Investigating Control Areas in Table Tennis

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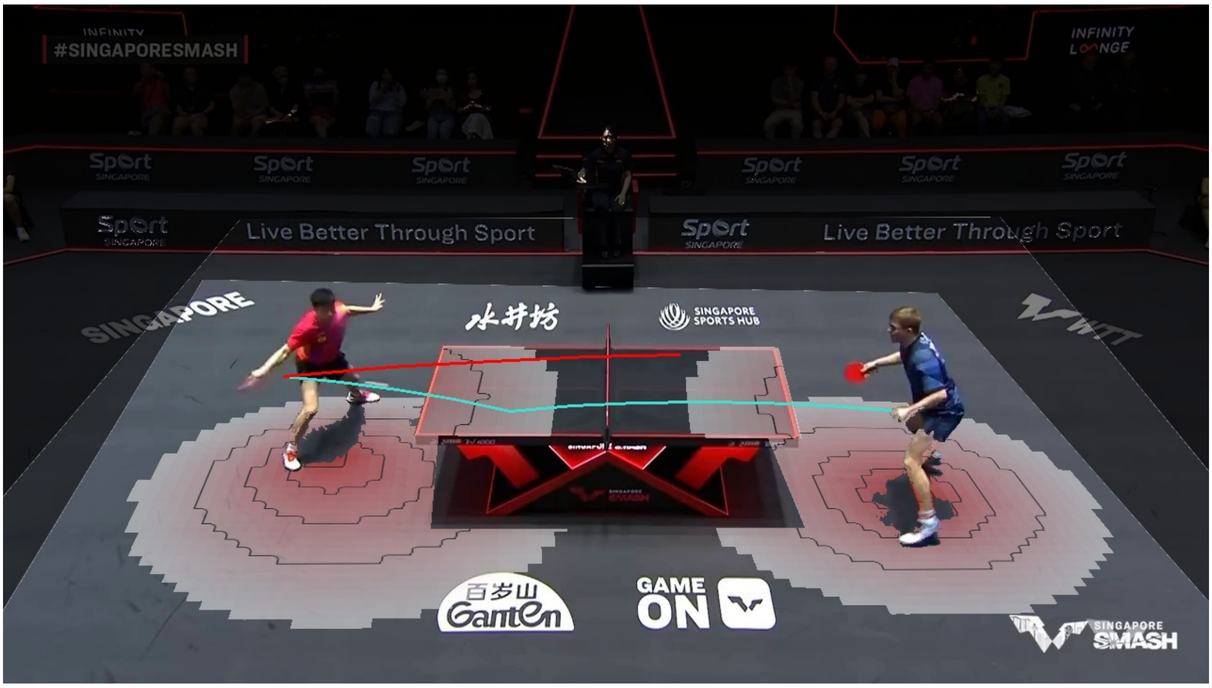


Figure 1: A video screenshot of a table tennis match at a key moment between Ma Long (left) and Alexis Lebrun (right). Alexis Lebrun executes a fast forehand stroke (green trajectory), and Ma Long returns the ball (red trajectory) to the right side of Alexis Lebrun, who fails to anticipate it. The red 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. In this paper, we investigate the construction of such control areas to identify strategic spaces players should aim for.

Abstract

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

CCS Concepts

• ***Human-centered computing*** $\rightarrow$ ***Information visualization;***

1. Introduction

Contextualizing movement is important in any visual analysis task where trajectories are often the key representation [AAB*13]. Context enhances the understanding of spatio-temporal data [CAA*19] with additional data attributes (e. g., events, historical data) and leveraging *derived data* to enrich original datasets with extra information. According to [Mun14], such an approach is highly effective for *designing a visualization tool for a complex, real-world use case [..]* to *extend the dataset beyond the original set of attributes that it contains*.

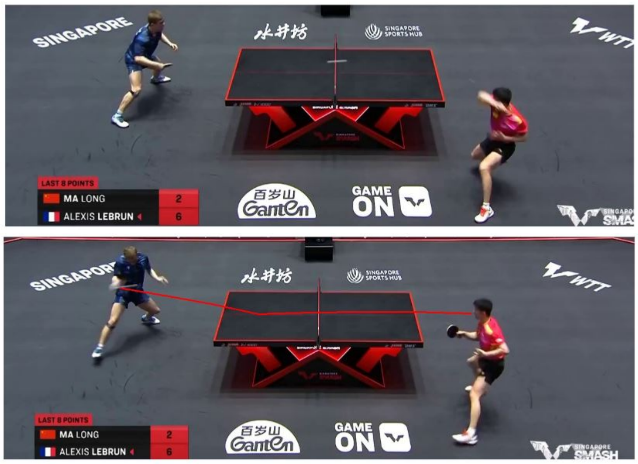
This paper contributes to this data augmentation strategy for spatio-tempora data by introducing a model and visualization of *control areas*, which are regions that can be reached quickly by a moving entity. Control areas are increasingly popular in sports analysis (also referred to as occupation areas, occupation models, or pitch control), e. g., in basketball [RVBR20], soccer [AAA*21, AV20, HGPW23], and badminton [DTJ*24]. 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 [ZCCW24].

