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Research article

Visualizing game dynamics at a specific time: Influence of the players' poses for tactical analyses in padel

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ABSTRACT

Tactical elements are crucial in team sports. The analysis of hypothetical game situations greatly benefits from positional diagrams showing where the players are. These diagrams often show the layout of the players through simple symbols, which provide no information about their poses. This paper investigates if the visualization of player poses is beneficial for tactical understanding of positional diagrams in padel. We propose a realistic, cartoon-like representation of the players and discuss its integration into a typical positional diagram. To overcome the cost of generating player representations depicting their pose, we propose a method to generate such representations from minimal user input. We conducted a user study to evaluate the effectiveness of our pose-aware diagrams. The tasks for the study were designed to encompass the main in-game scenarios in padel, which include the ballholder at the net with opponents defending, the reverse situation, and transitions between these two states. We found that our representation is preferred over a symbolic one that only indicates player orientation. The proposed method enables coaches to produce such representations within a matter of seconds, thereby significantly facilitating the creation of detailed and easily analyzable depictions of game situations.

1. Introduction

Tactics are essential in team sports, where player movements and technical actions must be continuously coordinated among team members. In this paper we focus on the analysis of tactical aspects in game situations occurring in padel, a young sport that shares some similarities with double tennis, but offers a collection of unique characteristics (Martín-Miguel et al., 2023). The most relevant difference is due to the walls that surround the padel court, which allow players to return the ball after one or more bounces (Fig. 1). This causes padel to exhibit a wide variety of technical actions, resulting in a wide range of shot types (Demeco et al., 2022).

Several padel characteristics, some of them unique to this sport, suggest that the players' poses and orientations are essential in decision-making processes and thus might play a relevant role in analyzing hypothetical in-game situations. Padel courts are relatively small (compared, for example, to tennis courts). This fact, combined with their enclosed walls and the fact that padel is always played in doubles, results in players being relatively close to their opponents. As a consequence, padel is a fast-paced game. Our analysis of a professional padel match (a women's final in an international tournament) revealed that the average time between shots was just 1.25 s, with 43% of shots occurring less than one second apart. This leaves players with minimal time to decide and execute technical actions. Given such short reaction windows, trying to return a ball from an inappropriate pose becomes a significant challenge. This suggests that padel players may gain a competitive advantage not only by knowing their opponents' positions, but also by being aware of their opponents' poses. Furthermore, padel players often return the ball while facing different directions and employing a variety of technical actions. This is due to the unique rules of the sport, which allow players to return the ball after it rebounds off the walls. In addition, in certain situations, players can deliberately hit the ball against the walls on their side of the court to execute a return. This provides players with greater flexibility compared

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Fig. 1. Padel courts are surrounded by walls, and players are allowed to return the ball before or after the ball bounces off the walls. Image from a public padel dataset (Javadiha et al., 2024).

to tennis, allowing them to return the ball at different moments and execute a wider range of technical actions, resulting in very distinct poses and orientations, some of which could present a considerable difficulty when preparing for the next return, especially given the fast-paced nature of the game.

Fig. 2 illustrates this by showing a padel player in a variety of poses. In the first image, the player attempts to return a ball that has rebounded from the back wall and travels parallel to the side glass. Since he is facing to the right, he is in a poor position to react effectively if the next shot is directed toward the center of the court. In the second image, the ball has also bounced off the back wall, but the player's orientation is opposite, executing a backhand shot. This positioning places him in a much better position to respond if the next shot is aimed at the center. In the third image, the ball is between the racket and the back wall, forcing the player to play a lob using his own wall. If the lob is not high enough, it is likely that he will struggle with the next return of the opponents. Finally, in the fourth image, the player is barely able to reach a ball sent into the corner and is likely to hit it while still running. Each of these poses represents a different level of difficulty in executing the next return; the opponents are likely to take advantage of this information to choose the most promising type of shot. This example highlights the potential relevance of poses in padel tactics.

Visualization tools in sports have proven highly valuable for representing, analyzing, and discussing tactics. In the case of padel, texts on tactics heavily rely on visual representations that depict real or hypothetical in-game situations. Diagrams in padel often include some representation of the players and the ball (see Fig. 3 for some examples). In some cases, extra symbols are used to represent different options for the player's short-term actions, such as where they should move, where they should direct the ball, and with what type of shot. Padel coaches frequently use whiteboards to sketch such situations and discuss them with the players before, during, and after matches.

Although the visualization of in-game situations has been studied for decades for many sports, to our knowledge, there are no studies on their use and effectiveness in padel, despite the widespread use of such visualizations in the padel literature (Martín Avilés, 2019; Magazine, 2023; Padelmania, 2013; Padel, 2020; Vidal, 2015; Remohi-Ruiz, 2019).

This paper explores the challenge of visualizing the state of a padel match to facilitate more effective tactical discussions. We argue that positional diagrams featuring players in realistic poses, rather than simple symbols, provide a more accurate and insightful representation of game situations. Therefore, our primary research question is whether *the visualization of player poses is helpful for tactical understanding of positional diagrams in padel*. However, evaluating the usefulness of visualizing poses requires contextual considerations, since such usefulness may vary depending on multiple factors. Considering the game situation, for instance, the shorter the distance between the two teams, the narrower the reaction window and the higher the potential relevance of the pose for a player to effectively move and return the next ball. On the other hand, the usefulness of depicting the player poses depends on other cues provided by the rest of the elements in the positional diagrams, such as paths representing player movement. Therefore we analyzed player positioning to identify the primary tactical scenarios in padel (serve, net attack, defense, and transitions) to ensure that our user study incorporated representative examples of each, and also consider the integration of our player representations with typical diagrams.

More specifically, the main contributions of this paper are:

- User study design: We design a user study (and the corresponding tasks) capable of revealing the potential impact of incorporating player poses into positional diagrams.
- Game situation classification in padel: Using hierarchical clustering, we analyze player positioning and movement and identify four primary tactical scenarios (serve, attacking at the net, defending, and transitions). This categorization provides a framework for analyzing the relevance of poses in positional diagrams.
- Findings: a study with 34 participants shows that pose-aware diagrams significantly enhance tactical interpretation compared to symbolic representations. These results confirm that integrating player poses improves game-state understanding.
- Automated pose generation: as a supporting tool for our pose-aware positional diagrams, we propose a method to generate realistic representations of the players in specific poses with minimal user input (type of shot, time offset with respect to the impact of the ball, speed of the player, and the direction of displacement).

2. Previous work

According to Perin et al. (2018), from a data visualization perspective, sports data can be categorized into three types: *box-score data*, *tracking data*, and *meta-data*. Box-score data includes discrete in-game events and their summary statistics, which are highly specific to each sport (Perin et al., 2018). In the case of padel , examples of such events are players hitting the ball (like a player executing a smash at a particular time), players approaching the net, or teams scoring points. Summary statistics, such as the frequency of each type of shot, the time players spend near the net, or the total points scored (Almonacid Cruz and Martínez Pérez, 2021), also belong to the box-score data category.

Tracking data refers to spatiotemporal information about players and their actions, typically collected using a combination of cameras and sensors (Javadiha et al., 2021). These data often include, for each moment in time, the positions of the players as well as details about their actions. In football, the actions of the players can include shots, passes, offensive maneuvers such as dribbling, defensive actions such as interceptions, and errors such as losing possession of the ball (Perin et al., 2013). In padel, player actions encompass shots and movements toward the net (attack zone) or toward the back of the court (defense zone). The position of the ball is critical, and shot descriptions often incorporate both the ball's origin and destination. Current video-based pose estimation methods also provide information on player poses (Javadiha et al., 2021). Finally, meta-data refer to general information about the sport (for instance, rules), the players (e.g., physical characteristics like height or dominant hand), or the environment.

