

# Tac-Anticipator: Visual Analytics of Anticipation Behaviors in Table Tennis Matches

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## Abstract

Anticipation skill is important for elite racquet sports players. Successful anticipation allows them to predict the actions of the opponent better and take early actions in matches. Existing studies of anticipation behaviors, largely based on the analysis of in-lab behaviors, failed to capture the characteristics of in-situ anticipation behaviors in real matches. This research proposes a data-driven approach for research on anticipation behaviors to gain more accurate and reliable insight into anticipation skills. Collaborating with domain experts in table tennis, we develop a complete solution that includes data collection, the development of a model to evaluate anticipation behaviors, and the design of a visual analytics system called Tac-Anticipator. Our case study reveals the strengths and weaknesses of top table tennis players' anticipation behaviors. In a word, our work enriches the research methods and guidelines for visual analytics of anticipation behaviors.

## CCS Concepts

• **Human-centered computing** → **Visual analytics**; • **Information systems** → **Data mining**;

## 1. Introduction

Anticipation skill is the ability to capture and interpret the current information to prejudge future events, such as the position of the ball and the action of a player in sports [WWSA04]. This skill is essential for professional racquet-sport players to take action in advance to hit the ball back with high-quality [ADK12, RPM\*18]. Conventionally, players' anticipation behaviors are investigated in labs with artificial tasks. Researchers would prepare an interference-free experiment environment and use cameras and sensors to record participants' detailed actions when conducting pre-designed anticipation tasks. However, such studies cannot support in-situ anticipation behaviors in real matches.

Real anticipation behaviors are difficult to quantify since cameras and sensors cannot be applied to real matches. Existing studies extract the response time and accuracy of anticipation behaviors from match videos for analysis [TBLRW13, AB17]. However, such approaches are not comprehensive since they overlook many contextual factors, such as key events and moving trajectories. To fill this gap, this work first solves the data acquisition problem.

Acquiring effective anticipation data faces two challenges: what to collect and how to collect it. To solve the first challenge, we collaborate with our domain experts, who have rich experience in match analysis for the Chinese table tennis team. Based on their

workflow and tasks, we define the content and structure of anticipation data. Specifically, an anticipation behavior should be presented by three types of data: attribute data (e.g., stroke technique and stroke placement), trajectory data (e.g., the trajectories of the ball and players), and event data (e.g., the ball-racket contact and the ball-table contact). To solve the second challenge, we refer to the state-of-the-art data-collection framework and develop a customized system to collect the data we need. The attribute data is collected per stroke and the trajectory data and the event data are collected per frame.

Such new anticipation data brings new challenges to analytics of anticipation behaviors. Current practices lack the necessary depth to go beyond the results of anticipation behaviors. For example, although the movement of a player based on the prediction of ball-landing location is a successful anticipation action, existing analytical methods cannot incorporate such information because involved data only include the anticipation results, not other process-related factors, such as the moving speed and distance of players, that lead to the successful results. Few methods are available to consider multiple factors in the evaluation of anticipation behaviors.

To solve this challenge, we construct an evaluation function to rate the performances of each anticipation behavior according to players' specific movements. Based on the function, we implement a visual analytics system, Tac-Anticipator, for anticipation behavior analysis from multi-scale perspectives. The system visually combines the three types of data to enable analysts to conduct an in-

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depth investigation. A case study based on using Tac-Anticipator reveals some design guidelines for analyzing anticipation behaviors in racquet sports. The contributions of this work are as follows:

- we formulate and define the data structure of anticipation behaviors for table tennis;
- we propose a function for evaluating anticipation performances of players in real matches;
- we develop a visual analytics system called Tac-Anticipator to show the effectiveness of our function; and
- we summarize a set of design guidelines for visual analytics on anticipation behaviors in racquet sports.

## 2. Related work

This section presents the literature review of sports visual analytics and anticipation analysis.

### 2.1. Anticipation analysis

Anticipation skill in sports has been studied since 1970s [JM78]. Researchers mainly investigate players' anticipation behaviors from the cognitive perspective through film occlusion tasks. For example, in tennis, Williams et al. played a test film that ended at the racquet-ball contact and asked participants to respond as quickly and accurately as possible based on the film content [WWKS02]. During the procedure, participants' actions were captured by cameras and inertial sensors. Through such an experiment, players' anticipation skills were quantitatively measured. Similar experiments were also conducted by Cañal-Bruland and Williams [CBW10] to study the key kinematic information during anticipation in tennis, Zhao et al. [ZLJZ18] to study the anticipation capabilities of players with different skill levels in table tennis, and Abernethy and Zawi [AZ07] to study the differences in anticipation skills of the professional and the recreational in badminton. According to the meta-analyses of Mann et al. [MWWJ07] and Travassos et al. [TAD\*13], the core interest of these studies is to investigate how skilled performers conduct anticipatory behaviors from cognitive perspectives. They wanted to identify the mechanisms underpinning players' superior anticipatory behaviors. For this purpose, diverse paradigms (e.g., temporal occlusion, spatial occlusion) have been proposed to examine players' anticipation behaviors [Ver20]. However, most of these studies were conducted in the lab, where laboratory tasks were designed to measure players' anticipation ability. Real anticipation behaviors in matches are rarely analyzed.

Triplet et al. [TBLRW13] and Alder and Broadbent [AB17] pioneered the method of using video coding to examine the nature and frequency of anticipation behaviors in actual tennis and badminton matches. They defined and collected data of anticipation behaviors from match videos. However, their method cannot directly be used for current data-driven analysis based on complicated mathematical models, because coded videos under this method are unstructured data. Moreover, their research paid attention to anticipation results only and ignored the whole anticipation process. Many important factors, such as moving speed and moving distance, were not considered during the analysis.

To fill the gap in data-driven analysis of anticipation behaviors, we propose a method to formalize and quantify anticipation behaviors from match videos. Based on the data, we proposed evaluation functions and a visual analytics system to facilitate the analysis.

### 2.2. Sports visual analytics

Recent years have witnessed a growing number in studies of sports visual analytics, as shown in the reviews [DY20, PVS\*18]. For example, in soccer, the key events during the matches [PVF13, PVF14], the team tactics hidden into players' trajectories [AAA\*19], the strategies lying into team passes [XWL\*21], the variation of team formations [WXW\*19], and the fusion of visualizations and videos [SJB\*16, SJL\*18] have all been investigated by considerable researchers. In basketball, the spatio-temporal characteristics of high-level team tactics were deeply studied by Goldsberry [Gol12] and Therón and Casares [TC10]. Besides, both Chen et al. [CLX\*16] and Zhi [ZLSM19] explored narrative visualization of basketball events. Moreover, Losada et al. [LTB16], Franks et al. [FMBG15], and Cervone et al. [CDBG14] introduced visual analytics approaches to investigate basketball players' performance statistics. In baseball, similar topics about game events [ODS18] and performance statistics [LOC\*16] are also studied by researchers. These works provide considerable insights into how to visually combine trajectory data and attribute data for sports analytics. They often overlay the trajectory data with the attribute data to help analysts understand the dynamics of the trajectory data, such as the formation flow in ForVizor [WXW\*19] and the Gameplay Viewer in StatCast Dashboard [LOC\*16]. However, these works cannot solve our problems due to the differences in the rules of team sports and racquet sports. We referred to the successful experience in these works when developing Tac-Anticipator.