Our work contributes to explore the use of control areas for a specific sport: table tennis. We aim at characteristic when players fails to reach or return the ball properly because it was sent into this strategic zone. As illustration, we selected game sequences from international table tennis matches where the ball was too far away (Figure 2a) in the match between Ma Long and Alexis Lebrun, Smash Singapore 2024; the ball was in a pivot zone (Figure 2b) in the match between Hugo Calderano and Alexis Lebrun, Champions Incheon 2024; and the player was wrong-footed (Figure 2c) in the match between Alexis Lebrun and Ma Long, Smash Singapore 2024.

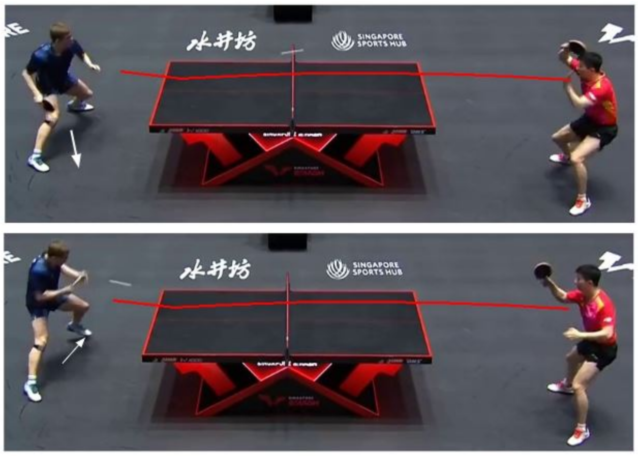
Building efficient control areas is challenging as it is highly dependent on the application domain, thus it needs a careful understanding of the task and level of analysis. The naive version of such concept is using Voronoi partitions [Vor08], which is well defined but not suited as it considers all directions as candidate for control. The standard way to build more efficient model is to adapt *space-time models* [TH00] to quantify available space for a single player relative to the space occupied by other players. Such a model enables to analyze of space-time data using the physical properties of movers (e. g., direction, speed) and enables accounting for players' inertia. For a fast-moving player, it is more difficult to control the area behind him, and some delay is induced by the fact that players have a finite force and can therefore not instantaneously change their velocity to a different value. It is thus necessary to develop a model characterizing the acceleration of the players. However, the distance to a point does not fully define the control of a point, but it is rather the time it takes for a player to reach the point which defines the controlled area.

Control areas are interesting due to their predictive nature, which captures the underlying physical model based on Newton's second law [RVBR20]. Such models are simplified versions of reality, taking into account parameters such as direction, speed, and force of a player in order to calculate the time it would take the

(a) **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.



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



(c) **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.

Figure 2: Motivating examples showcasing the need to contextualize motion with control areas.

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 [PVS*18] and already explored by the visualization community for soccer analyis [AAA*21, AV20].

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 [DTJ*24], 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.

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:

$$d_t^2 x = F_x \tag{1}$$

so that we have

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

To construct control areas, we need to evaluate this expression at each coordinate of the space. Following [RVBR20], 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, $t_{threshold}$, 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 $t_{threshold} = 0.8\,s$, meaning that any region that can be reached within 0.8 seconds will be considered as part of the control area. This time threshold guarantees that the model accounts for realistic movement constraints, where players can only cover limited distances within a given timeframe.

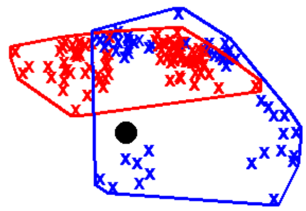


Figure 3: Alexis Lebrun's ball hits relative to his position. The black circle represents the player's position; the blue marks the positions of balls hit with the forehand, and the red marks the ball positions hit with the backhand. Since the player's position is taken using his hips, some hits may 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.