We focus here on tracking data because they are more closely related to the features that characterize the state of a match. Tracking data can be visualized in multiple ways (see Perin et al. (2018), Du and Yuan (2021) for a review), following more general

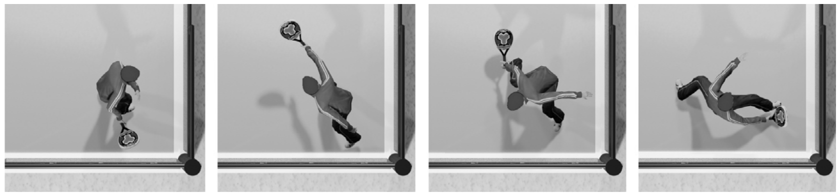
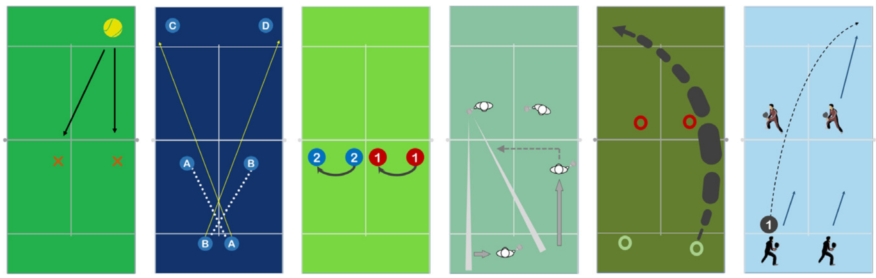


Fig. 2. Sample poses of a padel player, rendered by the authors from a public MoCap dataset of an amateur padel match (Javadiha et al., 2024). In all four game situations, the player is near the right corner at the back of the court, but his poses vary significantly.



(a) (b) (c) (d) (e) (f)

Fig. 3. Sample visualizations from padel tactics literature. All figures are our own work, but following the layout and visual style of the corresponding sources. Based on (from left to right): (Martín Avilés, 2019; Magazine, 2023; Padelmania, 2013; Padel, 2020; Vidal, 2015; Remohi-Ruiz, 2019). Arrows are used for various meanings: cause–effect relationships (a); serve targets (b); player movement (b), (c), (d), (f); range of shot directions (d); and ball trajectory (e), (f). Players are nearly always depicted with symbols (a)–(e), or using fixed-pose icons (f).

ideas of trajectory visualization and visual analytics of movement (Andrienko et al., 2013). Some techniques overlay the data on a schematic representation of the playing field, making them suitable for tactical analysis. For example, event density maps characterize the spatial distribution of certain events, such as the landing spots of balls in tennis or the locations of hit balls on a baseball field (Lage et al., 2016). Density maps can use simple primitives such as dots (Lage et al., 2016) or employ spatial bins to create discretized heat maps, where each bin is assigned a color corresponding to the number of events that occurred within it.

The trajectory of players and the ball is widely used to visualize tracking data, particularly in sports such as football (Shao et al., 2016). Using shorter trajectories, or *trails*, effectively conveys movement while reducing visual clutter. In padel, such trails have been used, for instance, to compare players' motions after a serve (Javadiha et al., 2023).

Representing spatio-temporal trajectories on top of sports pitches often leads to overplotting or "spaghetti" visuals (Perin et al., 2018), even when representing a subset of the game, making it a significant challenge in sports visualization, often addressed through spatio-temporal abstraction to simplify, smooth, or aggregate these trajectories. One of the approaches to deal with these challenges is to embed trajectory visualizations into game video footage (Stein et al., 2017). This approach is actively exploited in sport broadcasting now for communicating interpretations of game situations. However, it has its own limitations in analytical contexts.

Most existing methods for visualizing tracking data omit individual player representations or use very simple symbols such as dots and circles (Seidenschwarz et al., 2020). Consequently, detailed information such as players' poses is often not depicted either because pose data is missing or because the tracking data spans a long time period during which players' poses vary significantly.

In the case of padel, tactical diagrams in books, articles, and websites predominantly use symbolic representations of players (Martín Avilés, 2019; Magazine, 2023; Padelmania, 2013; Padel, 2020; Vidal, 2015). Few works employ realistic or anatomical representations and most of them use fixed poses only (Remohi-Ruiz, 2019).

The use of realistic representations of athletes, both in general sports illustrations and positional diagrams for tactical analysis, remains relatively uncommon. This is partly due to the perceived lack of significant advantages over symbolic representations, given the additional effort required to generate them. Creating pose-specific player depictions typically requires either manual illustration skills or proficiency with 2D or 3D computer graphics software. Consequently, the limited instances where realistic representations appear in positional diagrams show players in a restricted set of predefined poses (Remohi-Ruiz, 2019), significantly reducing their applicability.

Some works have explored automatic or semi-automatic methods to generate realistic player representations that accurately reflect their poses. For example, Lai et al. (2012) presented a tennis game in which players are represented by selecting, segmenting, and smoothing video clips from actual matches. Because the players are extracted directly from the video footage, they retain the same appearance, lighting, and point of view as in the source material. Designed for interactive gameplay, their method selects a clip for a hitting action based on the similarity of shape and texture. Recently, Zhang et al. introduced a reinforcement learning system that acquires tennis skills from video demonstrations of actual gameplay. The agents produced by this system can control physically simulated tennis players, that is, 3D animated characters capable of hitting the ball to specific target positions using a diverse range of shots and playing styles. This advancement opens new opportunities to render tennis players in arbitrary (albeit simulated) poses that accurately correspond to the incoming ball trajectory. However, as mentioned earlier, the walls that surround the court add complexity to the skills required to return the ball; therefore, the types of shots and the pose sequences of padel are more varied than tennis, and includes technical actions specific for wall bounces (see Fig. 2), such as left/right fence shots, side wall forehand/backhand, off the wall forehand/backhand, off the wall smash, double wall opening, double wall opening with rotation, double wall closing, and back wall boast (Almonacid Cruz, 2011; Almonacid Cruz and Martínez Pérez, 2021).

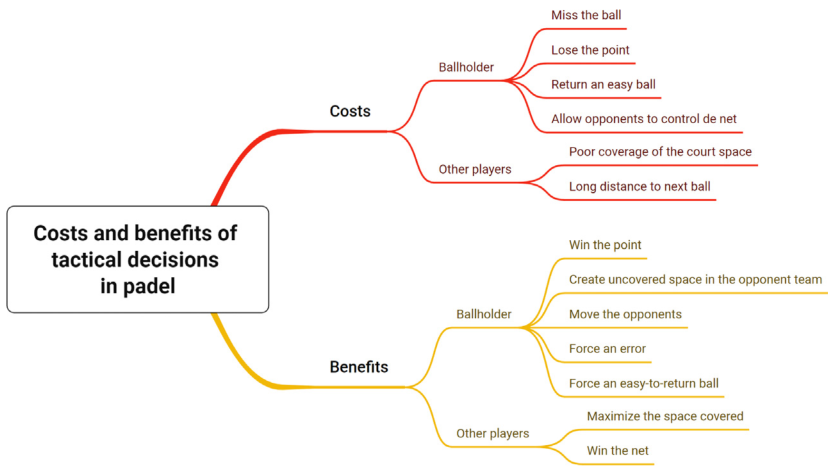


Fig. 4. Costs and benefits associated to motor tactics in padel.

3. Tactical aspects in padel

In this section, we delve into the tactical aspects of padel, identifying key features that influence decision-making during matches, paying particular attention to the position and pose of the players. This analysis will help identify key elements to include in player positioning diagrams and will provide the necessary context to evaluate the role of player poses in tactical analyses.

3.1. Background on padel tactics

Motor tactics refer to short-term decisions and actions taken by players during the game, for example, every time a player returns the ball (Almonacid Cruz and Martínez Pérez, 2021). Players must repeatedly perform a quick analysis of the game situation to identify and execute the most promising alternative. We can distinguish three phases (Mahlo, 1969): (a) perception and analysis of the game situation; (b) mental solution to the problem, that is, decision-making; and (c) execution of the chosen motor action.

At a given time, we can consider three different *motor roles* in padel (Almonacid Cruz and Martínez Pérez, 2021): (a) ballholder, (b) ballholder's partner, and (c) opponents. These roles are swapped every time a ball is returned. This makes it particularly challenging to account for all the actions a "player without the ball" can take. Unlike other sports such as football, ball possession in racket sports is limited to the ability to hit the ball.

For the ballholder (the player that is about to hit the ball), the main tactical principles refer to the following goals, according to Almonacid Cruz and Martínez Pérez (2021): (a) Return the ball without losing the point, (b) Execute the shot so that the ball flies far away from the opponents, (c) Execute the shot so that the ball gets to a specific target that hinders the return of the opponents and (d) Coordinate movement with the partner to appropriately cover the court space.

For players who do not hold the ball, the principles are, among others (again, according to Almonacid Cruz and Martínez Pérez (2021)): (a) Move to a location that, considering the uncertainty about the game, facilitates the return of the ball, (b) After a shot, get back to a waiting position as quickly as possible, and (c) Move to places that increase pressure on opponents.