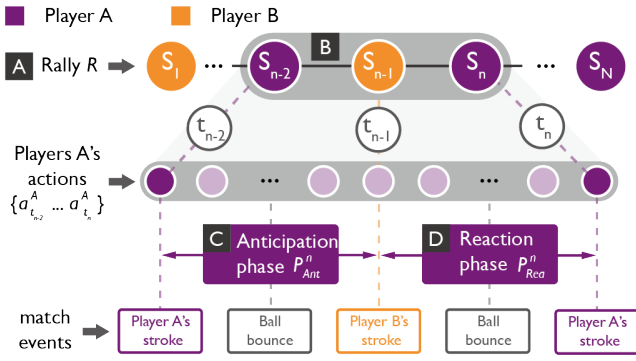
TenniVis [PYHZ14] is a pioneering work for the visualization of game statistics in tennis matches. However, it cannot be used for anticipation analysis since it only supports analysis of easily-collected data, such as point results and service. Anticipation analysis, on the other hand, usually involves complicated tracking data and annotated attribute data. Considerable works have been proposed to facilitate the analysis of these kinds of data. In badminton, Ye et al. [YCC\*20] introduced ShuttleSpace to support the analysis of badminton trajectories with virtual reality. Similarly, Polk et al. [PJHY20] developed CourtTime to investigate the trajectories of players and the ball in tennis matches. Wu et al. [WGW\*20] introduced a steerable glyph to facilitate sequence mining in racquet sports. In addition, iTTVis [WLS\*18] and Tac-Simur [WZD\*20] are developed to investigate stroke attributes in table tennis. These works allow analysts to efficiently discover players' tactics from tracking data and annotated attribute data. However, they cannot be directly applied in our work. Therefore, we develop Tac-Anticipator for the investigation of anticipation behaviors.

## 3. Background & requirement analysis

This section introduces our domain experts, the terminologies of table tennis, and the design requirements of the system.

### 3.1. Background

Experts: We conduct this study with two domain experts **E1** and **E2**. **E1** is a professor in Sports Science Department and was an excellent table tennis player who was also a professional coach and umpire. **E1** has helped the Chinese national table tennis team conduct match analysis for more than 18 years. **E2** is a postdoctoral researcher in Sports Science Department, a professional table tennis player, and a professional umpire. **E2** has served the Chinese



**Figure 1:** The definition of an anticipation behavior. (A) represents a rally that contains several strokes. (B) shows three consecutive strokes within an anticipation behavior. (C) is an anticipation phase, and (D) is a reaction phase of the anticipation behavior.

national table tennis team since 2015, providing data analysis services. E1 and E2 have profound knowledge and experience in analyzing elite table tennis players. Both experts are our co-authors. During the development of Tac-Anticipator, we iterated the system design with them. When a new version of Tac-Anticipator was ready, we would ask them to use the system for analysis and collect their feedback for further improvement.

**Terminologies:** Table tennis is a turn-based racquet sport. In a match, players hit the ball with their rackets to each other in turn. Due to the fast pace of table tennis, table tennis players must have excellent anticipation skills [ADK12] to receive the opponents' strokes with high quality. The terminologies are as follows.

- **Stroke & rally:** A stroke is a behavior in that a player hits the ball with the racket once. It is the basic unit in table tennis analysis [PZH10]. Therefore, we define our anticipation behavior based on it. A rally consists of multiple strokes, including a serve and a losing stroke (they can be the same stroke) (Fig. 1A). It is the basic unit of scoring. In this work, the result of a rally is taken as the result of the anticipation behaviors in this rally. We use  $R = \{S_1, \dots, S_N\}$  to denote a rally with  $N$  strokes and  $S_n$  to represent the  $n^{th}$  stroke in  $R$ . We assume that  $S_n$  belongs to Player A as Fig. 1 shows for ease of expression. Besides, we use  $T = \{t_1, \dots, t_N\}$  to denote the timestamp of each stroke within a rally, and the time unit is the frame.
- **Anticipation behavior:** An anticipation behavior is the process that a player observes the movements of the ball and the opponents, predicts the next stroke by the opponent, and takes action in advance to receive the stroke. If the player anticipates well, he/she can have sufficient time to prepare for the stroke. The anticipation behavior  $AB_n$  at  $S_n$  contains all Player A's actions (e.g., standing still, moving back and forth, etc.) that begin at  $S_{n-2}$  and end at  $S_n$  (Fig. 1B). We use  $a_t^A$  to denote an action of Player A at time  $t$ . In such a way,  $AB_n = \{a_{t_{n-2}}^A, \dots, a_{t_n}^A\}$ . Moreover,  $AB_n$  can be further divided into two phases: an anticipation phase  $P_{Ant}^n$  (Fig. 1C) and a reaction phase  $P_{Rea}^n$  (Fig. 1D).
- **Anticipation phase:** According to Triolet et al. [TBLRW13], the anticipation phase of  $S_n$  starts after  $S_{n-2}$  and ends before  $S_{n-1}$  (Fig. 1C). Therefore,  $P_{Ant}^n = \{a_{t_{n-2}}^A, \dots, a_{t_{n-1}}^A\}$ . In this phase, the player has uncertain information about the opponent's stroke and his/her actions are not 100% correct. If the player has more ac-

tions in this phase than the other, then his/her anticipation behaviors are worthier for the analysis for analysts.

- **Reaction phase:** The reaction phase is defined relative to the anticipation phase. According to Triolet et al. [TBLRW13], the reaction phase of the  $n^{th}$  stroke starts after the  $(n-1)^{th}$  stroke and before the  $n^{th}$  stroke (Fig. 1D). Therefore,  $P_{Rea}^n = \{a_{t_{n-1}}^A, \dots, a_{t_n}^A\}$ . In this period, the player has certain information about the opponent's stroke, and his/her behaviors should be 100% correct. If the player's actions mainly occur in this phase, then his/her anticipation behaviors have low analysis value.
- **Anticipation results:** The result of the rally where an anticipation behavior exists is the anticipation result of this behavior.

### 3.2. Development of design requirements

We held weekly meetings to interview our experts and observed their workflow in analyzing anticipation behaviors. They primarily use the video coding method. They use Dartfish [dar] to clip the match video into multiple segments and code it with different types of labels, such as "player" (e.g., player1, player2), "situation" (e.g., defensive, offensive), and "outcome" (e.g., win, lose). Based on the labels, they calculate basic statistics (e.g., mean and frequency of particular coded videos) and conduct descriptive analysis.

We identified two major challenges of this method. First, video coding is tedious and time-consuming. Analysts usually need to examine a match recording frame by frame, because in fast-paced table tennis matches, an anticipation behavior may only last several frames. Thus, analysts have to concentrate on the video intensively and constantly. Second, analysts cannot use statistical or pattern-mining models in their work because these methods require structured data, such as moving trajectories or technical attributes of strokes. Consequently, they could not conduct an in-depth analysis.

