Player-Centric Shot Maps in Table Tennis

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DOI: 10.1111/cgf.70109
Eurographics Conference on Visualization (EuroVis) 2025
W. Aigner, N. Andrienko, and B. Wang
(Guest Editors)

COMPUTER GRAPHICS *forum*

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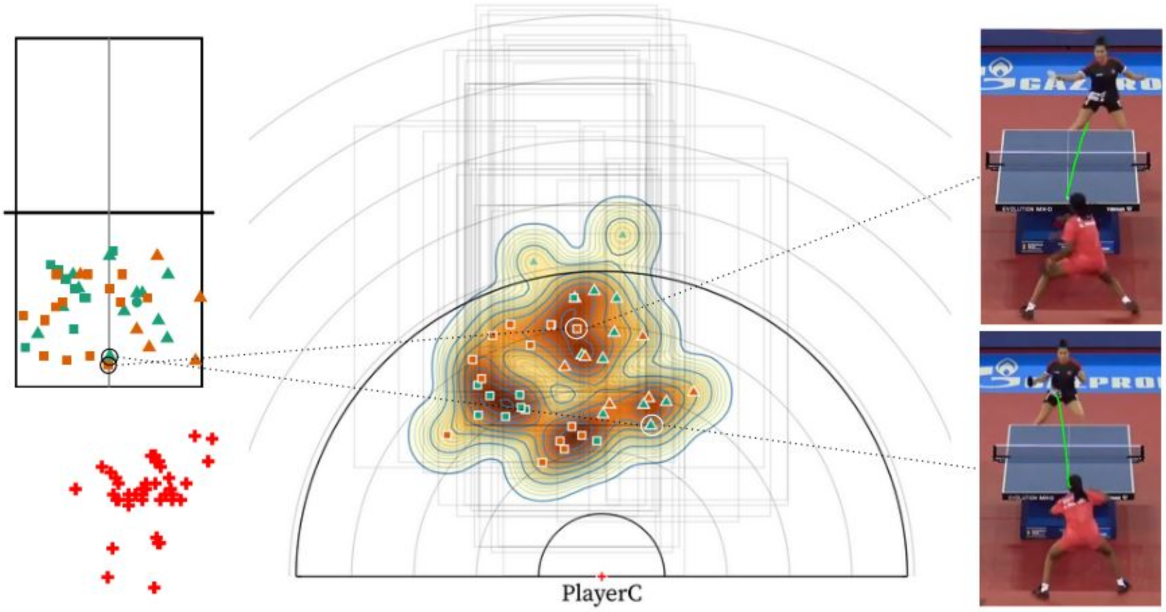

Figure 1: *Table tennis shot maps are usually represented as in (a), from a* table-centric *perspective, where players' positions ✚ and ball bounces ■ ▲ are plotted relative to the table. We introduce (b) a shot map representation that shifts the perspective to a unique player position ✚, providing a* player-centric *visualization to better group shots based on the distance to the incoming ball bounce. For example, in the figure above, the two highlighted ball bounces are close on the table as shown in (a), but they have different distances to the player as shown in (b): ■ is a lost backhand stroke because the receiving player in ✚ is far from the ball, while ▲ is a successful forehand stroke because the same player is close to the ball, thus easier to hit (as seen in (c), which are screenshots from the original video broadcasts).*

Abstract

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

CCS Concepts

• ***Human-centered computing*** → ***Information visualization;***

1. Introduction

Table tennis is a fast-paced sport where players have little time to react to an opponent's shot. This characteristic is heavily exploited by players to identify weaknesses during games, such as *reachability* e. g., close or distant shots relative to the player's position, or targeting the *pivot area* e. g., forcing rapid transitions between forehand and backhand. Thus, there are spatial regions around players that can be tactically exploited by opponents. Surprisingly, most sports visualizations do not adequately support the analysis of such areas, despite their frequent mention in expert analysis, TV game commentaries, and instructional books [Hod13]. The standard way to plot such data is by using a *(table tennis) table-centric* visualizations the way game occurs and data is collected through video annotation, tracking, or sensors [DWW*21, WWZ*23].

Standard sports data visualizations, such as *shot maps* that show where shots or attempts are made on the playing area, are typically created with table tennis tables as the primary element of analysis. These representations are among the most popular in sports visualization [PVS*18], but they have several drawbacks for analyzing reachability, pivot areas, or any player-centric techniques and tactical insights. For example, Figure 1 (a) shows that similar shots on the traditional shot maps, actually occur at different distances from the players (b) and therefore should not be directly compared. Shot maps introduce various biases when relying on absolute positions, not only because players hit from different positions, but also due to side-switching and differences between left- and right-handed players. This highlights the need for a representation-invariant approach, which could be achieved by normalizing data using relative distances to players instead of absolute ball positions.

