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Analyse Visuelle de la Tactique de Jeu au Tennis de Table

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INTRODUCTION

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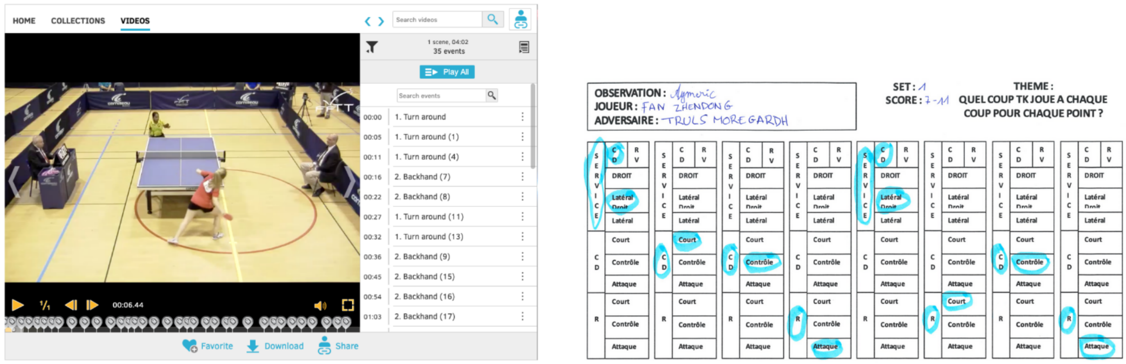
1.1 Context

Table tennis is an Olympic sport since 1988, this made it possible to include this thesis in the Science 2024 project. Science 2024 was created in 2018 in the run-up to the Paris 2024 Olympic and Paralympic Games. The aim was to put science at the service of performance, bringing researchers together so that they could help improve the performance of French athletes during the competition. Many different aspects were involved in the research to improve performance, including video analysis of competitions, which is the field studied in this thesis. This thesis was founded by École Centrale de Lyon. A partnership with the French Table Tennis Federation (FFTT) was established in order to bring the research closer to athletes and coaches and to provide financial support for the thesis. The work was coordinated by Christian Gaubert, scientific advisor within the FFTT.

Table tennis is one of the most popular sports in the world and one of the most watched at the Olympic Games. It is estimated that there are between 300 and 350 million players worldwide. It is a rapidly growing sport in France, with more than 6 million players and 210,000 licensed players. For 2025, almost 50 professional competitions are scheduled, bringing together several hundred players. Video analysis of matches has been used for years and has grown in popularity with the professionalization of the sport. Video analysis within the French team was done either manually or using Dartfish (Figure 1.1, a generic tool that did not offer the necessary flexibility. These analyses could take between 15 and 20 hours per match, which was too long to analyze many matches.



(a) (b)

Figure 1.1 – Examples of tools used by the FFTT to collect data and perform analyses. (a) Represents the Dartfish sequencer, a generic tool used in many sports. (b) Represents a paper sequencer that must be filled out by hand.

The thesis began on September 1, 2023, with the primary objective of improving the performance of French athletes in competition based solely on video analysis. Preparation for the Olympic Games began early on throughout 2024 and took shape with work carried out in direct collaboration with coaches and players starting on July 14, 2024. All of the work made during this thesis, carried out in collaboration with the FFTT was in place during the Paris 2024 Olympic Games. The FFTT decided to recruit two expert table tennis video analysts and professional players to help coaches prepare for matches. Video analysis is used ahead of matches (either the day before or the morning of, depending on the match time) to study opponents and develop tactics with coaches and players that are then applied during the match. During the Olympic Games, the FFTT asked me and video analyst Laurent Cova, who was in charge of video analysis for the men's players, to come so that we could directly help the players and coaches prepare for the matches. This competition was the first collaboration between researchers and coaches during a competition with the FFTT, and to our knowledge, it was also the only collaboration of this type among all the French teams present. The analysis was carried out in three stages. Once a French player's opponent was known, we had to retrieve previous matches between the two players, as well as other matches that could be helpful, the list being provided by the video analyst. Once the videos had been retrieved, we had to collect the data and use the research to obtain initial purely statistical analyses. Once this first step was completed, the video analyst would conduct a more table tennis-focused analysis using the videos and data, and request any additional data that might be needed. Finally, the last step was to prepare video compilations of the interesting points discovered during the analysis and hold a meeting with the coaches and players to develop a strategy.

A part of the next section about table tennis will be published in a book **Data Ping: Table Tennis Performance Analysis With Data**. This book, written in collaboration with Romain Vuillemot, aims to offer an approach to sports analysis through data. This contribution covers the entire process that was initially followed to conduct in-depth research on this subject.

[DP5] Aymeric Erades and Romain Vuillemot. *data ping: table tennis analysis using data.* Springer Nature 2025. [35]

1.2 What is Table Tennis?

Table tennis is a racket sport, played between two or four players, around a table by hitting a ball with a racket. Those interactions between players are called *rallies* that begin with a serve and end with a particular outcome, win or lose, by hitting the ball to the opposite side, until one of them wins the point. Points are won if the opposing player fails to return the ball (*e.g.* he cannot hit it, hits into the net or out of bounds, or if there are double bounces before the return) with a valid stroke.[1]

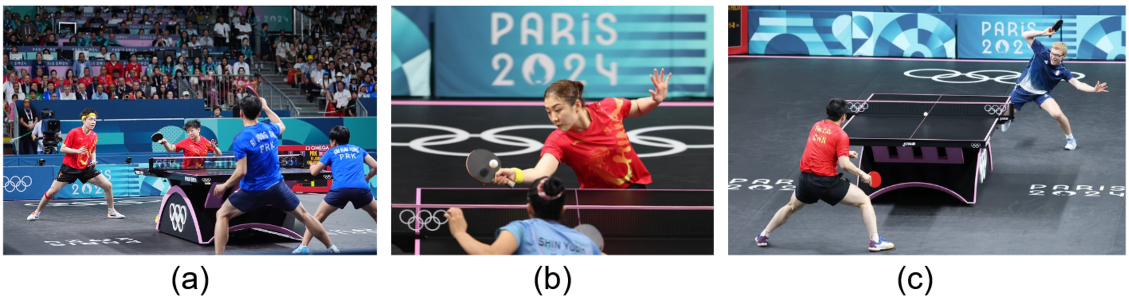


Figure 1.2 – Examples of different individual disciplines. (a) Mixed doubles, opposing the Chinese Olympic champion pair of Wang Chuqin and Sun Yingsha against the North Korean pair of Ri Jong-sik and Kim Kum-yong in the Olympic final. (b) Women's singles, Chinese Olympic champion Chen Meng faces South Korea's Shin Yu-bin in the semi-finals. (c) Men's singles, Chinese Olympic champion Fan Zhendong against France's Félix Lebrun in the Olympic semi-final.

Table tennis is an engaging sport as it is fast paced and technical, but also accessible as table tennis tables are pervasive and anybody can afford to play. Unlike performance-focused sports (*e.g.* running, swimming), which focus on

1. Rules can be slightly more complex in some situation we will see in Section 1.5. Also, in the beginning of the book we focus on male players but female and mixed game exists, as well as doubles.

athletes physical attributes (*e.g.* speed, strength, endurance), table tennis has more tactical aspects. And a very important aspect is that involves interaction with another player, that cannot be always controlled and predicted. The way one player plays will influence the way the other player plays, so the course of a match can be totally different depending on the players' choices. These choices are known as tactical choices. Tactics are the sequence of players' strokes. Good tactical choices can totally reverse the course of a match. This applies to both professional and amateur players. Understanding what works and what doesn't is crucial to a match.

A bit of History in Table Tennis: back in the late 19th Century

Table tennis originated in England in the late 19th century. It was originally created during a dinner party where prominent figures were discussing tennis and used the table to explain game patterns. The first game is said to have used a champagne cork as a ball, cigar boxes as rackets, and books as a net. At first, the game was seen as a pastime for the wealthy classes. In 1890, Englishman David Foster introduced the first table tennis game (Figure 1.3). The first national championships were held in Hungary in 1897. The first world championships took place in London in 1902, the same year that the British Table Tennis Federation was founded. Although designated as such, the first world championships recognized by the International Table Tennis Federation (ITTF) were officially held in London in 1926. It was on this occasion that the ITTF was created. Eight countries participated in this first edition: England, Austria, Germany, Hungary, India, Sweden, Czechoslovakia, and Wales. Hungary won the men's team event and Roland Jacobi of Hungary won the men's singles event. In the 1950s, table tennis became very popular in Asia, characterized by Japanese dominance, with the Japanese excelling in the World Team Championships between 1954 and 1959. Chinese supremacy began in the 1960s, notably with player Zhuang Zedong, who was three-time world champion in 1961, 1963, and 1965.

The history of table tennis is also shaped by equipment and techniques. In 1901, Englishman James Gibb brought back a celluloid ball from a trip to the United States. In 1902, E.C. Gould introduced rubber-covered rackets with rubber pimples for the first time. In 1926, with the creation of the ITTF, the official dimensions of the table (271x152x76cm) and the 38mm ball were established. In 1937, in order to encourage a more offensive style of play, the height of the net was lowered from 17.50 cm to 15.25 cm. This was mainly due to the 1936 World Championships. The first rally of the match between French-Polish player Alojzy Ehrlich and Romanian player Farcas Paneth lasted 2 hours and 12 minutes (the longest rally in history), and the longest match in the world between French player Michel Haguemauer and Romanian player Marin Goldberger lasted 7 hours and 30 minutes, ending in victory by coin toss. In 1977, during the World Championships in Birmingham,

Figure 1.3 – Lithograph segment, earliest known action game of tennis on a table: David Foster (ENG) 1890. One of 2 known examples.

the serve launched called "Chinese service" (Figure 1.4 (b)) was introduced for the first time, with Chinese players making it a central element of their tactics rather than a simple way of putting the ball into play. During the same period, fast glues appeared, making rackets much faster, and topspin also appeared. In 2000, the size of the ball was changed to 40 mm for improved television viewing. In 2001, game score changed from 21 to 11 points. Fast glues were banned in 2008. In 2016, celluloid balls were replaced by plastic balls. All these rule changes and equipment improvements have led to developments in the game tactical aspects.

Figure 1.4 – Example of how table tennis today. (a) Chinese player Zhang Jike performing a backhand flip while bending his legs. (b) Ma Long performing a "Chinese serve". (c) Lin Gaoyuan performing a topspin in a difficult position.

Table tennis is currently a high-level professional sport. It requires significant athletic abilities in terms of both endurance and strength in order to be among the world's best players, as can be seen in Figure 1.4 (a) with Zhang Jike on his toes performing a backhand flip. In addition to the physical aspect, the technical aspect is another particularly visible element, with players having to perform extremely precise shots, as can be seen in Figure 2 (c) where Lin Gaoyuan performs a forehand topspin shot in a difficult position and completely stuck to the table.

A more recent History: Olympics and the 2024 Paris Final

Table tennis became an Olympic sport at the 1988 Olympic Games in Seoul, with the first gold medals awarded to Korean player Yoo Nam-kyu and Chinese player Chen Jing. Chinese dominance is also evident in the Olympic Games, where China has won 37 gold medals out of the 42 awarded between 1988 and 2024. Notable examples include Ma Long, who holds the record for Olympic titles in the men's competition with three titles, and Deng Yaping and Zhang Yining in the women's competition with four titles each. Only one non-Chinese player has ever won the Olympic men's singles title: Sweden's Jan-Ove Waldner in Barcelona in 1992.

The Olympic Games final between **Fan Zhendong** and **Truls Moregardh** ended in victory for **Fan Zhendong** 4 games to 1. The top-ranked **Fan Zhendong**, reigning world champion, was the favorite for the match, but **Truls Moregardh** managed to keep him on his toes for the whole match, and his performance during the competition was a great surprise given his ranking and his last competitive performances. **Fan Zhendong** is a very strong player when rallies are played backhand to backhand, and this was the tactic he implemented from the start of the match, playing mostly on **Truls Moregardh**' left side. This tactic surprisingly led to the loss of **Fan Zhendong**'s first game. In the second game, **Fan Zhendong** decided to adapt his tactics by playing more on the right-hand side, which proved him right and won him the game. In addition to the direct confrontation between the two players, there was a tactical confrontation that was invisible at first glance. This naturally leads to the following questions: why did **Truls Moregardh** win the first game, how did **Fan Zhendong** manage to reverse the tendency, which player was better able to adapt? These seemingly simple conditions can lead to complex answers, which coaches seek to resolve before and during matches. In this book, we look at different approaches to answering these questions

1.3 Why Using Data?

Sports have so many facets that there is no one single data type needed to master to discover analytics. Sports can indeed be observed as spatially continuous trajectories chaning over time; discrete events; a network of passes; calendars of games; single aggregated performance score; and so on. This apparent compelxity can be approached with a hierarchical structure of available sports data. as the top are high-level *physical performances* or *games outcomes* that usually **aggregate** large datasets into a few measures. Those measures usually are derived from rules or interpretations of the game. At the bottom the hierarchy are what we call raw data or observations, which usually are captured by sensors or simple observations like position and basic events. Those raw data under their simplest form are a series of data points, with space and time attribute. They still need some treatment to be meaninful, such as trajectories reconstruction.

As mentioned earlier, tactics are important, and **Fan Zhendong** adopted a different tactic between the first and second games, which enabled him to reverse the outcome of the first game. To be seen, this tactical change requires a numerical analysis of game events. In the first game, **Fan Zhendong** played 28 strokes on the left-hand side of the table, compared with 6 on the right-hand side. In the second game, **Fan Zhendong** played 16 strokes on the left-hand side, compared with 29 on the right-hand side. By quantifying the information on the strokes' zones, we can easily compare the differences between the two games and see the change in tactics. This example highlights the importance of data in tactical analysis. Data covers all information specific to players, matches or competitions. Studies have been able to work with this data to improve sporting performance.

Simple data based on a single stroke, as for the service, could be studied [36]. The aim is to understand the tendencies of each player when serving, based on the placement of service bounces. With greater complexity, the sequence of several strokes is the most widely studied tactical analysis, and we can cite [132], such as the exploratory search for winning tactics based on the first strokes of rallies and their characteristics. To this end, data based on both strokes and player positions have been studied [40].

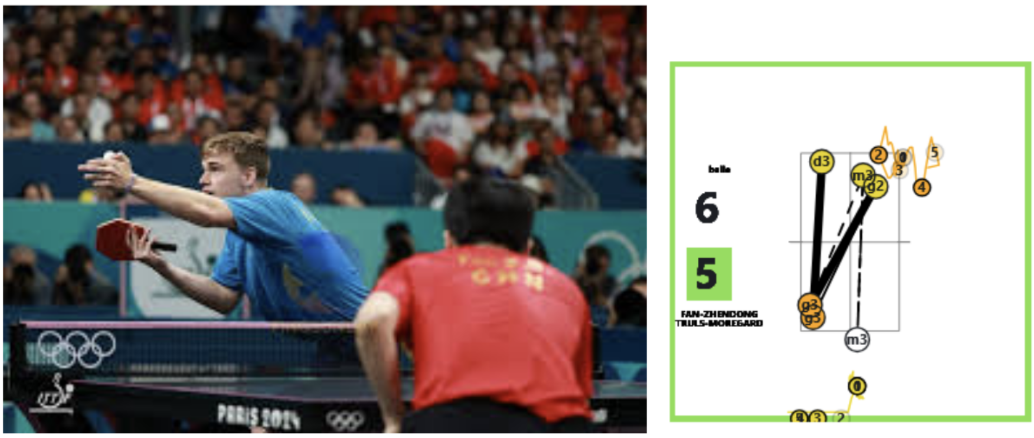


Figure 1.5 – Example of table tennis game: On the left, a screenshot captures **Truls Moregardh** when serving, facing **Fan Zhendong** positioned as the receiver during the 3rd set of the Paris 2024 Olympic final. On the right, data from the rally provides an analytical perspective of this serve.

1.4 Example of Table Tennis Tactics

The main table tennis tactics consist in winning points by exploiting opponents weakness. Different types of tactics exist, based on players' specific characteristics. Some tactics are player-independent, based on physical and biomechanical constraints.

In order to give several examples of analyses, we propose the study of these examples divided into different categories according to the type of analysis used. These categories are discussed in subsequent sections to illustrate how the data required for these analyses is collected. Tactics based on ball placement, as will tactics that relate ball placement to player position. Tactics involving a succession of shots.

Serve and Return

The serve and return are the first strokes made by both players. The choice of position and type of shot greatly determines the outcome of the points. Figure 1.6 illustrates the case of the side chosen to serve short. We can see that when **Truls Moregardh** serves short to **Fan Zhendong**'s left, he wins 10 points out of 15, while when he serves short to **Fan Zhendong**'s right, he wins 10 out of 19. This illustrates that one of the two sides (the left one) is more favorable to **Truls Moregardh**For the return, we can similarly observe that some areas are more favorable for **Fan Zhendong**Ẇhen he plays long, he wins 5 point 14, whereas when he plays short, he wins 16 out of 28. On the whole, he wins when he plays short, whereas he loses when he plays long. In addition to their positions, the returns can have different intentions. We distinguish between offensive returns (topspin and flip) and defensive returns (push). When **Fan Zhendong** makes an offensive return, he wins 10 rallies out of 17, whereas when he makes a defensive return, he wins 11 rallies out of 29. **Truls Moregardh** wins 9 rallies out of 15 on offensive returns and 14 out of 33 on defensive returns. This shows that offensive returns are more favorable to **Fan Zhendong** than defensive returns, and defensive returns are slightly more favorable to **Truls Moregardh** than offensive returns.

Examples of tactics:

1. Serve long: usually players short to avoid their opponent to attack, they serve long to surprise
2. Serve short without spin: a serve that forces the opponent to attack under unfavorable conditions
3. Return with the backhand in the short forehand: allows returner to attack short balls more powerfully than with the forehand.

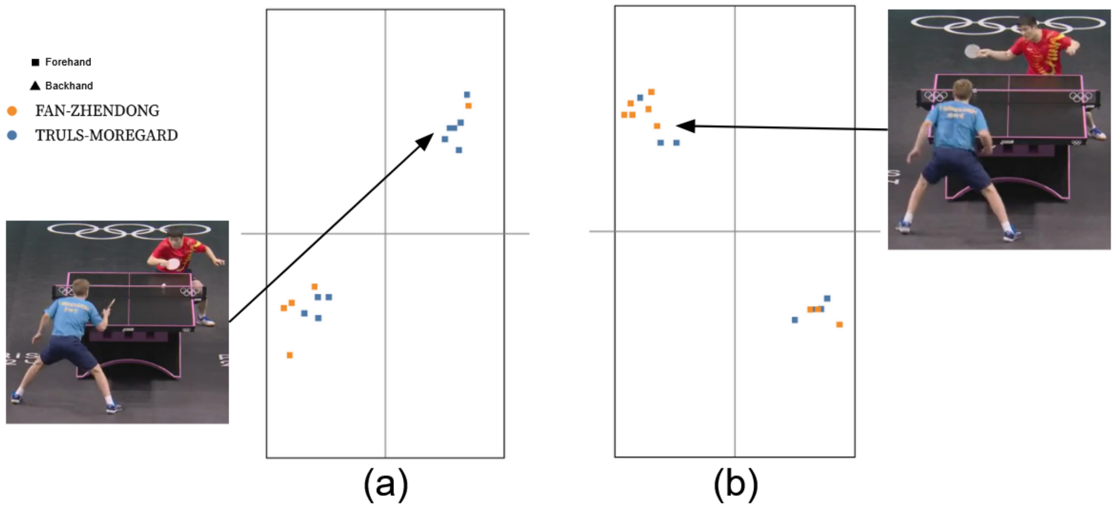


Figure 1.6 – Example of 2 different serving positions when **Truls Moregardh** serves short. Dots represents the bounce position and the color the winner of the rally. (a) Represents the left side. (b) Represents the right side.

In Sections 3.4 and Sections 3.5 of the Chapter 3, we present analyses that characterize both the services and returns of players, as well as the interdependence between these two strokes.

Ball Placement

Ball placement can reveal favorable or unfavorable zones for players. A first example was given with serves and returns. Figure 1.7 illustrates some groupings that are almost totally win-win for one of the two players, all strokes during the match are displayed. Although these zones are not always present during matches, when they are, they become very important as it is possible to greatly maximize your chances of winning points just by playing in these zones. We can see that when the 2 players play, they both have areas that are almost always losing and areas that are almost always winning. The obvious strategy resulting from this first analysis is simply to avoid zones that are losing almost all the time and to play in zones that are winning almost all the time.

Examples of tactics:

1. Play on side and the other side: playing one way and then the other makes your opponent move and have to switch from forehand to backhand (or vice versa), which can be technically costly.
2. Play in little-used zones: in a similar way to the long serve, playing in little-used zones allows players to surprise their opponent

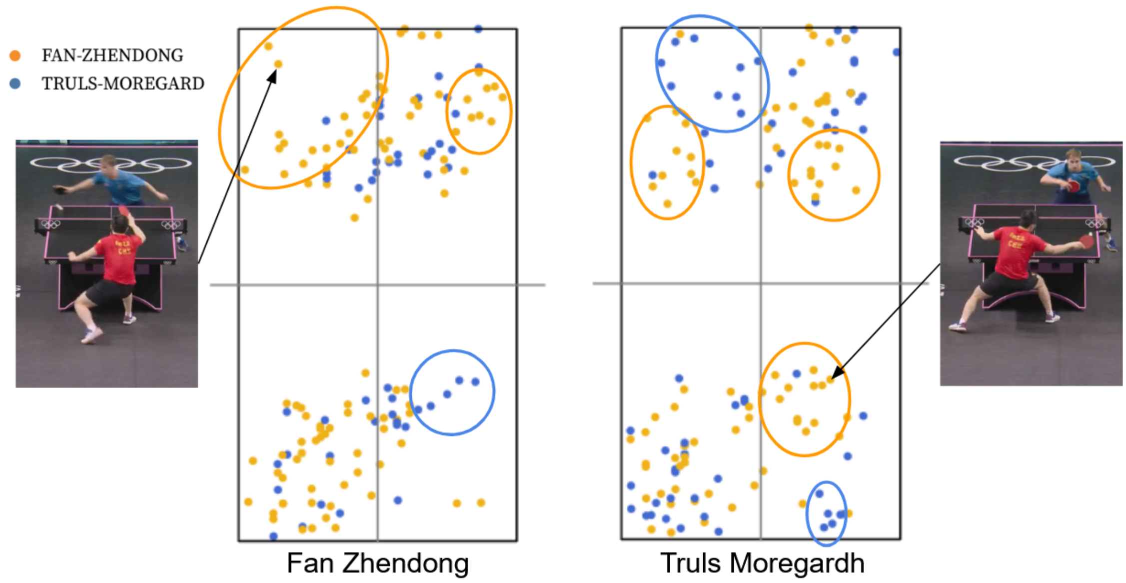


Figure 1.7 – Examples of winning groupings. The table on the left shows all **Fan Zhendong**'s bounces, the table on the right all **Truls Moregardh**bounces. In orange are the bounces that led to a **Fan Zhendong** victory, in blue those that led to a **Truls Moregardh** victory. The circles represent groups in which more than 90% of the rallies were scored by the same player, and their color represents the player who scored them.

3. Play on the short side: forces the opponent to make long moves without being able to attack in a favorable position.
4. Play in the two-bounces zone: an area where it is difficult to know whether a potential second bounce would be on the table or off, creating hesitation about whether to attack or not.

Ball Placement in Relation to Opponent's Position

The opponent's position is important in defining tactics. In many tactics, the aim is to play in a zone that will hinder the opponent. The expression "don't play in your racket" is often used to express the importance of playing in a zone that is difficult for the opponent to return. Several difficult zones can be identified: the zone far away from the opponent, the pivot zone and the wrong-footed zone. Another type of zone can be identified as a little-used zone that aims to surprise when found. Figure 1.8 shows an example of the 4 difficult zones mentioned above. These areas clearly reflect a strategic importance: during the match when **Truls Moregardh** serves, they account for 11 of his 25 rallies won. The forehand zone to surprise the opponent when **Truls Moregardh** serves, alone accounts for 10 of **Fan Zhendong**'s 22 rallies won.

Examples of tactics:

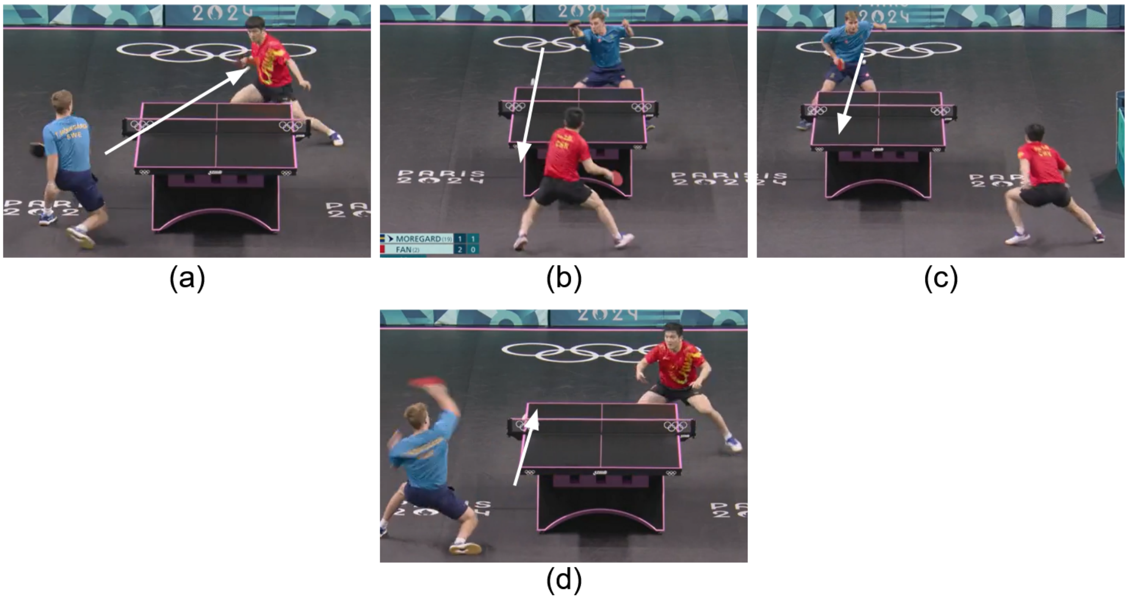


Figure 1.8 – Example of the 4 difficult zones for returning the ball: (a) The pivot zone, the area between the belly and the elbow, where the forehand and backhand are difficult to execute. (b) The wrong-footed, the area opposite your opponent's direction. (c) The zone far away. (d) The forehand zone, rarely used during this match, which surprises the opponent.

1. **Pivot zone**: Pivot zone is the zone between the elbow and the belly which is between the forehand and the backhand, for which both strokes are difficult to execute correctly.
2. **Wrong footed**: it is the zone opposite the opponent's movement his inertia makes it difficult to reach the zone
3. **Far away**: the zone that is far away from the opponent and where he needs time to reach it
4. **Opposite to that anticipated**: this is the zone opposite to the one that the opponent has anticipated, even if he doesn't move, he can wait for the ball in a zone, particularly with the orientation of his racket.

The **pivot zone** and the **far away zone** depend on the player's position and the bounce of the ball on a given stroke. These two examples are studied in Section 4.4 and Section 4.5 The **wrong footed** and **opposite to that anticipated** zones are tactics that depend on the dynamics of the players and cannot be studied at a given moment only. Section 4.5 offers analyses of these two examples of tactics.

Succession of Strokes

Tactics in table tennis are not limited to a single position: some tactics may require several consecutive strokes. Often the 4 first strokes are used to create tactics. Figure 1.9 shows an example of a multi-stroke tactic that wins 6 out of 7 times. This tactic is used when Trus Moregardh is serving. These are the points when **Truls Moregardh** serves short to **Fan Zhendong**'s left and then no longer plays to the right of the first shot, but always to the left of **Fan Zhendong**'s table. This is a winning tactic for **Truls Moregardh**

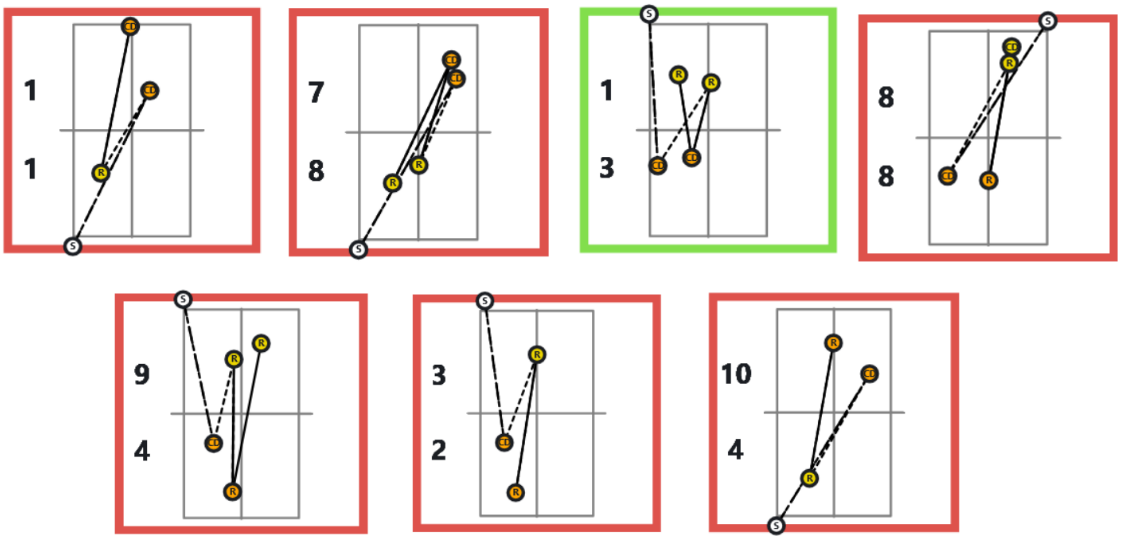


Figure 1.9 – Multi-stroke tactic. In red are the rallies won by **Truls Moregardh**, in green those won by **Fan Zhendong**. All this rallies start with **Truls Moregardh** serve. The tactic is a serve in the left side and the next stroke from **Truls Moregardh** still in the left side but more to the right than the serve. Only the 4 first strokes of the rallies are represented.

Examples of tactics:

1. Play short then long: forces the opponent to move forward then backward
2. Play twice in the same place: allows you to outflank the opponent if they anticipate a change.
3. Stay on the backhand side and then play on the forehand side: play everything on the backhand side to surprise the opponent when playing on the forehand side.

1.5 Rules of Table Tennis

As table tennis is a confrontational sport, there are clear and precise rules to ensure a structured game that leaves no room for interpretation. Like many other sports, table tennis has undergone a process of evolution, with both sporting and technological advances in the equipment used. This evolution has contributed to the evolution of table tennis rules. There are several categories of rules: those specific to rallies, those specific to strokes and those specific to equipment. In this section, we will look at the rules specific to singles, while doubles has its own rules[2]. The main rules are provides in Appendix 1

1.6 Scientific Challenges

To successfully analyze table tennis tactics in high-level competition, several scientific challenges must be addressed:

- **Automatic video segmentation**: Table tennis match videos contain moments of play during points and moments of non-play between points, during timeouts and side changes. In a match, playing time accounts for approximately 30% of the total match duration. Video segmentation allows only the moments of play to be kept for analysis, and also provides information on the timing and chronology of rallies. The difficulty in automating video segmentation lies in the complexity of understanding the sequences of play. different competitions have very different scenes in terms of colors and object layouts, and camera angles also vary greatly. All these conditions make it difficult to identify potential moments of play. Furthermore, understanding the movements of the players or the ball is necessary to obtain a precise delimitation of the beginning and end of rallies. Although this task greatly reduces the time needed for analysis, it represents only a small percentage of the time spent on manual data annotation, between 5 and 10% of the total time. This task is not studied in this manuscript; we opted for a manual approach that can be carried out independently of the collection of detailed data.

- **Identification of structured data from videos**: This is the most important step in data collection, as all tactical analysis is based on this data. It relies on three main detections: ball rebounds, player positions, and player strokes. Detecting the ball is a complex task because it is a small object moving very quickly, and there can be numerous occlusions, mainly due to the players. Table tennis has many different types of strokes that are important to distinguish during analysis. For example, an offensive stroke cannot be analyzed in the same way as a defensive stroke. Therefore, a precise distinction between the different strokes is necessary. At the highest level, there can be no errors in the stroke type data, this is the greatest

2. https://documents.ittf.sport/sites/default/files/public/2021-04/2021ITTFHandbook.pdf

constraint for this task. We have chosen to adopt a semi-automatic approach to collect structured data, aiming to automate continuous data collection and making the collection of so-called event data manual. This work is presented in Chapter 2. Automating the collection of all data automatically is very challenging given the zero-error requirements, and this is one of the prospects for all of this work.

- **Data analysis from collected data**: Data analysis is essential, but the difficulty lies in being able to identify relevant elements that are not just a record of what happened in a match, but an indication of strengths and weaknesses that can be used to develop strategies. Pattern detection is one of the important solutions, but the players' desire to vary their play greatly makes the task of comparing similarities quite complex. There are many different approaches to analyzing the rich data collected. We propose three different approaches, which are presented in Chapter 3.

- **Simple and effective data communication**: Our work is mainly aimed at coaches and players, people who are not trained in data analysis or understanding. The difficulty lies in being able to focus on communication that is easily understood by everyone, and to choose the relevant data wisely.This section is the main contribution of this thesis. It is presented in Chapter 4 through three different visualization approaches.

1.7 Contributions

7 papers have been published during this PhD on three different topics. Structured data extraction from table tennis videos, structured data analysis, and structured data visualization:

[35] Aymeric Erades, Pierre-Etienne Martin, Romain Vuillemot, Boris Mansencal, Renaud Peteri, Julien Morlier, Stefan Duffner, and Jenny Benois-Pineau. *"SportsVideo: A Multimedia Dataset for Event and Position Detection in Table Tennis and Swimming". In: MediaEval Workshop 2023. MediaEval (Multimedia Evaluation Benchmark) (2023).* [35]

[14] Gabin Calmet, Aymeric Erades and Romain Vuillemot. *"Exploring Table Tennis Analytics: Domination, Expected Score and Shot Diversity". In: Machine Learning and Data Mining for Sports Analytics.* Ed. by Springer Link. Communications in Computer and Information Science. Turin, Italy, Sept. 2023. url: hal-04240982 [14]

[43] Aymeric Erades, Thomas Papon and Romain Vuillemot. *"Characterizing*

Serves in Table Tennis". en. In: Machine Learning and Data Mining for Sports Analytics. Ed. by Ulf Brefeld, Jesse Davis, Jan Van Haaren, and Albrecht Zimmermann. Vol. 2460. Series Title: Communications in Computer and Information Science. Cham: Springer Nature Switzerland, 2025, pp. 3–13. url: https://link.springer.com/10.1007/978-3-031-86692-03 [43]

[40] Aymeric Erades and Romain Vuillemot. *"Player-Centric Shot Maps in Table Tennis".* In: Computer graphics Forum (Proc. Eurovis) (June 2025), p. 10. url:hal-04997867 [40]

[37] Aymeric Erades, Lou Peuch and Romain Vuillemot (2025). *"Investigating Control Areas in Table Tennis".* In: Sixteenth International EuroVis Workshop on Visual Analytics (EuroVA). Luxembourg, France, June 2025. url:hal-05032405 [37]

[7] Riad Attou, Marin Mathé, Aymeric Erades and Romain Vuillemot. *"Analysis of Service Returns in Table Tennis".* en. In: (Sept. 2025) [7]

[39] Aymeric Erades, Romain Vuillemot. *"How Camera Angle Impact Table Tennis Ball Bounce Tracking".* en. In: (Sept. 2025) [39]

1 book on analyzing table tennis through data is currently being submitted:

[DP5] Aymeric Erades and Romain Vuillemot. *data ping: table tennis analysis using data.* Springer Nature 2025. [35]

In addition to these papers, a datasets have been introduced. We provide different repositories of our work:

- `https://github.com/centralelyon/table-tennis-returns`
- `https://github.com/centralelyon/table-tennis-analytics`
- `https://github.com/centralelyon/table-tennis-control-areas`
- `https://github.com/centralelyon/player-centric-shot-maps`

A software repository was created to make the data collection and certain analyses available to the FFTT. Throughout the thesis, dissemination was carried out to a wide audience, enabling them to understand how science can help sport.