We designed a system to address these challenges. The system is aimed at improving the efficiency of video coding work and extracting necessary data and attributes for more advanced analysis. Drawing on our observation and discussion with the experts, we summarized the following tasks the system should support.

- **T1: Discovery of valuable matches.** Analysts often need to check information about individual matches to decide which matches to analyze. Usually, in matches with close scores, both sides tend to be conservative and unwilling to take risks to perform bold anticipation behaviors. Such matches would contain less anticipation behaviors than other matches.
- **T2: Identification of similar anticipation behaviors.** If analysts discover an interesting anticipation behavior, they want to analyze other similar behaviors. According to our experts, they are curious about the questions such as whether the two sides anticipate strokes similarly, and whether similar anticipation behaviors can lead to similar results.
- **T3: Evaluation of the performance of anticipation behaviors.** The performance of anticipation behaviors is essential. It can be evaluated from two aspects, the result and the process. First, analysts need to know whether the anticipation is accurate or whether the anticipation help the striker gain an advantage. Second, they need to know various factors, such as the moving direction and the moving speed. Therefore, multi-scale methods should be provided to support comprehensive evaluation.
- **T4: Explanations for good or poor anticipation behaviors.**

After identifying a good or poor anticipation behavior, analysts need to know the reasons for it. According to the experts, analysts often need to examine the attributes of the strokes within the anticipation process. In addition, they need to consider the influence of key events (e.g., ball bounce) and tactics within the process. Therefore, the context information should be provided.

- **T5: Access to anticipation video clips.** Analysts and coaches are familiar with match videos because they usually use video coding for analysis. Videos can provide the most details of an anticipation behavior for insight validation. Therefore, the system should allow analysts to access and play video clips of anticipation behaviors.

#### 4. Data collection and processing

This section describes the data structure, data collection method, and the approaches to anticipation projection and evaluation.

##### 4.1. Data description & collection

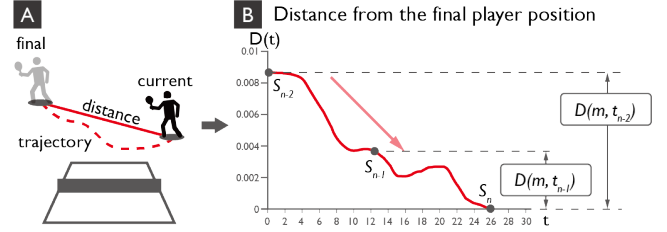
Existing works on anticipation behaviors focus on temporal features. Analysts usually record the timestamps and the results of each anticipation behavior in the video. Such data allows them to learn how effective a player's anticipation is, but cannot help them to explain why an anticipation behavior is good or poor, because data required for explanations, such as stroke attributes and player positions, is not collected. To fill this gap, we formulated and defined a data structure of anticipation behaviors. Specifically, for  $S_n$ , we combined three types of data: the attribute data of each stroke  $Attr_n$ , the trajectory data of players and the ball  $Tra_j_n$ , and the event data of the ball  $Even_n$  as the anticipation data of  $S_n$  as follows.

$$AB_n = \{Attr_n, Tra_j_n, Even_n\} \quad (1)$$

The attribute data of stroke  $S_n$  includes four attributes: stroke technique  $technique_n$  (a player's technique when striking the ball), stroke position  $position_n$  (a player's position when striking the ball), stroke placement  $placement_n$  (the ball's position when bouncing on the table), and launch position  $launch_n$  (a player's position at the beginning of an anticipation behavior). Moreover, we also recorded the hit player,  $hit_n$ , of each stroke. Therefore,  $Attr_n = \{technique_n, position_n, placement_n, launch_n, hit_n\}$ . All these attributes are categorical. Collecting the attributes requires domain knowledge. Therefore, we developed a tool for experts to help collect the data. They needed to spend half an hour to collect a match.

The trajectory data at time  $t$  includes the bounding boxes of all players  $players_t = \{box_1^t, \dots, box_M^t\}$ ,  $M \in \{2, 4\}$ , where  $box_m^t = \{(x_1, y_1), (x_2, y_2)\}$  and the ball  $ball_t = \{x, y\}$ . Therefore,  $Tra_j_n = \{\{player_{t_{n-2}}, \dots, player_{t_n}\}, \{ball_{t_{n-2}}, \dots, ball_{t_n}\}\}$ . Moreover, we also collected the key events  $e_t$  concerning the ball at time  $t$  (i.e., ball-racket contact, ball-table contact, flight) as the contextual information for anticipation analysis. In this way,  $Even = \{e_{t_{n-2}}, \dots, e_{t_n}\}$ . We referred to the state-of-the-art data collection framework, EventAnchor [DWW\*21], and developed a customized system to collect the data based on live videos (duration: 0.5 1 hour, resolution: 1920\*1080, fps: 25). The resolution and the framerate of the videos are high enough for the system. The system would first automatically track the position of the ball and players' bounding boxes. Then, annotators can directly interact with the video to fine-tune the automatically collected results. Before annotation, the

annotator agreement was checked. Each annotator needed to spend about half an hour annotating a match. You can refer to the supplementary material for more details about the collection system.



**Figure 2:** The moving curve used to calculate the similarity between two anticipation behaviors. The curve (B) is derived from the trajectory data we collected from the match videos (A).

##### 4.2. Anticipation similarity

To facilitate anticipation analysis, we calculate the similarity between anticipation behaviors (T2). We do not directly calculate the similarity between players' moving trajectories because we want to remove the influence of the absolute position of players on the court (Fig. 2A). We extend a moving curve that presents changes in the Euclidean distance between the current and final player positions (Fig. 2B). We assume the bounding box of the player of  $S_n$  at  $t$  is  $box_m^t = \{(x_1, y_1), (x_2, y_2)\}$ . Then the position  $Pos_m^t$  can be estimated by the center of the bounding box as follows.

$$Pos_m^t = \left( \frac{x_1 + x_2}{2}, \frac{y_1 + y_2}{2} \right) \quad (2)$$

The distance between the current ( $Pos_m^t$ ) and final player positions ( $Pos_m^{t_n}$ ), denoted by  $D(m, t)$ , can be calculated as follows.

$$D(m, t) = Dist(Pos_m^t, Pos_m^{t_n}), t \in [t_{n-2}, t_n] \quad (3)$$

where  $Dist$  is the Euclidean distance between  $Pos_m^t$  and  $Pos_m^{t_n}$ .

After adding the timestamps of the ball events, we can know when a play executes an anticipation action and whether the action is correct during the movement. For example, the curve in Fig. 2B shows that the player anticipates the stroke efficiently and takes action early to receive the stroke since the distance is reduced dramatically before the opponent's stroke. We further apply dynamic time warping (DTW) [BC94] to calculate the similarity between the moving curves of anticipation behaviors. In this way, we can remove the influence of players' specific positions on the court and focus on the moving tendencies.

