Analyse Visuelle de la Tactique de Jeu au Tennis de Table

Visual Analysis of Table Tennis Game Tactics

Aymeric Erades and Romain Vuillemot

English Abstract—The aim of this project is to enhance the tactical analysis of table tennis players as they prepare for high-level competitions. Our approach involves creating a visual analysis tool using unstructured content extracted from TV video streams, by detecting low-level events such as players strokes and ball positions. Through this process, we intend to establish a more precise understanding of tactics, which currently vary between coaches and athletes. An ongoing partnership with the French Table Tennis Federation (FFTT) will enable us to identify key challenges and validate the outcomes of our work.

1 Introduction

Table tennis is a sport that captivates millions of enthusiasts worldwide. As an Olympic discipline, it draws special attention from sports analysts who strive to enhance players' performance and secure gold medals. However, the path to improvement is a multifaceted process encompassing training, sleep, nutrition, and mental preparation, among others. These aspects are typically well-explored and coordinated by networks of experts in various scientific fields to maximize gains and prevent injuries in a domain where marginal improvements matter greatly. Despite this, there is a relatively unexplored research area: tactical analysis.

Tactical analysis in table tennis involves capturing players' overall playing style, as well as their strengths and weaknesses, to enhance preparation before and during games [18]. Currently, this approach remains highly subjective and specific to individual trainers and players. In our research, we aim to redefine and establish objective methods for data collection and efficient presentation of tactics. Our primary contribution lies in the visualization of table tennis tactics, providing coaches and players with powerful visualization tools to quickly and effectively interpret collected data. We will leverage recent advancements in computer vision, knowledge discovery, and visualization techniques, integrating them into a pipeline that will enable us to extract data from any video. Such data will then be included into interactive tools that we will design and evaluate in a user-centered approach with table tennis experts.

- *Aymeric Erades: Université de Lyon, École Centrale de Lyon, CNRS, UMR5205, LIRIS, France; E-mail: aymeric.erades@ec-lyon.fr.*
- *Romain Vuillemot: Université de Lyon, École Centrale de Lyon, CNRS, UMR5205, LIRIS, France; E-mail: romain.vuillemot@ec-lyon.fr.*

2 Related Work

Our research focuses on sports data visualizations, particularly tracking data [12]. Such data are often collected using deep learning methods like in the TTNet system [15] which tracks various visual elements, including players, the ball, the table, rebounds, and the scoreboard. Manual crowdsourcing, as seen in [6], [10], enable tracking and complex attributes input by experts. Ball tracking is particularly important in table tennis, leading to numerous studies on ball detection and trajectory reconstruction [3], [9]. These advances in data collection have enabled novel visualizations. ITTVis [20], for instance, presents sequences of table tennis points using a combination of matrices. Users can access detailed data visualizations by selecting specific attributes of interest. Another example is VisCommentator [5], which employs embedded visualizations that allow users to interact directly with moving objects in the video, providing information on strokes, ball placement, and stroke efficiency. Another approach is seen in Sporthesia [4], which utilizes natural language processing (NLP) on textual commentaries in tennis to generate augmented sports videos. Omnicular [8] offers interactive embedded visualizations for basketball fans during live streaming. It incorporates various data, such as player positions and techniques.

Work on tactics is relatively recent. [7] have developed a method that represents points as a directed acyclic graph (DAG), where each node represents a stroke type. This approach allows them to extract patterns of stroke sequences that contribute to winning or losing points. TacticFlow [19] has been applied to tennis and badminton, utilizing multivariate events to mine patterns from sequences. Tac-Miner [18] enables users to analyze, explore, and compare tactics based on three consecutive strokes and incorporates technical attributes.