At a lower level, the short-term decisions and actions of the players essentially consist of the following. For the ballholder, decide when and how to hit the ball: type of shot, direction, speed, and effect. For the rest of the players, decide (and continuously re-adjust) the best location to move to, and the best orientation and pose to adopt.

These low-level decisions have an associated *cost* (e.g. ball targets with minimal error margin are likely to fail and thus have a high cost in the long term) and *benefit* (such as winning the point, putting the opponents in a difficult situation, and gaining extra time). These costs and benefits are summarized in Fig. 4. Although the ultimate goal of a team is to win the match, this outcome depends on the accumulation of scored points, which in turn are mostly influenced by the cost/benefit of the decision (Hristovski and Balagué, 2020).

3.2. Pose of the players and its impact on the analysis of the game situation

We discuss first the perception and analysis from the ballholder's point of view. According to the tactical principles discussed in Section 3.1, the accurate perception of the position and orientation of the other players is essential for the ballholder to correctly analyze the game situation, as they influence the opponents' difficulty in returning the ball if directed to certain areas of the court, and the partner's possibility to cover the court space efficiently while waiting for the return. Notice that the players' poses are essential, as they provide important cues about their *planned* movements and thus allow the ballholder to *predict* their future displacements and their readiness to return the ball.

The rest of the players have to decide the best location to wait for the next return. Players do not know when and how the ballholder will return the ball. For instance, a short lob can be countered in various ways, such as with a powerful smash (high speed and high bounce) or a deceptive fake smash (low speed and low bounce). The gestures and poses of the ballholder give cues about how the ball will be returned, as he or she goes through the different phases of a shot: preparation, acceleration, contact point, follow through, termination, and recovery. This is because different types of shots usually involve quite distinct gesture sequences. For example, the preparation of a smash differs substantially from other types of shots, such as backhand volleys. Furthermore, the planned landing target for the ball correlates with the orientation of different body parts of the ballholder at the preparation phase, and the final direction of the ball after the stroke is influenced by the terminating pose. The high correlation between poses and associated technical actions means that poses convey valuable information for players to anticipate the ballholder's decisions and to better understand their effects.

Given the fast-paced nature of padel, the ability to anticipate others' technical actions, even some milliseconds ahead, provides

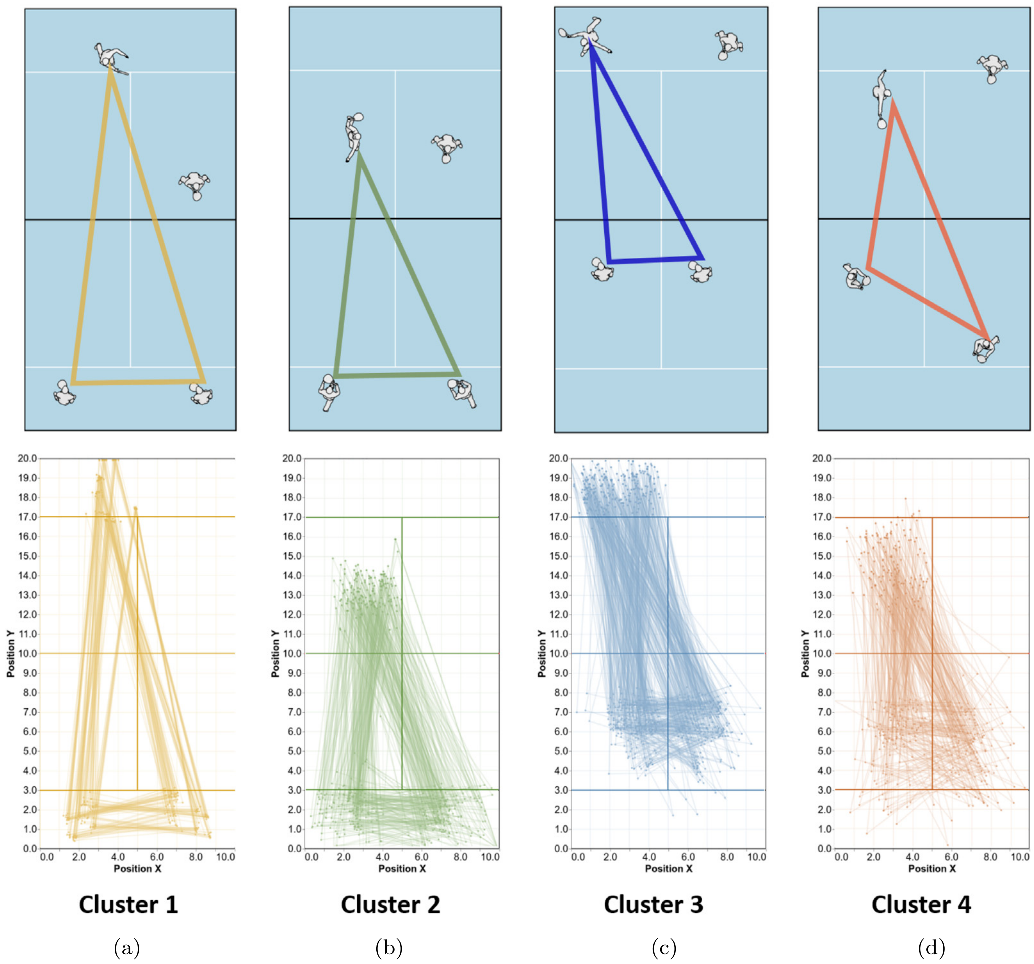


Fig. 5. The main game situations in padel. From left to right: (a) ballholder serving; (b) ballholder at the net and the opponents at defensive positions; (c) ballholder defending and the opponents at the net; (d) transitions and other game situations. The first row shows, using our proposed method described below, one example of each game situation. The second row shows the clusters we obtained from a professional match (each triangle connects the ballholder with the two opponents).

a significant competitive advantage, and thus professional players have developed skills to continuously analyze the game situation considering all these variables. This suggests that depicting the players' pose at different phases in positional diagrams (see Table 3) might provide relevant information for tactical analyses.

3.3. A classification of padel game situations

In this section, we analyze game situations in padel, building on the widely accepted premise that scoring a point is significantly easier when the player hitting the ball (ballholder) is positioned near the net. This advantage arises from several key benefits associated with playing shots from this position: (a) better angles, as being close to the net allows the ballholder to send the ball at angles more parallel to the net, making it difficult for the opponent to reach and return the ball; (b) less time for the opponents to react, thus increasing the likelihood of forced errors; (c) the possibility to execute finishing shots such as smashes; and (d) more control over the game dynamics, as the players close to the net generally control the rally better by pressuring the opponents into defensive positions. Conversely, winning a point from the back of the court is hard, at least at the professional level. Therefore, one of the main strategies in padel is *to win the net*, waiting there for the opportunity to execute a finishing shot, while keeping the opponents in defensive positions at the back of the court. As a consequence, game situations with all four players at the back of the court are uncommon in professional padel matches.

In summary, from the perspective of each team's intent, the goal is to gain and maintain control of the net. Therefore, we could expect the following *theoretical* game situations, that we describe from the point of view of the ballholder (see top row of Fig. 5):

Serve	During the serve, the ballholder stands behind the service line, with her partner positioned at the net, while the opponents take a defensive formation, as the serve must bounce on the ground before it can be returned. Immediately after serving, the player moves toward the net.
At the net	The ballholder's team is positioned at the net, with their opponents at the back of the court. The ballholder will aim to apply pressure on their opponents, trying to force them to return a ball that creates an opportunity for a finishing shot.
Defending	The opposite of the previous situation, exchanging the role of the attacking team (at the net) and the defending team (at the back): the ballholder in a defensive position, and the opponents at the net.
Transitions	Shifts between the states above: the team at the back of the court will try to force the opponents to move to a defensive position. One option for this is to play a lob, but this action is only safe if the ball

can be stroked at a convenient speed and height (for example, after bouncing on the wall); otherwise, a shallow lob may result, allowing the opponents to execute a smash.

Indeed, padel includes a type of shot (tray or "bandeja") that is unique to this sport, and whose main goal is to maintain the net control by countering a shallow lob with a shot similar to a soft smash, giving the ballholder enough time to recover the net.

In order to study and validate the theoretical game situations above, we analyzed all shots from two professional padel matches (a men's final and a women's final). The input for the analysis was a publicly available video of the matches. We annotated semi-automatically the shots in the video, adding for each shot the type of shot according to a detailed classification (Almonacid Cruz, 2011) and the (x,y) position of all players (ballholder, partner, and opponents).