##### 4.3. Anticipation evaluation

Currently, no quantitative models are available for the evaluation of anticipation behaviors. Based on what we have learned from domain experts, such models need to consider many factors, such as moving distance, moving speed, and anticipation accuracy. We developed two performance functions to support the quantitative evaluation of anticipation behaviors (T3). We held a series of meetings with domain experts to learn how they evaluate players' anticipation behaviors. According to the experts, the two most important points they would evaluate are whether a player anticipates his/her



opponent's strokes efficiently and correctly. Therefore, we identified two key aspects, anticipation efficiency and moving efficiency. Both aspects measure anticipation behaviors based on player positions. We develop a sub-function for each aspect.

*Anticipation efficiency sub-function  $F_{ant}(S_n)$* : For the first point, the experts want to know whether the player anticipates and takes action rapidly. They indicated that when the opponent's intention is obvious, the player would anticipate at the early stage of the anticipation phase and take action as soon as possible to reach the target position in advance. Otherwise, the player would not take any action until he was at the end of the anticipation phase or even the reaction phase. Based on this consideration, we designed  $F_{ant}(S_n)$  to evaluate the efficiency of players' anticipation behaviors. We divide the distance changing during the anticipation phase by the distance changing during the whole anticipation behavior (Fig. 2B). The sub-function can be written as:

$$F_{ant}(S_n) = \frac{D(m, t_{n-2}) - D(m, t_{n-1})}{D(m, t_{n-2})} \quad (4)$$

where function  $Dist$  calculates the Euclidean distance between two positions. If the value of the function is large (close to 1), it means that the player has almost moved to the final striking position of  $S_n$ . Otherwise, it means that the player does not anticipate the stroke in time and hardly moves during the anticipation phase. In other words, the player almost does not anticipate the stroke.

*Moving efficiency sub-function  $F_{mov}(S_n)$* : For the second point, the experts want to know whether the player anticipates correctly and takes action effectively. They indicated that sometimes, the player would incorrectly anticipate the stroke's direction and move in the opposite direction. In such a condition, most of the player's movements are invalid since he/she may need to move back and forth to save the ball. This point can be approximately evaluated by a widely-used indicator in baseball, namely, route efficiency [rou]. This indicator evaluates whether the player's route to the target position is efficient enough. In our condition, if the player anticipates correctly, then his/her route efficiency would be high. Otherwise, the route efficiency would be low. Based on this indicator, we designed  $F_{mov}(S_n)$  to evaluate the effectiveness of players' anticipation. Specifically, we divide the distance changing during an anticipation phase by the length of the trajectories the player moves during the anticipation phase. The sub-function is defined as:

$$F_{mov}(S_n) = \frac{|D(m, t_{n-2}) - D(m, t_{n-1})|}{\sum_{t=t_{n-2}+1}^{t_{n-1}} Dist(Pos_m^{t-1}, Pos_m^t)} \quad (5)$$

where the denominator calculates the length of the player's trajectories between two positions. If the value of the function is large (close to 1), it means that the player anticipates correctly and moves toward the final position. Otherwise, it means that the player anticipates wrongly and wastes time in invalid movements.

With these two sub-functions, we define the overall evaluation function as follows:

$$F(S_n) = \frac{1}{1 + e^{-X}} \times e^{F_{ant}(S_n) \cdot F_{mov}(S_n)} \quad (6)$$

$$X = 5 \times \frac{\sum_{t=t_{n-2}+1}^{t_{n-1}} Dist(Pos_m^{t-1}, Pos_m^t) - W/2}{W} \quad (7)$$

where  $W$  represents the width of the table. To avoid negative values, we use exponential functions. We use a sigmoid function to adjust the score to give lower scores to actions where the player does not move for enough distance. This certain distance is half of the table width, and the result of  $Trajectory(Pos_m^{t_{n-2}}, Pos_m^{t_n}) - W/2$  is divided by  $W$  to eliminate the influence of units. We also use the constant 5 to control the adjusting ability of the sigmoid function.

## 5. Visualization

This section describes the design goals, an overview of the system, and details of Tac-Anticipator.

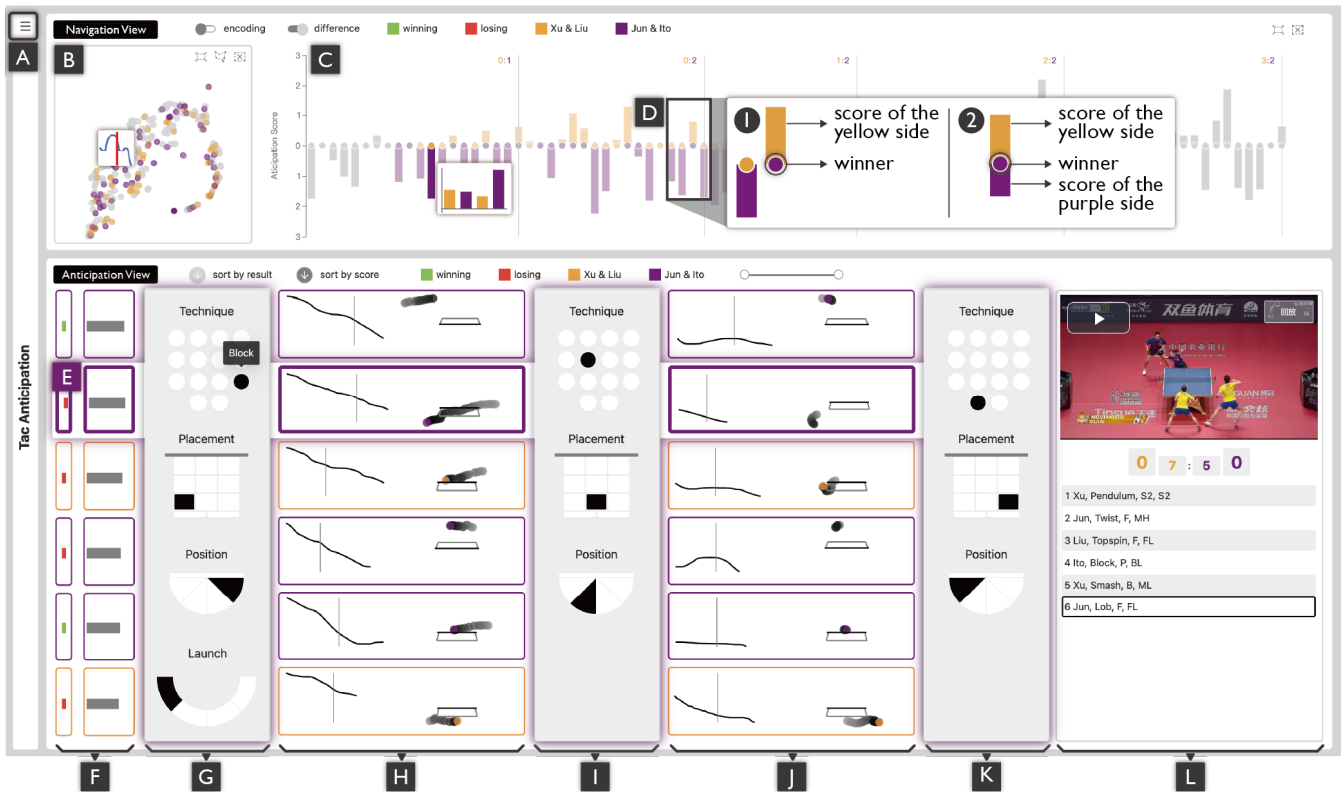
### 5.1. Design goals

We derived the design goals based on the tasks in Section 3.2.