Chapter 2

EXTRACTING STRUCTURED DATA FROM TABLE TENNIS VIDEOS

Contents

The goal of this chapter is to present the work dedicated to extracting structured data from videos. It is based on our assumption that such videos already exist from TV broadcasts channels available online. The work presented in this chapter is composed of the following two articles.

[35] Aymeric Erades, Pierre-Etienne Martin, Romain Vuillemot, Boris Mansencal, Renaud Peteri, Julien Morlier, Stefan Duffner, and Jenny Benois-Pineau. *"SportsVideo: A Multimedia Dataset for Event and Position Detection in Table Tennis and Swimming". In: MediaEval Workshop 2023. MediaEval (Multimedia Evaluation Benchmark) (2023).*

[39] Aymeric Erades, Romain Vuillemot. *"How Camera Angle Impact Table Tennis Ball Bounce Tracking"*. en. In: (Sept. 2025)

The work is completed with the tools built during the PhD such as annotation tools that were primarily related to code development.

2.1 Introduction

In table tennis, the various objects involved in the game provide the essential information for data collection. The various objects in the game are identified as the elements that influence rallies: the players, the ball, the rackets and the table. Spatio-temporal information and its evolution enable us to deduce so-called event data, which are complex data appearing at a given moment, combining attributes in addition to spatio-temporal information. This data is indispensable for sports analysis. Among the objects specific to table tennis, the table is fixed, the players can move independently of the other objects, the rackets are dependent on the players and the hand that holds them, and finally the ball, although independent of the movement of the other objects, has a trajectory induced by the strokes of the players. Object tracking is one way of obtaining spatio-temporal information from objects. Tracking consists in detecting the position of an object at a given moment and being able to follow it over time. In our case, based on the video, this means being able to detect and track it over all the frames of the video. Each of these objects has very different characteristics, such as their size or shape, making detection more difficult. Players are one of the most studied problems, giving rise to numerous approaches and solutions in the literature, while the difficulty lies in occlusion with the table, making their detection more complex. Ball tracking is one of the biggest problems in table tennis, as the ball is considered to be a small, fast object with a size of 40mm and a speed that can exceed 30 m/s, and cameras are unable to capture the shape and position of this object clearly and accurately. The table, on the other hand, is the only fixed object, which means that tracking is not necessary, only detection is important. Numerous computer vision algorithms have been developed and improved in recent years, making it possible to address the tracking problem for each of the different objects. In this section, we focus mainly on ball and player data, which are sufficient for game analysis.

2.2 Related Work

Match data extraction mainly falls within the field of computer vision. Several subfields are involved, such as object detection, tracking, and action detection. Other fields, such as visualization or data science, initially use these methods before processing the data.

2.2.1 Clip Segmentation

The general problem consists in breaking down a continuous video into segments that share a similar semantic: *e.g.* same action, individual or camera shot. Videos of sports competitions feature different camera angles, including shots other than those of the game itself. In table tennis, this translates into slow-motion shots or close-ups of the players or the audience. In team sports such as soccer or basketball, this translates into similar changes in camera angles when the ball is not in play. Tracking for sports analysis, particularly tactical analysis, is based on moments in the game. For basketball [128] uses the fact that different shots have distinctive color distributions to distinguish between different shots. It uses a Hidden Markov Model to segment shots based on these color differences. Similarly, for badminton [19] segments game footage into clips using a ResNet-18-based neural network. This allows each frame to be classified as either a court view or a non-court view based on the fact that court views contain clear and unique visual features.

2.2.2 Object Tracking

Object tracking is one of the essential steps in data collection in many sports. Regardless of the sport [94] highlights the issue of multiple object tracking, which faces problems of occlusions and re-identification of objects across images. These issues are particularly prevalent in sports where Objects cross paths in the camera's field of view. Tracking involves detecting objects in different frames and then associating the same unique identifier with an object in different frames. Recent advances in deep learning have led to the development of models that are highly effective at detecting objects. Recent tracking algorithms are based on deep learning models to perform detection. Among the methods cited by [94], the method that is widely used today is the detection and prediction method. This method aims to detect an object, then predict its future position and compare future detections with predictions to correctly associate objects from one frame to another.

Object detection is the first step in tracking. Several approaches are possible for object recognition based on object characteristics such as color, intensity, characteristic points, or spatialized color histograms. It is also possible to use a combination of several characteristics to obtain a better representation of the object. Or even shapes. Various examples of detection algorithms are given from [62]. Object detection can be performed once or on all images in the video. Semantic segmentation is very costly on a static image but much less so on moving objects. Moving objects can be detected using background subtraction or optical flow. These approaches are particularly useful in table tennis, where the camera is fixed, making the entire scene static. This makes it possible to isolate the foreground, which consists solely of moving objects, from the background, which consists of the static scene. Tracking an object in frame t is done by searching for the same object in frame t+1 in a region close to the detected position of the object in frame t, resulting in gains in both computation time and accuracy.

2.2.3 Players Tracking

Player tracking is a recurring task in sports analysis, and recent advances in deep learning have made it possible to address the issue of player detection effectively, such as [111], which uses the popular deep learning model YOLOv5 [59]. In team sports, a common method is to detect players across all frames and then identify them [111, 128]. To detect football players [111] uses YOLOv5 (Figure 2.1 (a)), while [128] uses Deformable Part Model for basketball players detection (Figure 2.1 (b)). Some models, such as [22] for badminton, classify pixels as background and foreground to detect players, who are moving objects.

Figure 2.1 – Example of different detection methods in two team sports. (a) Shows the process of detecting players, up to tracking, using Deformable Part Model for basketball player detection from [128]. (b) Shows object detection (players and ball) for soccer using the YOLOv5 model from [111].

The problem of identifying players varies greatly depending on the sport. In badminton [22], the side on which players position themselves based on the score is known, whereas in team sports [111, 128], the position of players does not allow for identification.For basketball [128] uses a player tracking method that minimizes the distance between the detection position and the prediction position. In this way, player identification is only performed once per sequence, whereas [128] performs player identification on each frame, which then allows player tracking. For player identification, [111, 128] adopt the same approach, using characteristics such as the players' morphology or clothing to extract features that allow them to be identified from one another.

Player tracking allows us to know the position of players in the image, which means that the position of players is in pixels. In order to obtain the actual position in the playing space, a transformation from the position in the image to a real position is necessary. To do this [111, 128, 22] all use the same method, employing a mathematical transformation called homography to achieve this. This transformation requires knowledge of reference points in the image and their corresponding locations in the real scene. For these three different sports, it uses recognition of the lines on the field as references (Figure 2.2).

2.2.4 Ball Tracking

Tracking the ball is different from tracking players. In a match, several people may be visible, including the players, the referee, and people outside the playing area, which requires identification among all the people to know who the players are. However, due to the characteristics of table tennis, we can be sure that there is only one ball present during the game. Good detection is sufficient to perform tracking. The ball is smaller than the players and moves faster. It must comply with the same standards for all competitions, namely a white color and a size of 40 mm. These specific characteristics mean that a different approach to player detection is possible.

The properties of the ball make it possible to detect it using its color and movements thanks to colorimetry and/or background subtraction methods [91, 90, 129, 103]. Background subtraction combined with colorimetry filtering makes it possible to recognize moving objects that have the same color as the ball [91]. The ball's trajectory follows the laws of physics, so it is possible to predict the ball's future position based on its previous positions. By using speed and acceleration [90] define a search area on the next frame in which to perform detection. The quality of detection can be quite sensitive to the choice of colorimetry filtering threshold. To make detection less sensitive to the threshold, [129] uses two adaptive thresholds. The first allows for coarse filtering, and the second allows for more precise filtering of the pixels belonging to the ball. These thresholds are adaptive, and are adjusted iteratively to allow for the detection of a single object as a ball. For tennis [103] takes a different approach to using background subtraction to detect the ball trajectory. It uses motion frames, which are frames derived from background subtraction, and merges 10 consecutive frames. This allows it to track

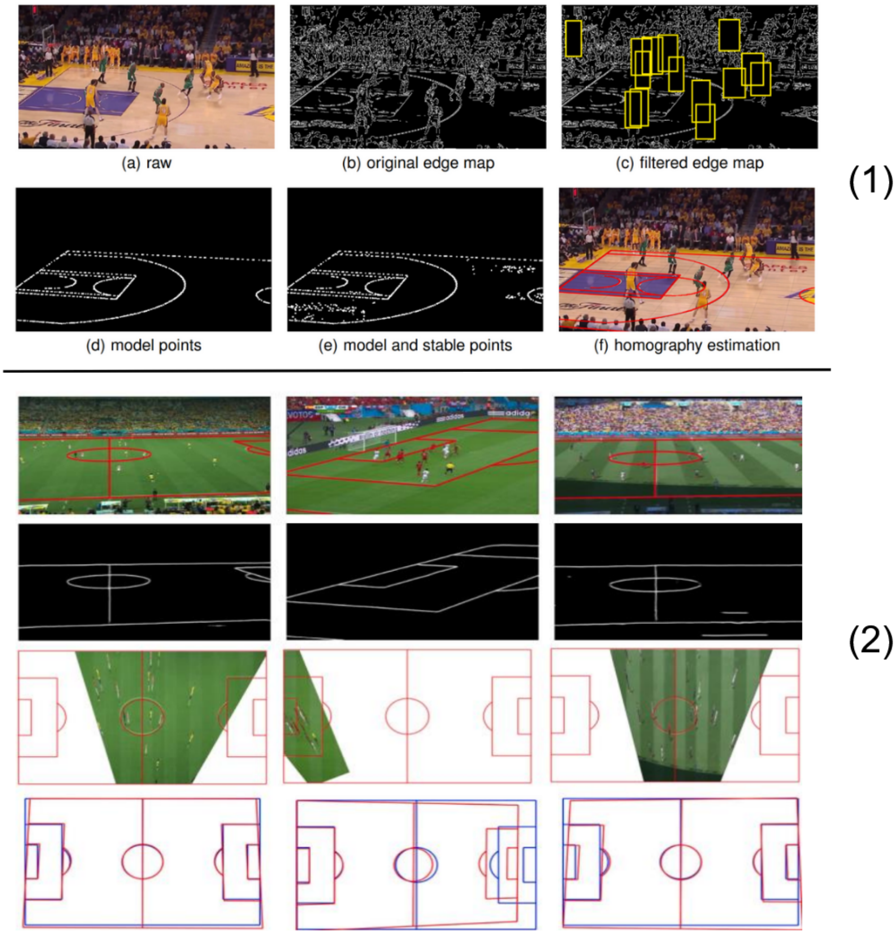
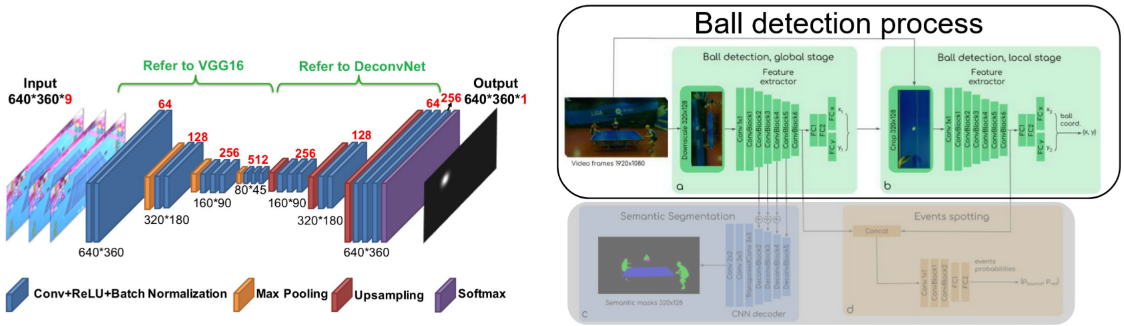


Figure 2.2 – Example of detecting lines on playing fields used as references to calculate the actual position of players in space using homographies. (1) Detection of lines on a basketball court using Canny edge detection, from [128]. (2) Detection of lines on a soccer field using Unet, a deep neural network architectural approach for semantic image segmentation, from [111]

the ball. By reducing the search area to the court area, they are able to detect the ball's trajectory directly and its bounce.

Advances in deep learning have also led to new methods for ball tracking. To detect the ball in soccer [111] uses the same model used for player detection, YOLOv5. For ball detection [51] studied two approaches: Mobilnet deep network architecture using the Single Shot Detection (SSD) method, which was not fast enough for their task, and a faster semantic segmentation approach. Semantic segmentation allows each pixel in the image to be assigned a probability that it belongs to the image. The ball is then detected by filtering the pixels around the pixel with the highest probability of belonging to the ball using a threshold. This segmentation is based mainly on the color of the pixels. Semantic segmentation is also used by [118, 58] to detect the position of the ball (Figure 2.3). TTNet [118]



(a) (b)

Figure 2.3 – Example of neural network architectures that can detect the ball using semantic segmentation. (a) Shows the Tracknet architecture [58], which takes three consecutive frames as input and outputs a heatmap showing the probability of pixels belonging to the ball in the last of the three frames. This heatmap is then used to detect the ball. (b) Shows the architecture used by TTNet [118]. The model is divided into two parts: the first performs a rough detection of the ball's position, and the second detects it precisely in the area extracted by the first part.

uses a two-step detection method: an initial detection roughly locates the ball, then a second detection accurately detects the ball within the region detected by the first detection. Tracknet [58] for tennis improves detection by using multiple frames as input to the network, allowing the model to learn the trajectory of the ball. This way, even if the position of the ball is obscured by a player, the model can still make an estimate. The high speed of the ball often makes it blurry and distorted in the image. To improve image quality [69] proposes a first step consisting of improving the image quality using continuous wavelet transform before performing detection using a Probabilistic Neural Network [112].

2.2.5 Pose Estimation and Classification

The tracking methods previously studied are based on detecting the entire player using a bounding box around the player or segmenting the player. This representation gives us more information than just a simple position, thanks to the arrangement of the person's body parts. In this way, it is possible to recognize what the player is doing and what type of game action is taking place.

The tracking methods previously studied are based on detecting the entire player using a bounding box around the player or segmenting the player. This representation gives us more information than just a simple position, thanks to the layout of the person's body parts. In this way, it is possible to recognize what the player is doing and what type of game action is taking place. To classify the players' actions and the umpire's calls in cricket [65] uses images of the players' actions and the umpire. To do this, they use a Convolutional Neural Network to classify the images of the players. It takes an image as input and classifies it into the different defined categories. Although this method has proven itself, it is based on a single input image, which means that there is a loss of information about the players' movements. Since shots are continuous actions, they are defined with a beginning and an end and are represented over several frames.

To take into account the temporal dimension of strokes [82] in the context of stroke analysis in table tennis, a deep learning algorithm is used that takes several frames as input. To do this, they use a 3D convolutional siamese network model, which allows two different inputs to be taken with two sub-networks sharing the same weights. Unlike 3D convolution, which allows convolution on a packet of images, this allows temporality to be taken into account. This network takes the video of the stroke and the corresponding optical flow as input.

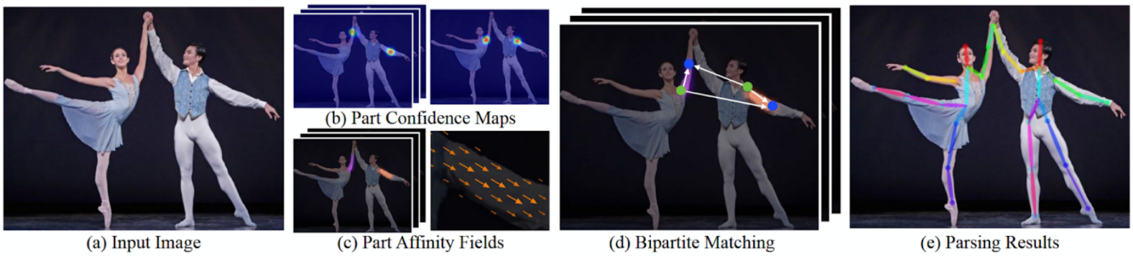


Figure 2.4 – Explanation of how Openpose works [16]. (a) Corresponds to the RGB image used as input to the network. (b) For each keypoint, it creates a confidence map highlighting possible keypoints. (c) Creation of Affinity Fields to match keypoints. (d) Matching of keypoints. (e) Final result of pose estimation.

Using videos of players allows us to recognize actions, but from one match to another, players may have different colored jerseys or different body types, so there are many visual differences. However, certain elements can provide a lot of information about players' actions, such as their characteristic points: hands, elbows, shoulders, etc. These characteristic points, called keypoints, correspond to human pose estimation [16, 45]. Pose estimation (Figure 2.5) consists of detecting a certain number of keypoints that generally correspond to the joints of the human body. There are two main methods for doing this. The first involves detecting all the keypoints and then reconstructing the entire body skeleton [16]. The second involves detecting people and then detecting the keypoints within the bounding boxes of the detected people [45]. To detect keypoints, both methods use a similar approach by creating a heatmap of the probability that a pixel in the image belongs to a keypoint for each of the keypoints. The keypoints are then found using thresholds. Once the keypoints have been detected for the second method, reconstructing the skeleton is simple, given that each keypoint is unique in the bounding boxes (if there is no overlap between people), [16] may have many different positions for each keypoint, In order to associate them correctly, it uses vectors that indicate the direction and strength of the connection between two keypoints, which are learned during model training, and calculates an affinity score between pairs of keypoints by integrating these vectors to obtain the actual connections between the keypoints.

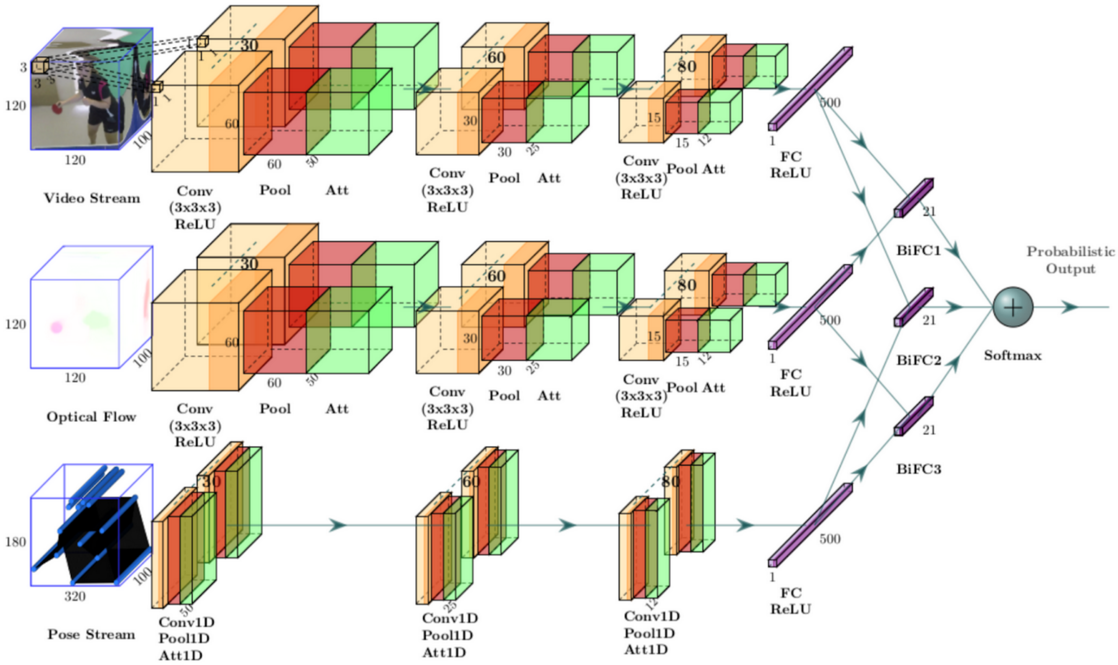


Figure 2.5 – Explanation of [83] model. The model takes three types of data as input: 100 frames from the RGB video, 100 frames from the optical flow, and 100 estimates of the player's pose. By merging the three branches of the network for the three inputs, it outputs the probabilities of possible actions.

The estimation therefore provides us with additional information about the players' posture, which can be used in action detection. To aid action detection in sports [83, 75] uses pose estimation. For table tennis [83] uses the model [82] by adding an input to the model that is the pose estimation of the player on each frame, which allows for greater accuracy on the same dataset.

2.3 SportsVideo: Reference Dataset

This contribution is the creation of a benchmark dataset open to the scientific community. This dataset consists of a series of six multimedia tasks on sports divided between two different sports, table tennis and swimming. This dataset is also associated with a competition open to the community for the completion of the tasks. The six different tasks focus on: detecting the position of players, events and their classification, searching for table perspective projections, detecting sound events and detecting scores. This work was carried out in collaboration with Pierre-Etienne Martin, who defended his thesis on video tracking applied to table tennis [81]. This work is based on a previous challenge [61].

Positions and actions detection/classification are one of the main challenges in visual content analysis and mining. Sports video offer such challenges due to the variety of scenes and actions they contain. Sports also provide a wide range of analysis, related to athletes' performances and tactics. We propose a series of 6 sports-related tasks, divided each into 2 subtasks. The main motivation is to provide a more complete and challenging benchmark for video analysis with complex scenes and actions. Table tennis is a fast-paced sport with a lot of actions and a narrow field of view, the tasks are based on these specific characteristics. The first four tasks are related to image and video analysis, the fifth to sound analysis and the last one to textual information extraction.

Those tasks have been identified and designed to be as independent as possible so that participants can choose to participate in one or more tasks. If combined, they can provide a more complete analysis of sports videos for both performance and tactical analysis. Participants are encouraged to release their code publicly with their submission. Similarly to the Sport Task 2022 edition [78], a baseline for both subtasks 2.1 an d 3.1 is shared publicly [1] [79]. Background on sports is provided in the following two PhD thesis in swimming [60] and in table tennis [80].

2.3.1 Tasks Description

The tasks we present, when taken together, enable us to perform all of the tactical analyses that can be found in the literature. Individually, they also allow us to focus on analyses specific to table tennis. They have been chosen for this purpose in order to provide data that can be used to perform all of the relevant and useful analyses for tactical analysis.

Task 1 - Position Detection. The main information in sports is related to positions of players in videos featuring different numbers of sides around a table tennis (seen from various angles). Participants need to provide bounding boxes for identified players, and their results are evaluated using Average Precision (AP) at an IoU ratio of 0.25, counting true positives and negatives across the dataset.
Subtask 1.1 – To detect 2 or 4 players (depending if single or double) and track them during the video especially during double games where players have a lot of overlaps, from videos recorded from various angles (e.g., side, corder).

Task 2 - Event Detection Key information in sports video is related to events, in particular strokes, which are related to a particular time and typology. Participants

1. https://github.com/ccp-eva/SportTaskME23

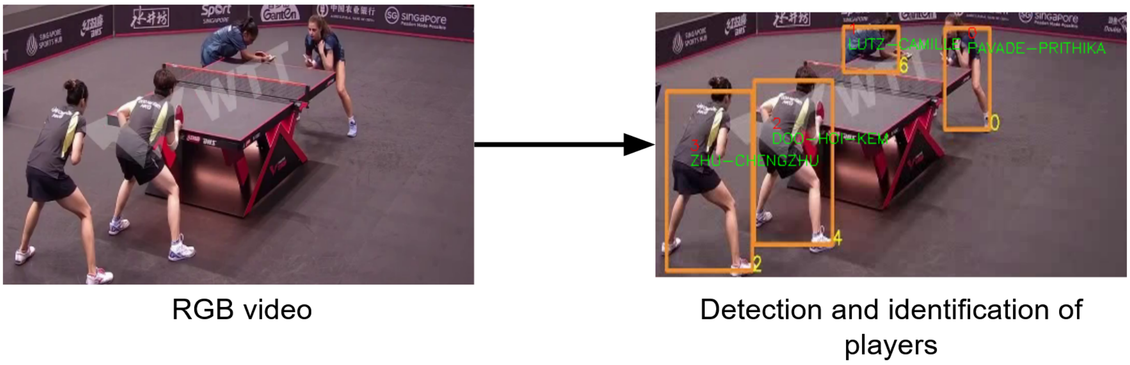


Figure 2.6 – Detection of players positions and tracking. Detection performed for a women's doubles match. Using the original RGB image, we first detect the players, then track them, and finally re-identify them to obtain the final tracking.

are however only required to identify the timestamp of the event, the classification is achieved with the next subtask.

Subtask 2.1 – To detect when a player is performing a stroke (i.e. a ball hit with the racket) using close-up videos. The goal is to detect the exact frame when the ball is hit by the racket (Figure 2.7). Videos are provided with ball positions. Evaluation is based on the F1-score, which measures the harmonic mean of precision and recall.

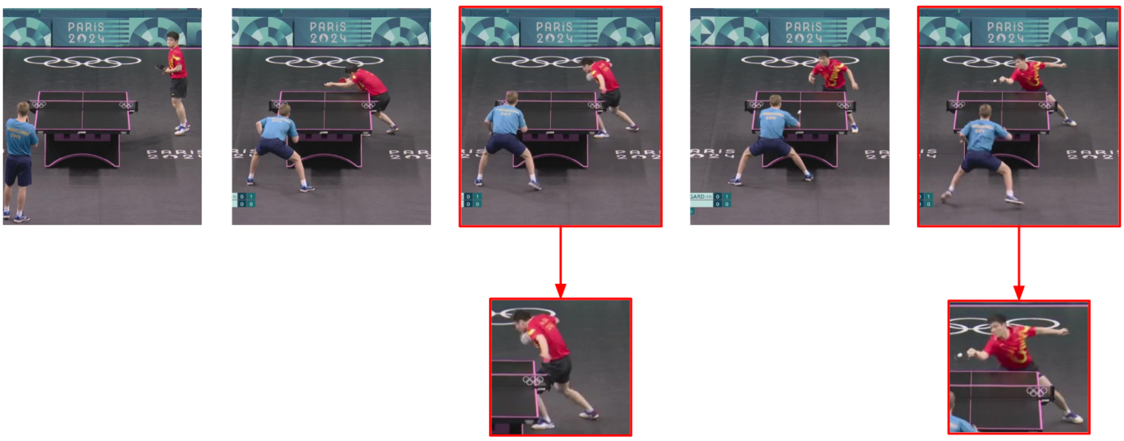


Figure 2.7 – Visual detection of the moments when the player hit the ball. The moment when the player hits the ball occurs when the player makes their stroke and touches the ball with the racket.

Task 3 - Event Classification The goal of this task is to classify the type of stroke performed by a player in table tennis. Participants need to categorize a collection of shortened table tennis stroke videos, each containing either a single stroke or no stroke at all. There are 20 potential stroke categories and an extra

category for non-strokes. Two sets with annotations are given: a training set with 807 videos and a validation set with 230 videos. The challenge is to classify a non-annotated test set comprising 118 videos, with the assurance that the trimmed videos in each set are derived from the same untrimmed videos but captured at different time instances without temporal overlap.
Subtask 3.1 – To classify different strokes in table tennis from trimmed videos in which only one stroke is present. There are 3 different categories of strokes, services, forehand and backhand (Figure 2.8). For services we have 6 different classes. For forehand and backhand we have 5 classes. 16 classes and one non-stroke class are provided, for a total of 1156 videos.

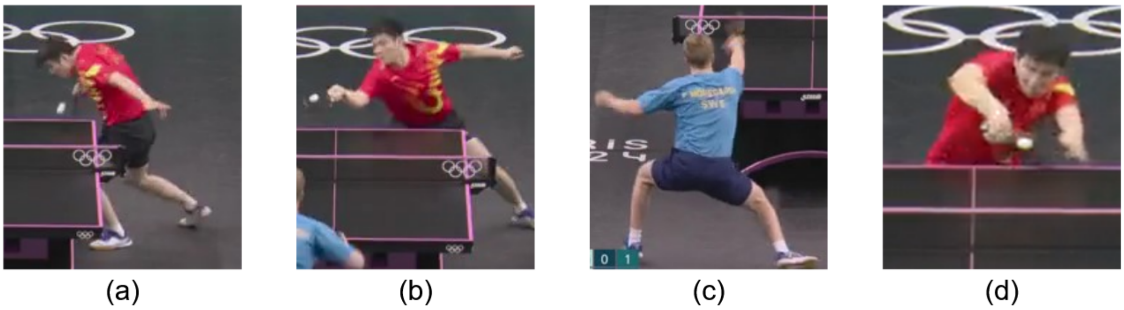


Figure 2.8 – Strokes classification. An exemple of 4 different strokes: a forehand serve (a), a forehand push which is a defensive stroke (b), a backhand topspin which is an offensive stroke (c) and a backhand flip which is an offensive stroke (d).

Task 4 - Table Perspective Projection Sports videos in general, and in particular the ones provided for the SportsVideo task, are usually recorded from the side. This task asks participants to find the homography transformation for each frame in the dataset. It consists in the projection that maps points of the table tennis space, to corresponding points in the video space. The precision of this projection is evaluated using Intersection over Union (IoU), with two metrics: IoU for the visible table parts and IoU for the entire table, including parts outside the camera's field of view.
Subtask 4.1 – To detect the table position for a given video frame of a whole table tennis. The dataset contains 54 annotated images with homography transformation from TV broadcasts of table tennis matches (Figure 2.9).

Task 5 - Sound Detection Sports are highly multi-modal events. Sound is an important modality that can be used to detect events. They can be used as additional cues (e.g., ball bounces). In this task, participants are asked to detect sound events in table tennis videos. In table tennis, the ball bounces on the table for every stroke.

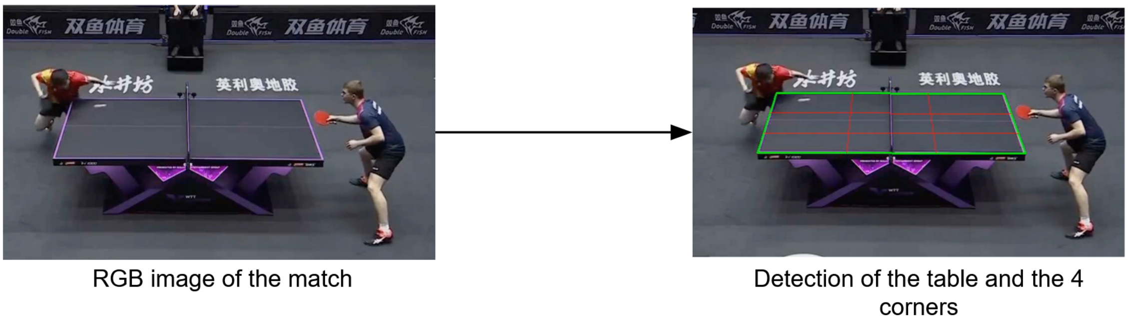


Figure 2.9 – Table detection using the RGB image as input. The table consists of a rectangular top and is defined by four corners.

Subtask 5.1 – Ball hits indicate the pace of the game. The goal is to detect the exact frame when the ball bounces on the table (Figure 2.10). Videos are provided with the ball annotated and evaluation is based on the F1-score.

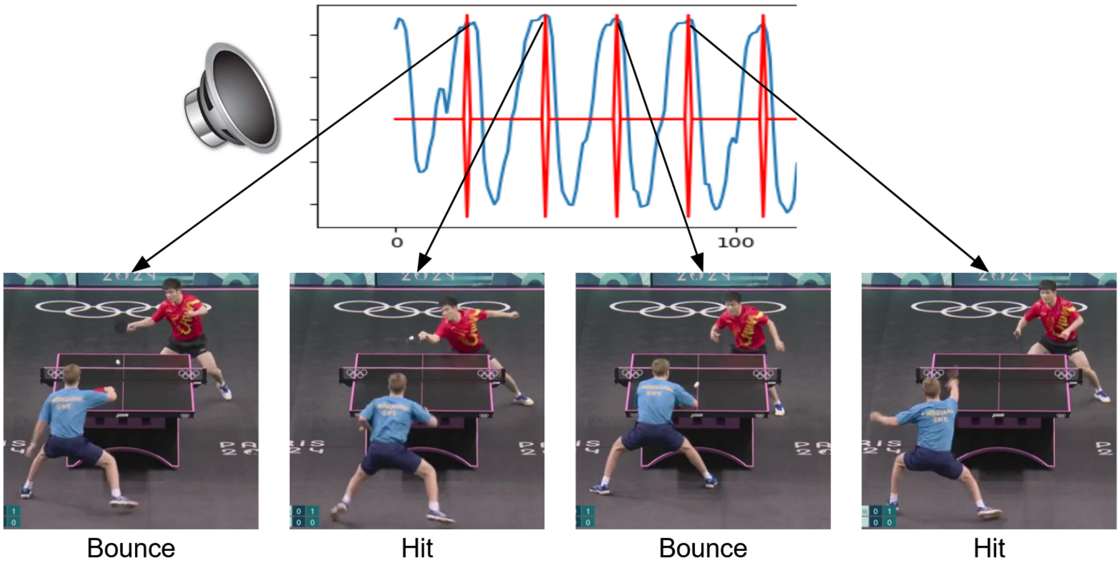


Figure 2.10 – Examples ball bounces and ball hits. When the ball bounces off the table, it emits an audible sound in the videos that is characterized by a peak in intensity at specific frequencies.

Task 6 - Score and Results Extraction In most sports, the outcome is presented on a scoreboard, featuring the current score of the game. These scoreboards are typically physical LCD screens close to the referee. Digital versions of scoreboards are also displayed on TV broadcasts as overlays.

Subtask 6.1 – The goal is to extract the current score of the match. In table tennis, the score can be embedded in the broadcast video or it can be shown by referees with scoreboards. When the score is embedded in the video stream, names of players are also displayed (Figure 2.11).

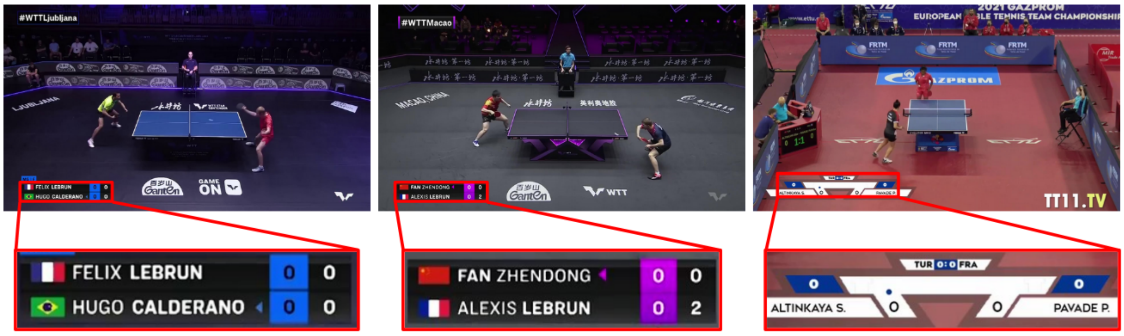


Figure 2.11 – Examples of scoreboards in different competitions. Scoreboards allow you to follow the current score throughout the match and see the names of the players. They are usually located in the corners so as not to obscure the play.

Conclusion

This benchmark dataset and challenge have made it possible to define the necessary foundations for implementing automatic methods for data collection, in particular by defining precise categories for each of the different strokes. In the future, we plan to enhance the video database by incorporating additional table tennis and swimming recordings, along with game characteristics (*i.e.*, more camera angles, extended video footage, interactive competitions, and parasports). We also plan to introduce a grand challenge task that requires participants to reconstruct entire games or races, involving the solution and assembly of all subtasks.

All tasks can be summarized in the following table:

Task Name	Data	Result
Position Detection	Video	Players' Coordinates + Tracking
Event Detection	Video	Time Segmentation
Event Classification	Video	Classification
Table Perspective Projection	Image	4 Coordinates
Sound Detection	Audio	Temporal moments
Score and Results Extraction	Image	Characters and Numbers

Table 2.1 – Summary of the 6 different tasks, presented for the challenge bringing together the main issues surrounding data collection in table tennis

2.4 Video Annotations Tool

We implemented a manual tool for detailed annotation of games recorded on TV that we used until the Olympics. Annotations included ball bounces, stroke techniques and games sequences outcomes (win/lose), to enable tactical [32], performance [14] and serves analysis [36]. We used a Python software, with pre-processing steps including table position detection in the images and pose estimation (OpenPose [16]) to calculate players positions towards the table. Many unsuccessful attempt at automating the annotation process due to the challenges table tennis offers which is a fast paced, tactical game [28]. Two other tools were forked from this annotation tool, to provide feature-focused utilities (*e.g.* video download, segmentation) to allow practitioners to prepare videos or collect simple statistics without having to install and use the detailed tool, which required Python modules and an external program running on a specific operating system. Videos and annotations were synchronized using a cloud client that stored all the videos on a remote, centralized server (Figure 2.12). The federation keeps using the feature-focused utilities to update their video database with simple statistics they use to create montage of winning/loosing points.