In this paper, we introduce player-centric shot maps, where data is viewed relative to the player's position. This representation stems from the observation that tactical analysis can focus on areas around players, rather than solely on table regions. The technique relies on a simple offset calculation between the player's position and the ball bounce, making the player's position stationary as a reference. This adjustment provides a novel reference system using a polar coordinate system (Figure 3) and influences the visual design, requires new visual landmarks such as distance and angle guides to facilitate the understanding and comparison of incoming ball bounces. This technique can be embedded in dashboards to provide more context (e. g., score, videos) and interactivity.

We implemented this technique by leveraging recent advances in 3D player position tracking [VFB20, CHS*21, CYC*22], which enable accurate identification of player body and ball positions relative to players and the table using 3D scene analysis as detailed in our pipeline (Figure 4) . We demonstrate how this technique facilitates reachability analysis, pivot area characterization, and selection based on radius and distance to the player, while also supporting tactical analysis with two case studies and feedback we collected from table tennis experts.

The contributions of this work are the following:

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

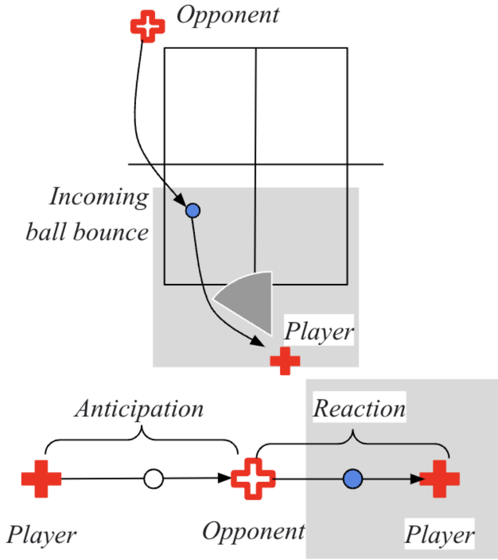

Figure 2: *A table tennis sequence represented spatially (above) as a traditional shot map, and its equivalent temporal sequence (below). The focus of this paper is on the gray area: the spatial and temporal regions related to players' reactions to an opponent's shot. Diagram inspired by [WWZ*23].*

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

2. Background

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

2.1. Definitions

Table tennis is an opposition sport involving two players (or four in the case of doubles) using rackets to play on a table separated by a net. A match consists of sets, each set is won by the player who reaches 11 rallies first (i. e., sequences of strokes starting with a serve). The match is won by the player who is the first to win three sets (sometimes four sets). Figure 2 illustrates the level of analysis we focus on in this paper: a subset of a rally, concentrating on specific incoming shots from a stroke. The key concepts in table tennis relevant to this paper include:

- **Stroke technique** refers to the technique used by the player (such as serve, topspin, quick attack, push, lob, smash, etc.).
- **Stroke position** is the player's position when striking the ball (forehand or backhand).
- **Stroke placement** is the position of the ball's bounce after a player's hit (position in centimeters).

More table tennis rules and definitions are provided in [Wan20]. However, a key difference in our approach is considering players' and ball positions *continuously*, rather than using discrete data divided into regions and events (for both players and ball positions).

2.2. 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 [LYBP20]. 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 7).

One recurring theme with our first expert is that tactical analysis of games is to *find the weaknesses of the opponent and develop a strategy to exploit them*. When analyzing games or coaching players, he pays particular attention to ball hits directed towards specific areas close to players, which he refers to as the *belly region* for a forehand stroke and close to the *elbow* when playing backhand. While those two regions are specific (elbow and belly), the *hip* can be seen as a way to encompass them under the so-called *pivot area*. According to him, reaching such an area is crucial, as players have limited time to change technique, often resulting in confusion and failure. He also reported that players have unique areas based on their technical skills and physical abilities. Such areas may also change during the game, making them difficult to identify and reach at the right time. The *pivot region* is also associated with analyses we reviewed from TV broadcast comments and table tennis learning materials. For instance, a table tennis expert on a YouTube channel analyzed the match between Ma Long and Fan Zhendong (world-class players) during the 2023 Asian Games final. During this game, the commentator indicated weak regions (using arrows) to hit the ball towards the pivot area. Ma Long effectively targeted this area, hitting the ball twice to Fan Zhendong at 10-7 to win the point and the first set: *"This is very well played [by Ma Long] as he plays twice on the elbow [of Fan Zhendong]. It is an important point as he unsettles his opponent twice, creating hesitation to use his forehand and backhand."* [Att23]. Similar analyses of the pivot area can be found in books like [Hod13] on page 209: *"Opponents are especially vulnerable to shots to their elbow, since they have to react to the shot."*. The author also adds that due to the fast-paced nature of the game, there is little time to adapt to the shot angle except when there is time, often due to the distance of the player from the table and the stroke technique (e. g., lob).

