Exploring Table Tennis Analytics: Domination, Expected Score and Shot Diversity

Gabin Calmet[1,2], Aymeric Eradès[1,2], and Romain Vuillemot[1,2][0000−0003−1447−6926]

[1] École Centrale de Lyon, France
[2] LIRIS CNRS UMR 5205

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

Keywords: Sports Analytics· Table Tennis· Visual Analysis

1 Introduction

A new generation of detailed sports data is emerging for sports analysis in general, including racket sports that require more precise analysis. A flagship example is the TTNet [13] video tracking system, which enables real-time identification of players and ball positions. This level of detail represents a paradigm shift, as tracking data [8] of this kind is typically under-explored in such sports. Meanwhile, a plethora of advanced tools are beginning to leverage this data, such as iTTvis [13], which is aimed at experts to explore game sequences and discover tactics. Other approaches also focus on sequence analysis to visually explore frequent patterns [3], using an a-cyclic graph to represent all points in a match, and extract tactics. TIVEE [2] leverages shot types, player positions, and shuttle trajectory and speed to find correlations between strokes, aiding in the discovery of tactics. TacticFlow [12] utilizes multivariate events in racket sports to mine frequent patterns and detect how these patterns change over time. Tac-Miner [11] allows users to analyze, explore, and compare tactics of multiple matches based on three consecutive strokes. All of these works share the commonality of being driven by the availability of detailed tracking data.

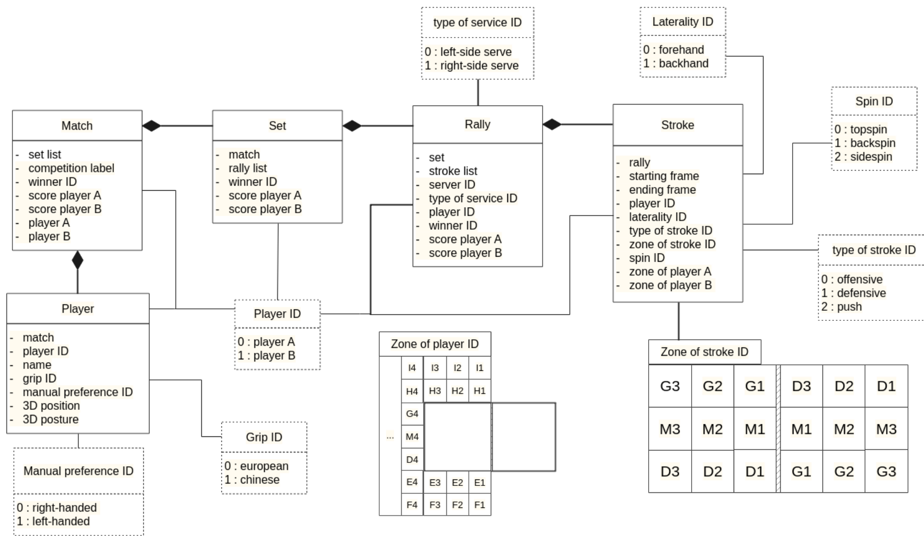

Fig. 1: Example of an extended table tennis detailed data model (from[3]). It includes additional metadata (e. g., players' names, score and winner) with advanced strokes types, players and ball rebound zones. It also takes into account continuous player positions and ball position (that we haven't yet collected).

We hypothesize that such detailed data provide deeper games analysis, and thus need to be anticipated. Fig. 1 illustrates a detailed table tennis data model that captures all data currently available (mostly meta and event-based data). In this work, we use a combination of event-based data and video tracking data, on a 2D space. Such data can be collected with regular technical skills using a blend of computer vision, deep learning and manual annotation tools. It extends the format previously used in [3] but with finer grained players position, orientation and ball rebound position. Some researches have been led to collect such data automatically. [6] uses Twin convolutional neural networks with 3D convolutions on RGB data and optical flow to classify strokes in table tennis. [5] shows the importance of optical flow and human detection algorithms to improve action detection. [9] uses a CNN layer inspired by optical flow algorithms for action recognition without having to compute optical flow. And TTNet [13] is a multi-task convolution-based neural network to collect positions and stroke events data simultaneously. 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 discuss this part in the last section of this paper.