- **G1: Providing match list with rich match information.** Rich match information (e.g., players, handedness, racket covering styles) helps analysts choose the matches with high analytical value (**T1**). are important. For example, how a player holds the racket is critical when choosing matches because players using penhold grip need more time to prepare their striking poses than those with shakehand grip and anticipate strokes earlier.
- **G2: Navigating analysis based on the similarity and evaluation score.** Analysts want to examine similar anticipation behaviors (**T2**). Therefore, a navigation view is preferred to help identify similar anticipation behaviors. The navigation view should provide an overview of the evaluation scores of anticipation behaviors (**T3**). Analysts can use it to identify the anticipation of interest for further detailed evaluation.
- **G3: Correlating sufficient context to the anticipation.** Detailed context information (e.g., stroke attributes, anticipation results, moving trajectories) of an anticipation behavior can facilitate a comprehensive evaluation of its performance (**T3**). Moreover, this context information can help explain its performance (**T4**). The system should support efficient correlation to combine the information with anticipation behaviors to facilitate analysis.
- **G4: Connecting anticipation behaviors with video clips.** Videos can help analysts validate their findings and facilitate their communication of discovered insights with others (**T5**). The system should link anticipation behaviors with corresponding video clips. Each clip should contain the whole rally of an anticipation behavior to present the anticipation behavior clearly.

### 5.2. System overview

Tac-Anticipator is a web-based visual analytics system. The system includes a back end for data processing and a front end for interactive visualization. The back end computes the anticipation similarity and evaluation scores. We implemented it with scikit-learn [sci] in Python. The front end consists of three views, the match list (Fig. 3A), the navigation view, and the anticipation view. The match list provides the metadata of each match and players' profile information (**G1**). The navigation view displays the similarity and



**Figure 3:** The interface of Tac-Anticipator. (A) is the button of the match list. The navigation view contains a scatterplot of behavior similarity (B) and a bar chart of evaluation scores (C). (D) presents the encoding of the bar chart. The anticipation view includes a panel to summarize the results and performance scores (F) of selected anticipation behaviors (E), two panels to visualize anticipation curves into two phases (H, J), three panels to show the distribution of the three strokes' attributes within an anticipation behavior (G, I, K), and a panel for replaying video clips of anticipation behaviors (L).

evaluation scores of anticipation behaviors (G2). The anticipation view presents the details of anticipation behaviors by correlating them with context information, such as stroke attributes and anticipation results (G3). Moreover, this view provides video clips of anticipation behaviors. We use two complementary colors, purple and yellow to encode the data of two teams. The interactions were developed according to the taxonomy by Shneiderman [Shn03] and Yi et al. [KS12]. We developed the front end with React.js [rea].

### 5.3. Using scenario

At first, analysts can examine match information in the match list. After choosing a match, they can use the navigation view to examine the similarity between different anticipation behaviors and choose a group of similar anticipation behaviors for further analysis. Moreover, they can also choose anticipation behaviors with low or high scores. After choosing anticipation behaviors, they can use the anticipation view to investigate the details of anticipation behaviors along with stroke attributes. They can check the video clips to validate and present the insights to coaches and players.

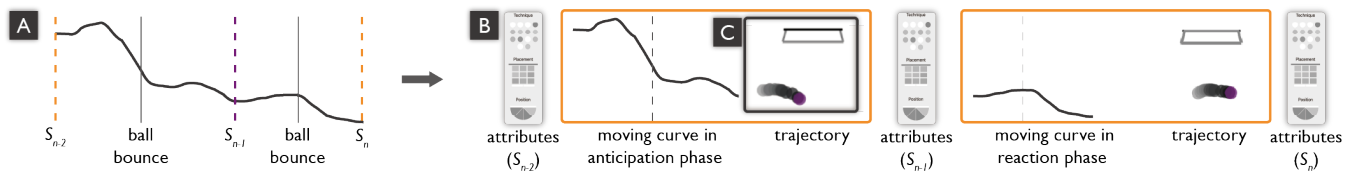
### 5.4. Match list

The match list presents match information (G1). We implement the match list as a drawer to save screen space. Clicking the but-

ton (Fig. 3A), analysts can examine the match information in the list. We display the match name, match score, and player information, such as player handedness, racket type, and racket covering (Fig. 6A). We use icons to visualize player information. The handedness, i.e., “left-handed” or “right-handed”, and racket type, i.e., “penhold” or “shakehand”, are straightforwardly encoded with hand icons and racket icons, respectively. Racket covering, i.e., “Out (O)”, “In (I)”, “Anti (A)”, and “Long (L)”, are encoded by the first letters of the names of racket two coverings. For example, “IA” refers to the racket whose coverings are “In” and “Anti”. Analysts can choose a match by clicking it.

### 5.5. Navigation view

The navigation view presents the similarity and the evaluation score of each anticipation behavior (G2). The similarity is visualized with a scatterplot (Fig. 3B). We project all anticipation behaviors based on their pairwise similarity by using t-SNE [VdMH08] (Fig. 3B). Each anticipation behavior is encoded by an unfilled circle. The evaluation score is displayed as a bar chart (Fig. 3C). The bar chart has two modes. One mode displays the difference in average evaluation scores between two sides within a rally, and the other shows the specific value of their average evaluation scores. Fig. 3D1 shows a result in the first mode, where the yellow side



**Figure 4:** The design of anticipation curves in the anticipation view. The design is based on the moving curve (A). The stroke attributes and the player trajectories (C) are added to correlate context information with the moving curve (B).

has a higher average evaluation score than the purple side in this rally. The filled circle represents the winner of this rally is the purple side. If the condition is reversed, then the bar would be purple and downward and the circle would be yellow.

We use color and bar direction to double encode the side with better anticipation performances. We do not display the score of each anticipation behavior in chronological order here, with the consideration of the visual scalability of this view. A match can have seven games at most. If all anticipation behaviors were presented, there would be too many bars, and each bar would be too thin to be easily observed for analysis.

Fig. 3D2 shows the design in the second mode to visualize the specific values of evaluation scores. The upward yellow bar represents the score of the yellow side and the other represents the purple's. The encoding of the middle point remains. This visual design can support the examination of the trend of the evaluation score on each side. Analysts can investigate the anticipation behaviors at some key events, such as those turning points of a game.

*Interaction:* The interactions in this view are as follows.

- **Selectors:** The scatterplot supports box and lasso selection. The bar chart supports box selection. If analysts select anticipation behaviors in the scatterplot, the bar charts highlight the rallies that contain the selected anticipation behaviors. Similarly, if analysts select rallies in the bar chart, the scatterplot highlights the anticipation behaviors that occur in the selected rallies.
- **Switches:** Analysts can click the “encoding” button to toggle the encoding meaning (i.e., players or the anticipation results) of each circle’s color in the scatterplot. In addition, they can use the “difference” button to change the display mode of the bar chart.
- **Tooltips:** In the scatterplot, analysts can click a circle and a tooltip displays a simplified moving curve of the corresponding anticipation behavior (Fig. 3B). The red line is the separator of the two phases (Fig. 1). In the bar chart, analysts can click a bar and a tooltip displays the score of all anticipation behaviors in the corresponding rally (Fig. 3C).
- **Filters:** The legends of this view can be used as filters. Analysts can click particular color encoding to activate/deactivate corresponding filtering conditions. They can filter anticipation behaviors from the perspective of results and players. They can choose to show all anticipation behaviors, a particular side’s behaviors, or winning/losing behaviors.