Our second expert has recent experience in deeply analyzing key tactical aspects of games using detailed data from annotation tools. Such data provide a finer grain of analysis, particularly based on ball position and distance to the player. Our expert is particularly interested in very simple aspects of sports tactics, such as *reachability area*, meaning hitting the ball where the player cannot reach it because it is too far away. This approach has not yet been explored deeply in table tennis, despite its importance. Our expert referred to other sports where such an approach was prominent, but usually in broader sport fields using macro analyses with simple formats, such as Voronoi partitions [Vor08]. This need resonates with advanced visual analytics of reachability that go beyond space partitions, using *space-time models* for soccer [SJB*16] or basketball [FB18], which provide more accurate space reachability estimation as they account for player speed and orientation, particularly for event-based characterizations such as analyzing 3-point shots in basketball [AV20]. In table tennis, reachability has been investigated through visual analysis of the distance between the opponent's position before hitting the ball and their actual position [WWZ*23]. Since table tennis games are fast-paced, the distance between the ball's hitting point and the player's position is an acceptable proxy—confirmed by our second expert—for assessing whether players are within a reachable distance or not.

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

2.3. Illustrative Scenario

To illustrate our work, we provide context and details on Figure 1 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 **PlayerC** and **PlayerD**, both highly ranked players at that time. The game was tight with a victory 3-1 for **PlayerC**. We picked two moments in the match where two shots by **PlayerC** were made, one leading to the point win and the other to the point loss. We can note that she made both a forehand and a backhand shot as seen on Figure 1 (a) shot map. In this representation, the ball bounce zones appear very close, the only difference being the type of shot made by **PlayerC** 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 **PlayerC**. We can hypothesize that the distance of the bounce relative to **PlayerC** was a decisive factor in the result, to be confirmed with further analysis of similar strokes. Watching the video footage also helped confirming this hypothesis, as we can see **PlayerC** struggling to play the shot during the lost point Figure 1 (c).

2.4. Summary: Requirements

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

R1 Data normalization and shift of perspective for all shots relative to the player in a given match or series of matches, emphasizing the ball bounce from a player's perspective. Such normalization allows for a consistent analysis and identification of shot patterns, regardless the context (e. g., absolute position of players).

R2 Characterize shots reachability and pivot area based on the angle θ and distance δ to the bouncing ball. By analyzing these parameters, we can define the efficient shot space for a player.

R3 Compare across data subsets and attributes to identify any evolution or change in performance. Thus, analysts can compare players to identify stylistic similarities, differences, or evolutions throughout the game.

R4 Contextualize strokes using videos from the games, score, or with whole rally multivariate sequences, to provide a more holistic understanding of the game's dynamic.

3. Related Work

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

3.1. Shot Maps in Sports

Shot maps (also referred to as shot distribution or shot density charts) are standard visualizations in sports [PVS*18]. They plot both sports events and trajectory data over the pitch or table, often revealing visual signatures of plays by highlighting key events such as 3-point shots in basketball [RVBR20]. These maps can also be animated with player trails [AAB*17] to provide spatial context. To facilitate interpretation, binning using a grid is often applied, as in CourtVision [Gol12]. Court landmarks [LCY*23] can be used for segmenting semantic regions. Shot maps can be embedded [PVF13] 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 [CXY*22]), which are often used in 3D immersive environments [YCC*21]. Changing the point of view is particularly interesting, as noted in [PVS*18], for providing a first-person perspective that closely aligns with how players experience a game. Still, player-centric visualizations remain an under-explored area and are primarily used in contexts where the sport centers around a specific player (e. g., a baseball hitter or a soccer goalkeeper).

A singularity of sports shot maps for adversarial sports is that they are heavily coupled to the type of games. The shots have a *converging* approach (e. g., Baseball [DKVS14]) 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 [PSBS12], and can be represented using a ring-based approach due to the importance of distance. The *diverging* approach, seen in sports such as Baseball [POGS*19, DKVS14], involves **outgoing** balls hit towards multiple directions. Often, the focus lies on the trajectory shape, distance, and the success of ball reception. In general, the analysis is closely linked to the collected data and technological advancements.

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

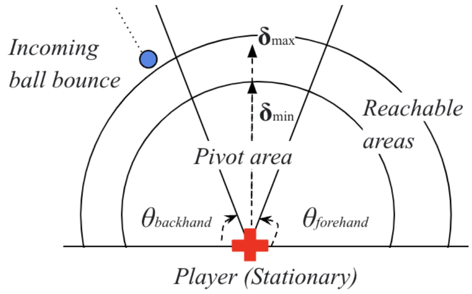

Figure 3: *Polar coordinate system for player-centric shot maps: the stationary player (red cross) relative position of balls (the circle represents a ball bounce), half-circles represent the distance δ from the player, and angles θ capture regions around the player.*

