N° d'ordre NNT : 2025ECDL0025

THESE DE DOCTORAT DE CENTRALE DE LYON
membre de l'Université de Lyon

École Doctorale N°512
InfoMaths - Informatique et Mathématiques de Lyon

Spécialité de doctorat: Informatique

Soutenue publiquement le XX XX 2025, par :

Aymeric ERADES

Analyse Visuelle de la Tactique de Jeu au Tennis de Table
Visual Analysis of Table Tennis Tactics

Devant le jury composé de :

Francois Rioult	Normandie Univ, GREYC	Rapporteur
Richard Kulpa	Université Rennes 2, IRISA	Rapporteur
Céline Robardet	INSA Lyon, LIRIS	Examinateur
Charles Perin	Univ. Victoria, Canada	Examinateur
Romain Vuillemot	École Centrale de Lyon, LIRIS	Directeur
Christian Gaubert	Fédération Française de Tennis de Table	Invité

Unité de recherche : LIRIS - Laboratoire d'InfoRmatique en Image et Systèmes d'information

Abstract

Success in high-level sports depends on several key factors, such as physical ability, technique, mental strength, and, in the case of confrontational sports like table tennis, tactics. In this sport, tactics play a decisive role in a player's performance. The difference between victory and defeat can sometimes come down to just two points, making any tactical mistake during the game potentially decisive. These tactical choices are often made before the matches during strategy sessions and training sessions with the coach. They are based in particular on knowledge of the opponents and an analysis of their previous matches. In this thesis, we focus on the visual analysis of such tactics in professional table tennis matches, in order to provide coaches with tools that facilitate their discovery and analysis, offering time savings, simplifying their exploratory work, and ensuring objectivity.

In the first part, we will present the process of collecting structured data. We will justify the choice to develop a semi-automatic data collection interface that offers a compromise between accuracy and speed. We will also propose a data benchmark open to the scientific community, to study the automation of data collection. Finally, we will study the influence of camera positions on the accuracy of the collected positional data.

In the second part, we will focus on the analysis of structured data through three studies: the first on performance indicators related to domination. The following two will focus on the characterization of serves and returns, as well as the dependency relationships between them.

In the third part, we will address the communication of data through visualizations using three approaches. The first focuses on the development of new visualizations allowing the study of spatial data in a player-centered view. The second focuses on the study of player reachable areas using visualizations integrated into the video. And the last concerns the development of interactive visualization dashboards.

We will conclude with research perspectives of this work focusing on the use of 3D spatial data, the automation of data collection, and real-time data collection.

Résumé

La réussite dans le sport de haut niveau repose sur plusieurs facteurs clef, comme le physique, la technique, le mental, ou encore pour les sports de confrontation, la tactique. Bien que chacun de ces axes soit important, leur importance varie selon le sport. Cela est particulièrement vrai pour le tennis de table, où la tactique joue un rôle déterminant dans la performance d'un joueur. La différence entre la victoire et la défaite peut parfois se jouer à deux points près, rendant toute erreur tactique potentiellement décisive. Ces choix tactiques sont souvent pris en amont des matchs lors de séances de réflexion avec le coach. Ils reposent notamment sur la connaissance des adversaires et l'analyse de leurs matchs précédents. Dans cette thèse, nous nous intéressons à l'analyse visuelle de la tactique de jeu des matchs de tennis de table professionnels, pour fournir aux coachs des outils facilitant cette analyse, favorisant à la fois un gain de temps, une simplification de leurs explorations et une objectivité statistique.

Dans la première partie, nous présenterons le processus de collecte de données structurées. Nous justifierons le choix du développement d'une interface de collecte de données semi-automatique qui offre un compromis entre précision et rapidité. Nous proposerons également un benchmark de données ouvert à la communauté scientifique dans le but d'étudier l'automatisation de la collecte de données. Et nous étudierons l'influence des positions des caméras sur la précision des données de positions collectées.

Dans la deuxième partie, nous nous concentrerons sur l'analyse des données structurées à travers 3 études, la première sur des indicateurs de performances liés à la domination. Et les deux suivantes porteront sur la caractérisation des services et des remises, ainsi que sur les relations de dépendance entre eux.

Dans la troisième partie, nous aborderons la communication des données à travers les visualisations suivant 3 approches. La première sur le développement de nouvelles visualisations permettant d'étudier les données spatiales dans un référentiel centré sur la position du joueur. La deuxième sur l'étude des zones d'accessibilité des joueurs à l'aide de visualisations intégrées à la vidéo. Et la dernière sur l'élaboration de tableaux de bord interactifs.

Nous conclurons en présentant les perspectives de recherche de ce travail, portant sur l'utilisation de données spatiales en 3D, l'automatisation de la collecte de données, ainsi que la collecte de données en temps réel.

CONTENTS

LIST OF FIGURES

LIST OF TABLES

Chapter 1

INTRODUCTION

Contents

1.1 Context

It is almost 2 p.m. on August 4, 2024, during the bronze medal match at the Paris Olympic Games. The French player **Felix Lebrun** is facing the Brazilian player **Hugo Calderano**. **Felix Lebrun** has lost the previous two matches against this player. But this time, he is leading 3 games to 0 (7-11 11-9 11-9 11-8) and needs to win one more to win the match (and the Olympic bronze medal). **Felix Lebrun** takes the advantage and moves closer to victory by earning five match points. The match point on his serve is the most important of the match. The pressure, the choice of serve, and the sequence of strokes are decisive for victory. For this rally, **Felix Lebrun** chose a short hook serve (Figure 3.9) into **Hugo Calderano**'s forehand, followed by a backhand attack in the middle of the table. These choices were not random. The day before the match, with his coach and video analysts, this particular serve had been identified as very effective in their previous encounters, as well as the backhand zone, which prevented **Hugo Calderano** from playing properly with a strong attack. This choice proved to be a winning one, and he won the match, and became the youngest Olympic medalist in table tennis at the age of 17. This rally reflects a decision made ahead of the match during preparation. This choice is called a tactical choice, a tactic is a succession of strokes chosen by a player at a specific moment of the game, **Felix Lebrun** chose a serve knowing the most likely return he would get and then hit his topspin. This sequence of three strokes makes up the tactic **Felix Lebrun** has chosen and executed. This thesis, through research axes, seeks to understand the efficiency of such tactical choices made by players during table tennis games, using data collected from videos.

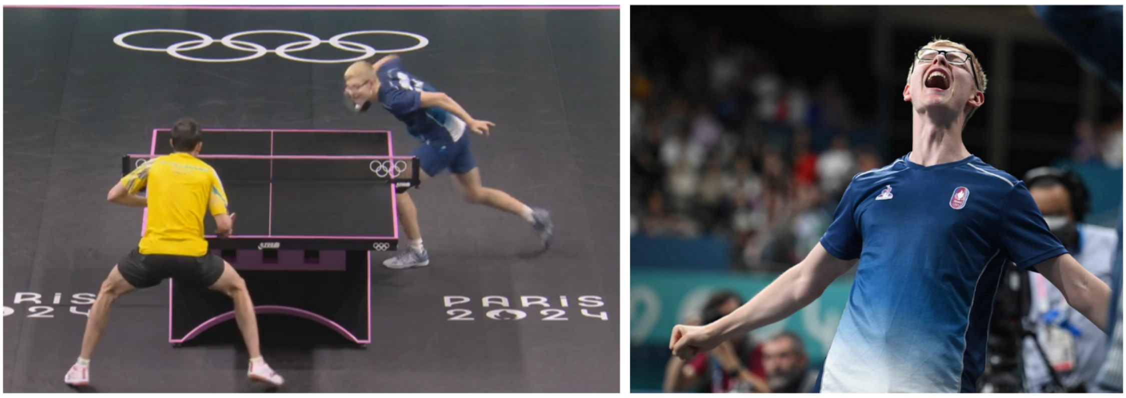


Figure 1.1. – August 4, 2024, bronze medal match in men's singles at the Paris Olympics. On the left, **Felix Lebrun** serves for the match using a serve he practiced the day before. On the right, **Felix Lebrun** celebrates winning the match 4-0.

Table tennis is one of the most popular sports in the world and one of the most watched at the Olympic Games[1]. It is estimated that there are between 300 and 350 million players worldwide in 2023[2]. It is a rapidly growing sport in France, with more than 6 million players and 210,000 licensed players in 2025[3]. In 2025, about 50 high level competitions were scheduled, bringing together several hundred professional players who are among the best players in the world. To help those players to improve their performance in addition to their daily training sessions, several axis are possible from food [29], health or mental preparation [109]. Among them, video analysis which involves watching and analyzing players' past matches and identifying what worked and what did not. This analysis serves multiple purposes, among them: it allows trainers to focus training on specific areas and also coaches to prepare for matches by choosing in advance most efficient tactics [31] that players will use. Video analysis of matches has been used for years in sports with the increasing availability of broadcast videos, and this thesis contributes to improve its use by collecting and analyzing data for more detailed and objective decisions.

Origin and Evolution of this Thesis

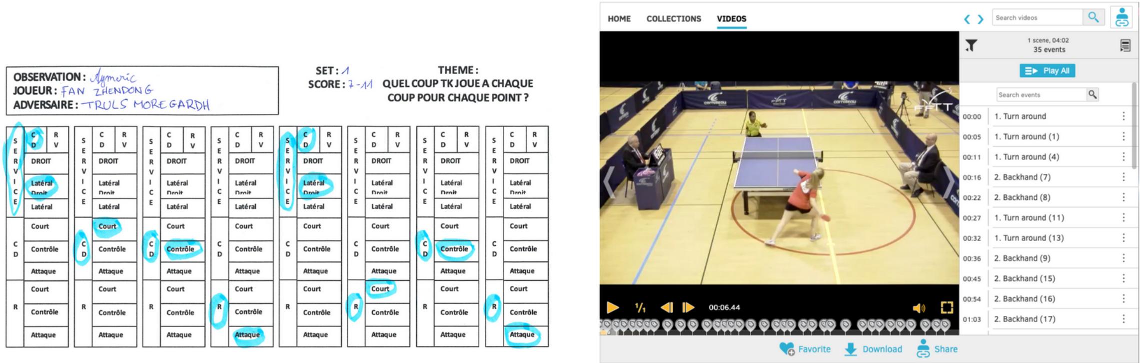
The French Table Tennis Federation (FFTT) has used videos analysis for years, in particular with the work of Christian Gaubert Scientific Coordinator at the

1. https://www.ittf.com/2017/01/04/television-figures-released-millions-upon-millions-watched-table-tennis-rio-2016/
2. https://www.ebsco.com/research-starters/sports-and-leisure/table-tennis
3. https://www.fftt.com/site/fftt/la-fftt-en-chiffres/chiffres-cles

FFTT, we collaborate with during this PhD. This thesis began on September 1, 2022, with the primary objective of improving the performance of French mixed doubles table tennis players and more specifically those selected for the Olympic Games, during competition based solely on video analysis. During 2022-2023, data collection tools were developed based on feedback from FFTT Christian Gaubert. We were initially inspired by feedback from the 2021 Tokyo Olympics, where the French mixed doubles team of **Emanuel Lebesson** and **Jia Nan Yuan** finished fourth, just missing out on a podium place. All of the work focused on the mixed doubles then, which at the time was France's best chance for a medal. Video analysis was done initially manually using paper as support and then using Dartfish[4] and a sequencer developed according to Christian Gaubert's requirements to facilitate the link between video and complex data. (Figure 1.2, a tool used primarily in sports for video analysis). Dartfish focuses mainly on visual annotation, video sequence comparison, and metric calculation. Although powerful and relevant in its use for table tennis, this tool is generic to all sports and did not offer the necessary flexibility required by the video analysts of the French national team, who have very specific needs. Also, the manual annotation analyses using paper could take between 15 and 20 hours per match, which was too long to analyze many matches. The second major issue is in searching for statistics, which requires manually searching through all the data each time, this problem is closely related to the fact that the model used (Figure 1.2 (a)) requires an average of 1 sheet for every 2 rallies, thus requiring a very large number of Microsoft Excel sheets for each match. The use of Dartfish still manual but with mechanisms to speed up the process has reduced the time to analyse to 5 hours per match, facilitated statistical calculations, reduced data storage to a single digital file and linked the data to the video. However, this process can be further improved to minimize this time, offer more complex data, new options for presenting and sharing data. One of the objective of this thesis is to develop a tool that will speed up this process while incorporating more complex data and providing appropriate visualization to analyse matches.

During 2023-2024, video based tools were developed to enable the collected data to be exploited. During this year, **Alexis Lebrun** and **Felix Lebrun** proved themselves, leading to a change in direction of the work with a focus on singles matches rather than mixed doubles matches. All of the tools were adapted to prioritize requests related to singles matches. With a data enrichment phase to satisfy new analytical demands. Starting in June 2024, as the Olympic Games approached, direct collaboration with coaches and players began to assist in the preparation of athletes who had qualified for the Olympic Games. This preparation led to the development of new tools focused directly on different and more specific needs. This collaboration continued during the Olympic Games to assist in match preparation. This collaboration was established following

4. https://www.dartfish.com/fr/



(a) (b)

Figure 1.2. – Examples of tools used by the FFTT to collect data and perform analyses. Theses tools were developed or given by Christian Gaubert expert of FFTT. (a) Represents the Dartfish tool, the different strokes are annotated with their timestamps. (b) Represents a paper sequencer that must be filled out by hand. The strokes of the first two rallies of the Paris Olympic Games are annotated.

the decision of the FFTT to recruit two expert table tennis video analysts and professional players to help coaches prepare for matches, the goal was to be able to work closely with experts to respond directly to the needs of coaches. We joined the video analyst team for five weeks including during the Olympic Games and used the tools developed as well as some of the work from this thesis.

During 2024-2025, further analyses were carried out using new visualizations, continuing the collaborative work done in preparation for matches. This year also allowed us to finish some paper and complete the writing of this manuscript.

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*[5] that begin with a serve and end with a particular outcome, win or lose, by hitting the ball to the opposite side, an action known as a *stroke*, 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.

Please note that table tennis rules can be slightly more complex in some situation we will see in Section 1.4. Doubles have also been investigated, but this thesis mainly focuses on singles and male games as they offered the greatest chances for Olympic performance and was the focus of the research in 2023.

5. A list of terms and their definition is available in the Appendix A

(a) (b) (c)

Figure 1.3. – Examples of different table tennis formats: (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 **Felix 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 athletes' physical attributes (*e.g.* speed, strength, endurance), table tennis has more tactical aspects. Among those, it involves interaction with another player, which cannot always be 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 other player's choices. These choices are known as tactical choices. In this thesis we define tactics **as a sequence of consecutive strokes made by players at a specific moment of the game, forming a deliberate pattern based on a short- or long-term strategy to win the match**. Thus the strategy can be seen as the combination of effective tactics that collectively aim to achieve victory. Tactics can have different levels of complexity, depending on both the number of attributes (types of strokes, ball rebounds, player positions) associated with the strokes and the number of strokes considered.

A Brief History of Table Tennis: Back in the Late 19th Century

Table tennis originated in England in the late 19th century[6][7]. It was 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 1.4). The first national championships were

6. https://www.ittf.com/history/documents/historyoftabletennis/
7. https://fr.cornilleau.com/content/141-histoire-du-tennis-de-table

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 first world championships, the first one 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. The FFTT was founded the next year in March 1927[8].

Surprisingly, the Asian supremacy in table tennis has arrived relatively late compared to the sport's history, it took more than 60 years for this supremacy to materialize, with popularity emerging in the 1950s in Asia. First characterized by Japanese dominance, excelling in the World Team Championships between 1954 and 1959. Chinese supremacy began in the 1960s, notably with player **Zhuang Zedong**, who was a three-time world champion in 1961, 1963, and 1965.

Figure 1.4. – Lithograph segment, the earliest known action game of tennis on a table: **David Foster** (ENG) 1890. One of 2 known examples. Credit: ITTF.

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, 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

8. https://www.fftt.com/site/fftt/la-fftt-en-chiffres/historique

in Birmingham, the serve launched called "Chinese service" (Figure 1.5 (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 to improve visibility on television. In 2001, the game score changed from 21 to 11 points. Fast glues were banned in 2008, for health concerns because fast glues contained toxic solvents [107]. In 2016, celluloid balls were replaced by plastic balls which slows down the ball and reduces its spin, allowing for longer rallies. All these rule changes and equipment improvements have led to developments in the game's tactical aspects. In particular, the reduced speed and spin of the ball made serves less effective, thereby increasing the importance of strokes that could initiate strong attacks.

Since the beginning of table tennis, the French national team has won 27 medals at the World Table Tennis Championships in all categories, including two world titles, the first in 1977 in mixed doubles with **Jacques Secrétin** and **Claude Bergeret**, and the second in 1993 with **Jean-Philippe Gatien** in singles. More recently, at the 2024 World Team Championships, the men's team won silver and the women's team won bronze.

(a) (b) (c)

Figure 1.5. – Example of how table tennis is nowadays. (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 such as tennis or soccer, demanding the same level of athletic abilities in terms of both endurance and strength to be among the world's best players, as can be seen in Figure 1.5 (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 1.5 (c) where **Lin Gaoyuan** performs a forehand topspin shot in a difficult position and is completely stuck to the table. In this thesis, we focus on the tactical aspect of the game. Tactics play a very important role at a high level once the technique that forms the basis of table tennis has been mastered. Although it is crucial, it remains difficult to define and implement. Tactics requires high mental abilities to be able to remain lucid despite fatigue and stress. Although it is not visible at first glance, unlike physical and technical abilities, it is just as decisive. An important aspect of tactic we did not investigate is their execution: at elite level we assume players can execute them with very high consistency, so what is observed is the result of a tactical choice and less likely due to lack of technical skills.

A More Recent History: Olympics Victories 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.

Before the Paris Olympics, France had only won two Olympic medals. The first was a silver medal in Barcelona in 1992, won by **Jean-Philippe Gatien**, who was ranked number one in the world at the time, and the second was a bronze medal in Sydney in 2000, won in doubles by **Jean-Philippe Gatien** and **Patrick Chila**. During the 2024 Paris Olympic Games, France won two new bronze medals, the first in singles thanks to **Felix Lebrun** and the second in men's team thanks to **Felix Lebrun**, **Alexis Lebrun** and **Simon Gauzy**.

The Olympic Games final between **Fan Zhendong** and **Truls Moregardh** ended in victory for **Fan Zhendong** 4 games to 1. **Fan Zhendong**, reigning world champion, and ranked among the world's top three since 2015, 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 of world number 26 and his last competitive performances with four first-round defeats in his last four singles competitions. **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 thesis, we look at different approaches to answering these questions.

1.3 Why Using Data?

Sport is so multifaceted, data covers all information specific to players, matches or competitions, that there is no single type of data [97] that needs to be mastered to discover performance indicators. Sports can indeed be observed as spatially continuous trajectories changing over time, discrete events, sequences of events, succession of games, single aggregated performance scores, and so on. This apparent complexity can be approached with a hierarchical structure of available sports data. At the bottom of the hierarchy are what we call raw data or observations, which are usually 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 attributes. They still need some treatment to be meaningful, such as trajectory reconstructions or predictions of different possibilities.

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 have become necessary to improve player performance, as mentioned by [134] with the Chinese federation, which has a team dedicated to match analysis. All data and metadata specific to table tennis matches can be used to achieve this.

The men's final of the Olympic Games provides a compelling example of the importance of data in match analysis. 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. **Fan Zhendong** adopted a different tactic between the first and second games, which enabled him to reverse the outcome of the first game. This tactical required a numerical analysis of game events to be seen and understood.

Simple data based on a single stroke, as for the service, could be studied [106]. 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 [134], 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 [126]. Nonetheless, it is essential to adopt a more global perspective, emphasizing overall tactics rather than isolated strokes or specific sequences. In table tennis, the data comes from professional players' matches. Professional matches are broadcast by the World Table Tennis[9] (WTT) and available online.

Figure 1.6. – Example of a table tennis rally: On the left, a screenshot captures **Truls Moregardh** when serving, facing **Fan Zhendong** positioned as the receiver during the 3rd game of the Paris 2024 Olympic final. On the right, data from the rally provides an analytical perspective of this serve we will use in this thesis to reveal players tactics.

1.4 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 misinterpretation. Like many other sports, table tennis has undergone a process of evolution, with both sporting and technological advances in the equipment used (Section 1.2). 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 (*e.g.* serves, hit, positions,...) and those specific to equipment (*e.g.* racket, ball, table,...). In this thesis, rules

9. https://www.worldtabletennis.com/

specific to *singles* are the ones we need to pay attention to, while *doubles* have their own rules [10]. The main rules in table tennis that concern the game are as follows:

- Each player takes turns and must make a valid stroke.
- A stroke is valid if it is made with the racket or the hand holding the racket and the ball bounces on the table.
- The ball must bounce on the opponent's side of the table and must pass over or around the net.
- Players are not allowed to volley.
- The serve must first bounce on the server's side of the table and then on the opposite side.
- The winner of a rally is the last player to return the ball validly to the table.
- A rally is over if the ball bounces more than once on the table, if it does not touch the table, if it touches anything other than the racket (or hand), the table, or the net. Or if the ball goes into the net.
- You must win 3 (or 4) games to win a match.
- To win a game, you must score at least 11 points, with 2 points more than your opponent.

More rules about strokes, play and equipment are provides in Appendix A.

1.5 Example of Table Tennis Tactics

As a sequence of consecutive strokes made by players at a specific moment of the game, forming a deliberate pattern based on a short- or long-term strategy to win the match, tactics aim to win points by exploiting opponents' weaknesses. Different types of tactics exist, based on players' specific characteristics. Some tactics are player-independent, based on physical and biomechanical constraints. This means that they do not depend on a technical weakness, some do not depend on the opponent and are used against all players.

To illustrate in more details the notion of table tennis tactics that is the core of this research, we now provide a series of examples of analyses. We propose the study of these examples divided into four categories according to the type of analysis used. These categories are discussed in subsequent sections to illustrate how the data required for these analyses are collected. We have identified tactics

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

based on serves and returns, tactics based on ball placement, tactics that relate ball placement to player position and 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, and are therefore often key strokes in tactics. Figure 1.7 illustrates the case of the side chosen to serve short. During the men's final of the Olympic Games, 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**. When he plays long, he wins 5 points out of 14, whereas when he plays short, he wins 16 out of 28. In general, 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.

Some tactics based on serves and returns are commonly used in table tennis that illustrate this possibility of gaining an advantage on these first two strokes. We hypothesize the following strokes to be a tactical choice:

1. **Serve long**: usually players serve short to avoid their opponent attacking, 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 the returner to attack short balls more powerfully than with the forehand.

In Section 3.4 and Section 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, and shot map based visualization of these strokes. In Section 4.3 we show better representations than such shot maps with novel visualizations overlays in videos.

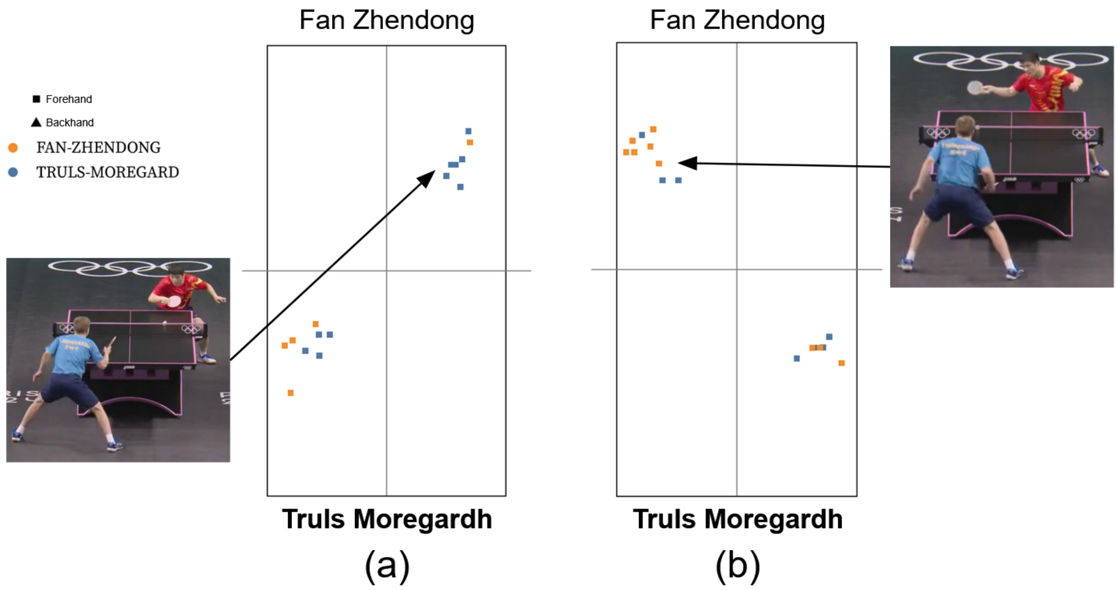


Figure 1.7. – Example of 2 different serving positions when **Truls Moregardh** serves short. Dots represent the bounce position and the color represents the winner of the rally. (a) Represents the left side. (b) Represents the right side.

Ball Placement

Ball placement can reveal favorable or unfavorable zones for players, which is often taken into account when choosing the strokes that make up a tactic. A first example was given with serves and returns. Figure 1.8 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.

We hypothesize the following ball placements to be a tactical choice:

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.
3. **Play on the short side**: forces the opponent to make long moves without being able to attack in a favorable position.

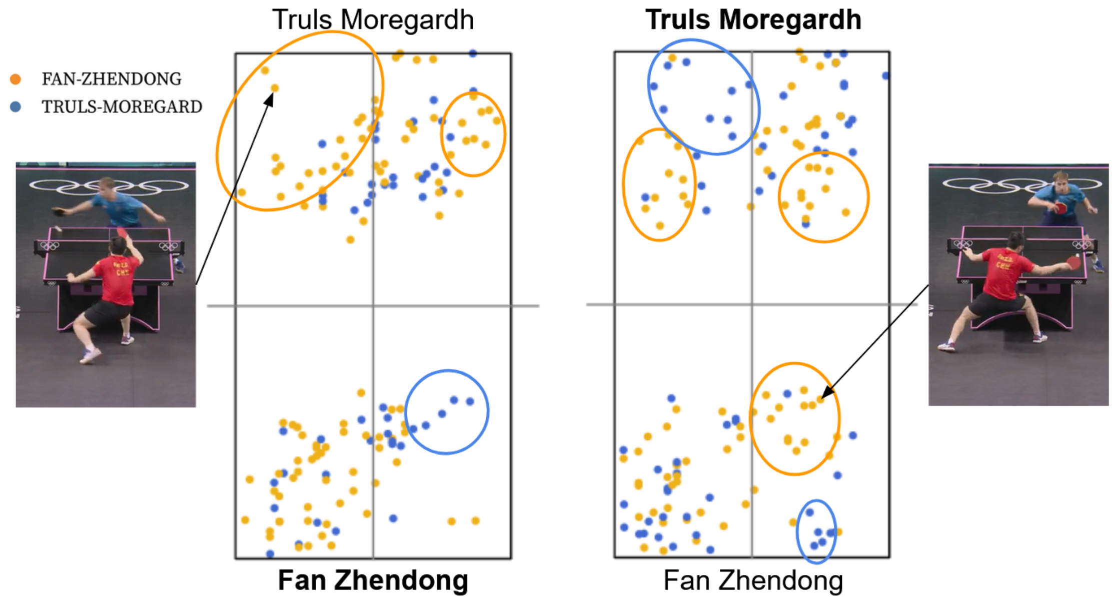


Figure 1.8. – Examples of winning groupings. The names in bold represent the players who made the stroke. The table on the left shows all **Fan Zhendong**'s bounces, the table on the right all **Truls Moregardh** bounces. In orange are the bounces that led to a **Fan Zhendong** victory, in blue those 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.

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 the choice of strokes that make up a tactic. In many tactics, the aim is to play strokes in a zone that will put the opponent in a difficult position. Table tennis coaches often use the expression "don't play in his racket" 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 (we will define them in details at the end of this section). Another type of zone can be identified as a little-used zone that aims to surprise when found. Figure 1.9 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.

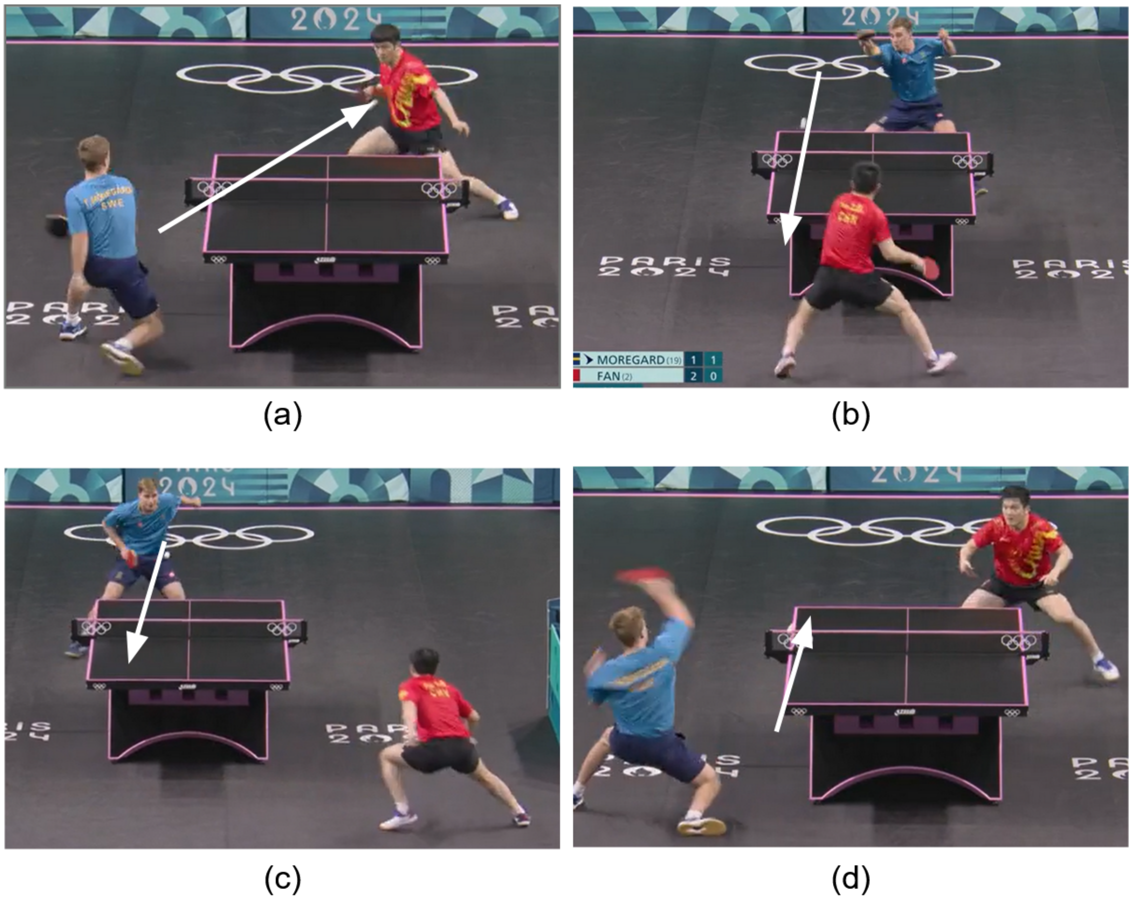


Figure 1.9. – Example of the 4 difficult zones for returning the ball: (a) The pivot zone, the area between the belly and the elbow, where the forehand and backhand are difficult to execute. (b) The wrong-footed, the area opposite your opponent's direction. (c) The zone far away. (d) The forehand zone, rarely used during this match, which surprises the opponent.

We hypothesize the following ball placements in relation to the opponent's position to be a tactical choice:

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/Non Reachable Areas**: the zone that is far away from the opponent and where he needs time to reach it.
4. **Lateral Zones**: they are the lateral zones which for some players are comfort zones and others are harder to manage.

5. **Opposite to that anticipated**: this is the zone opposite to the one that the opponent has anticipated, even if he does not 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 4.3 and Section 4.4 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 4.4 offers analyses of these two examples of tactics.

Succession of Strokes

Tactics in table tennis take into account multiple strokes, often the first 4 strokes are used to create tactics. Figure 1.10 shows an example of a multi-stroke tactic that wins 6 out of 7 times. This tactic is used when **Truls 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**.

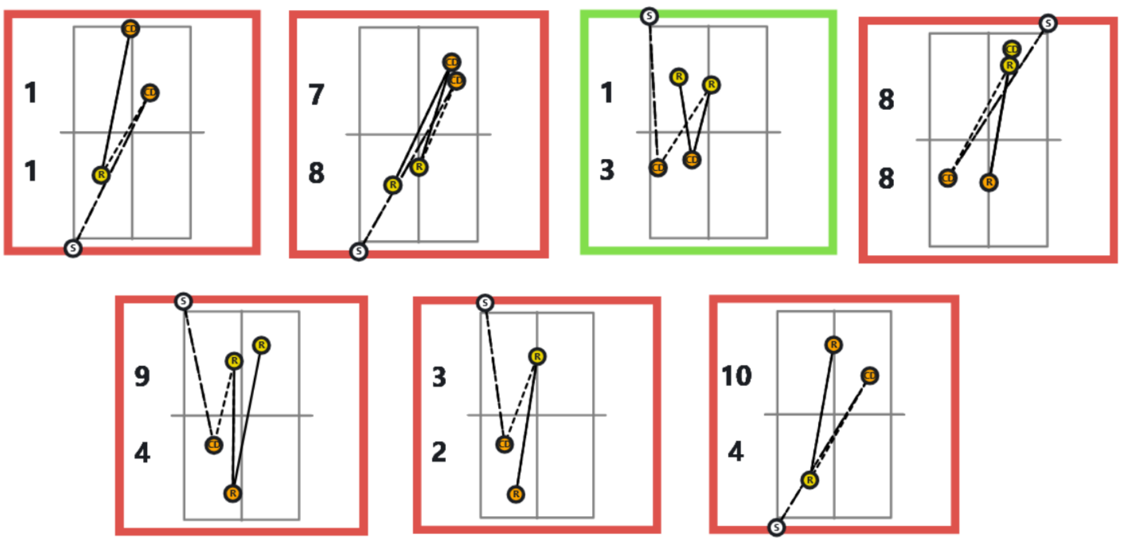


Figure 1.10. – Multi-stroke tactic. Above are shot maps, a simple top-down view of stroke sequences. In red are the rallies won by **Truls Moregardh**, in green those won by **Fan Zhendong**. All these rallies start with **Truls Moregardh** serve. The tactic is a serve on the left side and the next stroke from **Truls Moregardh** still on the left side but more to the right than the serve. Only the first four strokes of each rallies are represented.

We hypothesize the following succession of strokes to be a tactical choice:

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.

1.6 Scientific Challenges

We now summarize our hypothesis of work and the scientific challenges we tackle in this thesis. All this work is based on broadcast videos analysis of elite players. We focus on revealing the tactical aspect of the games and the sequences of consecutive strokes that form tactics. To achieve this, we identified the following scientific challenges:

- **Automatic broadcast video segmentation and classification**: Table tennis match videos contain moments of play during points (which is the focus of this work) and moments of non-play between points, during timeouts and side changes (which we do not analyze). 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. We opted for a manual approach we present in this manuscript, which can be carried out independently of the collection of detailed structured data. This work is presented in Section 2.4.

- **Extracting structured data from table tennis videos**: As videos, even segmented, are only pixels they need to be turned into data that can be processed by algorithms. It relies on objects detection and action recognition. Object detection is an important challenge, for example the ball is a small object moving very quickly, and there can be numerous occlusions, mainly due to the players. Action detection in table tennis faces a wide variety of strokes and it's important to distinguish all of them 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. In our context in collaboration with the FFTT, there can be no errors in the stroke type data, this is the greatest constraint for this task.

We have chosen to adopt a semi-automatic approach to collect structured data from broadcast matches. This work is presented in Chapter 2. In our work, we focus on player position for automatic collection and on the type of strokes and the position of the bounces for manual collection.

- **Data analysis from collected data**: Once data are extracted from videos, their 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. The main difficulty with this task lies in the fact that the data is very varied and there are many possible directions to explore, whether through scores, rallies, strokes, or even the spatio-temporal information of different objects. The second difficulty in these analyses is ensuring their relevance, as there are many performance factors and irrelevant interpretations may be made. We propose three different approaches of analysis, which are presented in Chapter 3.

- **Effective results communication**: The intended audience for our work includes data scientists interested in assessing data quality and elaborate models, to a non-technical audience that is not an expert in data and eventually not an expert in table tennis. This means that the communication of results must allow for quick understanding. To this end, visualizations offer a universal and rapid means of communication. They must be based on match data and facilitate exploration or research while maintaining a link to the original video, leaving the interpretation of the results up to the user. This section is the main contribution of this thesis. It is presented in Chapter 4 through different visualization approaches.

These various scientific challenges reflect the great complexity of video analysis in high-level table tennis which correspond to the following three chapters: video processing includes both segmentation and extraction (Chapter 2), analyses of structured data (Chapter 3), and visual communication (Chapter 4).