Figure 2.12 – Process of data collection. Professional matches are listed on the ITTF website. Metadata and videos are downloaded and then different annotations are performed. All annotations and metadata are structured and stored on a cloud.

We have developed two annotation tools (Figure 2.13), one for fast annotation with few details and the other for detailed annotation. Both tools offer a similar data structure, with the only difference being the level of detail in the information provided. Detailed annotation allows for much more in-depth and useful analysis for tactical advises, but data collection is time-consuming. Setting up an annotation interface with less detail allows for much faster collection while still allowing for certain annotations to be made. Independently of the complexity of the data required, interfaces have two important parts to managed independently. Data annotation is performed directly on the interface, giving the user the freedom to intervene at any moment. Finally, structuring and saving the data are entirely managed in the background by the interface, without user intervention. This separation is crucial to ensure a consistent and coherent structure, regardless of the type of annotation or the user performing the annotation. The fast annotation interface focuses on rallies, allowing us to annotate servers and winners of rallies while associating them with time. The detailed annotation interface focuses on strokes. It allows us to annotate all stroke information, including technique types, strike and bounce times, and positions. In order to be as efficient as possible, the interfaces have been optimized using logs on the annotation times for each element. The optimizations have led to the integration of game logic rules and keyboard shortcuts.

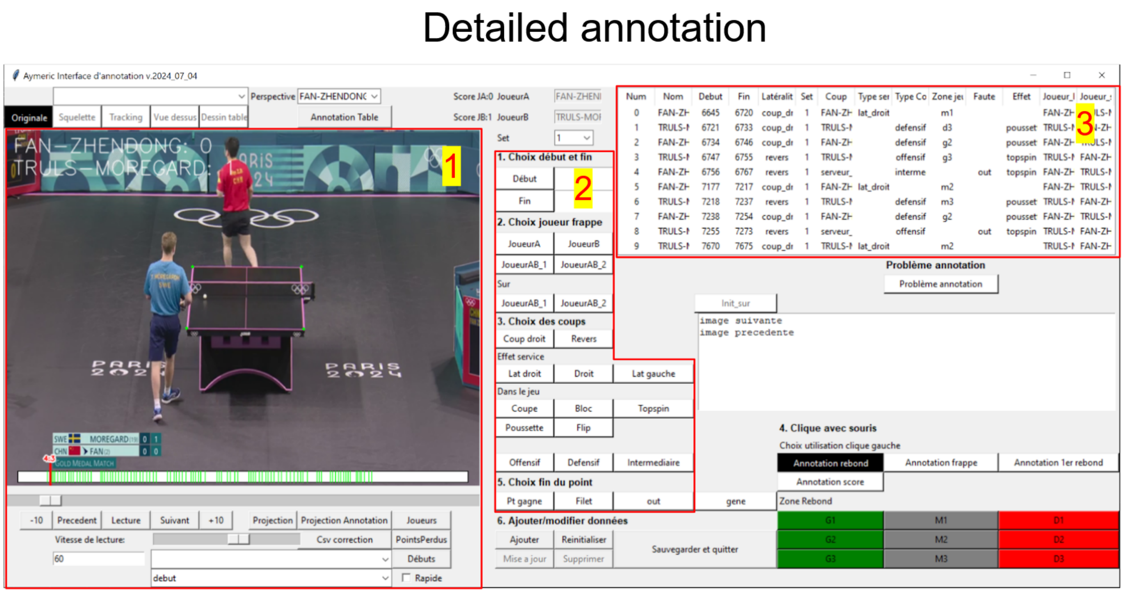


Figure 2.13 – Interface developed for the detailed annotation. (1) corresponds to the part that allows navigation within the video, (2) allows annotation of stroke attributes. (3) corresponds to the stroke data that has been annotated.

2.5 Validation of the Tool Accuracy

High-quality data is essential to obtain reliable results during data analysis. Due to possible differences in views during different competitions, conditions vary, which affects the accuracy of the data collected. This contribution presents a method and an empirical model to evaluate the influence of camera angle on the detection of ball bounces. Our model characterize the non-negligible impact that the way games are recorded on accuracy, which should be carefully considered when selecting camera positions and communicated along with collected data.

During competitions video tracking enables the collection of spatial information over time for objects in the scene such as players, the ball, in an non-intrusive way [118, 111, 128, 22, 58, 51]. These data fall into the categories of tracking data [96], which have proven valuable for sports analysis in general. This information can be used to identify players' strengths and weaknesses, analyze their tactics [123], to prepare for upcoming matches, and anticipate an opponent behavior during a rally [125]. Such tactical analysis relies heavily on collected data, and numerous approaches have shown how to effectively use this information for both analysis and visualization [132, 14, 123, 125]. Other research has shown that certain positional data can be re-configured relatively to players [40] showing the importance of position in analysis.

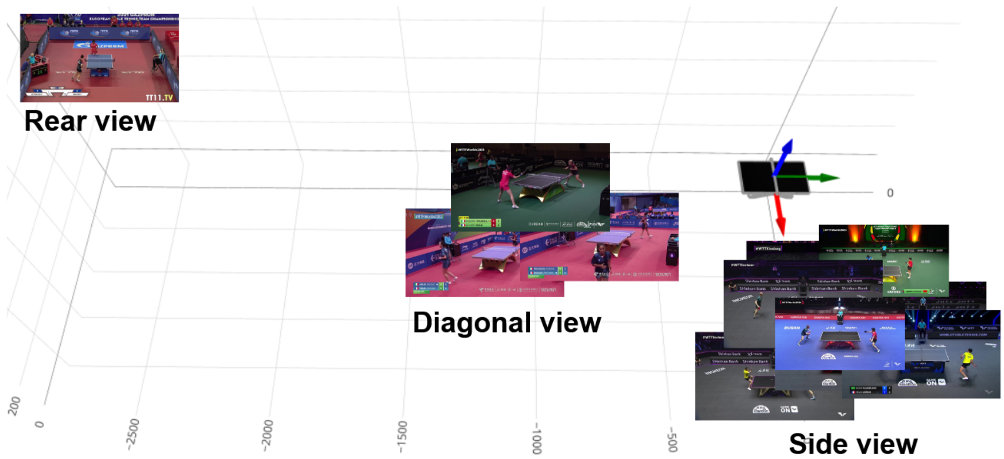


Figure 2.14 – Various points of views collected during table tennis international competitions and their positions in 3D space. On the table, the red axis corresponds to the x axis, the green axis to the y axis and the blue axis to the z axis.

Our approach to collect such data relies upon video tracking techniques, particularly through manual match annotation [97]. Indeed, despite the progress in the fields of computer vision and deep learning, it remains challenging to accuracy spot positions of the player and the ball, and classify as events [35]. The automatic detection of the table tennis ball fits into a broader issue in the world of sports:

the detection of *High-speed and Tiny Objects* [58, 141]. Automated ball tracking remains an open challenge as video quality and framerates are often low on TV. Traditional methods relied on a combination of background or motion subtraction to detect moving objects, and colorimetry to identify the ball among them [129, 90]. More recently, methods based on deep learning have been employed [138, 68], primarily using convolutional neural networks to enable ball detection within the image.

An underexplored are in ball tracking, regardless it is achieved manually or automatically, is understanding how camera angle impact the tracking quality. Figure 2.14 shows different camera angles from various table tennis competitions, these videos and their data are part of the dataset [38]. For this sport, roadcasters often use fixed cameras, which must comply with specific positioning guidelines that vary depending on the competition. Despite standardization efforts, notable differences can be observed from one competition to another. Based on Figure 2.14, we can roughly identify three distinct viewpoints: the *rear view* (in blue), the *side view* (in red), and the *diagonal view* (in green), each provide its own type of geometric distortion of the table tennis game. We next define the types of deformations and characterize they impact on ball bounce tracking accuracy.

2.5.1 Problem Formulation

A table tennis match can be represented as a 3D scene. The different objects present in this scene include the table (the only fixed object with the floor), and players, their rackets, and the ball, which are moving objects. In an orthographic view, the table has two axes of symmetry: one along the line formed by the net, and the other perpendicular to the net, passing through its midpoint. We chose the origin of the 3D coordinate system as the point of intersection of these two lines on the table, as shown in Figure 2.14 with a red, green and blue axis. A more abstract representation of such scene is Figure 2.15 which illustrates the principle of projecting 3D elements and onto the 2D image plane of the camera, as well as the geometric issues that arise from this projection. This projection—and consequently the resulting geometric distortion—depends on the camera, its intrinsic parameters, its position, and its orientation. As TV broadcast videos are usually undistorted, we neglect intrinsic parameters, in particular as we are primarily interested in camera angles rather than their distance. For the example in Figure 2.15, which respects the actual dimensions of a table, the table projection represents 0.18 times the table. This ratio means that 1 pixel is equivalent to approximately $5.5cm^2$

We can compute the projection $\mathbf{p}$ of any point $P = [X, Y, Z, 1]^T$, where X, Y, Z are the coordinates in 3D space, onto the camera image using the following equation:

$$\mathbf{p} = \mathbf{K} \cdot [\mathbf{R} \mid \mathbf{t}] \cdot \mathbf{P}$$

Here, **K** is the camera's intrinsic matrix, **R** is the rotation matrix, and **t** is the translation vector.

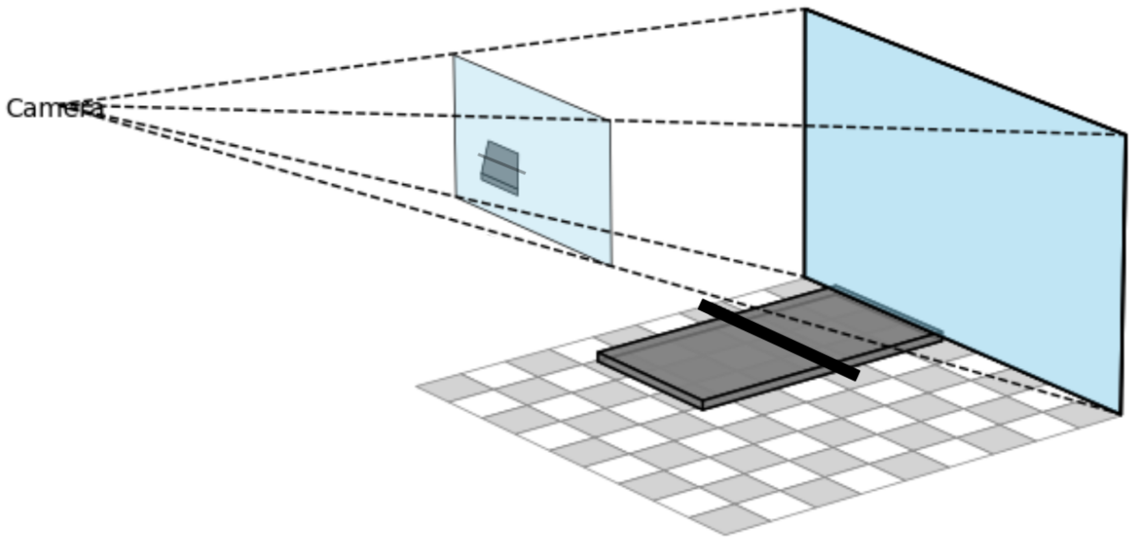


Figure 2.15 – Projection of a 3D scene onto a 2D image showing how physical object change of visual aspect when they are projected on the camera plan. This representation of the table corresponds to the rear view, with a camera located at a height of $10m$ and a distance of $15m$ from the table.

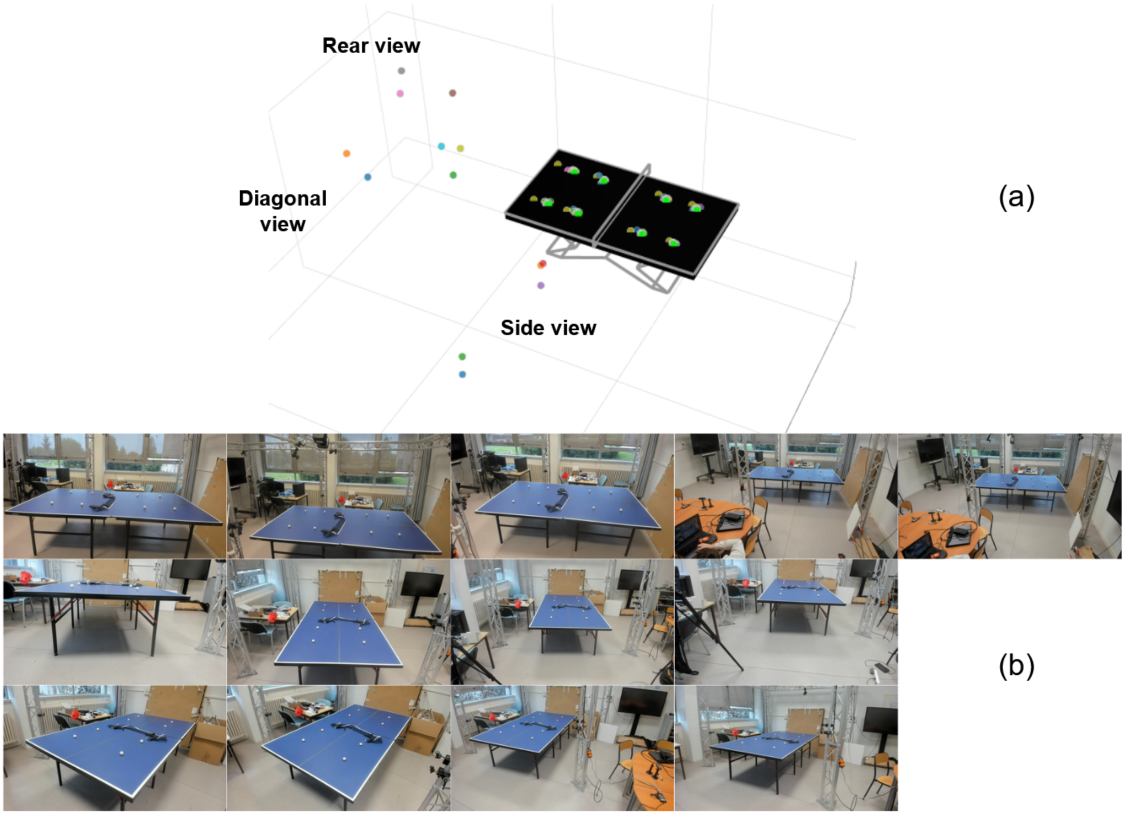
The angle between the camera and the table affects the geometric shape of the table's projection in the image. Positions of the form $(0, 0, z)$ for any strictly positive integer z are the only ones that preserve the rectangular shape of the table surface without distortion. This rectangular shape is important in sports video analysis as it enables to calculate positions. To measure the error between a real position on the table and its observation resulting from the projection of this 3D scene into the camera's 2D image, we used a simple Euclidean distance:

$$d(A, V) = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

where: $A = (x_1, y_1)$ is the annotated bounce and $B = (x_2, y_2)$ is the ground truth. To give an order of magnitude, we expect our ball bounce tracking to be below 10cm which is the accuracy of a player when targetting a particular position on the opposite side.

2.5.2 Protocol

As we cannot collect ball bounce ground truth in TV broadcast videos, we recorded videos with known position of balls on a regular table tennis table for various camera angles. The cameras are located at x-axis distances of up to $4.20m$, y-axis distances of up to $3.60m$ and z-axis heights of between $0.14m$ and $4.24m$ above table level. We placed 8 balls (4 on each side) and recorded 13 short videos (3 seconds each) from three camera viewpoints: rear (5 captures), side (4), and diagonal (4), each at varying distances and heights. Then we used an annotation tool we built to annotate all bounces from all camera images. Figure 2.16 (b) shows the setup of the experiment. We then annotated the ball positions and calculate the error rate with the ground truth. Figure 2.16 (a) shows the camera angles, ball ground truth and annotation results.



(a)

(b)

Figure 2.16 – (a) Positions of cameras we used in our experiment and balls positions on the table; (b) view from the cameras.

Influence of the Camera Distance

To study the accuracy of annotations, we calculated the deviation of theannotated ball position with their ground truth. We found that deviation over $10cm$

from ground truth come from three of the 13 viewpoints present (two in rear view and one in diagonal view), which leads us to the observations: the rear view is the one with the greatest deviations from ground truth, and the side view shows little deviation.

A linear regression plot of the distance between annotation and ground truth as a function of distance between camera and bounce, shows a positive slope 11 times over 13 as distance increases. Statistically, this shows that as the distance between camera and bounce increases, the distance between annotation and ground truth increases.

Influence of the Camera Angle

To study the effect of camera angle on annotation precision, we developed a second protocol where the camera's x and y positions were fixed, and only z position varied. We placed more balls on the table (40) to allow more comparisons. We performed 6 captures at different heights. We used the same process as for the previous protocol to capture the data.

The linear regression of absolute distance between each camera's annotation and the ground truth as a function of the camera height presents a negative slope 40 times out of 40, which means that the higher the height, the greater the precision. For each ball position on the table, the camera height therefore influences the annotation precision. The lowest camera is located at a height of $17cm$ relative to the table level, and it provides the most uncertainty in the annotation with an average of $27cm$ and up to more than $50cm$. From a height of $59cm$ (the second lowest position), the precision for all points is less than $10cm$. For the highest camera position at $130cm$, we obtain an average precision of $1.87cm$.

2.5.3 Empirical Model

As we are interested in capturing or anticipating the error rate in ball bounce accuracy, we built an empirical model that will provide an accuracy estimation based on our experimental setup (Figure 2.17). Using the deviations between the annotation and the ground truth as a function of the camera angle to the bounce, we performed an exponential regression shown on Equation 2.1:

$$y(\alpha) = a \cdot e^{b\alpha} \tag{2.1}$$

With α the camera angle, a initial value (when $\alpha = 0$), and b the slope.

Figure 2.17 shows that the smaller the camera angle, the greater the variation in accuracy, as is the case with the camera position with the smallest angle, which has an accuracy of between $5cm$ and $40cm$ depending on the table zone. We also note that from a certain angle between the camera and the table, annotated

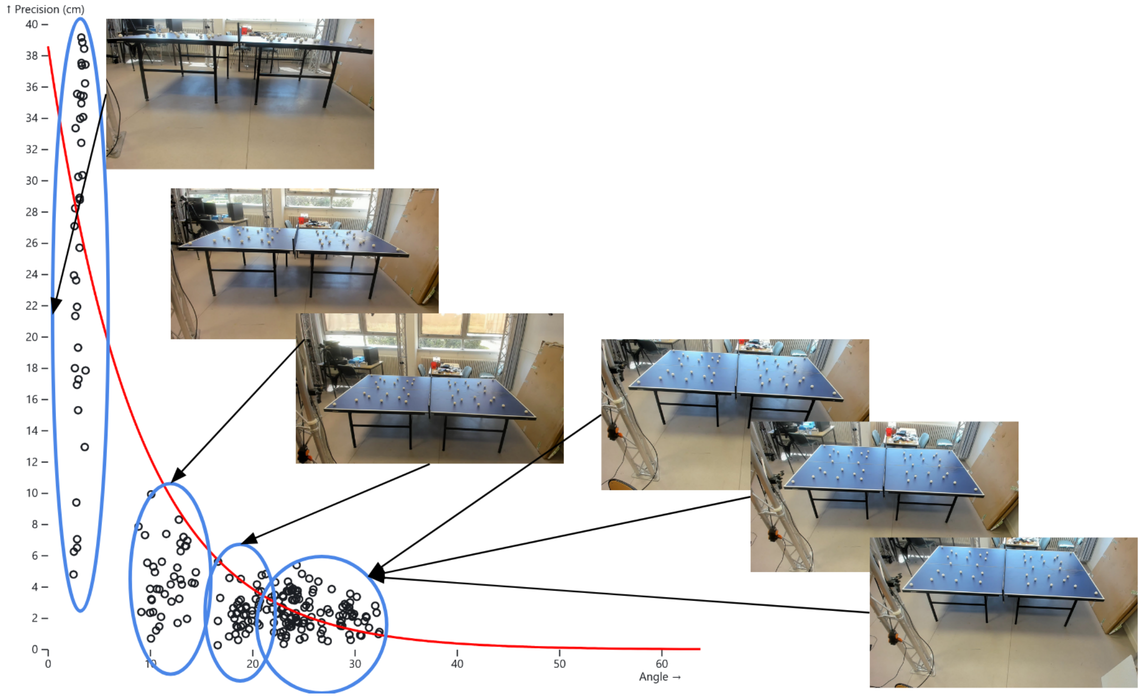


Figure 2.17 – Dots present deviations the annotation and the ground truth. On average, as the angle between the annotated bounce and the camera increases, so does the accuracy of the annotation. An exponential regression can model this trend (red curve).

bounces for the same camera view have angles that vary greatly from one another, giving overlapping annotation groupings for different views with different angles.

This model confirms our initial hypothesis that camera angle impacts ball bounce tracking precision. Still it has several limits beyond the few samples we used for our model. First, a camera does not have the same angle of incidence with all points on the table, so points closer to the camera have a larger angle than points further away. Also, our accuracy estimation is calculated on a discretized table using a $1cm$ by $1cm$ grid, to limit calculation times. Still this work paves the way form further investigations and application. For instance, Figure 2.18 shows 3 examples of accuracy predictions made on 3 different views from 3 matches using the model. Using our model, we can already estimate the confidence on collected data and eventually provide an error of margin either visually or for calculated statistics. We can see that, depending on the precision of the annotations, there are certain trends: on (b), which has a precision of over $10cm$ for the whole table, the top-down view of all bounces shows a certain trend, with balls close to the net being closer for the bottom half of the table. Whereas on (a), which has a precision of less than $3.5cm$, no clear trend emerges. More work research is needed on how to effectively communicate this confidence, either visually or statistically. Also more work is needed to model the impact of other factors such as frame rate, image resolution and camera distance on annotation accuracy.

Conclusion

This model provides an assessment of the accuracy of bounce data collected from a video based on the angle of the camera relative to the table. The model also allows us to simulate in advance of data collection what the accuracy will be based on the position on the table. In the future work, we plan to propose a new method for calculating the direction of deviation in accuracy and enabling data correction, with the aim of standardizing all position data both within a single match based on the side of the table and between multiple matches with different camera positions.

2.6 Conclusion and Perspectives

This work highlighted the complexity of automating stroke data collection in table tennis. The benchmark dataset provided the community with a dataset that can be used to develop new stroke detection methods, which are essential for various tactical analyses. For spatial data, regardless of whether the collection method is automatic or manual, the camera angle affects accuracy. We proposed a model to evaluate this accuracy during collection, allowing us to determine the acceptability of the data for tactical analysis based on the camera position. The work carried out in relation to data collection is an essential part of match tactics analysis. Professional matches are often decided by minute details, making the accuracy of the data collected essential to the success of athletes.

For this work, several perspectives for improving the structured data are being considered:

- The first approach consists of increasing the size of the database by including numerous professional matches from different competitions, which will provide a wide variety of players and scenes.
- The second approach consists of upgrading the semi-automatic annotation tool to an annotation verification tool. This way, annotation would be done automatically and the user would only use the tool to correct errors, thus making data collection faster without compromising accuracy.
- Finally, the last perspective concerns the correction of spatial annotation accuracy. We have proven that the camera angle influences the accuracy of the annotation, but we have not studied the direction of the discrepancy between the annotation and the truth. In this way, if a recurring pattern of discrepancy exists, the implementation of a correction system would improve accuracy.

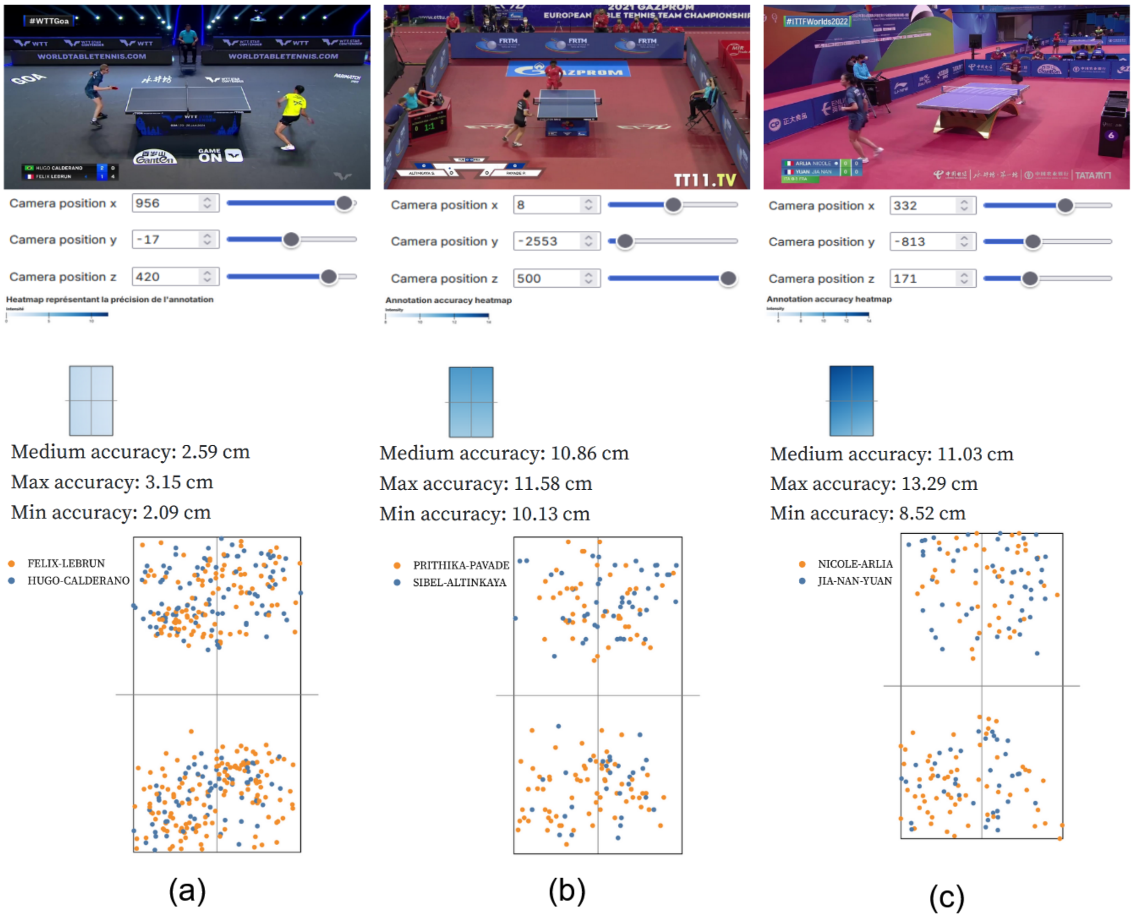


Figure 2.18 – Example of precision estimates for different views taken from broadcasts and table bounces we identified. (a) The side view, the area on the table with the lowest annotation accuracy is $3.15cm$. (b) The rear view, annotation accuracy on the table remains almost constant over the whole table, with a difference between the worst and best accuracy of less than $1.5cm$. (c) The diagonal view, the accuracy of the annotation on the table varies greatly depending on the zone, with a gap of almost $5cm$ between the two extremes.

CHAPTER 3

ANALYZING STRUCTURED TABLE TENNIS DATA

Contents

The purpose of this chapter is to present a work on the analysis of structured data presented in Chapter 2. Different types of approaches are proposed based on the following articles:

[14] Gabin Calmet, Aymeric Erades and Romain Vuillemot. *"Exploring Table Tennis Analytics: Domination, Expected Score and Shot Diversity". In: Machine Learning and Data Mining for Sports Analytics.* Ed. by Springer Link. Communications in Computer and Information Science. Turin, Italy, Sept. 2023. url: hal-04240982 [14]

[43] Aymeric Erades, Thomas Papon and Romain Vuillemot. *"Characterizing Serves in Table Tennis".* en. In: Machine Learning and Data Mining for Sports Analytics. Ed. by Ulf Brefeld, Jesse Davis, Jan Van Haaren, and Albrecht Zimmermann. Vol. 2460. Series Title: Communications in Computer and Information Science. Cham: Springer Nature Switzerland, 2025, pp. 3–13. url:

https://link.springer.com/10.1007/978-3-031-86692-03 [36]

[7] Riad Attou, Marin Mathé, Aymeric Erades and Romain Vuillemot. *"Analysis of Service Returns in Table Tennis".* en. In: (Sept. 2025) [7]

3.1 Introduction

With the professionalization of many sports, research into developing and optimizing performance has become increasingly prevalent. Currently, all professional sports are trying to maximize their performance by leveraging various factors. The analysis of sports-specific data is one of the major areas of focus in performance. In particular, in table tennis, which is a confrontation sport, knowledge and understanding of a match has become necessary to improve player performance. All data and metadata specific to table tennis matches can be used to achieve this. In recent years, data has been widely used to develop tactics ahead of matches, making tactics essential to compete with the world's best players. Table tennis matches can be decided by the smallest of details; a rally at a crucial moment can turn a match around. It is common for a match to reach 9-9 in the decider, in which case two points determine victory or defeat. A tactic that gives a 90% chance of winning will lead to victory, whereas the wrong tactic will lead to a very different outcome. This example reflects the importance of tactics in the outcome of a match. These tactics focus mainly on rallies, which contain all the information about the matches. In this chapter, we present match analyses using both rally data to understand the strengths and weaknesses of players, as well as more general match data to provide an understanding of how the match unfolded.

3.2 Related Work

Data analysis in sports focuses mainly on event and tracking data. There are two main types of analysis: analysis at a given moment in the match, during a play, and sequence analysis, which is a succession of events. In table tennis, we can give the examples: analysis of a serves is a give moment analysis, an analysis of rallies is a sequence analysis, with each rally being a succession of strokes.

3.2.1 Given Moment

Analyses at a given moment are often focused on the outcome of an action [109, 30, 17, 88].For the basketball [109] focuses on the spatial analysis of successful and unsuccessful shots. To avoid problems related to overlap in traditional shot maps, they used density maps. By combining the maps of missed shots with those of successful shots, they created a map of the probability of a successful shot based on the player's position. In badminton, [30] uses player pose data [45] and shuttlecock tracking data [58] to predict the probability of winning a rally at a given moment and state. To do this, they use a Long Short-Term Memory [56]. The model uses the players' positions, their pose estimates, the shuttlecock's position, and the action to determine this probability. Probability calculation is one of the foundations of the concept of expected goals introduced in soccer [8], which corresponds to the number of theoretical goals that should have been scored based on the probability of scoring of shots. For basketball [17] calculates the number of expected points at each moment during an attack. Based on a Markovian assumption using the position of the players and the ball, they create a model to calculate the probability of a player making a decision and the number of expected points for each decision made. Calculating this value at each moment of the action makes it possible to identify when a change is significant and understand why. For handball [88] directly adapts the soccer model, taking into account the specific characteristics of handball for the calculation. The main attributes used concern the player taking the shot (his position, the angle of the shot, distance from the goal, his speed), the goalkeeper (the goalkeeper's position, his distance from the shooter), but also information about the physiognomy of the match (the score, the duration of possession, etc.) and the situation of the teams (the number of defenders, the type of action, etc.).

The data is also used to characterize a player or team in the context of one or more matches. This makes it possible to understand behaviors [105, 27, 10, 26, 48, 127], or the strengths and weaknesses of players [9, 27, 48]. In soccer [10] seek to identify a team's identity based on the tracking of their players. The position of players in relation to each other is associated with distinct roles within the team (players can change roles during the match), so they can calculate the average position for a role for each match and compare this position between matches. By displaying all the positions of the roles in all of a team's matches, they can see how this position evolves from match to match and thus see whether or not there are variations for each role. These average positions of the roles create a team's identity, making it possible to identify a team using the average positions of the roles. This also makes it possible to predict how these positions will vary between two teams when they face each other. In soccer [26] characterize teams based on the position of key actions, combining spatial data with event data to obtain a characterization. In basketball [48] focus on the effectiveness of defense by studying the positions of defenders relative to attackers.

For racket sports [105, 27, 127], understanding a type of action is often important, particularly the serve. In elite table tennis [105] conducted a comparison of the differences in serves and returns based on gender. A comparison of service zones and types of discounts shows a difference in frequency of occurrence between these two distinct groups. in tennis [27] studied the spatio-temporal variation of players' serves, depending on the moment in the match. To study the variation in serves, they arranged the serve bounces into a temporal sequence by ranking the data according to the side of the net, court location, game number, and point number. Using this sequence, they calculated the distance between the serve positions of each pair of elements in the sequence. In this way, the average distance provides information about the variation. To highlight variation during important points, they assigned a value of importance to each point based on the score, which allowed them to group these points for analysis and efficiency calculation. Again in tennis [127] uses serve trajectories to find similarities between players. To classify different serves rather than using terms that could be open to interpretation, they classify serves by clustering trajectories. They break each serve down into two trajectories, before the bounce and after the bounce, and use the k-means method [73] on the two independent parts of the trajectory to classify the serves. The distribution of serves in these clusters allows them to define the players' styles.

In cricket [9] takes a very different approach to using data for analysis. Instead of relying on statistical data, they use match commentaries to determine the strengths and weaknesses of cricket players. They rely on human expertise available during the match to characterize the strengths and weaknesses of players in different game situations.

3.2.2 Sequences

Table tennis rallies are a succession of strokes, so they can be likened to sequences. Analyzing these sequences makes it possible to identify the most frequently used ones and assess their effectiveness. Sequences allow data mining algorithms to be used to extract interesting sequences. To analyse interactions during meetings [46] decided to use sequences in the form of acyclic graphs. In this way, they can mine interaction patterns of the influence of choices made by participants on the choices of other participants while maintaining the temporal aspect related to the graph. To discover the most effective tactics in table tennis [33] used sequences of strokes. To do this, they define tactics as a succession of three strokes composed of an attribute and a spatiality fomring sequences. They associate each sequence with the outcome of the point, which allows them to determine the effectiveness of a sequence. First, they search for the most frequent sequences using the SPADE algorithm [136], and then, among the most frequent sequences, they calculate the Weighted Relative Accuracy [116] measure based on both the frequency of occurrence and the win rate to rank the most effective sequences. In sports, Markov chains [77] have often been used to analyze sequences [98, 87]. To analyze table tennis performance [98] use Markov chains on table tennis game sequences. For their method, they use four models—game action, stroke position, stroke direction, and stroke technique—which have their own states. In this way, the model learns the transitions between the states of the models and up to the outcome of winning or losing the point. Using this method, they can calculate the effectiveness of a tactic based on the model's transition matrix.In tennis [87] analyzes game wins using different data, namely scores. They use all possible scores in games as states, combined with service information (first serve or second serve), and train a model to give the chances of winning a game by knowing the rallies that led to a given state. This approach allows them to focus on the important points in a game to optimize the chances of winning it. Other models have also been used for racket sports, such as the minimum description length principle [54], which allows important patterns in sequences to be discovered using multiple attributes [131]. Another example is the improved artificial fish swarm algorithm for exploring sequences [122].

3.3 General Match Indicators

This work explores three different aspects of a table tennis match. Multifactorial dominance is the combination of mental, physical, and factual observations (score). The concept of "Expected Score" that we have introduced, which is based on observations of sequences of shots and a statistical study, reflects the expected score based on the course of the match and the points. And finally, the study of the variation in shots related to their effectiveness. This work was carried out in collaboration with a student from Ecole Centrale de Lyon (Gabin Calmet).

Detailed sports data, including fine-grained player, ball positions, and action types, is becoming increasingly available thanks to advancements in sensor and video tracking technologies. In this study, we explore the potential of utilizing such data in table tennis to analyze player superiority, scoring opportunities, and creativity. Our approach involves adapting existing metrics by incorporating additional attributes provided by the detailed data, such as player zones and shot angles. Furthermore, we present a methodology for visualizing all metrics simultaneously during a single set, enabling a comprehensive assessment of their significance. We expect this approach to help for developing, comparing, and applying a broader range of metrics to table tennis and other racket sports. To facilitate further research and the benchmarking of novel metrics, we have made our code and dataset available as an open-source project.