3.2. Racket Sport Shot Maps

We focus on racket sports with a net separating players, such as tennis, table tennis, and badminton. In this context, shot maps can be characterized from a *side-to-side* perspective, with no particular converging or diverging patterns, as players move on both sides. Early work in racket sports [JB96] already introduced shot maps using iconic representations. Follow-up works have relied on similar shot maps to plot information and support analysis. In iTTVis [WLS*18], shot maps are displayed as glyphs by region and stroke placement to characterize rallies with connected matrices, while Rally Comparator [LWS*22] provides player-centered shot maps with stroke placement to reveal tactical patterns in games. Tac-Miner also relies upon glyph representations [WWC*21] that categorize balls hit position into regions. Tivee offers small multiple shot maps [CXY*22] that accounts for a third dimension to capture the height of the shots. ShuttleSpace [YCC*21] also presents shot maps from a player's perspective in 3D, including detailed shuttle trajectories, for badminton. However, this line of work does not take into account the relationship between the ball and players' positions. VisCommentator [CYC*22] highlights relative positions of players to the ball to simulate hypothetical placements, though the analysis remains a visual augmentation and is still table-centric. Recently, Tac-Anticipator [WWZ*23] introduces the concept of anticipation and reaction using shot maps combined with line charts encoding players anticipation, which is close to our work as it connects players with ball hits. Yet, it characterizes players-ball distance in a 1D space (as a line chart) that does not capture players orientation towards the incoming ball.

3.3. Tactical Analysis in Racket Sports

Table tennis tactics primarily focus on the first three consecutive strokes [WWC*21, Wan20, DLP*23], which are mostly represented as sequences of multivariate events. The spatial component (stroke placement) is often captured as a category using discretized table regions (e. g., in 3×3 grids). In [WLS*18], events are organized as connected matrices to provide an overview of a rally, where stroke placement is included as an attribute alongside stroke technique and position. In Tac-Simur [Wan20], the authors introduce a tactic discovery mechanism and visualize player simulations to analyze their performance. Tactic discovery can also be achieved using frequent

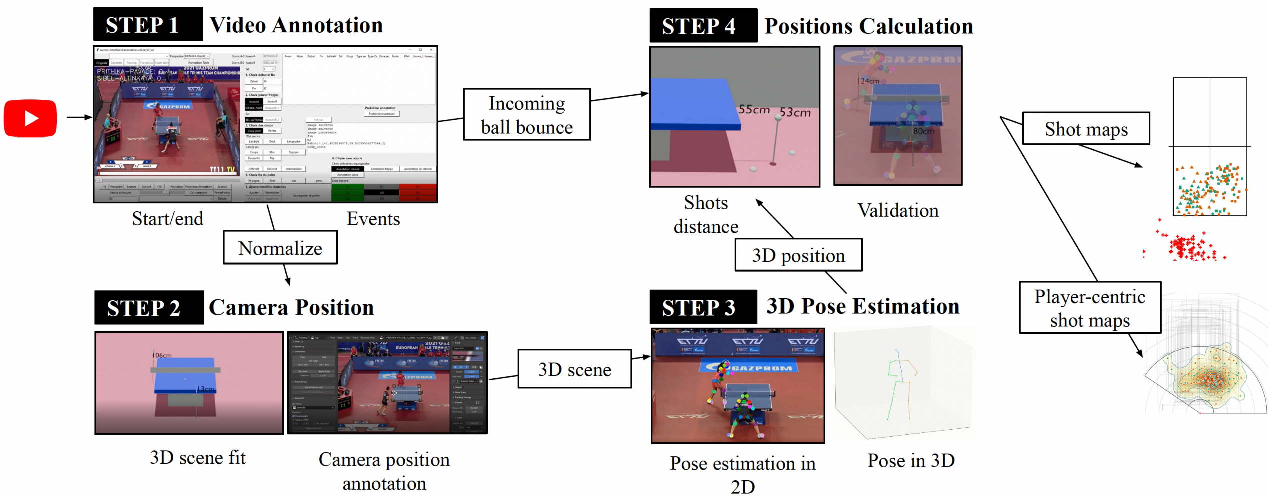

Figure 4: *Our 4-step data collection pipeline takes broadcast video as input and returns the relative spatial and temporal positions of players: **STEP 1** relies on manual annotation to browse and segment videos for game start/end, to click on video frames to locate ball bounce and hit positions, and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

patterns [DLP*23] to reveal efficient (and inefficient) strategies. Tac-Anticipator [WWZ*23] focuses on players' positions before their opponent hits the ball, characterizing their distance as a key factor in analyzing tactical efficiency. This work is most closely related to ours as it considers space continuously and accounts for players' relative positions. However, it primarily focuses on the *anticipation phase* in table tennis, defined as the duration between when a player hits the ball and when their opponent hits it back (Figure 2, bottom). Once the opponent hits the ball back, this phase is referred to as the *reaction phase*, which is the main focus of our work. This phase is typically so short that the player has little time to adapt to the opponent's shot. To the best of our knowledge, no prior work has explored this particular phase, which is closely related to the *pivot-based analysis* our expert referred to.

4. Data Collection

As no publicly available database of table tennis player positions exists, we collected data using a hybrid approach combining computer vision, deep learning, and manual annotation tools to extract player- and ball-related data (summarized in Figure 4). Our system processes broadcast RGB videos as input (without requiring any sensors or embedded tracking devices) and outputs players' positions relative to the table for incoming ball bounces. This approach aligns with existing methods for extracting table tennis ball data, such as the EventAnchor process [DWW*21]. However, it contrasts with fully automated systems like TTNet [VFB20] as our method is semi-automated, particularly to achieve a high level of spatial precision for 3D pose estimation.

