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Method Article

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Data-Driven Framework of Player Spatial Ownership in Football

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Abstract

Football players are commonly evaluated by their contributions with the ball, including goals, assists, passing accuracy, and ball recoveries. However, far less attention has been given to quantifying their ability to create and control space without the ball. Developing such metrics first requires estimating how much space each player dominates at any moment during a match. Dominant region models have previously been used for this purpose, but these existing approaches commonly rely on generalized movement assumptions that do not account for individual player characteristics. This work presents a fully data-driven framework for modeling Player Spatial Ownership using only optical tracking data, from which individualized movement parameters, including acceleration, deceleration, maximum speed, turning dynamics, and reaction time, are estimated. Rather than assuming identical physical capabilities, the proposed method incorporates these individualized movement parameters into two movement strategies: one in which the player continuously accelerates while adjusting their direction toward the target, and another in which the player first decelerates to a stop, completes the turn in place, and then accelerates toward the destination. By discretizing the field into uniformly sized regions, the framework estimates spatial ownership by assigning each region to the player with the shortest arrival time, even when the differences between competing players are minimal. The proposed methodology provides an interpretable and reproducible framework for individualized spatial analysis in football.

Keywords: Player Spatial Ownership, Dominant Region Models, Optical Tracking Data, Movement Modeling, Football Analytics

1 Introduction

Football players are commonly evaluated through statistics that measure actions while in possession of the ball, such as goals, assists, pass accuracy, and ball recoveries. Although these metrics capture important aspects of performance, they provide little information about a player’s influence when not in possession. Off-ball movement determines passing opportunities, defensive coverage, and the creation of attacking space, making spatial control a fundamental component of football performance. Quantifying these contributions requires first estimating the space that each player controls at any instant during a match. Such estimates provide the foundation for individualized analyses of player behavior beyond traditional statistics, enabling future studies to investigate how players and teams create, maintain, or lose control of space throughout a game.

The estimation of spatial control has evolved considerably over the last decades. The concept of dominant regions was first introduced to football by Taki and Hasegawa [1, 2], who estimated the area each player could reach before any other by combining positional tracking with player movement. Their work, built on the geometric principles of Voronoi diagrams [3], established the foundation for modern spatial analysis in football. Subsequent research further improved these models by incorporating physical motion equations [4], computational approximations [5, 6], individualized movement estimation [7], free space representations [8, 9], and spatial weighting strategies [10]. Together, these studies established dominant region models as the primary framework for estimating spatial ownership from tracking data.

Despite these advances, current dominant region models still rely on simplifying assumptions that limit their ability to represent individual player movement. Existing approaches commonly assume identical physical capabilities across players [8–10], simplified movement behaviors that do not fully account for dynamics in turning agility [9], or computationally demanding non-parametric representations that are difficult to reproduce efficiently [7]. In addition, none of these approaches explicitly incorporates individualized reaction time in estimating spatial ownership.

To address these limitations, we present a fully data-driven framework for modeling Player Spatial Ownership directly from optical tracking data. The proposed methodology estimates individualized movement parameters for each player, including acceleration, deceleration, turning dynamics, maximum speed, and reaction time, and integrates them into computationally efficient movement models that estimate spatial ownership across the field.

2 Methods

The objective of this work is to estimate the region of the field controlled by each player at any time during a football match. We define this region as *Player Spatial Ownership (PSO)*, previously referred to as *Individual Spatial Ownership* in an earlier conference publication [11], representing the area that a player can reach before any other player based on their individualized mobility capabilities. Unlike previous dominant region models, *PSO* is estimated using only optical tracking data and player specific movement characteristics extracted from historical observations. The input

consists of optical tracking data collected during a football match. The tracking system records positional information for every player participating in the match, including both starting players and substitutes that enter the game, as well as the three referees and the ball. For each player and referee, the system records the horizontal and vertical field coordinates, $(x_{i,t}, y_{i,t})$, together with the instantaneous speed, $v_{i,t}$, at a sampling frequency of 25 frames per second. For the ball, the tracking data include its three-dimensional position, $(x_{b,t}, y_{b,t}, z_{b,t})$, at the same sampling frequency. Consequently, all tracking information is updated every $\Delta t = 0.04$ s. The coordinates of the field are expressed in centimeters relative to the center of the field, where $(0,0)$ denotes the midpoint, $x \in [-5250, 5250]$ represents the longitudinal direction, and $y \in [-3400, 3400]$ represents the lateral direction. Although the complete tracking data set includes the referees and the ball, the proposed methodology estimates *PSO* exclusively from the player tracking data.

With the input data defined, we next estimate each player's individualized movement profile using basic kinematic equations and historical tracking data. The estimated movement profile includes maximum and minimum speed ($v_{i,\text{MAX}}, v_{i,\text{MIN}}$), maximum and minimum acceleration ($a_{i,\text{MAX}}, a_{i,\text{MIN}}$), and the average rates of acceleration increase and decrease ($a_{i,\Delta+}, a_{i,\Delta-}$). Angular movement characteristics are estimated in a similar manner using each player's historical tracking data. To reduce the influence of tracking noise on the estimation of angular movement, player positions are sampled every 0.4 s rather than every 0.04 s. From these sampled trajectories, the angular velocity ($\omega_{i,t}$) is estimated using $\omega_{i,t} = \frac{v_{i,t}}{r_{i,t}}$, where $v_{i,t}$ is the linear velocity of the player, which corresponds to the tangential velocity along the local trajectory, and $r_{i,t}$ is the radius of curvature. The angular acceleration ($\alpha_{i,t}$) is then calculated from consecutive changes in angular velocity. The resulting movement profile includes the maximum and minimum angular velocity ($\omega_{i,\text{MAX}}, \omega_{i,\text{MIN}}$), the maximum and minimum angular acceleration ($\alpha_{i,\text{MAX}}, \alpha_{i,\text{MIN}}$) and the average rates of angular acceleration increase and decrease ($\alpha_{i,\Delta+}, \alpha_{i,\Delta-}$).