1.7 Contributions

7 papers have been published during this PhD on three different topics to address the challenges introduced in the previous sections:

[32] 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). [32]

[13] 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. Turin, Italy. 2023. [13]

[33] Aymeric Erades, Thomas Papon and Romain Vuillemot. *"Characterizing Serves in Table Tennis."* en. In: *Machine Learning and Data Mining for Sports Analytics*. Springer Nature Switzerland, 2025. [33]

[38] Aymeric Erades and Romain Vuillemot. *"Player-Centric Shot Maps in Table Tennis".* In: Computer Graphics Forum (EuroVis'25). Luxembourg, June 2025. [38]

[34] Aymeric Erades, Lou Peuch and Romain Vuillemot. *"Investigating Control Areas in Table Tennis".* In: Sixteenth International EuroVis Workshop on Visual Analytics (EuroVA). Luxembourg, June 2025. [34]

[5] Riad Attou, Marin Mathé, Aymeric Erades and Romain Vuillemot. *"Analysis of Service Returns in Table Tennis".* In: Machine Learning and Data Mining for Sports Analytics, Porto, Portugal, Sept. 2025 [5]

[37] Aymeric Erades, Romain Vuillemot. *"How Camera Angle Impact Table Tennis Ball Bounce Tracking".* In: Sports Physics 2025. Sept. 2025 [37]

1 book on analyzing table tennis through data is currently being written and will be published in autumn 2025:

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

In addition to these papers, we provide different data and repositories of our work:

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

Throughout the thesis, dissemination was carried out to a wide audience, from high school students to an adult audience to explain the research work carried out. In particular, also through two appearances at the "Fête de la science", a day open to all in which interactive activities were offered. A summary of all the dissemination actions is available online [11].

11. https://centralelyon.github.io/table-tennis/

CHAPTER 2

EXTRACTING STRUCTURED DATA FROM TABLE TENNIS VIDEOS

Contents

This chapter focuses on extracting structured data from table tennis broadcast videos, which is one of the scientific challenges that we mentioned in the Introduction chapter (Section 1.6). It is based on our assumption that such videos already exist from TV broadcast channels, already recorded using a single camera from a static point of view, and are available online. The work presented in this chapter is based on the following two articles:

[32] 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).

[37] Aymeric Erades, Romain Vuillemot. *"How Camera Angle Impact Table Tennis Ball Bounce Tracking".* In: Sports Physics 2025. Sept. 2025

2.1 Introduction

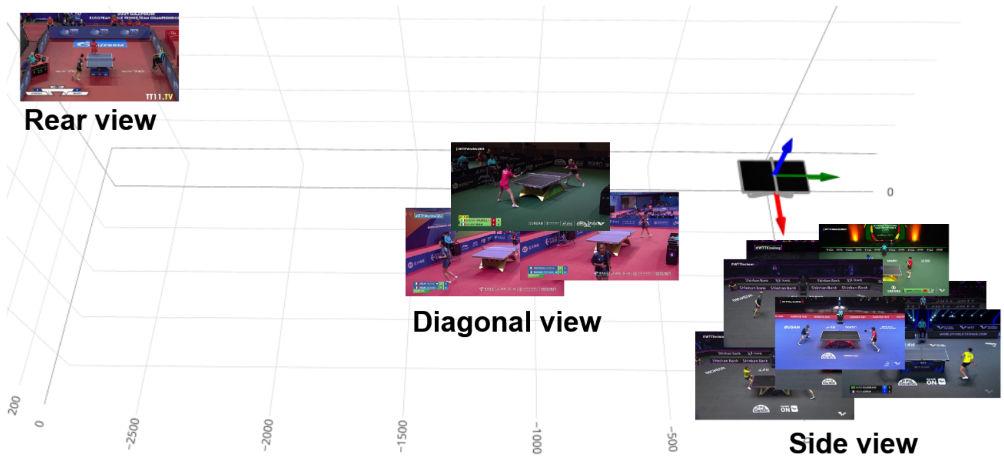


Figure 2.1. – Various points of view collected during table tennis international competitions and their positions in 3D space. On the table, the red axis corresponds to the x axis, the green axis to the y axis and the blue axis to the z axis.

The conditions for filming different table tennis competitions can vary greatly, resulting in a wide variety of scenes. Those variations are mainly due to the position of the cameras used to record and broadcast videos. Figure 2.1 shows different camera angles from various table tennis competitions, these videos and their data are part of the dataset [35] we present in Section 2.3 as benchmark dataset. For table tennis, broadcasters often use fixed RGB 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 2.1, we can roughly identify three distinct viewpoints: the *rear view* (in blue), the *side view* (in red), and the *diagonal view* (in green), each of which provide its own type of geometric distortion of the table tennis game. The different objects present in a table tennis 3D scene include the table (the only fixed object with the floor), players, their rackets, and the ball, which are moving objects. Projecting this 3D scene onto the camera's 2D plane makes conditions very different between competitions (an illustration of the projection is shown in Figure 2.20). This diversity of camera angles makes it difficult to adapt to different matches for data collection, and is further complicated by occlusions caused by the projection of the 3D scene onto the camera plane.

In table tennis we focus on events and positions. The different camera positions make it difficult to collect this data. Indeed, despite recent progress in computer vision and deep learning, it remains challenging to accurately spot the positions of the player and the ball, and classify them as events.

2.2 Related Work

Match video processing mainly falls within the field of computer vision and deep learning. Several subfields are involved, such as object detection, tracking, and action detection for tasks involving objects present in the scene, and segmentation and classification for different videos shots.

2.2.1 Clip Video Segmentation and Classification

The general problem of video segmentation consists of breaking down a continuous video footage into shorter segments that share a similar semantics, *e.g.* same action, individual or camera shot. This task is one of the main tasks of [84], which aims for table tennis and swimming to segment playing moments for table tennis and swimming moments for swimming. In table tennis, relevant segments are those involving the same actions, they can be divided into three types of actions: play, non-play phases between rallies, and coaching moments. These different actions are often characterized by changes of shots, but in some cases can only be differentiated by following the game, the way matches are recorded is defined by ITTF[1]. In table tennis, professional matches provided by WTT[2] have different shots, and the phase between plays is translated 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 of play that require to be extracted.

For basketball [130] uses distinctive color distributions to distinguish different shots. It uses a Hidden Markov Model to segment shots based on these color differences. Similarly, for badminton [17] segments game footage into clips using a ResNet-18-based neural network [54]. 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. They combined the segmentation and the classification with the same model. For kendo [95], which is a sport based on a succession of actions, they use amateur videos to create highlights by detecting people's actions using RGB video and 2D body joint positions (detailed in Section 2.2.4). For ice hockey [46], uses a different approach to segment clips and detect the most important actions by detecting spectator reactions using a deep 3D Convolutional Neural Network.

In table tennis, the task consists of distinguishing moments of play, *i.e.*, during rallies, and moments of non-play between rallies. To do this [136] proposes a

1. Example of recording guideline https://www.ittf.com/wp-content/uploads/2019/11/2020_WT_TV_Production_Guidelines.pdf

2. https://www.worldtabletennis.com

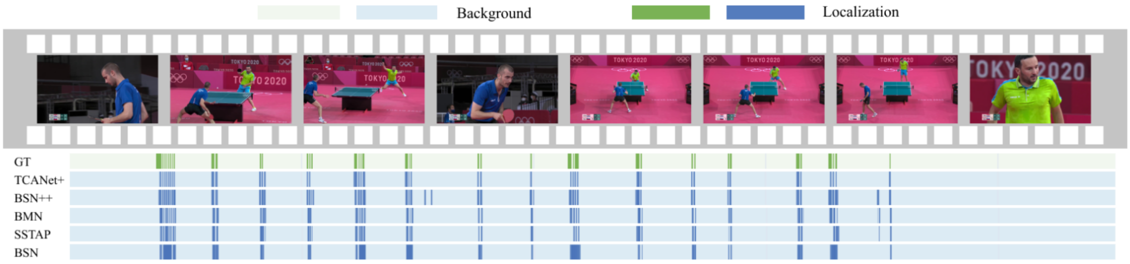


Figure 2.2. – Example of action segmentation for table tennis using different models [9]. Rallies can be identified with action segmentation groupings.

method combining YOLO [59] (an object detection algorithm using bounding boxes) and Openpose [14] (an algorithm for pose estimation) to classify each frame as play or non-play. P2ANet [9] proposed a benchmark for action recognition in table tennis and an evaluation of methods often used in action recognition. Detecting these actions, particularly the serve, using the original video of the match allows the game moments to be segmented by grouping the segments of actions corresponding to the rally moment. Figure 2.2 shows examples of segmentation. Similarly [129], focuses on service and return segmentation using a neural network that takes as input the pose estimation of both players over several frames (*i.e.*, 35 frames and 2 times 25 key-points coordinates x,y). This method has an accuracy of over 98% of services and can be used to detect the start of rallies.

2.2.2 Players Tracking

Player tracking involves detecting and tracking the positions of players throughout the video on each frame. It 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. In team sports, a common method is to detect players across all frames and then identify them. In football [114] uses YOLOv5 [59] to detect players (Figure 2.3 (a)). Once the players have been detected, to track players between frames, they perform player identification based on their characteristics such as their morphology or clothing to extract features that allow them to be identified from one another. In this way, the identification is performed on each frame. For basketball [130] uses a Deformable Part Model for player detection. To track players authors use a method that minimizes the distance between the detection position and the prediction position computed with previous positions. In this way, player identification is only performed once per sequence. Then the identification of players is also performed using players' characteristics based on visual features. For badminton [20], which is close to table tennis with only two players, they classify pixels as background and foreground to detect players, who are moving objects. Unlike team sports where all players can move around the entire court, in badminton, each player has their own side of the court, which is determined by the score. This makes it easy to identify players, as it is based on which side the player is on.

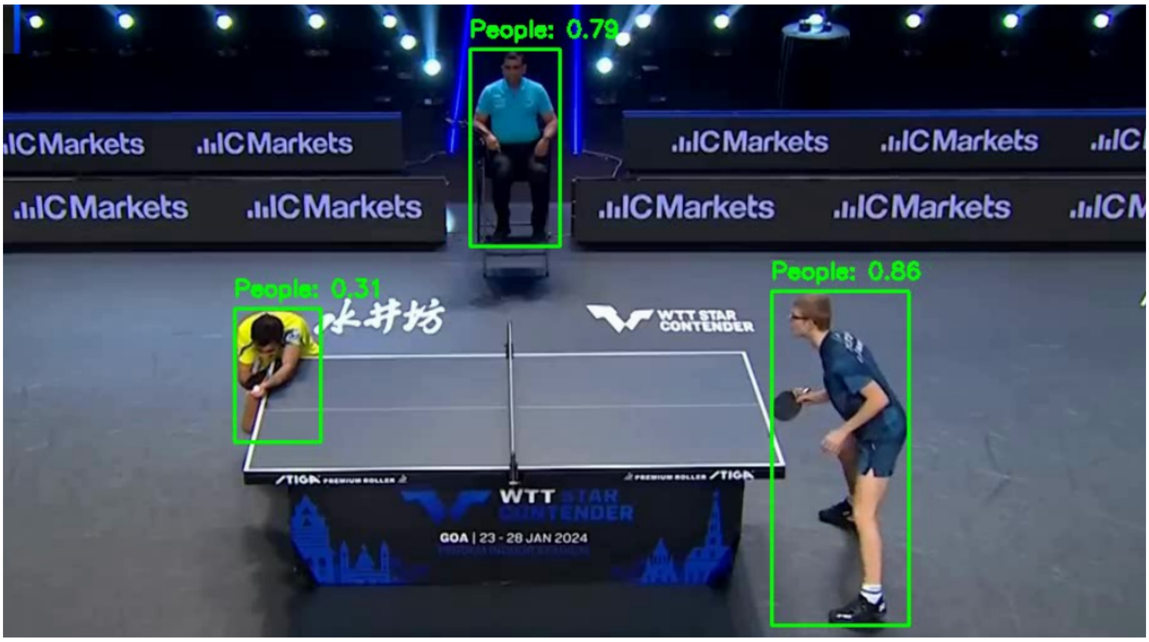


Figure 2.3. – Example of players' detection in table tennis players. Player detection is performed by using Yolov8 and bounding boxes surrounding the players.

In table tennis, several visual analyses perform player tracking without necessarily explaining their method in detail [24]. TTNet [122] uses a semantic segmentation to detect players without addressing a tracking task. The fact that many analyses provide little detail on the process of detecting players and tracking them in table tennis is because the majority of these analyses focus on the positions of ball bounces.

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 [114, 130, 20] 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 2.4).

Table tennis specific difficulty is to compute players' position in space. In badminton and other team sports, the court is used as a reference point to calculate the players' positions. In table tennis, the table is not at the same level as the players, making it difficult to use as a reference point.

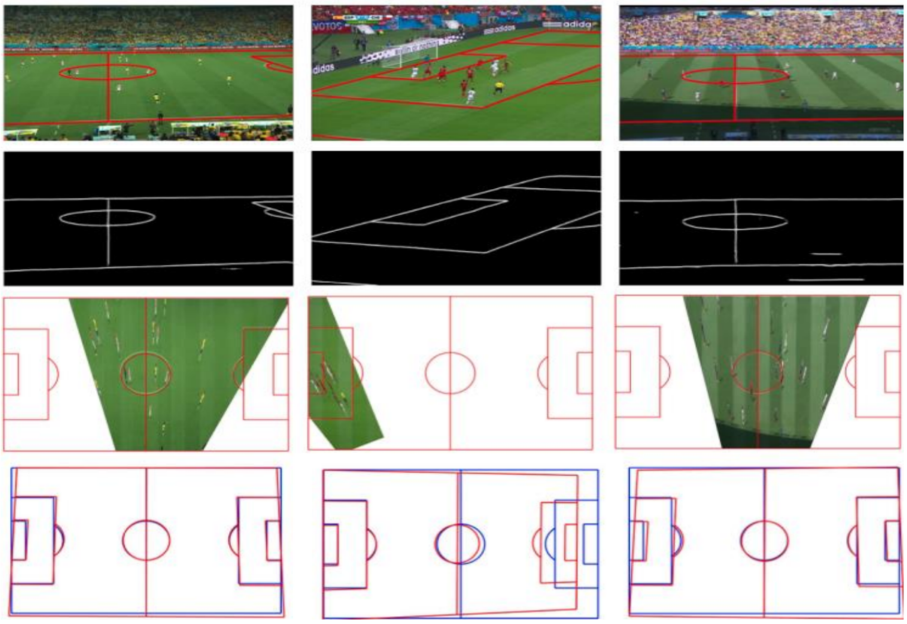


Figure 2.4. – Example of detecting lines on a soccer field used as references to calculate the actual position of players in space using homographies [114]. Detection of lines is performed by using Unet, a deep neural network architectural approach for semantic image segmentation.

2.2.3 Ball Tracking

Ball tracking involves detecting the ball and tracking its position on each frame of the video. It 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 table tennis characteristics, we can be sure that there is only one ball present during the game and to perform tracking, detection alone is sufficient. The ball is smaller than the players, with less than 10 pixels in diameter in the image and moves faster. This problem is defined as a problem of tracking small and fast-moving objects [141]. 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 ball's properties allow it to be detected based on its color and movement, using colorimetry and/or background subtraction methods (Figure 2.5). 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 –in theory– possible to predict the ball's future position based on its previous states (*e.g.* position, rotation, etc.). By using speed and acceleration [90] authors define a search area on the next frame in which to perform detection. Detection quality can be quite sensitive to the choice of

Figure 2.5. – Example of ball detection we performed using colorimetry and image subtraction (based on [91]), during the match of **Alexis Lebrun** against **Fan Zhendong** in Macao 2023. The detection is performed over the table to focus the detection.

colorimetry filtering threshold. To make detection less threshold sensitive, [131] 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 [104] takes a different approach than background subtraction to detect the ball trajectory. It uses motion frames, which are frames derived from background subtraction, and merges 10 consecutive frames, which allows to track 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 [114] uses the same model used for player detection, YOLOv5. For ball detection [48] 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 [122, 58] to detect the position of the ball (Figure 2.6). TTNet [122] 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

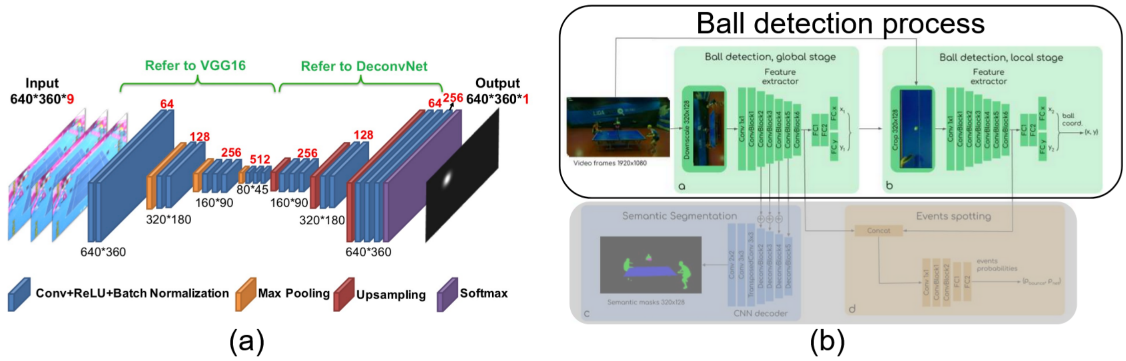


Figure 2.6. – Example of neural network architectures that can detect the ball using semantic segmentation. (a) Shows the Tracknet architecture [58], which takes three consecutive frames as input and outputs a heatmap showing the probability of pixels belonging to the ball in the last of the three frames. This heatmap is then used to detect the ball. (b) Shows the architecture used by TTNet [122]. 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.

blurry and distorted in the image. To improve image quality [68] proposes a first step consisting of improving the image quality using continuous wavelet transform before performing detection using a Probabilistic Neural Network [116]. BlurBall [49], on the other hand, uses the deformation of the ball as information. By detecting both the position of the ball and the start and end of the blur streak, it obtains information on both the speed and direction of the ball using the size and orientation of the shape. This additional information makes it possible to reconstruct the trajectory of the ball.

2.2.4 Pose Estimation and Classification

Pose estimation is based on detecting human articulations, which serve as key points for reconstructing the skeletal structure. These key points help characterize the players' movements by allowing each body part to be tracked independently. 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 [66] 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 is often used on videos, 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.

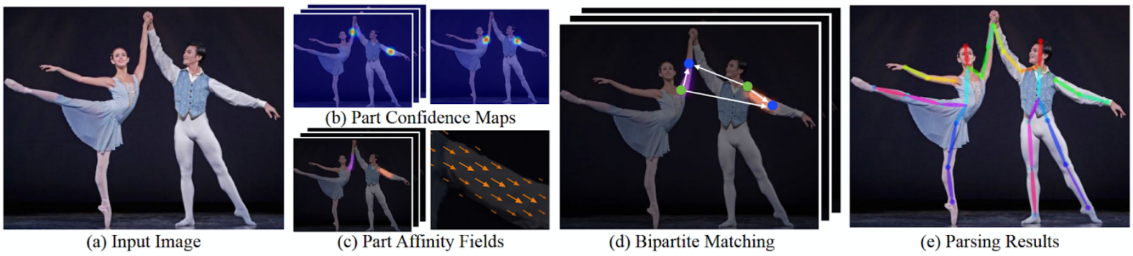


Figure 2.7. – Explanation of how Openpose works [14]. (a) Corresponds to the RGB image used as input to the network. (b) For each keypoint, it creates a confidence map highlighting possible keypoints. (c) Creation of Affinity Fields to match keypoints. (d) Matching of keypoints. (e) Final result of pose estimation with 18 connected keypoints.

To take into account the temporal dimension of strokes in the context of stroke analysis in table tennis [82] use a deep learning algorithm 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.

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 [14, 41]. Pose estimation (Figure 2.8) 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 [14]. The second involves detecting people and then detecting the keypoints within the bounding boxes of the detected people [41]. 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), [14] may have many different positions for each keypoint, 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.

The estimation therefore provides us with additional information about the players' posture, which can be used in action detection. To aid action detection

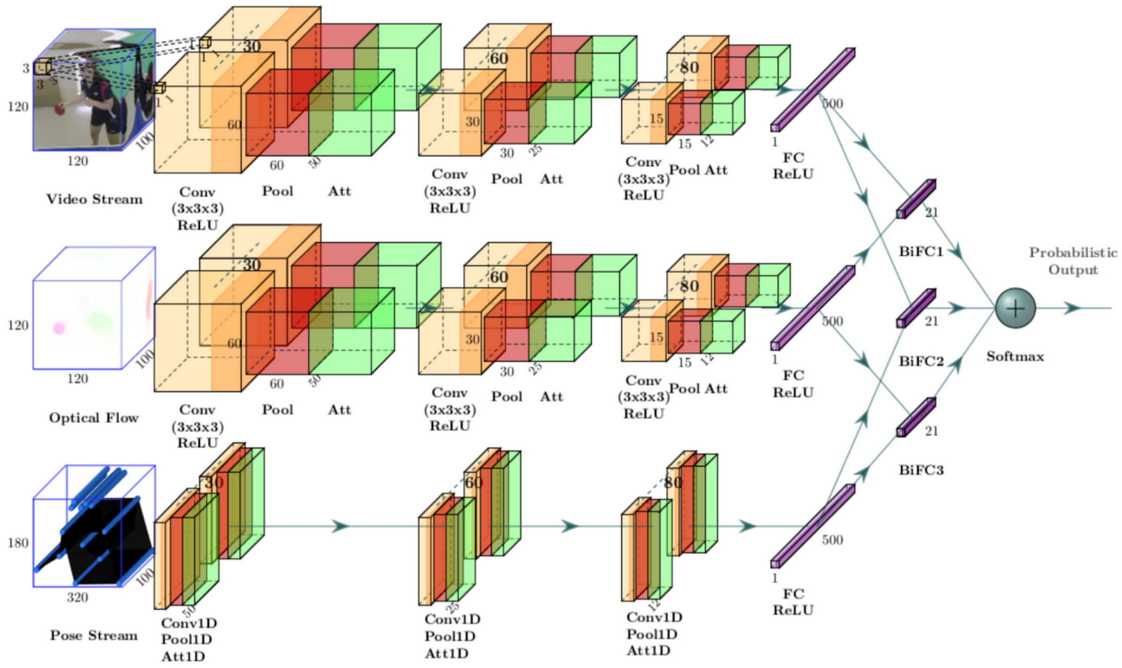


Figure 2.8. – Explanation of [83] model. The model takes three types of data as input: 100 frames from the RGB video, 100 frames from the optical flow, and 100 estimates of the player's pose. By merging the three branches of the network for the three inputs, it outputs the probabilities of possible actions.

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. For pose estimation, Openpose offers a simple solution for automatically detect all keypoints. This is the option we chose in order to enrich our data with the poses estimation of players across all frames in the Section 2.4.

2.3 SportsVideo: A Benchmark Dataset

To assess the current state of the research in video tracking and classification for table tennis, we built a benchmark that divides our needs for data into different sub-tasks. This benchmark is open to the Research community and 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 mainly on challenges we discussed in the previous sections: 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 [80]. This work is based on a previous challenge related to swimming [61], which explains why it contains two sports.

We propose a series of 6 sports-related tasks. 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 to achieve the goal of this thesis which is to capture and analyze players tactic. For this challenge, the participants were encouraged to release their code publicly with their submission. Similarly to the Sport Task 2022 edition [78] organized by Pierre-Etienne Martin, a baseline for both subtasks 2.1 an d 3.1 is shared publicly[3] [79]. Previous benchmarks are explained in Pierre-Etienne Martin's thesis [80] for the table tennis, and Nicolas Jacquelin's thesis [60] for swimming.

2.3.1 Tasks Description

The tasks we present, when taken together, enable us to perform most of the tactical analyses that can be found in Chapter 3.

Task 1 - Position Detection. The main information in sports is related to the positions of players in videos featuring different numbers of sides around a table tennis table (seen from various angles). Participants need to provide bounding boxes for identified players, by detecting 2 or 4 players (depending on whether single or double) and track them during the video. Their results are evaluated using Average Precision (AP) at an IoU ratio of 0.25, counting true positives and negatives across the dataset. For this task we provide a total of 50 videos.

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 are however only required to identify the timestamp of the strokes (*i.e.* a ball hit with the racket) using close-up video (Figure 2.10), the classification is achieved with the next task. Evaluation is based on the F1-score, which measures the harmonic mean of precision and recall. For this task we provide a total of 1155 videos of strokes.

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 3 different categories of strokes, services,

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

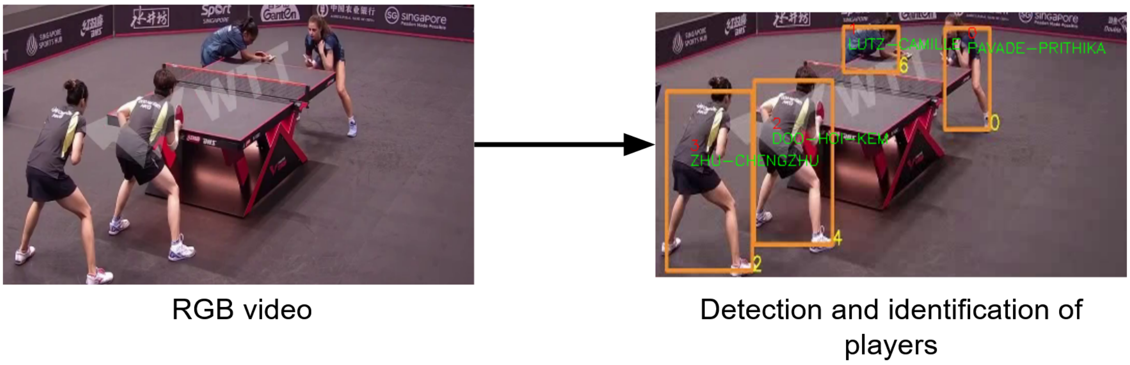


Figure 2.9. – Task 1: Detection of players' positions and tracking. Detection performed for a women's doubles match. Using the original RGB image, we first detect the players, then track them, and finally re-identify them to obtain the final tracking. (The detection was performed by computing bounding boxes with OpenPose [14] keypoints).

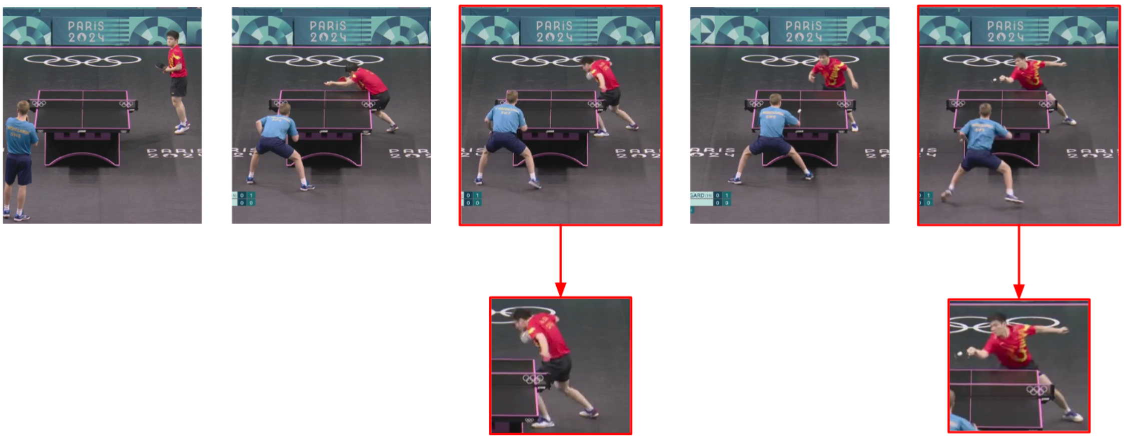
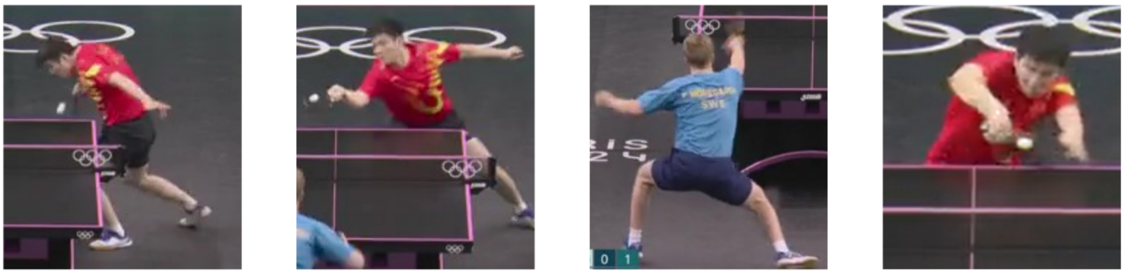


Figure 2.10. – Task 2: Visual detection of the moments when the player hits the ball. The moment when the player hits the ball occurs when the player makes their stroke and touches the ball with the racket.

forehand and backhand (Figure 2.11). 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. For this task we provide a total of 1155 videos.

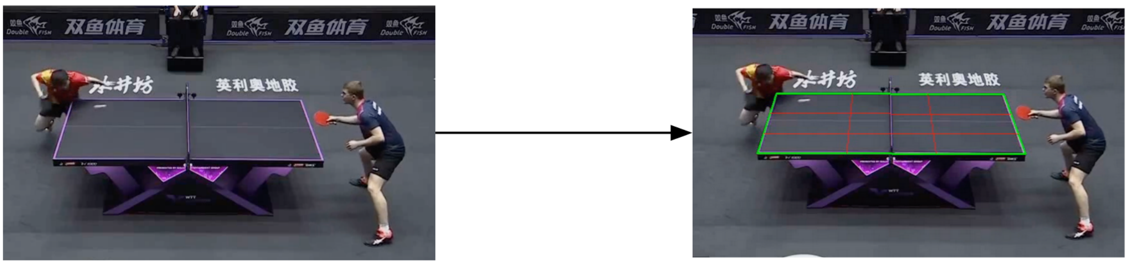
Task 4 - Table Perspective Projection Sports videos in general, and in particular the ones provided for the SportsVideo task, are usually recorded from the side. This task asks participants to find the homography transformation for each frame in the dataset. It consists of the projection that maps points of the table tennis



(a) (b) (c) (d)

Figure 2.11. – Task 3: Strokes classification. An example 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).

space, to corresponding points in the video space (Figure 2.12). 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. For this task we provide a total of 54 images containing a table.



RGB image of the match

Detection of the table and the 4 corners

Figure 2.12. – Task 4: Table detection using the RGB image as input. The table consists of a rectangular top and is defined by four corners.

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 the exact frame when the ball bounces on the table (Figure 2.13) using sound. In table tennis, the ball bounces on the table for every stroke. Videos are provided with the ball annotated and evaluation is based on the F1-score. For this task we provide a total of 56 audio files.

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

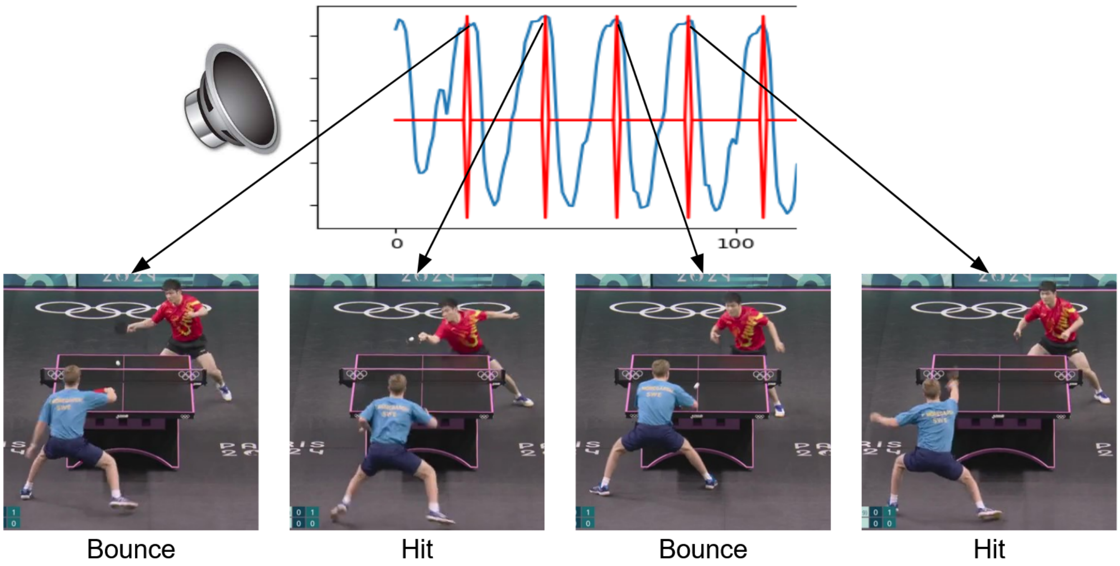


Figure 2.13. – Task 5: Examples ball bounces and ball hits. When the ball bounces off the table, it emits an audible sound in the videos that is characterized by a peak in intensity at specific frequencies.

are also displayed on TV broadcasts as overlays as in table tennis where score and payers' names are displayed (Figure 2.14). For this task we provide a total of 96 images containing a virtual scoreboard.

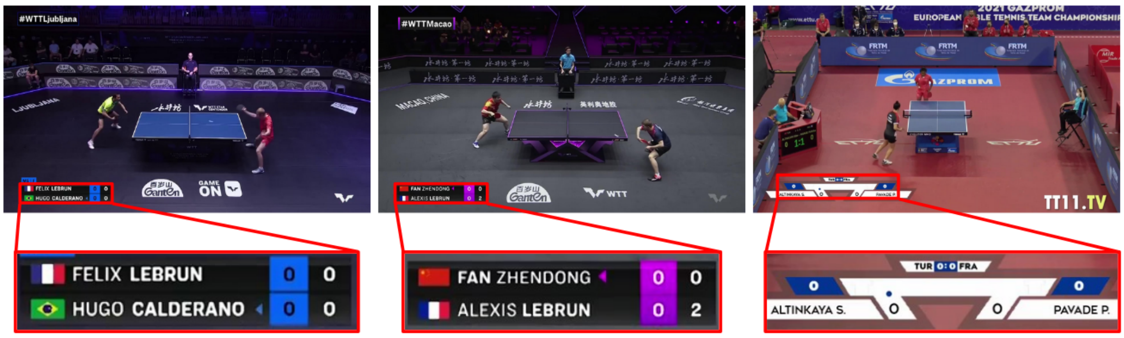


Figure 2.14. – Task 6: Examples of scoreboards in different competitions. Scoreboards allow you to follow the current score throughout the match and see the names of the players. They are usually located in the corners so as not to obscure the play.

Summary of the Dataset

This benchmark dataset made up of the 6 tasks summarized in the Table 2.1 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 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.

Task Name	Content	Result	Dataset Size
Position Detection	Video	Players' Coordinates + Tracking	50
Event Detection	Video	Time Segmentation	1155
Event Classification	Video	Classification	1155
Table Perspective Projection	Image	4 Coordinates	54
Sound Detection	Audio	Temporal moments	56
Score and Results Extraction	Image	Characters and Numbers	96

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

This benchmark and the challenge were carried out in 2023 with the aim of automating all data collection in table tennis. Among the participants, 4 were published on two different tasks. For score detection [62] used a hybrid approach with optical character recognition using PyTesseract[4] combined with CNN-based score extraction. For stroke classification [121] uses a Convolutional Neural Network (CNN) and Long Short-Term Memory [56] (LSTM) architecture and achieves an accuracy of 81.4% across all classes, using a Two-Stream Network and Attention Mechanism approach [30] achieves an accuracy of 74.6%, and using 3D CNNs with Attention Mechanisms [79] achieves an accuracy of 86.4

Although some other models from the state of the art, such as [122, 58] can exceed 95% accuracy under certain conditions, these values can decrease significantly depending on the environment. The constraint imposed by the FFTT of 100% accuracy makes automation difficult to achieve. To overcome this problem, we have chosen a semi-automatic approach with the development of a manual annotation interface we introduce in the next Section.

2.4 Video Annotations Tool

As the tracking methods did not provide the level of accuracy needed for our research, we explored the used of manual tools to obtain more reliable and detailed data. The kind of tool we used are called *annotation tools* that enable the collection of data that follows the data model we have defined and meets the needs of tactical analysis. Figure 2.15 illustrates the detailed table tennis

4. https://pypi.org/project/pytesseract/

data model we have chosen and we expect the annotation tools to capture. This format is based on a previously one used in [31] that includes fine-grained players' position, orientation and ball bounce 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, we also introduce in Chapter 4 the ball bounce position relative to players' positions to enrich this model.

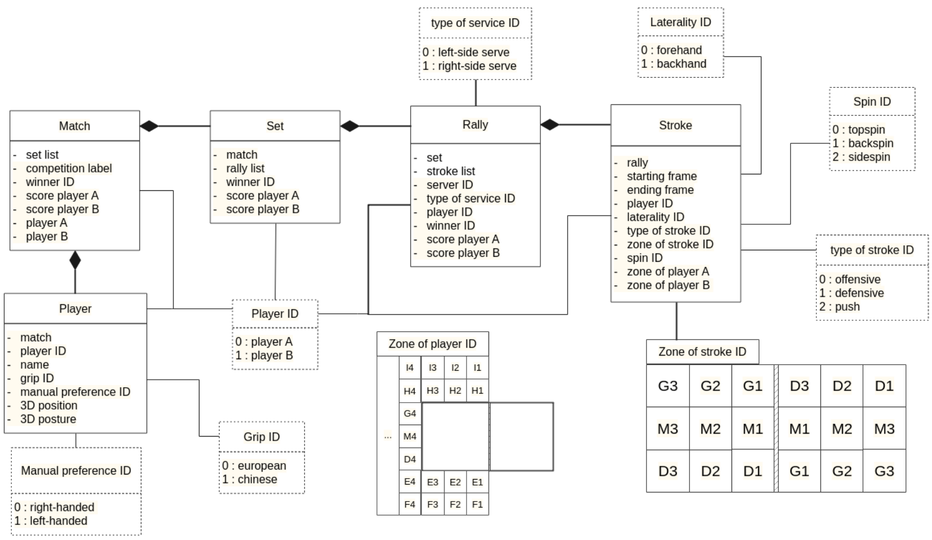


Figure 2.15. – Extended table tennis detailed data model (from[31]). It includes additional metadata (*e.g.* players' names, score and winner) with advanced stroke types, players and ball rebound zones. This model contains enriched data related to post-processing, such as player positions and ball trajectory modeling.