Introduction

Detailed data such as tracking data provided by TTNet [118], although essential for accurate and in-depth analysis, remains underutilized in a sport such as table tennis. Nevertheless, several advanced tools, often focused on complex

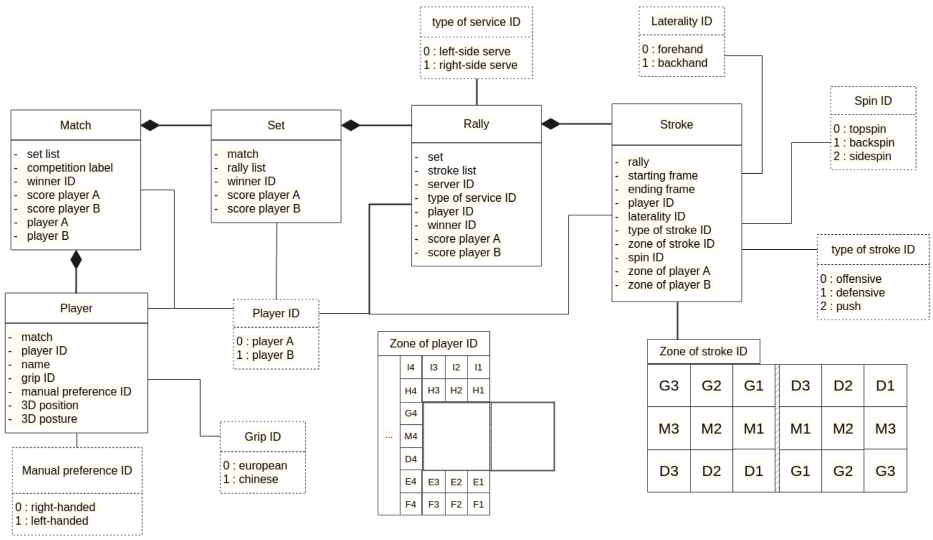


Figure 3.1 – Example of an extended table tennis detailed data model (from[33]). It includes additional metadata (*e.g.* players' names, score and winner) with advanced strokes types, players and ball rebound zones. It also takes into account continuous player positions and ball position (that we haven't yet collected).

visualization, are beginning to exploit this data, such as iTTvis [132], which is aimed at experts to explore game sequences and discover tactics, TIVEE [23] which exploits shot types, player positions, trajectory, and shuttlecock speed to find correlations between shots, allowing tactics to be discovered, TacticFlow [130] which uses multivariate events in racket sports to extract frequent patterns and detect how these patterns evolve over time, and Tac-Miner [123] which allows users to analyze, explore, and compare tactics from multiple matches based on three consecutive strokes. Other more statistically oriented approaches such as [33] also enable sequence analysis by exploring frequent game patterns. All of these works share the commonality of being driven by the availability of detailed tracking data.

We hypothesize that such detailed data provide deeper games analysis, and thus need to be anticipated. Figure 3.1 illustrates a detailed table tennis data model that captures all data currently available (mostly meta and event-based data). In this work, we use a combination of event-based data and video tracking data, on a 2D space. Such data can be collected with regular technical skills using a blend of computer vision, deep learning and manual annotation tools as we saw in Chapter 2. It extends the format previously used in [33] but with finer grained players position, orientation and ball rebound position. Additional data could be collected, such as the 3D position of players as well as ball effects, but this requires more work on video detection.

To illustrate our analysis, we use the following scenario from an international table tennis game: **Alexis Lebrun**, the French champion, against **Fan Zhendong**, the world champion and number one player in the world, in the quarter-final match during WTT[1] Championship in Macao, 2023. In this match, **Alexis Lebrun** wins 3 sets to 2. They took turns winning the sets. It was a really close game, and **Alexis Lebrun** won the decider 11-9 by touching the edge of the table. During this match, our experts noticed that **Alexis Lebrun** was very strong when attacking from the left side of the table. Usually, he would win the point just after his attack, often down the line with his backhand. If we focus on the first set, we can see that **Alexis Lebrun**'s domination decreased after the second point, while he didn't execute these shots. However, after his domination increased again, these shots began to be more and more common. Moreover, we noticed that during an important moment (7-4 for **Fan Zhendong**), he manages to score twice using these shots, and this made him take the lead of the set. We may suppose that this is an important feature of his game plan. In the first set, we found 4 points won by **Alexis Lebrun** when he makes these strokes (indicated by the red vertical lines in Figure 3.2):

- **Point A** (1-0) **Alexis Lebrun** serves, **Fan Zhendong** pushes on the left side of **Alexis Lebrun**'s table, then **Alexis Lebrun** attacks down the line with his forehand and wins the point.

- **Point B** (4-7) **Fan Zhendong** serves, **Alexis Lebrun** pushes short on **Fan Zhendong**'s forehand, who pushes long on the left side of **Alexis Lebrun**'s table. **Alexis Lebrun** attacks with his forehand on the left side of **Fan Zhendong**'s table.

- **Point C** (5-7) **Alexis Lebrun** serves short on **Fan Zhendong**'s forehand, who pushes long on the left side of **Alexis Lebrun**'s table. **Alexis Lebrun** attacks with his backhand down the line.

- **Point D** (9-7) **Alexis Lebrun** serves long on **Fan Zhendong**'s backhand, who attacks on **Alexis Lebrun**'s left side of the table. **Alexis Lebrun** counters with his backhand and wins the point after a few shots.

We derived a series of high level questions from this game analysis, as a way to address more general tasks analysts often conduct when processing table tennis data:

1. Why is a particular point effective during a game?
2. What is the effect of shots diversity?
3. What shots combination are the most efficient?
4. What are strokes difference between players?
5. How a stroke can win you a point?

1. World Table Tennis, a commercial organization that runs table tennis tournaments.

6. Can we classify players by their playing style?

To address these questions, we first selected a *domination metric* commonly used in adversarial sports or games to measure the advantage held by a player and designed it to capture both local efficiency for each shot and global trends. We then used another metric often used in soccer matches by bookmakers to assess the reliability of the match outcome: *Expected Goals* [85]. This metric calculates the probability that a scoring opportunity will result in a goal, providing insight into whether the winning team had the most dangerous scoring opportunities or not. Finally, we included a last metric that captures creativity in the choice of shots techniques, based on a shot similarity distance.

3.3.1 Domination Analysis in Table Tennis

Analyzing the pressure or domination is popular in team sports. In general, it is an umbrella term that encompasses all the ways to prevent the opposite team to develop an attack [4]. There is always an objective component of the domination that is calculated at a given moment without depending on the past. But most games and sports requires physical, technical and mental capacities that can't be objectively quantified without depending on the past. In racket sports, usually more fragmented than team sports that have long, continuous actions, but also that have high scoring opportunities, there is a need to re-define this notion to account for those characteristics. In such context with two opponents, we define it broadly as follows:

Definition 3.1 (Domination)**.** A situation in which a player (or a team) consistently outperforms their opponents and maintains a significant advantage.

We used various data from Figure 3.1 (scores, positions of both players, zone of rebound, type of stroke, laterality) to define the domination function $D(t)$ normalized between -1 and 1 to indicate which team dominates. At the beginning of the match, no team dominates, in other words $D(0) = 0$. As domination usually relies on many factors (*e.g.* endurance, precision, self-confidence, power, speed, trajectory prediction, agility, decision-making, strategy, to name a few) we will therefore consider multiple types of domination: **score**, **physical** and **mental**. However, we know that three functions won't be enough to analyze every aspect of a table tennis match, this definition is an initial approach that inevitably contains many limitations.

- **Score Domination** is calculated using the current scores at a given instant. It is highly reliable because the scores are what the winner is declared on at the end of the match, and because they are considered an absolute truth during the game. In this case, we consider that the score domination is proportional to the winning chances of player A, $P_{a,b}$. The value of $P_{a,b}$ between 0 and 1

is then linearly re-scaled between -1 and 1 to give us the score domination $S_d(t)$.

- **Physical Domination** in table tennis is supposedly based on three factors: endurance, aggression and playing angle. At each stroke, we calculate the distance $d_X(t)$ covered by each player, the playing angle $a(t)$ and we update also their respective rate of offensive shots $r_X(t)$. We then combine the three contributions to get the full physical domination function:

$$P_h(t) = \frac{1}{3}\left(a(t) + d(t) + r(t)\right)$$

- **Mental Domination** in table tennis is difficult to quantify because it depends a lot on the players and on the context of the match. However, we assume that certain mental characteristics are found in a majority of cases [140]. Our model takes into account defeat anxiety $l(t)$, self-confidence $c(t)$ and the stress of long rallies $s(t)$. We combine those three factors to get the mental domination function:

$$M(t) = \frac{1}{3}\left(l(t) + c(t) + s(t)\right)$$

- **Global Domination** On a larger scale, the three types of domination are also combined to obtain the global domination function:

$$D(t) = 0.4S_c(t) + 0.3P_h(t) + 0.3M(t)$$

From this definition of domination, we can see on Figure 3.2 that domination is highly correlated to the score difference, which is due to the score domination term. During the last set, the domination function fluctuates a lot because the score is very tight, and because this set is decisive. Moreover, during the decider, there is a lot of stress because both player can easily win or loose, so the mental domination is also at stake. The physical domination is not very decisive, and it's most of the time almost null. This can be explained by the fact that both players are probably physically prepared and that they are authorized to rest between and during sets. Nevertheless, we can notice that some score domination period are correlated with physical domination peaks.

We defined the different metrics as follow:

Definition of the Winning Probability $P_{a,b}$

Considering the scores being a for player A, and b for player B, we define the probability for A to win the next point by $p = \frac{a}{a+b}$.

Then we can calculate the winning probability of A knowing the scores (noted $P_{a,b}$) by using the following recursive formula,

$$P_{a,b} = pP_{a+1,b} + (1-p)P_{a,b+1} = \frac{1}{a+b}\left(aP_{a+1,b} + bP_{a,b+1}\right)$$

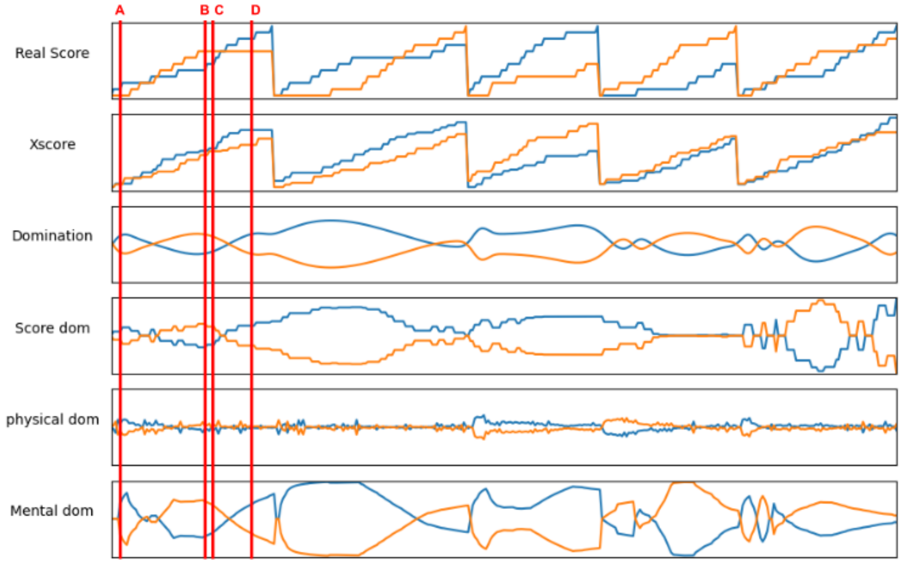


Figure 3.2 – Detailed metrics during the first set of a match between **Alexis Lebrun** and **Fan Zhendong** at the WTT Championships in Macao, China in 2023. Red vertical lines the 4 points during the first set we focused on.

and by applying those limit conditions:

- If $a \geq 11$ and $b < a - 1$, therefore $P_{a,b} = 1$,
- If $b \geq 11$ and $a < b - 1$, therefore $P_{a,b} = 0$,
- If $a = b$, therefore $P_{a,b} = 0.5$.

Because of the quite extreme winning probabilities that we encounter for low scores, we added another condition to complete the model:

- If $a + b < 5$, therefore $P_{a,b} = 0.5$.

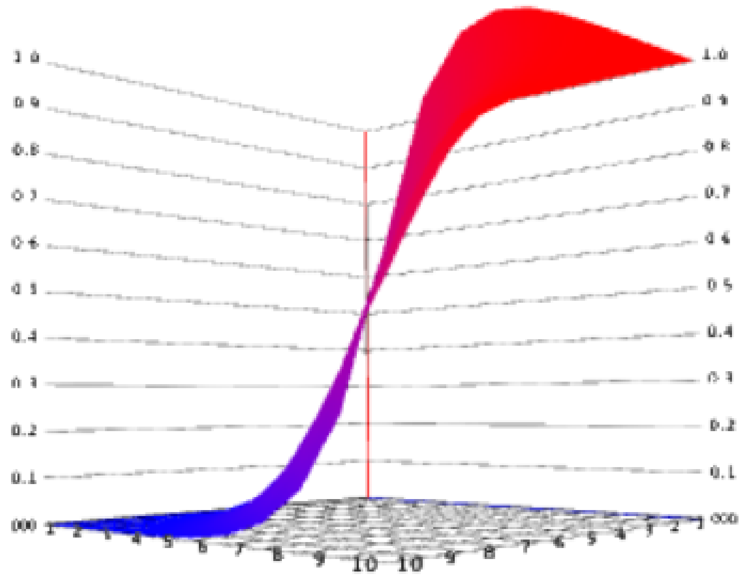


Figure 3.3 – Winning probability $P_{a,b}$ (vertical axis) as a function of the scores a and b (horizontal axes)

For the winning probability of a match, the same process is applied, taking into account the probability to win the current set.

Definition of the Three Factors of Physical Domination

We can extract domination function for the endurance and aggressiveness values:

- $d(t) = \dfrac{d_B(t) - d_A(t)}{d_A(t) + d_B(t)}$ for the domination of endurance,
- $r(t) = \dfrac{r_A(t) - r_B(t)}{r_A(t) + r_B(t)}$ for the domination of aggressiveness

The playing angle measures if the receiver of the ball is physically put in trouble by the one who sent it. Given A and B the position of the players, and C the rebound point of the ball, the playing angle depends on the scalar product $\alpha = \overrightarrow{AC} \cdot \overrightarrow{CB}$ which is 1 when the receiver is not in trouble (points are aligned) and -1 in the worst case. Thus, the playing angle is defined as:

$$a(t) = \begin{cases} \dfrac{\alpha - 1}{2}, \text{ if A receives the ball} \\ \dfrac{1 - \alpha}{2}, \text{ if B receives the ball} \end{cases}$$

so that $a(t) = 1$ if B is in trouble (meaning that A dominates) and $a(t) = -1$ if it is the opposite.

Definition of the Three Factors of Mental Domination

If a player is close to defeat or is caught by the score, his anxiety about losing increases. If a player makes several winning shots in a row, his self-confidence increases, but if he makes a lot of mistakes in a row, he loses his self-confidence. And each time a rally takes place, the losing player's stress increases by an amount proportional to the length of the rally. We get ourselves three functions ($l_X(t)$ for loss anxiety, $c_X(t)$ for self-confidence, and $s_X(t)$ for stress) for each player (A and B). We first combine them two by two to get three functions between -1 and 1:

- $l(t) = \dfrac{l_B(t) - l_A(t)}{l_A(t) + l_B(t)}$ for the domination of loss anxiety
- $c(t) = \dfrac{c_A(t) - c_B(t)}{c_A(t) + c_B(t)}$ for the domination of self-confidence,
- $s(t) = \dfrac{s_B(t) - s_A(t)}{s_A(t) + s_B(t)}$ for the domination of stress of long rally.

These definitions are highly debatable, as we consider the relationship between the player and the context as unidirectional : the context of the match impacts the player mental state. We know that this is not necessary the case, some player may have the ability to self-regulate and boost his self-confidence, which impacts the game in return. However, table tennis is known to be a highly stressful sport where mental characteristics of players can vary a lot. We tried to build this mental domination metric, with advice from experts and elite table tennis players.

3.3.2 Expected Score (XScore) in Table Tennis

We have developed a second metric that draws inspiration from Expected Goals (often referred to as ExpG or XG) in soccer [**mead_expected_2023-1**, 53]. The objective of this metric is to predict the outcome of a point based solely on the first three strokes. By consistently applying this prediction to all points in a set, we can construct an **expected score (XScore)** that indicates the logical winner of the set. We accomplish this by exploring a tree that represents all possible three-stroke playing patterns and calculating a winning probability based on the statistics of the branch in which each **expected point** is situated, and defined as:

Definition 3.2 (Expected Points)**.** A statistical metric to estimate the probability of winning a point based on various factors such as player skill, shot quality, and opponent performance.

To construct the similarities between the games, we build a Playing Patterns Trees (**PPT**) described by those simple rules:

1. The children of a zone node or of the root are laterality nodes: **backhand** and **forehand**

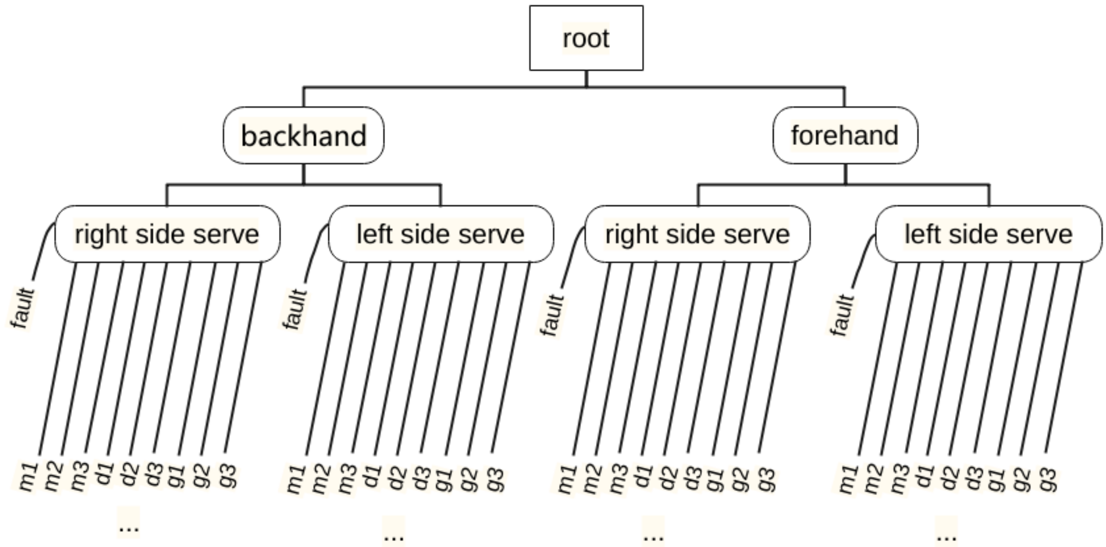


Figure 3.4 – Theoretical structure of the Playing Patterns Trees (PPT) that enumerates all shot attributes combination.

2. The children of a laterality node are type nodes: **right side** and **left side** for services and **offensive**, **push** and **defensive** for the others strokes.
3. The children of a type node are zone nodes according to the zone of rebound of the ball (**d1, d2, d3, m1, m2, m3, g1, g2, g3**. It also has a child named **fault** if the rally ends there.

Each node stores the probability that the sequence results in a win. Theoretically, the PPT up to the third stroke contains 62,651 nodes, but in reality, many of them are never explored because they represent unlikely sequences. For instance, after an offensive stroke, it is unlikely to find a short zone of rebound like d1, m1, or g1. Actually, the trees that are built on several real match analyses haven't more than 2,000 nodes. We have built our PPT from the analysis of 9 simulated matches, augmented from 3 different set annotated manually.

This metric is particularly interesting because it allows us to introduce the concept of chance (or unlikely success) and its analysis can explain certain subtleties of mental domination. As Figure 3.2 suggests, the expected score respects the global match outcome 3-2 for **Alexis Lebrun**. However, the set winners are not always the same as expected. The third set is particularly interesting because **Alexis Lebrun** wins by a wide margin and dominated during the whole set. But the expected score is totally different: he is expected to lose by a wide margin. This can be explained by the fact that he just lost the previous set and needs now to be careful. Moreover, **Fan Zhendong** just came back to a draw and may be less concentrated: he still plays aggressively, which means he has occasions but commits mistakes. The fourth set is similar, both players are very close in terms of expected score, but **Alexis Lebrun** loses by a wide margin, as **Fan Zhendong** did in the previous set: he just won the previous set, he is less concentrated, and he makes mistakes. This is an important feature that could be useful for the understanding of mental domination.

An important remark is that this metric isn't used to point the finger at players who are lucky; it is used to show how luck can sometimes work in a player's favor to gain a mental advantage. Moreover, what we call 'luck' is only those sequences that are statistically losing and still result in a win. It is quite possible that a precise refinement of the quality of the stroke will be undetectable in our analysis and will allow a losing sequence to become a win. For instance, this metric doesn't quite work with players that are extremely creative, like **Alexis Lebrun**. This leads us to our last metric.

3.3.3 Shots Diversity in Table Tennis

Being able to vary playing patterns during a match is one of the keys to victory in table tennis. A player who always responds in the same way to a sequence is bound to lose in the long term, even if their technique is perfect. However, it is well known that humans are particularly bad at creating randomness, especially when things are going fast and when the mind is in automatic mode. Therefore, analyzing the variation of playing patterns during a set should be an interesting way to look at the mental domination.

Definition 3.3 (Shots Diversity)**.** Variety of shots and techniques employed by a player during a match, including variations in racket side, placement, and shot selection.

In a previous paper [33], we saw that some players tend to serve in the same way, while they did not lose a point after such a serve. Here, we are going further in the sense that we explore more strokes into the rally, and because we create a metric representing the distance between two openings. By collecting the three first strokes of every rally of a match, we can calculate similarities between sequences.

An opening U is defined as a list of nodes of the PPT that are successively one of the children of the previous node. The first element of an opening is always the root of the PPT. The distance between two openings, U and V, of the same length n, is defined as:

$$D(U,V) = \sum_{i=1}^{n} (n-i) \cdot d(U_i, V_i) \tag{3.1}$$

with

- $d(U_i, V_i) = 0$ if $U_i = V_i$,

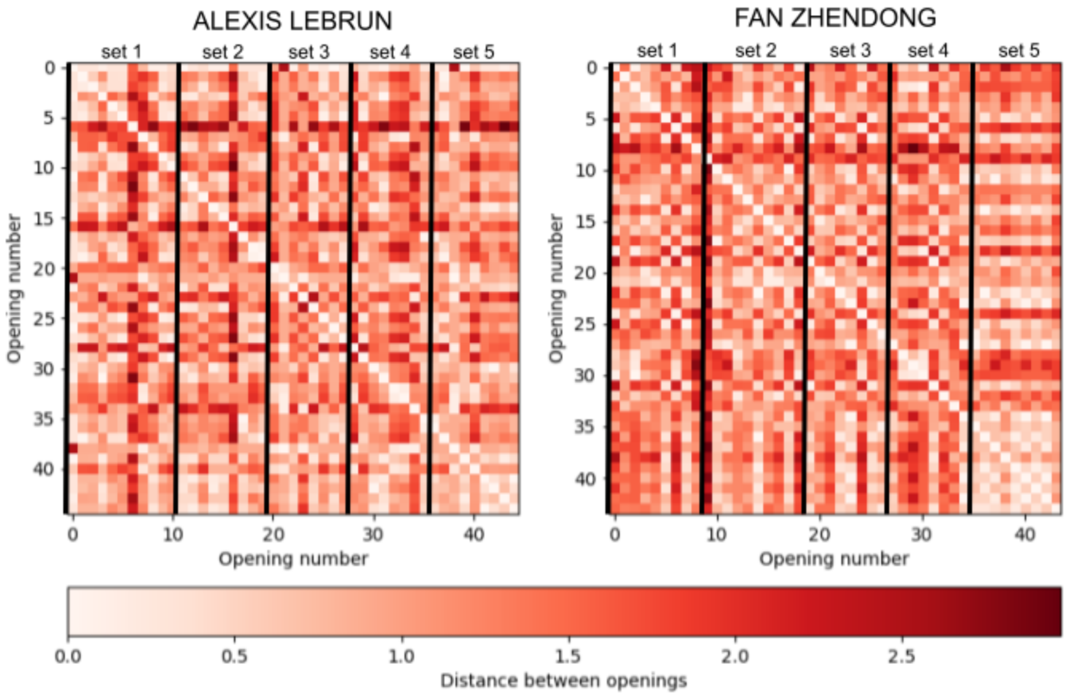


Figure 3.5 – Distance matrix between openings of the match between **Alexis Lebrun** and **Fan Zhendong** at the WTT Championships in Macao, 2023. At the beginning **Alexis Lebrun** doesn't vary much, probably to start with his strength and take the lead. Only then, he starts to change to keep surprising his opponent with new openings. During the first set, **Fan Zhendong** started to lose when **Alexis Lebrun** started to vary openings. The most interesting analysis is from the last set. We can see that **Fan Zhendong** didn't change a lot of opening during this set (white square). We can suppose that he noticed that these tactics were efficient, and he wanted to take the lead at the beginning of it. But **Alexis Lebrun** adapted to this and managed to come back. Then, **Fan Zhendong** never tried to change pattern and lost the match. This may reflect a mental fatigue of **Fan Zhendong** (maybe with the stress he wanted to stay with something familiar to him, or maybe he wasn't lucid enough to take the decision to change of opening).

- $d(U_i, V_i) = 1$ if $U_i \neq V_i$ and if U_i and V_i are laterality nodes or type nodes,
- $d(U_i, V_i) = M_{j,k}$, if U_i and V_i are zone nodes, where M is the zones' adjacency matrix and where j and k are respectively the indices for the zones U_i and V_i in M.

For a given list of openings $M = (M_i)_{i \in [0,m]}$, we can build the distance matrix defined as $Dist(M) = (D(M_i, M_j))_{i,j \in [0,m]^2}$. A feature worth attention on Figure 3.5 is the similarity of consecutive sequences, that appears as white squares on the diagonals of both matrix. Because of the temporal aspect of this figure, we can see **Fan Zhendong** tends to vary less in his opening at the end of the match, and this can be a sign of a mental fatigue.

Conclusion

In this work, we used complex data from table tennis matches to create performance metrics that help us understand how a match unfolds and the concept of dominance based on mental, physical, and scoring factors. Precise stroke data also enabled us to develop the concept of expected score, inspired by expected goals in soccer, allowing us to calculate the expected score in each game. This data also enabled us to study the variation in serves during matches and to understand how players choose their serves based on dominance. The main limitation of our work is the volume of data used for analysis, which remains limited to a single game (despite we collected and released data for multiple games). The reason is that table tennis is an adversarial sport, so only comparable situations can be compared, as players adapt their behavior against players with similar styles (which was one of our early questions). Another limitation is that we currently communicated and analyzed the metrics separately, while there is an opportunity to combine them. Furthermore, although we collected tracking data with detailed position, we only operated on aggregation by zone to capture strategic choices and filter out noise. Position data presents an opportunity for designing novel metrics. We anticipate the development of more continuous metrics based on ball position and players' body, such as spatial occupation [107].

3.4 Analysis of Services

This work explores serves of table tennis match with the three steps of analysis: exploration, categorisation an tactics. Serves play a crucial role as they are the first and only shot during which players have full control of the game. We explore serve techniques and tactics using a dataset of 9 games and a total of 510 serves collected semi-automatically for 5 players. We first provide a descriptive analysis and group the data into clusters to identify what we refer to as a serve repertoire, which are serve categories specific to players. We then identify which serve is used during the game and the tactic players employ during competitions. In particular, we provide a better understanding of the notion of variation, a concept often used in table tennis, and we show the differences in serves that are used in key moments of a game (*e.g.* during score domination, decisive points). This work was carried out in collaboration with a student from Ecole Centrale de Lyon (Thomas Papon).

Introduction

Serves are the very first action in table tennis. According to Larry Hodges [57] they are *the most strategic and tactical part of your game*. They consist of a ball bouncing on the two sides of the table, following a set of specific rules. There are several types of serves, each with unique techniques and tactical purposes. Examples of techniques are numerous. The *topspin serve*, which generates forward spin to make the ball bounce higher and faster. The *backspin serve*, which produces reverse spin, causing the ball to slow down and stay low. The *side-spin serve*, which gives a horizontal spin to make the ball curve sideways. And the *no-spin serve* which aims to surprise the opponent by having minimal to no spin. Serves can also be grouped by ball placements with *short* and *long serves*, and *pivot serves* between the forehand and backhand area. Further nuances can be added by adjusting the speed, angle, ball toss of the serve, offering players a wide palette of tactical options to initiate play effectively. Some serves also have colorful names such as the Ghost Serve (heavy backspin), Tomahawk (the racket is swung like a tomahawk), Pendulum (the server swings the paddle in a pendulum-like motion generating a lot of side-spin), or Lollipop (slow shot with little spin). In general, there is no official or formal classification in particular related to data that can be collected for this sport. Regarding the tactical aspect of serves, the goal is to find efficient serves according to the opponent and the score of the game, with variations to make the opponent's prediction and anticipation difficult.

We aim to characterize serves in a deeper way. Indeed, while both technique and ball placement can characterize them, they are limited for advanced tactical analysis. The first limitation is that the current classification of techniques and ball placement does not capture the intent of the player to anticipate the next shot. The second is that this classification is too coarse, so similar serves may be grouped in different categories, and different serves can be grouped in the same category. Besides making it impossible to accurately classify serves, the key tactical notion of variations cannot be fully explored. If accurate categorization is achieved, then many longstanding open questions in table tennis can be answered: What is the total number of serves?[2] What are the signature serves and the ones used for critical points of the game? What are the main profiles of servers?

To achieve this, we first collected a detailed dataset of serves that includes both the players' positions and techniques, ball placement in an accurate way, and the opponent's returning stroke. This provided a way to group serves by second ball bounce placements to reveal clusters on the opponent's side. To refine such clusters, we split them by the first ball bounce and the technique of the server as a style prior [127]. This led us to a specific number of clusters we referred to as the *serve repertoire* from which the server can pick. We then conducted an analysis of the use of this repertoire to identify when they are used first, their variations, and their use in key moments. We released our code and data as an open-source project to foster more research in this area.

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2. Some players claim they have around 100 serve variations https://www.canalplus.com/sport/extrait-interieur-sport-la-nouvelle-dynastie-les-freres-lebrun/h/24369553_50001 (in French)

Background and Related Work

Serves follow specific rules beyond the two bounces. Each player serves two consecutive points, alternating throughout the game, with adjustments during the final game at deuce. The server must place the ball on their open hand, throw it vertically at least 16 cm, and strike it so it bounces on their side before crossing the net to the opponent's side. Players have to hit the ball behind the edge of their side of the table. The serve must be visible to the opponent, and the free hand must not obstruct the view. Let serves, which touch the net but land correctly, are replayed, while fault serves result in a point for the opponent.

In table tennis, most analyses are based on *rallies*, which can be seen as multivariate sequences and are the focus of most analytical methods [130, 33, 132, 123]. In these works, the serve is only considered as a particular technique attribute. They eventually serve as a descriptor of the type of hit in [66], with explicit use of the pendulum, reverse, and tomahawk serves. However, as far as we know, there does not exist a detailed analysis of serves, particularly due to the categorization of the ball placement on the 3×3 grid [33, 14, 132] or in a $3 \times 3 \times 3$ grid in 3D [23], which does not capture placement subtleties. Additionally, none of them focus on the exact ball position and first rebound analysis.

Other similar racket sports (*e.g.* tennis, badminton) share similarities as two players alternate hitting the ball, with one player serving and one player winning the point. Still there is little work focusing on serves analysis. In table tennis [140] introduces a serve prediction method. They extensively review the current performance of prediction models. However, they only rely on shot-by-shot data and do not leverage the potential of tracking data [96], particularly what Hawk-Eye-like systems could provide [86]. In badminton [23] analyze rallies solely based on trajectories reconstructed from the shuttle's kinematic features. Both works are difficult to translate to table tennis, where there is a first bounce and heavy ball spin that is difficult to detect.

3.4.1 Data Collection and Exploratory Data Analysis

Our first step was to collect a detailed and representative dataset of serves. We used TV broadcast videos available on the ITTF Channel on YouTube to collect data from professional games. We employed a combination of automated (*e.g.* OpenPose [16]) and semi-automated computer vision techniques to extract players' positions, ball hit locations, and event characterizations. We picked this approach as there is currently no fully automated and accurate table tennis game reconstruction despite recent advances in this area [118]. We collected full rallies, but here, we focus only on the analysis of the first stroke (serve) and the return technique used (not its placement). We also collected context data such as the outcome of the point (winning/losing) and contextual elements such as scores

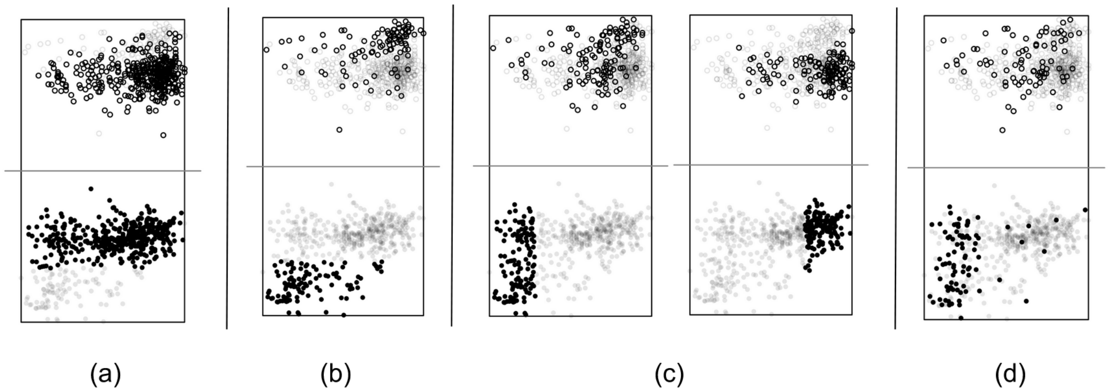


Figure 3.6 – Spatio-temporal representation of serves we collected, normalized, and filtered. The server is at the top; the dots on the upper part are the first bounce, the ones below are the second bounce, and the receiver is at the bottom. Gray dots represent all the serves, and the black ones: (a) short serves, (b) long serves, (c) side serves, and (d) pivot serves.

and players' names. We collected a total of 9 games and up to 510 serves for 5 players. The dataset has been released publicly and is available online[3]. We removed data from left-handed players as they provided spatial inconsistencies, so we only investigated games against right-handed players. We augmented the collected dataset using several post-processing steps to calculate the score and various metrics [14] (explained Section 3.3) for the section related to tactical analysis. We also reconstructed 3D ball trajectories [13] to gather details on the server's technique. We stored both the collected data and the augmented data in a database that can be quickly queried and joined with other metadata.

We then conducted an exploratory data analysis [117] of serves to grasp the distribution of serves and identify the attributes and parameters that could separate different types of serves. This step also helped to diagnose any data inaccuracies and inconsistencies. Figure 3.6 shows that standard ways to explore ball placement (*e.g.* by position on the table) are not sufficient to distinguish between types of serves. However, it revealed some interesting patterns, such as regions that are physically impossible to reach due to ball rebound physics (*e.g.* close to both sides of the net). Also, many serves are not attempted because their trajectory would lead to a fault if both bounces occur on the same side. Some possible bouncing regions are intentionally avoided for tactical purposes, such as those close to the receiver's forehand, which is the most efficient stroke. Another tactical pattern that was revealed was outliers, which are uncommon and may surprise the opponent. These outliers can be easily observed as their ball placement and trajectories are distinctive.

3. https://github.com/centralelyon/table-tennis-services/

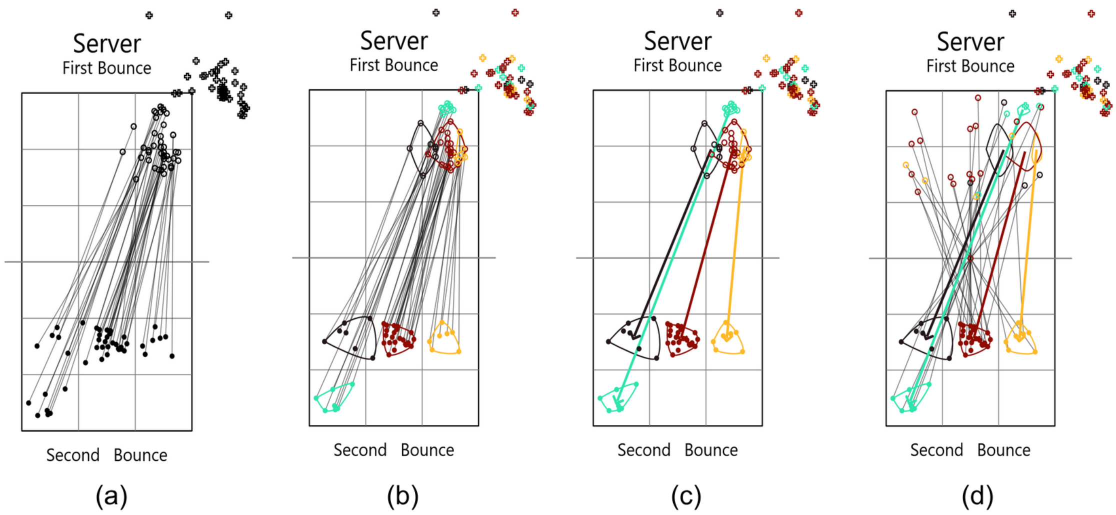


Figure 3.7 – Steps to create serves clusters (a) a single game is picked for a player, (b) K-means clusters are created based on the second-bounce, (c) the clusters are connected to their corresponding first-bounces, (d) we show the corresponding returns by the other players with lines.