We conducted a clustering analysis on the set of shots. In order to simplify a bit the analysis, we only considered the position of the ballholder and the two opponents, as these are the variables that mostly influence the ballholder's decision about the technical action to execute next. These resulted in a collection of 6D points (x1, y1, x2, y2, x3, y3), one for each shot occurring in the match. Each 6D point can be represented graphically as the triangle connecting the position of the ballholder and the two opponents. We mirrored the player positions around the net so that the ballholder was located always at the top of the diagram. Additionally, and although the player on the drive side and the player on the backhand side have slightly different roles, we also flipped both sides when needed, so that the ballholder was located always at the left side of the diagrams.

We then used t-SNE to reduce the dimension of the dataset from the original 6D space to only two dimensions. Fig. 6 shows the shots in the analyzed match, after projection (for the men's match; the women's match had a similar embedding). Then we used a hierarchical clustering technique (using the Euclidean 2D distance for point samples, Ward linkage for clusters, and a target of n=4 clusters) to group the shots. The bottom row of Fig. 5 shows the resulting clusters. As expected, the four clusters reflect the theoretical situations we anticipated in the analysis above.

The analysis of the clusters provides additional insights about the different game situations: (a) The serve is easy to differentiate from most other shots, since both opponents have to wait for the ball at the back of the court; it also shows clear subclusters, which reflect the serve rotations in a padel match; (b) When the ballholder is attacking (at the net), the variance is more apparent in the position of the opponents, who have to move around trying to return the ball while withstanding pressure from the attacking team; (c) When the ballholder is defending at the back of the court, the two opponents are likely to send the ball to the corner, whose return is more difficult due to the walls; here, a large amount of the within-cluster variance can be observed in the position of the ballholder, who suffers the pressure from the opponents; (d) There are many game situations that do not clearly fit in any of the situations above; most of these situations can be considered as transition situations. However, notice that they exhibit a lot of variance, reflecting the fast-paced movement of the players while trying to return shots involving relatively large displacements (such as lobs, smashes, and drop shots) and waiting for the ball at appropriate locations. This observation aligns with the discourse presented in Section 3.1, as one of the strategic principles in padel involves executing a shot in such a manner that the ball reaches a specific location intended to hinder the opponents' ability to respond effectively. The substantial variance within clusters, with the exception of the cluster relating to serves, indicates that the diversity of game situations in padel, at a more detailed level, is considerable. The user study discussed in Section 6 encompasses game states derived from the scenarios indicated in situations (b)–(d). We excluded serves from the study due to their inherently rigid configuration and minimal variation in player posture.

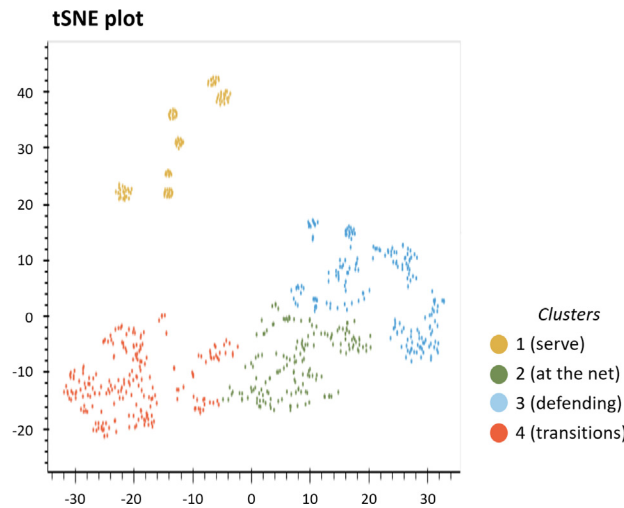


Fig. 6. Embedding of the 6D game situations from the professional match onto 2D, using t-SNE. Clusters are labeled from the point of view of the ballholder.

4. Visual representation of the state of a padel match

The added value of player poses in tactical analyses has to be evaluated in the context of the rest of the elements depicted in positional diagrams. We thus describe the different components of the game state and then discuss how these components can be visualized.

4.1. Components of the state

We define the *state of a padel match* as the collection of features that characterize the situation of a match referring to a particular instant of time. We only consider features that might be relevant for tactics, i.e., that might influence the short-term decisions made by the players. Although the state features must take as reference a particular time within the match, the state might include data about the past (e.g. position of the players immediately before) and the future (e.g. expected trajectory of the ball, according to the last ball return, or hypothetical displacement of the players). Fig. 7 shows our classification of such features, based on the discussion in Section 3.

4.2. Visual representation of spatial features

We focus now on the spatial features represented in typical figures illustrating tactical aspects (for example, Martín Avilés (2019), Magazine (2023), Padelmania (2013), Padel (2020), Vidal (2015), Remohi-Ruiz (2019)). Table 1 summarizes the features about the padel players. Body pose and body shape refer to similar features, but with a different level of abstraction: bone/joint positions/rotations according to some skeletal-based human model, or a complete representation of the player's body, including muscles and skin.

Regarding the ball, its short-term behavior is hard to understand if only its current position and velocity are given, so illustrations on padel tactics often represent the (expected) path of the ball. The most meaningful part of the ball trajectory, for a

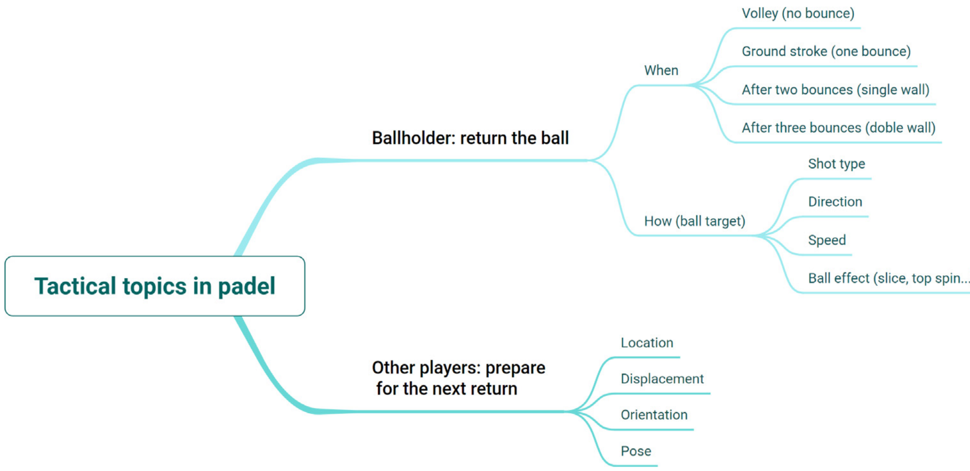
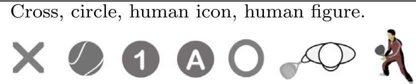
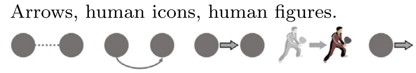
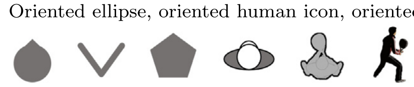
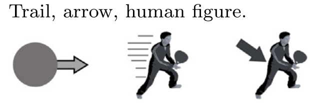


Fig. 7. Classification of variables related to motor tactics in padel, i.e. variables involved in the motor decisions taken by the players during a padel match.

Table 1
Spatial features and examples of visual representations in padel illustrations.

Feature	Sample representations
Body Position	Cross, circle, human icon, human figure. 
Body Displacement	Arrows, human icons, human figures. 
Body Orientation	Oriented ellipse, oriented human icon, oriented human figure, arrow. 
Body Velocity	Trail, arrow, human figure. 
Racket Position	Racket icon, racket image.
Body Pose	Anatomical or realistic representations
Body Shape	Realistic representations of the human body

given state, spans from the last shot to the next shot; but since the next shot cannot be anticipated, the ball trajectory should span all points for which a valid return exists. Furthermore, zenithal views hinder the perception of the ball's height at different points along its trajectory. This can be partially addressed by showing ball bounces (with the ground, walls, and metallic mesh).

4.3. Visual representation of the players' state

The analysis in Section 3.2 suggests that the visual representation of the players' position, orientation, *and body pose* plays a key role in aiding the analysis of a given state. In this paper, we consider the following factors: (a) Player Representation (PRep): Symbolic, Anatomical, Realistic; and (b) Pose Depiction (PoseD): Fixed or Dynamic, depending on whether players are represented in a fixed, arbitrary pose, or players show distinctive poses depending on the game situation. We will analyze these two factors in the context of positional diagrams showing a zenithal view of the court.