Annotation interfaces are popular ways to collect data for sports. For climbing [44] focused on the design of the interface to optimize annotation speed while maintaining accuracy. For baseball [100], propose a methodology based on an interface that facilitates the creation of tracking data. To annotate faster than annotating from scratch, they automatically annotate the video based on questions asked to users (questions are about what users saw on the video), with the answers, the solution matches with similar annotations already saved. After this users can modify the annotations to correctly correspond. During the automatic annotation by matching with already annotated video, the user can impose some criteria. To annotate numerous matches with varied information, it often takes a lot of people dedicated to these tasks. To overcome this problem, for soccer [98] uses fans to annotate matches. They focused on tracking data and use multiple fans they divide the task of annotation into smaller and easier annotation tasks. By having multiple people to annotate, they assign different tracking tasks to different people and also different players to different people, to facilitate annotation. By giving the same task to different people to annotate, they can also have a validation, if a certain percentage gave the same annotation, they can have good confidence in this annotation.

For table tennis [24], integrated object and event detection algorithms to make annotation faster. Among the automated tasks, they use FOT [73] (OCR model) to recognize player names and scores on scoreboards. They perform a binary classification of each frame to determine which frames are associated with the game. They use TrackNet [58] to detect the trajectory of the ball and Openpose [14] to estimate the pose of the players in order to detect different events such as bounces and player strokes. 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. This work is also used by [126].

We have chosen to develop a data collection tool in which a large part is manual. Data we focused on included ball bounces, stroke techniques and game sequences outcomes (win/lose), to enable tactical analyses detailed in Chapter 3. We used a Python software, with pre-processing steps including table position detection in the images and pose estimation (OpenPose [14]) to calculate players' positions towards the table. Two other tools were forked from this annotation tool (DOWNLOAD_VIDEO and FAST_ANNOTATION) to provide utilities 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 2.16). The video analysts at FFTT were trained to used those software and managed to contributed to the data collection process.

We have developed two annotation tools (Figure 2.17), one for fast annotation with few details and the other for detailed annotation (FAST_ANNOTATION and 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 manage independently. Data annotation is performed directly on the interface, giving the user the freedom to intervene interact at any moment. Event annotations are made using buttons linked to keyboard shortcuts, and spatial annotations are made by clicking directly on the image to retrieve the coordinates (in Section 2.5 we provide more details on the process).

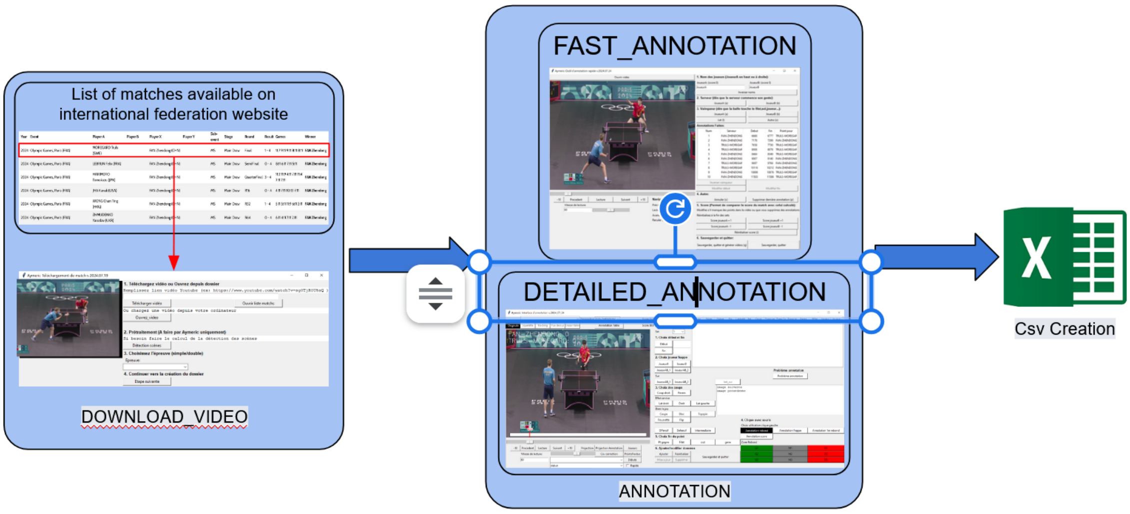


Figure 2.16. – Overview of the data collection tools we built during this PhD. Professional matches are listed on the ITTF website. Match-specific data called metadata and videos are downloaded and then different annotations are performed (*e.g.* FAST_ANNOTATION and DETAILED_ANNOTATION). Then CSV files containing structured data are created.

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, allows 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 of the annotation times for each element. The optimizations have led to the integration of game logic rules and keyboard shortcuts. Optimizations the interface is very important in saving time, we explored certain directions without publication. In our perspectives Section 5.2.2, we explain some optimization techniques we experimented and that could save time during annotation.

We augmented the data consisting of annotated events (*e.g.* strokes, rebounds, and faults) 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. Since the videos are recorded from a static viewpoint we fit a 3D structure in the scene (table tennis table sizes are given in Appendix A)—using a reference frame with minimal occlusion and visible corners, based on [76] and calculate a more accurate player positions than the initial calculated with the interface, with 3D coordinates. This process also enabled the calculation of intrinsic camera parameters to correct

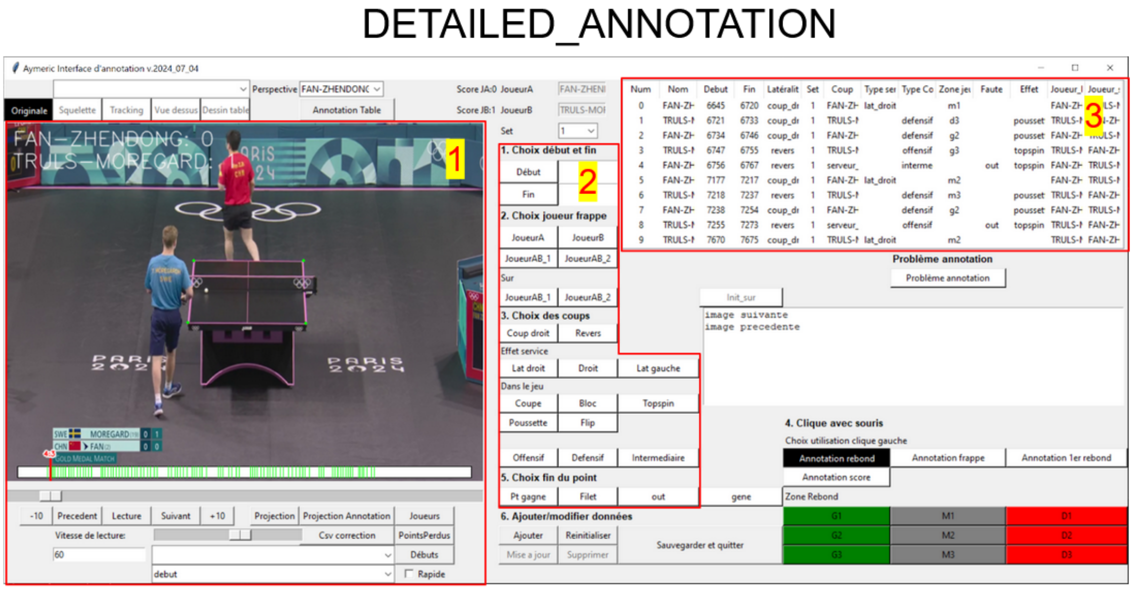


Figure 2.17. – DETAILED_ANNOTATION interface. (1) corresponds to the part that allows navigation within the video, (2) allows annotation of stroke attributes. (3) corresponds to the stroke data that has been annotated.

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 the points 2D players' reference points in 3D.

In particular we augmented the players positions using OpenPose [14] to provide us 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 [142]. 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 to align the 3D poses with the table coordinates. We located each 3D pose 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 animations as overlays of the videos to assess the results. The process of this data collection can be illustrated in the Figure 2.18.

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

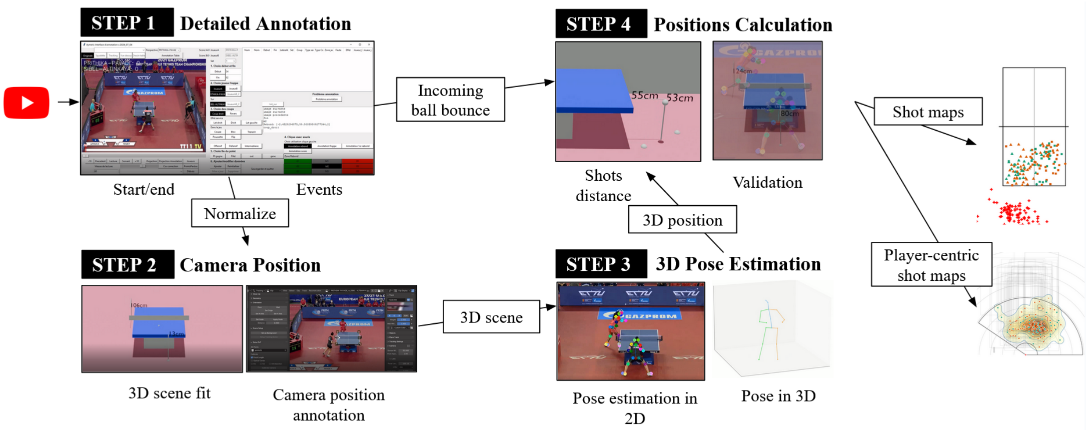


Figure 2.18. – Our 4-step data collection pipeline takes broadcast video as input and returns the relative spatial and temporal positions of players: **STEP 1** relies on manual annotation to browse and segment videos for game start/end, to click on video frames to locate ball bounce and hit positions, 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.

(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 with the ground truth provided by the motion capture system. We also validated, in a qualitative way, our approach by plotting the 3D model and the ball trajectory as a video overlay, showing coherent matching of the player and the ball temporal and spatial detection. This work was mainly engineering work involving interface development and has not been published except for the accuracy precision protocol presented in the following section.

2.5 Validation of the Tool Accuracy

The annotation tools developed are designed to ensure data quality that meets FFTT expectations and our needs to reveal players tactic. For classification tasks (strokes and type of strokes), this quality is ensured by the expert user who validated such data. To guarantee the quality for positions, and more specifically those of ball bounces, we have implemented a method and an empirical model to evaluate the influence of camera angle on the detection of ball bounces. As we previously saw, various camera positions are used to record matches (Figure 2.20). An underexplored domain in ball tracking, regardless of whether it is achieved manually or automatically, is understanding how camera angle impacts the tracking quality. Our model characterizes the non-negligible impact that the way games are recorded has on accuracy, which should be carefully considered when selecting camera positions and communicated along with collected data. Research has shown that certain positional data can be re-configured relatively to players [38] showing the importance of position in analysis. In the next section we provide the problem formulation related to orthographic projection, our methodology is based on an homography to compute bounce positions. Thus results have been published in [32].

2.5.1 Problem Formulation

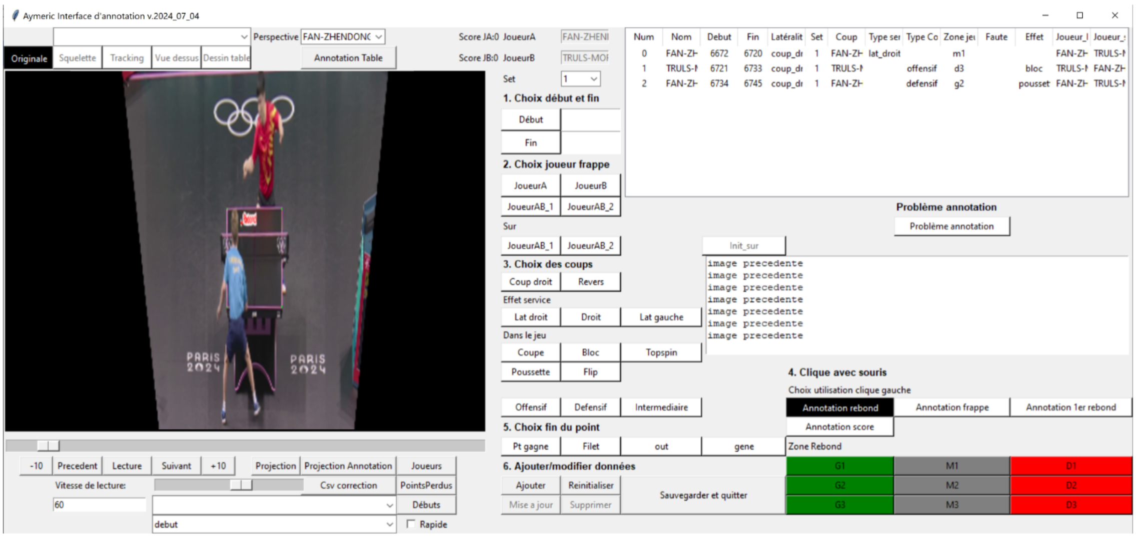


Figure 2.19. – Detailed annotation interface using the orthographic view to annotate a bounce in the match between **Fan Zhendong** and **Truls Moregardh** during the Olympic Games final 2024.

In an orthographic view (Figure 2.19), 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. A more abstract representation of such a scene is Figure 2.20 which illustrates the principle of projecting 3D elements 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 try to minimize distortion, as mentioned by the European Broadcasting Union [5] (EBU), a maximum height distortion tolerance

5. https://tech.ebu.ch/docs/tech/tech3249.pdf

of between $+1\%$ and -1% is permitted for video broadcasts (except for wide angles, where the tolerance is between $+2\%$ and -2%), we neglect intrinsic parameters, in particular as we are primarily interested in camera angles rather than their distance. For the example in Figure 2.20, 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 $5.5cm^2$, this represents approximately half of the area of the ball's projected circle on the image.

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:

$$\mathbf{p} = \underbrace{\begin{bmatrix} f_x & s & c_x \\ 0 & f_y & c_y \\ 0 & 0 & 1 \end{bmatrix}}_{\mathbf{K}\text{ (intrinsic)}} \cdot \underbrace{[\mathbf{R} \mid \mathbf{t}]}_{\text{extrinsic}} \cdot \underbrace{P}_{\text{3D point}} \tag{2.1}$$

$\mathbf{K}$ is the camera's intrinsic matrix:

- f_x, f_y: focal length in pixels (according to x and y)
- s : skew coefficient (often 0)
- c_x, c_y: optical center (usually the center of the image)

Extrinsic parameters:

- $\mathbf{R}(3 \times 3)$ is the rotation matrix
- $\mathbf{t}(3 \times 1)$ is the translation vector

$\mathbf{p} \in \mathbb{R}^3$: homogeneous image coordinates Coordinates in pixels in the 2D image:

- $(u, v) = \left(\frac{p_x}{p_z}, \frac{p_y}{p_z}\right)$

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. 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

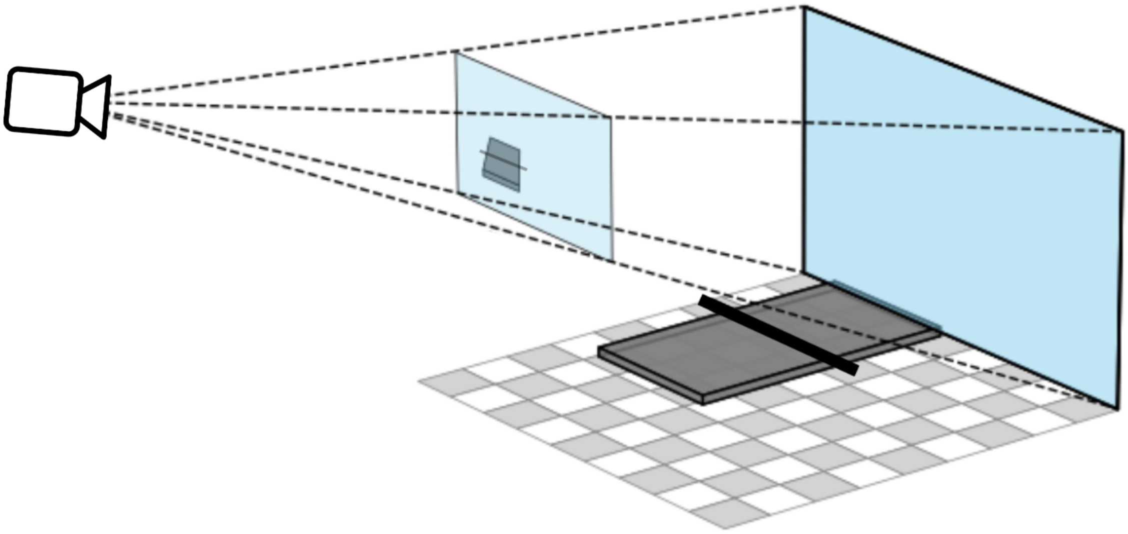


Figure 2.20. – Projection of a 3D scene onto a 2D image showing how physical objects change their visual aspect when they are projected on the camera plan. This representation of the table corresponds to the rear view, with a camera located at a height of 10m and a distance of 15m from the table.

below 10cm which is the accuracy of a player when targeting a particular position on the opposite side.

2.5.2 Protocol

The objective of this protocol is to estimate the impact of the camera angle and position on the accuracy of ball bounce detection. As we cannot collect ball bounce ground truth in TV broadcast videos, we recorded videos with the 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. To implement the camera position calculation introduction in the previous Section, we used OpenCV's calibration functions [6], which allow us to determine the position of a camera using the known positions of six points in 3D space. As reference points, we chose the six characteristic points of the table (the four corners and two at the net), which are of a standard and known type. We placed 8 balls (4 on each side). To position the balls, we measured the distances on the table and marked the positions where the balls should be placed. The table was slightly rough, which enabled us to keep the balls in place without having to add anything to secure them. We recorded 13 short videos (3 seconds each) from three camera viewpoints: rear (5 captures), side (4), and diagonal (4), each at varying distances

6. https://docs.opencv.org/4.x/dc/dbb/tutorial_py_calibration.html

and heights. Then we used an annotation tool we built to annotate all bounces from all camera images. Figure 2.21 (a) shows the camera angles, ball ground truth and annotation results, (b) shows the setup of the experiment. To annotate the ball's positions, we have to click on the ball's position in the image, allowing for pixel-level annotation. The tool then uses a homography to calculate the ball's position on the table. For a point $p = [u, v]^T$ to compute the real position (x, y) on the table, we use the equation:

$$\tilde{\mathbf{p}} = \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} \quad \Rightarrow \quad \tilde{\mathbf{P}} = \mathbf{H} \cdot \tilde{\mathbf{p}} = \begin{bmatrix} x' \\ y' \\ w \end{bmatrix} \quad \Rightarrow \quad (x, y) = \left(\frac{x'}{w}, \frac{y'}{w} \right) \tag{2.2}$$

where $\mathbf{H}(3 \times 3)$ is the homography matrix computed with the Opencv functions[7] using at least 4 known points in the plane and their correspondences in the projected plane (we chose the table corners as references).

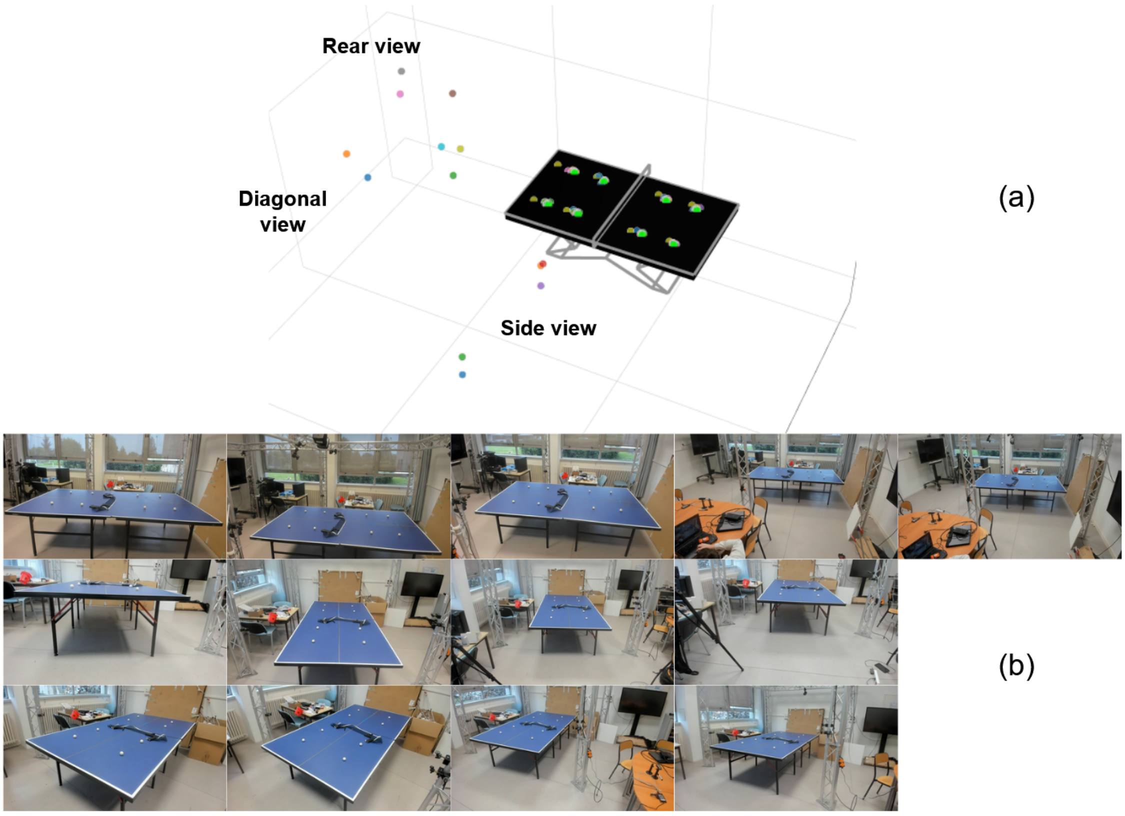


Figure 2.21. – (a) Positions of the cameras we used in our experiment and the balls positions on the table; (b) view from the cameras. This experiment was conducted at Centrale Lyon in the Amigo platform.

7. https://docs.opencv.org/4.x/d2/de8/group__core__array.html

Influence of the Camera Distance

To study the accuracy of annotations, we calculated the deviation of the annotated ball position from its ground truth determined by manually placing the balls at known locations. We found that deviations 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 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. We applied linear, exponential, and power regressions, all yielding similar results with predominantly positive slopes. This indicates a growing trend: as the distance between the camera and the bounce point increases, the annotation error relative to the ground truth also 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 video captures at different heights using the same protocol as previously to capture the data.

We then again analyzed the data and identified a correlation between camera angle and annotation accuracy. 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 fixing 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 2.22). 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. We chose to use exponential regression because we noticed in the data that for small angle values there was a high degree of variability in accuracy, and that above 30 degrees the accuracy stabilized and approached 0. Based on this observation, we eliminated polynomial regressions, which made it difficult to meet the stabilization constraints. We tested linear, logarithmic, exponential, and power regressions. We calculated the coefficient of determination to determine how well the regressions explain the data, and the exponential regression had the best value of 0.7 (Table 2.2). The regression is shown on Equation 2.3:

$$y(\alpha) = a \cdot e^{b\alpha} \tag{2.3}$$

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

Regression	Coefficient of Determination
Linear	0.52
Exponential	0.70
Logarithmic	0.68
Power	0.66

Table 2.2. – Coefficient of determination for different types of regressions.

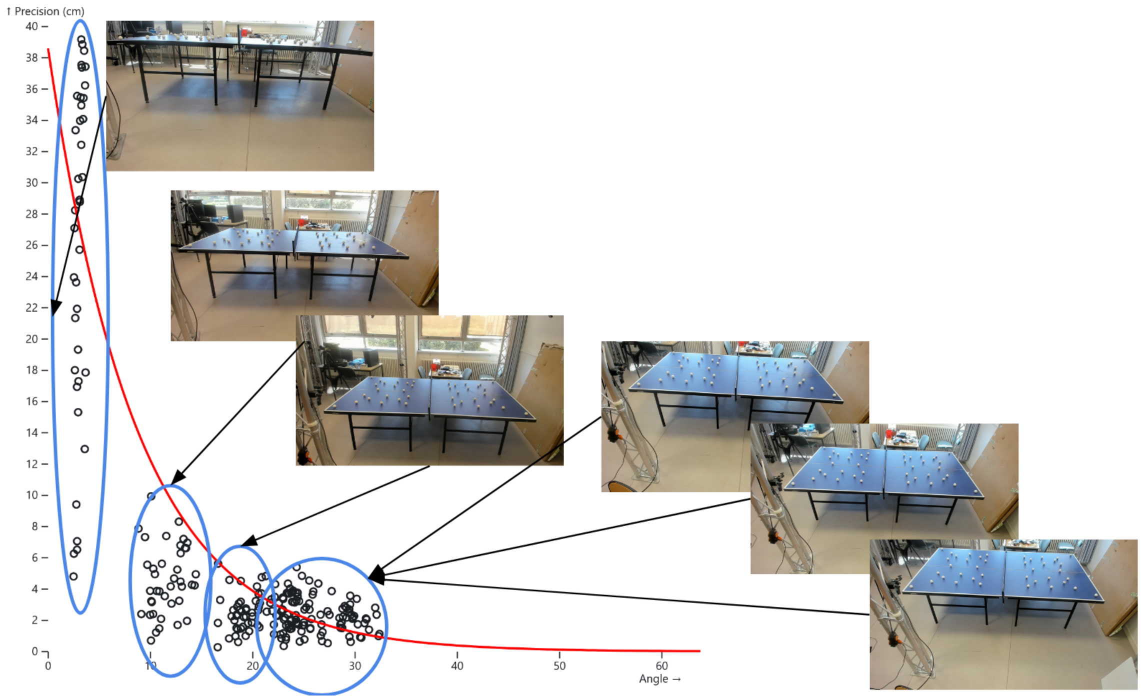


Figure 2.22. – Dots present deviations between annotation and the ground truth. On average, as the angle between the annotated bounce and the camera increases, so does the accuracy of the annotation. An exponential regression can model this trend (red curve).

Figure 2.22 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 5*cm* and 40*cm* depending on the table zone. We also note that from a certain angle between the camera and the table, annotated 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 1*cm* by 1*cm* grid, to limit calculation times. Still this work paves the way for further investigations and applications. For instance, Figure 2.23 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 in collected data and eventually provide an error 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 10*cm* 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 3.5*cm*, no clear trend emerges. More 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

We have characterized one aspect of the accuracy of the video annotation tool that uses broadcast video using camera angles. We identified a model which 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 future work, we plan to propose a new method for calculating the direction of deviation in accuracy and enabling data correction, to standardize all position data both within a single match based on the side of the table and between multiple matches with different camera positions. Also more areas connected to accuracy needs to investigate, such as the type of motion of the ball, and potential human errors in the annotation process due to different interpretation of ball position.

2.6 Conclusion and Perspectives

We first created a benchmark dataset open to the community which allows the most important tasks in automatic data collection in table tennis (e.g., player position detection, event detection, event classification, table perspective projection, sound detection, and score extraction). For spatial data, regardless of whether the collection method is automatic or manual, we then investigated 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. Automatic data collection methods can replace manual methods, which can be time-consuming, and generate the data needed for tactical analysis.

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

- The first perspective 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 number of matches is important, but the diversity of games is just as crucial in order to capture specific conditions, such as varied recording setups or specific in-game actions, allowing for a more comprehensive evaluation of the tools. Using annotation tools, we have already annotated 49 matches in detail and segmented more than 300 matches.

- The second perspective 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. Detailed annotation takes approximately 3 hours per match. We have identified that movement in the video is what takes the most time, with approximately 15% to 25% of the time spent moving from one rally to another. We discuss about this perspective in Section 5.2.2

- Finally, the last perspective concerns the correction of spatial annotation accuracy. We have shown 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. Depending on the camera angle, a discrepancy between the annotation and the truth may appear. This deviation can be modified statistically depending on the player and the camera position. Another perspective aligned to this one is to include the accuracy of data collection as a confidence factor in the statistical model and visualizations we will introduce in the next sections.

Structured data are the foundation on which we build in the following chapters to provide relevant analyses. In the next Chapter 3, we propose to analyze such data, and in Chapter 4, we propose new visualizations that allow for data exploration and leave the possibility of analysis to the user.

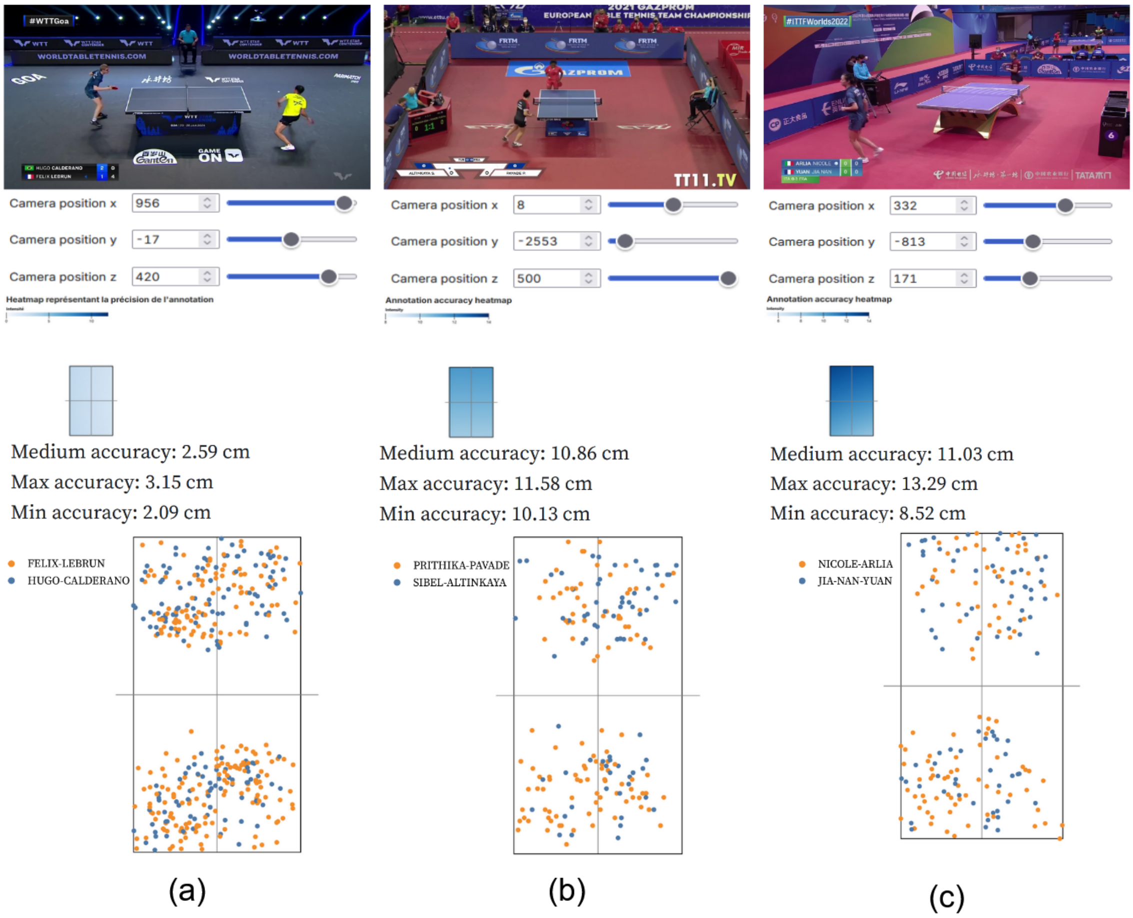


Figure 2.23. – Screenshots of a tool we built to explore the results of our model for different views taken from broadcasts and table bounces we identified. (a) The side view, the area on the table with the lowest annotation accuracy is $3.15cm$. (b) The rear view, annotation accuracy on the table remains 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

This chapter presents a work on the analysis of structured data extracted manually from Chapter 2, and is based on the following articles:

[13] 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. Turin, Italy. 2023. [13]

[33] Aymeric Erades, Thomas Papon and Romain Vuillemot. *"Characterizing Serves in Table Tennis."* en. In: *Machine Learning and Data Mining for Sports Analytics*. Springer Nature Switzerland, 2025. [33]

[5] Riad Attou, Marin Mathé, Aymeric Erades and Romain Vuillemot. *"Analysis of Service Returns in Table Tennis".* In: Machine Learning and Data Mining for Sports Analytics, Porto, Portugal, Sept. 2025 [5]

3.1 Introduction

Structured data is in general used by analysts to make better decisions by seeking out opponents' weaknesses and avoiding their strengths. Our work is aligned with this approach to reveal the tactical aspect of table tennis games using data science methods such as exploratory data analysis or statistical modelling, to give analysts keys to better make decisions. In many sports, data analysis plays an important role in preparing for matches or defining tactics. One notable example is baseball, one of the first sports to use data to improve performance. It has been proven that there is a positive correlation between a team's success and its use of sabermetrics [25]. In table tennis, ITTVis [134] mentions that the Chinese national team, which has dominated the world of table tennis for years, has experts who use statistics to prepare for matches. We can take the example of the final of the Paris Olympic Games in Section 1.3, where **Fan Zhendong** changed tactics after the first game by playing more balls on the right-hand side, changing from 6 strokes to 29 strokes, enabling him to reverse the score. The data therefore enables the capture of specific game situations and tactics, providing insights into what influenced the course of play.

3.2 Related Work

Analyses in sport use different types of data, [97] identified three different types of data used: Box-Score Data (*e.g.* number of strokes, number of rallies or percentage of winning serves), Tracking Data (*e.g.* players' positions and ball positions), and Meta-Data (*e.g.* ranking of players, style of play or preferred hand). Table tennis has certain specific characteristics, notably a game based on sequences of events, which complement these three types of data. We therefore chose to focus on four main types of analysis: Event-Based analysis, Tracking data-based analysis, Meta-data based analysis and Sequence-Based analysis.

3.2.1 Event-Based

Event-Based analysis are important actions that occur at specific moments in the game, such as a point scored, a fault, or a stroke. In table tennis, these events are often related to strokes. For the basketball [112] focuses on the spatial analysis

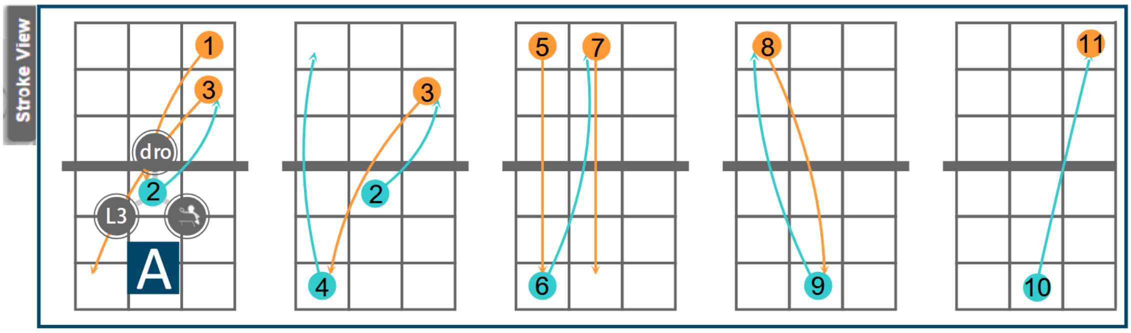


Figure 3.1. – Representation of the view used by iTTVis [134] to analyze a stroke in detail. Each circle with a number represents a ball bounce associated with a stroke. The bounces are linked together to maintain the chronology of the strokes (and displayed one several table to avoid overlap). Details of a stroke can be obtained by clicking on one of the circles to view its attributes. An example is given with bounce number 2. This approach gives the user the freedom to interpret the strokes in a sequence.

of successful and unsuccessful. Authors propose a visual analysis methods of events based on 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 tennis [23] 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. In cricket [7] 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. Commentaries are directly linked to events in the video. They rely on human expertise available during the match to characterize the strengths and weaknesses of players in different game situations. For baseball [92], they studied pitches from Japanese professional baseball games played between 2014 and 2019 and focused on the pitching zones and the zones requested by the catchers, which allowed them to compare the effectiveness of outside and inside pitches independently of the batter.

When these events are linked to a player's action, they are related to the probability of success of the action. Probability calculation is one of the foundations of the concept of expected goals introduced in soccer [6], which corresponds to the number of theoretical goals that should have been scored based on the probability of scoring of shots. This probability calculation is generally made based on a player's shot depending on their position and the position of the other players. 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.).

In table tennis, although analyses focus on sequences, event-based analyses remain common, particularly analyses of events within sequences. Tac-Anticipator [126] uses stroke events to compare players' anticipations. Using player position attributes, it determines the anticipation for each stroke in order to compare them with each other. Tac-Simur [127], although they focus on stroke sequences, also base their analyses on certain events. They focus on simulating game sequences and their win rates by training a model based on observed matches. In stroke sequences, by focusing on a particular stroke, they can modify certain attributes to study variations in win rate and thus identify which strokes are decisive in the sequences. EventAnchor [24] focuses on events such as strokes or ball bounces not for analysis purposes, but to annotate and enable others to perform analyses, as is the case with VisCommentator [19], which uses its data to enable users to analyze certain events such as the probabilities of a stroke rebounding within a defined area on the table. These analyses leave more room for interpretation by the user. iTTVis [134] bases part of its analysis on events, including searching for rallies that are interesting for analysis based on score-related events, which assigns importance to each rally according to criteria provided by coaches. They also allow for a detailed view of the attributes of each stroke in a sequence, highlighting the key strokes within it, as illustrated in Figure 3.1.

3.2.2 Tracking Data-Based

As we saw in Chapter 2, tracking data corresponds to continuous position data over time. In sports, tracking data mainly focuses on the positions of players, the ball, or the striking equipment (racket, cross, bat, etc.). In badminton [27], uses player pose data [41] and shuttlecock tracking data [58] to predict the probability of winning a rally at a given moment and state. To do this, authors use a Long Short-Term Memory. The model uses the players' positions, their pose estimates, the shuttlecock's position, and the action to determine this probability. In soccer [8] 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. Figure 3.2 (a) gives an example of team characterizations. In soccer again [22] characterize teams based on the position of key actions, combining spatial data with event data to obtain a characterization. In basketball [43] focus on the effectiveness of defense by studying the positions of defenders relative to attackers. Figure 3.2 gives examples of shot density. In tennis [128] 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 [74] 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. Figure 3.2 (c) gives an example of serve clustering.