3.4.2 Serves Categorization

We detail in this section our method to group serves in a way to reveal players repertoire by grouping similar serves as a combination of second-bounce ball placement and technique.

Our goal is to group balls that land on the other side of the table into meaningful clusters. Similarly to [127] relied upon K-means clustering to automatically find a way to partition 2D space based as the clusters we are looking for are roughly circular, centered around an aiming placement. Figure 3.7 (b) shows a clear separation with centroid representing the center of the target point and the spread around it (likely due to inaccuracies). Other methods could be used such as HDBSCAN [84] used in Badminton [135] or in Tennis [140]. But those methods are trajectory based and we consider that the current method we used was not sufficiently accurate to reconstruct them. We used K-means [74, 73] combined with the *elbow method* (an heuristic aiming at maximizing similarity within clusters while minimizing similarity between clusters) to determine the number of clusters. Despite the simplicity of this method, we visually assessed the resulting clusters and found them relevant in both the number, shape and centroid of the groups, to globally separate serves. We also found those clusters relevant to group serves from different games with the same players.

We refined the grouping based on the technique used when serves as two different techniques could lead to the same second-bounce cluster but with a different incoming trajectory (Figure 3.8). Also, as the clusters were sometimes

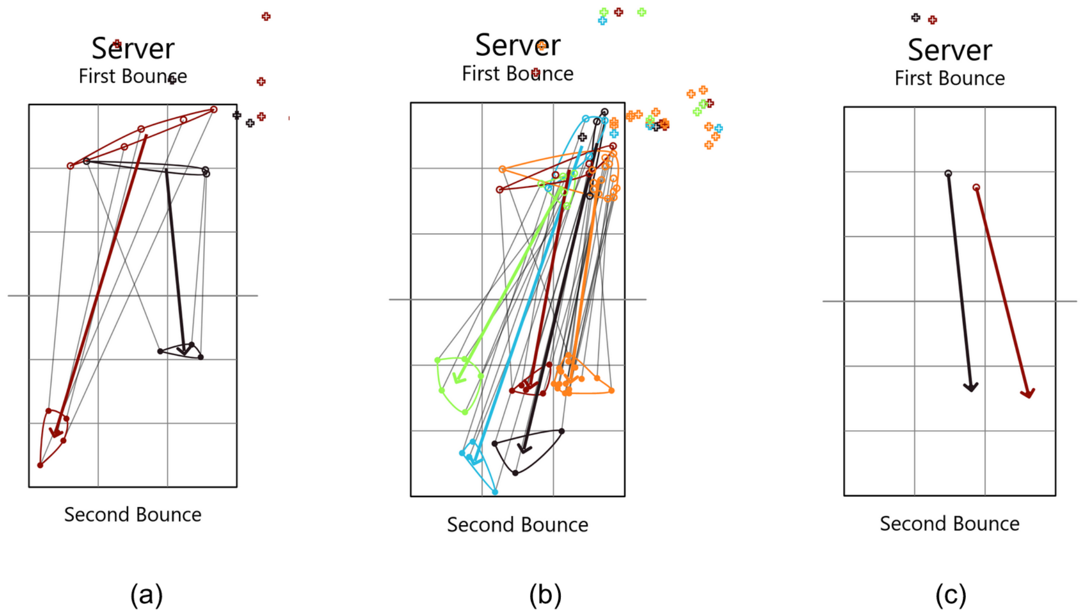


Figure 3.8 – Each clusters were then separated using serving technique (a) forehand serve with right side-spin, (b) forehand serve with left side-spin (c) backhand serve with left side-spin.

too large, and differences were caused by the effect in the serve. Figure 3.7 (c) shows such deeper separation by including the serve technique. Finally we found a total of N clusters which will be identified later as $C_1, C_2, \ldots, C_N$, ranked by number of serves in each. Each cluster C_i is represented by an area, a density and a distance to the first-bonce cluster (to indicate if this is a short or a long serves). We displayed on Figure 3.9 the results from the application of the methodology we previously used by picking a single game for our collection of players.

3.4.3 Servers Tactics

In this part we define as tactics the use of efficient serves, and our goal is to reveal which serves are concerned and when they are used.

Serves Repertoire

Table 3.1 provides a shorter, more descriptive summary of all the serves clusters we identified for top ranked players. Those are only from male, right-handed players to obtain some comparable results. This enabled to characterize the general signature of players showing either that they limit to same serves in general or have a high level of diversity.

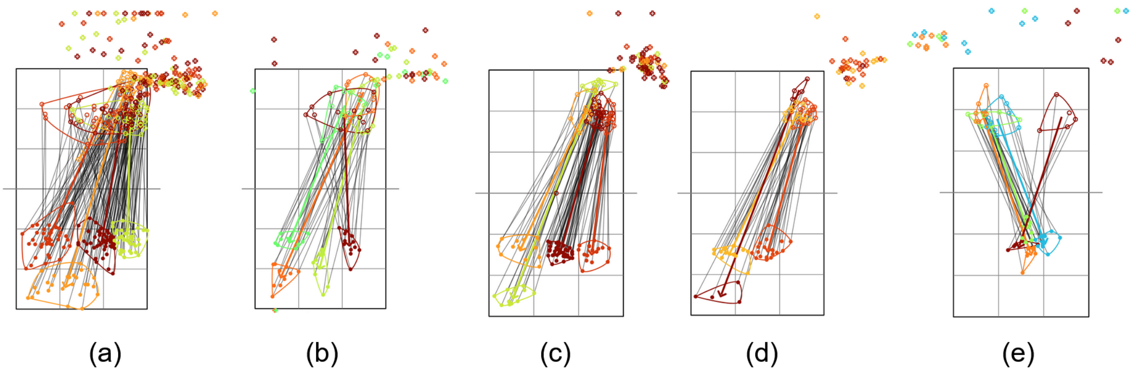


Figure 3.9 – Server's repertoire for top players: a small first bouncing area ((d) **Ma Long**, (c) **Fan Zhendong**), which is explained by a static position; spreading the first bounce across the width ((e) **Darko Jorgic**); the same serve but from different initial positions ((a) **Alexis Lebrun**, (b) **Felix Lebrun**).

Player	$C_1(area, density, dist)$	C_2	C_3	C_4
Felix Lebrun	(13%, 0.0196, 154)	(8%, 0.0139, 229)	(6%, 0.0160, 174)	(4%, 0.0192, 195)
Alexis Lebrun	(15%, 0.0127, 144)	(8%, 0.0085, 237)	(7%, 0.0079, 156)	(1%, 0.0437, 146)
Fan Zhendong	(18%, 0.0056, 259)	(18%, 0.0017, 160)	(9%, 0.0034, 166)	(14%, 0.0018, 155)
Ma Long	(36%, 0.0023, 175)	(34%, 0.0036, 159)	(36%, 0.0007, 246)	
Darko Jorgic	(3%, 0.0289, 145)	(2%, 0.0383, 160)	(1%, 0.0319, 131)	(1%, 0.0241, 218)

Table 3.1 – Details of the 4 most frequent serves from each of the top-player repertoire we picked. The area % is calculated compared to one half of the table. The distance (*dist*) is in cm (length of a Table is 274cm and diagonal 313cm).

Serves Similarity

We define a way to group serves based on their similarities. An example of low similarity would be **Fan Zhendong** who does a long serve C_1 and then a short serve C_3. This aims to capture the level of difference between clusters (we assume inter-cluster serve variations are due to how serves were executed, with a certain level of imperfection). To formalize this intuition, we extend the *shot diversity* metric introduced in [14]. The metric used below follows the following order of priority: serves with different lateralities will be more dissimilar than serves with different side-spins, which in turn will be more dissimilar than serves that bounce a second time in different clusters. We will also consider the distance between different clusters, starting from the centroids of these clusters. Finally, to highlight the variations induced by long serves, we will introduce a higher coefficient for distances along the length of the table than for the width. Here is the exact definition of the distance between two serves used:

$$D(S_1, S_2) = d_{lat}(S_1, S_2) + d_{sidespin}(S_1, S_2) + d_{cluster}(S_1, S_2) \tag{3.2}$$

with

- $d_{lat}(S_1, S_2) = 0.3$ if both serves have different lateralities (say, one is a forehand while the other one is a backhand), and $d_{lat}(S_1, S_2) = 0$ otherwise.
- $d_{sidespin}(S_1, S_2) = 0.22$ if both serves have different sidespins (say, one is a Left side serve while the other one is a Right side serve), and $d_{sidespin}(S_1, S_2) = 0$ otherwise.
- $d_{cluster}(S_1, S_2) = \|C_2 - C_1\|_1$ if both serves have their second bounce inside a different cluster, and $d_{cluster}(S_1, S_2) = 0$ otherwise. We define C_1 and C_2 the centroids of the first serve's cluster and the second serve's cluster respectively.

Then again, we must define the L1-norm used here: let (x_1, y_1) and (x_2, y_2) be the centroids of two different clusters, C_1 and C_2. Therefore,

$$\|C_2 - C_1\|_1 = \frac{|x_2 - x_1|}{76} \times 0.1 + \frac{|y_2 - y_1|}{137} \times 0.38$$

If 76 and 137 are the dimensions of half a table tennis table in centimeters, meant to homogenize the x and y distances, the coefficients 0.1 and 0.38 are chosen arbitrarily to allow the distance D between two serves to fall within [0,1], and to highlight the variation introduced by a long serve within a series of serves. Such a definition then results in typical distances of 0.12 between a cluster of serves on the opponent's forehand side and another on the backhand side, and 0.16 between a short serve and a long serve, both in the middle of the table.

Finally, the term *diversity* is introduced to help quantify the diversity of serves used by a player over the course of a set. It is defined as:

$$diversity = \sum_{i=1}^{n-1} \left(\frac{D(S_i, S_{i+1})^2}{n-1} \right) \times 100$$

with S_i being the i^{th} serve of a predetermined player in a set, and n being the number of times he served this set. Below is the *diversity* results found for **Alexis Lebrun** and **Fan Zhendong**, depending on the set :

Table 3.2 – Diversity across sets for each player

Player / Set	Set 1	Set 2	Set 3	Set 4	Set 5
Player 3	0.77	1.09	2.2	0.95	0.45
Player 2	10.20	14.47	3.03	4.96	4.39

Serving Tactics

We are now interested in understanding the tactics that motivate the change of serves. We will explore such tactics based on diversity and variations of serves,

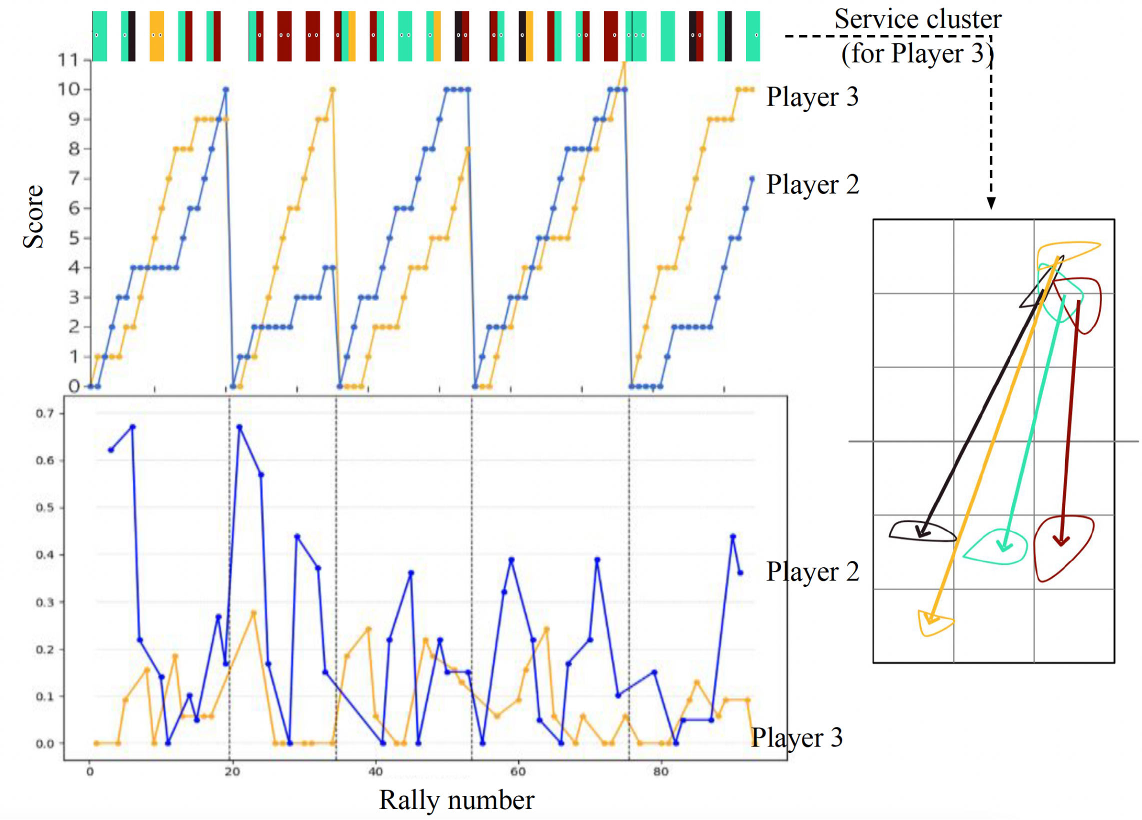


Figure 3.10 – From top to bottom: serves used by **Fan Zhendong** against **Alexis Lebrun** (colors represent the point's winner); score evolution; and distances between 2 consecutive serves (colors represent the server).

e.g. to understand which players prefer to create surprise or the ones that stick to efficient serves.

Figure 3.10 illustrates the distances and variation metrics of serves during a single game between **Alexis Lebrun** and **Fan Zhendong**. It clearly shows that **Alexis Lebrun** tends to use a more diverse range of serves compared to **Fan Zhendong**. Due to his extensive repertoire, **Alexis Lebrun** explores various serves while occasionally sticking to effective ones before introducing new tactics. Table 3.2 supports this observation, showing that **Alexis Lebrun** won the second set by employing a wide variety of serves, surprising his opponent with new tactics rather than relying on a single effective serve. In terms of the score's influence, a notable trend is that dominating players often adopt a conservative approach, preferring to stick with reliable serves, which aligns with the tactic outlined by [57]: *"Keep using what works"*. On the other hand, **Fan Zhendong** utilizes fewer serves, resulting in less variation overall, particularly in crucial points. Further investigation is necessary to refine the identified clusters and potentially uncover subtle variations.

Conclusion

In this work, we have provided an initial approach to exploring, characterizing, and analyzing serves based on the precise positions of bounces and the types of serves used. We have shown that it is possible to define clusters based on non-uniform zones specific to each player. We have defined a similarity metric between serves to study variations in serves in relation to dominance (Section 3.3). This work is a preliminary attempt to characterize table tennis serves using detailed data on bouncing positions from both sides of the table. However, it has several limitations primarily related to the level of details and volume of the data used. Regarding the volume, we aim to collect more serves to build a representative repertoire, as the games we analyzed likely constitute only a subset of all serves used, particularly the less frequently observed ones. The reconstruction of detailed ball trajectories remains an ongoing challenge in computer vision [118]. The second perspective of this work concerns the study of service efficiency. For the moment, we have characterized certain services without taking their efficiency into account. The study of service efficiency remains an essential element in tactical analysis for implementing a strategy. There are two possible approaches to studying effectiveness: the first is to look at the outcome of rallies (winners or losers), and the second is to look at the duration of rallies and the types of strokes used by the opponent. Losing a rally after the tenth stroke is different from losing after the third, as the duration reduces the influence of the serve on the loss of a rally. The final perspective, which requires more data, is the use of different dominance metrics to study how each player's clusters evolve.

3.5 Analysis of Returns

Service returns are the initial response by the receiver to the serves. Unlike serves, where the player has complete control over the stroke, the receiver is constrained: they must react quickly and adapt their response based on several factors (*e.g.* spin, speed, and placement of the ball) within a very short time frame to influence the course of the rally. The fact that the return is enforced by the service allows to explore the relationship between received serves and returns. Our study allows us to determine for each player whether there is a link between the serve and the return in the areas used. We also studied how this relationship evolves in moments of pressure. This work was carried out in collaboration with two students from Ecole Centrale de Lyon (Riad Attou and Marin Mathé).

There are various ways to respond to a serve, whether by returning in identified zones or by making a specific striking technique. While these tactical choices are crucial. As we previously saw existing studies focus on serve dynamics, or general tactics that include service returns, but without specifically addressing them. The question of how players adjust their returns based on the nature of the serves or the match context remains largely unexplored.

We aim to explore these interactions in depth by identifying recurring patterns and tactical choices related to service returns. It provides an exploratory analysis of a substantial dataset and presents the results of statistical tests. These analyses have enabled us to identify player profiles, meaning a list of actions frequently executed in similar situations. This information serves as a foundation for developing strategies and refining players' gameplay.

3.5.1 Methods

As for serves, we used k-means to generate clusters of returns and we defining two key metrics—domination, which captures transient momentum shifts via a time-decayed aggregation of past point outcomes, and pressure, which quantifies each point's contextual importance by combining factors such as score gap and match-critical situations. Using the same dataset as used in Section 3.4, which comprises 1,195 returns from 15 unique players, we first apply k-means clustering to categorize return patterns into distinct behavioral groups. To determine the optimal value of k, we applied the elbow method to the combined match data for each studied player. We then define the domination and pressure metrics and finally apply the χ^2 test to assess the dependence between return clusters and these metrics. These steps underpin our exploratory analysis and the subsequent interpretation of how players adapt their returns to evolving match dynamics.

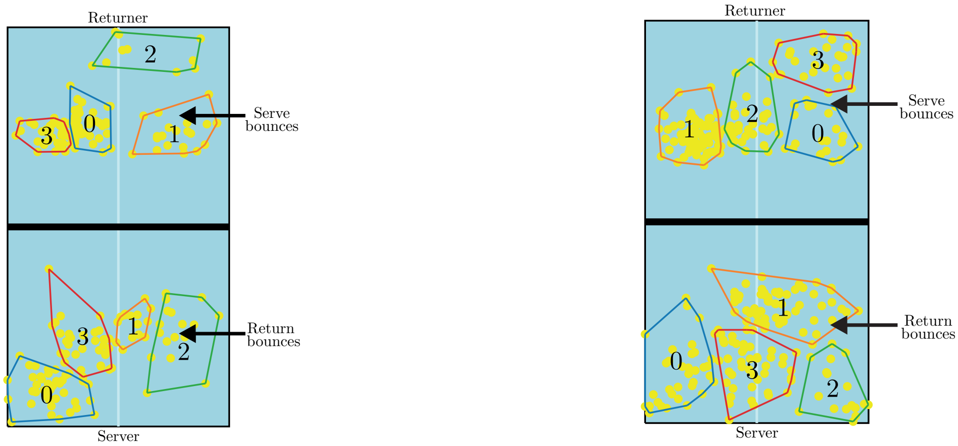
The visualization of these clusters provides insights into emerging trends for each player and allows us to observe differences in playing styles. An example of such a comparison is shown in Figure 3.11. In these figures, the server is always positioned at the bottom of the table, while the receiver is at the top. Consequently, the second bounces of the serves are represented in the upper half of the table, and the bounce of the service return in the lower half.

We define two metrics:

- A local domination indicator D_t to capture transient control during a match. For a match between player A and player B at time t:

  $$D_t = \sigma\left(\sum_{i=1}^{t-1} \beta_{t-i} V_{t-i}\right), \quad \beta_j = \frac{5 \cdot j^p}{\sum_{i=0}^{t-1} i^p}, \quad \sigma(x) = \frac{1}{1+e^{-x}},$$

  where $V_j = +1$ if A won point j (else -1), and weights β_j decrease with time to emphasize recent points. We categorize $D_t > 0.6$ as A dominating, $D_t < 0.4$ as B dominating, else neutral. A significant χ^2 test on the contingency of "dominant player" vs. return cluster indicates if players adapt returns to domination phases.



(a) All service returns from matches of . Returns by at the bottom, serves received by at the top.

(b) All service returns from matches of . Returns by at the bottom, serves received by at the top.

Figure 3.11 – Comparison of all returns by on the left and on the right. It can be observed that is less likely to play short compared to and tends to avoid playing long balls to the opponent's forehand.

- A point-by-point pressure metric by combining sub-indicators:

$$\text{pressure}_{\text{score}} = \frac{1}{1 + \text{score\_gap}},$$

$$\text{pressure}_{\text{set\_end}} = \frac{1}{1 + |10 - \min(10, \max(s_A, s_B))|},$$

$$\text{pressure}_{\text{key\_moments}} = \begin{cases} 1, & \text{if set/match point with gap} < 2 \\ 0, & \text{otherwise} \end{cases},$$

$$\text{pressure}_{\text{set}} = \frac{1}{1 + \text{set\_gap}},$$

$$\text{pressure}_{\text{decisive\_set}} = \begin{cases} 1, & \text{in decisive set} \\ 0, & \text{otherwise} \end{cases},$$

with s_A and s_B representing the scores of players A and B, respectively. These combine as

$$\text{pressure}_{\text{total}} = \sum_{i=1}^{5} \alpha_i \cdot \text{sub\_indicator}_i,$$

with $(\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5) = (2.25, 2.25, 2.25, 0.75, 2.50)$. We then test independence between pressure-level bins and return clusters via χ^2.

Serve \ Return	0	1	2	3
0	14	2	0	2
1	8	33	10	19
2	6	5	0	2
3	8	1	2	3

Dominant \ Return	0	1	2	3
Felix Lebrun	9	16	6	7
Opponent	11	17	22	7
Nobody	5	6	4	11

Pressure \ Return	0	1	2	3
Low	7	12	5	12
Medium	9	20	4	2
Fairly High	11	9	4	2
High	6	5	1	5

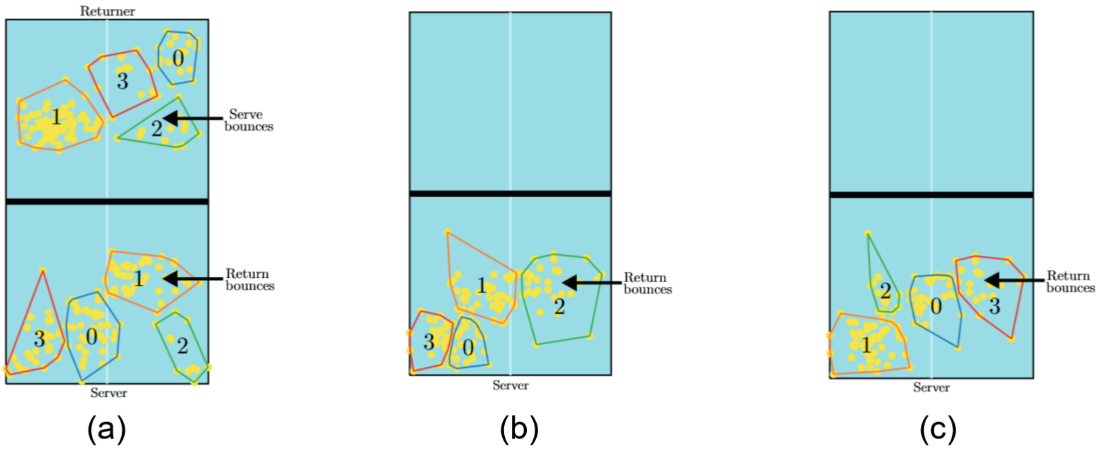


Figure 3.12 – Example of dependency between return clusters based on different parameters. (a) Shows an example of the dependence of **Fan Zhendong** return clusters on the service clusters of these opponents. (b) Shows an example of the dependence of Félix Lebrun's return clusters on the dominant player in the match. (c) Shows an example of the dependence of Félix Lebrun's return clusters on the pressure in the match.

3.5.2 Results

We report our main findings through three complementary analyses: the dependence between serve placement and return zones; the adaptation of return choices during domination phases; and the influence of match pressure on return behavior.

We can observe quite different results between players in terms of the dependence between service clusters and return clusters. Although in some players the return clusters are independent of the service clusters, in others the return clusters are strongly linked to the service clusters. An example of dependency in Figure 3.12 (a) shows the dependency of **Fan Zhendong** returns on services. We can see, for example, that the return of **Fan Zhendong** in cluster 2 is only linked to a service in cluster 1 or 3 (mostly 1). Using the dominance or pressure metric, we can see that the same player can have a completely different distribution across clusters. In Figure 3.12 (b), which shows the distribution of rebounds according to the dominant player, we see that when Félix Lebrun is dominated, he finds cluster 2 much more often, which is the least found when he dominates or when no one dominates. Regarding pressure, in Figure 3.12 (c), we see that Félix Lebrun often finds cluster 3 when the pressure is low, and when it increases, he finds this cluster much less often.

Conclusion

We contributed to novel insights on service returns in table tennis, by employing statistical methods and clustering techniques such as *k*-means. The findings reveal that the relationship between the type of serve and subsequent return varies notably across players. Moreover, the investigation into the influence of match pressure and domination phases further underscores how situational dynamics can shape the tactical responses. These results not only enhance our understanding of the underlying strategies but also pave the way for developing predictive models aimed at optimizing players' performance. Although this approach is promising for relevant analyses, it does have certain limitations. The main limitation, which is a recurring issue in many analyses, is the limited amount of data. This makes it difficult to characterize the different dependencies of player return clusters based on services, and the dependency of clusters based on different metrics is also limited, particularly by the fact that some players have not necessarily been in certain metric limit cases, such as high pressure, which is not necessarily present in all matches. The data limitation also influences the diversity of opponents with playing styles that can be very different. The second limitation concerns the metrics calculated, which are the same for all players, even though not all players feel pressure or domination at the same score or moment in the match. However, this limitation remains very difficult to address because it is not based on quantifiable elements. The final limitation concerns the variation in discount clusters based on metrics, as we have seen that discount clusters can be influenced during periods of pressure or dominance, but services can also be influenced, thus creating a new dependency on the influence of services based on dominance or pressure. To address this limitation, an analysis of the dependence of services on upstream dominance metrics would allow for a better assessment of this dependence.

In this work, we noted two main perspectives. The first concerns the increase in data. This will make it possible to obtain more relevant player characterizations. In addition, the advantage of obtaining more data is that it is possible to analyze and characterize players based on a limited group of matches, particularly based on players with a similar playing style. This leads to an analysis of the evolution of dependencies based on the playing styles of opponents. The second perspective of this work is to quantify the effectiveness of passes. We have observed that for some players there is a real dependency between return clusters based on serve clusters or different metrics, but we have not determined whether there is a real dependency between these clusters and their effectiveness. An analysis of rallies won and lost based on return clusters would help us understand which ones are effective. Continuing with this idea, a different approach to cluster construction based on both the spatiality of returns and the outcome of rallies would allow us to create more clusters by directly obtaining information on the effectiveness of a cluster.

3.6 Conclusions and Perspectives

In this chapter, we used a database of matches that we collected to study measures of dominance, based on physical, mental, and scoring criteria. We used stroke data to analyze the first two strokes of rallies, namely the serve and the return, and finally we used dominance metrics to study certain variations in strokes based on dominance. These studies showed that for serves, there are distinct clusters specific to each player, as is the case for returns. Returns are unique in that they are influenced by serves in certain cases. Some players have return clusters that are closely related to their opponents' serve clusters, which is the stroke preceding their return. The use of dominance measures and a pressure index shows that for some players, the distribution within clusters varies according to these indices; some players, when under pressure or when they are dominated, decide to change the proportion in their return clusters.

For this work, several perspectives for improving the analyses are being considered:

- The most important aspect of this work concerns data enrichment. As already mentioned, more data would allow for better generalization of player behavior and would also make it possible to study variations for a given player depending on the opponent group. With the aim of increasing the amount of data, we can revisit the perspectives mentioned in Chapter 2 on automating data collection, which would increase the amount of data available.

- The second perspective, following on from the serve and return, is the study of the third stroke. This is the server's second stroke, with the serve often considered to be the stroke that sets up the often decisive third stroke. The study of the third stroke is very interesting in that we have seen that the return can depend on the serve. In this way, studying the influence of the third stroke based solely on the return, then studying the third stroke based solely on the serve, and finally studying the third stroke based on both the serve and the return, will allow us to identify the influence of each stroke in the implementation of a tactic. In our work on serves and returns, it was mainly the positions of the rebounds that were used to create clusters. In a study of the third stroke, it is important to distinguish between the different types of strokes. Incorporating this parameter adds complexity but also makes the analyses more relevant.

- Finally, the last perspective, which has already been mentioned, concerns the study of stroke effectiveness, whether for the serve, return, or third stroke. To do this, by defining a new metric, we can create new clusters that provide a less descriptive approach and one that is more focused on coaching and strategy implementation. This metric must take into account both the outcome of the rally and the difficulty posed to the opponent, often characterized by the offensiveness of their stroke. This new metric will allow us to create new clusters and understand the importance of a stroke in the outcome of a rally.

Chapter 4

VISUALIZING STRUCTURED TABLE TENNIS DATA

Contents

The goal of this chapter is to present work on the design of new visualizations of the structured data presented in Chapter 2. These approaches aim to make the data simple and understandable to everyone and to enable tactical interpretations of the game. This chapter is based on the following articles:

[40] Aymeric Erades and Romain Vuillemot. *"Player-Centric Shot Maps in Table Tennis"*. In: Computer graphics Forum (Proc. Eurovis) (June 2025), p. 10. url:hal-04997867 [40]

[37] Aymeric Erades, Lou Peuch and Romain Vuillemot (2025). *"Investigating Control Areas in Table Tennis".* In: Sixteenth International EuroVis Workshop on Visual Analytics (EuroVA). Luxembourg, France, June 2025. url:hal-05032405 [37]

[35] Aymeric Erades and Romain Vuillemot (2023). *Visual Analysis of Table Tennis Game Tactics.* Journées visu, 22 juin 2023, Orsay (France). [42]

4.1 Introduction

Table tennis data can be very complex and, despite various data mining algorithms, can be difficult to interpret or subjective. When a coach develops strategies, all of the data used is based on video analysis, making video central to the analysis. One of the major challenges is making the data easy to understand and quickly linkable to the videos. For these reasons, data visualization has become an essential element in sport, the aim being to enable both rapid and simple exploration of the data and understanding by everyone without the need for special training. In this chapter, we present work that aims to address this issue, with the goal of being able to use complex data and represent it in a simple visual way while maintaining the link with the video, allowing a coach to perform an exploratory analysis of the data themselves in order to develop a strategy.

4.2 Related Work

Data visualization is a crucial step in table tennis match analysis. It enables effective communication of the results obtained during data analysis and allows users to explore the data so they can search for specific elements or discover new ones. Visualizations must meet certain important criteria to be effective: they must be easy to understand, allow users to explore the data, enable data filtering, and highlight certain important elements from the analyses. All of the data used for the analyses was collected from videos of matches, which makes the link between the video and the visualization very important. There are three different levels of visualization: visualizations focused solely on the data, visualizations linking the video and the data, and visualizations directly included in the videos.

4.2.1 Abstract Visualizations

Representing only the data without focusing on the video can quickly highlight tactical elements. This method has the advantage of not requiring too much time spent watching numerous rally videos and prevents the user from having a potential bias by focusing solely on the data. Vis-Sail [100] (Figure 4.1 (a))

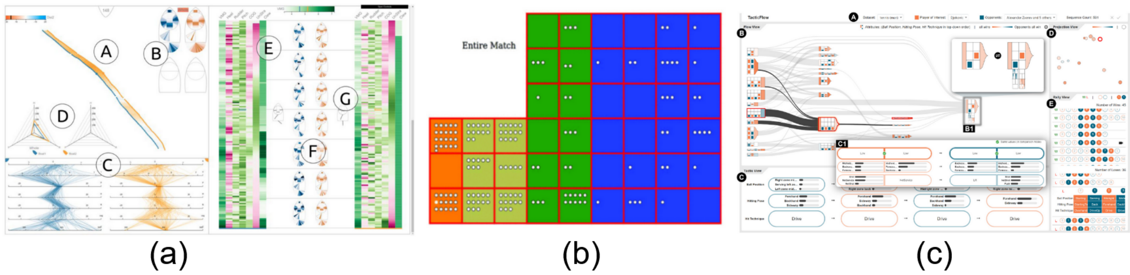


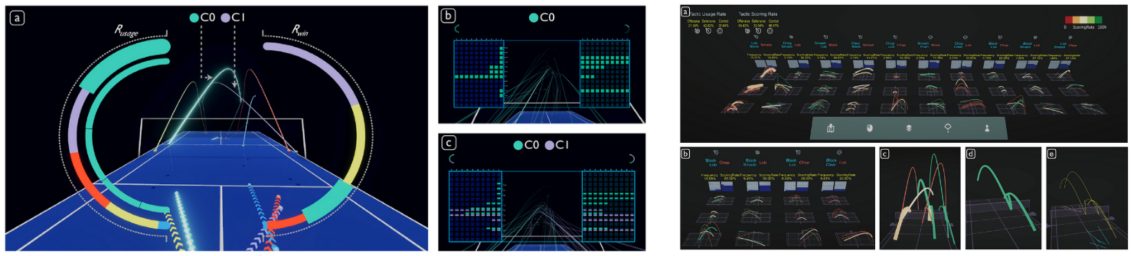
Figure 4.1 – Examples of abstract data visualizations. (a) Represents a performance analysis for boats using sensor data, from [100]. (b) Represents a sequence analysis of tennis strokes from [102]. (c) Represents an analysis of tactical evolution in a rally using Sankey diagrams for tennis and badminton, from [130]

uses sensor data from boat races, which is completely uncorrelated with video data, to determine which techniques make boats faster. To do this, they use a dashboard that displays all the sensor data, which is mainly related to certain angles of the boat or parts of the boat. The dashboard combines temporal visualizations, including heat maps, spatial visualizations such as boat trajectories, and spatiotemporal visualizations such as variations in inclination during the race.

To analyze tennis stroke sequences [102] (Figure 4.1 (b)) uses a visual approach to study patterns by focusing on the first four strokes of rallies, each of which has an attribute describing it. They represent all rallies in matrix form, aligning all points with the same strokes used by the server on the same row and those used by the returner on the same column. This makes it easy to find the most commonly used tactics by incorporating the number of times the tactic was used into the cells. Similarly, to determine effectiveness, it is possible to give the number of wins and losses. For its part, TacticFlow [130] (Figure 4.1 (c)) for tennis and badminton is based on Sankey diagrams to study the evolution of tactics in rallies. Each node represents a tactic, and the flow between two tactics indicates that the player has switched from one tactic to another. They also incorporate a feature that allows users to obtain a representation of the points that have this tactic or to project the view into a 2D space to see the similarities between them.

For soccer, PassVizor [133] allows you to visualize the dynamics of passes. The tool allows you to explore passing phases using a temporal representation of the sequence, and offers exploration using passing patterns based on a heatmap representation. By selecting a sequence of passes, the user obtains detailed visualizations of these sequences with a shotmap detailing the passes and stats.

For table tennis, Tac-simur [126] focuses on exploring tactics by combining both real and simulated data. They define tactics as a sequence of three strokes, each with the attributes of stroke placement, technique, and stroke position. The exploration is based on a representation of tactics consisting of the three strokes.



(a) (b)

Figure 4.2 – Examples of abstract data visualizations in virtual reality. (a) Represents an analysis of the trajectory of several strokes in a badminton match, from [135]. (b) Represents small multiples of tactics in badminton, from [25].