Considering PRep, Table 1 already shows some examples in padel illustrations. Symbolic representations simplify athletes into minimalist forms, such as circles, which are easy to create but employ a high degree of abstraction that can obscure relevant information. Anatomical representations offer a more concrete portrayal of the human body, yet they still simplify individual body parts into basic geometric shapes like line segments. Realistic representations provide a detailed representation of the whole human body. While symbolic forms might enhance clarity and facilitate recognition, anatomical and realistic depictions provide greater insight into body mechanics and can adequately convey the pose of the athletes. On the downside, they require more resources to produce and may lack the clarity needed for specific analytical applications. Notice that PoseD is only feasible with anatomical and realistic representations. Overall, the basic principle in choosing the best representation is to balance its informative value with the simplicity and easiness of creation, depending on the illustration's intended purpose.

However, player representations showing specific poses can compete with symbolic representations if they can be generated in seconds with minimal effort. Therefore, we developed an easy-to-use method to generate pose-aware realistic representations of padel players from minimal input (Section 5).

4.4. Visual representation of the other elements

While our primary focus is on representing the players, we also establish baseline depictions for the other elements within the illustration (Fig. 8). Players' trajectories, utilized in analyses of hypothetical displacement decisions, are illustrated as dotted, wavy curves that originate from each player's current position and extend to their intended target locations, each terminating with an arrowhead.

The ball's trajectory is illustrated with a curved line connecting the point where it is struck to its expected landing spot, including

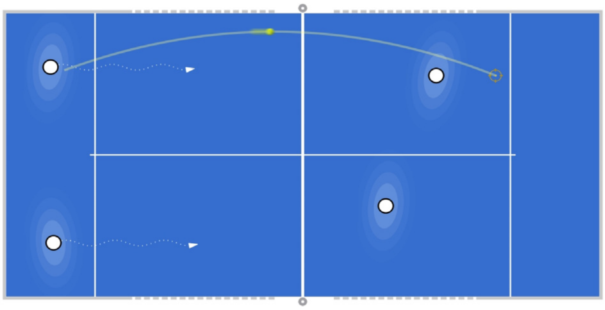


Fig. 8. Elements of our baseline representation of the state of a padel match.

additional bounces as necessary. The curvature depends on the maximum height of the wall, so that lobs exhibit a higher curvature than other strokes. The ball is depicted as a yellow circle, complemented by a short blurred trail that indicates its direction of motion.

The court is depicted from an orthographic top view, highlighting its fundamental elements such as the court boundaries, net, midline, and service lines. This top view, although neglecting height information, ensures clear visibility of all key features.

5. Generating pose-specific depictions of padel players

5.1. Overview

We propose a simple method to generate anatomical and realistic representations of padel players from minimal user input. Our method relies on motion capture (MoCap) data from a padel match. The basic idea is to allow the user to specify a few basic parameters, and the application retrieves and renders a rigged and skinned 3D model in poses mostly similar to the user input. From now on, we focus on realistic representations, but anatomical ones can be generated by just replacing the 3D character mesh with a minimalist model representing bones with simple shapes.

The method requires MoCap data to be categorized into two primary motor actions: not-shooting (idle, walking, running...) and shooting. Additionally, shooting clips must be labeled with the specific type of shot. In order to recover a frame from all the shot phases discussed in Section 3, for each shot we require the index of the keyframe corresponding to the racket's impact on the ball (contact point).

The user input consists of the following elements: (a) type of shot (none if the hypothetical player is just idle or moving); (b) signed delta time Δt with respect to the impact time (only needed for shots); (c) player displacement speed v; (d) deviation angle ψ between the body direction vector and the player's displacement vector (for example, 90° for sideways running). One input example is: `Drive@-100 ms, 3 m/s, 0°`, which asks for a player running forward while about to execute a drive shot (see Table 3 for the output).

5.2. Searching for similar poses

The pose recovery works as follows. If the shot type is none, the search is limited to the MoCap intervals labeled as not-shooting. The method computes the following magnitudes for each candidate pose in the data: player speed v', computed as the speed of the root joint, and the deviation angle ψ' between the body direction vector (hip joint) and the player's displacement vector (root joint displacement between consecutive keyframes). Then, each candidate pose is ranked using the penalty formula $\lambda_p = \omega|v - v'| + |\psi - \psi'|$ where ω is a user-defined weight. Then a few distinct poses with the lowest penalty are recovered, and one is randomly chosen for rendering.

If the user-selected shot type is not none, the search is limited to the MoCap data labeled with the specified type of shot. The search is further restricted to those frames at the user-provided Δt from the impact. The ranking works as above, since some shots are performed while the player is moving. Varying values of Δt allows users to generate poses immediately before and immediately after the ball impact, as discussed in Section 3.2.

5.3. Rendering

We use a 3D rigged and skinned model (a model from Microsoft Rocketbox Avatar library (Gonzalez-Franco et al., 2020), slightly modified to appear gender-neutral) to render the realistic representation of the player at the retrieved poses. The original material and textures of the 3D model were replaced by an emission (shadeless) white material outlining in black the (inner and outer) silhouettes of the model. The system automatically imports the MoCap data, selects the retrieved poses, and renders the model from a top camera on a transparent background (we used a script for Blender to automatize all these tasks). The camera's target is always set to the model's root position, so that the image is approximately centered at the body's center of mass. The resulting PNG image is ready to be used in image editing software. The user can then place and rotate the player image as desired.

5.4. Implementation

We implemented the approach above with a publicly available MoCap dataset from an amateur padel match (Javadiha et al., 2024), captured with a professional Xsens MVN Awinda system at 60 Hz. We labeled manually a subset of the dataset (four games) by identifying and labeling the shots, and identifying their ball impact frames. We used the detailed shot classification proposed by Almonacid Cruz (2011) and slightly refined in Javadiha et al. (2021). Being an amateur match, some specific types of shots were not represented in the dataset; for these cases, we returned a roughly similar type of shot.

5.5. Sample results

Table 2 shows output images for different user inputs asking for idle, walking, or running poses. In essence, the user just selects a speed value v to retrieve these padel poses. Notice that null speed results in the typical waiting pose in padel (first two rows). One of the examples also uses the angle ψ to select a pose where the player was running slightly sideways, as illustrated by the feet separation along the coronal plane of the body.

Table 3 shows our results for user inputs looking for specific shots. Notice the importance of the Δt value to select poses immediately before (negative values) or after (positive ones) the ball impact. The last two rows illustrate the use of speed and angle parameters to select poses where the player was moving at the time of the shot. This allows getting poses where the player was forced to move intensely in order to return the ball.

Fig. 9 shows additional results. This time, we modified the script to generate also the images for the frames in the interval [-400 ms, 200 ms] around the retrieved pose. Fig. 10 shows the results for the same inputs, rendered with a camera at 25° from the vertical direction.

Regarding the time performance, our Blender script runs at interactive rates. Each image generation takes less than one second; about 100 ms for retrieving the pose, and 300 ms for rendering an 800 × 800 image (with the Eevee render engine on commodity hardware). This allows users to quickly adjust any of the parameters to find a suitable pose, if needed.

Table 2
Sample results for user inputs asking for non-shooting frames.

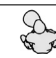
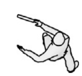
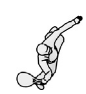
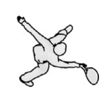
Speed v		Angle ψ'	Output image
0 m/s	Idle	0°	
0 m/s	Idle	0°	
2.5 m/s	Walking	0°	
2.5 m/s	Walking sideways	45°	
3.5 m/s	Running	0°	

Table 3
Sample results for user inputs asking for shooting frames.

Shot type	Delta Δt	Speed v	Angle ψ	Output image
Backhand	−200 ms	0 m/s	0°	
Backhand	100 ms	0 m/s	0°	
Off the wall smash	−300 ms	0 m/s	0°	
Off the wall smash	300 ms	0 m/s	0°	
Smash	−200 ms	0 m/s	0°	
Drive	−100 ms	3 m/s	0°	
Drive	0 ms	1.5 m/s	45°	

6. User study

6.1. Research question

The method proposed in the previous section allows users to generate realistic representations of players dependent on poses in seconds. Having thus an authoring time comparable to that of traditional symbolic representations, our research question is whether this pose-aware representation is more useful than traditional symbolic representations, in the context of tactical analyses.