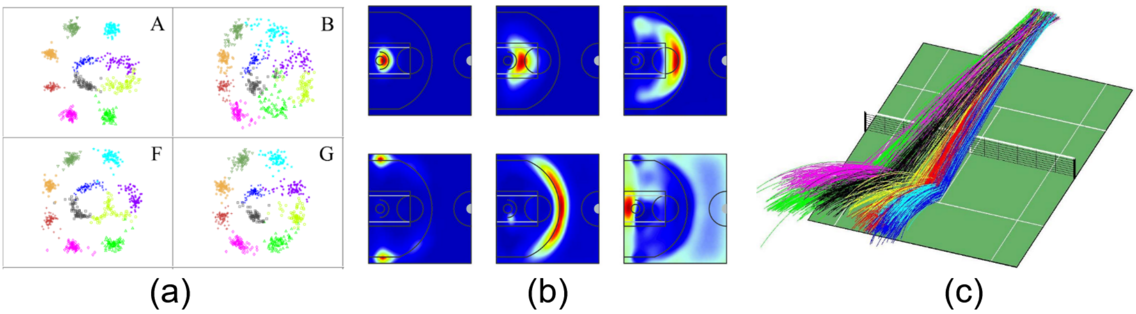


Figure 3.2. – Example of tracking data-based analysis. (a) Shows examples of soccer team characterization based on player roles (characterized by color) [8]. (b) Heatmap representation of shots based on shot types for basketball [43]. (c) Example of tennis serve clustering [128].

By extension, using the expected goals model introduced in soccer [6], it is possible to use tracking data to calculate this probability, allowing the dynamics of all players to be taken into account rather than focusing solely on the moment of the shot. For basketball [15] 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.

In table tennis, tracking data is often used for analysis, in particular by using players' and ball positions. To characterize players' areas of presence [53] use heatmaps (Figure 3.3) to provide visual feedback. These heatmaps are used to calculate a probability of presence for each of the x and y axes. This probability of presence produces a curve that allows comparisons between players. These comparisons make it possible to distinguish differences between groups of players or to classify players according to their probabilities of presence. Tac-Anticipator [126] uses the position of players to study their anticipations. By defining anticipation as the movement of players between their stroke and their opponent's stroke, they compare the movements of players over this period. They transform it so that it is no longer dependent on an absolute position. In this way, by knowing the trajectory of each stroke and the outcome of the rallies associated with those strokes, they are able to identify strengths and weaknesses based on anticipatory behavior. Tac-Simur [127] and iTTVis [134] use tracking data differently. They do not use this data as a whole, but rather use the positions of players or the ball at specific moments, such as during rebounds and hits. This allows them to integrate this data into their event-based or sequence-based analyses.

3.2.3 Meta-Data Based

Meta-data corresponds to general data about players, matches, competitions, or stadiums. For baseball [115] used metadata related to the distance between home plate and the backstop to study the impact on pitchers' confidence in their best pitches. They showed that this data related to field characteristics had an influence with a decline in self-confidence with a distance of greater than 25 feet. Based on baseball park data, [65] studied the influence of parks on the number of home runs. For racket sports, understanding a type of action is often important, particularly the serve. In elite table tennis [106] 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 table tennis again [53], highlighted comparisons between players based on certain characteristics, comparing offensive players with defensive players, players with a shakehand grip with penholders, and right-handed players with left-handed players. One example is right-handed and left-handed players (Figure 3.3), where there is a difference in position, with right-handed players predominantly on the left side of the table and left-handed players predominantly on the right side of the table. This difference is highlighted using heat maps on player tracking data.

Metadata also concerns player and match data, and match data can provide important and decisive analysis. Match data can be divided into two categories: historical data before the match and match data that is the statistical data of matches based on strokes and rallies. Historical data can be used to establish the relative strengths of the two players and make predictions about the outcome of a match. This data generally includes each player's history, ranking, win percentage, number of competitions won, etc., as well as data on their head-to-head matches, win percentage, average game duration, etc. Match-specific data allows for a quick

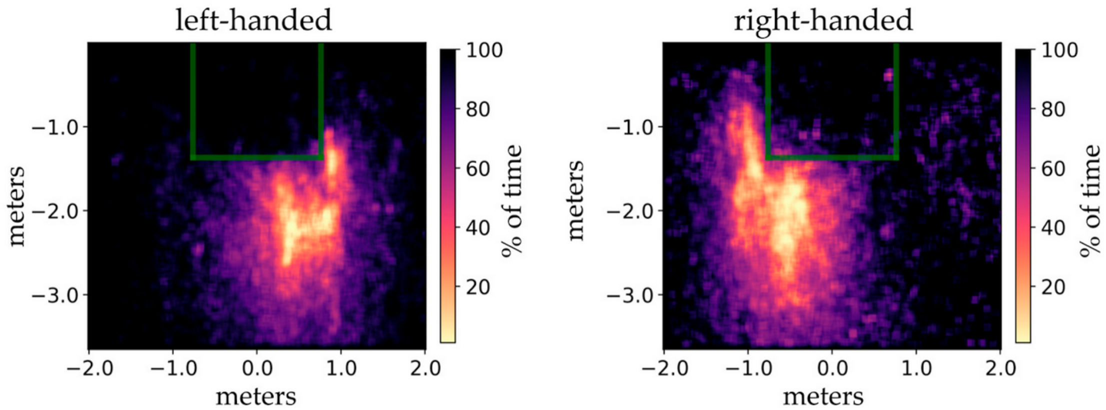


Figure 3.3. – Comparison between the positions of right-handed and left-handed players [53]. Left-handed players are on the left and right-handed players are on the right. A purple color (purple = 60%) indicates that the player had been in the area (purple or lighter) 60% of the time. The lighter the color (light yellow), the more often the players had been in that area.

explanation of a match through simple match-specific data, such as the number of points scored, service success rate, number of faults, etc. An example of metadata comparing two players is shown in Figure 3.4, with the final match of the 2024 Paris Olympic Games between **Fan Zhendong** and **Truls Moregardh**.

In general meta-data are used to enhance visualizations and provide context or filter but are not the core of analysis. Tac-Simur [127] uses metadata on right-handed and left-handed players to filter player's opponents during analysis. Tac-Anticipator [126] uses metadata again, distinguishing between right-handed and left-handed players to provide additional visual information during analysis.

3.2.4 Sequence-Based Analysis

Table tennis rallies consist of a succession of strokes and can be analyzed as sequences. Analyzing these sequences offers several benefits, among them to identify identify the most frequently used ones and assess their effectiveness. Sequences allow data mining algorithms to be used to extract interesting sequences. These sequences can be found in many fields, including those other than sports. To analyse interactions during meetings [42] 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 [31] used sequences of strokes. To do this, they define tactics as a succession of three strokes composed of an attribute and a position forming sequences. They associate each sequence with the outcome of

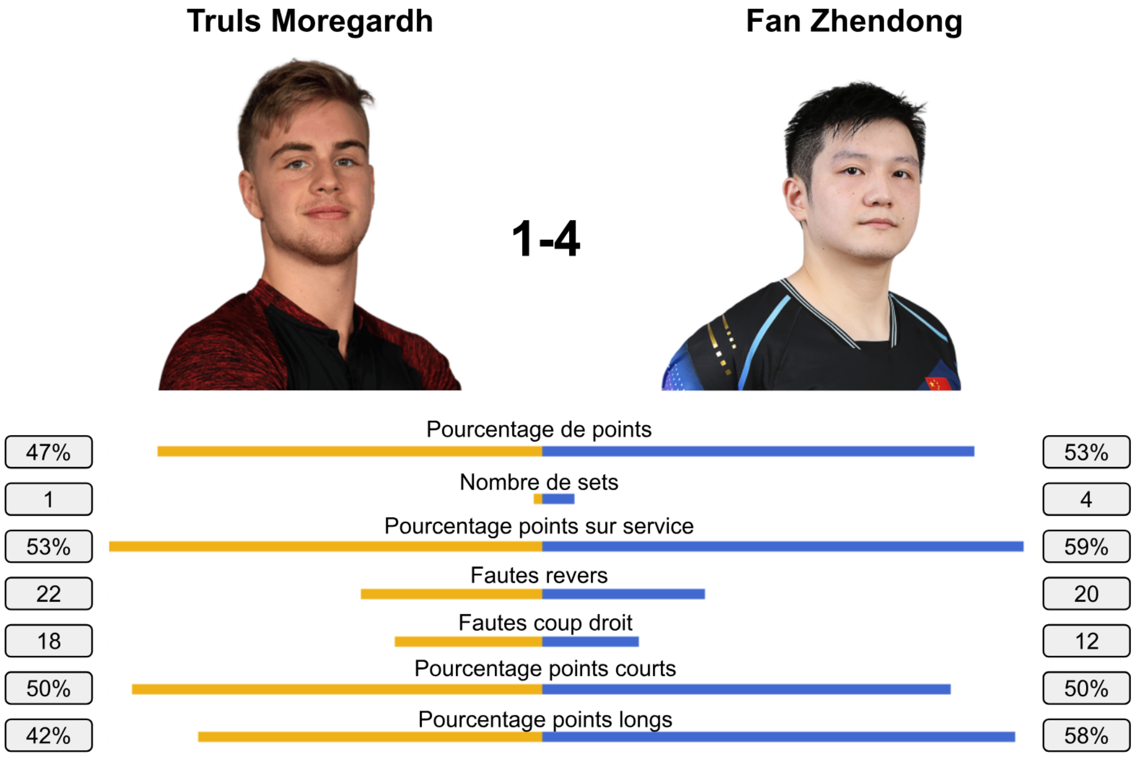


Figure 3.4. – Example of meta-data (*e.g.* players names, picture) used to contextualize match-specific data that compare players performance from data we collected and we built for the FFTT. We can see that the two players are very close in many respects, with only 6% of points won separating them, and they scored the same number of short rallies (rallies of less than 5 strokes).

the point, which allows them to determine the effectiveness of a sequence. First, they search for the most frequent sequences using the SPADE algorithm [139], and then, among the most frequent sequences, they calculate the Weighted Relative Accuracy [119] measure based on both the frequency of occurrence and the win rate to rank the most effective sequences. Figure 3.5 gives an example of the sequence representation in graph form.

In sports, Markov chains [77] have often been used to analyze sequences [99, 87]. To analyze table tennis performance [99] 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 model 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

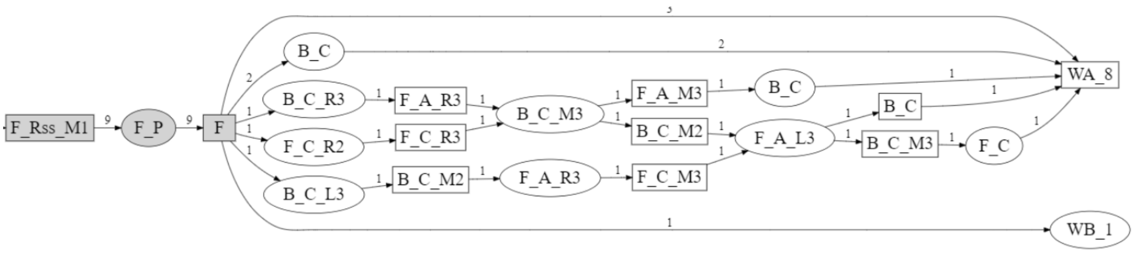


Figure 3.5. – Example of a sequence of strokes used in table tennis to characterize rallies [31]. The rallies are represented from left to right, with the serve on the far left and the end of the rally on the far right. Each element represents a stroke of a rally.

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 [52], which allows important patterns in sequences to be discovered using multiple attributes [133]. Another example is the improved artificial fish swarm algorithm for exploring sequences [124].

In table tennis, a lot of work has been done on sequence-based analysis, iTTvis [134], which is aimed at experts to explore game sequences and discover tactics. To do this, they focus on stroke sequences, associating each stroke with a matrix representation of similarity to other strokes based on its characteristics. This allows them to study the correlations between strokes and the frequency of use of these sequences. Tac-Miner [125] allows users to analyze, explore, and compare tactics from multiple matches based on three consecutive strokes. It presents a tactic in either a global way, including frequency and winning rate, or a precise way, including display correspondence and detailed attributes. TacticFlow [132] aimed to explore sequences, tactics and how tactics change during a rally through a new mining algorithm based on Minimum Description Length. They incorporate a visual exploration of sequences based on Sankey diagrams, where each node represents a tactic and the flow between two tactics indicates that the player has switched from one tactic to another. These approaches focused on visualizations and we will discuss in more detail in Chapter 4.

3.3 Match Performance Indicators

As we collected multiple games back in 2023 using the tools introduced in the Section 2.4, we initiated our analysis at the match-level, to highlight interesting moments. Then ultimately, such analysis would help to provide context to tactics that would be identified. The reason we focused on match-level is to capture changes in player behavior, and understand their impacts. To do this, we explore multifactorial dominance based on physical, mental, and factual (with the score) factors, the concept of "expected score" which bases its calculation on the history of rallies and their outcomes, and we also explore the variation in the start of rallies during a match. This work was carried out in collaboration with a student from Ecole Centrale de Lyon (Gabin Calmet) and published in the 10$^{\text{th}}$ Workshop on Machine Learning and Data Mining for Sports Analytics.

Example

To illustrate our analysis at the match-level, we use the following scenario from an international table tennis match: **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 (11-7 8-11 11-5 5-11 11-9). 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 (Christian Gaubert Scientific Coordinator at the FFTT and Laurent Cova video analyst for the FFTT) 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 did not 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 managed 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 3.6):

- **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.

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

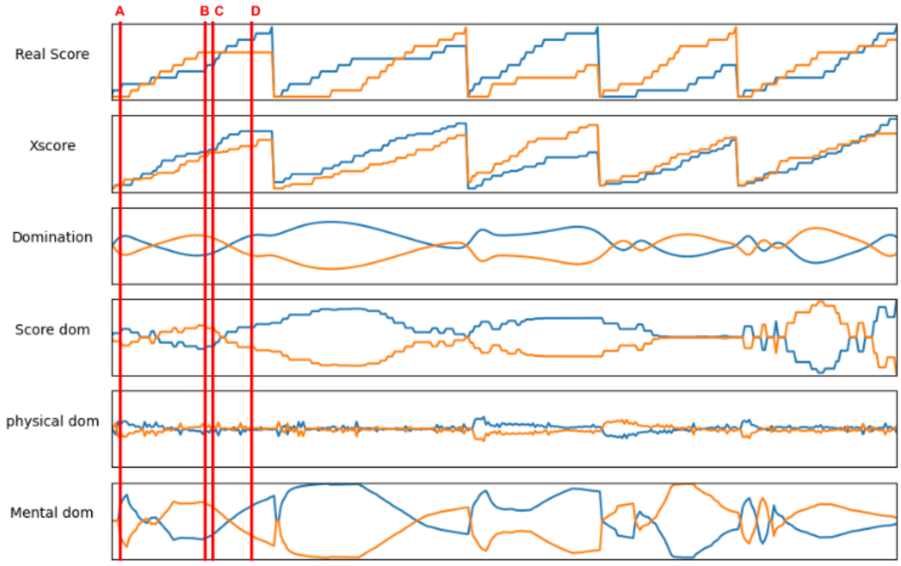


Figure 3.6. – Detailed metrics during the first game of the match between **Alexis Lebrun** and **Fan Zhendong** at the WTT Championships in Macao, China in 2023. Red vertical lines corresponds to the 4 rallies during the first game we focused on. A **Alexis Lebrun** serves, **Fan Zhendong** pushes on the left side of **Alexis Lebrun**'s table, then **Alexis Lebrun** attacks down the line with his forehand and wins the point. B **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. C **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. D **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.

- **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 shot diversity?
3. What shot combinations are the most efficient?
4. What are the stroke differences between players?
5. How a stroke can be decisive in winning a point?
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* [86]. 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 shot 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 from developing an attack [3]. 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 require physical, technical and mental capacities that can not be objectively quantified without depending on the past. In racket sports, which are usually more fragmented than team sports that have long, continuous actions, but also have high scoring opportunities, there is a need to redefine this notion to account for those characteristics. In such a 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 2.15 (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 focus on the following types of domination: **score**, **physical** and **mental**. However, we know that three types may not 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 rescaled 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 also update 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 [143]. 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 in Figure 3.6 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 players can easily win or lose, so the mental domination is also at stake. The physical domination is not very decisive, and it is 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 periods are correlated with physical domination peaks.

We define the different metrics as follows:

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,

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

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 $P_{a,b} = 0.5$.

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

Definition of the Three Factors of Physical Domination

We can extract the 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 whether 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

Mental domination is based primarily on scores and the actions that led to those scores, such as faults or winning strokes. Players' anxiety about losing increases when a player is close to defeat or is caught by the score. The self-confidence of players increases when they make several winning strokes in a row, but decreases when they make a lot of mistakes in a row. 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.

Again, 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's mental state. We know that this is not necessarily the case, some players may have the ability to self-regulate and boost their self-confidence, which impacts the game in return. However, table tennis is known to be a highly stressful sport where the 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 [51, 86]. 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 game, we can construct an **expected score (XScore)** that indicates the logical winner of the game. We accomplish this by exploring a tree that represents all possible three-stroke (Figure 3.7) 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 Figure 3.7 (**PPT**) described by those simple rules:

1. The children of a zone node or of the root are laterality nodes: **backhand** and **forehand**.
2. The children of a laterality node are type nodes: **right side** and **left side** for services and **offensive**, **push** and **defensive** for the other 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 which correspond to all

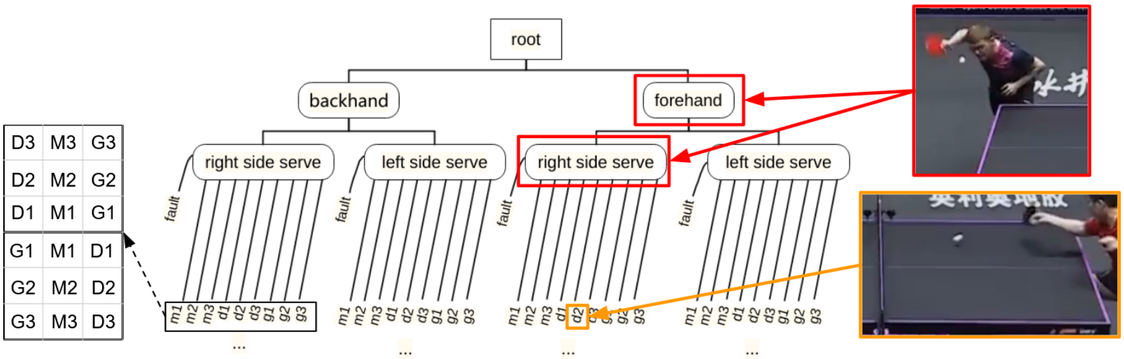


Figure 3.7. – Theoretical structure of the Playing Patterns Trees (PPT) that enumerates all shot attribute combinations. Using the example of a serve by **Alexis Lebrun** who hits a forehand serve to the right side in zone d2. The table on the left shows how the 9 zones are arranged.

possible combinations of the different attributes for the first three consecutive strokes, 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 (the areas are explained in Figure 3.7). Actually, the trees that are built on several real match analyses have no more than 2,000 nodes because certain combinations are not possible, such as performing a push on topspin. We have built our PPT from the analysis of 9 simulated matches, augmented from 3 different sets 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 3.6 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 now needs 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 is not 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 does not quite work with extremely creative players, 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. Therefore, analyzing the variation of playing patterns during a game 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 [31], authors 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 in the rally, and because we create a metric representing the distance between two openings. By collecting the first three 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 $U_i = V_i$,
- $d(U_i, V_i) = 1$ 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 in Figure 3.8 is the similarity of consecutive sequences, which appears as white squares on the diagonals of both matrices. Because of the temporal aspect of this figure, we can

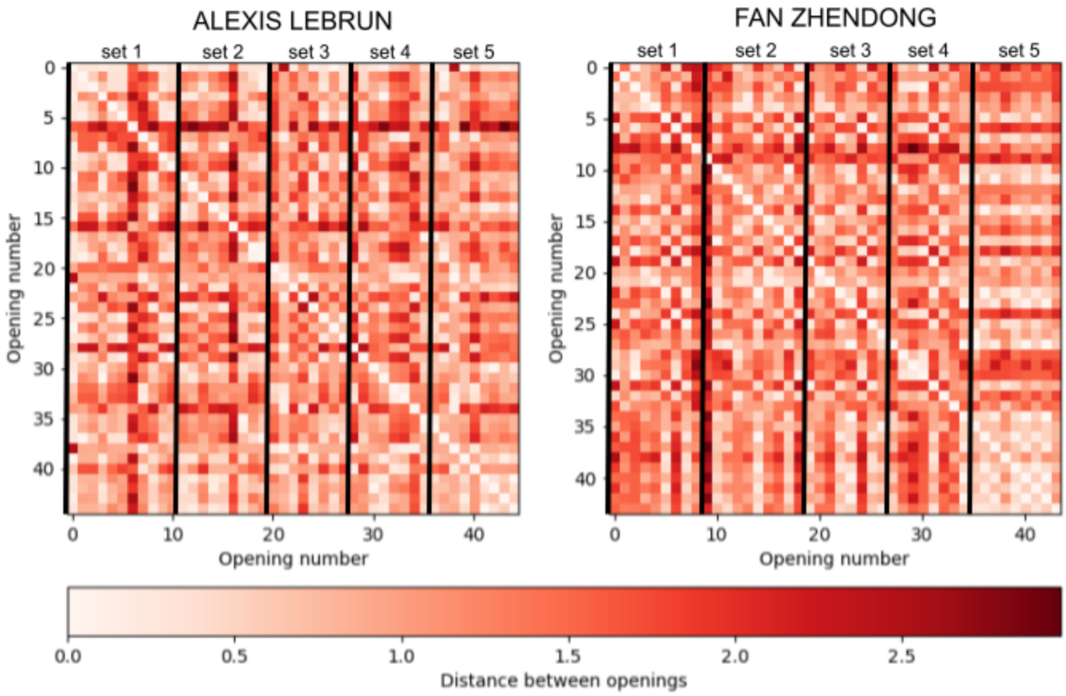


Figure 3.8. – Distance matrix between openings of the match between **Alexis Lebrun** and **Fan Zhendong** at the WTT Championships in Macao, 2023. Each matrix represents a player's openings. An element in row i and column j represents the distance between openings in rallies i and j. The closer the color is to white, the shorter the distance between openings. At the beginning **Alexis Lebrun** does not 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** did not 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 the 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 was not lucid enough to take the decision to change of opening).

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

The main limitation of our work is the volume of data used for analysis, which remains limited to a single match. 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). 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 noted several perspectives on this work. The first concerns increasing the number of matches by choosing confrontations between the same players in order to compare whether the metrics show similarities and compare them against other players. The second perspective for this work concerns new metrics that can be developed. We noticed a metrics using continuous tracking data, and two metrics that characterize player behavior during the match, with one metric highlighting risk-taking by taking into account the types of strokes and their positions close to the edges of the table, and another metric reflecting the variation in strokes used. Finally, the last perspective is to enrich our data set using these metrics to characterize moments of dominance and enable analysis based on dominance.

3.4 Analysis of Table Tennis Serves

In table tennis, the serves are the first stroke, and it is the only stroke where the player has full control and does not depend on their opponent. Thus in this sport, training is built around the serves, which means that players adopt a playing style based on their serves. 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 (Figure 3.9), each with unique techniques and tactical purposes. The serves' techniques mainly influences the spin of the serves, and for each technique, different areas of the table are accessible from different positions of the server, thus making the number of different serves very important. All this serves combined with different speeds and quantities of spin offer players a wide palette of tactical options to initiate play effectively[2]. 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 stroke. 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

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

Figure 3.9. – Examples of different serve techniques. (a) (top) **Alexis Lebrun** performing a pendulum serve with his forehand. (bottom) **Alexis Lebrun** performing a reverse pendulum serve with his forehand. (b) **Alexis Lebrun** performing a backhand serve. (c) **Alexis Lebrun** performing a tomahawk serve with his forehand. (d) (top) **Lin Shidong** performing a hook serve with his forehand. (bottom) **Alexis Lebrun** performing a lollipop serve with his forehand.

category. Figure 3.10 illustrates an example of two services that are very close but in two different categories due to bounce zone classification.

From our dataset of 9 games and a total of 510 serves collected semi-automatically for 5 players, we used serves that includes both the players' positions and techniques, ball placement, the opponent's returning stroke and context data such as the outcome of the point (winning/losing) and contextual elements such as scores and players' names. 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 [128]. We also 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) and published in the 11$^{\text{th}}$ Workshop on Machine Learning and Data Mining for Sports Analytics.

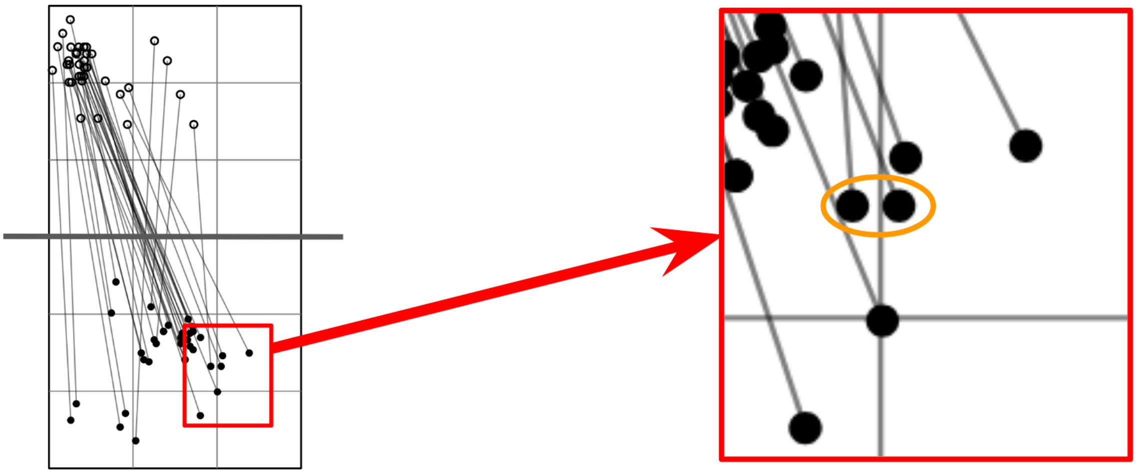


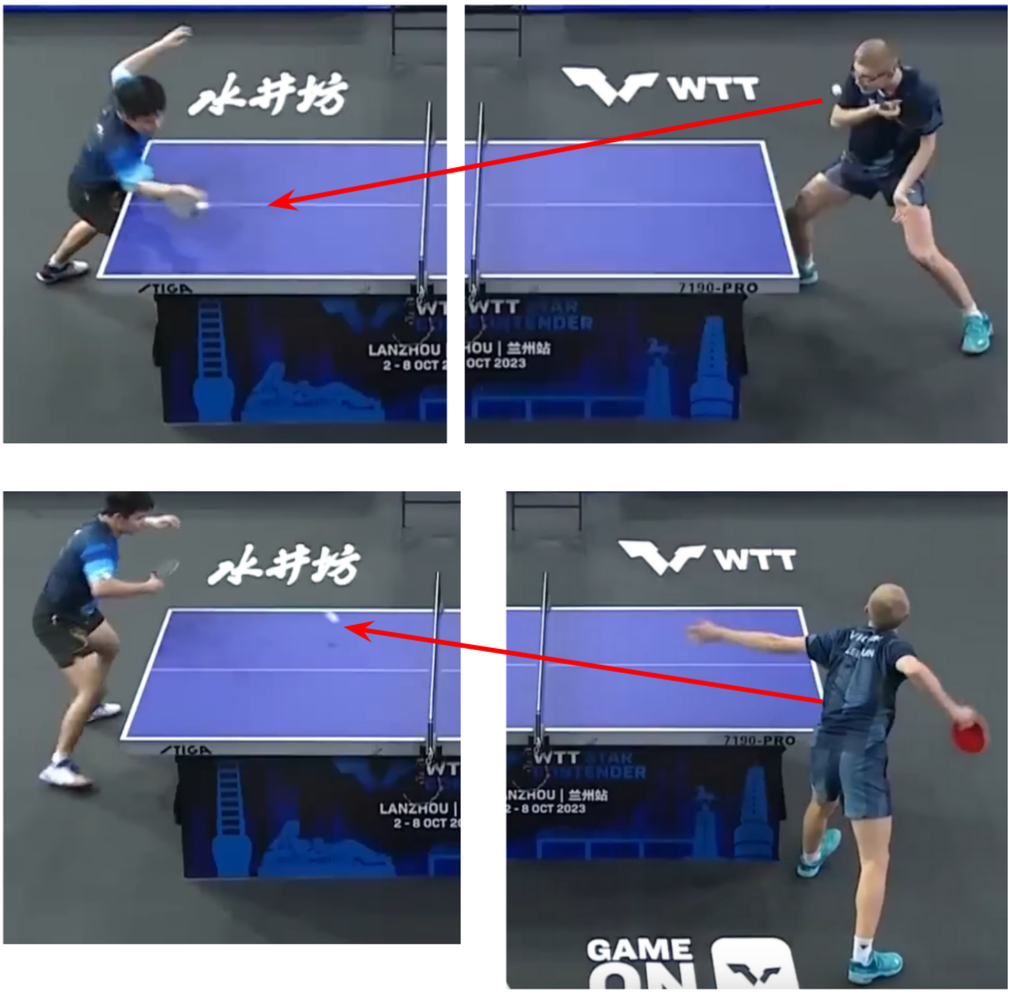
Figure 3.10. – Example of spatial distribution of services and classifications by zone. On the left are the services of , with the first bounce at the top and the second at the bottom. On the right is an example of two services circled in orange that are in two different zones, despite being spatially very close to each other.

Example

During his match against **Lin Shidong** at the Star Contender in Lanzhou in 2023, **Felix Lebrun** completely turned the match around by changing his serve. The match is being played in three games, with the score tied at one game all. While **Lin Shidong** is leading 9-6 in a very important game, **Felix Lebrun** decides to position himself differently at the table to serve and to change his serving technique, using a serve he has not used before. Up until that point in the match, he was positioned on the left side of the table and was using a forehand serve with spin that deflected the ball to his opponent's left, mainly to **Lin Shidong**'s backhand side (Figure 3.11 (a)). After that, he positioned himself on the right side of the table and started serving short with his backhand to his opponent's right, which is his forehand (Figure 3.11 (b)). From that moment on, he won 12 out of 15 rallies on his serve. This is mainly because **Lin Shidong** was unable to find a solution to disrupt **Felix Lebrun** with his returns. One example of this is that when he wanted to play to **Felix Lebrun**'s backhand, he would switch from a cross-court stroke to a stroke down the line in the direction of **Felix Lebrun**'s repositioning. This demonstrates the importance of the serve in matches, a notion reinforced by the fact that in our database, 54% of rallies are won by the server.

Background

Serves follow specific rules 1.4 beyond the two bounces. Each player serves two consecutive points, alternating throughout the game, with adjustments during the



(a)

(b)

Figure 3.11. – Example of a change in service by **Felix Lebrun** from a position on the left side of the table with a forehand into **Lin Shidong**'s backhand (a) to a position on the right side of the table with a backhand service into **Lin Shidong**'s forehand (b).

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 works on table tennis we mentioned in the related work Section 3.2, the serve is only considered as a particular technique with sometime some particular attributes. 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 [31, 13, 134], which does not capture placement subtleties. Additionally, none of them focus on the exact ball position and first rebound analysis. Even if in badminton [21] or tennis [143] they share a same problematic of serves, 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

Exploratory Data Analysis [120] is the process of summarizing and visualizing data to uncover patterns (and sometimes anomalies). In this context, as the question was new to us, it allowed us to grasp the relevant attributes in our structured data to determine the tactical aspect of serves. We used a total of 9 games and up to 510 serves for 5 players from our dataset. 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. This was necessary because in table tennis, the preferred area for serves is mainly the backhand side, with a predominance of short serves, and the long side on the forehand is completely avoided (this is due to the ease with which players can attack strongly with their forehand on long serves). For left-handed players, these areas are completely reversed. In addition, the most commonly used forehand serve has a spin that deflects the ball towards the opponent's backhand when they are right-handed, which means the forehand for left-handed players, forcing right-handed players to completely change their serving styles when facing left-handed players. We augmented the collected dataset using several post-processing steps to calculate the score and various metrics [13] (explained Section 3.3) for the section related to tactical analysis. We also reconstructed 3D ball trajectories [12] to gather details on the server's technique.

We then conducted an exploratory data analysis 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 3.12 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 as we said before. 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/

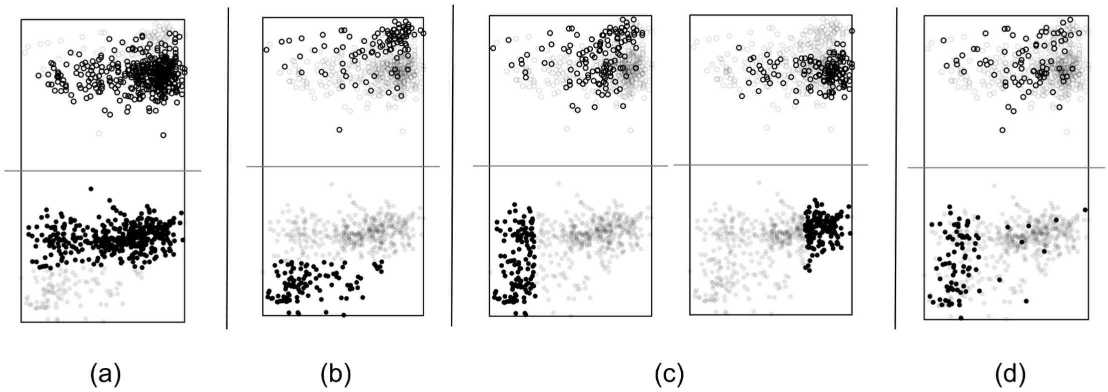


Figure 3.12. – Exploratory data analysis using spatio-temporal representation of the serves we collected, normalized, and filtered. The server is at the top; the dots on the upper part are the first bounce, the ones below are the second bounce, and the receiver is at the bottom. Gray dots represent all the serves, and the black ones: (a) short serves, (b) long serves, (c) side serves, and (d) pivot serves.

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 [128] which relied upon K-means clustering to automatically find a way to partition 2D space based on the clusters we are looking for are roughly circular, centered around an aiming placement. Figure 3.13 (b) shows a clear separation with centroids representing the center of the target point and the spread around it (likely due to inaccuracies). Other methods could be used such as HDBSCAN [85] used in Badminton [138] or in Tennis [143]. 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] 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, because serves have two different techniques that could lead to the same second-bounce cluster but with a different incoming trajectory (Figure 3.14). Also, as the clusters were sometimes too large, and differences were caused by the effect of the serve. Figure 3.13 (c) shows such a deeper separation by including the serve technique. Finally, we

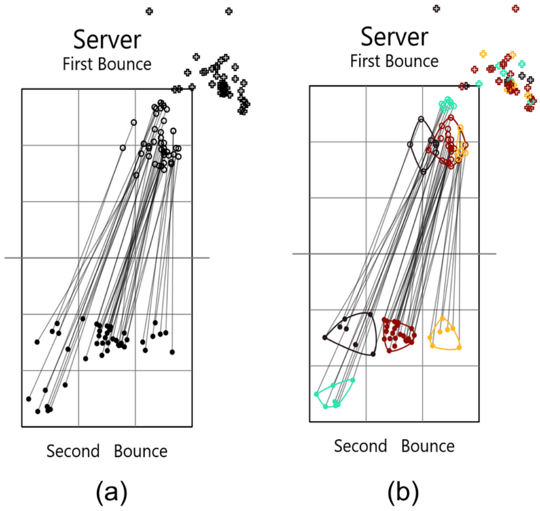


Figure 3.13. – Steps to create serves clusters (a) a single game is picked for a player, (b) K-means clusters are created based on the second-bounce, (c) the clusters are connected to their corresponding first-bounces, (d) we show the corresponding returns by the other players with lines.