Interaction allows a tactic to be selected and a new exploration to be carried out on simulated tactics obtained by slightly modifying the simulated tactic. They use a Markov chain-based model to generate the simulated sequences and their winning rate. This allows us to explore theoretically more effective tactical possibilities. For table tennis, in order to compare sequences [66], they propose a tool consisting of three views: an overview of the analyzed identity attributes, the pattern view, and the detail view. The central part is the pattern view, which allows sequences to be compared. To do this, they use an encoding for each stroke based on its attributes and arrange them chronologically.

The use of virtual reality allows for effective visualization of spatial data that is important on three axes, such as the trajectories of shuttlecocks in badminton [135, 25]. In order to visualize all shuttlecock trajectories [135] (Figure 4.2 (a)) offers an immersive view as if the user were in the player's place, with a 3D court and trajectories integrated into the court. The tool provides a global visualization with clustering of the different trajectories and displays only the average trajectory of each cluster, giving the user an overview of the types of shots that have been used. This initial visualization incorporates several pieces of information. On either side of the user's central view, there is a proportion for each cluster showing the number of uses and the percentage of wins. The player's movement is also highlighted on the ground. For more details on a cluster, the user can select a cluster and display all of the trajectories in that cluster. The use of colors allows comparisons to be made between several selected clusters. In order to visualize more than just trajectories, [25] (Figure 4.2 (b))proposes to visualize tactics that are composed of several trajectories, using small multiples where each shot map represents a tactic with a 3D view of the field and trajectories. The small multiples form a grid of fields, and to facilitate exploration, each shot map is classified according to certain criteria. Similar tactics are found in the same column, and the order of the columns is chosen according to a criterion of importance based on frequency of use and effectiveness. The interaction offers the possibility of

Figure 4.3 – Example of data visualizations integrating the link with video in sports. (a) Represents an analysis of table tennis players' anticipation of certain types of strokes, from [124]. (b) Represents an analysis of game wins in tennis based on score progression in games, from [104].

selecting a tactic and viewing it in detail, with the option of an immersive view showing all trajectories, as in [135].

4.2.2 Visualizations Linking the Video and the Data

Linking match videos to visualizations is an approach that is closer to how coaches in sports analyze matches, allowing for a subjective interpretation of the data. Visualizations of this type often focus on a main view of the visualization with the option to view the video linked to selected data. For table tennis, iTTVis [132] allows game sequences to be analyzed. They offer an exploration based mainly on the importance of rallies according to the score, with a more detailed study of a selected rally focusing on its first strokes, where each stroke has a matrix representation of similarity with other strokes based on its characteristics. This highlights the correlations between strokes and the frequency of these sequences, while also providing a video illustrating the rally. Tac-Anticipator [124] (Figure 4.3 (a)), on the other hand, focuses on analyzing individual strokes, seeking to represent players' anticipations. By defining anticipation as the time between a player's stroke and their opponent's stroke, they use the trajectory of the players' movements during the anticipation phase in a space independent of absolute position to compare different strokes in order to detect anticipatory behavior thanks to the similarities that are visible on the video. TenniVis [104] (Figure 4.3 (b)) offers tennis match analysis with an overview of the game, representing each game with a 180-degree radial gauge that shows how the game unfolded. The upper 90 to 180 degrees correspond to one player and the lower 0 to 90 degrees to their opponent. The gauge is constructed by advancing one notch for each point in the direction of the player who won the point. For each notch, it keeps a mark that serves as a history of the gauge's evolution.

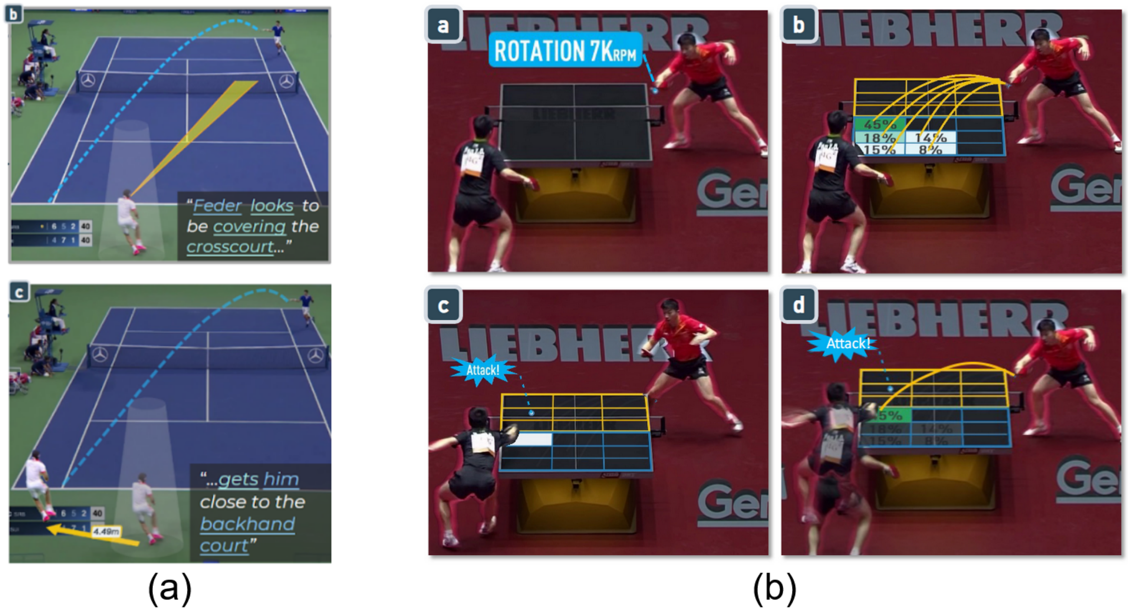


Figure 4.4 – Example of data visualizations integrated directly into the video. (a) Represents data extracted from commentators' comments in tennis, from [20]. (b) Example of augmented videos for table tennis, from [21].

4.2.3 Visualizations Included in the Videos

The use of visualization directly in the video allows the video to be placed at the center of the analysis, and the data to be used as a complement, in particular by providing information to better understand what the user sees. However, this approach often requires the user to be an expert in the sport and able to analyze the video directly. EventAnchor [28] allows information extracted using machine learning algorithms to be included. Using tracking algorithms, they detect certain events specific to table tennis, which serve as anchors in terms of temporality. This allows users to move directly to events and readjust the calibration of anchors or add annotation information. This tool therefore allows for rapid visualization of events with interaction that enables simple exploration and data enrichment. The annotation mechanisms are directly incorporated into the video. Events are linked to visual observations and are highlighted directly on the video by highlighting the tracking data used.

VisCommentator [21] (Figure 4.4 (b)) allows you to create augmented videos by incorporating visualizations based on data focused on table tennis analysis. They have identified several types of data that can be visualized in different ways. There is data at a given moment, providing information at that moment, such as the position of the players or the ball, continuous data, such as the trajectory of the ball, either a past trajectory or a future trajectory that allows you to see what is going to happen, and finally prediction data, which is used to show the different

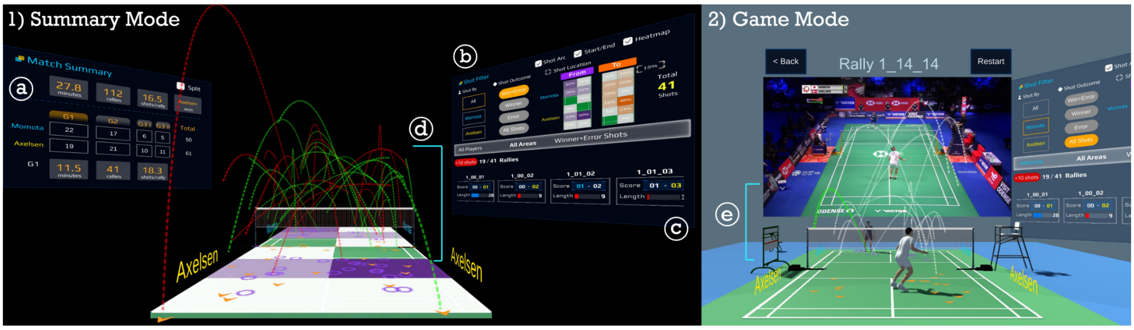


Figure 4.5 – Example of data visualizations integrating 3D game scene generation to provide additional new views to the video, from [70].

possibilities, for example (bouncing on XG) certain positions and situations greatly constrain the areas that a player can find, which means that there is a certain probability that they will find certain areas. The visualizations used depend on the types of data. For example, objects can be highlighted using lighting effects, areas can be traced and highlighted, and trajectories can be traced.

Sporthesia [20] (Figure 4.4 (a)) allows videos to be enhanced using commentators' comments. In this way, comments are used as data to be visualized. They have identified several main types of data that can be visualized: objects, actions, and emotions. The tool uses machine learning algorithms to detect all the objects present in the video and detect events. This allows them to highlight the data expressed in the comments. For objects, this involves highlighting them; for actions, adding graphic elements to highlight areas or movements; and for emotions, adding emojis.

4.2.4 Generated Video

One final category of visualization is generated videos, which are videos created using data. They can be generated in 3D, offering the possibility of movement or choice of view that is not available with the original video. For badminton coaching [70] (Figure 4.5) allows badminton rallies to be analyzed using 3D visualization in virtual reality. The trajectories are represented in 3D, and using the extracted data, they create a 3D model of the entire game, thus providing new angles of the match. In their tool, the original video is always available for viewing, and the 3D representation provides a better understanding of the point from another immersive perspective.

4.3 Visual Analysis of Table Tennis Game Tactics

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 [123]. 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.

Related Work

Our research focuses on sports data visualizations, particularly tracking data [96]. Such data are often collected using deep learning methods like in the TTNet system [118] which tracks various visual elements, including players, the ball, the table, rebounds, and the scoreboard. Manual crowdsourcing, as seen in [97, 28], 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 [90, 13]. These advances in data collection have enabled novel visualizations. ITTVis [132], 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 [21], 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 [20], which utilizes natural language processing (NLP) on textual commentaries in tennis to generate augmented sports videos. Omnicular [71] 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. In table tennis [34] 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 [130] has been applied to tennis and badminton, utilizing multivariate events to mine patterns from sequences. Tac-Miner [123] enables users to analyze, explore, and compare tactics based on three consecutive strokes and incorporates technical attributes.

4.3.1 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 [121] 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 [95]. 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 4.6. This design also follows the principles of overview, zoom, and detailed analysis [110] so experts can first look at an interesting rally and pick one (Fig 4.6, top) and then get the details and video playback (Fig 4.6, bottom left). We included a preliminary work on tactics discovery [34] represented as a directed acyclic graph (Fig 4.6, 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 4.6, 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

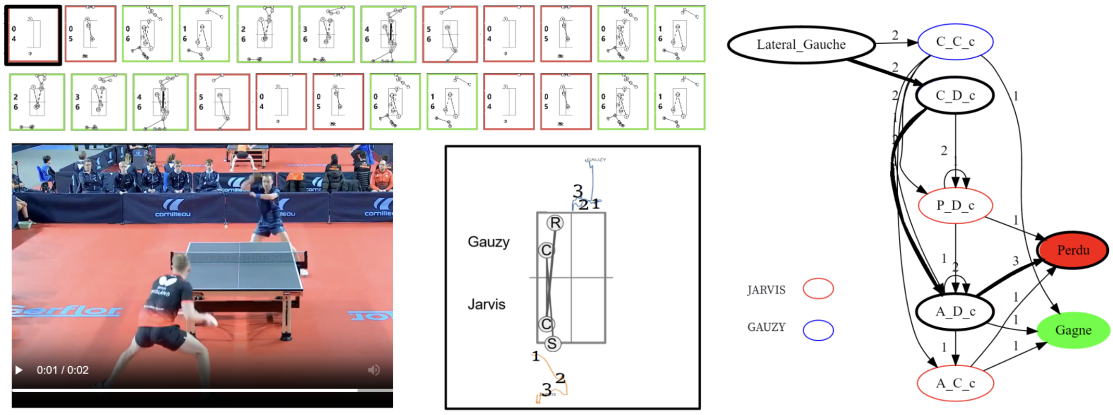


Figure 4.6 – Example of game sequence visualization using table tennis game overview (top), the focus on a particular rally (left) and a set summary using a graph-based approach (right).

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.

4.3.2 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 [120], spatial occupation [107, 1], and motion visualization [134]. 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 [12]. 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.

4.4 Player Centric Data

Shot maps are popular in many sports as they typically plot events and player positions in the way they are collected, using a pitch or a table as an absolute coordinate system. We introduce a variation of a table tennis shot map that shifts

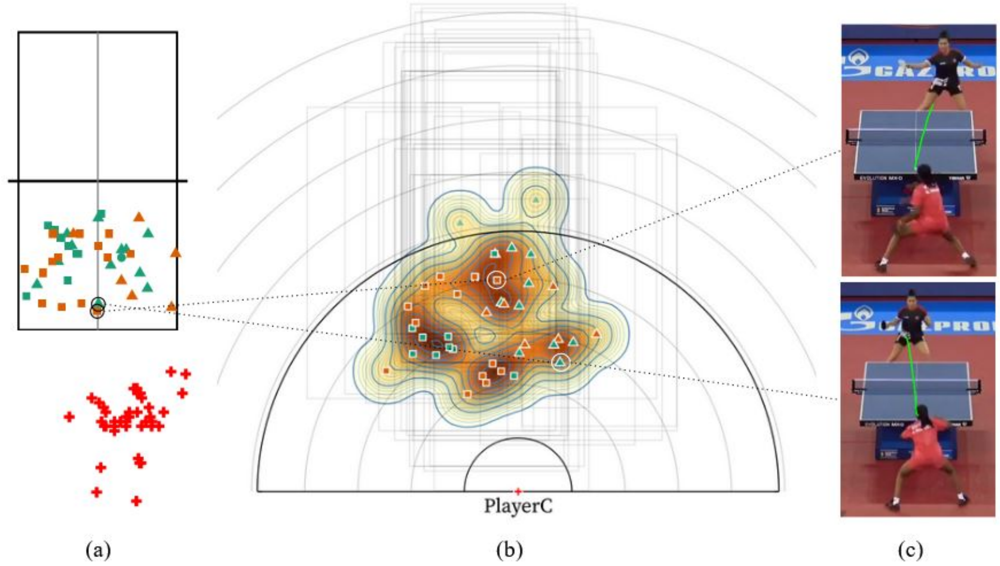


Figure 4.7 – Table tennis shot maps are usually represented as in (a), from a *table-centric* perspective, where players' positions ✚ and ball bounces ■ ▲ are plotted relative to the table. We introduce (b) a shot map representation that shifts the perspective to a unique player position ✚, providing a *player-centric* visualization to better group shots based on the distance to the incoming ball bounce. For example, in the figure above, the two highlighted ball bounces are close on the table as shown in (a), but they have different distances to the player as shown in (b): ■ is a lost backhand stroke because the receiving player in ✚ is far from the ball, while ▲ is a successful forehand stroke because the same player is close to the ball, thus easier to hit (as seen in (c), which are screenshots from the original video broadcasts).

the point of view from the table to the player. This results in a new reference system to plot incoming balls relative to the player's position rather than on the table. This approach aligns with how table tennis tactical analysis is conducted, focusing on identifying empty spaces and weak spots around the players. We describe the motivation behind this work, built through close collaboration with two table tennis experts, and demonstrate how this approach aligns with the way they analyze games to reveal key tactical aspects. We also present the design rationale and the computer vision pipeline used to accurately collect data from broadcast videos. Our findings show that the technique enables capturing insights that were not visible with the absolute coordinate system, particularly in understanding regions that are reachable and those close to the pivot area of the player.

Introduction

Table tennis is a fast-paced sport where players have little time to react to an opponent's shot. This characteristic is heavily exploited by players to identify weaknesses during games, such as *reachability e.g.* close or distant shots relative to the player's position, or targeting the *pivot area e.g.* forcing rapid transitions between forehand and backhand. Thus, there are spatial regions around players that can be tactically exploited by opponents. Surprisingly, most sports visualizations do not adequately support the analysis of such areas, despite their frequent mention in expert analysis, TV game commentaries, and instructional books [57]. The standard way to plot such data is by using a *(table tennis) table-centric* visualizations the way game occurs and data is collected through video annotation, tracking, or sensors [28, 124].

Standard sports data visualizations, such as *shot maps* that show where shots or attempts are made on the playing area, are typically created with table tennis tables as the primary element of analysis. These representations are among the most popular in sports visualization [96], but they have several drawbacks for analyzing reachability, pivot areas, or any player-centric techniques and tactical insights. For example, Figure 4.7 (a) shows that similar shots on the traditional shot maps, actually occur at different distances from the players (b) and therefore should not be directly compared. Shot maps introduce various biases when relying on absolute positions, not only because players hit from different positions, but also due to side-switching and differences between left- and right-handed players. This highlights the need for a representation-invariant approach, which could be achieved by normalizing data using relative distances to players instead of absolute ball positions.

In this paper, we introduce player-centric shot maps, where data is viewed relative to the player's position. This representation stems from the observation that tactical analysis can focus on areas around players, rather than solely on table regions. The technique relies on a simple offset calculation between the player's position and the ball bounce, making the player's position stationary as a reference. This adjustment provides a novel reference system using a polar coordinate system (Figure 4.9) and influences the visual design, requires new visual landmarks such as distance and angle guides to facilitate the understanding and comparison of incoming ball bounces. This technique can be embedded in dashboards to provide more context (*e.g.* score, videos) and interactivity.

We implemented this technique by leveraging recent advances in 3D player position tracking [118, 16, 21], which enable accurate identification of player body and ball positions relative to players and the table using 3D scene analysis as detailed in our pipeline (Figure 4.10) . We demonstrate how this technique facilitates reachability analysis, pivot area characterization, and selection based on radius and distance to the player, while also supporting tactical analysis with two case studies and feedback we collected from table tennis experts.

The contributions of this work are the following:

- A review of sports analysis tasks indicating the need to shift the reference system and limits of current design approaches.
- A design rationale and implementation of a player-centric shot map using real data, as an interactive prototype released as an open-source project.
- A data collection pipeline using computer vision techniques to obtain accurate 3D data from broadcast videos.

Our primary findings indicate–according to our experts– the technique it *aligns with [his] narrative when analyzing the pivot area*. We also report on the main challenges related to interpretation of a non-standard point of view and interactions, as well as the requirements for specific data filters. We also demonstrate the applicability of this approach beyond table tennis to other racket sports (*e.g.* Tennis). We release our code and data as an open-source project, enabling further user studies and improvements of the technique, especially when 3D data collection will become more accurate, to allow a deeper analysis of players reachability areas.

Background

We first provide general table tennis definitions, and then detail the role and importance of understanding the *reachability* and *pivot area* in table tennis.

Definitions

Table tennis is an opposition sport involving two players (or four in the case of doubles) using rackets to play on a table separated by a net. A match consists of sets, each set is won by the player who reaches 11 rallies first (*i.e.* sequences of strokes starting with a serve). The match is won by the player who is the first to win three sets (sometimes four sets). Figure 4.8 illustrates the level of analysis we focus on in this paper: a subset of a rally, concentrating on specific incoming shots from a stroke. The key concepts in table tennis relevant to this paper include:

- **Stroke Technique** refers to the technique used by the player (such as serve, topspin, quick attack, push, lob, smash, etc.).
- **Stroke Position** is the player's position when striking the ball (forehand or backhand).

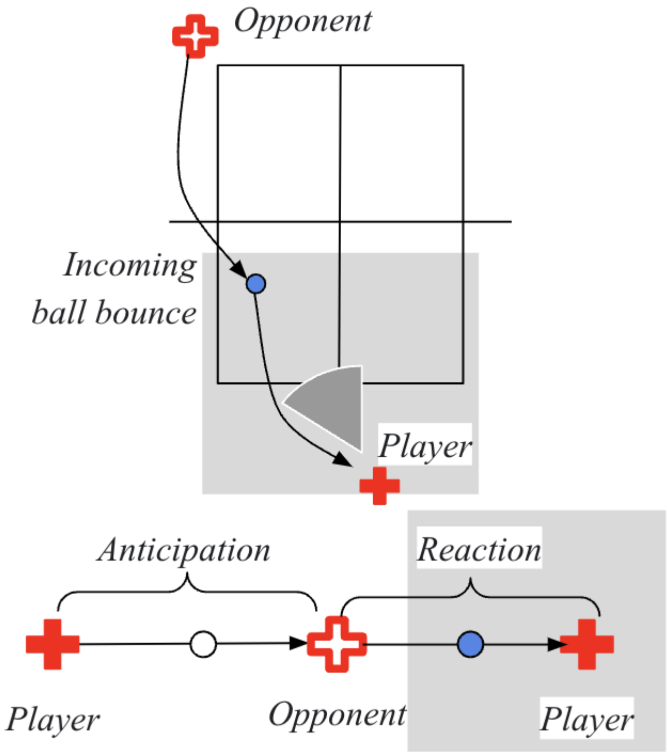


Figure 4.8 – A table tennis sequence represented spatially (above) as a traditional shot map, and its equivalent temporal sequence (below). The focus of this paper is on the gray area: the spatial and temporal regions related to players' reactions to an opponent's shot. Diagram inspired by [124].

- **Stroke Placement** is the position of the ball's bounce after a player's hit (position in centimeters).

More table tennis rules and definitions are provided in [126]. However, a key difference in our approach is considering players' and ball positions *continuously*, rather than using discrete data divided into regions and events (for both players and ball positions).

Motivation

Our motivation for this work originates from a multi-year collaboration with a table tennis expert working for a National Federation, and a recent collaboration with another one involved in the recent 2024 Paris Olympics. As it is known sports experts have limited time [72]. To address this, we contextualized their statements with related work in sports analytics and examples, and we later built case studies for illustration (in Section 4.4.4).

One recurring theme with our first expert is that tactical analysis of games is to *find the weaknesses of the opponent and develop a strategy to exploit them*. When analyzing games or coaching players, he pays particular attention to ball hits directed towards specific areas close to players, which he refers to as the *belly region* for a forehand stroke and close to the *elbow* when playing backhand. While those two regions are specific (elbow and belly), the *hip* can be seen as a way to encompass them under the so-called *pivot area*. According to him, reaching such an area is crucial, as players have limited time to change technique, often resulting in confusion and failure. He also reported that players have unique areas based on their technical skills and physical abilities. Such areas may also change during the game, making them difficult to identify and reach at the right time. The *pivot region* is also associated with analyses we reviewed from TV broadcast comments and table tennis learning materials. For instance, a table tennis expert on a YouTube channel analyzed the match between Ma Long and Fan Zhendong (world-class players) during the 2023 Asian Games final. During this game, the commentator indicated weak regions (using arrows) to hit the ball towards the pivot area. Ma Long effectively targeted this area, hitting the ball twice to Fan Zhendong at 10-7 to win the point and the first set: *"This is very well played [by Ma Long] as he plays twice on the elbow [of Fan Zhendong]. It is an important point as he unsettles his opponent twice, creating hesitation to use his forehand and backhand."* [5]. Similar analyses of the pivot area can be found in books like [57] on page 209: *"Opponents are especially vulnerable to shots to their elbow, since they have to react to the shot."*. The author also adds that due to the fast-paced nature of the game, there is little time to adapt to the shot angle except when there is time, often due to the distance of the player from the table and the stroke technique (*e.g.* lob).

Our second expert has recent experience in deeply analyzing key tactical aspects of games using detailed data from annotation tools. Such data provide a finer grain of analysis, particularly based on ball position and distance to the player. Our expert is particularly interested in very simple aspects of sports tactics, such as *reachability area*, meaning hitting the ball where the player cannot reach it because it is too far away. This approach has not yet been explored deeply in table tennis, despite its importance. Our expert referred to other sports where such an approach was prominent, but usually in broader sport fields using macro analyses with simple formats, such as Voronoi partitions [119]. This need resonates with advanced visual analytics of reachability that go beyond space partitions, using *space-time models* for soccer [113] or basketball [47], which provide more accurate space reachability estimation as they account for player speed and orientation, particularly for event-based characterizations such as analyzing 3-point shots in basketball [1]. In table tennis, reachability has been investigated through visual analysis of the distance between the opponent's position before hitting the ball and their actual position [124]. Since table tennis games are fast-paced, the distance between the ball's hitting point and the player's position is an acceptable proxy—confirmed by our second expert—for assessing whether players are within a reachable distance or not.

In summary, there exists a vast body of literature and expertise supporting the need for the type of analysis we are addressing, either already existing in table tennis tactical analysis (*e.g.* pivot area) or for other sports but not applied yet to table tennis (*e.g.* reachability).

Illustrative Scenario

To illustrate our work, we provide context and details on Figure 4.7 to provide a specific table tennis scenario that highlights the importance of pivot area-based analysis. We selected a game from the 2021 European Team Championships between two top teams, in Cluj-Napoca, Romania. The game was between female players and , both highly ranked players at that time. The game was tight with a victory 3-1 for . We picked two moments in the match where two shots by were made, one leading to the point win and the other to the point loss. We can note that she made both a forehand and a backhand shot as seen on Figure 4.7 (a) shot map. In this representation, the ball bounce zones appear very close, the only difference being the type of shot made by on these two bounces. The difference becomes visible in (b) when we change the perspective and focus on the player. We see that the two points are no longer close at all, one being far ahead and the other closer to the right of . We can hypothesize that the distance of the bounce relative to was a decisive factor in the result, to be confirmed with further analysis of similar strokes. Watching the video footage also helped confirming this hypothesis, as we can see struggling to play the shot during the lost point Figure 4.7 (c).

Summary: Requirements

We capture the missing research area from the previous sections as a list of requirements for our contribution in this paper:

- **R1** **Data normalization and shift of perspective** for all shots relative to the player in a given match or series of matches, emphasizing the ball bounce from a player's perspective. Such normalization allows for a consistent analysis and identification of shot patterns, regardless the context (*e.g.* absolute position of players).
- **R2** **Characterize shots reachability and pivot area** based on the angle θ and distance δ to the bouncing ball. By analyzing these parameters, we can define the efficient shot space for a player.
- **R3** **Compare across data subsets and attributes** to identify any evolution or change in performance. Thus, analysts can compare players to identify stylistic similarities, differences, or evolutions throughout the game.
- **R4** **Contextualize strokes** using videos from the games, score, or with whole rally multivariate sequences, to provide a more holistic understanding of the game's dynamic.

Related Work

Our work is related to racket sports data visualization and analysis. We particularly focus on the design of shot maps and the visual analytics tasks associated with them.

Shot Maps in Sports

Shot maps (also referred to as shot distribution or shot density charts) are standard visualizations in sports [96]. They plot both sports events and trajectory data over the pitch or table, often revealing visual signatures of plays by highlighting key events such as 3-point shots in basketball [107]. These maps can also be animated with player trails [4] to provide spatial context. To facilitate interpretation, binning using a grid is often applied, as in CourtVision [50]. Court landmarks [71] can be used for segmenting semantic regions. Shot maps can be embedded [95] as facets over the playfield, providing general context and connections with previous events. Most shot maps are viewed from above, but they can include different perspectives (*e.g.* tilted shot maps [24]), which are often used in 3D immersive environments [135]. Changing the point of view is particularly interesting, as noted in [96], for providing a first-person perspective that closely aligns with how players experience a game. Still, player-centric visualizations remain an under-explored area and are primarily used in contexts where the sport centers around a specific player (*e.g.* a baseball hitter or a soccer goalkeeper).

A singularity of sports shot maps for adversarial sports is that they are heavily coupled to the type of games. The shots have a *converging* approach (*e.g.* Baseball [29]) which means that they mostly follow a similar direction. In basketball, all **incoming** shots are directed towards the net, given that shooting is the primary objective in this sport (and is the key event being plotted). Ice Hockey shots also follow a converging pattern, as depicted in [101], and can be represented using a ring-based approach due to the importance of distance. The *diverging* approach, seen in sports such as Baseball [99, 29], involves **outgoing** balls hit towards multiple directions. Often, the focus lies on the trajectory shape, distance, and the success of ball reception. In general, the analysis is closely linked to the collected data and technological advancements.

As far as we know, there is no diverging/converging shot map centered on players for racket sports, in particular table tennis.

Racket Sport Shot Maps

We focus on racket sports with a net separating players, such as tennis, table tennis, and badminton. In this context, shot maps can be characterized from a *side-to-side* perspective, with no particular converging or diverging patterns, as players move on both sides. Early work in racket sports [63] already introduced shot maps

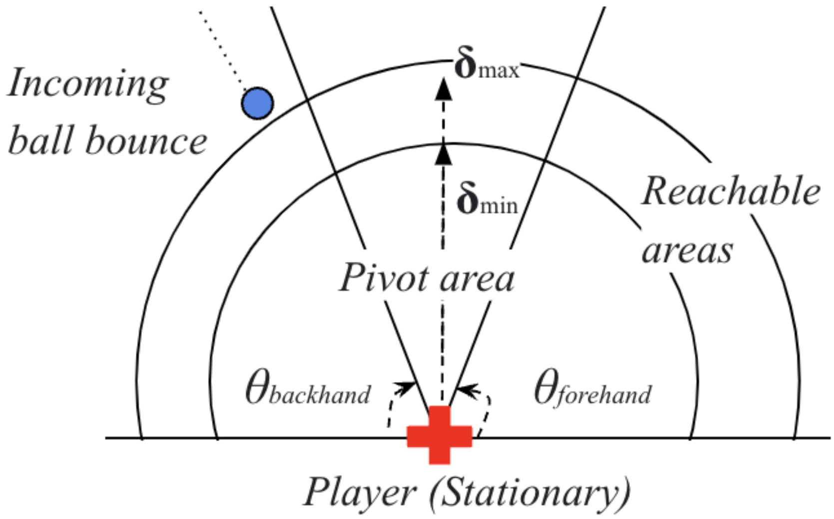


Figure 4.9 – Polar coordinate system for player-centric shot maps: the stationary player (red cross) relative position of balls (the circle represents a ball bounce), half-circles represent the distance δ from the player, and angles θ capture regions around the player.

using iconic representations. Follow-up works have relied on similar shot maps to plot information and support analysis. In iTTVis [132], shot maps are displayed as glyphs by region and stroke placement to characterize rallies with connected matrices, while Rally Comparator [66] provides player-centered shot maps with stroke placement to reveal tactical patterns in games. Tac-Miner also relies upon glyph representations [123] that categorize balls hit position into regions. Tivee offers small multiple shot maps [24] that accounts for a third dimension to capture the height of the shots. ShuttleSpace [135] also presents shot maps from a player's perspective in 3D, including detailed shuttle trajectories, for badminton. However, this line of work does not take into account the relationship between the ball and players' positions. VisCommentator [21] highlights relative positions of players to the ball to simulate hypothetical placements, though the analysis remains a visual augmentation and is still table-centric. Recently, Tac-Anticipator [124] introduces the concept of anticipation and reaction using shot maps combined with line charts encoding players anticipation, which is close to our work as it connects players with ball hits. Yet, it characterizes players-ball distance in a 1D space (as a line chart) that does not capture players orientation towards the incoming ball.

Tactical Analysis in Racket Sports

Table tennis tactics primarily focus on the first three consecutive strokes [123, 126, 33], which are mostly represented as sequences of multivariate events. The spatial component (stroke placement) is often captured as a category using discretized table regions (*e.g.* in 3×3 grids). In [132], events are organized as connected matrices to provide an overview of a rally, where stroke placement

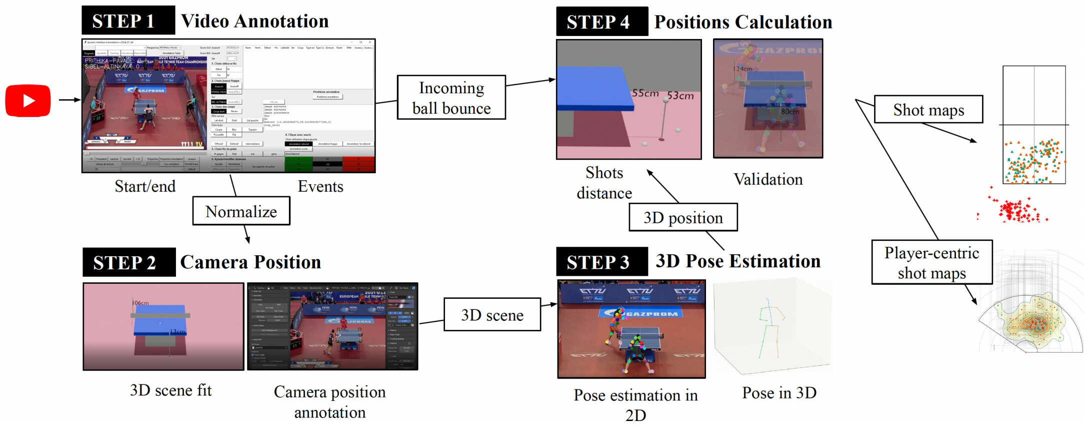


Figure 4.10 – Our 4-step data collection pipeline takes broadcast video as input and returns the relative spatial and temporal positions of players: **STEP 1** relies on manual annotation to browse and segment videos for game start/end, to click on video frames to locate ball bounce and hit positions, and select stroke techniques and laterality from a list of options; **STEP 2** is another manual step to fit the 3D scene with the video to retrieve camera parameters; **STEP 3** automatically extracts players' poses and converts them into 3D; **STEP 4** combines all data to create player-centric shot maps (please refer to the supplementary video for more details and an animated version of these steps).

is included as an attribute alongside stroke technique and position. In Tac-Simur [126], the authors introduce a tactic discovery mechanism and visualize player simulations to analyze their performance. Tactic discovery can also be achieved using frequent patterns [33] to reveal efficient (and inefficient) strategies. Tac-Anticipator [124] focuses on players' positions before their opponent hits the ball, characterizing their distance as a key factor in analyzing tactical efficiency. This work is most closely related to ours as it considers space continuously and accounts for players' relative positions. However, it primarily focuses on the *anticipation phase* in table tennis, defined as the duration between when a player hits the ball and when their opponent hits it back (Figure 4.8, bottom). Once the opponent hits the ball back, this phase is referred to as the *reaction phase*, which is the main focus of our work. This phase is typically so short that the player has little time to adapt to the opponent's shot. To the best of our knowledge, no prior work has explored this particular phase, which is closely related to the *pivot-based analysis* our expert referred to.

4.4.1 Data Collection

As no publicly available database of table tennis player positions exists, we collected data using a hybrid approach combining computer vision, deep learning, and manual annotation tools to extract player- and ball-related data (summarized in Figure 4.10). Our system processes broadcast RGB videos as input (without requiring any sensors or embedded tracking devices) and outputs players' positions relative to the table for incoming ball bounces. This approach aligns with existing methods for extracting table tennis ball data, such as the EventAnchor process [28]. However, it contrasts with fully automated systems like TTNet [118] as our method is semi-automated, particularly to achieve a high level of spatial precision for 3D pose estimation.

STEP 1 **Video Annotation**. We first downloaded table tennis broadcast videos found online (*e.g.* YouTube). Such videos are the input of the system, and we developed a manual annotation tool to segment them by game, set, and point. These segments were then used for automated tracking of player positions in STEP 2. We also enriched each segment with game events such as serves, strokes, and ball bounces, providing spatial and temporal information to normalize data for STEP 4 at key events. We also included metadata about the games (players) and outcomes (scores) to facilitate querying the collected data. Finally, we augmented the annotations with ball trajectories to provide a continuous representation of the ball to enable visual inspection of the game later reconstructed in 3D. Although the ball trajectory data was not part of the technique, it illustrates the figures in this paper. The annotation process took an average of 2h per game and required a table tennis expert for game events (*e.g.* stroke types), but temporal and spatial information (*e.g.* ball hit and bounce) could be annotated without expertise by a sport amateur.

STEP 2 **Camera Position.** To calculate accurate player positions, we required 3D coordinates. Since the videos are recorded from a static viewpoint we fit a 3D structure in the scene (table tennis table have official dimensions: 2.74m long and 1.525m wide)—using a reference frame with minimal occlusion and visible corners, based on [76]. This process also enabled the calculation of intrinsic camera parameters to correct lens distortion (we annotated two additional reference points near the net to reach a greater accuracy). The result was a transformation matrix that converts 2D points from camera space to the 3D scene. This matrix also determined the camera 3D position and rotation, saved for projecting points 2D players' reference points in 3D in STEP 3.

STEP 3 **3D Pose Estimation.** Manually annotating players' body positions in STEP 1 would have been too tedious, but recent advances in deep learning enable efficient body tracking methods such as OpenPose [16]. OpenPose provided us with a player skeleton, from which we identified the ground position and players' feet. However, the skeleton with its 25 joints was provided in the camera plane rather than the 3D plane. To address this, we applied a post-processing step using MotionBert [139]. This augmented the skeleton with a Z position, as MotionBert estimates each player's 3D pose in their own reference frame. However, such poses needed to be placed in the 3D scene, requiring additional post-processing in STEP 4 to align the 3D poses with the table coordinates.