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

STEP 2 **Camera Position.** To calculate accurate player positions, we required 3D coordinates. Since the videos are recorded from a static viewpoint we fit a 3D structure in the scene (table tennis table have official dimensions: 2.74m long and 1.525m wide)—using a reference frame with minimal occlusion and visible corners, based on [MUS15]. This process also enabled the calculation of intrinsic camera parameters to correct lens distortion (we annotated two additional reference points near the net to reach a greater accuracy). The result was a transformation matrix that converts 2D points from camera space to the 3D scene. This matrix also determined the camera 3D position and rotation, saved for projecting points 2D players' reference points in 3D in STEP 3.

STEP 3 **3D Pose Estimation.** Manually annotating players' body positions in STEP 1 would have been too tedious, but recent advances in deep learning enable efficient body tracking methods such as OpenPose [CHS*21]. OpenPose provided us with a player skeleton, from which we identified the ground position and players' feet. However, the skeleton with its 25 joints was provided in the camera plane rather than the 3D plane. To address this, we applied a post-processing step using MotionBert [ZML*23]. This augmented the skeleton with a Z position, as MotionBert estimates each player's 3D pose in their own reference frame. However, such poses needed to be placed in the 3D scene, requiring additional post-processing in STEP 4 to align the 3D poses with the table coordinates.

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

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

5. 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 3). This visualization aims to reveal the *reachability* and *pivot area*, two under-explored tactical factors in table tennis.

5.1. 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 1 (a)), but then data normalization is applied, and the perspective shifts using the same visual encoding **R1** (Figure 1 (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 [GAW*11]. 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**.

5.2. Visual Encoding

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

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

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

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

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

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

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

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

Interactions are provided to select subsets of shots relative to the player's position with θ and δ values **R2** (such parameters can be automatically set as described in the next section). Widgets are provided to filter by stroke techniques and other attributes **R3** collected during the annotation process (shown on Figure 9).

5.3. Shot Map Clustering and Pivot Area

A side effect of the technique is that it groups shots into a smaller area than the table, leading to significant over-plotting. We experimented with various grouping methods (both supervised and unsupervised) to highlight global trends. We opted for an unsupervised approach and used kernel density estimation (KDE) to emphasize groups [SG18] using the density of shots in the two-dimensional space of the table [RPD21]. 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:

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

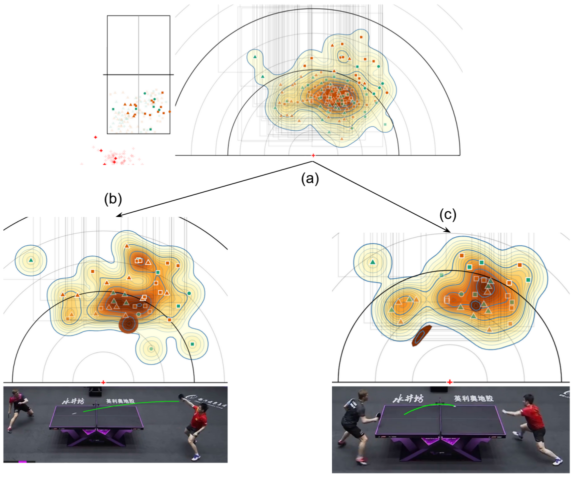

Figure 5: *Case study 1 on reachable areas for PlayerA: (a) selection by distance, (b) filter by topspin, and (c) filter by push.*

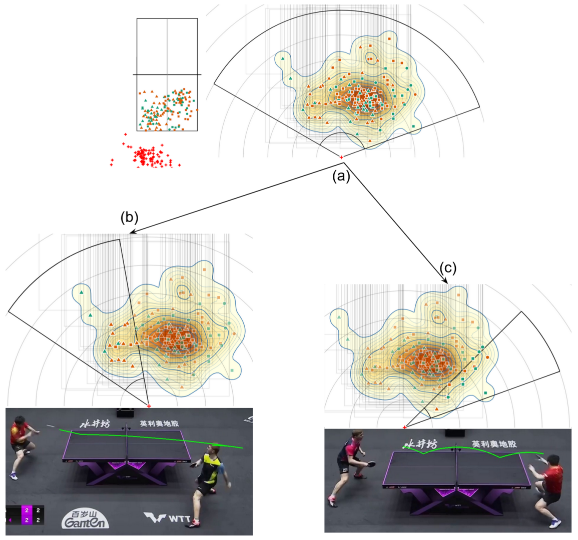

Figure 6: *Case study 1 on lateral areas for PlayerA: selection by left angle shows a winning region (a), and by right angle shows a loosing region (b).*

6. Implementation

We implemented the shot map visualization in JavaScript using D3 [BOH11] and Observable Notebooks with a SVG rendering. The technique heavily relies on a normalized dataset around players' positions which is achieved by our pipeline. We used both linear and radial scales in D3, that enable a smooth transition from the table-centric visualization to the player-centric one. The density calculation is based on the kernel density method implemented through [Obs25], 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 [Ope25a] and a Blender Plugin. We wrote custom Python codes for the pose estimation and 3D reconstruction by relying upon Blender for matching in the 3D feet of the players with the table ground. We share our code on the following supplemental material website: `https://github.com/centralelyon/player-centric-shot-maps` as part of an open-source project under a permissive license.