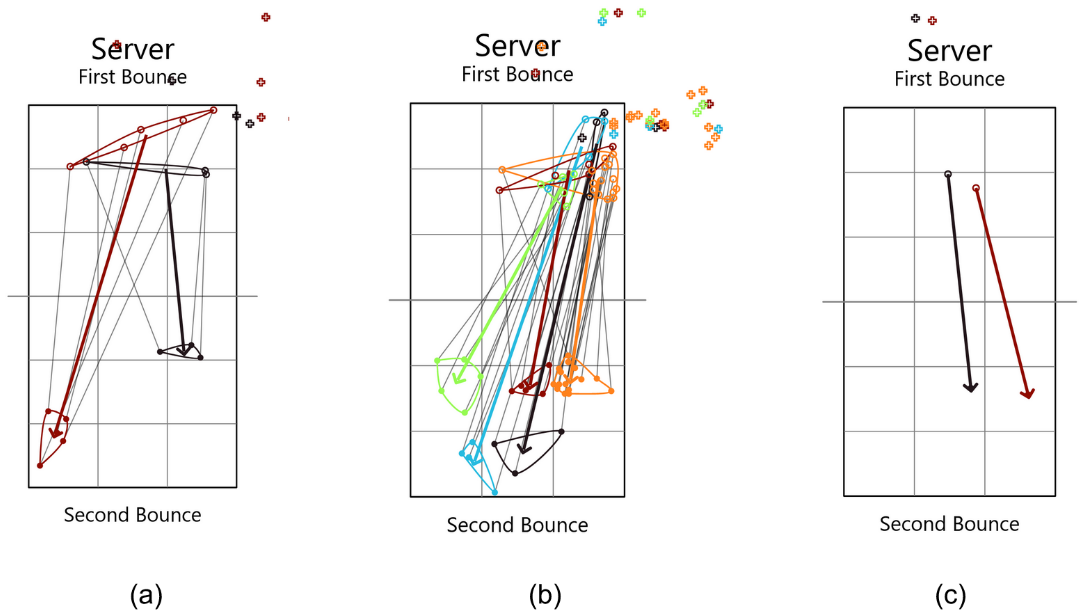


Figure 3.14. – Each clusters were then separated using serving technique (a) forehand serve with right side-spin, (b) forehand serve with left side-spin (c) backhand serve with left side-spin.

found a total of N clusters which will be identified later as $C_1, C_2, \ldots, C_N$, ranked by the number of serves in each. Each cluster C_i is represented by an area, a density and a distance to the first-bounce cluster (to indicate if this is a short or a

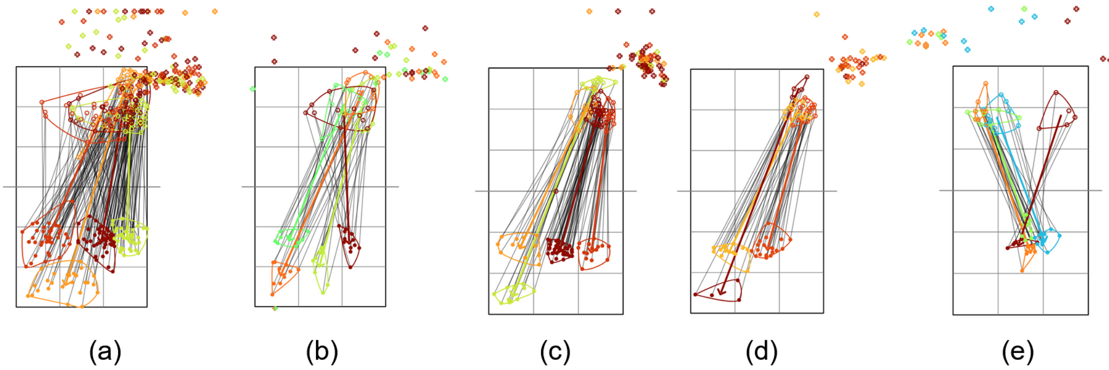


Figure 3.15. – Server's repertoire for top players: a small first bouncing area ((d) **Ma Long**, (c) **Fan Zhendong**), which is explained by a static position; spreading the first bounce across the width ((e) **Darko Jorgic**); the same serve but from different initial positions ((a) **Alexis Lebrun**, (b) **Felix Lebrun**).

long serve). We displayed in Figure 3.15 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 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 us to characterize the general signature of players showing either that they limit to the same serves in general or have a high level of diversity.

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 players' 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 [13]. 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, *e.g.* to understand which players prefer to create surprise or the ones that stick to efficient serves.

Figure 3.16 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

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 detail and volume of the data

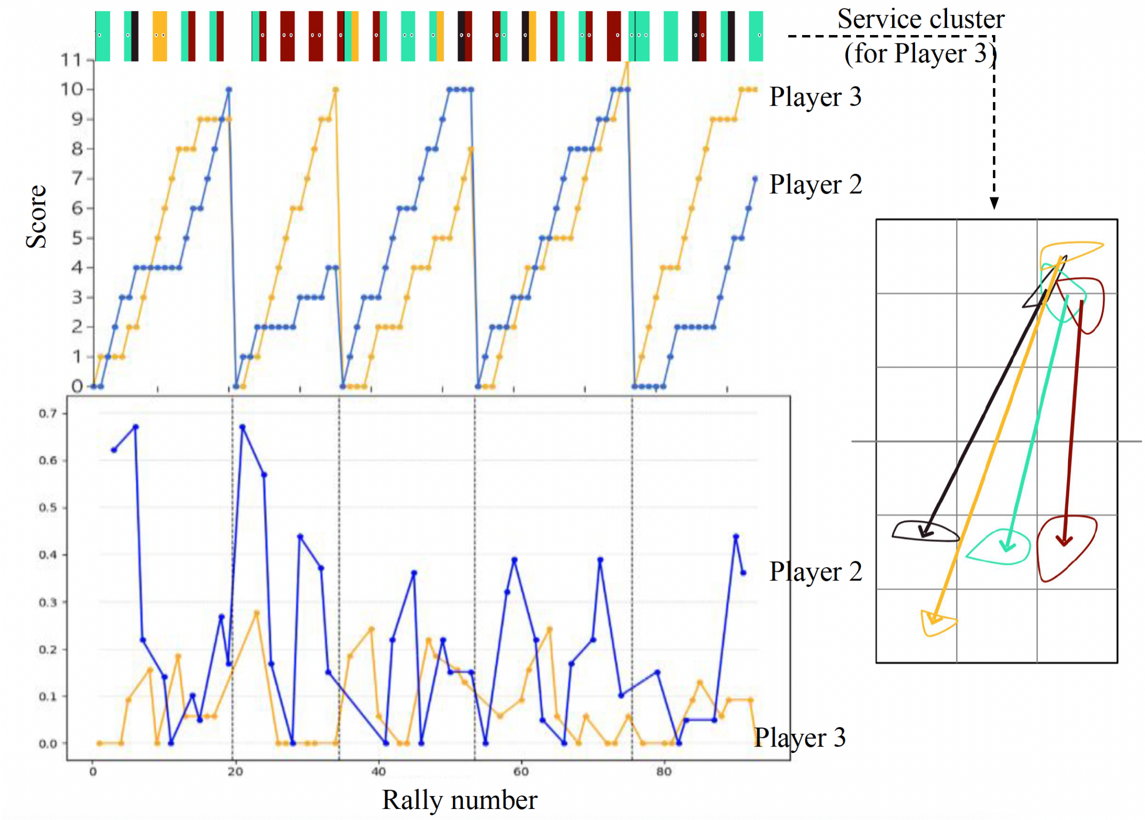


Figure 3.16. – From top to bottom: serves used by **Fan Zhendong** (Player 3) against **Alexis Lebrun** (Player 2), colors represent the cluster used; score evolution; and distances between 2 consecutive serves (colors represent the server).

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 and one the perspectives of this thesis Section 5.2.1. 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.

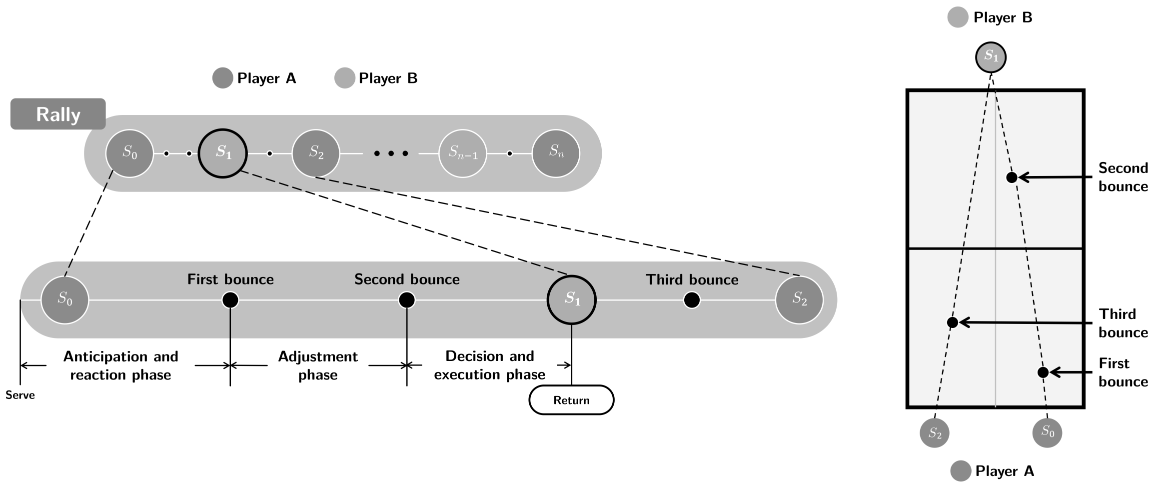


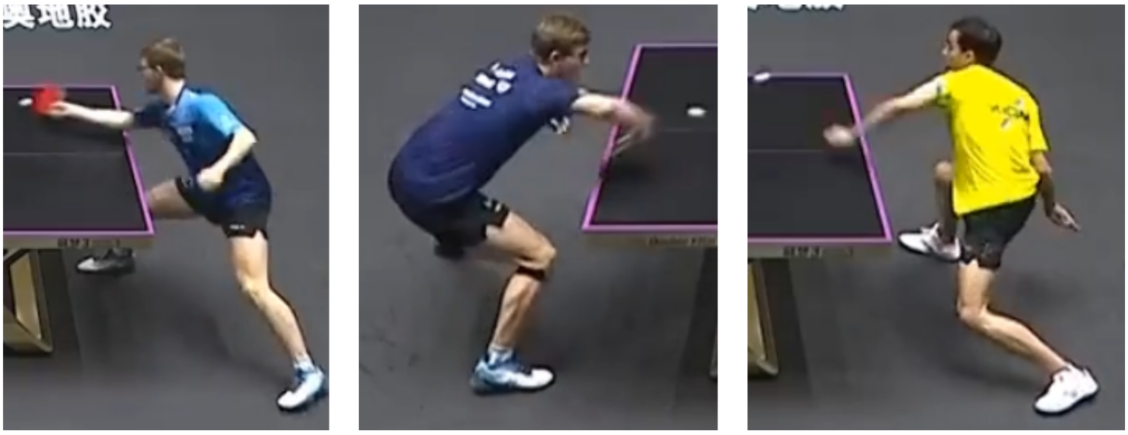
Figure 3.17. – Phases of the service return (left) and spatial layout of serve S_0 and return S_1 (right). Note that in this study we focus specifically on the return S_1. The anticipation and reaction phase extends from just before the serve S_0 until the ball's first bounce. The adjustment phase takes place between the first and second bounces. Finally, the decision and execution phase occurs between the second bounce and contact with the ball S_1.

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 us 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) and published [5] and published in the 12th Workshop on Machine Learning and Data Mining for Sports Analytics.

Returns can be broken down into three phases: an anticipation phase between the service hit and the first bounce, an adjustment phase between the first bounce and the second bounce, and a decision and stroke execution phase between the second bounce and the hit (Figure 3.17).

There are various ways to respond to a serve, whether by returning in identified zones or by using a specific striking technique. While these tactical choices are crucial. There are three different return techniques: the push, which is a defensive stroke, and the flip and topspin, which are offensive strokes (Figure 3.18). It should be noted that the topspin is an attack on a long ball, whereas the flip is an attack on a short ball. Some serves leave no choice of response, but many serves have backspin, leaving the choice between attack and defense. This choice is determined by the player based on whether they can attack effectively.



(a) (b) (c)

Figure 3.18. – Examples of different return techniques. (a) **Alexis Lebrun** performing a forehand push (defensive stroke). (b) **Alexis Lebrun** performing a backhand flip (offensive stroke). (c) **Hugo Calderano** performing a forehand topspin (offensive stroke).

Example

During the match between **Felix Lebrun** and **Hugo Calderano** at the WTT Star Contender in Goa in 2024, during the first three games, **Hugo Calderano** used a short serve to **Felix Lebrun**'s forehand side 17 times, and in response to this serve, **Felix Lebrun** pushed 16 times. This shows a very strong dependency between **Felix Lebrun**'s return and **Hugo Calderano**'s serve. **Felix Lebrun** won 8 of these rallies and lost 9, making this dependency mostly unsuccessful. From the fourth game onwards, **Felix Lebrun** changed his returns, and out of the 21 serves in the same zone, he returned 9 with flips and 12 with pushes, breaking the dependency of the first three games. The absence of dependency makes **Felix Lebrun**' returns harder for **Hugo Calderano** to predict, and as a result, his ratio of rallies won with push shots increases significantly, reaching 9/12. Similarly, his win ratio when he hits a flip is high, with 8 rallies won out of 10. This example (Figure 3.19) shows us that there can be dependencies between returns and serves and that these have a direct effect on the chances of winning rallies.

As we saw, the choice of return type is a strategic decision that must be made based on the success of the strokes. Some time choices seem counter-intuitive such as during the 2023 World Championships final in Durban between **Fan Zhendong** and **Wang Chuqin**. In the return game, **Wang Chuqin** won 8 out of 17 rallies when he pushed and 12 out of 30 when he flipped. This shows that the defensive

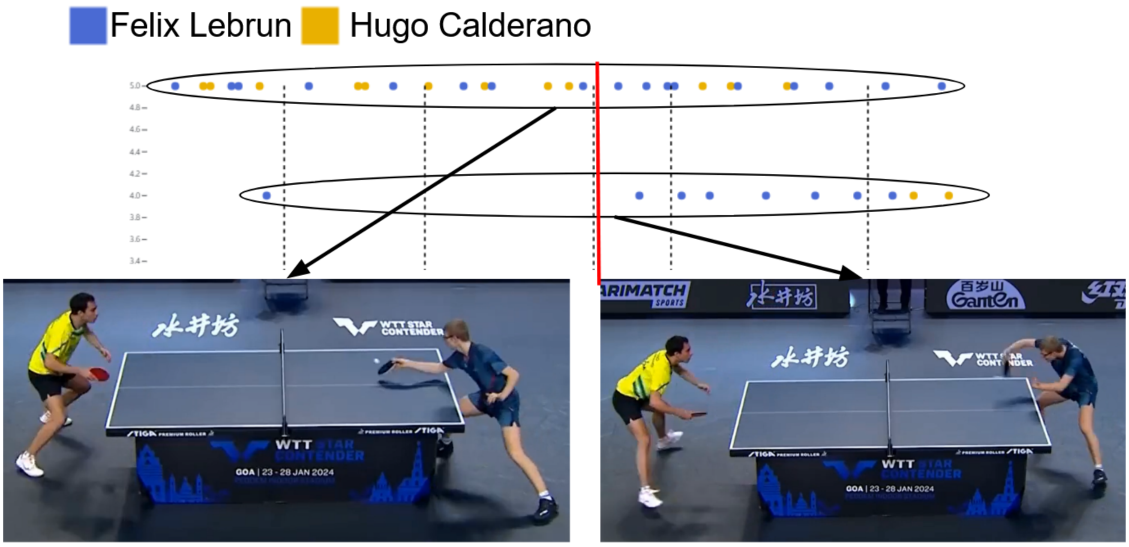


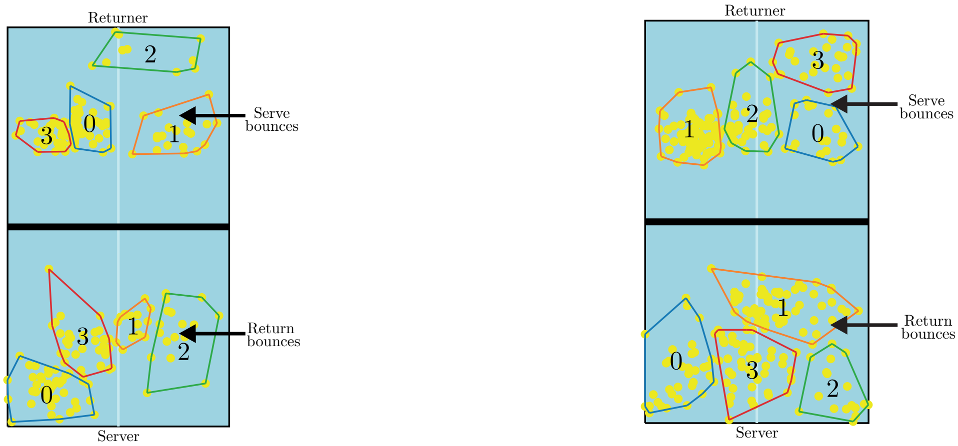
Figure 3.19. – Example of dependency between returns and serves during the match between **Felix Lebrun** and **Hugo Calderano** at the WTT Star Contender in Goa in 2024. Each dot corresponds to a rally, and the line on which the dots are located represents the type of return made by **Felix Lebrun**. The top line represents pushes and the bottom line represents flips. **Hugo Calderano**'s serves are short serves in **Felix Lebrun**'s forehand zone. The color encodes the winner of the rally, and the vertical black dashed bars correspond to the games. There is a dependency between the type of return and the serve in the first three games, with 16 pushes out of 17 rallies, but this dependency ends from the fourth game onwards and the number of rallies won by **Felix Lebrun** increases significantly.

stroke was more effective than the offensive stroke. Similarly, **Alexis Lebrun** against **Hugo Calderano** in 2024 at the Incheon Champions won 4 out of 8 rallies when he made a long push and only 4 out of 18 when he made a short push, highlighting the importance of choosing the right zone, knowing that the long zone is always possible to find.

We aim to explore these interactions in depth by identifying recurring patterns and tactical choices related to service returns. We provide 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

For the study of returns, we used the same method as in the previous Section 3.4 on serves' analyses, based on bounce groupings. As for serves, we used K-means to generate clusters of returns and we defined two key metrics—domination,



(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 3.20. – 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.

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 3.20. 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 point-by-point pressure metric by combining sub-indicators:

$$\begin{aligned}
\text{pressure}_{\text{score}} &= \frac{1}{1+\text{score_gap}}, \\
\text{pressure}_{\text{set_end}} &= \frac{1}{1+|10-\min(10,\max(s_A,s_B))|}, \\
\text{pressure}_{\text{key_moments}} &= \begin{cases} 1, & \text{if set/match point with gap} < 2 \\ 0, & \text{otherwise} \end{cases}, \\
\text{pressure}_{\text{set}} &= \frac{1}{1+\text{set_gap}}, \\
\text{pressure}_{\text{decisive_set}} &= \begin{cases} 1, & \text{in decisive set} \\ 0, & \text{otherwise} \end{cases},
\end{aligned}$$

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.

For this work, we redefined metrics that differ from those in Section 3.3. The domination metric uses only scored rallies, providing a measure that focuses on the tactical aspects related to winning or losing rallies. The pressure metric calculates a player's pressure independently of their opponent's.

3.5.2 Results

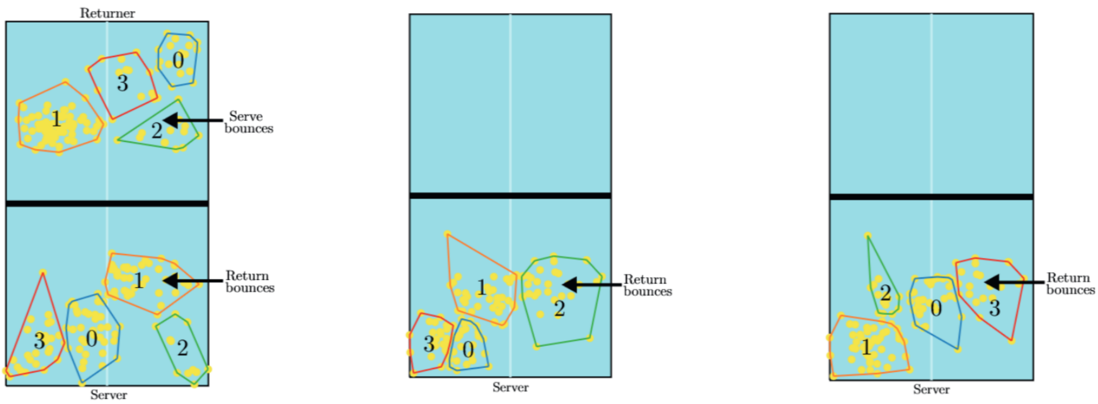
We report our main findings through three complementary analyses: the dependence between serve placement and return zones; the adaptation of return choices during domination phases; and the influence of match pressure on return behavior.

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

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



(a) (b) (c)

Figure 3.21. – 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 **Felix Lebrun**'s return clusters on the dominant player in the match. (c) Shows an example of the dependence of **Felix Lebrun**'s return clusters on the pressure in the match.

clusters are strongly linked to the service clusters. An example of dependency in Figure 3.21 (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 3.21 (b), which shows the distribution of rebounds according to the dominant player, we see that when **Felix 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 3.21 (c), we see that **Felix Lebrun** often finds cluster 3 when the pressure is low, and when it increases, he finds this cluster much less often.

Conclusion

The main limitation, which is a recurring issue in our other analyses, is the limited amount of data. Especially during the high-pressure study, only a small percentage of services are present during high-pressure moments. The second limitation concerns the metrics calculated, which are parameterized the same way for all players, even though not all players feel pressure or domination at the same score or moment in the match. The final limitation concerns the variation in return clusters based on metrics, as we have seen that return 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 mitigate the issue of missing data we seek to increase mainly through matches where high-pressure moments are present so that the analyses are relevant. The second perspective of this work is to quantify the effectiveness of returns. 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. To do this, we calculate the percentage of rallies won for each dependency cluster. This provides useful information for match preparation, as it indicates the player's most likely response when in a given dependency situation, as well as their probability of winning the rally.

3.6 Conclusions and Perspectives

In this chapter, we 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 volume augmentation and 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. At the end of this PhD we collected detailed data for up to 49 games so the metrics could be applied, but more data is needed in particular confrontation between the same players to have a more comparable way of the use of tactics.

- The second perspective, following on from the serve and return, is the study of the third stroke. This is the server's second stroke, the serve is often considered the stroke that sets up the third stroke. We have seen that the return can depend on the serve. In this way, we want to study the dependence between the third stroke and the previous strokes (serve and return). 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, distinguishing between the different types of strokes becomes more important because some strokes can be offensive or defensive. 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. we plan to create an aggregate metric that combines all our measures into one performance indicator. 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 the design and evaluation of new visualizations of the structured data presented in Chapter 2 and performance indicators presented in Chapter 3. Visualizations aims to make the data more understandable to a target audience, ranging from analysts, coaches and anyone interested in tactical interpretations of table tennis matches. This chapter is based on the following articles:

[39] Aymeric Erades and Romain Vuillemot (2023). *"Visual Analysis of Table Tennis Game Tactics."* Journées Visu, 22 juin 2023, Orsay (France). [39]

[34] Aymeric Erades, Lou Peuch and Romain Vuillemot. *"Investigating Control Areas in Table Tennis".* In: Sixteenth International EuroVis Workshop on Visual Analytics (EuroVA). Luxembourg, June 2025. [34]

[38] Aymeric Erades and Romain Vuillemot. *"Player-Centric Shot Maps in Table Tennis".* In: Computer Graphics Forum (EuroVis'25). Luxembourg, June 2025. [38]

4.1 Introduction

In Chapter 3, we saw that structured data enables in-depth analysis, with some methods directly applicable to match coaching and analysis. These analyses remain quite complicated to communicate to non-technical audience in order to enable their use, and therefore require appropriate means of communication such as visualizations.

In this chapter, we focus on a design that makes data easy to understand, always linked to video, and with the possibility of performing advanced queries using interaction techniques. We explored two directions to graphically represent table tennis data and indicators: the first is using dedicated visualizations (Section 4.3), and the second is directly in the video (Section 4.4). The first allows for easy comparisons of several rallies or matches, while the second focuses more on the current rally. An example of visualization is in Figure 4.1 which provides an example of the used of videos to create an *embedded* [11] and *moving* [137] visualization. It highlights the trajectory of the ball as well as the players' areas of accessibility (Section 4.4). To conclude, we discuss dashboards that enable the integration of multiple visualizations, facilitating the link between the visualizations and the video, as well as user interaction (Section 4.5).

4.2 Related Work

Data visualization is a crucial step in sports data analysis in general [97], and in particular for table tennis match analysis. It allows users to explore the data so they can search for specific elements or discover new ones and enables effective communication of the results obtained during data analysis. Visualizations must meet certain important criteria to be effective: they must be easy to understand, allow users to explore the data, enable interaction (*e.g.* data filtering, sorting,

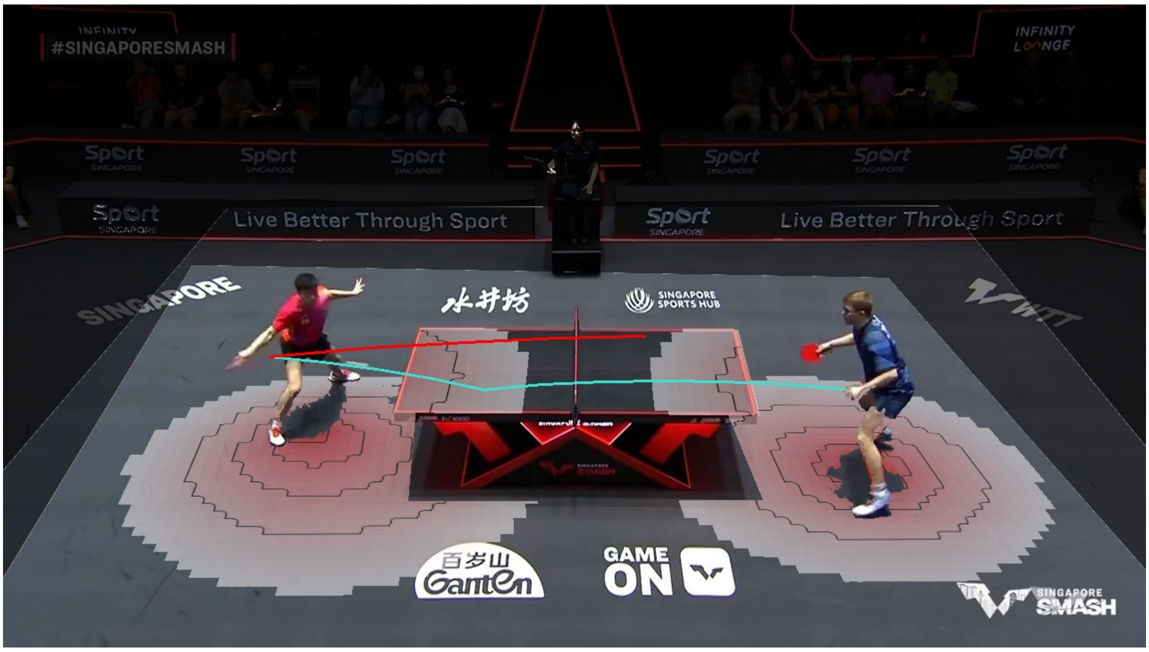


Figure 4.1. – A video screenshot of a table tennis match at a key moment between **Ma Long** (left) and **Alexis Lebrun** (right). **Alexis Lebrun** executes a fast forehand stroke (green trajectory), and **Ma Long** returns the ball (red trajectory) to the right side of **Alexis Lebrun**, who fails 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. This figure represents an example of embedded visualization.

aggregation, among others), and highlight certain important elements from the analyses.

4.2.1 Abstract Visualizations

Abstract visualizations are representations of data that augment human cognition [64] using geometric shapes and visual attributes (*e.g.* color). ComVis-Sail [101] is a flagship example of such abstract visualization for sports as it uses sensor data from boat races (Figure 4.2 (a)), 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 [103] (Figure 4.2 (b)) uses a visual approach to study patterns by focusing on the first four strokes of rallies, each of which

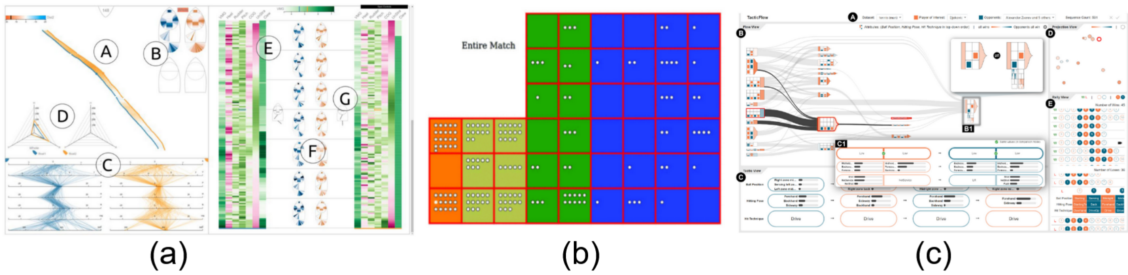


Figure 4.2. – Examples of abstract data visualizations. (a) Represents a performance analysis for boats using sensor data, from [101]. (b) Represents a sequence analysis of tennis strokes from [103]. (c) Represents an analysis of tactical evolution in a rally using Sankey diagrams for tennis and badminton, from [132].

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 soccer, PassVizor [135] 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 [127] 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. To explore tactics, the tool uses three small half-table representations divided into nine zones (as shown in Figure 3.7), with the zone found by the stroke colored with the hitter's color. They are positioned in chronological order of strokes, and donut charts are used to characterize the effectiveness of the tactics. 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. This exploration of simulated tactics again uses half tables to visualize positions, and creates a list of different possibilities for each of the three strokes in the tactic, combining position and stroke type (represented by three letters). This allows us to explore theoretically more effective tactical possibilities. For table tennis again, in order to compare sequences RallyCompartor [67] proposes 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. For its part, TacticFlow [132] (Figure 4.2 (c)) for tennis and badminton is based on Sankey diagrams, to study the evolution of tactics in rallies. Sankey diagrams are a type of flow diagram that allows the visualization of the distribution or transfer of quantities between different categories or states. Each flow is represented by an arrow whose thickness is proportional to the value it carries. 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.

4.2.2 Multiple Coordinated Visualization with Videos

(a) (b)

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 [126]. (b) Represents an analysis of game wins in tennis based on score progression in games, from [105].

Using multiple coordinated views called dashboards is a standard way to show the multiple facets of the collected and analyzed data. A particularity of sports like table tennis is their strong tie to the video used to extract data. That is why linking match videos to visualizations is an approach that is closer to how coaches in sports analyze matches. Visualizations of this type often focus on a main view of the visualization with the option to view the video linked to selected data. Surprisingly, little research has been done to link video and visualizations.

TenniVis [105] (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.

For table tennis, iTTVis [134] 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, similarity in the matrix is displayed using dots of different sizes, the larger the dot, the greater the similarity. A view focused on tactics is available and shows tactics consisting of 3 strokes using a representation of half a table divided into 9 zones highlighting the bounce zone of the stroke and an icon representing the type of stroke. Different colors are used to distinguish between players' strokes. This highlights the correlations between strokes and the frequency of these sequences, while also providing a video illustrating the rally. Tac-Anticipator [126] (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. An interactive scatter plot allows for visualizing the anticipation that is projected in a space, bringing similar anticipation close together. Selecting a stroke on the scatter plot allows to view the player's anticipation curve in detail, as well as its trajectory in relation to the table, represented by a series of dots. Color is used to distinguish between players' strokes and players' scores.

4.2.3 Embedded Visualizations in 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. Research in this area is still emerging, with recent work such as iBall [144] for basketball, where user gaze is used to highlight players and overlay information directly onto the video.

VisCommentator [19] (Figure 4.4 (b)) allows 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 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 [18] (Figure 4.4 (a)) allows videos to be enhanced using commentators' comments. In this way, comments are used as data to be visualized. They

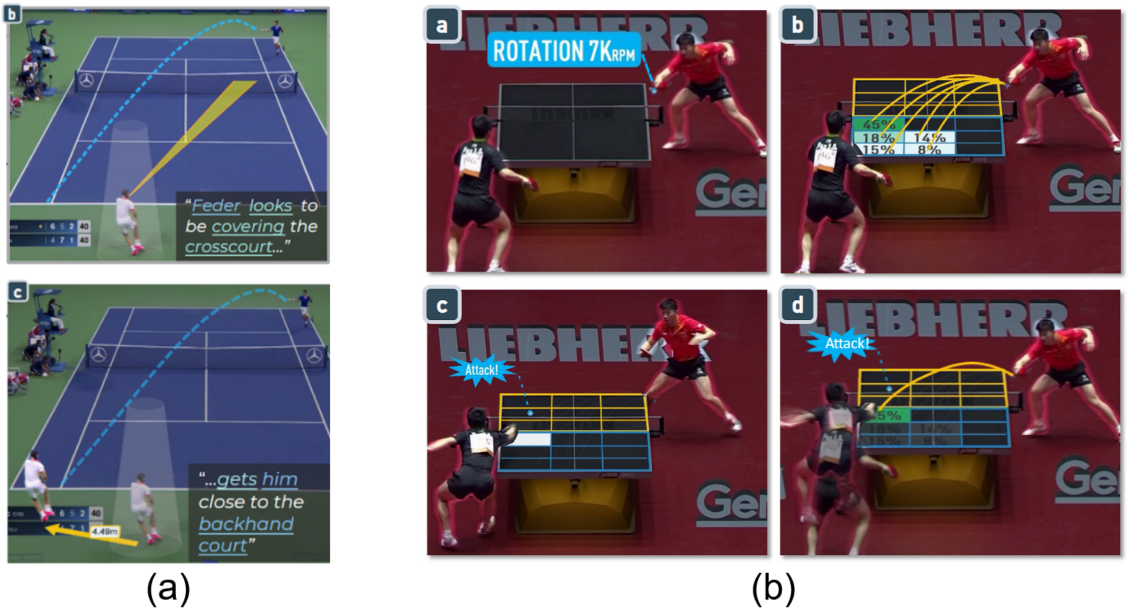


Figure 4.4. – Example of data visualizations integrated directly into the video. (a) Represents data extracted from commentators' comments in tennis, from [18]. (b) Example of augmented videos for table tennis, from [19].

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. For table tennis, we were also able to contribute to the creation of augmented videos [36], this time using an approach based on ecological principles. In this contribution, we sought to increase users' concentration on certain aspects, such as the position of rebounds by surrounding the rebound areas, and highlighting certain strokes using slow motion to make it easier to focus on the technique of very fast movements (Section 4.5.3).

4.2.4 Virtual Reality

Immersive environments (*e.g.* virtual reality, augmented reality, interactive walls) have shown promising opportunities to explore abstract datasets in an interactive way [16]. In particular, virtual reality often uses headsets and controllers to interact with data with six degrees of freedom in 3D. Since the early generation of headsets available in the 1970s, there has been significant technological progress, to make it more accessible with cheaper, smaller, and more portable devices. Virtual reality is interactive by also enables the creation of complex visualizations,

(a) (b)

Figure 4.5. – Example of PingVR. (a) Represents the 2023 French Championships, where participants have areas in which they can play. (b) Represents the playing area with the table in the middle, which is reconstructed in virtual reality. Credit: FFTT.

providing a new dimension for exploration in 3D. It also makes it possible to recreate real match conditions, allowing players to rework situations they have already encountered. In particular with realistic physics simulators such as the game Eleven Table Tennis [1], released in 2016. This game aims to recreate the sport as closely as possible to reality. It is played with a virtual reality headset and a connected controller. The creation of this game led to the FFTT launching a related discipline called PingVR [2] in 2022, and the creation of French championships.

Virtual reality is also used to create interactive visualizations for integrating data into sports. Omnicular [70] offers interactive embedded visualizations for basketball fans during live streaming. It incorporates various data, such as player positions and techniques. This system can be integrated into match videos, but we have chosen to integrate it into a 3D reconstruction of a match, simplifying access to the data. For badminton [138], used virtual reality to study the accuracy of shots, and [21] used it to study tactics in the form of shot maps with 3D trajectories. For badminton coaching [69] (Figure 4.6) 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.

We experimented with visualizing our collected data using Virtual Reality headsets (*e.g.* Oculus Meta Quest 3), but this required a significant development phase and offered limited interactions as well as limited possibilities to include abstract visualization and video efficiently.

1. https://elevenvr.com/
2. https://www.fftt.com/site/jouer/ping-loisirs-nouvelles-pratiques/pingvr

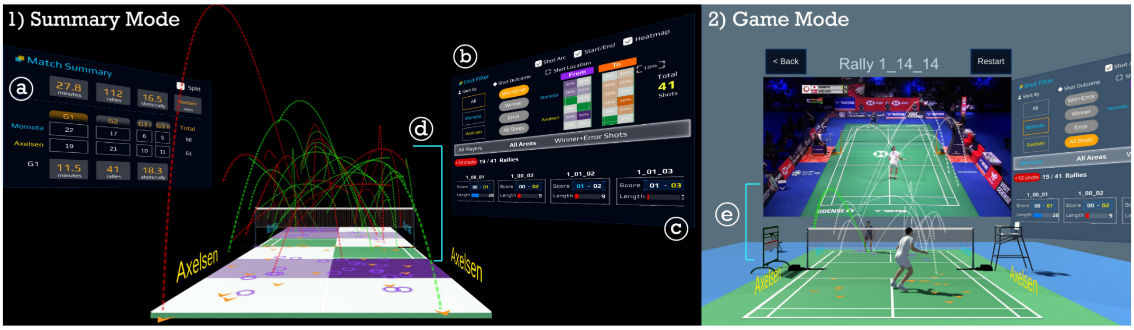


Figure 4.6. – Example of data visualizations integrating 3D game scene generation to provide additional new views to the video, from [69].

4.2.5 Shot Map

Shot maps (also referred to as shot distribution or shot density charts) are standard visualizations in sports [97]. They plot on a top-down view of a pitch or a table spatial sports events and tracking data, often revealing visual signatures of plays by highlighting key events such as 3-point shots in basketball [110]. These maps can also be animated with player trails [3] to provide spatial context. To facilitate interpretation, binning using a grid is often applied, as in CourtVision [47]. Court landmarks [70] (*e.g.* Free-throw line, Three-point line, the Key) can be used for segmenting semantic regions. Shot maps can be embedded [96] 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 [21]), which are often used in 3D immersive environments [138]. 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 have patterns dependent on the type of sport. The shots have a *converging* approach (*e.g.* Baseball [26]) 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 [102], and can be represented using a ring-based approach due to the importance of distance. The *diverging* approach, seen in sports such as Baseball [100, 26], 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.

For soccer, SoccerStories [96] uses interactive visualizations based on shot maps. Among the visualizations used, they use shot maps (Section 4.2.5) to visualize all shots, which are represented by lines connecting the starting point and the end point of the shots. The color distinguishes between goals, missed shots, and saved shots. For passes, they use a shot map with a pass graph linking players on the field, with the thickness of the links highlighting the number of passes made.