STEP 4 **Positions Calculation.** We conducted a final post-processing step to calculate player-centric positions. We located each 3D pose from STEP 3 in the 3D scene by matching reference body joints (the feet) to the ground. Fitting the entire body remains an open problem, as it requires inverse-kinematic models. We chose the midpoint between the feet as the player's position (since players are typically on both feet when waiting for the ball). We reviewed this choice with our experts and found it relevant by generating 3D animation as overlays of the videos to assess the results.

Validation. We validated our approach in several ways. We recorded data from a known set of positions and player activities using a Qualisys motion capture system (120fps) with markers put at the same positions as OpenPose joints, along with video feeds from the cameras (50fps, HQ). We also added our own camera system and recorded several games from high-level players (60fps, 4k). The same 3D reconstruction methodology was applied, resulting in an overall accuracy of 2cm for player positions by comparing our results from the ground truth provided by the motion capture system. We also validated our approach by plotting the 3D model and the ball trajectory as a video overlay, showing accurate matching of the player and the ball temporal and spatial detections.

4.4.2 Visual Design of the Technique

We introduce a shot map visualization with a perspective shift, where the player is in a stationary position, and balls and tables have relative positions to them (Figure 4.9). This visualization aims to reveal the *reachability* and *pivot area*, two under-explored tactical factors in table tennis.

Design Rationale

Our design philosophy to shift the shot map perspective is to follow a *converging* shot map design, as a replacement for the *side-to-side* representation, for incoming balls from the opponent onto the player we focus on. The technique's default settings show the table as a standard shot map (Figure 4.7 (a)), but then data normalization is applied, and the perspective shifts using the same visual encoding **R1** (Figure 4.7 (b)). Players' positions are thus grouped to make the player virtually stationary, and all surrounding events become relative to their position. We also used temporal alignment using a technique similar to *sentinel event*, by picking a particular shot (the player stroke) to temporally align all incoming balls. As a result, our shot maps enable a comparison technique using data normalization as an *explicit* encoding [49]. At any time, the user can switch back and forth to the original shot map to perform another type of analysis or retrieve the original shot context **R4**.

Visual Encoding

The shot map visual encoding is similar to a shot map with players and balls on a 2D space, but with different positions as mentioned earlier to follow **R1**. We included additional visual elements to enable **R2**, in particular, to cope with a radial layout which distances and angle are challenging to grasp (in comparison to linear layouts).

∪ **Radial layout** is used to plot strokes with respect to players stationary position. Such layout represents an arc with radius ranges between $[-180, 180]$ degrees. We assume there is not stroke hit behind the player.

✚ **Stationary player** is represented as a red cross. We used the result from our pose estimation to locate this red cross on the 2D playing field.

● (win) ● (lose) **Incoming ball bounces on the table** are stroke placement from the opponent, encoded as a colored circle representing the bounce on the table relative to the player. Colors encode successful and unsuccessful bounces, and triangles ▲ encode forehand strokes, and squares ■ backhand strokes.

θ **Angle between the ball and the player** backhand (θ_B) and forehand (θ_F) regions based on the ball bounce locations on the table.

δ **Distance between the ball and the player** stationary position for both δ_{min} (minimum) and δ_{max} (maximum) extensions.

▽ **Pivot area** is the result of combining the previous distance-based (θ) area and the angle-based (δ) parameters.

Guides and references are radial guides to better understand the distance between the player and the balls, as well as to compare distances across points. Tables' absolute bounce positions are represented as rectangles.

Interactions are provided to select subsets of shots relative to the player's position with θ and δ values **R2** (such parameters can be automatically set as described in the next section). Widgets are provided to filter by stroke techniques and other attributes **R3** collected during the annotation process (shown on Figure 4.15).

Shot Map Clustering and Pivot Area

A side effect of the technique is that it groups shots into a smaller area than the table, leading to significant over-plotting. We experimented with various grouping methods (both supervised and unsupervised) to highlight global trends. We opted for an unsupervised approach and used kernel density estimation (KDE) to emphasize groups [108] using the density of shots in the two-dimensional space of the table [106]. The technique operates as follows: given a set of 2D ball bounce locations related to the player (x_i, y_i) the kernel density estimation for a point (x, y) is calculated using a Gaussian kernel. The density is then encoded as a continuous background heatmap with contour lines that represent similar values. The visibility of such a heatmap heavily depends on the chosen bandwidth parameter (in our case, $h = 10$) to emphasize the cluster of shots without compromising the readability of the shot map. While we did not alter the opacity of the shots, they were provided with a white stroke contour to enhance their visibility. Finally, we used the main cluster to automatically set the pivot area boundaries θ_B, θ_F, as well as the δ_{min} and δ_{max} extensions to create a pivot area as a *circular segment* of outer radius $\theta_P = |\theta_B - \theta_F|$ and a *circular segment width* of $\delta_{width} = \delta_{max} - \delta_{min}$. The area A of the circular segment can be calculated as follows:

$$A_P = \pi \times (\delta_{max}^2 - \delta_{min}^2) \times \frac{\theta_P}{360°}$$

4.4.3 Implementation

We implemented the shot map visualization in JavaScript using D3 [11] and Observable Notebooks with a SVG rendering. The technique heavily relies on a normalized dataset around players' positions which is achieved by our pipeline. We used both linear and radial scales in D3, that enable a smooth transition from the table-centric visualization to the player-centric one. The density calculation is based on the kernel density method implemented through [92], which we parameterized experimentally. We have released an implementation as an Observable Plot on `https://observablehq.com/@liris/player-centric-shot-maps`, showcasing the technique's broad applicability. We also provide examples demonstrating its integration into a multiple-view coordinated dashboard. We implemented the computer vision pipeline steps on 3D model fit using the `solvePnP` function from OpenCV [93] and a Blender Plugin. We wrote custom Python codes for the pose estimation and 3D reconstruction by relying upon Blender for matching in the 3D feet of the players with the table ground. We share our code on the following supplemental material website: `https://github.com/centralelyon/player-centric-shot-maps` as part of an open-source project under a permissive license.

4.4.4 Case Studies and Experts Feedback

We first report on illustrative case studies of the use of our player-centric shot map to support *reachability* and *pivot areas* tactical analysis in table tennis. We first detail scenarios of use that we identified as typical ways to analyze table tennis games using our technique. These stem from our collaboration with two experts, but due to their limited availability [72] and the need to avoid disclosing important tactical elements, we wrote them based on the expertise in table tennis of one

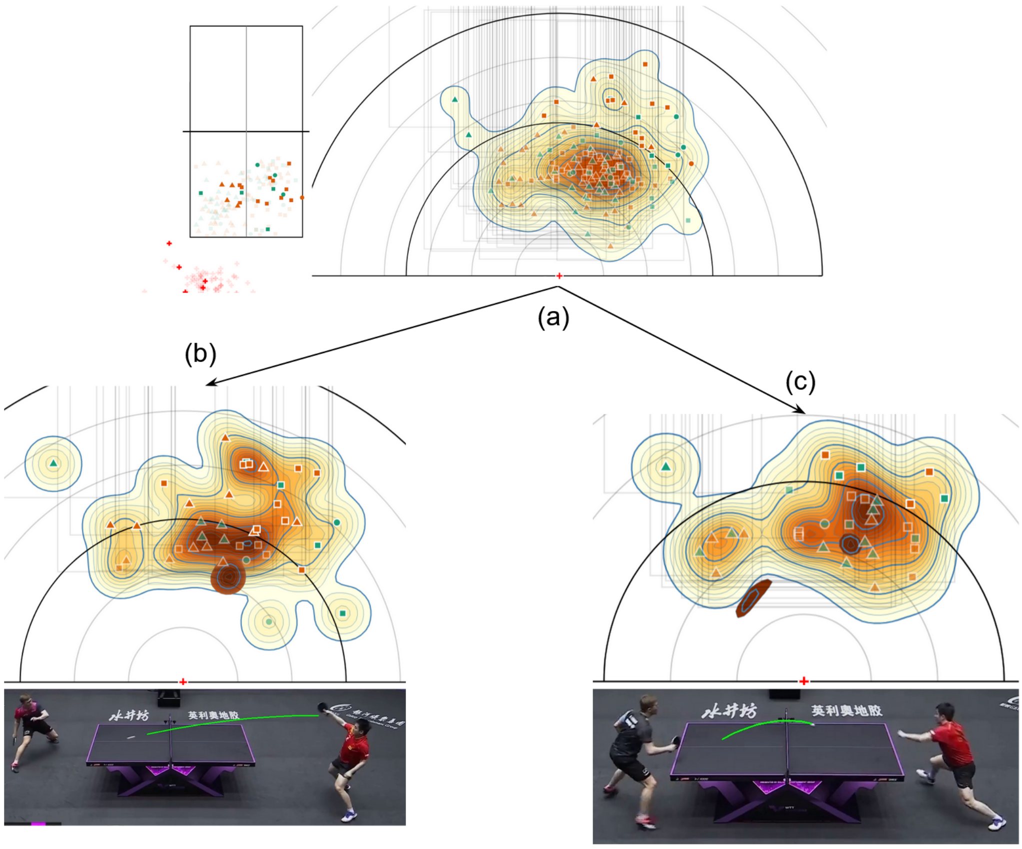


Figure 4.11 – Case study 1 on reachable areas for **Fan Zhendong**: (a) selection by distance, (b) filter by topspin, and (c) filter by push.

of the co-authors of this paper. We then collected feedback from our experts by interviewing them during 2-hour Zoom sessions. Our procedure was as follows: the prototype was demonstrated remotely with a simple presentation scenario (15 minutes), with visualizations integrated into a dashboard to provide context on the games, *e.g.* videos and score timelines (Figure 4.15). For the remaining time (105 minutes), we followed a think-aloud protocol, allowing our experts to provide their feedback and how they would see themselves analyzing games we loaded into the tool (a total of 15 recent games were available).

Case Study 1: Reachability Area

In this case study we report on **Fan Zhendong** tactical elements we found that stand out with the new reference system rather than using the table-centric visualization.

(Non) Reachable Areas In table tennis, one of the simplest tactics to win the point is to make the opponent not be able to touch the ball. This can be translated into playing in an area sufficiently far away which can be selected using the distance selector (Figure 4.11). We observed that beyond 150 cm, there is a

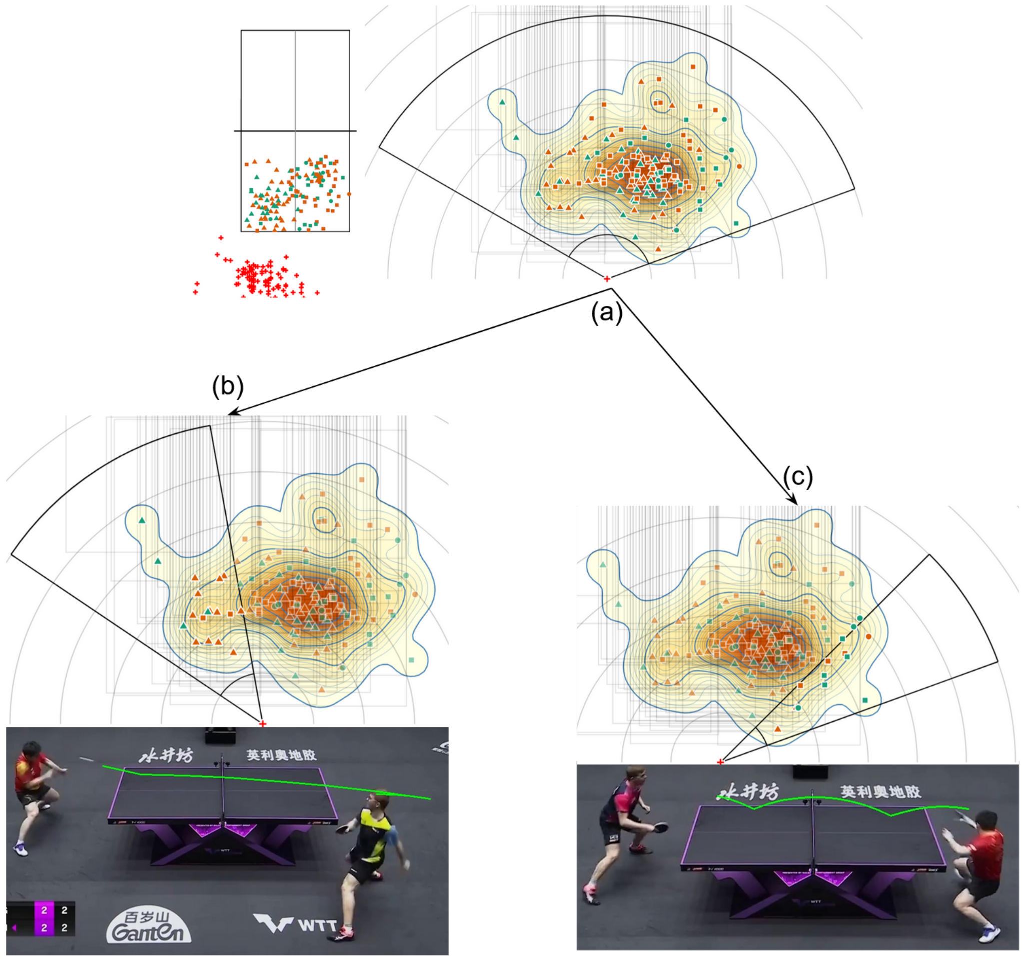


Figure 4.12 – Case study 1 on lateral areas for **Fan Zhendong**: selection by left angle shows a winning region (a), and by right angle shows a loosing region (b).

correlation with a reduction of the player's success rate. This can be explained by different factors: the ball was short and the player was far away, or the player was far from the table. These factors need to be analyzed differently, *e.g.* by stroke type. With a filter by **pushes**, the results show a relatively balanced trend (Figure 4.11, b). However, it becomes evident that **Fan Zhendong** losing points occur on the shortest balls near the table. When filtering exclusively for **topspins** (Figure 4.11, a), the area shows a clear losing trend. This can be interpreted that when **Fan Zhendong** is far from the ball and the opponent plays a topspin, he tends to be dominated, leading to low efficiency.

Lateral Areas In this second part, we study the lateral zones relative to the player to identify the ones the player feels comfortable and those where he/she does not (and ultimately find their *comfort zone*–the area where they are best positioned to execute their shot effectively). By studying lateral zones, analysts aims to identify losing and winning zones, to determine the areas to avoid or target during play. Using filters that divide the playing space into zones relative to the player's position at a specific angle, we can observe that **Fan Zhendong** has a losing zone on his **left side** (Figure 4.12, a). This highlights an area where **Fan Zhendong** is not well-positioned to execute his shot, resulting in lower-quality returns. Conversely, when analyzing the lateral zone on the opposite side, it is evident that this area is a winning one (Figure 4.12, b). Since this other side corresponds to his forehand zone, it shows that **Fan Zhendong** is more effective with his forehand, able to deliver higher-quality shots even when in suboptimal positions.

Expert 1 Feedback. Once the introductory was presented, our expert explored the regions the farthest from the player. He also found the losing trend in the deep zone seems logical because it lies beyond the player's comfort zone, where they are not in optimal conditions to be effective. It could be interesting to analyze how players are drawn into these areas by studying the **preceding shots**, *i.e.* the ones before our scope (left part of the sequence on Figure 4.8). Lateral zones help the trainer to quickly identify if players have specific areas where they struggle. Our expert thought of using the technique to **characterize players' profiles**, which he thinks would be particularly valuable. Such profile would provide quick overviews of player distance and angles, and would allow analysts to look for these same patterns in other games and against different opponents. Another crucial aspect was the ability to **filter data**. The expert emphasized that not all points can be interpreted in the same way — for instance, a push and a topspin in the deep zone are too different to be analyzed together. Despite filters were added following **R3**, more were needed in particular to filter by incoming ball direction.

Case Study 2: Pivot Area

The second case study illustrates how analysts can read the pivot area using our shot map. As a recall, one way to be efficient in table tennis is by hitting the ball directly to the center or middle of the opponent hips area in the **weak region** of the player.

Revealing the Pivot Area. It is often a complicated analysis because it is based on many factors and is unique to each player; it depends on their waiting position (*e.g.* more on forehand or backhand side). Figure 4.11 shows that for , a zone where she loses points appears to emerge on her left side which is the center of the cluster and close to how the opponent sent the ball. With a mouse selection, further attributes related to the shots can be revealed: the majority of points played in this zone are played using the forehand. However, if we look at the area slightly to the left, we can see that this one is winning by using backhands. Therefore, we can assume that her waiting position leans more towards waiting for backhands, which explains why the problematic zone is slightly shifted towards her forehand side. She struggles when forced to play with her forehand in this zone; however, if she can use her backhand, she's very effective. Through the

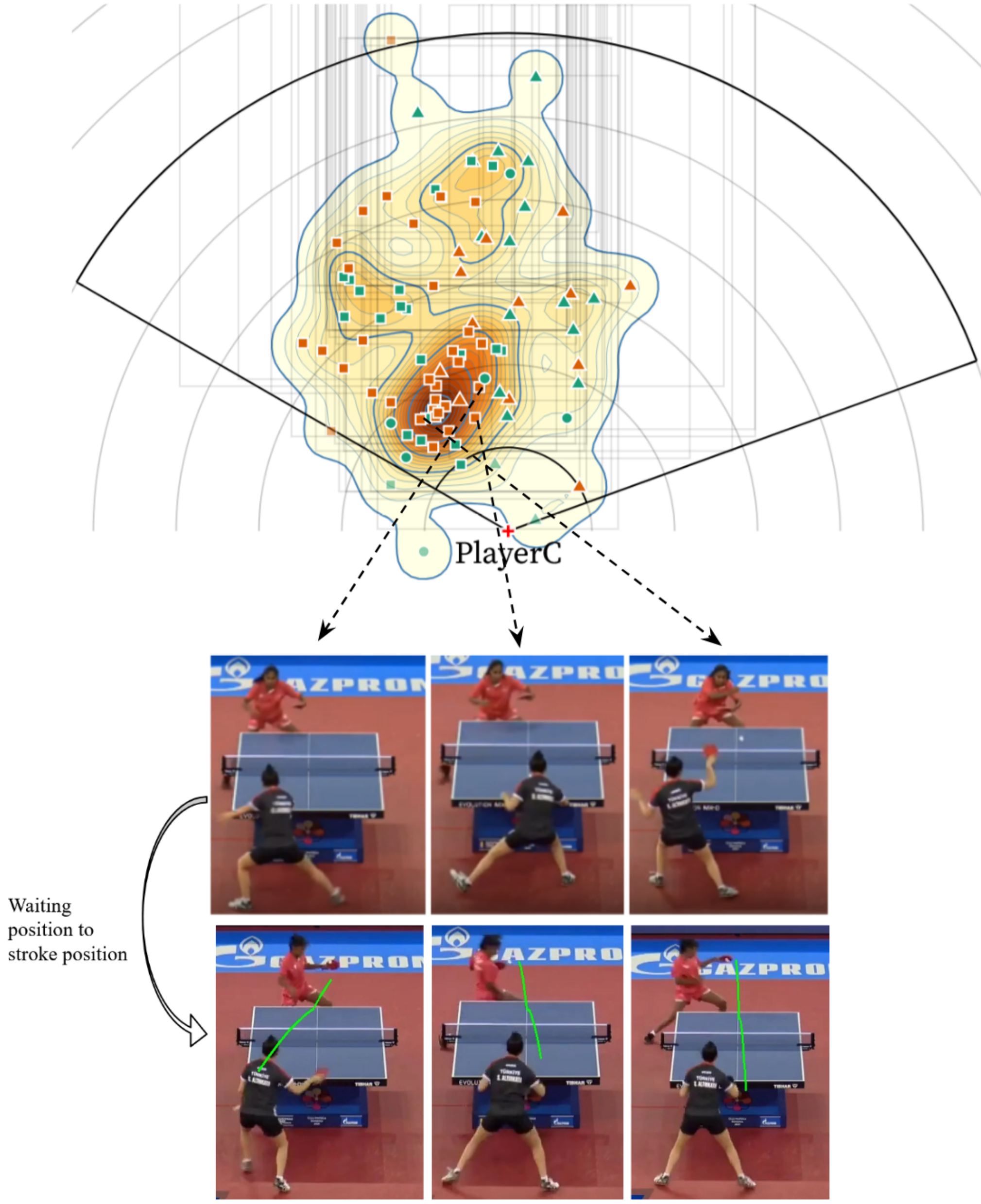


Figure 4.13 – Case study 2 on revealing the pivot area: characterizing the pivot region of by selecting angles and distances that capture weaknesses. The waiting position when the opponent hits the ball (anticipating a backstroke); the opponent hits the pivot area which makes it difficult for her to return the ball.

video, we can observe this waiting position is exploited by the opponent who aims at this particular region.

Pivot Area when Returning Serves. In this second case, we refine pivot area by focusing on a particular stroke technique: serves. This stroke technique is singular as the receiver waiting position has a consistent position towards the

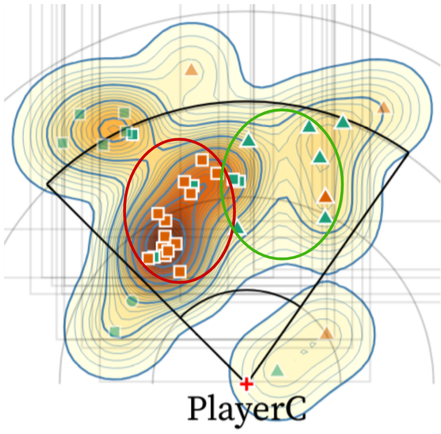


Figure 4.14 – Case study 2 on pivot areas when returning serves: two clusters emerge within the pivot area, based on player performance for each stroke. Those clusters correlated with forehand and backhand technique, which means half of the pivot is respectively a weakness (red) and the other half actually a strength (green).

table; thus our shot map shows comparable distances towards the ball bounce. By conducting the very same player-centered analysis as in the previous case study, Figure 4.14 shows a similar separation of performance with two clusters that stand out: in the forehand area, she still struggles, while in the backhand area, she's still effective (8 success out of 11 points). The interesting part with those clusters is that they are situated within the pivot area we identified in the previous, but with only a subset of strokes. The interpretation is that the weakness can be explained by the fact that with her backhand, can execute offensive flips. Therefore, in this zone using her backhand, she can attack, significantly increasing her chances of winning points. Moreover, it creates uncertainty for her opponent; even if she pushes, her opponent anticipates an attack (which is likely not to happen), making her pushes much more effective. However, with her forehand, she struggles to execute an effective offensive flip, resulting in less uncertainty and more predictable play. Therefore, the backhand pivot area in should not be engaged during serves.

Expert 2 Feedback. Once the introductory in scenario was presented, his first reaction was *it perfectly aligns with my narrative when analyzing the pivot area* as the technique reflects his mindset. There were however many concerns and questions raised to fully understand the visual encoding. First he questioned the player stationary position being used: the choice of the hip is relevant as an overview, but should be refined based on the type of stroke (backhand or forehand). His second reaction was that a good starting point was to begin by detecting winning/losing zones instead of pinpointing the transition zone we detected automatically. This resonates with the cases showing the pivot region is relevant based on the opponent stroke techniques and success rate. He found

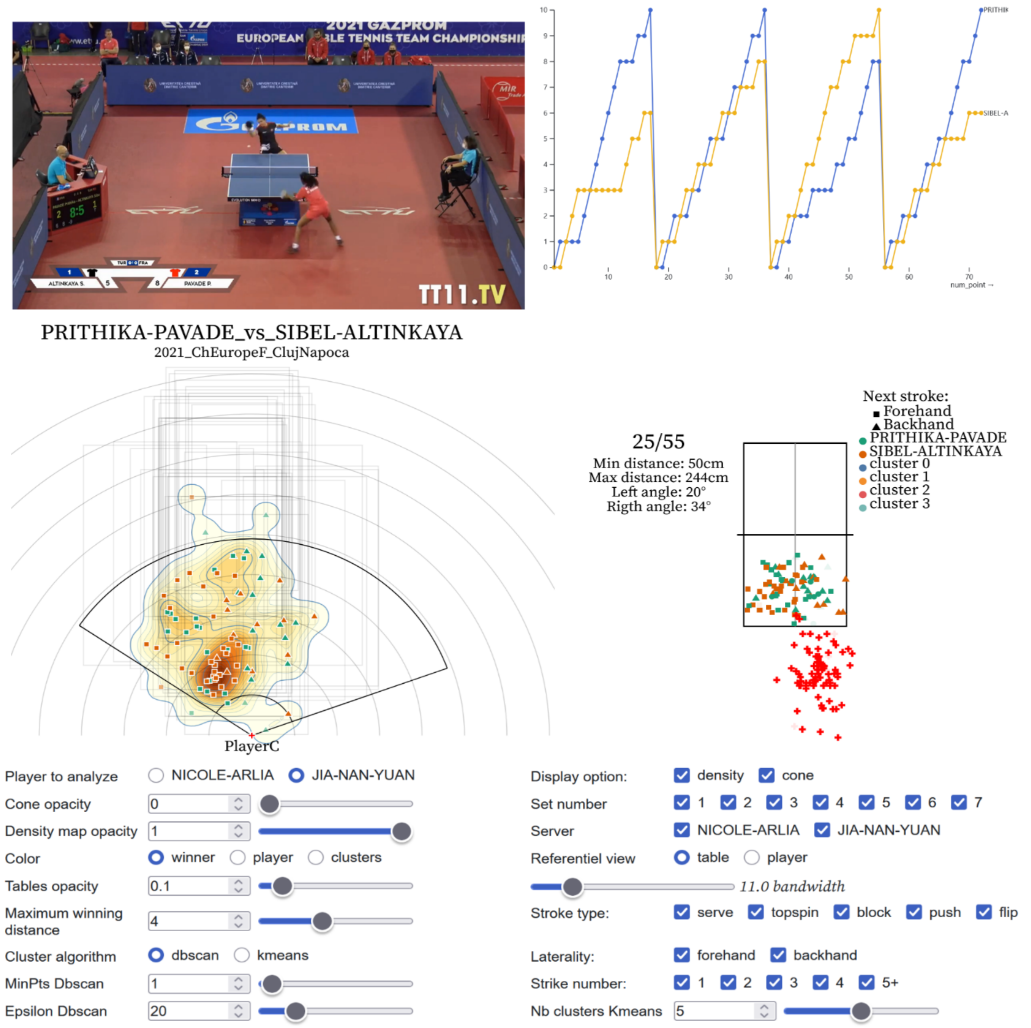


Figure 4.15 – Dashboard with the player-centric shot map we presented to our experts to collect their feedback.

however very interesting the pivot area selection as an explanatory mechanism of the success rate.

Regarding the parameters to characterize the pivot area, he questioned the use of the default density-based parameters. For the distance, in table tennis he says *we are dealing with short distances. When balls are short, they are slow, so we have the opportunity to move, thus players have time to adapt.* Thus distance in pivot areas might not be decisive except for long strokes. Regarding the angle, *"it is key to detect the transition zone, but it only puts players in difficulty in two situations: after the first attack or when you plan to start with a forehand, so the opponent sends the ball back a bit more towards the backhand [..] in general the pivot area is decisive mostly for the first two shots of a rally."*. This last comment also pinpoints the need to filter more relevant and homogeneous subsets of strokes, and also confirms that tactical analysis concerns the first shot. Thus the shot map should display by default the first three shots and discard the others.

Then he found that **starting the analysis from pivot area visualizations** might be simpler than analyzing the entire match. Indeed, it provides a more general approach to tactics with fewer parameters compared to a table-centric design, where absolute player and ball positions carry significant weight in the analysis. By starting through the pivot areas, one can identify certain elements such as points lost on the second or third ball. He says he will re-think the way he analyzes games from now on. Still as a final comments, he mentioned that all the analysis he made during the session should be refined with the players' history and training knowledge that only players and coaches hold.

4.4.5 Discussion

Relevance for Tactical Visual Analysis

We presented a method to conduct tactical analysis using advanced data that are currently underutilized in most tactical tools and techniques: ball and players' positions. Such positions are often encoded categorically, while crucial for supporting fine grained analysis. Tac-Anticipator [124] closely aligns with our approach as it considers players' distances but with respect to their previous positions. Based on our experts' feedback, the player-centric approach is relevant, although it requires strokes filtering and careful grouping of similar strokes to fully characterize a pivot region. Regarding our design, our aim was to maintain consistency with current shot maps. However, additional explanations are necessary for complete comprehension to be communicated without assistance. We also plan to explore glyph-based representations [100, 67], which could provide more compact and easier-to-compare visualizations of pivot areas, as a means to display small multiples that would allow new tasks such as comparative analysis during or across games. We plan to scale the technique using multi-class density maps [64], which will preserve the color encoding for shot efficiency—an important component of analysis.

Limits and Perspectives

Visual Design and Dashboard. When we presented our technique to our experts, it required both explanations and transitions from the original shot map to be understood. Thus, there is a need to improve the design to become a standalone technique. The use of other views also shifted our expert attention from the shot map to side views. Such limit is also applicable to standard shot map techniques that are rarely presented as standalone visualizations, but are easier to grasp due to the spatial nature of the plotted data. We identified several areas of improvements for the visual design of the technique, *e.g.* orientation of the table, grids, grouping, labels and ball trajectories. The dashboard we built (Figure 4.15) follows an exploratory approach [110] by exposing all data at once, to let users filter by attributes and get details using the video footage of the game, which also acts as context **R4**. A user study is needed to develop a domain-specific interface, similar to [124].

Contextual Information. An observation made by both of our experts during the study was that interpreting shot efficiencies requires placing them in the context of previous shots, especially those at a distance often employed as a tactic to draw players into a particular area. This tactic was also present in the TV broadcast material we reviewed during the Asian Games 2023 final *[Fan Zhendong] attracts the player in the right side of the region to hit with a forehand, so then he leaves the other empty region empty* [6]. Larry Hodges [57] on page 48 also mentions such tactic *"Imagine an opponent who goes way out of position to loop with his forehand from his backhand side, and he loops to your backhand, leaving his forehand side wide open."*. It resonates with Sporthesia [20] which example *Nole crosscourt with a sharp angle* highlights the importance of relative position in terms of ball reachability. Therefore, we believe there should be a distance threshold for the strokes we plot, as they may not be relevant for pivot area characterization and analysis. Instead, such strokes should be examined using control area models (*e.g.* [2, 1, 50, 47]) that consider the dynamics of players to define the reachability of specific regions based on reaction time and movement dynamics.

Data. Data accuracy was also questioned, particularly regarding pivot areas, which are typically very narrow and demand precise ball and player pose detection. However, one of our experts mentioned that players shot accuracy is within a range of 20cm, falling below the tracking accuracy (dependent on video resolution, approximately 2cm). As technological advancements continue, tracking data will likely become available with increased precision. This enhancement could include additional data such as ball trajectory and spin effects, providing a more comprehensive analysis of shots. In particular, by considering another body part for position and distance to the table calculation (currently the feet of the players). More data was requested by our experts to explore pattern variations across games. As our annotation process remains long, automation could be introduced by leveraging previous annotations [99]. A major limitation remains the broadcast video which leads to occlusions and causes some shots to be inaccurately processed. We plan to explore the inclusion of a confidence score (for both human and automated analysis) to provide more transparency on the actual data quality.

Perspective on Perspective and 3D. We picked the player's perspective as the referent for the relative position, with the incoming ball bounce as the reference event. However, our normalization and visualization techniques are flexible and allow for other positions and events as referent. For instance, one could align the data based on the position and time of all racket hits, providing different insights on the incoming and outgoing ball trajectories. Despite our data collection pipeline operates in 3D, this work only focuses on 2D visualization shot maps due to their wide use. While 3D data has potential for ball trajectory-based analysis, body motion, and both to capture 3D shots reachability [44], it still requires highly accurate reconstruction methods to capture spin, the Magnus effect and human movement dynamics.

Conclusion

We introduced table tennis shot maps where data are plotted relative to the player's position, as opposed to standard shot maps where data are relative to the table. This approach arises from the need for experts to identify weak spots around players, referred to as *reachable* and *pivot regions*, which can be targeted to win points. From our literature review, no prior work has explored this specific change in coordinate systems for tactical analysis. We reported on case studies illustrating the use of the technique, as well as feedback from table tennis experts who found it valuable beyond standard shot maps. We finally discussed perspectives that include providing better ways to filter data and enhancing the visual design to better grasp contextual information on the game.

4.5 Space Occupation

Control areas are models designed to determine which portions of space can be reached by a moving entity. Such models have powerful applications in various domains where spatio-temporal data is key, ranging from urban analysis to sports spatial analysis. In this article, we explore the use of these models in table tennis to understand player strategies. We build upon existing models, originally designed for large-field or team sports, and adapt them to the adversarial context of table tennis—where the goal is to determine which regions a player can effectively return the ball to. In particular, we account for player reachability using a peripheral model that captures arm and racket positions. We report on an early evaluation of our model using TV broadcast videos and discuss potential improvements for our control area models.

Introduction

Contextualizing movement is important in any visual analysis task where trajectories are often the key representation [3]. Context enhances the understanding of spatio-temporal data [18] with additional data attributes (*e.g.* events, historical

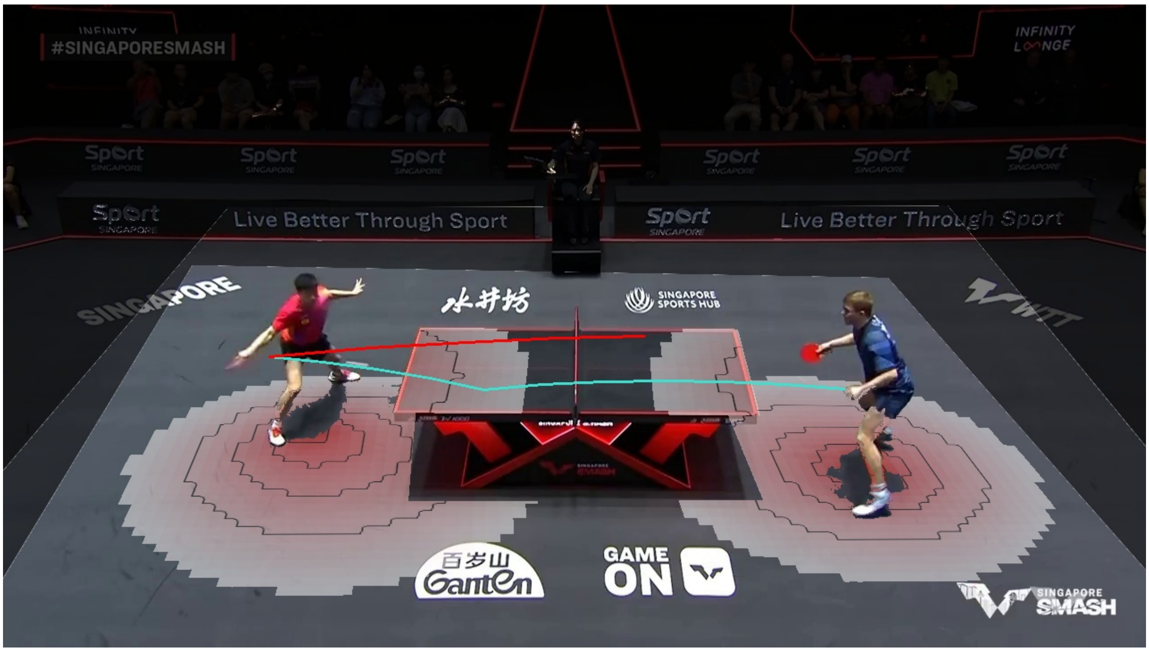


Figure 4.16 – A video screenshot of a table tennis match at a key moment between **Ma Long** (left) and **Alexis Lebrun** (right). **Alexis Lebrun** executes a fast forehand stroke (green trajectory), and **Ma Long** returns the ball (red trajectory) to the right side of **Alexis Lebrun**, who fails to anticipate it. The red trajectory shows that **Ma Long** targets a region far from **Alexis Lebrun**, outside his *control area* (represented as a heatmap), as he leaves his right side exposed, ultimately losing the point. In this paper, we investigate the construction of such control areas to identify strategic spaces players should aim for.

data) and leveraging *derived data* to enrich original datasets with extra information. According to [89], such an approach is highly effective for *designing a visualization tool for a complex, real-world use case [..]* to *extend the dataset beyond the original set of attributes that it contains*.