7. Case Studies and Experts Feedback

We first report on illustrative case studies of the use of our player-centric shot map to support *reachability* and *pivot areas* tactical analysis in table tennis. We first detail scenarios of use that we identified as typical ways to analyze table tennis games using our technique. These stem from our collaboration with two experts, but due to their limited availability [LYBP20] 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 paper. We then collected feedback from our experts by interviewing them during 2-hour Zoom sessions. Our procedure was as follows: the prototype was demonstrated remotely with a simple presentation scenario (15 minutes), with visualizations integrated into a dashboard to provide context on the games, e. g., videos and score timelines (Figure 9). 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).

7.1. Case Study 1: Reachability Area

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

(Non) Reachable Areas In table tennis, one of the simplest tactics to win the point is to make the opponent not be able to touch the ball. This can be translated into playing in an area sufficiently far away which can be selected using the distance selector (Figure 5). We observed that beyond 150 cm, there is a correlation with a reduction of the player's success rate. This can be explained by different factors: the ball was short and the player was far away, or the player was far from the table. These factors need to be analyzed differently, e. g., by stroke type. With a filter by **pushes**, the results show a relatively balanced trend (Figure 5, b). However, it becomes evident that **PlayerA** losing points occur on the shortest balls near the table. When filtering exclusively for **topspins** (Figure 5, a), the area shows a clear losing trend. This can be interpreted that when **PlayerA** is far from the ball and the opponent plays a topspin, he tends to be dominated, leading to low efficiency.

Lateral Areas In this second part, we study the lateral zones relative to the player to identify the ones the player feels comfortable and those where he/she does not (and ultimately find their *comfort zone*–the area where they are best positioned to execute their shot effectively). By studying lateral zones, analysts aims to identify losing and winning zones, to determine the areas to avoid or

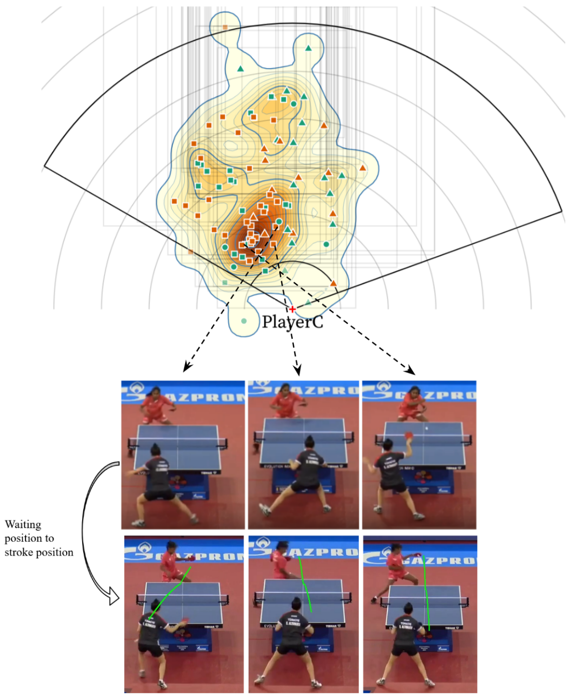

Figure 7: *Case study 2 on revealing the pivot area: characterizing the pivot region of **PlayerC** by selecting angles and distances that capture weaknesses. The waiting position when the opponent hits the ball (anticipating a backstroke); the opponent hits the pivot area which makes it difficult for her to return the ball.*

target during play. Using filters that divide the playing space into zones relative to the player's position at a specific angle, we can observe that **PlayerA** has a losing zone on his **left side** (Figure 6, a). This highlights an area where **PlayerA** 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 6, b). Since this other side corresponds to his forehand zone, it shows that **PlayerA** is more effective with his forehand, able to deliver higher-quality shots even when in suboptimal positions.