Although it is possible to consider separately the Player Representation, PRep (symbolic, anatomical, realistic) and the Pose Depiction, PoseD, (fixed or dynamic), we argue that the two most promising combinations are Realistic+Dynamic pose (RealPose) and Symbolic+Fixed (Symbolic). On the one hand, the symbolic representation cannot represent the player pose, and thus cannot be combined with dynamic poses. On the other hand, using a realistic representation with a predefined pose for all players (Fig. 3-g) seems a bad choice not worth exploring, as such a predefined pose would fail to provide a per-player context on the game situation being analyzed, while losing the visual simplicity of symbolic representations. The key advantage of fixed-pose representations is that one or two images (front/back views) serve to represent any player; however, this advantage is no longer relevant since our method greatly simplifies the authoring of pose-dependent representations.

6.2. Hypothesis

We hypothesize that padel enthusiasts, when discussing tactical aspects, will find more useful those game state representations depicting the pose of the player (RealPose), rather than

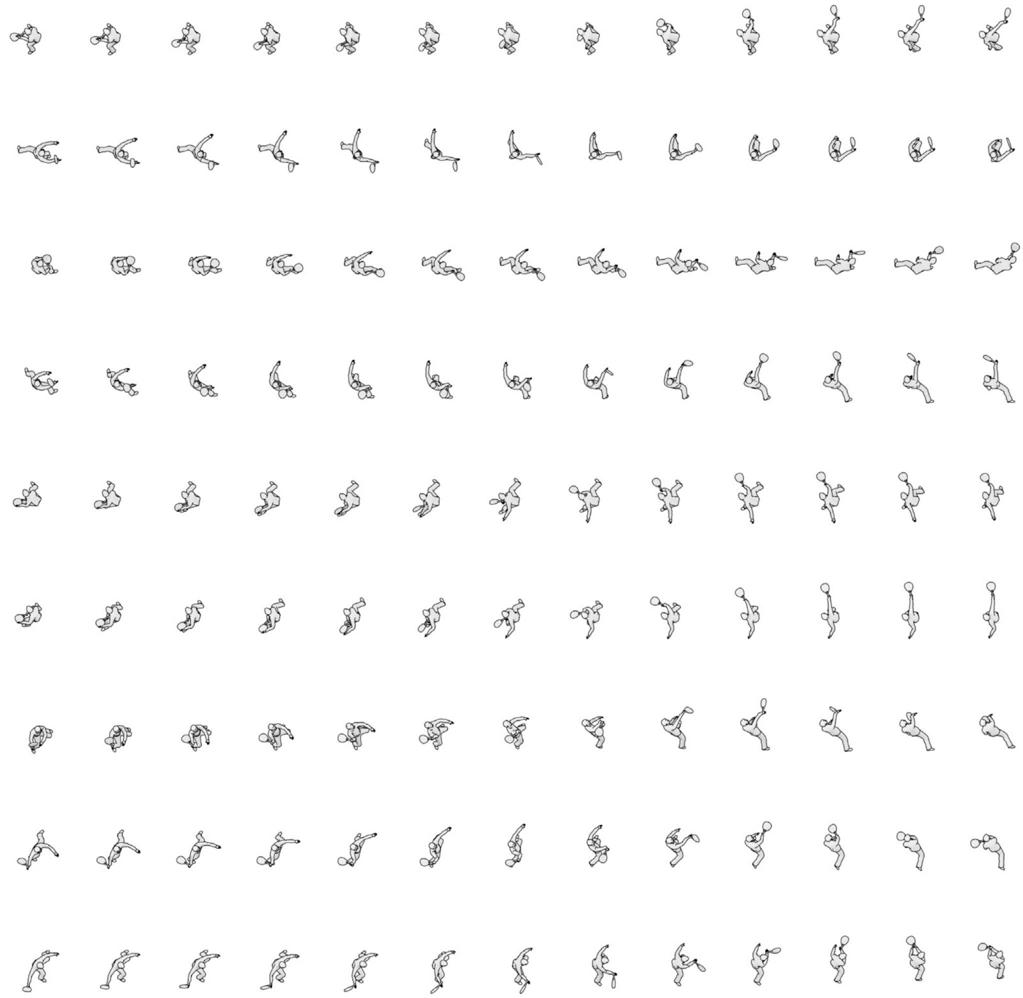


Fig. 9. Results of different queries, with Δt varying in [-400 ms, 200 ms]. From top to bottom: PLR; VD; VD 1.5 m/s 60°; VD, R, R-lob, R1, BPD, SPD. Shot codes are as follows. PLR: side wall backhand; VD: forehand volley; R: backhand; R1: smash; BPD: off the wall forehand smash; SPD: off the wall forehand.

simpler symbolic representations obscuring this piece of information (Symbolic). The rationale behind this hypothesis is that padel is a team sport played in a small confined space, with fast-paced rallies and ball returns occurring with minimal time gaps. All these elements suggest that the pose of the players might be nearly as essential as their position and orientation when it comes to understanding the match dynamics at a specific time.

6.3. Experiment design

Independent variable. Fig. 11 illustrates some visual representations of the padel players. As indicated above, we considered two conditions: Symbolic (Fig. 11-c) and RealPose (Fig. 11-d).

Tasks and dependent variables. Participants were asked to complete two types of tasks. In the first task (Choose) participants were presented a short text with a tactical discussion along with two images depicting the same game situation, one using Symbolic and the other one RealPose (shown in random order). Participants were asked to read the text about the tactical problem and choose the most useful image for the analysis. In the second task (Rate), participants were presented several tactical problems, each illustrated by one of the two images, and participants had to rate to which extent they agreed with the statement "The figure helps to understand the tactical analysis" using a 1–7 Likert scale. Notice that both tasks evaluate the two conditions in a real-world scenario, in combination with the court and ball elements, and in the context of tactical questions.

Apparatus. We created an online survey that included informed consent, demographic questions, a brief explanation of the elements depicted in the figures, and then three questions for the Choose task and four questions for the Rate task. Since typical online forms have large margins and leave little space for side-to-side comparisons, we developed the survey using the SurveyJS JavaScript library. Order randomization was used for both types of questions. The survey was anonymous.

The sample images depicting the game state were created with a Python script, using PyQt5's QPainter to draw the court, ball, and labels, and our Blender scripts to create the images of the players at specific poses. The game situations were chosen from the literature on padel geared toward novice padel players; Fig. 12 shows three sample situations included in the study.

Participants. We contacted students enrolled in a Bachelor's Degree in Physical Activity and Sport Sciences. A total of 34 participants completed the study (9 women, 25 men, all in the 18–25 year interval). Participants were asked to complete the survey online, using a PC or laptop. Most of the participants (23 of 34) were familiar with padel, playing it occasionally or regularly. Even though some reported not having played padel themselves (11 of 34), all participants were familiar with padel and had experience with racket sports such as badminton, thus with they possessed sufficient knowledge to evaluate the method. However, most participants (22 of 34) had little to no experience with padel diagrams.