This paper contributes to this data augmentation strategy for spatio-tempora data by introducing a model and visualization of *control areas*, which are regions that can be reached quickly by a moving entity. Control areas are increasingly popular in sports analysis (also referred to as occupation areas, occupation models, or pitch control), *e.g.* in basketball [107], soccer [2, 1, 55], and badminton [31]. They build on the idea that moving objects have inertia, allowing the prediction of their next move and the locations they can reach in the next second. In terms of representation, the standard approach is a heatmap, which has been found to be effective in a VR context for displaying future positions related to control areas [137].

Our work contributes to explore the use of control areas for a specific sport: table tennis. We aim at characteristic when players fails to reach or return the ball properly because it was sent into this strategic zone. As illustration, we selected game sequences from international table tennis matches where the ball was too

Figure 4.17 – Ball too far away: Alexis Lebrun (left) is on the left side when Ma Long (right) sends the ball to the far right. Alexis Lebrun is too far away to reach the ball as it passes nearby. This often happens when a player is on one side and the opponent sends the ball to the opposite side or when the player is far from the table and the opponent plays a short ball.

far away (Figure 4.17) in the match between **Ma Long** and **Alexis Lebrun**, Smash Singapore 2024; the ball was in a pivot zone (Figure 4.18) in the match between and **Alexis Lebrun**, Champions Incheon 2024; and the player was wrong-footed (Figure 4.19) in the match between **Alexis Lebrun** and **Ma Long**, Smash Singapore 2024.

Building efficient control areas is challenging as it is highly dependent on the application domain, thus it needs a careful understanding of the task and level of analysis. The naive version of such concept is using Voronoi partitions [119], which is well defined but not suited as it considers all directions as candidate for control. The standard way to build more efficient model is to adapt *space-time models* [115] to quantify available space for a single player relative to the space occupied by other players. Such a model enables to analyze of space-time data using the physical properties of movers (*e.g.* direction, speed) and enables accounting for players' inertia. For a fast-moving player, it is more difficult to control the area behind him, and some delay is induced by the fact that players have a finite force and can therefore not instantaneously change their velocity to a different value. It is thus necessary to develop a model characterizing the acceleration of the players. However, the distance to a point does not fully define the control of a point, but it is rather the time it takes for a player to reach the point which defines the controlled area.

Control areas are interesting due to their predictive nature, which captures the underlying physical model based on Newton's second law [107]. Such models are simplified versions of reality, taking into account parameters such as direction, speed, and force of a player in order to calculate the time it would take the player to reach a certain point. These models allow us to visualize zones that can be rapidly reached by the player, graphically, in a similar way a spotlight highlights certain regions. This is made possible by the broader availability of

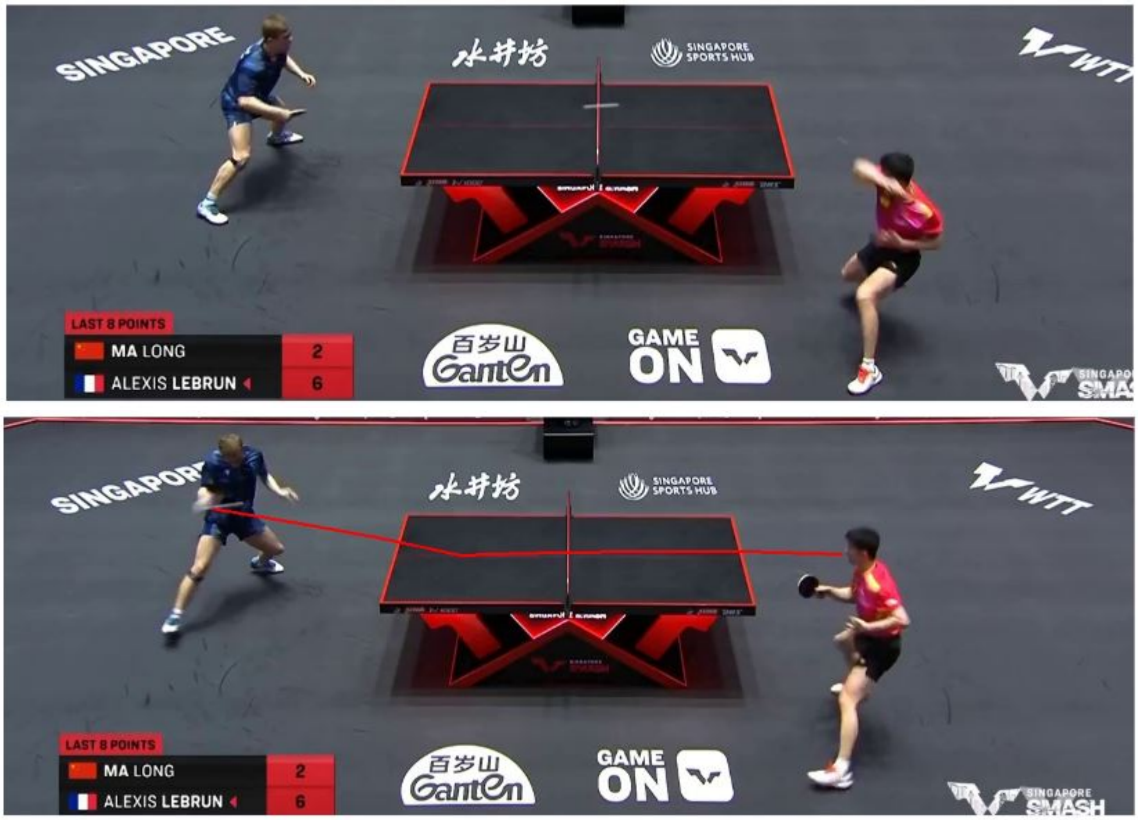


Figure 4.18 – Ball in pivot zone: Alexis Lebrun is in a backhand stance, but the ball arrives in the pivot zone, causing him to hesitate and switch to a forehand, missing the strike. This zone is difficult to manage as it limits both forehand and backhand movements, and Alexis Lebrun can't move fast enough to make space for his forehand.

tracking data [96] and already explored by the visualization community for soccer analyis [2, 1].

Our goal is to build on existing models that were initially developed for ball-oriented sports like basketball and soccer, which treat athletes as occupying a unique position. Recent works have adapted these models for racket sports like badminton [31], using deep learning to predict players' next positions. We particularly aim to provide a finer-grained approach that captures not only the next position but also the actions players can perform once they reach a specific area. This work is typically carried out without external data, relying solely on a physical motion model to derive information. In our work, we incorporate data to define a reachability area. We also report on the implementation and design challenges and release our code as an open-source project to promote research in this area.

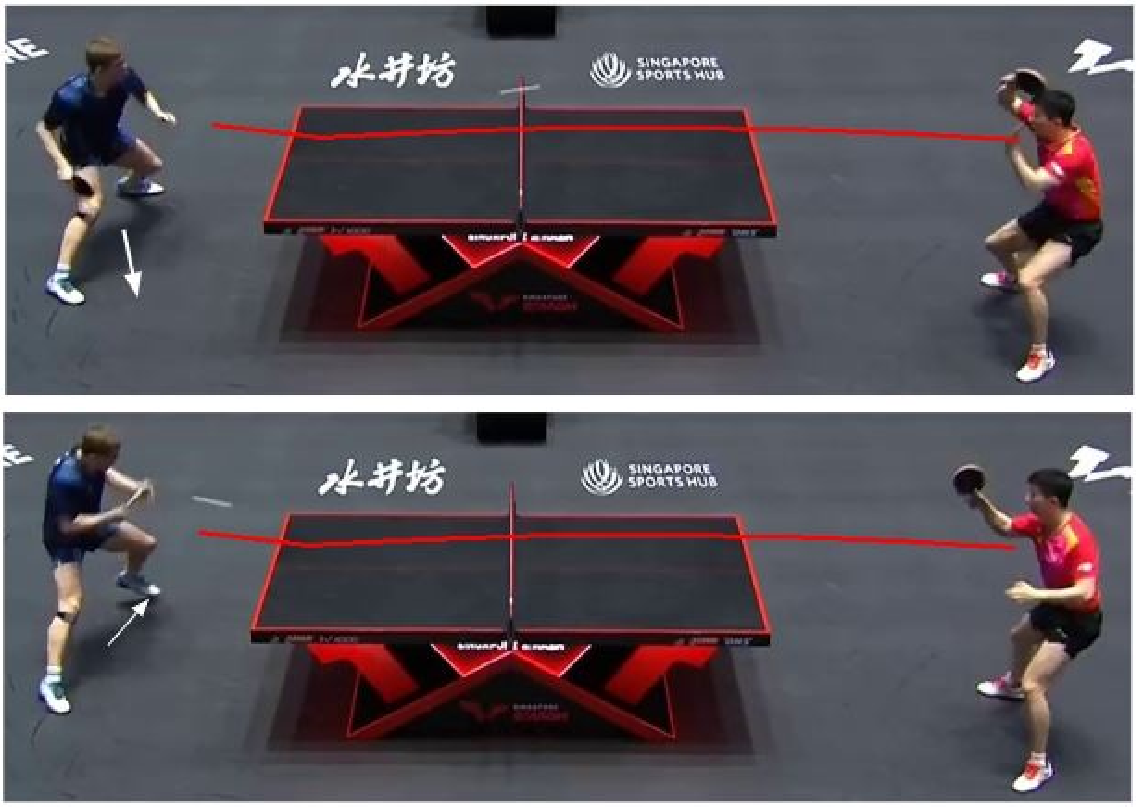


Figure 4.19 – Wrong-footed: After sending the ball into Ma Long forehand, Alexis Lebrun anticipated a cross-court shot and moved to his right, but Ma Long chose to send the ball down the line. Alexis Lebrun had to change direction quickly, which prevented him from returning the ball correctly.

4.5.1 Calculation using Newton's Law

We want to compute, for a moving player on a domain how much time it takes to reach a given point. At the initial time the velocity of the player at position $\mathbf{x}(t=0) = (x_0, y_0)$ is

$$\mathbf{u}(x_0, y_0, t=0) = (u_0, v_0).$$

We will assume that the player applies a constant force (per unit mass) in a given direction, with a magnitude of

$$|\mathbf{F}|^2 = F_x^2 + F_y^2.$$

This assumption enables a simple analytical solution, particularly by allowing the two directions to be considered separately. According to Newton's law, this can be written for the x-direction as:

$$d_t^2 x = F_x \tag{4.1}$$

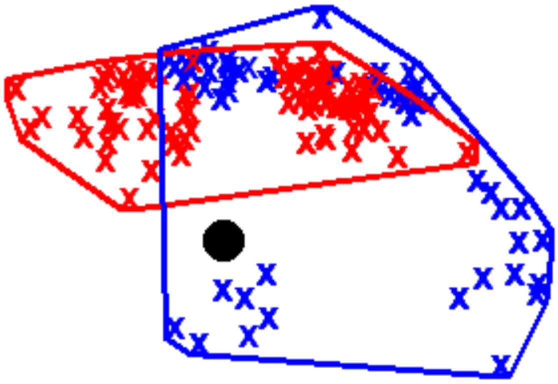


Figure 4.20 – Alexis Lebrun's ball hits relative to his position. The black circle represents the player's position; the blue marks the positions of balls hit with the forehand, and the red marks the ball positions hit with the backhand. Since the player's position is taken using his hips, some hits may occur behind the player with his forehand. We use this distribution as a proxy for ball reachability as a complement to the control area model.

so that we have

$$x(t) = x_0 + u_0 t + \frac{1}{2} F_x t^2. \tag{4.2}$$

To construct control areas, we need to evaluate this expression at each coordinate of the space. Following [107], this approach provides a way to analytically solve the equation and choose the smallest positive real solution. One adjustable parameter in this process is the value of F, which represents the force applied by the player during movement. The force F directly impacts the player's acceleration and, consequently, their reachability. A higher F allows for quicker acceleration, enabling the player to reach a larger area in a shorter time, while a lower F limits the player's ability to quickly change positions. For this work, we chose a force of $5\,ms^{-2}$, as it falls within the typical range for human movement in sports, with $1 < F < 10\,ms^{-2}$. This value is a balance between realistic movement dynamics and practical reachability in the context of table tennis.

The second adjustable parameter is the time threshold, $t_{\text{threshold}}$, which represents the maximum amount of time it takes for a player to reach a specific point in space. This threshold helps determine whether a region is within the player's reach based on the available time to react. In this work, we set $t_{\text{threshold}} = 0.8\,\text{s}$, meaning that any region that can be reached within 0.8 seconds will be considered as part of the control area. This time threshold guarantees that the model accounts for realistic movement constraints, where players can only cover limited distances within a given timeframe.

Once the force F and the time threshold $t_{\text{threshold}}$ are defined, we colorize the unit cell based on the reaching time t. In our parameterization, the dimension of a unit cell is $10\,\text{cm} \times 10\,\text{cm}$. If the time to reach that cell is within the threshold, it will be colorized accordingly, indicating that the player can reach it within the given time, which overall results into an heatmap.

4.5.2 Calculation Including Peripheral Reachability

As table tennis is a smaller-scale sport, players use a variety of techniques to return the ball, such as forehand or backhand strokes, and executing movements close to or far from the body, from the front or side. Unlike sports like soccer, where players catch the ball consistently around 40 cm in front of them, table tennis requires a more nuanced model due to these differences in player movement and stroke types. To create a more accurate model of a player's reachability, it is essential to account for these subtleties.

We iterated on the previous model to capture local reachability by focusing on the racket's ability to reach specific areas rather than just the player's body. In table tennis, the player's racket defines the reach, so we create a zone around the player that the racket can quickly access. Furthermore, the player's orientation, typically facing the table, must be considered. For example, when a player moves away from the table, they are not running toward the ball but moving backward, which affects the reachable area. However, for simplicity, we used a statistical approach based on shot distribution to capture the peripheral reachability area, as illustrated in Figure 4.20. This reachability will complement the previous model by extending it to include every location the player can reach, assuming they can perform all types of shots once there. In other words, for each red region, we overlap Figure 4.20's reachability region as the new control area (which expands it quite extensively). To reduce its size, we split the forehand and backhand strokes, which will be represented separately.

4.5.3 Implementation and Visual Design

Players positions and events (*e.g.* hits) are derived from [41], which is a combination of manual annotation and automated tracking. This data results in a 3D scene reconstruction, but we only used player positions to create the 2D heatmap of the control area. To render the heatmap, we calculated the mean image assuming the camera is static to remove the players. We then rendered the visualizations over the background image, including both the control area and other trajectories. This approach is similar to that in [114]. We used visual overlays in a manner similar to how Viscommentator operates [21] to communicate trajectories. Still a key difference regarding the mapping is that it both applies to the table but also to the ground. This gives a *spotlight* effect from above.

The color is defined using the RGB model, where $(255, 255, 255)$ represents white and $(255, 0, 0)$ represents red.

$$color_{unit\ cell}(t) = \begin{cases} (255, & G(t), & B(t)) & \text{if } t < t_{threshold} \\ (255, & 255, & 255) & \text{otherwise} \end{cases} \tag{4.3}$$

where $G(t) = B(t) = (t - t_{min}) * \frac{255}{t_{threshold} - t_{min}}$ (with t_{min} being the shortest time to reach a point in the entire playing area). Finally, we divide the control area into four zones to categorize the level of control with a black iso-contour.

An animated version of the control areas can be found as supplemental material https://centralelyon.github.io/table-tennis-control-areas/video.mp4 All our code and analysis are available as an open-source project at https://github.com/centralelyon/table-tennis-control-areas/.

4.5.4 Results and Perspectives

The results we show in this paper are preliminary but promising for table tennis analytics. We applied the simple model using Newton's Law on our three motivation scenarios and the results are show on the teaser image Figure 4.16 and also on Figure 4.22, Figure 4.21 and Figure 4.23. The result are visually conclusive, the reason being that they concern extreme case where local reachability does not play an important role. Regarding the model with peripheral reachability, Figure 4.24 showing the forehand and backhand regions that can be reached. Overall there seems to be an effect of averaging as some local reachability is lost.

Further work is needed to refine our control area models. Since table tennis requires more of a micro-level analysis, the model we used does not account for the reaction time of the arms or other parts of the body. Thus, we seek research directions that capture such local motions to refine an overall model that would be a composition of smaller, relative ones. To refine the peripheral control area, detailed statistics of players should be considered, including individual factors such as reaction time, stamina, skill, and focus. In this work, the control area was based on shot statistics; however, it could be further developed using a physical reachability model, as suggested in [44]. Also, some specific motions should be taken into account, such as moving backward, which does not mean the player should have a reachable region behind them, but rather still forward but with less depth.

A shortcoming of control area models we noticed is that 1) they provide a binary quantification (by ownership) of the 2D space with control regions (even if we can associate a degree of ownership), and 2) control vanishes at the boundary of control regions. Such non-visible areas are currently displayed in the same way as non-controlled areas. It may be interesting to reveal these areas, as illustrated in Figure 4.25, to characterize *non-controlled areas*, either during a specific rally or more generally (*e.g.* close to the net). Finally, it may be valuable to consider the feasibility of hitting the ball in such areas (*e.g.* hitting close to the net is rarely physically possible). Another limitation is that the model only captures shots at a

Figure 4.21 – Ball in pivot zone. Zone between the elbow and the stomach, making it difficult to return the ball. **Alexis Lebrun**, left player, struggling to return the ball.

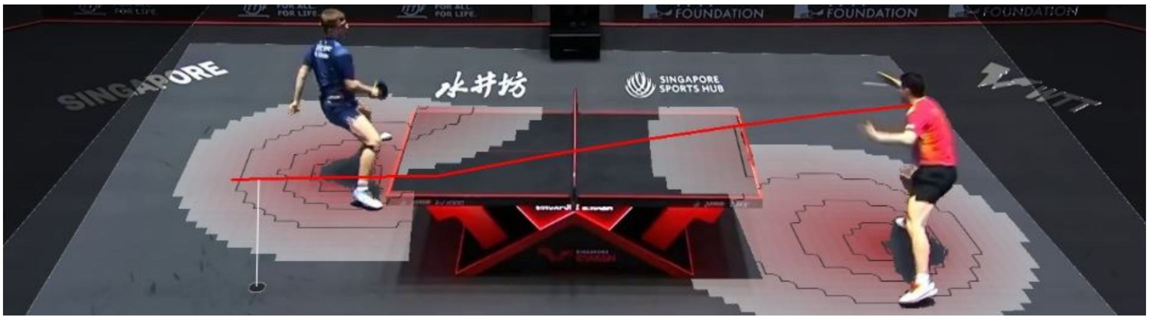


Figure 4.22 – Ball too far away. **Alexis Lebrun**(left player) is completely out of position on his left, which allows **Ma Long**to play on the other side and puts the ball too far away from **Alexis Lebrun**.

Figure 4.23 – Wrong-footed. **Alexis Lebrun**is positioned on the left and moves to the right, **Ma Long**plays on the left of **Alexis Lebrun**, forcing him to stop his movement and start again in the opposite direction.

given instant, while table tennis builds on a sequence of strokes and variations designed to surprise opponents.

Control areas should also be contextualized using game metrics when analyzed, such as domination [14], to identify their characteristics and allow for comparisons

Figure 4.24 – Results from the model that includes peripheral reachability: for each position in the control area, we project the reachability model (the region that captures the distribution of previous shots) to capture additional areas that can be hit by the player. By separating these regions into forehand (blue) and backhand (green), we show how they can be accessed. The cyan region in between is reachable by both techniques.

between players or across different matches. For instance, fatigue may reduce reaction time and speed, which would lead to a decrease in the size of a player's reachable area. Such variations in the size of control areas and their correlation with game events is a promising approach for analyzing tactics, as has already been explored in soccer [1].

More physical factors need to be considered. For example, it is important to take into account the table and any other obstacles on the field. These factors can impact the player's speed or the direction of their movements and should be considered when evaluating the control area. Finally, players' poses should be taken into account, as they sometimes bend forward or backward to rest, which affects their ability to reach the ball and should be incorporated into the analysis of the control area.

Since we have released our code and models as an open-source project, we expect the community to continue exploring research in this promising area.

4.6 Conclusion and Perspectives

In this chapter, we have proposed two approaches for visualizing complex table tennis data. The first approach is based on transforming rebound position data into a new data space, allowing us to discover new losing or winning clusters that were not identifiable using the untransformed data. Among these identified clusters, we were able to characterize two examples corresponding to real tactical zones in table tennis: the pivot zone and the reachable zones. The second approach aimed to stay as close as possible to the match video, so we decided to create augmented videos highlighting the areas that players could reach at any time

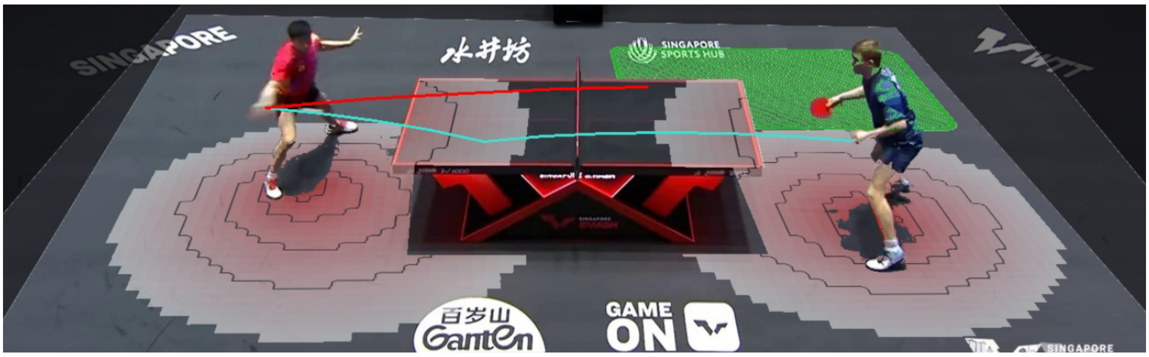


Figure 4.25 – Highlight (in green) of the target area by **Ma Long** which is not calculated by our control area model (it results from a manual annotation), but is a promising perspective to automatically construct non-controlled areas.

during a rally. These two different approaches still have the same objective of enabling coaches and trainers to understand the data in a simple way. For this work, several perspectives for improving the visualizations are being considered:

- First, increasing the amount of data remains one of the most important perspectives when seeking to characterize players and create characterizations based on a given group of opponents.

- The second perspective concerns comparisons. For the first approach, all the data that can be compared with each other is specific to the match being analyzed. Being able to use data from several different matches will make it possible to characterize observations based on whether they are specific to a match or specific to a player. The second approach involves comparing rallies with each other. By comparing the evolution of accessible zones, it is possible to find similarities between rallies and cluster them based on accessible zones.

- The final perspective concerns zone detection. Currently, the proposed methods allow us to visualize and find either winning or losing clusters for the first approach or unreachable zones for the second approach. By automating zone detection for the first approach, it will be possible to find the parameters that facilitate the detection of areas of interest. For the second approach, this will make it possible to find the moment in rallies when an opening was created without being exploited by the players.

Chapter 5

CONCLUSION AND PERSPECTIVES

Contents

This chapter summarizes all of the different contributions presented in the manuscript. Each contribution has its own limitations and perspectives. We also propose a research perspective that combines both the field of analysis and the field of visualization. This perspective represents an important evolution in data and its use, enabling new, more complex analyses that are closer to reality.

5.1 Summary of the Contributions

Throughout the contributions we have seen throughout the manuscript, we have been able to see how analysis in table tennis can be carried out using match data. We have seen all the important steps, starting with the collection of accurate data essential to the analysis, which highlights the strengths and weaknesses of the players, and finally we have seen how to create new visualizations that allow us to maintain the link between the data and the video in a simple way.

SportsVideo: A Multimedia Dataset for Sports Event and Position Detection inTable Tennis and Swimming

This work consists of creating a benchmark dataset that is open to the scientific community. The dataset is divided into six independent parts that enable the automation of data collection for table tennis matches. The six tasks include: detecting player positions, detecting events, classifying events, detecting the table, detecting sound rebounds, and detecting the score embedded in the videos. This dataset is also part of the MediaEval challenge, which aims to achieve the highest accuracy across the various tasks.

How Camera Angle Impact TableTennis Ball Bounce Tracking

This work proposes a method for establishing a protocol to calculate the accuracy of a rebound position annotation on the table based on the position of the camera relative to the position of the camera. A method for predicting accuracy takes the position of a camera as input and allows the accuracy to be evaluated across all points on the table.

Table TennisAnalytics: Domination, Expected Score and Shot Diversity

This paper proposes a study of dominance in a table tennis match using metrics. These metrics are based on physical, mental, and score evolution approaches. An adaptation of the expected goal concept, initially introduced in soccer, proposes a calculation of the expected score based on the sequences of strokes that took place during rallies. Finally, a last study on the diversity of openings through the example of a match showed how players with different profiles vary depending on the moment in the match and the pressure.

Characterizing Serves in Table Tennis

This paper proposes a study of serves in table tennis. It is an approach that allows each player's position clusters used in different matches to be characterized. This approach allows players to be classified according to their own serve clusters. A study of the similarity between a player's serves during a match shows that score dominance can be linked to the similarity or dissimilarity of the serves used.

Analysis of Service Returns in Table Tennis

This study examines returns in table tennis, which are the strokes immediately following serves. The study shows that each player has their own cluster of returns and that for some players there is a correlation between their clusters of returns and their clusters of serves. Using dominance and pressure metrics, we found that for some players there is a correlation between their clusters of returns and the metrics.

A Table Tennis Shot Map From a Player Perspective

This study examines ball rebounds by positioning them in a new frame of reference, no longer centered on the table, but this time linked to the position of the players at the moment of rebound. This highlights that new losing or winning clusters are visible in this new frame of reference, whereas they were not in the initial frame of reference. It also allows us to identify certain situations that are characteristic of table tennis and to statistically confirm that these are predominantly losing situations for players.

Investigating Control Areas in Table Tennis

This work proposes a way to visualize data on areas reachable by players by creating augmented videos that aim to incorporate the data directly into rally videos in a fluid and understandable way.

5.2 Perspectives and New Challenges

The various prospects and new challenges are mainly related to the limitations we encountered in our various projects. We have identified three main prospects: the use of 3D data, the automation of data collection, and real time.

5.2.1 3D Data

Table tennis remains a sport played in a 3D playing space, and many of the analyses we have seen only take into account the position of the ball's bounce and the player's position [132, 124, 33]. These analyses do not take into account the z component of the positions, and in particular for the ball, only one position at the moment of bounce is used, thus ignoring the trajectory of the ball. The trajectory remains important, in particular because it allows us to highlight why, for two different bounces in the same area, the opponent will attack on one and defend on the other. The height of the bounce in these particular cases often provides the answer. In badminton [135], the entire trajectory of the shuttlecock is used for analysis. This allows for a direct comparison of 3D trajectories rather than just the positions of the shots. Badminton, due to its technical specificities, makes the use of 3D trajectories mandatory, as the high clearance is an important shot. This sport highlights the relevance of using 3D trajectories for comparing trajectories and searching for strokes.

For tennis, [127] uses a similar approach for serves, clustering the different 3D trajectories. In table tennis, approaches to collect the trajectory of the ball

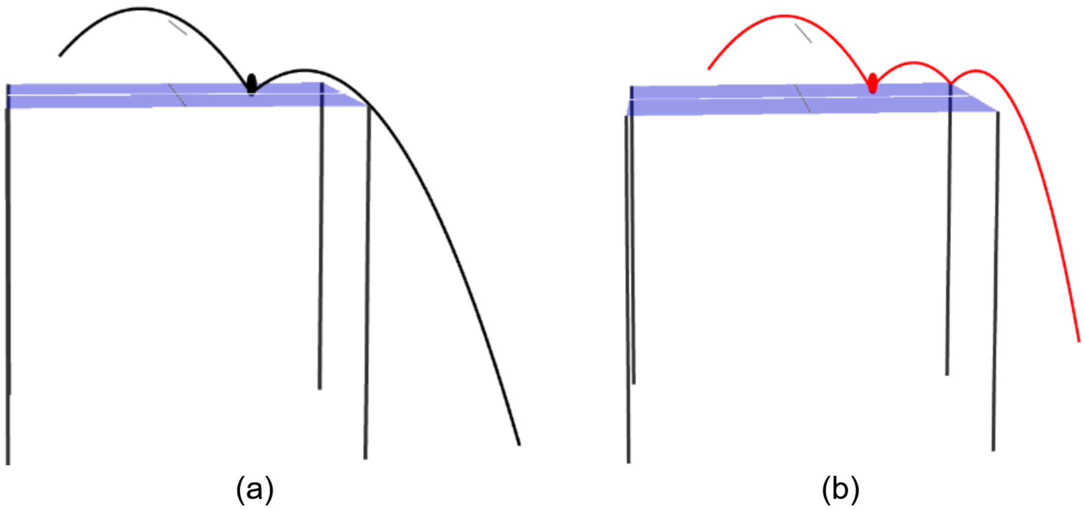


Figure 5.1 – Example of ball trajectories extended to the second bounce. (a) Extension of the trajectory of a long serve, the second bounce is on the ground. (b) Extension of the trajectory of a short serve, the second bounce is on the table.

have been used, often requiring the use of multiple cameras to obtain a 3D representation [90], but some approaches using a single camera allow the 3D position of the ball to be obtained [13]. To do this, they use semantic detection of the ball, correct blurring using a CNN, and then use the fact that the further away a ball is from the camera, the smaller its size will be in the image to detect the 3D position of the ball, knowing the position of the camera. To go beyond a simple 3D representation of the ball's position [52], they perform a 3D reconstruction of the entire table tennis scene. It represents the position of the ball as well as the players' poses in 3D. To do this, they seek to minimize the distance between the projection of a 3D representation of the positions on the image and the 2D positions detected on the image.

The 3D estimation of players' posture mainly allows us to study the biomechanics of players, but it also makes it possible to characterize the intensity of strokes based on how this posture changes throughout the stroke. The 3D trajectory of the ball offers more possibilities for analysis, as new clusters can be created by taking into account the entire trajectory or certain characteristics specific to each trajectory, such as maximum height or distance traveled. But it also allows for new analyses that help us understand certain responses to a stroke.

On a serve, it is very difficult to attack effectively if the serve is short, whereas it becomes very easy if it is long. There is therefore an area partly in the long serve zone and partly in the short serve zone that is quite difficult for players to manage. This area creates hesitation among players about whether to attack strongly, and if they make the wrong choice, losing the rally is almost certain. Knowing the position of the bounce alone is not enough to determine whether a serve is short or long; its complete trajectory is necessary to know this. The trajectory of a ball follows the laws of physics, which means that it is possible to model the trajectory of the ball using equations. In this way, it is possible to extend the trajectory of the ball beyond a player's shot to see whether the serve was long or not. The second bounce is called the simulated bounce, which is obtained by extending the trajectory of the ball beyond the hit. If the serve is short, the second bounce occurs on the table; if not, it occurs on the floor. Figure 5.1 shows an example of an extended trajectory for a short serve and a long serve.

This new approach, which uses the extension of the trajectory to the second bounce, enriches the service data by indicating whether it is long or short based on the simulated second bounce. This makes it possible to create new clusters by distinguishing between these two types of services, providing new analyses for services, returns, and sequences beginning with a service.

The use of 3D position data in this example of a simulated second bounce demonstrates the value of collecting and analyzing 3D position data.

5.2.2 (Semi) Automation of Data Collection

The increase in data is an essential element for analysis, particularly in the characterization of player profiles, which requires numerous matches for each player in order to characterize their playing style. This is why automating data collection is so important and crucial for obtaining highly accurate analyses covering all game possibilities. More matches for each player provide a better understanding of how a player plays and allow us to see how they evolve over time. It also allows us to study more specific data by filtering the data in greater detail while keeping it representative.

As mentioned in Chapter 2, different areas are affected by automation. These include segmentation, object tracking, and action detection. Advances in computer vision, particularly neural networks, have led to significant improvements in detection and tracking. One notable example is Yolo [59], which has become very popular in object detection for sports.

Fully automating data collection would make it possible to analyze all professional matches, thereby providing highly relevant analyses of all players.

5.2.3 Real Time

The data collection we discussed is done once the matches are over. However, table tennis matches are broadcast live via video streams on streaming platforms such as YouTube. It is possible to collect data in real time, as neural networks such as Yolo [59] and pose estimation with Openpose [15] are very fast and can be used in real time. This approach allows data to be obtained simply by playing a video stream.

Real-time data collection offers new perspectives for analysis during matches. Having data and analysis available during the match can help coaches coach players during timeouts or side changes. This approach to analysis is different in that it focuses exclusively on the strokes and rallies of the match. Initially, this is done to identify players' strengths and weaknesses during the match, but also to study tactical developments and effectiveness over the course of the games. This approach allows players to be provided with direct data on what they are doing, and to adapt or change the tactics put in place before the match.

This approach presents new challenges in terms of both the technical and scientific aspects of data collection, as well as interaction with coaches and how to communicate results and respond to their requests.

Appendix

1 Rules of Talbe Tennis

Rallies

The rules specific to rallies essentially concern the course of the match and how to win it:

1. A match is played to the best of 7 games (5 in some competitions).
2. The winner is the first to score 4 games (3 in some competitions), after which the match ends.
3. To win a game, you must be the first to score 11 points and have 2 points more than your opponent.
4. A point is won by the last player to make a legal stroke on the table during the rally.
5. Each rally starts with a serve, the server alternates every two rallies, if both players have at least 10 points each, the server changes at each rally.
6. At each new game, the players change sides, if each players have won 3 games (or 2 games in some competition), when the first player reaches 5 points, the players change sides.
7. Between games or during time-outs, players are allowed one minute to talk to their coach, each player is entitled to one time-out.
8. A match or rally has no time limit (except in special cases where the match is too long, a rule may be applied to limit the number of strokes per rally).

Strokes

The rules governing strokes are mainly concerned with how players should play during rallies:

1. For the serve to be legal, the server must present the ball in the palm of his hand, he must throw the ball vertically to at least 15cm, the ball all the time being visible by the opponent. The ball must always be visible to the opponent. It must be hit above and behind the table
2. The serve must bounce off the server's side of the table and then onto the opponent's side
3. For a stroke to be legal, it must be returned to the opponent's side, and the ball must pass over or around the net
4. A stroke cannot be a volley, but must wait for the bounce

5. The player loses the rally if he touches the ball with anything other than the racket or the hand holding the racket (glasses, T-shirt, arm, etc.) or if the ball bounces a second time (on the table or on the ground).

Double

The rules we have outlined above apply to all matches regardless of discipline (singles, doubles, men's, women's). In singles, the same rules apply to men's and women's matches. This means that unlike tennis, where Grand Slam matches are played as best-of-three sets for men and best-of-two sets for women, in table tennis the same rules apply, so the women's final between Sun Yingsha and Chen Meng ended 4 games to 2 for Chen Meng in 1 hour and 10 minutes, which is longer than the match between **Fan Zhendong** and **Truls Moregardh**. However, doubles have a few rules that are specific to them:

- Matches are always played as best of three games.
- No player on the same team may hit the ball twice in a row on the same point.
- Each server serves every eight points (Player 1 Team 1 x2 → Player 1 Team 2 x2 → Player 2 Team 1 x2 → Player 2 Team 2 x2).
- During a given game, a player always plays against the same opponent and always receives balls from the other opponent.
- At the start of each new game and when the first team scores 5 points in the decider, there is a reversal of the player being played and the player playing against us.
- The serve must be made only in the right diagonal (the first bounce and the second).

Equipment

Equipment is also subject to rules. These include the ball, the table and the racket, Figure 2 illustrates the official dimensions of the table:

1. The table tennis ball measures 40mm and weighs 2.7g, and must be made of matt white plastic.
2. Its bounce is also subject to rules. When dropped on a rigid surface 30 cm high, it must bounce between 23 cm and 26 cm.
3. The table must be 2.74m long, 1.525m wide and 0.76m high. The table must be flat and uniform, with a matte finish to avoid reflections.

4. The net measures 15.25cm and protrudes 15.25cm on both sides of the table. It separates the sides of the table along its length.
5. The racket may be of any size or shape
6. The racket consists of a blade and two rubbers
7. The wood must make up at least 85% of the total thickness of the blade
8. The blade must be a flat surface
9. The rubbers must be ITTF-approved
10. One of the rubbers must be black and the other may be red, pink, blue, green or violet
11. The ruber must be no more than 4mm thick.

Figure 2 – Official dimensions of a table tennis table. Example of a table produced by Cornilleau [1], specialists in table tennis equipment.

1. https://cornilleau.com/

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