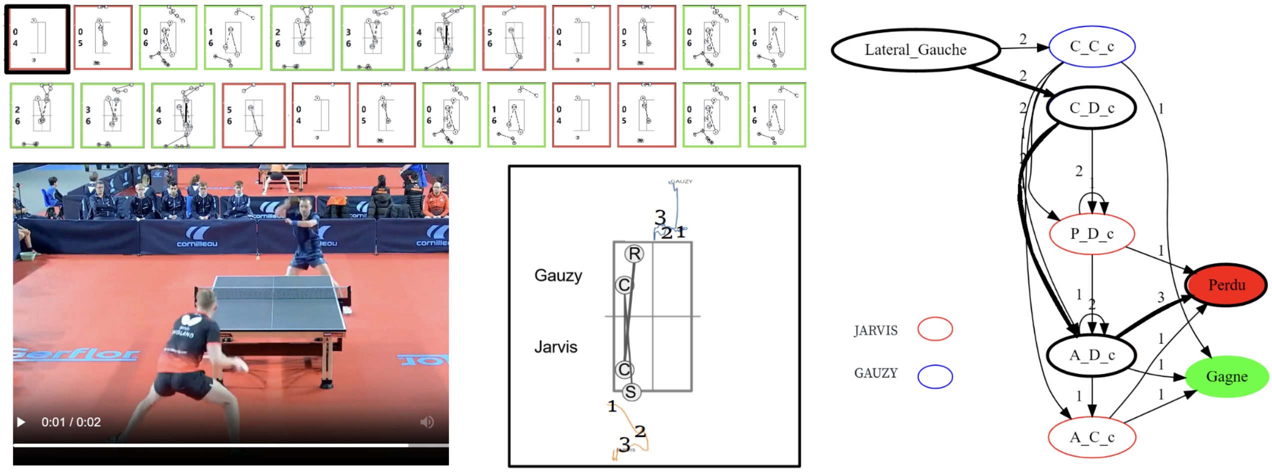

Fig. 1. Example of game sequence visualization using table tennis game overview (top), the focus on a particular rally (left) and a set summary using a graph-based approach (right).

3 Preliminary Visualizations

We are currently conducting a user-centered design study to present table tennis data we collected from various tracking methods. Our goal is to get a better understanding of the data characteristics and role in the analysis process. We are using a *boundary object* approach [17] to enable us to encompass all design aspects related to the table and its associated layers of data. We selected this approach after initial iterations involving table tennis experts revealed limitations with dashboard-based approaches and aggregated statistics, including heatmaps on the table. This finding aligns with previous research in soccer [11]. As a result, our focus has shifted towards incorporating more spatially located events by leveraging detailed player positions (zones, distance to the table), stroke and ball motion details, and a more comprehensive and accurate dataset, as depicted in Fig 1. This design also follows the principles of overview, zoom, and detailed analysis [14] so experts can first look at an interesting rally and pick one (Fig 1, top) and then get the details and video playback (Fig 1, bottom left). We included a preliminary work on tactics discovery [7] represented as a directed acyclic graph (Fig 1, right) over which the selected rally is emphasized (using a black stroke).

Our table tennis experts can now analyze a specific game, i.e. the one from this example which is from the 2023 European championships. This particular match featured French player Gauzy against his English opponent Jarvis. With the game sequence representation (Fig 1, top), analysts can observe the point sequences during which Jarvis served in the first set. By doing so, they can quickly identify the sequences that resulted in points lost (with a red outline). Examining the losing points reveals how they were initiated and which stroke made the pivotal difference. In this example, when Jarvis serves, Gauzy loses three out of four points when he attempts a forehand attack. Analysts can then filter and isolate points for this specific game situation, thereby visualizing the movements of the players and the ball for each point, which can be linked to the corresponding video footage. For instance, on the first point, Jarvis wins by playing near Gauzy, implying that he hit the ball with force and targeted his opponent's elbow, a known weakness among table tennis players. Further analysis will be obtained as we will iterate through the designs.

All visualizations are implemented using D3, ObservableHQ and Plot. This enabled us to quickly share our findings to analysts and collect feedback.

4 Discussion and Future Work

Our next objective is to evaluate the current iteration and move into a next stage of design. Additionally, we plan to adopt a technique-driven approach by exploring the utilization of existing techniques such as direct manipulation of players' positions [16], spatial occupation [1], [13], and motion visualization [21]. We are also eager to deepen the contextualization by contributing to the emerging field of *situated visualizations*, which refers to graphics that depict data in a manner that is relevant and situated within the context of people's activities [2]. In our specific context, we aim to situate events on players' rackets and bodies. We also have initiated a survey to better refine the notion of tactic, targeting head coaches of national teams, as well as a network of coaches and players, for both simple and double games. From the answers, we seek to have a better understanding and incorporation of insights into our designs, either by situating them directly or by using abstract representations as needed.

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