To illustrate our analysis in this paper, we use the following scenario from an international table tennis game: **Lebrun**, the French champion, against **Zhendong**, the world champion and number one player in the world, in the quarter-final match during WTT[3] Championship in Macao, 2023. In this match, **Lebrun**

[3] World Table Tennis, a commercial organization that runs table tennis tournaments.

wins 3 sets to 2. They took turns winning the sets. It was a really close game, and **Lebrun** won the decider 11-9 by touching the edge of the table. During this match, our experts noticed that **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 **Lebrun**'s domination decreased after the second point, while he didn't execute these shots. However, after his domination increased again, these shots began to be more and more common. Moreover, we noticed that during an important moment (7-4 for **Zhendong**), he manages to score twice using these shots, and this made him take the lead of the set. We may suppose that this is an important feature of his game plan. In the first set, we found 4 points won by **Lebrun** when he makes these strokes (indicated by the red vertical lines in Fig. 2):

- **Point A** (1-0) **Lebrun** serves, **Zhendong** pushes on the left side of **Lebrun**'s table, then **Lebrun** attacks down the line with his forehand and wins the point.
- **Point B** (4-7) **Zhendong** serves, **Lebrun** pushes short on **Zhendong**'s forehand, who pushes long on the left side of **Lebrun**'s table. **Lebrun** attacks with his forehand on the left side of **Zhendong**'s table.
- **Point C** (5-7) **Lebrun** serves short on **Zhendong**'s forehand, who pushes long on the left side of **Lebrun**'s table. **Lebrun** attacks with his backhand down the line.
- **Point D** (9-7) **Lebrun** serves long on **Zhendong**'s backhand, who attacks on **Lebrun**'s left side of the table. **Lebrun** counters with his backhand and wins the point after a few shots.

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

1. Why is a particular point effective during a game?
2. What is the effect of shots diversity?
3. What shots combination are the most efficient?
4. What are strokes difference between players?
5. How a stroke can win you a point?
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* [7]. This metric calculates the probability that a scoring opportunity will result in a goal, providing insight into whether the winning team had the most dangerous scoring opportunities or not. Finally, we included a last metric that captures creativity in the choice of shots techniques, based on a shot similarity distance.

We have released our benchmark code and datasets (collected and augmented) in a public GitHub repository[4].

2 Domination Analysis in Table Tennis

Analyzing the pressure or domination is popular in team sports. In general, it is an umbrella term that encompasses all the ways to prevent the opposite team to develop an attack [1]. There is always an objective component of the domination that is calculated at a given moment without depending on the past. But most games and sports requires physical, technical and mental capacities that can't be objectively quantified without depending on the past. In racket sports, usually more fragmented than team sports that have long, continuous actions, but also that have high scoring opportunities, there is a need to re-define this notion to account for those characteristics. In such context with two opponents, we define it broadly as follows:

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

- **Score domination** is calculated using the current scores at a given instant. It is highly reliable because the scores are what the winner is declared on at the end of the match, and because they are considered an absolute truth during the game. In this case, we consider that the score domination is proportional to the winning chances of player A, $P_{a,b}$ (see Appendix A for detailed definition). 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 update also their respective rate of offensive shots $r_X(t)$. We then combine the three contributions to get the full physical domination function (see Appendix A for further explanation):