Expert 1 Feedback. Once the introductory was presented, our expert explored the regions the farthest from the player. He also found the losing trend in the deep zone seems logical because it lies beyond the player's comfort zone, where they are not in optimal conditions to be effective. It could be interesting to analyze how players are drawn into these areas by studying the **preceding shots**, i. e., the ones before our scope (left part of the sequence on Figure 2). Lateral zones help the trainer to quickly identify if players have specific areas where they struggle. Our expert thought of using the technique to **characterize players' profiles**, which he thinks would be particularly valuable. Such profile would provide quick overviews of player distance and angles, and would allow analysts to look for these same patterns in other games and against different opponents. Another crucial aspect was the ability to **filter data**. The expert emphasized that not all points can be interpreted in the same way — for instance, a push and a topspin in the deep zone

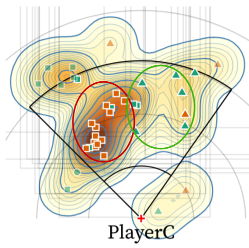

Figure 8: *Case study 2 on pivot areas when returning serves: two clusters emerge within the pivot area, based on player performance for each stroke. Those clusters correlated with forehand and backhand technique, which means half of the pivot is respectively a weakness (red) and the other half actually a strength (green).*

are too different to be analyzed together. Despite filters were added following **R3**, more were needed in particular to filter by incoming ball direction.

7.2. Case Study 2: Pivot Area

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

Revealing the Pivot Area. It is often a complicated analysis because it is based on many factors and is unique to each player; it depends on their waiting position (e. g., more on forehand or backhand side). Figure 5 shows that for **PlayerC**, a zone where she loses points appears to emerge on her left side which is the center of the cluster and close to how the opponent sent the ball. With a mouse selection, further attributes related to the shots can be revealed: the majority of points played in this zone are played using the forehand. However, if we look at the area slightly to the left, we can see that this one is winning by using backhands. Therefore, we can assume that her waiting position leans more towards waiting for backhands, which explains why the problematic zone is slightly shifted towards her forehand side. She struggles when forced to play with her forehand in this zone; however, if she can use her backhand, she's very effective. Through the video, we can observe this waiting position is exploited by the opponent who aims at this particular region.

Pivot Area when Returning Serves. In this second case, we refine **PlayerC** pivot area by focusing on a particular stroke technique: serves. This stroke technique is singular as the receiver waiting position has a consistent position towards the 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 8 shows a similar separation of performance with two clusters that stand out: in the forehand area, she still struggles, while in the backhand area, she's still effective (8 success out of 11 points). The interesting part with those clusters is that they are situated within the pivot area we identified in the previous, but with only a subset of strokes. The interpretation is that the weakness can be explained by the fact that with her backhand, **PlayerC** 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

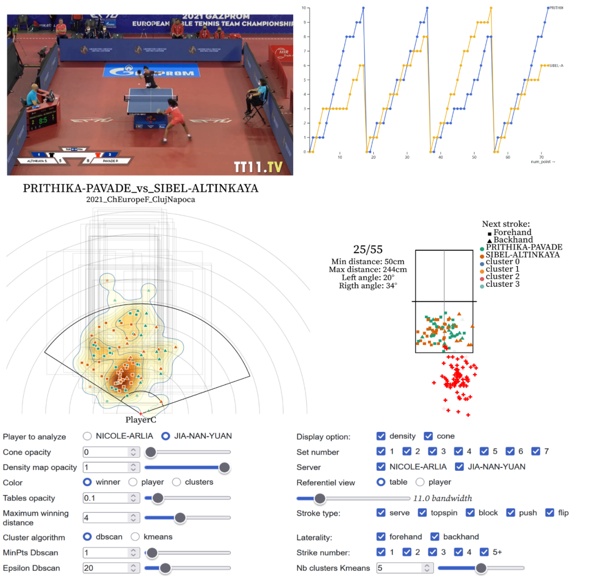

Figure 9: *Dashboard with the player-centric shot map we presented to our experts to collect their feedback.*

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 **PlayerC** should not be engaged during serves.

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

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

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

8. Discussion

8.1. Relevance for Tactical Visual Analysis

We presented a method to conduct tactical analysis using advanced data that are currently underutilized in most tactical tools and techniques: ball and players' positions. Such positions are often encoded categorically, while crucial for supporting fine grained analysis. Tac-Anticipator [WWZ*23] closely aligns with our approach as it considers players' distances but with respect to their previous positions. Based on our experts' feedback, the player-centric approach is relevant, although it requires strokes filtering and careful grouping of similar strokes to fully characterize a pivot region. Regarding our design, our aim was to maintain consistency with current shot maps. However, additional explanations are necessary for complete comprehension to be communicated without assistance. We also plan to explore glyph-based representations [PMB*23, LCP*12], which could provide more compact and easier-to-compare visualizations of pivot areas, as a means to display small multiples that would allow new tasks such as comparative analysis during or across games. We plan to scale the technique using multi-class density maps [JVDF19], which will preserve the color encoding for shot efficiency—an important component of analysis.