### 5.6. Anticipation view

The anticipation view allows users to explore anticipation behaviors from different perspectives. It has four types of panels. First, the panel in Fig. 3F summarizes the results of the rallies where

those anticipation behaviors were located and the performances of each anticipation behavior. Second, the panels in Fig. 3H and Fig. 3J visualize the moving curves in the anticipation phase and the reaction phase, respectively. Third, the panels in Fig. 3G, Fig. 3I, and Fig. 3K present the distributions of attributes of  $S_{n-2}$ ,  $S_{n-1}$ , and  $S_n$ , respectively. Finally, the panel in Fig. 3L allows users to replay the video clips of a selected anticipation behavior (G4).

The results and performances of anticipation behaviors (Fig. 3F) are critical during analysis. The color of the contour of each row encodes the owner of a behavior. The left column in the panel shows the result of the rally relative to the behavior owner. For example, in Fig. 3E, the anticipation behavior belongs to the purple side and the purple side lost this rally. The right column visualizes the performance score of each anticipation behavior with a horizontal bar.

Fig. 4A shows a moving curve of an anticipation behavior. The curve starts from  $S_{n-2}$ , and ends with  $S_n$ .  $S_{n-1}$  is between them and divides the curve into two phases: anticipation phase and reaction phase (Fig. 1). The ball bounces on the table once in each phase. The anticipation behavior is related to movements in both phases and three strokes, so our design should provide all of the data.

Fig. 4B is the final visualization of an anticipation behavior. It presents the two moving curves of the two phases and the attributes of the three strokes. To help users better understand a player’s movement, we add a view (Fig. 4C) next to each curve to show the movement trajectory of the player on the court. Each trajectory is visualized by plotting the position at each timestamp with a transparent dot. In such a manner, if the player moves fast, then the dots will be sparsely distributed and the trajectory will be light. Otherwise, the dots will be densely distributed and the trajectory will be dark. Besides, the attributes of the three strokes are displayed in three panels (Fig. 3G, Fig. 3I, Fig. 3K) among the curves. When there are multiple curves, the panels display the distributions of different attributes (Fig. 5D, Fig. 5E, and Fig. 5F). We use luminance to encode the distribution. The darker, the more frequent.

*Interaction:* Interaction tools included in this view are as follows.

- **Sorters:** The left two buttons at the top of the anticipation view are used to sort the anticipation curves based on the results or evaluation scores, supporting ascending or descending order.
- **Filters:** The legends of this view have the same filtering function as those in the anticipation view. The slider allows the analysts to filter the anticipation curves by setting a range of the evaluation score. In addition, analysts can click on a particular anticipation curve to filter the attributes. For example, Fig. 3E shows a situation where an analyst chooses an anticipation curve. The contour of this curve will be highlighted, and the attributes in the three panels (Fig. 3G, Fig. 3I, Fig. 3K) will only display the attributes of the three strokes within this anticipation behavior.

- **Video players:** Analysts can click a particular anticipation curve to examine the video of the whole rally (Fig. 3L) where the anticipation behavior occurs. The video player also presents the stroke attributes of all strokes within the rally and highlights the third stroke of the anticipation behavior.

## 6. Evaluation

We designed an experiment to evaluate the performance functions and conducted two cases to present the usability of the system.

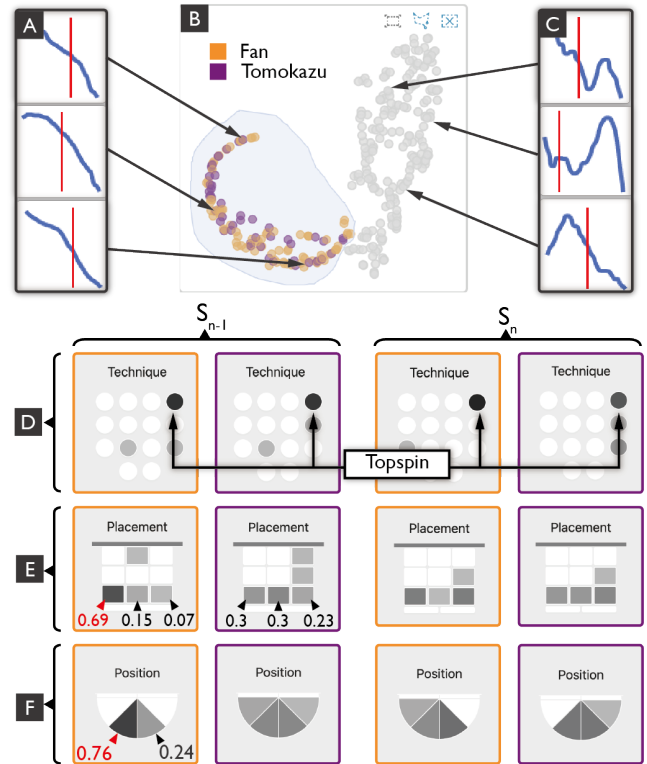
### 6.1. Evaluation of performance functions

We first calculated the scores of all anticipation behaviors in a match using our functions and categorized them into two groups: “good” and “bad”, based on the scores. Then, we randomly selected one anticipation behavior from each group for **E1** and **E2** to evaluate, to see if our experts’ judgment aligns with the group classification. The participants were our experts since evaluating anticipation behaviors requires rich experience of table tennis analysis.

**Apparatus:** We used the final match of men’s singles in the 2019 Men’s World Cup between Fan Zhendong and Harimoto Tomokazu as the experiment data. We first calculated the scores of all anticipation behaviors. Then we categorized these behaviors into two groups based on the scores. The top 30% were in the “good” group and the bottom 30% were in the “bad” one. We randomly chose two good behaviors ( $Good_i^{Fan}$  &  $Good_i^{Har}$ ,  $i \in \{1, 2\}$ ) and two bad ones ( $Bad_i^{Fan}$  &  $Bad_i^{Har}$ ,  $i \in \{1, 2\}$ ) for each player to generate four comparison groups ( $(Good_i^{Fan}, Bad_i^{Fan}) * 2$  &  $(Good_i^{Har}, Bad_i^{Har}) * 2$ ). Then, we generated another four comparison groups ( $(Good_i^{Fan}, Bad_i^{Har}) * 2$  &  $(Good_i^{Har}, Bad_i^{Fan}) * 2$ ) in similar way. In such a manner, we generated eight comparison groups, each containing a good behavior and a bad one. We choose anticipatory actions with a larger score difference for the expert to compare because even experts may struggle to accurately distinguish those with smaller performance differences. For all of the chosen behaviors, we used the corresponding video clips to present the behaviors for experts to evaluate for all of the chosen behaviors. Each video clip contains three strokes, as defined in Fig. 1. The order of all groups was randomized, and the order of the video clips within each group was also randomized.