In racket sports with a net separating players, such as tennis, table tennis, and badminton, 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 using iconic representations. Follow-up works have relied on similar shot maps to plot information and support analysis. For badminton, Tivee offers small multiple shot maps [21] that account for a third dimension to capture the height of the shots. ShuttleSpace [138] 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 the players' positions. For table tennis, VisCommentator [19] highlights relative positions of players to the ball to simulate hypothetical placements, though the analysis remains a visual augmentation and is still table-centric. In iTTVis [134], shot maps are displayed as glyphs by region and stroke placement to characterize rallies with connected matrices, while Rally Comparator [67] provides player-centered shot maps with stroke placement to reveal tactical patterns in games. Tac-Miner also relies upon glyph representations [125] that categorize ball hit position into regions. Recently, Tac-Anticipator [126] introduced 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.

4.3 Player-Centric Shotmaps

As we have seen in the previous section, shot maps capture events relative to a field or a table, but not to other elements such as players. This is important to provide better player-centric representations to identify weaknesses relative to players' positions during matches, such as *reachability e.g.* close or distant shots, or targeting the *pivot area e.g.* forcing rapid transitions between forehand and backhand, these weaknesses are the basis for certain tactics that we introduced in the introduction. 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]. As we have seen, shot maps are very popular in many sports to plot spatial data by using a pitch or a table as an absolute coordinate system, but they have several drawbacks for analyzing reachability, pivot areas, or any player-centric techniques.

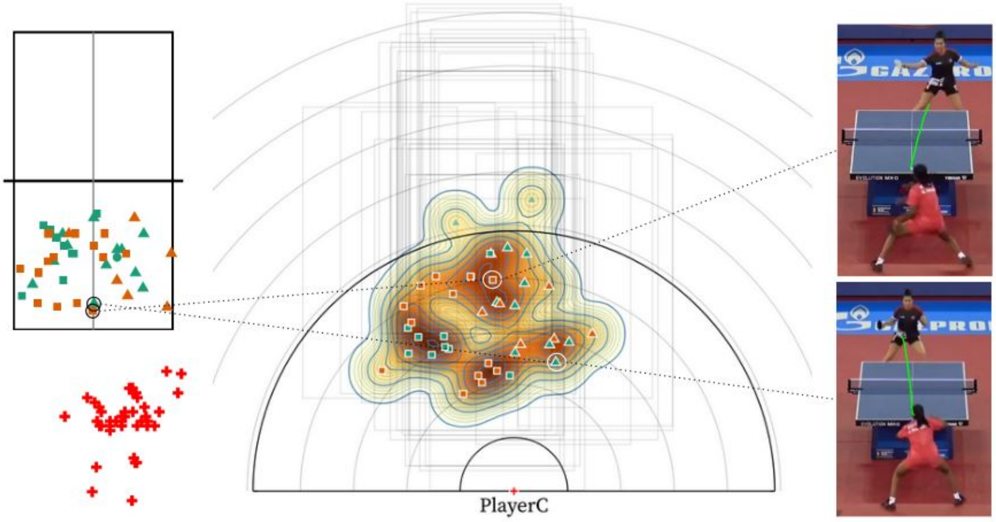


Figure 4.7. – Example of a standard shot map on the left (a), from a *table-centric* perspective, where players' positions ✚ and ball bounces ■ ▲ are plotted relative to the table. (b) Introduces a shot map representation that shifts the perspective to a unique player position ✚, providing a *player-centric* 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).

Example

To illustrate our work, we provide context and details in 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 **Prithika Pavade** and **Sibel Altinkaya**, both highly ranked players at that time. The game was tight with a victory 3-1 (11-6 11-8 8-11 11-6) for **Prithika Pavade**. We picked two moments in the match where two shots by **Prithika Pavade** 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 in 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 **Prithika Pavade** 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 **Prithika Pavade**.

We can hypothesize that the distance of the bounce relative to **Prithika Pavade** was a decisive factor in the result, to be confirmed with further analysis of similar strokes. Watching the video footage also helped to confirm this hypothesis, as we can see **Prithika Pavade** struggling to play the shot during the lost point Figure 4.7 (c).

Figure 4.7 shows that similar shots on the traditional shot maps (which are top-down views of the table incorporating spatial data such as bounces or player positions) introduce various biases when relying on positions relative to the table, 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.

Our primary findings indicate–according to our experts– the technique *aligns with [his] narrative when analyzing the pivot area* (Section 1.5). We also report on the main challenges related to the interpretation of a non-standard point of view and interactions, as well as the requirements for specific data filters. Figure 4.8 illustrates the level of analysis we focus on: a subset of a rally, concentrating on specific incoming shots from a stroke.

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 4.3.3).

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 the *pivot area* (Section 1.5). 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

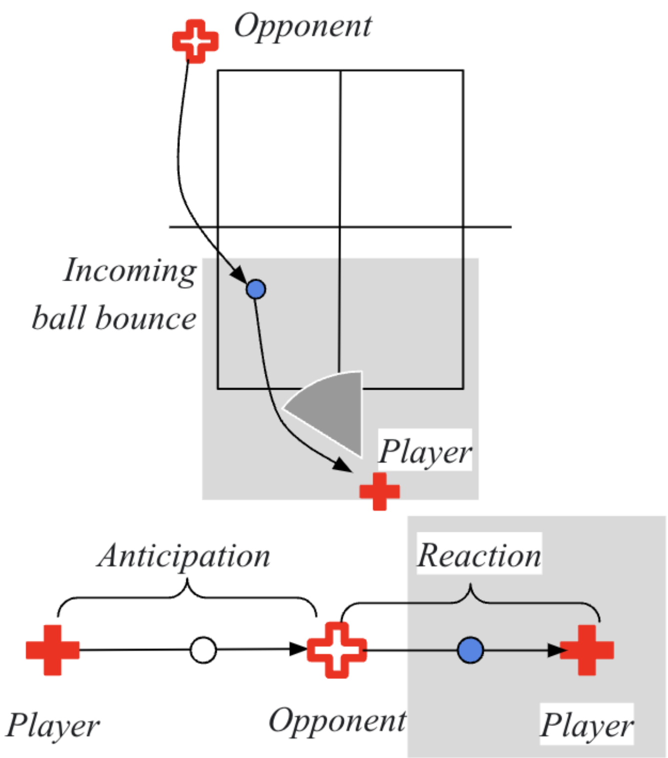


Figure 4.8. – A table tennis sequence represented spatially (above) as a traditional shot map, and its equivalent temporal sequence (below). The focus of this work is on the gray area: the spatial and temporal regions related to players' reactions to an opponent's shot. Diagram inspired by [126].

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."* [4]. 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).

To address this need to study these tactical areas, we took a user-centered approach based on discussions with experts (Christian Gaubert, Research Director at the FFTT, and Laurent Cova, video analyst for the FFTT) and developed the following requirements to build new visualizations:

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 of the context (*e.g.* absolute position of players).

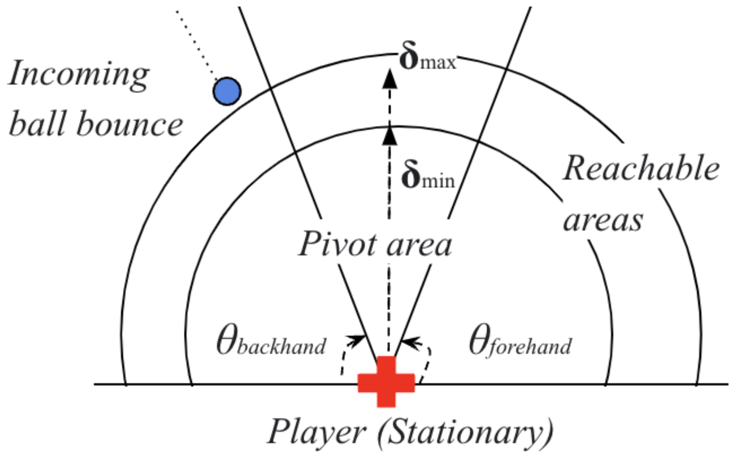


Figure 4.9. – Polar coordinate system for player-centric shot maps: the stationary player (red cross) relative position of balls (the circle represents a ball bounce), half-circles represent the distance δ from the player, and angles θ capture regions around the player.

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.

4.3.1 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* we introduced previously.

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 [45]. 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 angles are challenging to grasp (in comparison to linear layouts).

- ∪ **Radial layout** is used to plot strokes with respect to the player's stationary position. Such a layout represents an arc with a radius that ranges between $[-180, 180]$ degrees. We assume there is no 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 in Figure 4.24).

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 (Figure 4.7 (a)). We opted for an unsupervised approach and used kernel density estimation (KDE) to emphasize groups [111] using the density of shots in the two-dimensional space of the table [108]. 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:

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

4.3.2 Implementation

We implemented the shot map visualization in JavaScript using D3 [10] 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, which 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 [93], 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 [94] and a Blender Plugin. We wrote custom Python codes for the pose estimation and 3D reconstruction by relying upon Blender for matching 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.

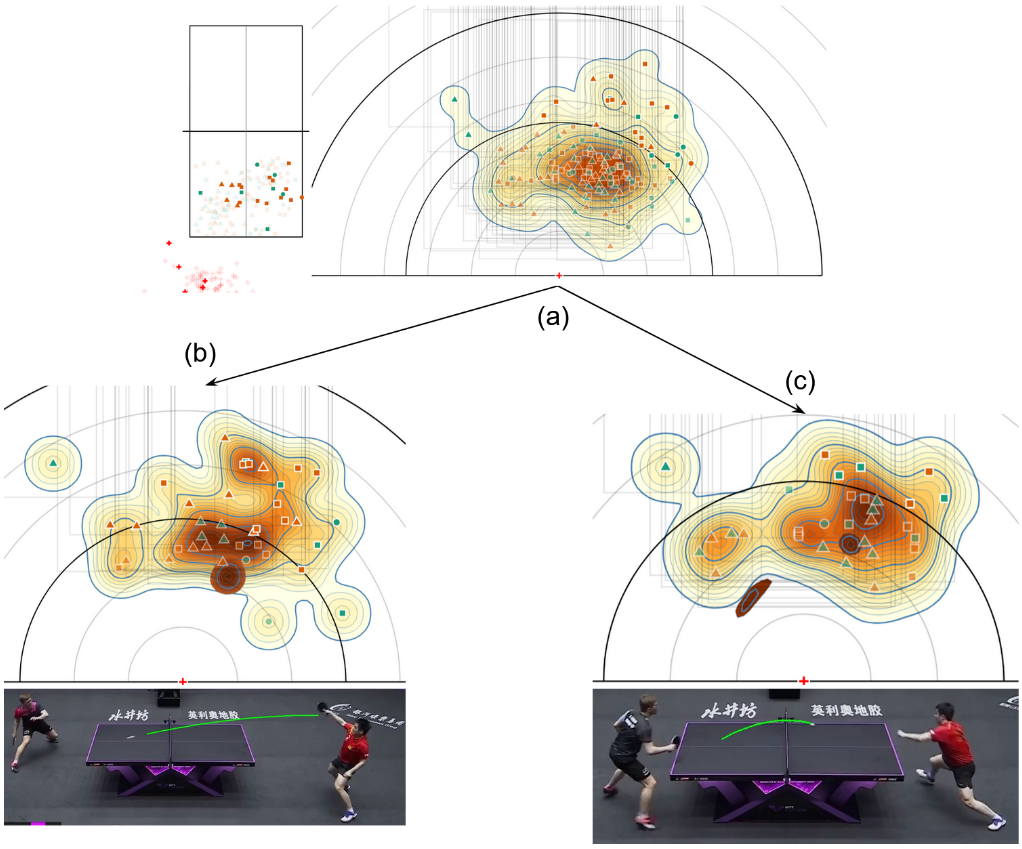


Figure 4.10. – Case study 1 on reachable areas for **Fan Zhendong**: (a) selection by distance, choosing to keep only rebounds that are far from the position of **Fan Zhendong** we observe a majority of strokes leading to the defeat of the rally, (b) filter this area by topspin again we observe a majority of strokes leading to the defeat of the rally, and (c) filter this area by push, we observe a balance in the number of strokes leading to defeat or victory in the rally.

4.3.3 Case Studies and Experts Feedback

We now 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 of the co-authors of this work. 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 4.24). 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 at that time).

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 Figure 4.10 we observed that beyond 150 cm, there is a correlation with a reduction in 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 4.10, b). However, it becomes evident that **Fan Zhendong** losing points occur on the shortest balls near the table. When filtering exclusively for topspins (Figure 4.10, a), the area shows a clear losing trend. This can be interpreted as meaning 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 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 4.11, 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 4.11, 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 in 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

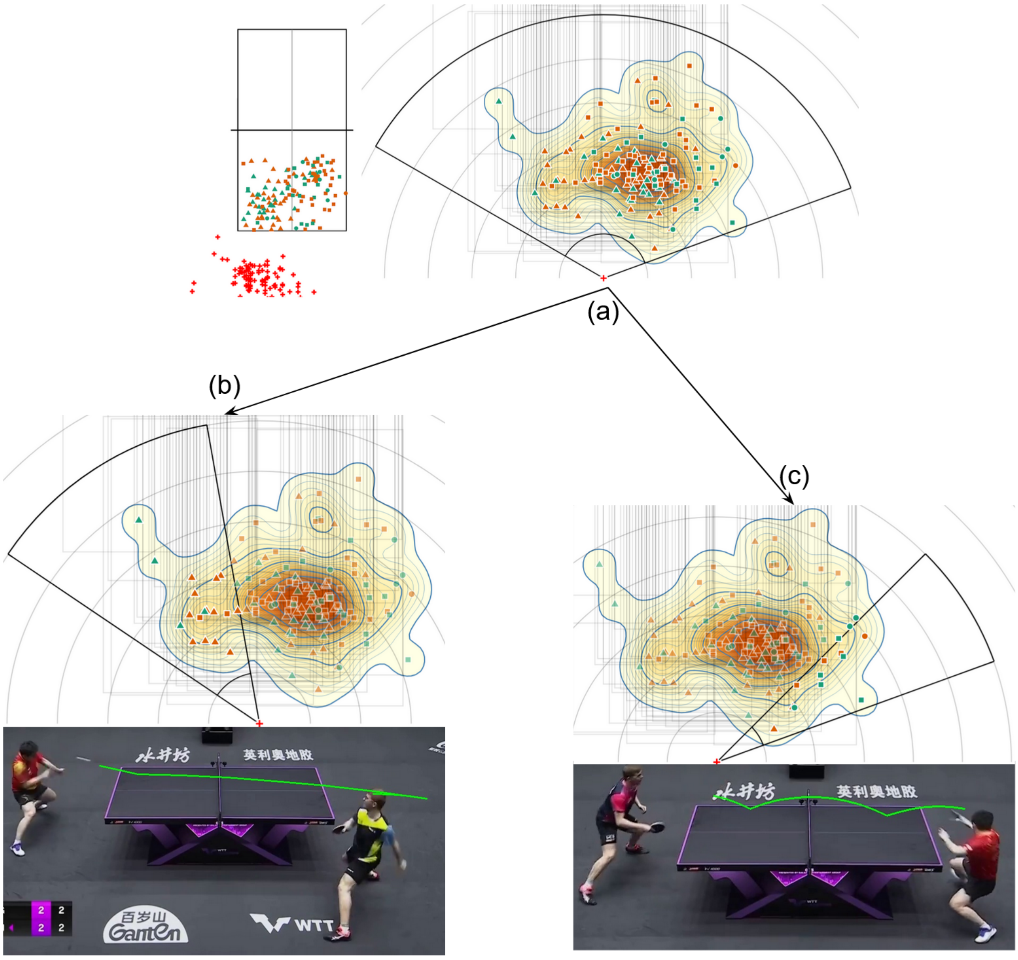


Figure 4.11. – Case study 1 on lateral areas for **Fan Zhendong**: All data are represented with a classic shot map on the left and a player-centric shot map on the right (a), selection by left angle shows a winning region (b), by right angle shows a loosing region (c).

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's hip area in the **weak region** of the player.

Revealing the Pivot Area. Figure 4.10 shows that for **Prithika Pavade**, 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

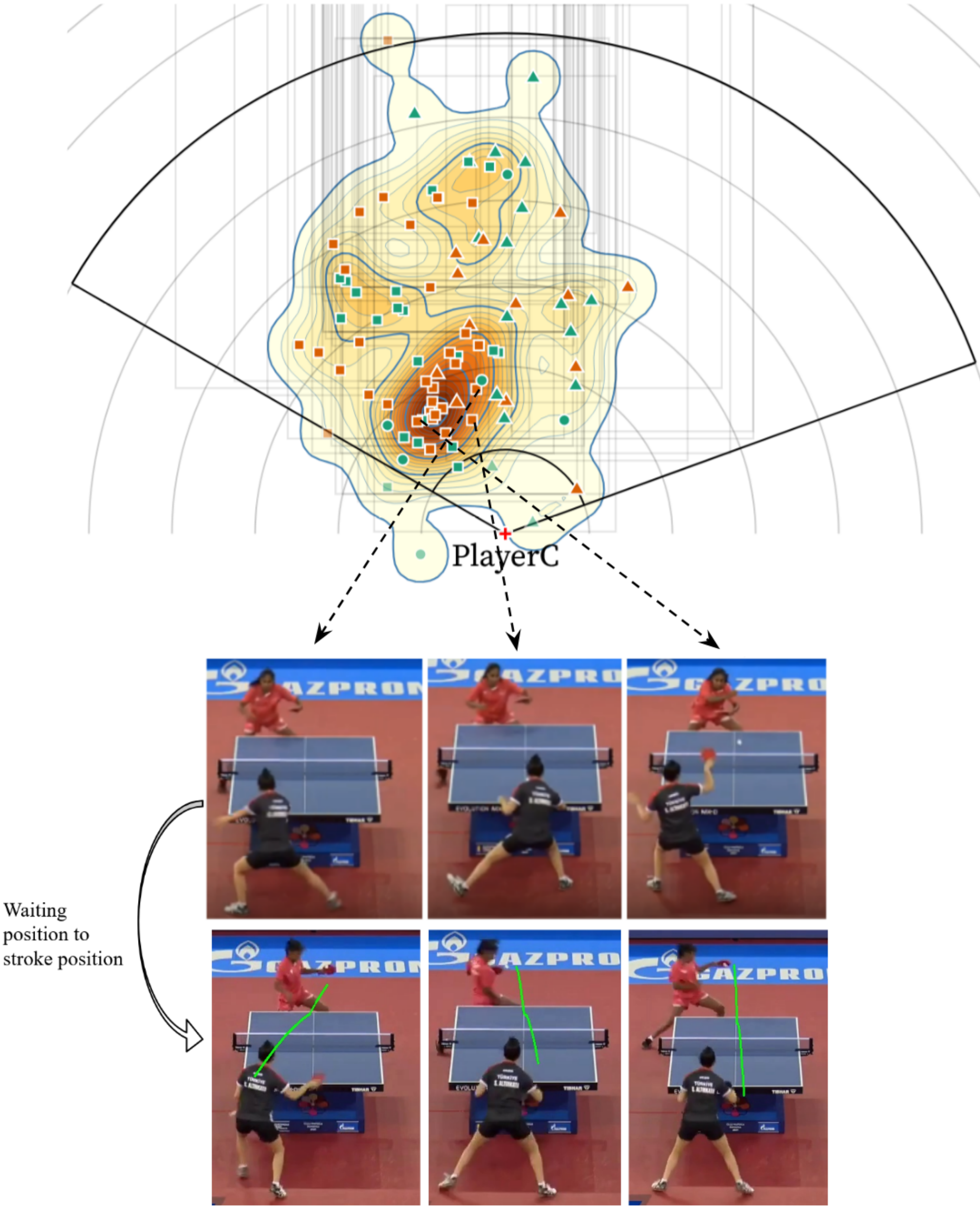


Figure 4.12. – Case study 2 on revealing the pivot area: characterizing the pivot region of **Prithika Pavade** by selecting angles and distances that capture weaknesses. The waiting position when the opponent hits the ball (anticipating a backstroke); the opponent hits the pivot area which makes it difficult for her to return the ball.

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

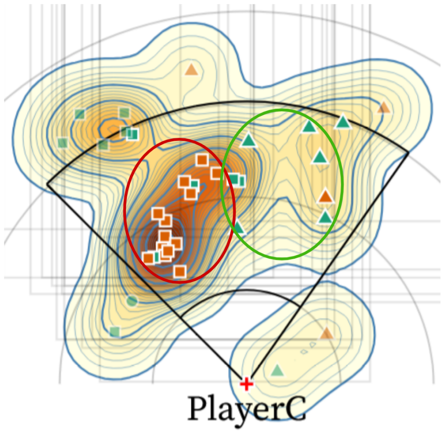


Figure 4.13. – Case study 2 on pivot areas when returning serves: two clusters emerge within the pivot area, based on player performance for each stroke. Those clusters correlated with forehand and backhand technique, which means half of the pivot is respectively a weakness (red) and the other half actually a strength (green).

video, we can observe that 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 **Prithika Pavade** pivot area by focusing on a particular stroke technique: serves. This stroke technique is singular as the receiver's waiting position has a consistent position towards the 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 4.13 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 is still effective (8 successes out of 11 points). The interesting part with those clusters is that they are situated within the pivot area we identified in the previous section, but with only a subset of strokes. The interpretation is that the weakness can be explained by the fact that with her backhand, **Prithika Pavade** 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 **Prithika Pavade** 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's 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 however the pivot area selection to be a very interesting and 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 rethink the way he analyzes games from now on. Still as a final comment, 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.

Conclusion

The feedback from the experts allowed us to demonstrate the usefulness and effectiveness of our approach through case studies of common game situations in professional table tennis which are basis of some tactics we saw Section 1.5, and to identify certain limitations. The first limitation concerns the interface design and the transition from shot maps to player-centered representation, which is not easy for non-experts to understand. This approach does not take into account the context of strokes, particularly the trajectory of the ball. Since its position is taken at the moment of bounce, the trajectory can in some cases deflect the ball to the right or left after the bounce, making the grouping of bounces alone less relevant. Although our data collection pipeline operates in 3D, this work only focuses on 2D visualization of shot maps due to their wide use. While 3D data has potential for ball trajectory-based analysis, body motion, and to capture the reachability of

3D shots. Finally, these visualizations currently leave most of the data exploration to the user and do not incorporate Chapter 3 analyses, which could offer a new way to filter data if integrated into the visualization.

4.4 Control Areas

We have seen that the player's position in relation to the rebound is an important element in tactical analysis, highlighting certain areas that are difficult for players to manage, particularly those that are far away. In this way, there are areas that are accessible to players. These depend on the position of the players. As the positions are continuous, we have chosen to study the evolution of these areas continuously according to the position of the players.

To reveal the tactical aspect that space plays, we introduce control areas which 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. Control areas which are regions that can be reached quickly by a moving entity are increasingly popular in sports analysis (also referred to as occupation areas, occupation models, or pitch control), *e.g.* in basketball [110], soccer [2, 1, 55], and badminton [28]. 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 [140].

Example

During the 2024 Singapore Smash, **Alexis Lebrun** was facing **Ma Long** and ended up losing a rally by being too far away from the ball on a stroke. This situation occurred on **Alexis Lebrun**'s previous stroke. During strokes, he shifted to his left side and ended up too far away from his right side to return the ball. This area therefore became inaccessible on the previous stroke. An occupancy model that takes into account his position and movement can highlight this inaccessible area. In Figure 4.14, at the moment of **Fan Zhendong**'s stroke, beyond the accessible area of **Alexis Lebrun** shown in red, the inaccessible area shown in green is the area that **Fan Zhendong** found and in which **Alexis Lebrun** was unable to retrieve the ball. This occupancy model highlights that certain losses of rallies based on positions and movements are predictable and that areas of inaccessibility are visible during rallies.

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

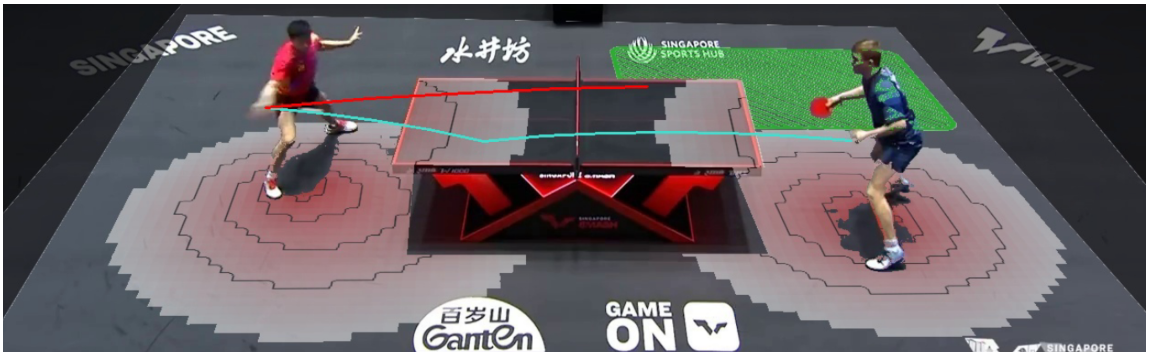


Figure 4.14. – Red areas are reachable areas computed on a physical model for each player. In green, a tactical area we manually annotated, that **Ma Long** targets because it is far away from **Alexis Lebrun** and he does not have enough time to move into the ideal position for his stroke.

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 from our dataset and discuss potential improvements for our control area models.

4.4.1 The Importance of Space in Table Tennis

Figure 4.15. – 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.

We aim at characteristics when players fail 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 far away (Figure 4.15) in the match between **Ma Long** and **Alexis Lebrun**, Smash Singapore

2024; the ball was in a pivot zone (Figure 4.16) in the match between and **Alexis Lebrun**, Champions Incheon 2024; and the player was wrong-footed (Figure 4.17) in the match between **Alexis Lebrun** and **Ma Long**, Smash Singapore 2024.

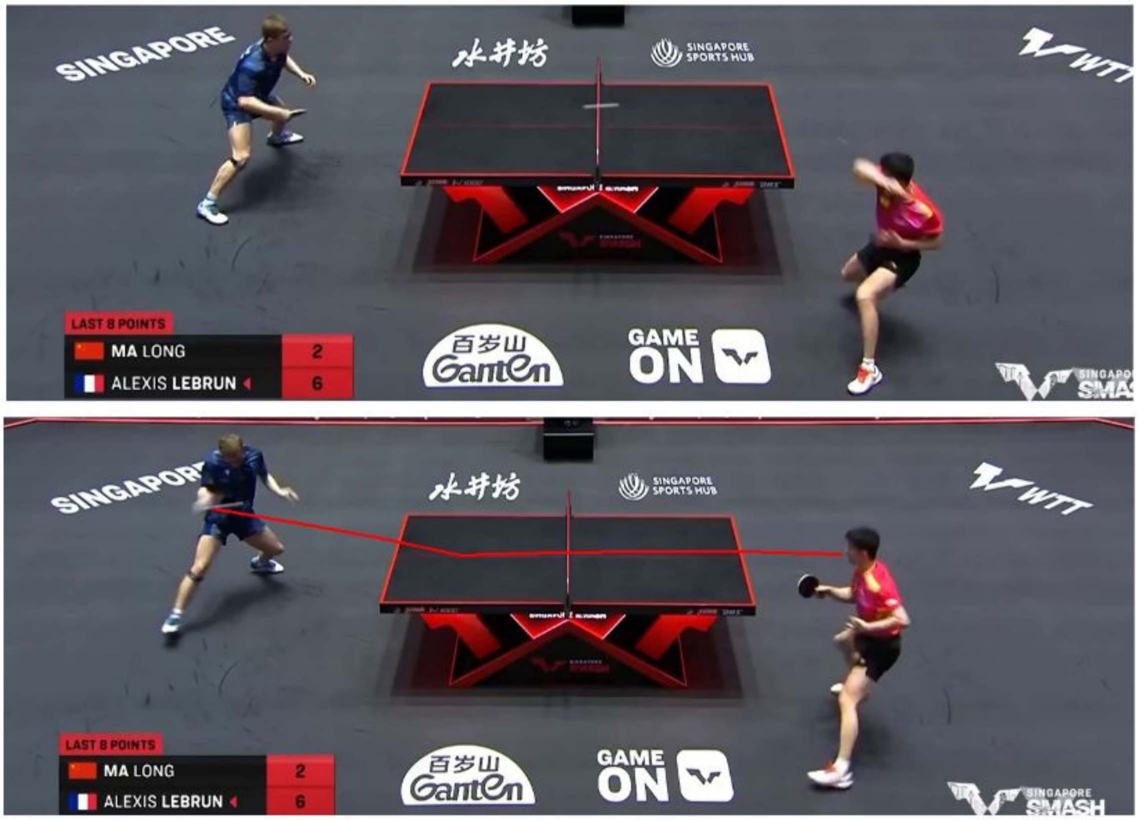


Figure 4.16. – Ball in pivot zone: Alexis Lebrun is in a backhand stance, but the ball arrives in the pivot zone, causing him to hesitate and switch to a forehand, missing the strike. This zone is difficult to manage as it limits both forehand and backhand movements, and **Alexis Lebrun** can not move fast enough to make space for his forehand.

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 a concept is using Voronoi partitions [123], which is well defined but not suited as it considers all directions as candidates for control. The standard way to build a more efficient model is to adapt *space-time models* [118] 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 rather the time it takes for a player to reach the point which defines the controlled area.

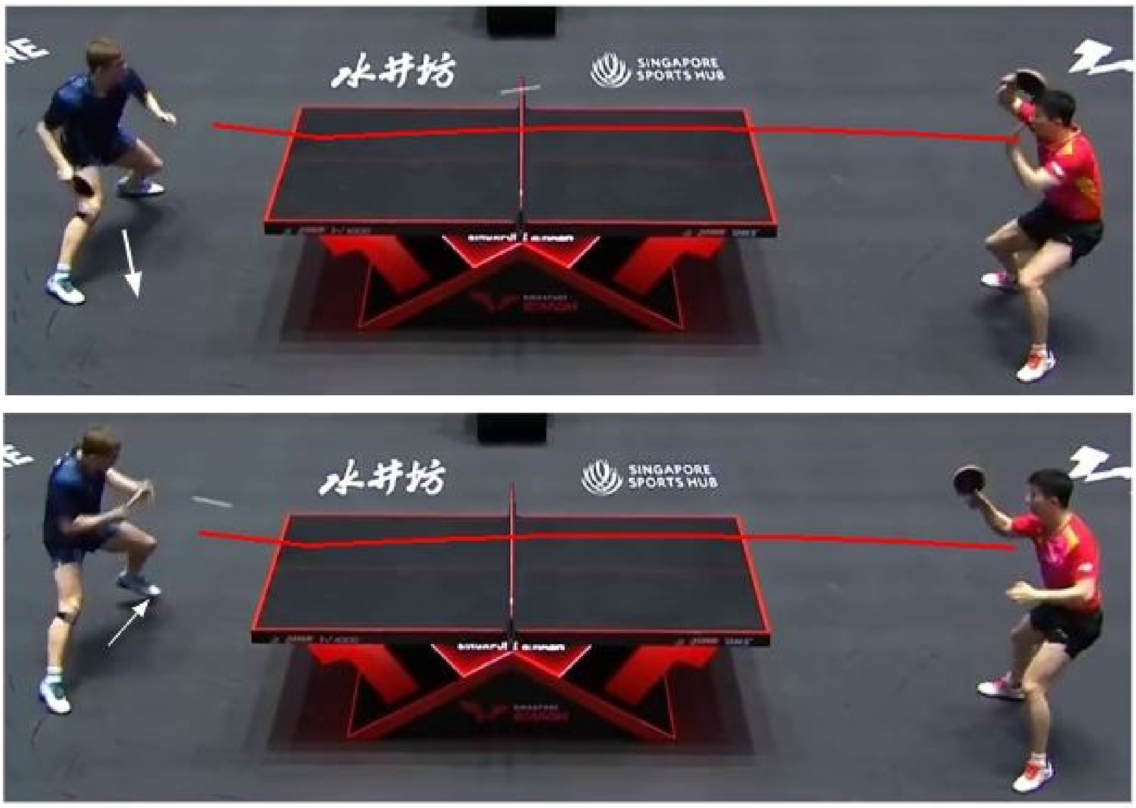


Figure 4.17. – Wrong-footed: After sending the ball into **Ma Long** forehand, **Alexis Lebrun** anticipated a cross-court shot and moved to his right, but **Ma Long** chose to send the ball down the line. **Alexis Lebrun** had to change direction quickly, which prevented him from returning the ball correctly.

Control areas are interesting due to their predictive nature, which captures the underlying physical model based on Newton's second law [110]. Such models are simplified versions of reality, taking into account parameters such as direction, speed, and force of a player 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 tracking data [97] 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 [28], 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.

4.4.2 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:

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

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 [110], 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

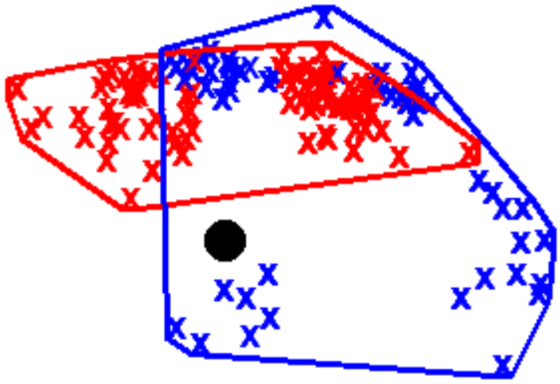


Figure 4.18. – Alexis Lebrun's ball hits relative to his position. The black circle represents the player's position; the blue marks the positions of balls hit with the forehand, and the red marks the ball positions hit with the backhand. Since the player's position is taken using his hips, some hits 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.

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 a heatmap.

4.4.3 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 execute 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 4.18. 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 4.18'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.

4.4.4 Implementation and Visual Design

Players' positions and events (*e.g.* hits) are derived from [38], 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 [117]. We used visual overlays in a manner similar to how Viscommentator operates [19] 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.

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

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.

Conclusion

The results we show 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 shown on the teaser image Figure 4.1 and also on Figure 4.20, Figure 4.19 and Figure 4.21. The results are visually conclusive, the reason being that they concern extreme cases where local reachability does not play an important role. Regarding the model with peripheral reachability, Figure 4.22 shows 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

Figure 4.19. – Ball in pivot zone. Zone between the elbow and the stomach makes it difficult to return the ball. **Alexis Lebrun**, left player, struggling to return the ball.

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 [40]. 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 4.14, 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 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 [13], to identify their characteristics and allow for comparisons 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 are 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

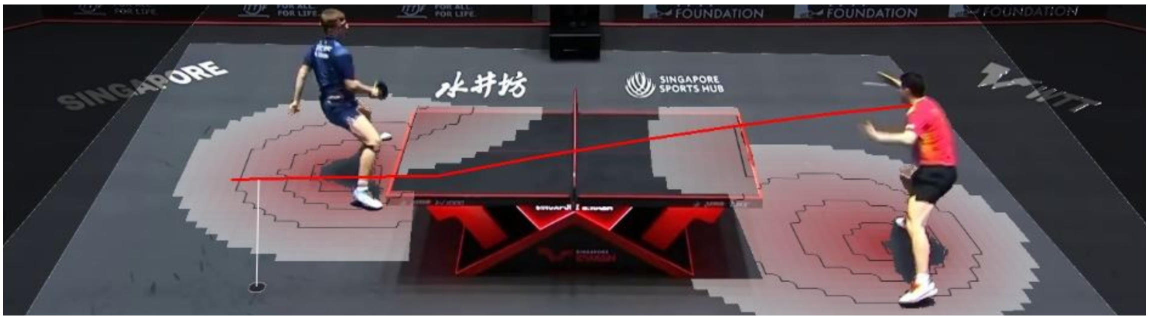


Figure 4.20. – Ball too far away. **Alexis Lebrun**(left player) is completely out of position on his left, which allows **Ma Long** to play on the other side and puts the ball too far away from **Alexis Lebrun**.

Figure 4.21. – 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.

Figure 4.22. – 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.

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.

4.5 Integrating Visualization as a Unified Dashboard

The visualizations presented in the previous sections can be integrated into a single interface with multiple views coordinated with the video, we call *dashboards*. This allows analysts to explore visualizations at once, to answer specific requests from coaches during match preparation. We present two interactive dashboards, the first allowing exploration of rallies, which is a perspective for researching tactics and the second a dashboard developed for the exploration of player-centric data. This work was primarily used as internal tool by the FFTT and have not been published due to their critical role they played for the performance of the French players.

4.5.1 Exploratory Visualizations

For this first dashboard our goal is to get a better understanding of the data characteristics and their role in the analysis process so we explored all design aspects related to all the dimensions of the data we collected (Chapter 2) and analyzed (Chapter 3). 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 [96] showing the importance of detailed data we collected, in particular tracking data. 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, from our dataset, as depicted in Figure 4.23. This design also follows the principles of overview, zoom, and detailed analysis [113] so experts can first look at an interesting rally and pick one (Figure 4.23, top) and then get the details and video playback (Figure 4.23, bottom left). We included a preliminary work on tactics discovery [31] represented as a directed acyclic graph (Figure 4.23, right) over which the selected rally is emphasized (using a black stroke).