8.2. Applicability to Other Racket Sports (e. g., Tennis)

As standard shot maps are pervasive across sports, we wanted to explore the applicability of our technique in an another sport beyond table tennis. We picked Tennis, as ball tracking dataset are available, e. g., of the 2021 French Open Final opposing Novak Djokovic and Stefanos Tsitsipas. This dataset was found online [Ope25b] and loaded them into our tool with some minor preprocessing steps, required to adapt to a different data model. In total we load 8K ball positions samples tracked during a game. We filtered out to only keep ball bounces and ball hit, which ended up to 3K points. We then keep the serves to show if, based on the serve direction and the other player waiting position, a particular pattern emerge. Figure 10 shows that indeed patterns emerge as a general trend on how players adapt between the first and the second serve: Djokovic hits the second serve balls much closer than Tsitsipas. We would expect another direct applicability for other net-separated sports like badminton, and even for team sports like volley-ball. We may expect the technique to be useful for sports

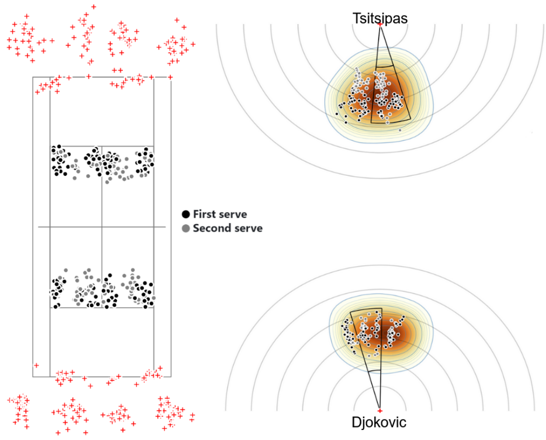

Figure 10: *Our technique applied to other sports such as Tennis. We notice that Djokovic hits second serve balls much closer than the first one, while Tsitsipas does not change his behavior.*

where shots have a converging/diverging patterns, e. g., during the penalty shootouts.

8.3. Limits and Perspectives

Visual Design and Dashboard. When we presented our technique to our experts, it required both explanations and transitions from the original shot map to be understood. Thus, there is a need to improve the design to become a standalone technique. The use of other views also shifted our expert attention from the shot map to side views. Such limit is also applicable to standard shot map techniques that are rarely presented as standalone visualizations, but are easier to grasp due to the spatial nature of the plotted data. We identified several areas of improvements for the visual design of the technique, e. g., orientation of the table, grids, grouping, labels and ball trajectories. The dashboard we built (Figure 9) follows an exploratory approach [Shn96] by exposing all data at once, to let users filter by attributes and get details using the video footage of the game, which also acts as context **R4**. A user study is needed to develop a domain-specific interface, similar to [WWZ*23].

Contextual Information. An observation made by both of our experts during the study was that interpreting shot efficiencies requires placing them in the context of previous shots, especially those at a distance often employed as a tactic to draw players into a particular area. This tactic was also present in the TV broadcast material we reviewed during the Asian Games 2023 final *[Fan Zhendong] attracts the player in the right side of the region to hit with a forehand, so then he leaves the other empty region empty* [Att24]. [Hod13] on page 48 also mentions such tactic *"Imagine an opponent who goes way out of position to loop with his forehand from his backhand side, and he loops to your backhand, leaving his forehand side wide open."*. It resonates with Sporthesia [CYX*22] which example *Nole crosscourt with a sharp angle* highlights the importance of relative position in terms of ball reachability. Therefore, we believe there should be a distance threshold for the strokes we plot, as they may not be relevant for pivot area characterization and analysis. Instead, such strokes should be examined using control area models (e. g., [AAA*21,AV20,Gol12,FB18]) that consider the dynamics of players to define the reachability of specific regions based on reaction time and movement dynamics.

Data. Data accuracy was also questioned, particularly regarding pivot areas, which are typically very narrow and demand precise ball and player pose detection. However, one of our experts mentioned that players shot accuracy is within a range of 20cm, falling below the tracking accuracy (dependent on video resolution, approximately 2cm). As technological advancements continue, tracking data will likely become available with increased precision. This enhancement could include additional data such as ball trajectory and spin effects, providing a more comprehensive analysis of shots. In particular, by considering another body part for position and distance to the table calculation (currently the feet of the players). More data was requested by our experts to explore pattern variations across games. As our annotation process remains long, automation could be introduced by leveraging previous annotations [POGS*19]. A major limitation remains the broadcast video which leads to occlusions and causes some shots to be inaccurately processed. We plan to explore the inclusion of a confidence score (for both human and automated analysis) to provide more transparency on the actual data quality.

Perspective on Perspective and 3D. We picked the player's perspective as the referent for the relative position, with the incoming ball bounce as the reference event. However, our normalization and visualization techniques are flexible and allow for other positions and events as referent. For instance, one could align the data based on the position and time of all racket hits, providing different insights on the incoming and outgoing ball trajectories. Despite our data collection pipeline operates in 3D, this work only focuses on 2D visualization shot maps due to their wide use. While 3D data has potential for ball trajectory-based analysis, body motion, and both to capture 3D shots reachability [EBFFG21], it still requires highly accurate reconstruction methods to capture spin, the Magnus effect and human movement dynamics.

9. Conclusion

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

10. Acknowledgment

We thank the reviewers for their very valuable feedback. This work was conducted under the partnership with the French Table Tennis Federation (FFTT).

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