**Procedure:** Our experts participated in the experiment individually. We first played the two video clips for the experts in each comparison group. Then we asked them to choose one that they thought was better. We did not tell them the answer until the end of the experiment. The whole experiment lasted for ten minutes.

**Result:** Both experts achieved 100% accuracy, which meant the function could tell good behavior from bad one as accurately as the experts regardless of the players. During the experiment, we found several interesting cases where our experts hesitated about which one was better even though the differences in scores of the two behaviors were large. We thought this was because assessing anticipation behaviors only based on players’ positions was not enough for some complicated conditions. For example, a player may consider the opponents’ commonly-used tactics when anticipating strokes. Including other context information, such as techniques and tactics, could improve the comprehensiveness of the function in these conditions. We will improve the function in the future.



**Figure 5:** Case 1. (B) is the scatterplot in the navigation view; (A) and (C) show the moving curves with different patterns; (D), (E), and (F) present distribution comparison of three stroke attributes between two players in  $S_{n-1}$  and  $S_n$ .

### 6.2. Case study

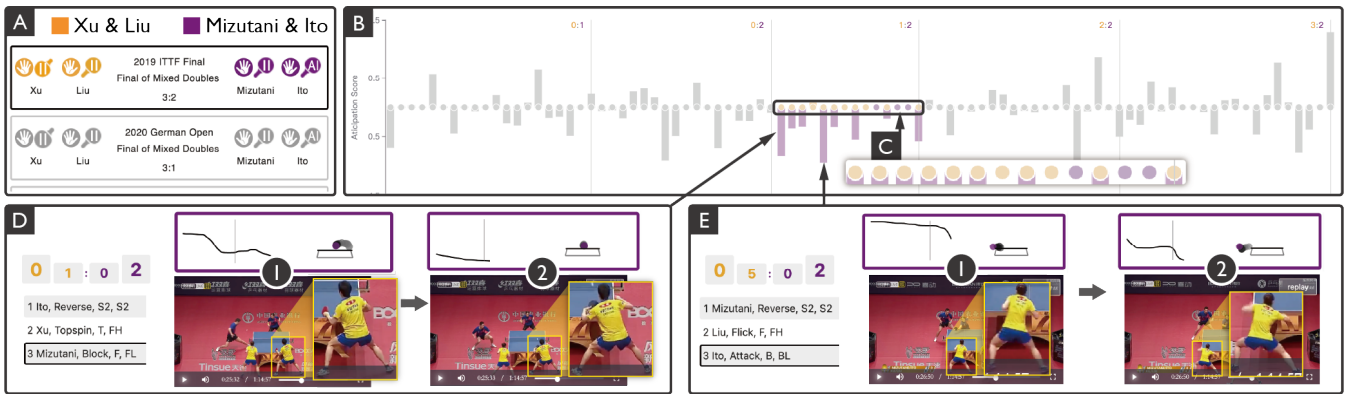
We conducted two cases with our experts (**E1** and **E2**). **E1** analyzed the final of men’s single in the 2019 Men’s World Cup between Fan Zhendong and Harimoto Tomokazu and **E2** analyzed the final of mixed doubles in the 2019 ITTF Final between Xu Xin & Liu Shiwen and Mima Ito & Jun Mizutani. We introduced the system to each expert and asked them to try it for free for half an hour. After familiarizing themselves with the system, they analyzed the matches in a think-aloud way.

#### 6.2.1. Case 1: Fan should hit strokes to “long backhand”

The world rankings of Fan ( $1^{st}$ ) and Harimoto ( $4^{th}$ ) were close. Their handedness, racket type, and racket coverings are also the same. **E1** first investigated the scatterplot in the navigation view (Fig. 5B). By hovering the cursor over some points to examine the corresponding moving curves, **E1** found that all anticipation behaviors could be generally divided into two parts. Actions on the left part of the scatterplot have monotonically decreasing curves (Fig. 5A), indicating more efficient anticipation behaviors, while the curves of those actions on the right are nonmonotonic with troughs or peaks (Fig. 5C), revealing inefficient anticipation actions. **E1** was more interested in those efficient behaviors, so those points on the left were chosen.

**E1** directly went to the anticipation view and set the sliders to only show the anticipation curves with a score larger than 1. Then,





**Figure 6:** Case 2. (A): information about the match and players; (B): anticipation behavior performances of two teams; (C): Comparison of team performances in the third game (Ito & Mizutani anticipated better); (D) and (E): anticipation curves and details of videos of two outstanding anticipation behaviors by Ito & Mizutani.

**E1** clicked the color encoding of players in this view to examine the distributions of the stroke attributes of the two players separately. As shown in Fig. 5D, the technique distributions of  $S_{n-1}$  and  $S_n$  are similar between the two players. The darkest point is “Topspin”, a frequently-used technique by players with a shake-hand racket having two “In” coverings. This finding confirms what **E1** already knew. However, the distributions of stroke placement in  $S_{n-1}$  of two players are quite different (Fig. 5E). Fan used “long backhand” more frequently, with a score of 0.69, implying that Fan was good at anticipating Harimoto’s strokes hit to long backhand. **E1** explained that if Fan hit the stroke to Harimoto’s long backhand in  $S_{n-2}$ , Fan would anticipate the opponent’s stroke more easily. This is an interesting finding. Moreover, from the position distribution graphs (Fig. 5F), **E1** found that Fan was also good at anticipating Harimoto’s strokes hit by “backhand” (score: 0.76). This further confirmed the above finding, because players often receive the strokes at “long backhand” with “backhand”. For the stroke placement and stroke position in  $S_n$ , **E1** said that the difference between the two players was insignificant.

In the end, **E1** concluded that while the anticipation behaviors of the two players were similar, Fan’s anticipation exhibited some unique characteristics. He could easily anticipate Harimoto’s strokes received at “long backhand” with “backhand”. This suggests that Fan should hit the stroke to Harimoto’s “long backhand”.

### 6.2.2. Case 2: Ito and Mizutani are good at anticipation.

In table tennis doubles, two players must alternate hits within a rally. Players must have excellent anticipation skills to be at the right place and at the right time for making their own hits or letting their partner hit. The world ranking for Xu & Liu was the 3<sup>rd</sup>, while Ito & Mizutani was the second-best pair in the event. **E2** chose the match because the two teams are unique. Xu is a penholder (Fig. 6A), which is rare among world-class players. Penholders need more time to prepare their striking poses than those with shakehand grips, so they have to anticipate strokes earlier. Ito’s racket coverings are different from most players. She uses antispin rubber (Fig. 6A), which can effectively handle difficult spin strokes (e.g., topspin), giving her more time to prepare.