This particular match from the 2023 European championships featured French player **Simon Gauzy** against his English opponent **Tom Jarvis**. With the game sequence representation (Figure 4.23, top), analysts can observe the point sequences during which **Tom 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

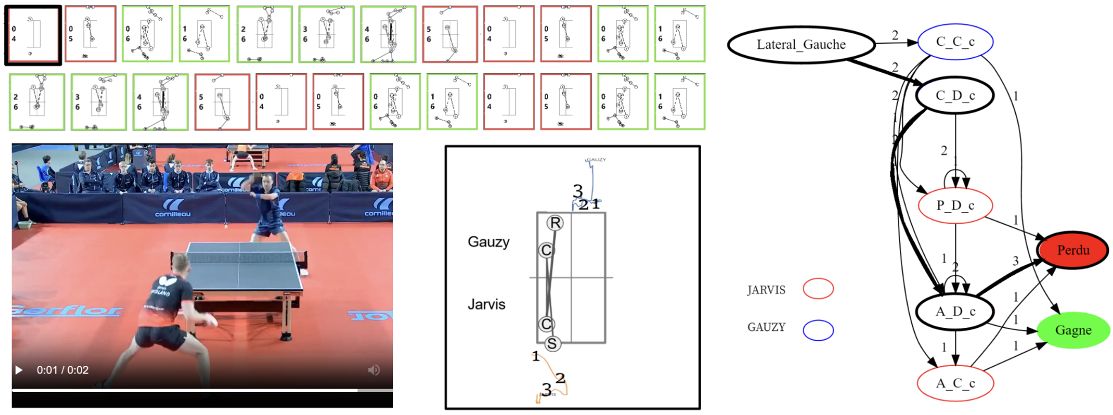


Figure 4.23. – Example of game sequence visualization using table tennis game overview (top), the focus on a particular rally (left) and a set summary using a graph-based approach (right).

pivotal difference. In this example, when **Tom Jarvis** serves, **Simon Gauzy** loses three out of four points when he attempts a forehand attack. Analysts can then filter and isolate points for this specific game situation, thereby visualizing the movements of the players and the ball for each point, which can be linked to the corresponding video footage. For instance, on the first point, **Tom Jarvis** wins by playing near **Simon 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 iterate through the designs.

Those dashboards were used by FFTT analysts in an expected way: more to create playlists of interesting shots (*e.g.* winning ones, similar ones, etc.) rather to reveal particular tactical aspects. This is why we then augmented them with additional, more sophisticated visualizations presented in the next sections.

4.5.2 A First Dashboard Player-Centric Dashboard

We built another dashboard around the player-centric visualization in Figure 4.24, we kept the shot map of the player-centered view in the center of the visualization, with a classic shot map showing the table view to its right. Below these visualizations are all the filters that are directly linked to the visualizations, allowing coaches to filter the rallies they want to analyze together. As with the first exploration dashboard, the video of the rallies is also linked to the visualizations. This link is done differently: the player-centric shot map groups all the strokes together in a single visualization, thus linking the interaction between the strokes and the video, rather than between the rallies and the video. This dashboard allows data exploration through the strokes while retaining the ability to compare the rallies to which they belong using the video.

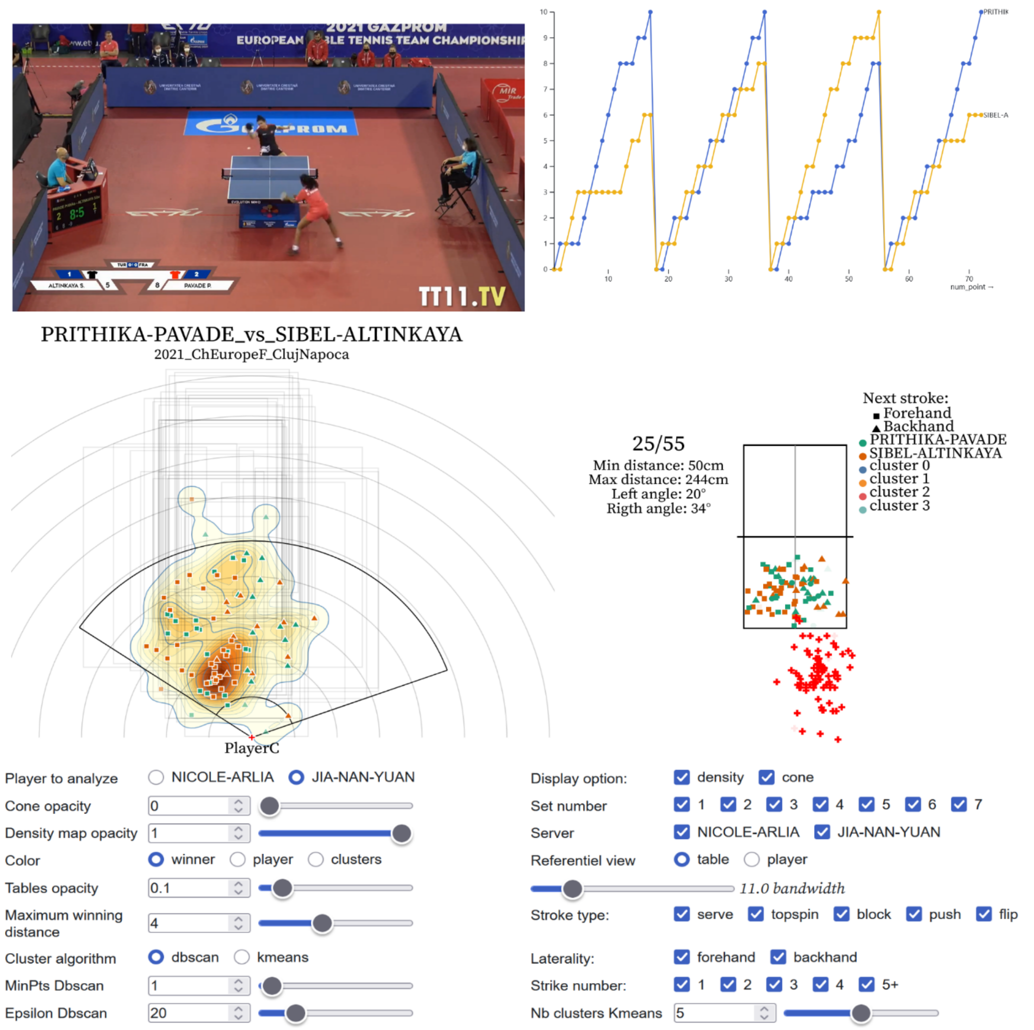


Figure 4.24. – Dashboard with the player-centric shot map we presented to our experts to collect their feedback.

This dashboard offers advanced analysis by including video as an integral part of the dashboard, rather than as an additional option as presented in some works. According to expert feedback, this is a promising approach that could expand the body of knowledge in the field of visualization .

4.5.3 Augmented Videos

Dashboards allow visualizations to be linked to video so that coaches can analyze it. However, visualizations remain disconnected from the videos, despite the underlying data used actually come from those videos. Thus, we explored ways to re-include the data within the video using so-called *embedded* visualizations [144] which come from the emerging field of *situated visualizations* which depict data within the context of people's activities [11].

Nowadays, many broadcast sports already incorporate embedded visualizations, notably with the addition of scores or certain statistics such as world records shown as a moving yellow line in swimming, or the distance to the goal displayed when soccer players kick off toward the goalkeeper. More complex visualizations are sometimes added such as shot maps and tactical visualisations but usually during post-game sessions with experts. The research is emerging in this area, with recent work such iBall [144] and SportsBuddy [71] in basketball with embedded visualizations to highlight players, notably with spotlights.

To achieve embedded visualization in table tennis, an end-to-end computer vision pipeline is needed, but fortunately we set it up during this thesis. Still, design steps were needed to determine which data is important and define the transformations to be made so that they provide information without distracting users. We identified the players and ball bounces as essential elements. For the transformations, we focused on two types: changes in video speed and visual additions. Changes in speed allow viewers to focus on the technical aspects by slowing down the video, enabling them to see the players' strokes in detail. Visual additions highlight the players and bounces. Figure 4.25 shows an example of video transformation using such visual additions. We used slow motion during serve to give the possibility to the viewer to concentrate on the serve technique. Ball bounces are highlighted by framing their bounce areas and marking the bounce location with a dot.

Figure 4.25. – Augmented video highlighting the ball bounce. The ball bounce position is marked with a dot and its area is outlined. Other transformations have been achieved and explored (*e.g.* video speed, video motion effects) but are not visible on this screenshot.

Augmented videos are another promising research direction we started to explore as our tracking methods provide an understanding of the underlying scene in table tennis videos such as the position of the table and players (Chapter 2). An interesting research perspective would be to add advanced statistics (Chapter 3), but this requires careful design to avoid hindering the video-watching experience by hiding important details or adding too many distractions.

Conclusion

The dashboards made it possible to link several visualizations for analysis, the match video, and to add interaction related to all the elements. This allows coaches to use them to analyze matches. Several perspectives are considered through this work. The first is to obtain feedback from users in order to improve both the design and ergonomics of the dashboards, using preliminary design studies [89] that need to be conducted. The second is to be able to combine these visualizations with the analyses carried out in Chapter 3, which will enable new mechanisms to be developed for filtering data, particularly game metrics, and highlighting certain interesting game sequences. We have only scratched the surface of the potential of such visualizations, which remain promising directions for future research.

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 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 considerations when seeking to characterize players and generate insights based on a given group of opponents. With more data, additional derived statistics can be calculated, with features that can be visualized in particular using the potential 3D data offer, such as players' posture when hitting or waiting for the ball, as well as ball trajectory analysis to calculate speed and height.

- 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 control area 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 this manuscript. We also propose a research perspective for this thesis.

5.1 Summary of the Contributions

Throughout this manuscript, we have demonstrated how match data can be used to conduct meaningful analysis in table tennis. 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 to explore and communicate such data.

[32] 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). [32]

This work consists of creating a benchmark dataset that is open to the scientific community. The dataset is divided into six independent parts that could 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, it was released publicly so the research community could advance and achieve the highest accuracy across the various tasks.

[37] Aymeric Erades, Romain Vuillemot. *"How Camera Angle Impact Table Tennis Ball Bounce Tracking"*. In: Sports Physics 2025. Sept. 2025 [37]

This work proposes a method for establishing a protocol to calculate the accuracy of a bounce position annotation on the table based on the position of the camera relative to the table. A model for predicting accuracy is introduced, it takes the position of a camera as input and allows the accuracy to be evaluated across all points on the table. We also introduce a tool to anticipate the accuracy based on the model we introduced.

[13] 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. Turin, Italy. 2023. [13]

This paper proposes a study of dominance in a table tennis match using metrics 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.

[33] Aymeric Erades, Thomas Papon and Romain Vuillemot. *"Characterizing Serves in Table Tennis."* en. In: *Machine Learning and Data Mining for Sports Analytics*. Springer Nature Switzerland, 2025. [33]

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.

[5] Riad Attou, Marin Mathé, Aymeric Erades and Romain Vuillemot. *"Analysis of Service Returns in Table Tennis".* In: Machine Learning and Data Mining for Sports Analytics, Porto, Portugal, Sept. 2025 [5]

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.

[38] Aymeric Erades and Romain Vuillemot. *"Player-Centric Shot Maps in Table Tennis".* In: Computer Graphics Forum (EuroVis'25). Luxembourg, June 2025. [38]

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 confirm that these are predominantly losing situations for players statistically.

[34] Aymeric Erades, Lou Peuch and Romain Vuillemot. *"Investigating Control Areas in Table Tennis".* In: Sixteenth International EuroVis Workshop on Visual Analytics (EuroVA). Luxembourg, June 2025. [34]

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. A physical model is used to calculate the areas that players can reach, and visualizations are built around the players' positions in the video.

5.2 Perspectives

The perspectives for this research are mainly related to the limitations we encountered in our various projects and related to the volume and velocity of data collection. We have identified three main directions: the use of 3D data, the automation of data collection, and real-time analysis and visualization of table tennis data.

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 [134, 126, 31]. 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 [138], 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, [128] uses a similar approach for serves, clustering the different 3D trajectories. In table tennis, approaches to collect the trajectory of the ball 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 [12]. 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 [50], 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 and ball trajectory provides an interesting angle of analysis for research. The 3D estimation of players' posture allows the study of the biomechanics of players, but it also makes it possible to characterize the intensity of strokes based on how posture evolves throughout the motion. 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 stroke 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

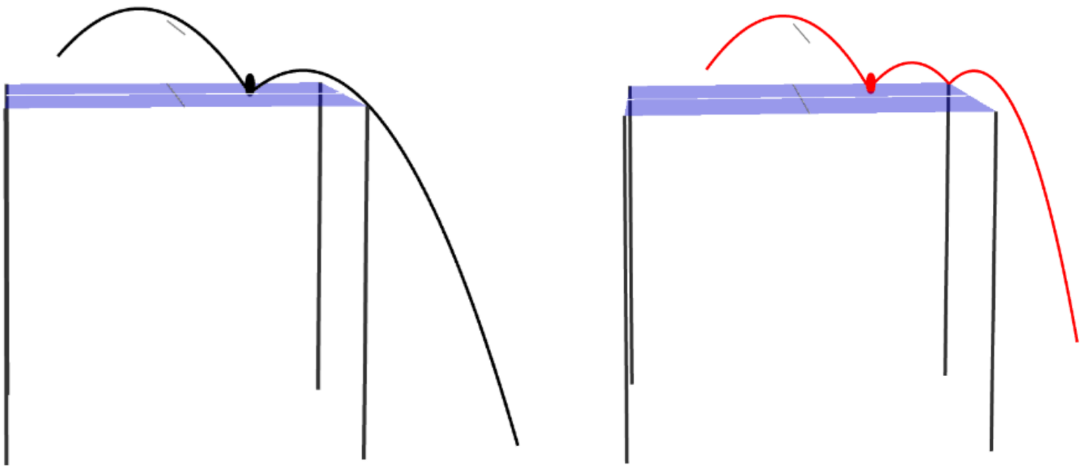


Figure 5.1. – Example of 3D ball trajectories analysis that is a perspective of this work: a virtual extension to the second (theoritical) bounce. (a) Extension of the trajectory of a long serve, the second bounce is on the ground. (b) Extension of the trajectory of a short serve, the second bounce is on the table.

on the table, if not, it occurs on the floor. Figure 5.1 shows an example of how an extended trajectory could distinguish between a short serve and a long serve.

This new approach, which uses an extension of the trajectory to the second bounce, could provide analysis based on 3D data. It could enrich 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. Analyzing 3D trajectories would open up many possibilities for advanced analysis, but this reconstruction is complicated. In particular, since in table tennis players the key is to keep moves hidden from your opponent, capturing such 3D data, both for the ball and the player, is a real challenge.

5.2.2 (Semi) Automation of Data Collection

The increase in data is an essential element for analysis, and was a constant limit in the projects we conducted in this PhD. In order to collect data with interfaces (Section 2.4), we sought to automate certain tasks to speed up the annotation process, thereby enabling data collection on a larger number of matches. 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

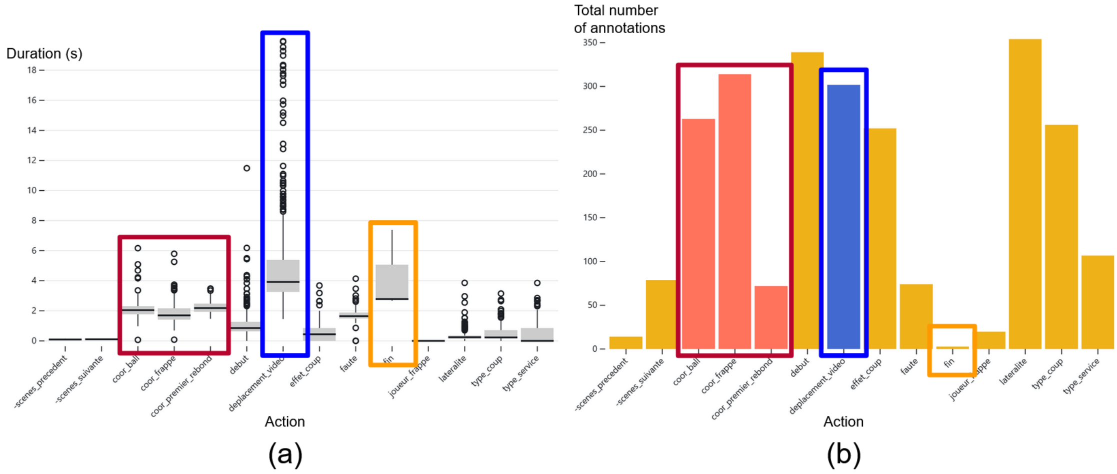


Figure 5.2. – Example of action duration during the annotation of the match between **Alexis Lebrun** and **Hugo Calderano** during the 2024 WTT Champions in Incheon. On the left, a box plot showing duration based on the action performed. On the right, a bar chart shows the number of actions performed. The yellow bars represent annotations made using buttons, the pink bars represent annotations made using the mouse, and the blue bars represent movement within the video.

they evolve over time. It also allows us to study more specific data by filtering the data in greater detail while keeping it representative.

The total automation of data collection is a difficult problem, as we saw in the Section 2. Some parts of the annotation are more likely to be automated as they offer greater time savings than others. To do this, we need to diagnose which annotation steps are time-consuming with our annotation interface. For the DETAILED_ANNOTATION interface, we recorded user annotations in a log file for each annotation that records all actions performed by users, with the time taken to perform these actions. This allows us to observe the annotation time required for each task.

Figure 5.2 (a) illustrates an example of a box plot of annotation times for the match between **Alexis Lebrun** and **Hugo Calderano** in Incheon during the WTT Champions of 2024. We can see that the most time-consuming parts of the annotation are navigating through the video (boxed in blue) and annotating the end (boxed in orange). In Figure 5.2 (b), which shows the total number of each action performed during annotation, we can see that navigating through the video is very important, while end annotation is the least important of all actions. This shows that automating navigation through the video can be defined as a priority in the search for time savings. It should be noted that the duration of the actions is related to the mechanism used. In the end, we did not use a keyboard shortcut but a simple button. Spatial annotations (boxed with a red rectangle) are made using the mouse, are time-consuming, and are also used frequently, as can be seen in Figure 5.2 (b). Other actions apart from fault annotation are performed using keyboard shortcuts and are much faster.

Navigating through videos is characterized by the transition between the end of one rally and the beginning of the next. To reduce this time, two approaches are possible: the first is to segment rallies so that annotation focuses solely on rallies, and the second is to detect the start of rallies, allowing navigation from start to start. Rally segmentation can be done in several ways. As we saw in Section 2.3 with the benchmark we performed, it is possible to develop models for segmentation. These models can be complex and their accuracy is not always sufficient.

As shown in Figure 5.2, spatial annotations also require a significant amount of time. Based on work such as [49], on ball detection, it is possible to automate the annotation of the ball's bounce on the table as well as the annotation of the strike position. Along with the automation of rally start detection, this is one of the important steps in saving time for annotation. Similar to 3D reconstruction, the characteristics of table tennis games make it difficult to fully automate the extraction process, for example to determine the exact point of contact for a serve or assessing certain faults (even some referee decisions, such as whether the ball touched the table or the net, can be debatable).

5.2.3 Real Time Analysis and Visualization

The data collection we discussed is done once the matches are fully recorded. However, table tennis matches are often broadcast live via video streams on platforms such as YouTube. There is therefore an under-explored potential to collect data in real-time. The concept of real-time depends on both the data and the desired accuracy. Certain tracking data, such as ball position, which requires high accuracy to detect bounces to the nearest frame, must have a detection calculation time of less than the temporal resolution (0.04 seconds if 25 frames per second). While other data, such as that characterizing the start and end of rallies, requires detection within 1 second. This is because the ball bounces at a specific moment and its position requires frame-by-frame detection, whereas the start and end of a rally are ambiguous and analyses require less precision.

As we saw in Chapter 2, data collection can be done manually or automatically. In Section 2.4, we presented the fast annotation interface, which allows real-time annotation of the start and end, and the names of the server and winner of the rallies. This annotation is a trade-off between data complexity and annotation speed. As shown in Figure 5.2 in the previous section, some annotations require very little time. Fast annotation takes advantage of this by focusing on simple data that is quick to annotate and requires less than 1 second of precision. Manual real-time annotation is possible for simple data. Using several people to annotate the same match by dividing the tasks has already proven successful [98]. However, table tennis is a fast-paced sport, and even for simple annotation tasks, the high frequency of events can pose a challenge. During the 2023 European Team Championships, we annotated the forehand and backhand for each stroke in all of the French team's matches. The conclusion from these annotations was that the annotators could not annotate more than 4 strokes in the same rally.

To solve this problem, annotation automation is one possible solution. Certain algorithms used for object tracking, such as Yolo [59], or pose estimation with Openpose [14], enable real-time detection. The latest versions of Yolo, notably Yolo 11, enable detection in 0.056 seconds on CPU alone (image size: 640x640) [1]. The use of more powerful hardware, particularly graphics cards, can significantly reduce detection time. With an T4 TensorRT10 [2], detection takes 0.0015 seconds for a 640x640 image. Model optimization is another important aspect and often a matter of trade-offs: larger neural networks generally offer higher accuracy but require longer computation times.

However, although tracking data can be collected in real-time, the main action detection algorithms do not allow for real-time detection. [81] uses the entire video as input for detection, which requires a prior stroke segmentation step. This model can be adapted by using a sliding window of approximately 0.8 seconds, on the video to perform both segmentation and detection tasks [83]. However, this method still requires adaptation and optimization of the model. It was trained on a video containing a single visible person, so to adapt it to a table tennis match, a first step must be taken to select a region where only one player is present in order to apply the model.

Real-time data collection could offer 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. It makes it possible to study tactical developments and effectiveness over the course of the games. 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. New opportunities are also emerging for the general public, especially in enabling real-time commentary and analysis of matches, beyond only focusing on advanced tactical analysis.

1. https://docs.ultralytics.com/fr/models/yolo11/#performance-metrics
2. https://www.nvidia.com/fr-fr/data-center/tesla-t4/

APPENDIX A

APPENDIX

A.1 Rules of Table 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 player has won 3 games (or 2 games in some competitions), 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 at least 15cm, the ball must be visible to the opponent at all times. 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 $\rightarrow$ Player 1 Team 2 x2 $\rightarrow$ Player 2 Team 1 x2 $\rightarrow$ 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 A.1 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 rubber must be no more than 4mm thick.

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

1. https://cornilleau.com/

A.2 Glossary

- **Decider**: deciding game when both players have the same score in terms of games won.
- **Fault**: event that marks the end of a rally and awards the point to one of the players.
- **FFTT**: Fédération Française de Tennis de Table
- **Flip**: type of stroke, an attack on a short ball.
- **ITTF**: International Table Tennis Federation
- **Long Ball**: ball that must bounce only 1 time on the table before leaving the boundaries of the table.
- **Opening**: type of first strokes used in a rally.
- **Push**: type of stroke, a defense resulting in a backspin.
- **Rally**: succession of strokes starting with a serve and ending with a fault.
- **Return**: first stroke after the serve.
- **Serve**: first stroke of a rally.
- **Short Ball**: ball that must bounce at least 2 times on the table before leaving the boundaries of the table.
- **Stroke**: action performed by a player to hit the ball. It has various attributes, such as stroke type and bounce position.
- **Stroke Placement**: position of the ball's bounce after a player's hit (position in centimeters).
- **Stroke Position**: player's position when striking the ball (forehand or backhand).
- **Stroke Technique**: refers to the technique used by the player (such as serve, topspin, push, etc.).
- **Tactics**: succession of strokes (often 3) that are thought out and chosen by the players in the hope of winning rallies. Tactics can be losing if the number of occurrences belonging to losing rallies is greater than the number of occurrences belonging to winning rallies and winning otherwise.
- **Topspin**: type of stroke, an attack on a long ball.

- **WTT**: World Table Tennis

BIBLIOGRAPHY

[1] Jules Allegre and Romain Vuillemot. "Visualizing and Analyzing Disputed Areas in Soccer". en. In: *2020 Visualization in Data Science (VDS)*. Salt Lake City, UT, USA: IEEE, Oct. 2020, pp. 52–60. URL: https://ieeexplore.ieee.org/document/9355217/ (visited on 01/06/2025) (cit. on pp. 110, 113, 117).

[2] Gennady Andrienko, Natalia Andrienko, Gabriel Anzer, Pascal Bauer, Guido Budziak, Georg Fuchs, Dirk Hecker, Hendrik Weber, and Stefan Wrobel. "Constructing Spaces and Times for Tactical Analysis in Football". In: *IEEE Transactions on Visualization and Computer Graphics* 27.4 (Apr. 2021). Conference Name: IEEE Transactions on Visualization and Computer Graphics, pp. 2280–2297. URL: https://ieeexplore.ieee.org/document/8894420 (visited on 11/22/2023) (cit. on pp. 110, 113).

[3] Gennady Andrienko, Natalia Andrienko, Guido Budziak, Jason Dykes, Georg Fuchs, Tatiana Von Landesberger, and Hendrik Weber. "Visual analysis of pressure in football". en. In: *Data Mining and Knowledge Discovery* 31.6 (Nov. 2017), pp. 1793–1839. (Visited on 06/12/2023) (cit. on pp. 62, 96).

[4] Attitude Ping. *Ma Long vs Fan Zhendong FINAL 2023 Asian Games [analyse de match]*. Sept. 2023. URL: https://www.youtube.com/watch?v=L4GcbAn6ttc (visited on 11/30/2023) (cit. on p. 100).

[5] Riad Attou, Marin Mathé, Aymeric Eradès, and Romain Vuillemot. "Analysis of Service Returns in Table Tennis". en. In: *Machine Learning and Data Mining for Sports Analytics*. Porto, Portugal, Sept. 2025 (cit. on pp. 19, 52, 80, 126).

[6] V. Barnett and S. Hilditch. "The Effect of an Artificial Pitch Surface on Home Team Performance in Football (Soccer)". en. In: *Journal of the Royal Statistical Society. Series A (Statistics in Society)* 156.1 (1993), p. 39. URL: https://www.jstor.org/stable/2982859?origin=crossref (visited on 08/17/2025) (cit. on pp. 53, 55).

[7] Swarup Ranjan Behera and Vijaya V. Saradhi. *Cricket Player Profiling: Unraveling Strengths and Weaknesses Using Text Commentary Data*. en. arXiv:2311.06818 [cs]. Nov. 2023. URL: http://arxiv.org/abs/2311.06818 (visited on 08/17/2025) (cit. on p. 53).

[8] Alina Bialkowski, Patrick Lucey, Peter Carr, Yisong Yue, Sridha Sridharan, and Iain Matthews. "Identifying Team Style in Soccer Using Formations Learned from Spatiotemporal Tracking Data". en. In: *2014 IEEE International Conference on Data Mining Workshop*. Shenzhen, China: IEEE, Dec. 2014,

pp. 9–14. URL: http://ieeexplore.ieee.org/document/7022571/ (visited on 08/17/2025) (cit. on pp. 54, 55).

[9] Jiang Bian, Xuhong Li, Tao Wang, Qingzhong Wang, Jun Huang, Chen Liu, Jun Zhao, Feixiang Lu, Dejing Dou, and Haoyi Xiong. *P2ANet: A Dataset and Benchmark for Dense Action Detection from Table Tennis Match Broadcasting Videos*. en. arXiv:2207.12730 [cs]. Mar. 2024. URL: http://arxiv.org/abs/2207.12730 (visited on 09/11/2025) (cit. on p. 24).

[10] M. Bostock, V. Ogievetsky, and J. Heer. "D3; Data-Driven Documents". In: *IEEE Transactions on Visualization and Computer Graphics* 17.12 (Dec. 2011), pp. 2301–2309 (cit. on p. 103).

[11] Nathalie Bressa, Henrik Korsgaard, Aurelien Tabard, Steven Houben, and Jo Vermeulen. "What's the Situation with Situated Visualization? A Survey and Perspectives on Situatedness". en. In: *IEEE Transactions on Visualization and Computer Graphics* 28.1 (Jan. 2022), pp. 107–117. URL: https://ieeexplore.ieee.org/document/9552238/ (visited on 10/01/2025) (cit. on pp. 89, 122).

[12] Jordan Calandre, Renaud Peteri, Laurent Mascarilla, and Benoit Tremblais. "Extraction and analysis of 3D kinematic parameters of Table Tennis ball from a single camera". en. In: *2020 25th International Conference on Pattern Recognition (ICPR)*. Milan, Italy: IEEE, Jan. 2021, pp. 9468–9475. URL: https://ieeexplore.ieee.org/document/9412391/ (visited on 05/09/2023) (cit. on pp. 73, 128).

[13] 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: https://hal.science/hal-04240982 (cit. on pp. 19, 51, 72, 73, 77, 117, 126).

[14] Zhe Cao, Gines Hidalgo, Tomas Simon, Shih-En Wei, and Yaser Sheikh. "OpenPose: Realtime Multi-Person 2D Pose Estimation Using Part Affinity Fields". In: *IEEE Transactions on Pattern Analysis and Machine Intelligence* 43.1 (Jan. 2021), pp. 172–186. URL: https://doi.org/10.1109/TPAMI.2019.2929257 (visited on 11/23/2023) (cit. on pp. 24, 29, 32, 37, 39, 132).

[15] Dan Cervone, Alexander D'Amour, Luke Bornn, and Kirk Goldsberry. "POINTWISE: Predicting Points and Valuing Decisions in Real Time with NBA Optical Tracking Data". en. In: *MIT Sloan Sports Analytics Conference* (2014) (cit. on p. 55).

[16] Tom Chandler, Maxime Cordeil, Tobias Czauderna, Tim Dwyer, Jaroslaw Glowacki, Cagatay Goncu, Matthias Klapperstueck, Karsten Klein, Kim Marriott, Falk Schreiber, and Elliot Wilson. "Immersive Analytics". en. In: *2015 Big Data Visual Analytics (BDVA)*. Hobart, Australia: IEEE, Sept. 2015, pp. 1–8. URL: https://ieeexplore.ieee.org/document/7314296 (visited on 10/06/2025) (cit. on p. 94).

[17] Wei-Ting Chen, Hsiang-Yun Wu, Yun-An Shih, Chih-Chuan Wang, and Yu-Shuen Wang. "Exploration of Player Behaviors from Broadcast Badminton Videos". en. In: *Computer Graphics Forum* (2023) (cit. on p. 23).

[18] Zhutian Chen, Qisen Yang, Xiao Xie, Johanna Beyer, Haijun Xia, Yingcai Wu, and Hanspeter Pfister. *Sporthesia: Augmenting Sports Videos Using Natural Language*. en. Tech. rep. arXiv:2209.03434. arXiv:2209.03434 [cs] type: article. arXiv, Sept. 2022. URL: http://arxiv.org/abs/2209.03434 (visited on 11/28/2022) (cit. on pp. 93, 94).

[19] Zhutian Chen, Shuainan Ye, Xiangtong Chu, Haijun Xia, Hui Zhang, Huamin Qu, and Yingcai Wu. "Augmenting Sports Videos with VisCommentator". en. In: *IEEE Transactions on Visualization and Computer Graphics* 28.1 (Jan. 2022), pp. 824–834. URL: https://ieeexplore.ieee.org/document/9552848/ (visited on 11/28/2022) (cit. on pp. 54, 93, 94, 97, 116).

[20] Wei-Ta Chu and Samuel Situmeang. "Badminton Video Analysis based on Spatiotemporal and Stroke Features". en. In: *Proceedings of the 2017 ACM on International Conference on Multimedia Retrieval*. Bucharest Romania: ACM, June 2017, pp. 448–451. URL: https://dl.acm.org/doi/10.1145/3078971.3079032 (visited on 08/07/2025) (cit. on pp. 24, 25).

[21] Xiangtong Chu, Xiao Xie, Shuainan Ye, Haolin Lu, Hongguang Xiao, Zeqing Yuan, Zhutian Chen, Hui Zhang, and Yingcai Wu. "TIVEE: Visual Exploration and Explanation of Badminton Tactics in Immersive Visualizations". In: *IEEE Transactions on Visualization and Computer Graphics* 28.1 (Jan. 2022). Conference Name: IEEE Transactions on Visualization and Computer Graphics, pp. 118–128. URL: https://ieeexplore.ieee.org/document/9557225 (visited on 11/26/2023) (cit. on pp. 73, 95–97).

[22] Tom Decroos and Jesse Davis. "Player Vectors: Characterizing Soccer Players' Playing Style from Match Event Streams". en. In: *Machine Learning and Knowledge Discovery in Databases*. Ed. by Ulf Brefeld, Elisa Fromont, Andreas Hotho, Arno Knobbe, Marloes Maathuis, and Céline Robardet. Vol. 11908. Series Title: Lecture Notes in Computer Science. Cham: Springer International Publishing, 2020, pp. 569–584. URL: https://link.springer.com/10.1007/978-3-030-46133-1_34 (visited on 08/17/2025) (cit. on p. 55).

[23] Damien Demaj. "Geovisualizing spatio-temporal patterns in tennis: An alternative approach to post-match analysis". en. In: *International Cartographic Conference* (2013) (cit. on p. 53).

[24] Dazhen Deng, Jiang Wu, Jiachen Wang, Yihong Wu, Xiao Xie, Zheng Zhou, Hui Zhang, Xiaolong (Luke) Zhang, and Yingcai Wu. "EventAnchor: Reducing Human Interactions in Event Annotation of Racket Sports Videos". In: *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. CHI '21. New York, NY, USA: Association for Computing Machinery, May 2021, pp. 1–13. URL: https://doi.org/10.1145/3411764.3445431 (visited on 05/23/2023) (cit. on pp. 25, 37, 54).

[25] Madelyn Dickinson. "X-Rays Vision: Finding Success Through Sabermetrics in Major League Baseball". en. In: *Johnson & Wales University - Providence* (2023) (cit. on p. 52).

[26] Carlos Dietrich, David Koop, Huy T. Vo, and Cláudio T. Silva. "Baseball4D: A tool for baseball game reconstruction & visualization". In: *2014 IEEE Conference on Visual Analytics Science and Technology (VAST)*. Oct. 2014, pp. 23–32. URL: https://ieeexplore.ieee.org/document/7042478 (visited on 10/20/2023) (cit. on p. 96).

[27] Ning Ding, Kazuya Takeda, and Keisuke Fujii. "Deep Reinforcement Learning in a Racket Sport for Player Evaluation With Technical and Tactical Contexts". en. In: *IEEE Access* 10 (2022), pp. 54764–54772. URL: https://ieeexplore.ieee.org/document/9775086/ (visited on 08/17/2025) (cit. on p. 54).

[28] Ning Ding, Kazuya Takeda, Wenhui Jin, Yingjiu Bei, and Keisuke Fujii. "Estimation of control area in badminton doubles with pose information from top and back view drone videos". en. In: *Multimedia Tools and Applications* 83.8 (Mar. 2024), pp. 24777–24793. URL: https://doi.org/10.1007/s11042-023-16362-1 (visited on 05/04/2024) (cit. on pp. 110, 113).

[29] Stella Dion, Gabriel Walker, Kelly Lambert, Anita Stefoska-Needham, and Joel C. Craddock. "The Diet Quality of Athletes as Measured by Diet Quality Indices: A Scoping Review". en. In: *Nutrients* 17.1 (Dec. 2024), p. 89. URL: https://www.mdpi.com/2072-6643/17/1/89 (visited on 09/23/2025) (cit. on p. 2).

[30] Pengcheng Dong, Hongxin Xie, Fuqiang Zheng, and Jiande Sun. "Two-Stream Network and Attention Mechanism for Sports Video Classification in Table tennis". en. In: *MediaEval 2023* (2023) (cit. on p. 35).

[31] Pierre Duluard, Xinqing Li, Marc Plantevit, Céline Robardet, and Romain Vuillemot. "Discovering and Visualizing Tactics in a Table Tennis Game Based on Subgroup Discovery". In: *Machine Learning and Data Mining for Sports Analytics*. Ed. by Ulf Brefeld, Jesse Davis, Jan Van Haaren, and

Albrecht Zimmermann. Vol. 1783. Cham: Springer Nature Switzerland, 2023, pp. 101–112. URL: https://link.springer.com/10.1007/978-3-031-27527-2_8 (visited on 05/16/2023) (cit. on pp. 2, 36, 57, 59, 67, 72, 119, 127).

[32] 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) (cit. on pp. 19, 41, 125).

[33] Aymeric Erades, Thomas Papon, and Romain Vuillemot. "Characterizing Serves in Table Tennis". In: *11th Workshop on Machine Learning and Data Mining for Sports Analytics*. Communications in Computer and Information Science book series (Sept. 2024) (cit. on pp. 19, 51, 126).

[34] Aymeric Erades, Lou Peuch, and Romain Vuillemot. "Investigating Control Areas in Table Tennis". In: *Sixteenth International EuroVis Workshop on Visual Analytics (EuroVA)*. Luxembourg, June 2025. URL: https://hal.science/hal-05032405 (cit. on pp. 19, 89, 127).

[35] Aymeric Erades, Martin Pierre-Etienne, Romain Vuillemot, and Stefan Duffner. "Fine Grained Action Classification and Position of Table Tennis and Swimming Videos for MediaEval 2023". In: *MediaEval Workshop 2023*. MediaEval (Multimedia Evaluation Benchmark) (2023) (cit. on p. 22).

[36] Aymeric Erades, Anais Servais, Christophe Hurter, and Romain Vuillemot. "Un design space de vidéos augmentées de matches de tennis de table". In: Journée Visu. June 2024. URL: https://hal.science/hal-04617611 (cit. on p. 94).

[37] Aymeric Erades and Romain Vuillemot. "How Camera Angle Impact Table Tennis Ball Bounce Tracking". en. In: *Sports Phsyics 2025*. Rennes, France, Sept. 2025 (cit. on pp. 19, 126).

[38] Aymeric Erades and Romain Vuillemot. "Player-Centric Shot Maps in Table Tennis". In: *Computer graphics Forum (Proc. Eurovis)* (June 2025), p. 10. URL: https://hal.science/hal-04997867 (cit. on pp. 19, 41, 89, 116, 127).

[39] Aymeric Erades and Romain Vuillemot. "Visual Analysis of Table Tennis Game Tactics". In: Journée Visu. June 2023. URL: https://hal.science/hal-04241005 (cit. on p. 89).