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

[4] `https://github.com/centralelyon/table-tennis-analytics`

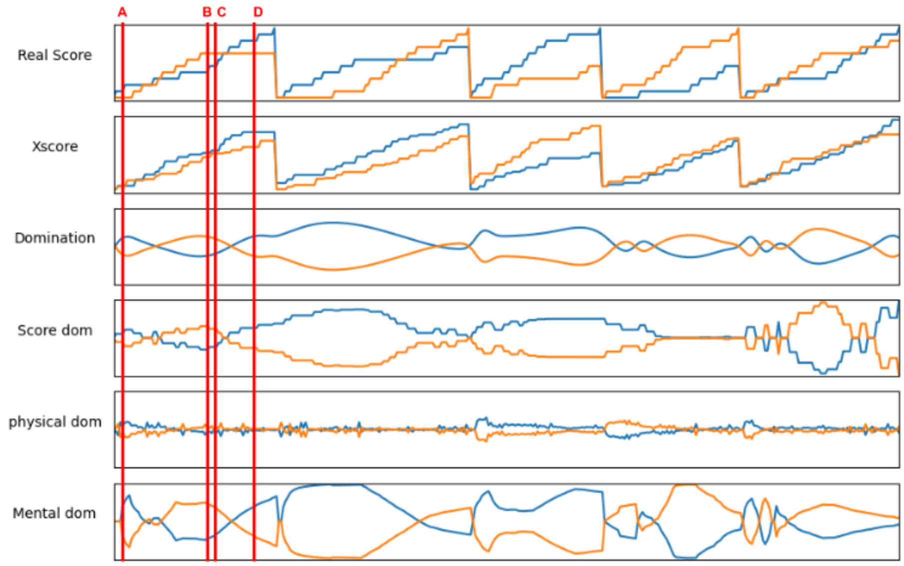

Fig. 2: Detailed metrics during the first set of a match between **Lebrun** and **Zhendong** at the WTT Championships in Macao, China in 2023. Red vertical lines the 4 points during the first set we focused on.

– **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 [14]. Our model takes into account defeat anxiety $l(t)$, self-confidence $c(t)$ and the stress of long rallies $s(t)$ (see Appendix A for detailed definition). We combine those three factors to get the mental domination function:

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

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

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

From this definition of domination, we can see on Fig. 2 that domination is highly correlated to the score difference, which is due to the score domination term. During the last set, the domination function fluctuates a lot because the score is very tight, and because this set is decisive. Moreover, during the decider, there is a lot of stress because both player can easily win or loose, so the mental domination is also at stake. The physical domination is not very decisive, and it's most of the time almost null. This can be explained by the fact that both players are probably physically prepared and that they are authorized to rest between and during sets. Nevertheless, we can notice that some score domination period are correlated with physical domination peaks.

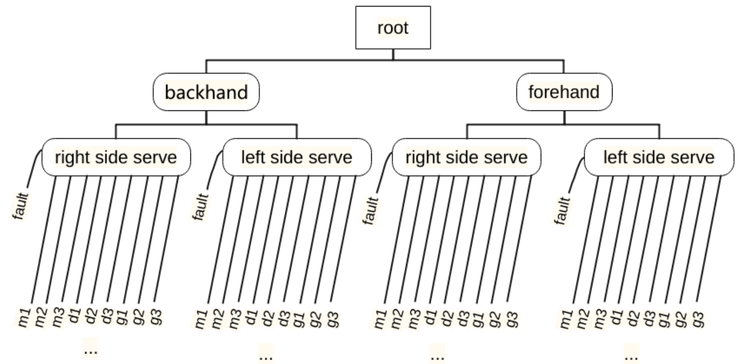

Fig. 3: Theoretical structure of the Playing Patterns Trees (PPT) that enumerates all shot attributes combination.

3 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 [4] [7]. The objective of this metric is to predict the outcome of a point based solely on the first three strokes. By consistently applying this prediction to all points in a set, we can construct an **expected score (XScore)** that indicates the logical winner of the set. We accomplish this by exploring a tree that represents all possible three-stroke playing patterns and calculating a winning probability based on the statistics of the branch in which each **expected point** is situated, and defined as:

Definition 2 (Expected Points). *A statistical metric to estimate the probability of winning a point based on various factors such as player skill, shot quality, and opponent performance.*

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

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

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

This metric is particularly interesting because it allows us to introduce the concept of chance (or unlikely success) and its analysis can explain certain subtleties of mental domination. As Fig. 2 suggests, the expected score respects the global match outcome 3-2 for **Lebrun**. However, the set winners are not always the same as expected. The third set is particularly interesting because **Lebrun** wins by a wide margin and dominated during the whole set. But the expected score is totally different: he is expected to lose by a wide margin. This can be explained by the fact that he just lost the previous set and needs now to be careful. Moreover, **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 **Lebrun** loses by a wide margin, as **Zhendong** did in the previous set: he just won the previous set, he is less concentrated, and he makes mistakes. This is an important feature that could be useful for the understanding of mental domination.