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

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 executing movements close to or far from the body, from the front or side. Unlike sports like soccer, where players catch the ball consistently around 40 cm in front of them, table tennis requires a more nuanced model due to these differences in player movement and stroke types. To create a more accurate model of a player's reachability, it is essential to account for these subtleties.

We iterated on the previous model to capture local reachability by focusing on the racket's ability to reach specific areas rather than just the player's body. In table tennis, the player's racket defines the reach, so we create a zone around the player that the racket can quickly access. Furthermore, the player's orientation, typically facing the table, must be considered. For example, when a player moves away from the table, they are not running toward the ball but moving backward, which affects the reachable area. However, for simplicity, we used a statistical approach based on shot distribution to capture the peripheral reachability area, as illustrated in Figure 3. 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 3'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. Implementation and Visual Design

Players positions and events (e. g., hits) are derived from [?], 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 [SJL*18]. We used visual overlays in a manner similar to how Viscommentator operates [CYC*22] 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.

$$color_{unit\ cell}(t) = \begin{cases} (255, \quad G(t), \quad B(t)) & \text{if } t < t_{threshold} \\ (255, \quad 255, \quad 255) & \text{otherwise} \end{cases} \tag{3}$$

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

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

5. Results and Perspectives

The results we show in this paper are preliminary but promising for table tennis analytics. We applied the simple model using Newton's Law on our three motivation scenarios and the results are show on the teaser image Figure 1 and also on Figure 4, Figure 5 and Figure 6. The result are visually conclusive, the reason being that they concern extreme case where local reachability does not play an important role. Regarding the model with peripheral reachability, Figure 7 showing the forehand and backhand regions that can be reached. Overall there seems to be an effect of averaging as some local reachability is lost.

Further work is needed to refine our control area models. Since table tennis requires more of a micro-level analysis, the model we used does not account for the reaction time of the arms or other parts of the body. Thus, we seek research directions that capture such local motions to refine an overall model that would be a composition of smaller, relative ones. To refine the peripheral control area, detailed statistics of players should be considered, including individual factors such as reaction time, stamina, skill, and focus.

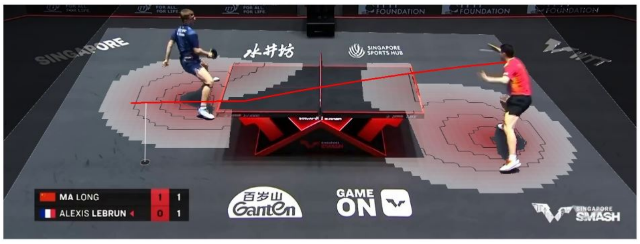


Figure 4: **Ball too far away**.

Figure 5: **Ball in pivot zone**.

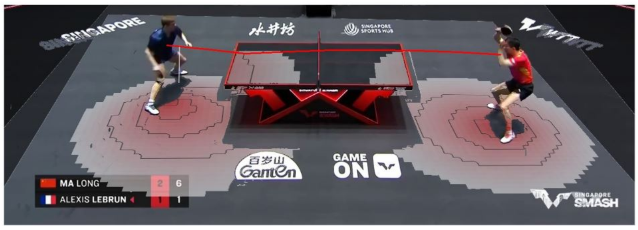


Figure 6: **Wrong-footed**.

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 [EBFFG21]. 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 8, 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 [CEV23], to identify their characteristics and allow for comparisons between players or across different matches. For instance, fatigue may reduce reaction time

Figure 7: 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.

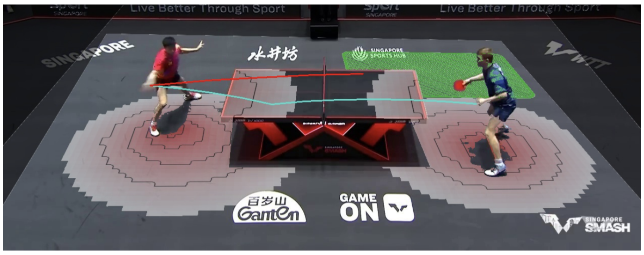


Figure 8: Highlight (in green) of the target area by Ma Long which is not calculated by our control area model (it results from a manual annotation), but is a promising perspective to automatically construct non-controlled areas.

and speed, which would lead to a decrease in the size of a player's reachable area. Such variations in the size of control areas and their correlation with game events is a promising approach for analyzing tactics, as has already been explored in soccer [AV20].

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

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

6. Acknowledgment

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