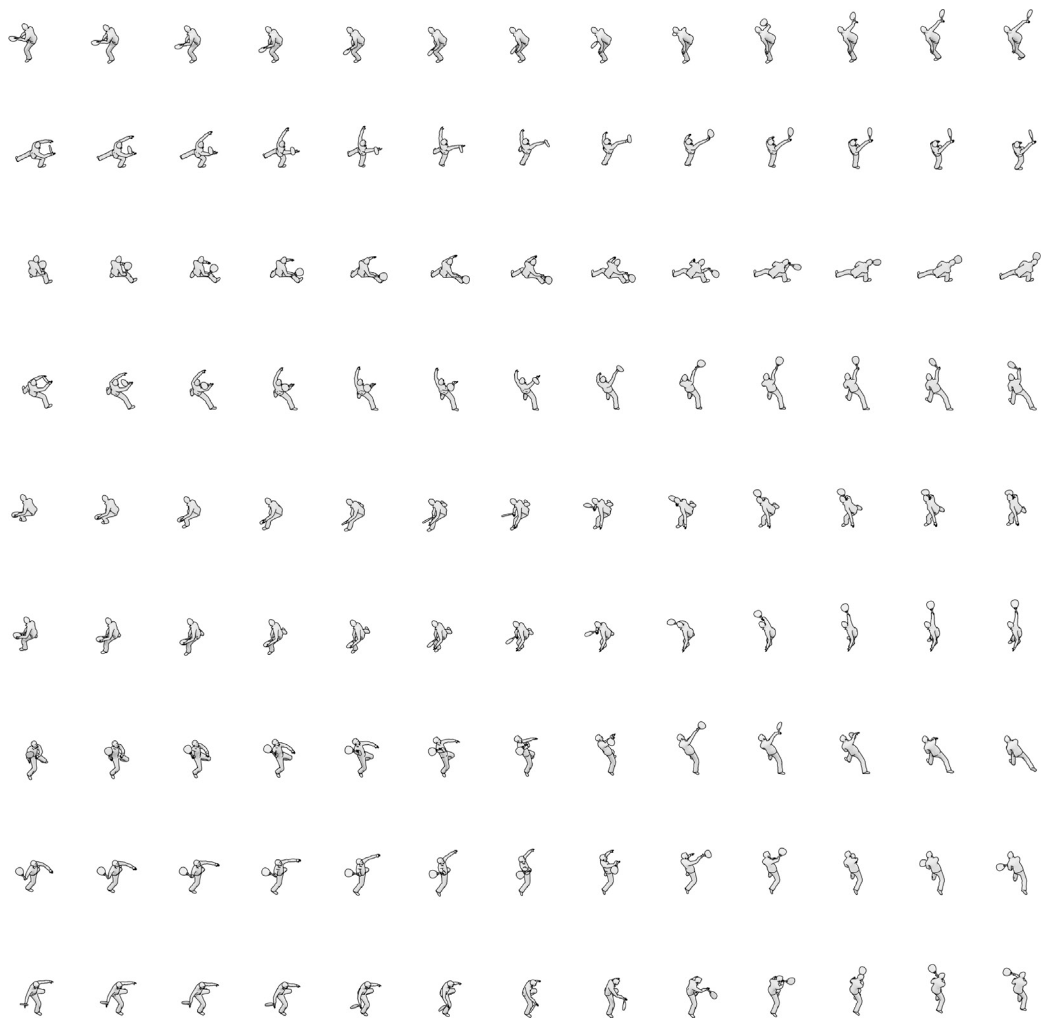
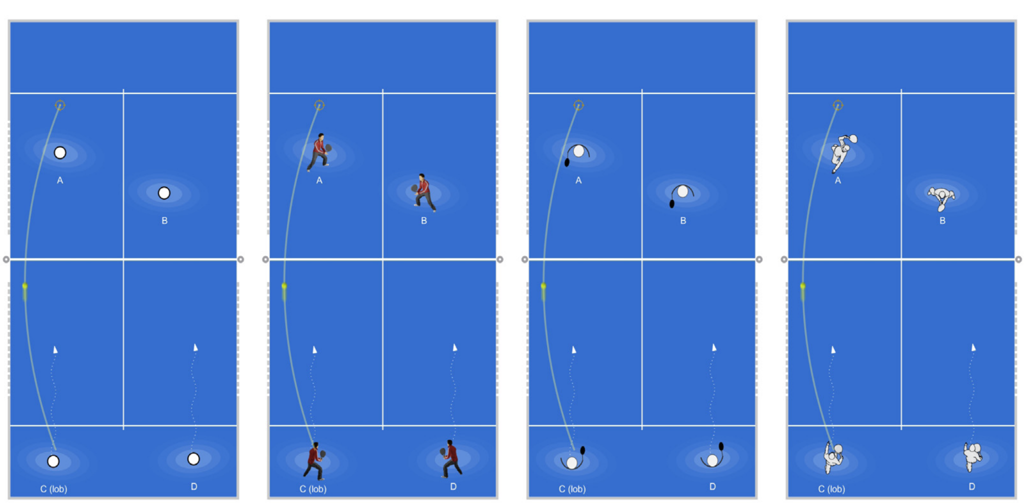


Fig. 10. Same results as above, with a camera at 25° from the vertical direction.



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

Fig. 11. Different representations of the padel players: just a circle (a); realistic representation with a fixed front/back pose for all players (b), our Symbolic representation conveying orientation but not pose (c), and our RealPose representation (d). Our user study compared (c) and (d) types of representations.

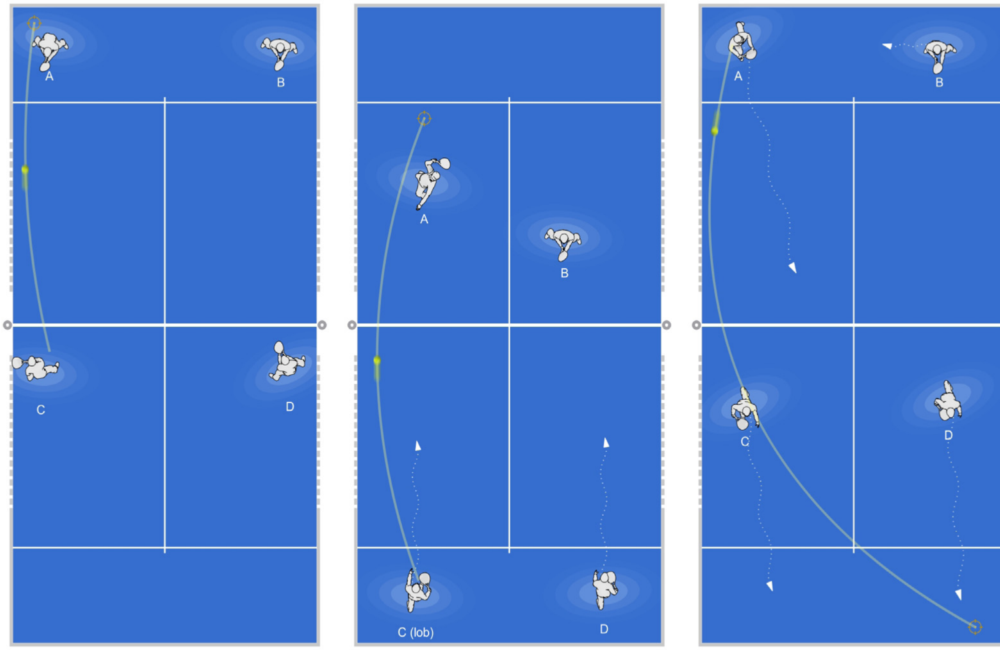


Fig. 12. Game situations included in the Choose task of the user study. The first situation, with the last ballholder at the net, emphasizes coordinated team actions, highlighting the court coverage, particularly Player D's expected movement toward the midline. The second situation, with the last ballholder at the back of the court, examines potential player displacements in anticipation of an opponent's readiness to execute a smash. Finally, the third scenario, with the last ballholder at the back of the court, depicts a typical situation where one player attempts to win the net with a lob, forcing the opponents to move backwards. In this case, the emphasis is in the coordination between teammates to win the net, with a focus on Player B's incorrect movement. Notice that these situations are good representatives of those analyzed in Section 3.3.

6.4. Results

We analyzed the results with a significance level $\alpha = 0.5$. For the Choose task, we calculated which condition each participant selected most frequently as the most useful. We found that 27 participants chose RealPose as the most useful, while 7 chose Symbolic. We used a one-sample proportion z-test (one-tailed) to check if the difference between the observed proportion $\hat{p}$=27/34 and the no-effect proportion $P_0 = 0.5$ is significant. The z-test revealed that this difference is significant ($p < 0.001, Z = 3.43$), with a medium effect size ($h = 0.63$).

For the Rate task, we computed, for each participant and condition, the overall rate given by the average Likert scores for the questions using Symbolic (M=4.8, SD=1.2) and RealPose (M=5.4, SD=1.3). Fig. 13 shows the box plots. The results of the paired t test indicated that there is a significant difference between the two conditions, t(33)=2.1,$p = 0.040$. However, the observed effect size d is small, 0.37.

We explored possible gender effects by performing the statistical tests separately for men and women. The z-test revealed that the differences between the observed proportions (20/25 for men and 7/9 for women) and the no-effect proportion is significant (p=0.0013 for men,$p = 0.047$ for women), with a medium effect size in both cases.

These results suggest that RealPose is more advantageous than Symbolic for tasks involving tactical problems.