[40] João Marcelo Evangelista Belo, Anna Maria Feit, Tiare Feuchtner, and Kaj Grønbæk. "XRgonomics: Facilitating the Creation of Ergonomic 3D Interfaces". In: *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. CHI '21. event-place: Yokohama, Japan. New York, NY, USA: Association for Computing Machinery, 2021. URL: https://doi.org/10.1145/3411764.3445349 (cit. on p. 117).

[41] Hao-Shu Fang, Jiefeng Li, Hongyang Tang, Chao Xu, Haoyi Zhu, Yuliang Xiu, Yong-Lu Li, and Cewu Lu. *AlphaPose: Whole-Body Regional Multi-Person Pose Estimation and Tracking in Real-Time*. en. arXiv:2211.03375 [cs]. Nov. 2022. URL: http://arxiv.org/abs/2211.03375 (visited on 08/08/2025) (cit. on pp. 29, 54).

[42] Anna Fariha, Chowdhury Farhan Ahmed, Carson Kai-Sang Leung, S. M. Abdullah, and Longbing Cao. "Mining Frequent Patterns from Human Interactions in Meetings Using Directed Acyclic Graphs". en. In: *Advances in Knowledge Discovery and Data Mining*. Ed. by David Hutchison, Takeo Kanade, Josef Kittler, Jon M. Kleinberg, Friedemann Mattern, John C. Mitchell, Moni Naor, Oscar Nierstrasz, C. Pandu Rangan, Bernhard Steffen, Madhu Sudan, Demetri Terzopoulos, Doug Tygar, Moshe Y. Vardi, Gerhard Weikum, Jian Pei, Vincent S. Tseng, Longbing Cao, Hiroshi Motoda, and Guandong Xu. Vol. 7818. Series Title: Lecture Notes in Computer Science. Berlin, Heidelberg: Springer Berlin Heidelberg, 2013, pp. 38–49. URL: https://link.springer.com/10.1007/978-3-642-37453-1_4 (visited on 08/18/2025) (cit. on p. 57).

[43] Alexander Franks, Andrew Miller, Luke Bornn, and Kirk Goldsberry. "Characterizing the spatial structure of defensive skill in professional basketball". en. In: *The Annals of Applied Statistics* 9.1 (Mar. 2015). arXiv:1405.0231 [stat]. URL: http://arxiv.org/abs/1405.0231 (visited on 08/17/2025) (cit. on p. 55).

[44] Bruno Fruchard, Cécile Avezou, Sylvain Malacria, Géry Casiez, and Stéphane Huot. "A Case Study on the Design and Use of an Annotation and Analytical Tool Tailored To Lead Climbing". en. In: *Extended Abstracts of the 2023 CHI Conference on Human Factors in Computing Systems*. Hamburg Germany: ACM, Apr. 2023, pp. 1–8. URL: https://dl.acm.org/doi/10.1145/3544549.3573876 (visited on 05/16/2024) (cit. on p. 36).

[45] Michael Gleicher, Danielle Albers, Rick Walker, Ilir Jusufi, Charles D. Hansen, and Jonathan C. Roberts. "Visual comparison for information visualization". In: *Information Visualization* 10.4 (2011), pp. 289–309. URL: http://ivi.sagepub.com/content/10/4/289.short (visited on 02/19/2015) (cit. on p. 102).

[46] Marco Godi, Paolo Rota, and Francesco Setti. *Indirect Match Highlights Detection with Deep Convolutional Neural Networks*. en. arXiv:1710.00568 [cs]. Oct. 2017. URL: http://arxiv.org/abs/1710.00568 (visited on 09/08/2025) (cit. on p. 23).

[47] Kirk Goldsberry. "Courtvision: New visual and spatial analytics for the nba". In: *2012 MIT Sloan sports analytics conference*. Vol. 9. 2012, pp. 12–15 (cit. on p. 96).

[48] Sebastian Gomez-Gonzalez, Yassine Nemmour, Bernhard Schölkopf, and Jan Peters. "Reliable Real Time Ball Tracking for Robot Table Tennis". en. In: *Robotics* 8.4 (Oct. 2019). arXiv:1908.07332 [cs], p. 90. URL: http://arxiv.org/abs/1908.07332 (visited on 12/12/2022) (cit. on p. 27).

[49] Thomas Gossard, Filip Radovic, Andreas Ziegler, and Andrea Zell. *Blur-Ball: Joint Ball and Motion Blur Estimation for Table Tennis Ball Tracking*. en. arXiv:2509.18387 [cs]. Sept. 2025. URL: http://arxiv.org/abs/2509.18387 (visited on 09/25/2025) (cit. on pp. 28, 131).

[50] Thomas Gossard, Andreas Ziegler, and Andreas Zell. "TT3D: Table Tennis 3D Reconstruction". en. In: *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) Workshops*. arXiv:2504.10035 [cs]. arXiv, June 2025. URL: http://arxiv.org/abs/2504.10035 (visited on 05/12/2025) (cit. on p. 128).

[51] Sam Green. "Assessing the performance of premier leauge goalscorers". In: *OptaPro Blog* (2012) (cit. on p. 65).

[52] Peter D. Grünwald. *The minimum description length principle*. en. Adaptive computation and machine learning series. Cambridge, Massachusetts: MIT Press, 2007 (cit. on p. 59).

[53] Fabiola Haas, Tobias Baumgartner, Timo Klein-Soetebier, Florian Seifriz, and Stefanie Klatt. "Heatmap Analysis to Differentiate Diverse Player Types in Table Tennis A Training and Tactical Strategy Development Potential". In: *MDPI* (2023) (cit. on pp. 55–57).

[54] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. *Deep Residual Learning for Image Recognition*. en. arXiv:1512.03385 [cs]. Dec. 2015. URL: http://arxiv.org/abs/1512.03385 (visited on 09/07/2025) (cit. on p. 23).

[55] Lewis Higgins, Tobias Galla, Brian Prestidge, and Terry Wyatt. "Measuring the pitch control of professional football players using spatiotemporal tracking data". en. In: *Journal of Physics: Complexity* 4.2 (May 2023). Publisher: IOP Publishing, p. 025008. URL: https://dx.doi.org/10.1088/2632-072X/acb67d (visited on 02/17/2025) (cit. on p. 110).

[56] Sepp Hochreiter and Jürgen Schmidhuber. "Long Short-Term Memory". en. In: *Neural Computation* 9.8 (Nov. 1997), pp. 1735–1780. URL: https://direct.mit.edu/neco/article/9/8/1735-1780/6109 (visited on 08/17/2025) (cit. on p. 35).

[57] Larry Hodges. *Table Tennis Tactics for Thinkers*. English. Leipzig: CreateSpace Independent Publishing Platform, Feb. 2013 (cit. on pp. 69, 78, 97, 100).

[58] Yu-Chuan Huang, I.-No Liao, Ching-Hsuan Chen, Tsì-Uí İk, and Wen-Chih Peng. *TrackNet: A Deep Learning Network for Tracking High-speed and Tiny Objects in Sports Applications*. en. arXiv:1907.03698 [cs]. July 2019. URL: http://arxiv.org/abs/1907.03698 (visited on 05/12/2025) (cit. on pp. 27, 28, 35, 37, 54).

[59] Muhammad Hussain. *YOLOv5, YOLOv8 and YOLOv10: The Go-To Detectors for Real-time Vision*. en. arXiv:2407.02988 [cs]. July 2024. URL: http://arxiv.org/abs/2407.02988 (visited on 08/07/2025) (cit. on pp. 24, 132).

[60] Nicolas Jacquelin. "Automatic Analysis of Elite Swimming Race Videos". These de doctorat. Ecully, Ecole centrale de Lyon, Dec. 2022. URL: https://www.theses.fr/2022ECDL0017 (visited on 11/02/2023) (cit. on p. 31).

[61] Nicolas Jacquelin, Theo Jaunet, Romain Vuillemot, and Stefan Duffner. *SwimTrack: Swimmers and Stroke Rate Detection in Elite Race Videos*. Jan. 2023. URL: https://hal.science/hal-03936053 (cit. on p. 31).

[62] Bhuvana Jayaraman, Mirnalinee Tt, Harshida Sujatha Palaniraj, Mohith Adluru, and Sanjjit Sounderrajan. "Automated Recognition of Sports Scores using PyTessaract OCR and CNN: SportsVideo Task at MediaEval 2023". en. In: *MediaEval* (2023) (cit. on p. 35).

[63] Liqun Jin and David C Banks. "Visualizing a tennis match". In: *Proceedings IEEE Symposium on Information Visualization'96*. IEEE, 1996, pp. 108–114 (cit. on p. 97).

[64] Stuart T Kard, Jock D Mackinlay, and Ben Scheiderman. "Readings in Information Visualization, Using vision to think". en. In: *Morgan Kaufmann Publishers Inc* (1999) (cit. on p. 90).

[65] Eiji Konaka. *Park factor estimation improvement using pairwise comparison method*. en. arXiv:2109.09287 [stat]. Sept. 2021. URL: http://arxiv.org/abs/2109.09287 (visited on 09/11/2025) (cit. on p. 56).

[66] Md. Kowsher, M Ashraful Alam, Md. Jashim Uddin, Faisal Ahmed, Md Wali Ullah, and Md. Rafiqul Islam. "Detecting Third Umpire Decisions & Automated Scoring System of Cricket". en. In: *2019 International Conference on Computer, Communication, Chemical, Materials and Electronic Engineering (IC4ME2)*. Rajshahi, Bangladesh: IEEE, July 2019, pp. 1–8. URL: https://ieeexplore.ieee.org/document/9036705/ (visited on 08/07/2025) (cit. on p. 28).

[67] Ji Lan, Jiachen Wang, Xinhuan Shu, Zheng Zhou, Hui Zhang, and Yingcai Wu. "RallyComparator: visual comparison of the multivariate and spatial stroke sequence in table tennis rally". en. In: *Journal of Visualization* 25.1 (Feb. 2022), pp. 143–158. URL: https://doi.org/10.1007/s12650-021-00772-0 (visited on 11/21/2023) (cit. on pp. 91, 97).

[68] Weiqiang Li. "Tactical Analysis of Table Tennis Video Skills Based on Image Fuzzy Edge Recognition Algorithm". en. In: *IEEE Access* 12 (2024), pp. 40425–40438. URL: https://ieeexplore.ieee.org/document/10471521/ (visited on 08/07/2025) (cit. on p. 28).

[69] Tica Lin, Alexandre Aouididi, Zhutian Chen, Johanna Beyer, Hanspeter Pfister, and Jui-Hsien Wang. *VIRD: Immersive Match Video Analysis for High-Performance Badminton Coaching*. arXiv:2307.12539 [cs]. Aug. 2023. URL: http://arxiv.org/abs/2307.12539 (visited on 11/28/2023) (cit. on pp. 95, 96).

[70] Tica Lin, Zhutian Chen, Yalong Yang, Daniele Chiappalupi, Johanna Beyer, and Hanspeter Pfister. "The Quest for: Embedded Visualization for Augmenting Basketball Game Viewing Experiences". English. In: *IEEE Transactions on Visualization and Computer Graphics* 29.01 (Jan. 2023). Publisher: IEEE Computer Society, pp. 962–971. URL: https://www.computer.org/csdl/journal/tg/2023/01/09903338/1GZojZ9otHO (visited on 05/22/2023) (cit. on pp. 95, 96).

[71] Tica Lin, Ruxun Xiang, Gardenia Liu, Divyanshu Tiwari, Meng-Chia Chiang, Chenjiayi Ye, Hanspeter Pfister, and Chen Zhu-Tian. *SportsBuddy: Designing and Evaluating an AI-Powered Sports Video Storytelling Tool Through Real-World Deployment*. en. arXiv:2502.08621 [cs]. Feb. 2025. URL: http://arxiv.org/abs/2502.08621 (visited on 10/03/2025) (cit. on p. 122).

[72] Tica Lin, Yalong Yang, Johanna Beyer, and Hanspeter Pfister. "SportsXR - Immersive Analytics in Sports". In: *CoRR* abs/2004.08010 (2020). arXiv: 2004.08010. URL: https://arxiv.org/abs/2004.08010 (cit. on pp. 99, 104).

[73] Xuebo Liu, Ding Liang, Shi Yan, Dagui Chen, Yu Qiao, and Junjie Yan. *FOTS: Fast Oriented Text Spotting with a Unified Network*. en. arXiv:1801.01671 [cs]. Jan. 2018. URL: http://arxiv.org/abs/1801.01671 (visited on 09/28/2025) (cit. on p. 37).

[74] S. Lloyd. "Least squares quantization in PCM". en. In: *IEEE Transactions on Information Theory* 28.2 (Mar. 1982), pp. 129–137. URL: https://ieeexplore.ieee.org/document/1056489/ (visited on 08/18/2025) (cit. on pp. 55, 74).

[75] Diogo C. Luvizon, David Picard, and Hedi Tabia. *2D/3D Pose Estimation and Action Recognition using Multitask Deep Learning*. en. arXiv:1802.09232 [cs]. Mar. 2018. URL: http://arxiv.org/abs/1802.09232 (visited on 08/08/2025) (cit. on p. 30).

[76] Eric Marchand, Hideaki Uchiyama, and Fabien Spindler. "Pose estimation for augmented reality: a hands-on survey". In: *IEEE transactions on visualization and computer graphics* 22.12 (2015). Publisher: IEEE, pp. 2633–2651 (cit. on p. 38).

[77] Andreï Markov. "Extension of the limit theorems of probability theory to a sum of variables connected in a chain". In: *Chain, Izvestiya Fiziko-Matematicheskogo Obshchestva pri Kazanskom Universitete, 2nd series, vol. 15, pp. 135–156* (1906) (cit. on p. 58).

[78] Pierre-Etienne Martin. "Baseline Method for the Sport Task of MediaEval 2022 with 3D CNNs using Attention Mechanism". In: *Working Notes Proceedings of the MediaEval 2022 Workshop, Bergen, Norway and Online, 12-13 January 2023*. 2022. URL: https://ceur-ws.org/Vol-3583/paper19.pdf (cit. on p. 31).

[79] Pierre-Etienne Martin. "Baseline Method for the Sport Task of MediaEval 2023 using 3D CNNs with Attention Mechanisms for Table Tennis Stoke Detection and Classification." en. In: *MediaEval* (2023) (cit. on pp. 31, 35).

[80] Pierre-Etienne Martin. "Fine-grained action detection and classification from videos with spatio-temporal convolutional neural networks : Application to Table Tennis." Theses. Université de Bordeaux, Dec. 2020. URL: https://theses.hal.science/tel-03128769 (cit. on p. 31).

[81] Pierre-Etienne Martin, Jenny Benois-Pineau, Renaud Peteri, and Julien Morlier. "3D attention mechanism for fine-grained classification of table tennis strokes using a Twin Spatio-Temporal Convolutional Neural Networks". en. In: *2020 25th International Conference on Pattern Recognition (ICPR)*. Milan, Italy: IEEE, Jan. 2021, pp. 6019–6026. URL: https://ieeexplore.ieee.org/document/9412742/ (visited on 06/13/2023) (cit. on p. 132).

[82] Pierre-Etienne Martin, Jenny Benois-Pineau, Renaud Peteri, and Julien Morlier. "Sport Action Recognition with Siamese Spatio-Temporal CNNs: Application to Table Tennis". en. In: *2018 International Conference on Content-Based Multimedia Indexing (CBMI)*. La Rochelle: IEEE, Sept. 2018, pp. 1–6. URL: https://ieeexplore.ieee.org/document/8516488/ (visited on 08/07/2025) (cit. on pp. 29, 30).

[83] Pierre-Etienne Martin, Jenny Benois-Pineau, Renaud Péteri, and Julien Morlier. "Three-Stream 3D/1D CNN for Fine-Grained Action Classification and Segmentation in Table Tennis". en. In: *Proceedings of the 4th International Workshop on Multimedia Content Analysis in Sports*. arXiv:2109.14306 [cs]. Oct. 2021, pp. 35–41. URL: http://arxiv.org/abs/2109.14306 (visited on 03/15/2024) (cit. on pp. 30, 132).

[84] Pierre-Etienne Martin, Jordan Calandre, Boris Mansencal, Jenny Benois-Pineau, Renaud Péteri, Laurent Mascarilla, and Julien Morlier. *Sports Video: Fine-Grained Action Detection and Classification of Table Tennis Strokes from Videos for MediaEval 2021*. en. arXiv:2112.11384 [cs]. Dec. 2021. URL: http://arxiv.org/abs/2112.11384 (visited on 05/02/2023) (cit. on p. 23).

[85] Leland McInnes and John Healy. "Accelerated hierarchical density based clustering". In: *2017 IEEE international conference on data mining workshops (ICDMW)*. IEEE, 2017, pp. 33–42 (cit. on p. 74).

[86] James Mead, Anthony O'Hare, and Paul McMenemy. "Expected goals in football: Improving model performance and demonstrating value". In: *PloS one* 18 (Apr. 2023), e0282295 (cit. on pp. 62, 65).

[87] Christopher Moretti. "Analyzing a Tennis Game with Markov Chains". 2015 (cit. on p. 58).

[88] Alexis Mortelier, François Rioult, and John Komar. "What Data Should Be Collected for a Good Handball Expected Goal model?" en. In: *Machine Learning and Data Mining for Sports Analytics*. Ed. by Ulf Brefeld, Jesse Davis, Jan Van Haaren, and Albrecht Zimmermann. Vol. 2035. Series Title: Communications in Computer and Information Science. Cham: Springer Nature Switzerland, 2024, pp. 119–130. URL: https://link.springer.com/10.1007/978-3-031-53833-9_10 (visited on 08/17/2025) (cit. on p. 54).

[89] Tamara Munzner. "A Nested Model for Visualization Design and Validation". en. In: *IEEE Transactions on Visualization and Computer Graphics* 15.6 (Nov. 2009), pp. 921–928. URL: http://ieeexplore.ieee.org/document/5290695/ (visited on 10/06/2025) (cit. on p. 123).

[90] Hnin Myint, Patrick Wong, Laurence Dooley, and Adrian Hopgood. "Tracking a table tennis ball for umpiring purposes". en. In: *2015 14th IAPR International Conference on Machine Vision Applications (MVA)*. Tokyo, Japan: IEEE, May 2015, pp. 170–173. URL: http://ieeexplore.ieee.org/document/7153160/ (visited on 12/12/2022) (cit. on pp. 26, 128).

[91] Hnin Myint, Patrick Wong, Laurence Dooley, and Adrian Hopgood. "Tracking a Table Tennis Ball for Umpiring Purposes Using a Multi-Agent System". en. In: *International Conference on Image Processing, Computer Vision & Pattern Recognition (IPCV 2016)* (2016) (cit. on pp. 26, 27).

[92] Hiroshi Nakahara, Kazuya Takeda, and Keisuke Fujii. *Pitching strategy evaluation via stratified analysis using propensity score*. en. arXiv:2208.03492 [stat]. Aug. 2022. URL: http://arxiv.org/abs/2208.03492 (visited on 10/03/2025) (cit. on p. 53).

[93] ObservableHQ. *Plot: Density Marks*. 2025 (cit. on p. 103).

[94] OpenCV. *OpenCV: Open Source Computer Vision Library*. 2025 (cit. on p. 103).

[95] Antonio Tejero-de Pablos, Yuta Nakashima, Tomokazu Sato, Naokazu Yokoya, Marko Linna, and Esa Rahtu. *Summarization of User-Generated Sports Video by Using Deep Action Recognition Features*. en. arXiv:1709.08421 [cs]. Apr. 2018. URL: http://arxiv.org/abs/1709.08421 (visited on 09/08/2025) (cit. on p. 23).

[96] C. Perin, R. Vuillemot, and J.-D. Fekete. "SoccerStories: A Kick-off for Visual Soccer Analysis". In: *IEEE Transactions on Visualization and Computer Graphics* 19.12 (Dec. 2013), pp. 2506–2515 (cit. on pp. 96, 119).

[97] C. Perin, R. Vuillemot, C. D. Stolper, J. T. Stasko, J. Wood, and S. Carpendale. "State of the Art of Sports Data Visualization". en. In: *Computer Graphics Forum (EuroVis'18)*. Computer Graphics Forum (EuroVis'18) 37.3 (2018), pp. 663–686. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/cgf.13447 (visited on 03/06/2019) (cit. on pp. 9, 52, 89, 96, 113).

[98] Charles Perin, Romain Vuillemot, and Jean-Daniel Fekete. "Real-Time Crowdsourcing of Detailed Soccer Data". en. In: *1st Workshop on Sports Data Visualization IEEE VIS* (2013) (cit. on pp. 36, 131).

[99] Mark Pfeiffer, Hui Zhang, and Andreas Hohmann. "A Markov Chain Model of Elite Table Tennis Competition". In: *International Journal of Sports Science & Coaching* 5 (June 2010), pp. 204–222 (cit. on p. 58).

[100] Jorge Piazentin Ono, Arvi Gjoka, Justin Salamon, Carlos Dietrich, and Claudio T. Silva. "HistoryTracker: Minimizing Human Interactions in Baseball Game Annotation". en. In: *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. Glasgow Scotland Uk: ACM, May 2019, pp. 1–12. URL: https://dl.acm.org/doi/10.1145/3290605.3300293 (visited on 01/24/2023) (cit. on pp. 36, 96).

[101] M. Pieras, R. Marroquim, D. Broekens, E. Eisemann, and A. Vilanova. "ComVis-Sail: Comparative Sailing Performance Visualization for Coaching". en. In: *Computer Graphics Forum* 42.1 (2023), pp. 86–100. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/cgf.14722 (visited on 11/29/2023) (cit. on pp. 90, 91).

[102] Hannah Pileggi, Charles D. Stolper, J. Michael Boyle, and John T. Stasko. "SnapShot: Visualization to Propel Ice Hockey Analytics". In: *IEEE Transactions on Visualization and Computer Graphics* 18.12 (Dec. 2012). Conference Name: IEEE Transactions on Visualization and Computer Graphics, pp. 2819–2828. URL: https://ieeexplore.ieee.org/document/6327288 (visited on 10/20/2023) (cit. on p. 96).

[103] Shiraj Pokharel, Ying Zhu, and Satish Puri. "Micro-Level Analysis and Visualization of Tennis Shot Patterns with Fractal Tables". In: *2019 IEEE 43rd Annual Computer Software and Applications Conference (COMPSAC)*. Milwaukee, WI, USA: IEEE, July 2019, pp. 97–102. URL: https://ieeexplore.ieee.org/document/8754444/ (visited on 06/07/2024) (cit. on pp. 90, 91).

[104] Mihai Polceanu, Andreea-Oana Petac, Hassan Ben Lebsir, Bruno Fiter, and Cedric Buche. "Real Time Tennis Match Tracking with Low Cost Equipment". en. In: *FLAIRS-31 (31st International Florida AAAI Research Society Conference)* (2018) (cit. on p. 27).

[105] Polk, Tom and Yang, Jing and Hu, Yueqi and Zhao, Ye. "TenniVis: Visualization for Tennis Match Analysis". In: *IEEE Transactions on Visualization and Computer Graphics* 20 (2014), pp. 2339–2348. URL: https://ieeexplore.ieee.org/document/6876044 (cit. on p. 92).

[106] Francisco Pradas, Víctor Toro-Román, Carlos Castellar, and Luis Carrasco. "Analysis of the spatial distribution of the serve and the type of serve-return in elite table tennis. Sex differences". en. In: *Frontiers in Psychology* 14 (Aug. 2023), p. 1243135. URL: https://www.frontiersin.org/articles/10.3389/fpsyg.2023.1243135/full (visited on 08/17/2025) (cit. on pp. 10, 56).

[107] Olle Ramnäs, Gunnar Barrefors, and Göran Petersson. "Ambient solvent hydrocarbons from the gluing of table tennis bats". en. In: *Toxicological & Environmental Chemistry* 47.1-2 (Jan. 1995), pp. 1–6. URL: http://www.tandfonline.com/doi/abs/10.1080/02772249509358120 (visited on 09/24/2025) (cit. on p. 7).

[108] Tobias Rapp, Christoph Peters, and Carsten Dachsbacher. "Visual Analysis of Large Multivariate Scattered Data using Clustering and Probabilistic Summaries". In: *IEEE Transactions on Visualization and Computer Graphics* 27.2 (Feb. 2021). Conference Name: IEEE Transactions on Visualization and Computer Graphics, pp. 1580–1590. URL: https://ieeexplore.ieee.org/abstract/document/9222076 (visited on 11/30/2023) (cit. on p. 103).

[109] Gustaf Reinebo, Sven Alfonsson, Markus Jansson-Fröjmark, Alexander Rozental, and Tobias Lundgren. "Effects of Psychological Interventions to Enhance Athletic Performance: A Systematic Review and Meta-Analysis". en. In: *Sports Medicine* 54.2 (Feb. 2024), pp. 347–373. URL: https://link.springer.com/10.1007/s40279-023-01931-z (visited on 09/23/2025) (cit. on p. 2).

[110] Gabin Rolland, Romain Vuillemot, Wouter Bos, and Nathan Rivière. "Characterization of Space and Time-Dependence of 3-Point Shots in Basketball". In: *MIT Sloan Sports Analytics Conference*. Boston, United States, Mar. 2020. URL: https://hal.archives-ouvertes.fr/hal-02482706 (visited on 05/13/2020) (cit. on pp. 96, 110, 113, 114).

[111] Alper Sarikaya and Michael Gleicher. "Scatterplots: Tasks, Data, and Designs". In: *IEEE Transactions on Visualization and Computer Graphics* 24.1 (Jan. 2018). Conference Name: IEEE Transactions on Visualization and Computer Graphics, pp. 402–412. URL: https://ieeexplore.ieee.org/abstract/document/8017602 (visited on 11/30/2023) (cit. on p. 103).

[112] Luca Scrucca and Dimitris Karlis. "A model-based approach to shot charts estimation in basketball". en. In: *Computational Statistics* 40.4 (Apr. 2025), pp. 2031–2048. URL: https://link.springer.com/10.1007/s00180-025-01599-1 (visited on 08/17/2025) (cit. on p. 52).

[113] B. Shneiderman. "The eyes have it: a task by data type taxonomy for information visualizations". In: *, IEEE Symposium on Visual Languages, 1996. Proceedings*. Sept. 1996, pp. 336–343 (cit. on p. 119).

[114] Olena Sorokivska, Iaroslav Lytvynenko, Oleksandr Sorokivskyi, and Halyna Kozbur. "Methodology of the Formation of Sports Matches Statistical Information Using Neural Networks". en. In: *Proceedings ITTAP'2023: 3rd International Workshop on Information Technologies: Theoretical and Applied Problems* (Nov. 2023) (cit. on pp. 24–27).

[115] Darrin Sorrells and Kyle Kempf. "Effects of Distance between Home Plate and the Backstop on Self-confidence of Intercollegiate Baseball Players". en. In: *Universal Journal of Psychology* 5.3 (June 2017), pp. 140–148. URL: http://www.hrpub.org/journals/article_info.php?aid=5963 (visited on 09/11/2025) (cit. on p. 56).

[116] Donald F Specht. "Probabilistic Neural Networks". en. In: *Neural Networks, Vol. 3. pp. 109 118* (1990) (cit. on p. 28).

[117] Manuel Stein, Halldor Janetzko, Andreas Lamprecht, Thorsten Breitkreutz, Philipp Zimmermann, Bastian Goldlücke, Tobias Schreck, Gennady Andrienko, Michael Grossniklaus, and Daniel A. Keim. "Bring It to the Pitch: Combining Video and Movement Data to Enhance Team Sport Analysis". In: *IEEE Transactions on Visualization and Computer Graphics*. Vol. 24. Jan. 2018, pp. 13–22 (cit. on p. 116).

[118] Tsuyoshi Taki and Jun-ichi Hasegawa. "Visualization of dominant region in team games and its application to teamwork analysis". In: *Proceedings computer graphics international 2000*. IEEE, 2000, pp. 227–235 (cit. on p. 112).

[119] Ljupčo Todorovski, Peter Flach, and Nada Lavrač. "Predictive Performance of Weighted Relative Accuracy". en. In: *Principles of Data Mining and Knowledge Discovery*. Ed. by G. Goos, J. Hartmanis, J. Van Leeuwen, Djamel A. Zighed, Jan Komorowski, and Jan Żytkow. Vol. 1910. Series Title: Lecture Notes in Computer Science. Berlin, Heidelberg: Springer Berlin Heidelberg, 2000, pp. 255–264. URL: http://link.springer.com/10.1007/3-540-45372-5_25 (visited on 08/18/2025) (cit. on p. 58).

[120] John W. Tukey. *Exploratory data analysis*. Vol. 2. Reading, Mass., 1977 (cit. on p. 73).

[121] Jansi Rani Sella Veluswami. "ConvLSTM for Table Tennis Stroke Classification". en. In: *CEUR Workshop Proceedings (MediaEval'23)* (2023) (cit. on p. 35).

[122] Roman Voeikov, Nikolay Falaleev, and Ruslan Baikulov. "TTNet: Real-time temporal and spatial video analysis of table tennis". en. In: *2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*. Seattle, WA, USA: IEEE, June 2020, pp. 3866–3874. URL: https://ieeexplore.ieee.org/document/9150877/ (visited on 05/12/2025) (cit. on pp. 25, 27, 28, 35).

[123] Georges Voronoi. "Nouvelles applications des paramètres continus à la théorie des formes quadratiques. Deuxième mémoire. Recherches sur les parallélloèdres primitifs." In: *Journal für die reine und angewandte Mathematik (Crelles Journal)* 1908.134 (1908). Publisher: De Gruyter Berlin, New York, pp. 198–287 (cit. on p. 112).

[124] Hai Wang, Wenbo Qu, and Qunli Shen. "Table tennis video data mining based on performance optimization of artificial fish swarm algorithm". en. In: *Computer Modelling and New Technologies* (2014) (cit. on p. 59).

[125] Jiachen Wang, Jiang Wu, Anqi Cao, Zheng Zhou, Hui Zhang, and Yingcai Wu. "Tac-Miner: Visual Tactic Mining for Multiple Table Tennis Matches". In: *IEEE Transactions on Visualization and Computer Graphics* 27.6 (June 2021). Conference Name: IEEE Transactions on Visualization and Computer Graphics, pp. 2770–2782. URL: https://ieeexplore.ieee.org/document/9411869 (cit. on pp. 59, 97).

[126] Jiachen Wang, Yihong Wu, Xiaolong Zhang, Yixin Zeng, Zheng Zhou, Hui Zhang, Xiao Xie, and Yingcai Wu. "Tac-Anticipator: Visual Analytics of Anticipation Behaviors in Table Tennis Matches". en. In: *Computer Graphics Forum* 42.3 (2023), pp. 223–234. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/cgf.14825 (visited on 11/20/2023) (cit. on pp. 10, 37, 54, 56, 57, 92, 93, 97, 100, 127).

[127] Wang, Jiachen and Zhao, Kejian and Deng, Dazhen and Cao, Anqi and Xie, Xiao and Zhou, Zheng and Zhang, Hui and Wu, Yingcai. "Tac-Simur: Tactic-based Simulative Visual Analytics of Table Tennis". In: *IEEE Transactions on Visualization and Computer Graphics* 26 (2020), pp. 407–417. URL: https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=8807264 (cit. on pp. 54, 56, 57, 91).

[128] Xinyu Wei, Patrick Lucey, Stuart Morgan, Peter Carr, Machar Reid, and Sridha Sridharan. "Predicting serves in tennis using style priors". In: *Proceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*. 2015, pp. 2207–2215 (cit. on pp. 55, 70, 74, 128).

[129] Zhong-Kai Wei and Jieh-Ren Chang. "Automatic Segmentation of Table Tennis Match Video Clips Based on Player Actions for Enhanced Data Acquisition". en. In: *Journal of Advances in Information Technology* 15.12

(2024), pp. 1374–1379. URL: https://www.jait.us/show-247-1615-1.html (visited on 09/11/2025) (cit. on p. 24).

[130] Wei-Lwun Lu, J.-A Ting, J. J. Little, and K. P. Murphy. "Learning to Track and Identify Players from Broadcast Sports Videos". en. In: *IEEE Transactions on Pattern Analysis and Machine Intelligence* 35.7 (July 2013), pp. 1704–1716. URL: http://ieeexplore.ieee.org/document/6516867/ (visited on 08/07/2025) (cit. on pp. 23–25).

[131] K. Wong. "Tracking Table Tennis Balls in Real Match Scenes for Umpiring Applications". en. In: *British Journal of Mathematics & Computer Science* 1.4 (Jan. 2011), pp. 228–241. URL: https://journaljamcs.com/index.php/JAMCS/article/view/1270 (visited on 12/12/2022) (cit. on p. 27).

[132] Jiang Wu, Dongyu Liu, Ziyang Guo, Qingyang Xu, and Yingcai Wu. "TacticFlow: Visual Analytics of Ever-Changing Tactics in Racket Sports". In: *IEEE Transactions on Visualization and Computer Graphics* 28 (2022), pp. 835–845. URL: https://ieeexplore.ieee.org/document/9552436 (cit. on pp. 59, 91).

[133] Jiang Wu, Dongyu Liu, Ziyang Guo, and Yingcai Wu. *Beep: Balancing Effectiveness and Efficiency when Finding Multivariate Patterns in Racket Sports*. en. arXiv:2307.11780 [cs]. July 2023. URL: http://arxiv.org/abs/2307.11780 (visited on 08/18/2025) (cit. on p. 59).

[134] Yingcai Wu, Ji Lan, Xinhuan Shu, Chenyang Ji, Kejian Zhao, Jiachen Wang, and Hui Zhang. "iTTVis: Interactive Visualization of Table Tennis Data". In: *IEEE Transactions on Visualization and Computer Graphics* 24.1 (Jan. 2018). Conference Name: IEEE Transactions on Visualization and Computer Graphics, pp. 709–718 (cit. on pp. 9, 10, 52–54, 56, 59, 72, 92, 97, 127).

[135] Xiao Xie, Jiachen Wang, Hongye Liang, Dazhen Deng, Shoubin Cheng, Hui Zhang, Wei Chen, and Yingcai Wu. *PassVizor: Toward Better Understanding of the Dynamics of Soccer Passes*. en. arXiv:2009.02464 [cs]. Sept. 2020. URL: http://arxiv.org/abs/2009.02464 (visited on 08/28/2025) (cit. on p. 91).

[136] Cheng Yan, Xin Li, and Guoqiang Li. "A New Action Recognition Framework for Video Highlights Summarization in Sporting Events". en. In: *2021 16th International Conference on Computer Science & Education (ICCSE)*. Lancaster, United Kingdom: IEEE, Aug. 2021, pp. 653–666. URL: https://ieeexplore.ieee.org/document/9569708/ (visited on 09/08/2025) (cit. on p. 23).

[137] Lijie Yao, Anastasia Bezerianos, Romain Vuillemot, and Petra Isenberg. "Visualization in Motion: A Research Agenda and Two Evaluations". en. In: *IEEE Transactions on Visualization and Computer Graphics* 28.10 (Oct. 2022),

p. 3546. URL: https://inria.hal.science/hal-03698837 (visited on 11/29/2023) (cit. on p. 89).

[138] Shuainan Ye, Zhutian Chen, Xiangtong Chu, Yifan Wang, Siwei Fu, Lejun Shen, Kun Zhou, and Yingcai Wu. "ShuttleSpace: Exploring and Analyzing Movement Trajectory in Immersive Visualization". en. In: *IEEE Transactions on Visualization and Computer Graphics* 27.2 (Feb. 2021), pp. 860–869. URL: https://ieeexplore.ieee.org/document/9222313/ (visited on 04/12/2023) (cit. on pp. 74, 95–97, 128).

[139] Mohammed J Zaki. "SPADE: An Efficient Algorithm for Mining Frequent Sequences". en. In: *Machine Learning, 42, 31–60* (2001) (cit. on p. 58).

[140] Chenkai Zhang, Ruochen Cao, Andrew Cunningham, and James A. Walsh. "Whatever could be, could be: Visualizing Future Movement Predictions". In: *2024 IEEE Conference Virtual Reality and 3D User Interfaces (VR)*. ISSN: 2642-5254. Mar. 2024, pp. 126–136. URL: https://ieeexplore.ieee.org/document/10494165/ (visited on 03/04/2025) (cit. on p. 110).

[141] Zhewen Zhang, Fuliang Wu, Yuming Qiu, Jingdong Liang, and Shuiwang Li. "Tracking Small and Fast Moving Objects: A Benchmark". en. In: *Computer Vision – ACCV 2022*. Ed. by Lei Wang, Juergen Gall, Tat-Jun Chin, Imari Sato, and Rama Chellappa. Vol. 13847. Series Title: Lecture Notes in Computer Science. Cham: Springer Nature Switzerland, 2023, pp. 552–569. URL: https://link.springer.com/10.1007/978-3-031-26293-7_33 (visited on 05/12/2025) (cit. on p. 26).

[142] Wentao Zhu, Xiaoxuan Ma, Zhaoyang Liu, Libin Liu, Wayne Wu, and Yizhou Wang. "Motionbert: A unified perspective on learning human motion representations". In: *Proceedings of the IEEE/CVF International Conference on Computer Vision*. 2023, pp. 15085–15099 (cit. on p. 39).

[143] Ying Zhu and Ruthuparna Naikar. "Predicting Tennis Serve Directions with Machine Learning". en. In: *Machine Learning and Data Mining for Sports Analytics*. Ed. by Ulf Brefeld, Jesse Davis, Jan Van Haaren, and Albrecht Zimmermann. Cham: Springer Nature Switzerland, 2023, pp. 89–100 (cit. on pp. 63, 73, 74).

[144] Chen Zhu-Tian, Qisen Yang, Jiarui Shan, Tica Lin, Johanna Beyer, Haijun Xia, and Hanspeter Pfister. "iBall: Augmenting Basketball Videos with Gaze-moderated Embedded Visualizations". en. In: *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. Hamburg Germany: ACM, Apr. 2023, pp. 1–18. URL: https://dl.acm.org/doi/10.1145/3544548.3581266 (visited on 10/02/2025) (cit. on pp. 93, 121, 122).