost advantage when Ito was against Sun. That's why Sun could always defeat Ito.

5.2.3 Expert Feedback

After the case study, we interviewed **E1** and **E2**, and collected their feedback. The experts were satisfied with our system for three reasons. First, the summary view helped them identify the tactics of interest more efficiently. The four buttons in the scatterplot further enabled them to explore the tactics from multi-scale perspectives. The sliders largely helped alleviate the issue of visual clutter and facilitate identifying key tactics. Second, the experts appreciated our glyph. They pointed out that the glyph vividly depicted the confrontation between two players in a match. Moreover, the glyph enabled them to hide or display attributes intuitively for specific analysis tasks. Their only concern was that the learning curve of the glyph was high for the first use of the system. Finally, the experts preferred the display view a lot. They stated that the video clips and the animations not only verified their results achieved from previous analysis but also helped communicate the results to coaches and players since it was straightforward and familiar to them. The experts also suggested that the system can provide recommendations on how to counter specific tactics.

6 Discussion

Re-implementability. Our system can be directly re-implemented in other data as long as the input data structure is the same. The input data of the system is tabular data where each row records the attributes of a stroke (the figure below). The only issue to consider is the parameters of the embedding models and projection algorithms. Analysts may need to adjust the parameters to obtain a reasonable layout for the projection plot in the summary view.

Generalizability. The analysis paradigm and the visual design of Tac-Miner can be extended to other sports. Specifically, for racket sports (e.g., tennis and badminton), Tac-Miner can be easily applied to the analysis of singles matches due to the similar data structure. As for doubles matches, we can take players at the same side as a whole for analysis and use Tac-Miner to analyze the tactics of teams. The only problem is that the teamwork between the two players is omitted, and more visual analytics components are needed to investigate the teamwork. We are going to study this problem in the future. For invasion sports (e.g., soccer and basketball), Tac-Miner can also be extended to them by defining new analysis units similar to the stroke. For example, in soccer, we can define a pass as the basic analysis unit, and the encoding of the starting point of the pass, passing direction, and passing player can be similar to the encoding of stroke placement, stroke position, and hit player in the glyph. In this way, Tac-Miner can be used to investigate patterns of pass sequences of a soccer team, which is also a popular topic in the tactical analysis of soccer [17], [57]. Of course, soccer analysis is more complicated than the analysis of table tennis since the interactions between soccer players are more flexible and complex. More analysis perspectives (e.g., the passing network and the formations) are needed. We will extend the generalizability of Tac-Miner in soccer analysis in the future.

Limitation. Tac-Miner has two limitations. First, our glyph cannot encode other important contextual attributes. In the future, we hope to design a more scalable glyph to encode contextual attributes. Second, our system does not provide suggestions for strategy improvement. We hope to add a recommendation system in the future to help experts establish improved strategies to counter specific tactics.

Scalability. In the summary view, the encoding of the projection plot can cause overplotting and invisibility of some data points. To alleviate this problem, we added sliders to filter the data points displayed on the plot. In this way, experts can easily investigate and quickly select the data points they are interested in for further study regardless of the visual clutter. The detailed view is scalable for the tasks of tactic analysis. Usually, experts would select up to 20 tactics for detailed analysis. Although the detailed view can only show around 10 tactics, the scalability has been improved by providing a button for tactic sorting. When conducting analysis, experts often only require to compare two or three adjacent tactics with similar frequencies. Therefore, the detailed view can fulfill the experts' requirements.

7 Conclusions and future work

In this work, we solved the issue of tactical analysis for multiple table tennis matches. We summarized the analysis workflow and identified the problem domain through collaboration with domain experts. We further developed Tac-Miner for multi-scale tactical analysis. We evaluated our glyph through a controlled user study, and conducted two cases and obtained new insights which have been approved by our experts and coaches in the Chinese national table tennis team. In the future, we hope to extend our work from following three aspects. First, we plan to conduct more experiments about encoding effectiveness of glyph. We want to further improve the scalability and generalizability of our glyph. Second, we consider to expand the generalizability of our system. We plan to add more components, such as tactic definition, so that users can easily apply the system to different sports.

Acknowledgments

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