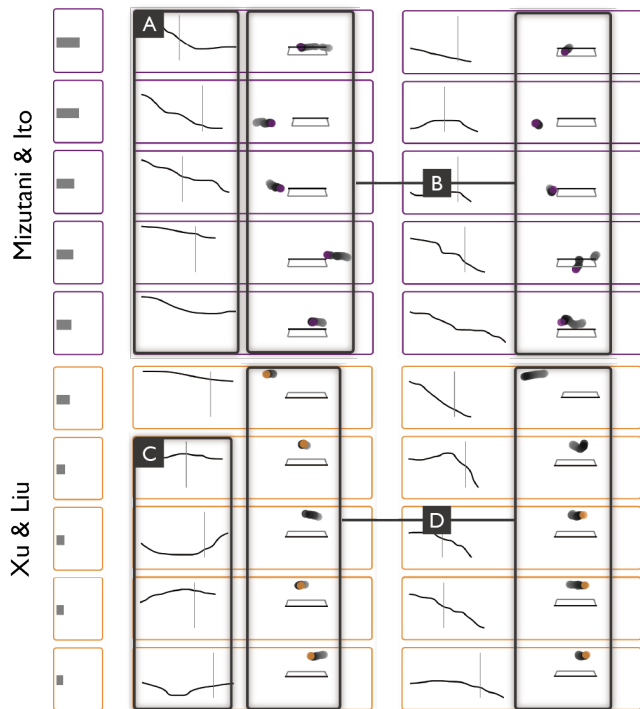
**E2** first explored the bar chart in the navigation view (Fig. 6B).

Turning on the “difference” button, **E2** found that the two teams’ anticipation performances were almost balanced through the whole match, except in the third game, which was the turning point for Xu & Liu. In the third game, Ito & Mizutani exhibited better anticipation behaviors than their opponents in eight rallies, but surprisingly lost in most of these rallies (Fig. 6C). This observation was puzzling, so **E2** decided to deepen the analysis.

To validate the evaluation scores, **E2** selected the two longest bars within the third game, respectively. After each selection, **E2** went to the anticipation view and found that there was only one anticipation behavior. **E2** clicked the anticipation behavior to examine the corresponding video clips. For the first bar, the anticipation occurred at the third stroke by Mizutani (Fig. 6D). He anticipated early and moved to the final position at the end of the anticipation phase (Fig. 6D-1). As a result, he almost stood still in the reaction phase to receive Xu’s stroke with enough preparation (Fig. 6D-2). For the second bar, the anticipation behavior also occurred at the third stroke by Ito (Fig. 6E). She anticipated Liu’s stroke and rushed to the predicted position in advance as the curve dropped suddenly at the end of the anticipation phase (Fig. 6E-1). While both players anticipated well, they still lost the rally. **E2** commented that this might be because of the low success rate of Ito & Mizutani.

**E2** further selected all bars within the third game by box selection. In the anticipation view, **E2** clicked the “sort by score” buttons to sort all anticipation curves based on their score in descending order. Then, **E2** clicked the legends of two colors to check the anticipation curves of both teams separately. Fig. 7 compares the moving curves of two teams. Indeed, Ito & Mizutani anticipated better overall, as shown in the score bars. In addition, they often preferred to take action in anticipation phases (Fig. 7B). In comparison, Xu & Liu almost stood still in anticipation phases (Fig. 7D). This observation is consistent with what moving curves in anticipation phases imply: most curves of Ito & Mizutani are monotonically decreasing with large gradient (Fig. 7A), indicating efficient and correct anticipation actions, while the curves by Xu & Liu are largely nonmonotonic (Fig. 7C), indicating back-and-forth movements and even movements with a wrong direction. “This phenomenon shows that Ito and Mizutani tried to play more aggressively by frequently anticipating Xu and Liu’s strokes and taking action early,” commented by **E2**. One explanation for such behaviors is that having a

big lead in the game score (2:0), Ito & Mizutani took more aggressive strategies with the hope of winning the game. E2 concluded that Ito & Mizutani's anticipation skills outperformed that of Xu & Liu in this match. By improving their success rates of receiving strokes, they can go further.



**Figure 7:** Anticipation curves in case 2. (A) shows the curves by Ito & Mizutani are monotonically decreasing. Graphs in (B) visualize their position distributions on the court in both phases. (C) shows that most curves by Xu & Liu are non-monotonic. Their position distribution is shown in (D).

### 6.3. Expert feedback

We held a post-interview with the experts. According to them, our work is significant for analyzing anticipation behaviors in real matches. They believe the system offers a new perspective to explore, compare, and understand anticipation behaviors. Our approach to using formalized data, quantitative scores for performance evaluation, and rich interactive visualization tools can greatly improve the efficiency and quality of the analysis of not just anticipation behaviors, but also other sports behaviors. The experts also offered three suggestions for further improvement as follows.

- **Behaviors:** The function only evaluates moving efficiency and anticipation efficiency and does not integrate other behaviors, such as back-and-forth movement, which may allow a more comprehensive understanding of anticipation behaviors.
- **Teammates:** The interactions between teammates have significant impacts on anticipation behaviors in doubles matches. However, the current function for doubles matches has not considered team-related activities, such as distance between teammates.
- **Strategies:** According to the experts, high-level strategies, such as tactics (the first three strokes in a rally), were always important

factors when analyzing matches. Considering the effect of such strategies can also enhance our evaluation model.

## 7. Discussion

**Generalizability:** Tac-Anticipator can be extended to analyze anticipation in various sports. For example, the system can support analyzing the anticipation of each pass in a soccer match. Furthermore, Tac-Anticipator's focus on spatio-temporal data makes it useful in urban computing [ZCWY14]. For example, in route planning problems, routes can be analogized as anticipation curves. Specifically, similar to how anticipation behaviors are divided into two phases based on strokes, routes can be divided into several phases according to the locations they include. Each location can contain various attributes, such as congestion levels. In such a manner, Tac-Anticipator can be used for analyzing the performance (i.e., distance and duration) of different routes.

**Scalability:** Our system provides various selection and filtering tools that allow users to control to what extent information should be presented. Users can see all extracted behaviors to have an overview of a match or apply various filters to focus on smaller data sets in less cluttered views. Our design can easily handle long table tennis matches including around 400 anticipation behaviors.

**Limitation:** There are two limitations to this work. First, our data collection method is weak in certain situations where information is incomplete. For example, players may be occluded by other objects, such as the teammate in doubles. Second, our approach is limited to analyzing one match each time. Analyzing multiple matches will be more beneficial to understanding anticipation behaviors.

**Future work:** The analysis in this work is based on players' trajectories in videos because trajectories can most directly reflect a player's anticipation reaction when receiving the stroke. However, only considering trajectories is not comprehensive enough. Other contexts such as players' poses and techniques, should be considered. For example, if a player's posture is not stable, it indicates that he/she has anticipation delay or anticipation error. Besides, if a player's technique requires significant body movement, it can cause them to have insufficient time to anticipate their opponent's shot. More factors should be considered in future work.

## 8. Conclusion

In this work, we proposed a method for visual analytics on anticipation behaviors in table tennis. We made the first attempt to formalize and collect the data for anticipation behavior analysis from videos of real matches. We also developed a model to measure anticipation behaviors. A visual analytics system, Tac-Anticipator, was implemented to support the multi-scale investigation of anticipation behaviors. In the future, we will continue our work by considering more factors to improve the evaluation function.

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