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

4 Shots Diversity in Table Tennis

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

Definition 3 (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 [3], we saw that some players tend to serve in the same way, while they did not lose a point after such a serve. Here, we are going further in the sense that we explore more strokes into the rally, and because we create a metric representing the distance between two openings. By collecting the three

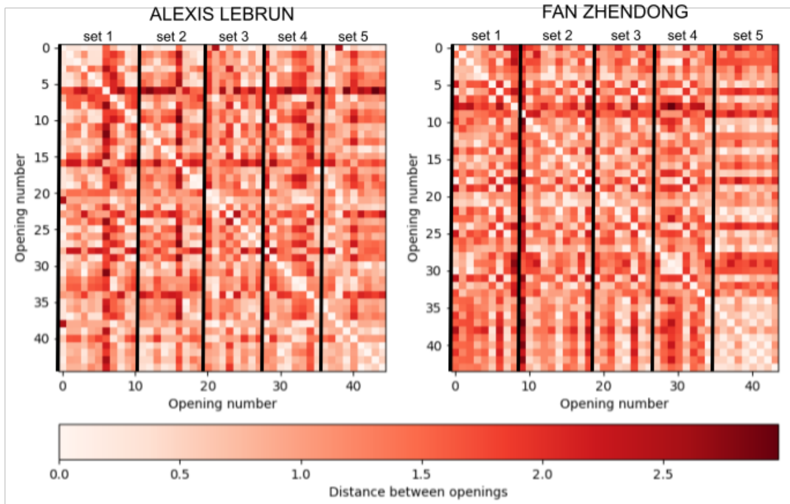

Fig. 4: Distance matrix between openings of the match between **Lebrun** and **Zhendong** at the WTT Championships in Macao, 2023. At the beginning **Lebrun** doesn't vary much, probably to start with his strength and take the lead. Only then, he starts to change to keep surprising his opponent with new openings. During the first set, **Zhendong** started to lose when **Lebrun** started to vary openings. The most interesting analysis is from the last set. We can see that **Zhendong** didn't change a lot of opening during this set (white square). We can suppose that he noticed that these tactics were efficient, and he wanted to take the lead at the beginning of it. But **Lebrun** adapted to this and managed to come back. Then, **Zhendong** never tried to change pattern and lost the match. This may reflect a mental fatigue of **Zhendong** (maybe with the stress he wanted to stay with something familiar to him, or maybe he wasn't lucid enough to take the decision to change of opening).

first strokes of every rally of a match, we can calculate similarities between sequences.

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

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

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 on Fig. 4 is the similarity of consecutive sequences, that appears as white squares on the diagonals of both matrix. Because of the temporal aspect of this figure, we can see **Zhendong** tends to vary less in his opening at the end of the match, and this can be a sign of a mental fatigue.

5 Discussion, Limits and Perspectives

In this work, we adapted three metrics that relied upon detailed table tennis data that we collected and augmented to analyze a specific game. It showed that these metrics already enabled a general analysis of the game, as well as particular key moments. In particular, metrics that account for a global context (e. g., domination) enabled to provide more nuance to hypothesize on players' strategic decisions. For instance, we showed a player can become more conservative in their technical choices when dominated to reduce the chance of errors, as we have seen in the last set of our game.

The main limitation of our work is the volume of data used for analysis, which remains limited to a single game (despite we collected and released data for multiple games). The reason is that table tennis is an adversarial sport, so only comparable situations can be compared, as players adapt their behavior against players with similar styles (which was one of our early questions). Another limitation is that we currently communicated and analyzed the metrics separately, while there is an opportunity to combine them. Furthermore, although we collected tracking data with detailed position, we only operated on aggregation by zone to capture strategic choices and filter out noise. Position data presents an opportunity for designing novel metrics. We anticipate the development of more continuous metrics based on ball position and players' body, such as spatial occupation [10].

As we have released our code and datasets (both collected and augmented) as an open-source project, we hope it will foster research to develop and compare new metrics. We also plan to update these datasets with even more detailed data, including better 3D pose estimation, ball spin effects, and trajectories.

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A Appendix

A.1 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 $P_{a,b} = 0.5$.

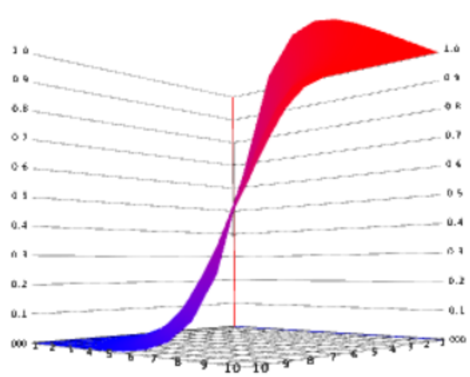

Fig. 5: Winning probability $P_{a,b}$ (vertical axis) as a function of the scores a and b (horizontal axes)

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

A.2 Definition of the three factors of physical domination

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

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

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

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

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

A.3 Definition of the three factors of mental domination

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

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

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