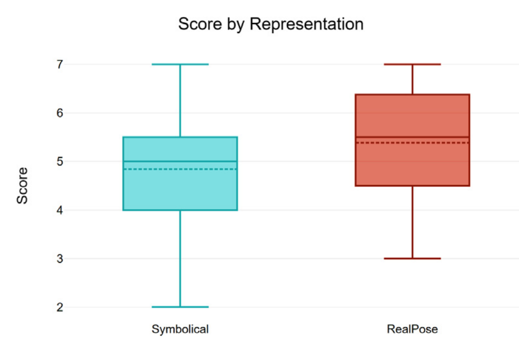


Fig. 13. Box plots for the user scores in the Rate task.

6.5. Discussion

Our results indicate that padel coaches and enthusiasts are likely to benefit from realistic representations of the players depicting their pose, as suggested by the significant difference found for the Choose and Rate task, which confirms our hypothesis. Our best explanation for this is that the pose of the players carries relevant information for tactical analyses, and that our realistic representation conveys this information effectively. For the ballholder, the pose can convey aspects such as the type of shot, and reveal, for example, if the player was forced to move intensely in order to return the ball. For players who do not hold the ball, the pose better conveys the displacement of the player, with idle poses that are easy to distinguish from running poses. The often pose conveys simultaneously multiple player orientations (head, shoulders, feet), whereas symbolic representations typically represent only one of these.

In contrast to other sports such as football, where players have to run long distances, padel movements occur on a court ten times smaller than a football pitch. With much shorter distances, the player's orientation and the relative position of the body parts gain relevance.

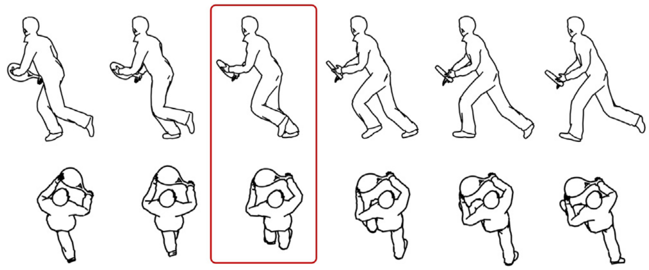


Fig. 14. Several frames from a running sequence from our dataset. The top row shows side views of the player, whereas the bottom row shows the same frames from a zenithal view. The speed is nearly constant across the sequence (about 3.45 m/s). Some frames (highlighted in red) barely convey speed as the two legs are nearly parallel to each other. The problem is exacerbated in the zenithal view, as the player appears to be static. Priming running frames with the feet apart (rightmost images) seems to improve the identification of the motion, especially for side views.

6.6. Limitations

A limitation of our pose retrieval algorithm is that it requires labeled MoCap data, with shot classification being the task requiring most of the effort. We plan to extend the pose retrieval algorithm to support nonlabeled data. Instead of the type of shot, pose retrieval could be based on parameters describing the swing motion, computed from the start/end position of the racket, swing duration, and the relative height of the ball (estimated from the racket position) with respect to the player's shoulder and the player's hit. Alternatively, shot-recognition methods can be applied to the MoCap data to automatically label the data set.

Another limitation is that the difference between walking and running poses is not clearly discernible, especially in some frames retrieved by our method. Queries searching for specific types of shots almost always return images that effectively facilitate shot recognition or at least provide relevant visual cues. This is largely because the upper body remains clearly visible from a zenithal perspective. However, for non-shooting poses, we aim to convey movement direction and speed, information that relies heavily on an accurate representation of the lower body. Overcoming this limitation requires addressing two key issues. First, while our pose retrieval method considers movement speed, it selects an arbitrary frame within the walking/running cycle. One way to address this issue is to retrieve the pose as we currently do, but then refine the selection by searching neighboring frames to prioritize those where the feet are as far apart as possible. This would prevent the method from selecting frames near the mid-stance/mid-swing phase of the running cycle, where the legs are too parallel to effectively convey motion (see Fig. 14). Second, although a zenithal perspective provides a clear view of the court and players, it also introduces occlusions that can partially hide the body, particularly the lower torso. To mitigate this, occlusion handling techniques, such as alpha blending, showing silhouette edges in body parts otherwise occluded, as well as cast shadows, could enhance the perception of the full-body pose. As part of our future work, our aim is to refine our pose retrieval method by prioritizing walking and running frames with better leg separation. In addition, we plan to explore shadow-based techniques to reduce leg occlusion (see Fig. 15). Nevertheless, the practical impact of the speed ambiguity in our player poses depends on the rest of the cues provided by the positional diagrams. The player representation is the only visual cue for the orientation of players in a ready position, and the only visual cue for the player's pose before/after a shot. However, for the players moving around, other cues come into play, since our positional diagrams represent the players' trajectories as wavy paths. Even though the speed/angle cues of the player representation could show some ambiguity, these are plausible with the user's input and thus easy to align with the movement cues provided by the trajectory.

Fig. 15. Side views of the players (left) are more suitable than zenithal views (middle) to convey the speed of movement in walking and running sequences. One way to combine side views with our zenithal ones is through lateral shadows (right).

The MoCap data we used were quite accurate, except for the racket, which sometimes shows orientations in disagreement with the swing motion. In a few frames, this caused the racket to penetrate the player's body, which we did not handle.

Finally, although most of the participants of our study (23 of 34) were familiar with padel, some of them only had experience with racket sports other than padel.

7. Conclusions

In this paper, we addressed the problem of visualizing padel match states to improve tactical discussions focusing on the added value of representing player poses as part of the positional diagrams. Key contributions include classifying essential tactical elements like player movements and decision-making moments, defining key features for state representations, classifying theoretically and validating empirically the primary game situations in padel, proposing a simple method for generating realistic player poses, and finally presenting user study findings on the effectiveness of pose-aware visualizations in supporting tactical analysis.

Traditionally, a major benefit of symbolic and anatomical representations has been the ease of creation. However, the increasing number of freely available MoCap databases on racket and other sports is decreasing the gap between the generation of symbolic and realistic representations. The method we have proposed is capable of generating a top-view representation of padel players in less than a second, using a minimalistic user input to describe the intended pose. We foresee that on-line implementations of this kind of methods will enable the creation of richer, easy-to-analyze depictions of game situations.

Our work focused exclusively on zenithal views. Non-zenithal views, although much less common in tactical literature, might be useful for some tactical problems for which height plays an essential role. Our image generation method, since it is based on MoCap data, can be trivially extended to render images from nonzenithal viewpoints. On the downside, the user input would require extra parameters describing the camera angle, to ensure an agreement between that of the court and that of the players.

An interesting avenue for future work is to compare our approach with prompt-based, data-driven models using a transformer architecture. State-of-the-art generative models are able to generate realistic representations of tennis players, but obtaining the desired view, pose, and shot is extremely difficult. Furthermore, images exhibit considerable style differences and often include unwanted elements (Fig. 16), revealing that a better conditioning of the diffusion process is required. Finally, we wish to apply our visualization approach to show not only hypothetical game situations but real ones from video-recorded matches. Current 3D pose estimation approaches could fit a parameterized human model to the players. With proper motion priors

Fig. 16. Comparison with sample outputs from DALL-E 3 (2024-10-05) with prompts attempting to reproduce our method. DALL-E 3 combines a transformer architecture with diffusion models for image generation. The prompt used was: "*Create a minimalistic image of a padel player wearing white, depicted solely with black outlines. The player should be captured when preparing the backswing for a backhand shot, viewed from a perfectly vertical, top-down perspective. The background must be solid white, and the image should focus exclusively on the player, with no additional court elements*". The last image is the output of our method with the input "Backhand@-200 ms, 0 m/s, 0° ", which is the only one depicting the requested backhand preparation pose from a zenithal camera.

from padel, resulting poses could be highly natural. Traditional 2D pose estimation methods could also provide the necessary input for our method, opening the possibility of a completely automatic translation from video frames to *editable* schematic representations of them.

CRediT authorship contribution statement

Mohammadreza Javadiha: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Data curation, Conceptualization. **Carlos Andujar:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Software, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization. **Enrique Lacasa:** Writing – review & editing, Validation, Methodology, Investigation, Data curation, Conceptualization. **Gota Shirato:** Software, Conceptualization. **Natalia Andrienko:** Writing – review & editing, Methodology, Conceptualization. **Gennady Andrienko:** Writing – review & editing, Methodology, Conceptualization.

Ethical approval

The research was reviewed and approved by the Ethics Committee of Universitat Politècnica de Catalunya (CEUPC) at its November 6th, 2024 meeting. The approval reference number is 2024-024.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability statement

Blender files and scripts for pose retrieval and rendering will be released upon acceptance.

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