The next step is to define the spatial discretization of the field. A standard football field measures 105 m in length and 68 m in width according to the IFAB Laws of the Game [12]. Although field dimensions may vary slightly between competitions, player coordinates can be easily rescaled to this reference system before applying the proposed methodology. Rather than estimating spatial ownership at every possible location, the field is discretized into a regular grid of square regions. The side length of each region was chosen as 50 cm, approximately corresponding to the average lateral reach of a player [13], while also providing a computationally efficient discretization. Under the standard field dimensions, this results in a grid of 210 divisions along the longitudinal axis and 136 divisions along the lateral axis, yielding a total of 28,560 regions. Each region is assigned a unique identifier together with representative reference points that are later used to estimate spatial ownership, as illustrated in Fig. 1.

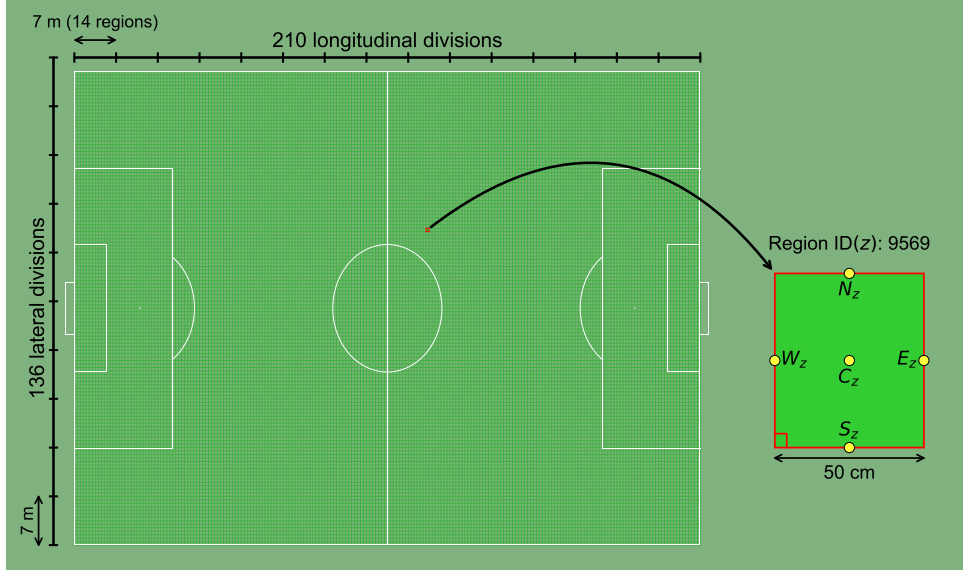


Fig. 1 Standard football field (105 m $\times$ 68 m) discretized into 28,560 square regions of 50 cm $\times$ 50 cm. For visualization purposes, grid markings are shown every 7 m (14 regions). Each region is assigned a unique identifier, numbered sequentially from left to right and then from top to bottom. The highlighted example (Region ID (z): 9569) illustrates the reference points associated with every region: the center (C_z) and the midpoints of its four edges (N_z , S_z , E_z , and W_z). These reference points are used in subsequent calculations to estimate *PSO* boundaries.

115 To estimate *PSO*, every region of the discretized field is independently evaluated
 116 and assigned to the player with the shortest estimated arrival time. Consequently,
 117 spatial ownership is determined by estimating each player's arrival time to every region
 118 using individualized movement models. These calculations are performed for all 28,560
 119 regions whenever the ball is in play. Since the same procedure is applied to all regions,
 120 the remainder of this section focuses on region $z = 9569$, shown in Fig. 1. Likewise,
 121 although all players are evaluated simultaneously through vectorized computations,
 122 the following derivations are presented for a representative player, denoted player i ,
 123 for clarity.

124 After defining the representative player and target region, the next step is to esti-
 125 mate the time required for the player i to reach the region z . At any instant t , the
 126 player's movement state is defined by their position, linear velocity, linear accelera-
 127 tion, angular velocity, and angular acceleration, obtained directly from the tracking
 128 data and individualized movement profile. Then, two complementary movement mod-
 129 els are evaluated. The first, *Continuous Accelerated Movement* (CAM), assumes that
 130 the player continuously adjusts direction while maintaining forward motion. The sec-
 131 ond, *Staged Reactive Movement* (SRM), assumes that the player first decelerates
 132 while changing direction before accelerating toward the target region. Both models
 133 are simulated independently, and the shortest estimated arrival time is retained.

Before either movement model begins, both assume that the player requires a finite amount of time to perceive a new situation and initiate a response. Rather than adopting a fixed reaction time, an individualized reaction time, denoted by t_{r_i} , is estimated directly from historical tracking data. Although previous studies report average human reaction times close to 0.26 s under controlled visual stimuli [14], football players continuously process multiple sources of information during a match, making the reaction time inherently player dependent. Since changes in ball movement are the primary stimulus that governs the game, candidate reaction events are identified whenever the ball undergoes a velocity change of at least 10 m/s. Only players within $\pm\pi/6$ radians of the ball's direction of motion are considered potential responders. For each candidate player, the first frame at which either the change in linear acceleration exceeds 1.25 m/s² or the angular acceleration exceeds 10 rad/s² is identified, and the elapsed time since the ball event is recorded as a reaction time observation. Repeating this procedure over multiple matches produces a collection of observations whose average defines the individualized reaction time t_{r_i} used throughout the proposed methodology. The complete procedure is illustrated in Fig. 2.

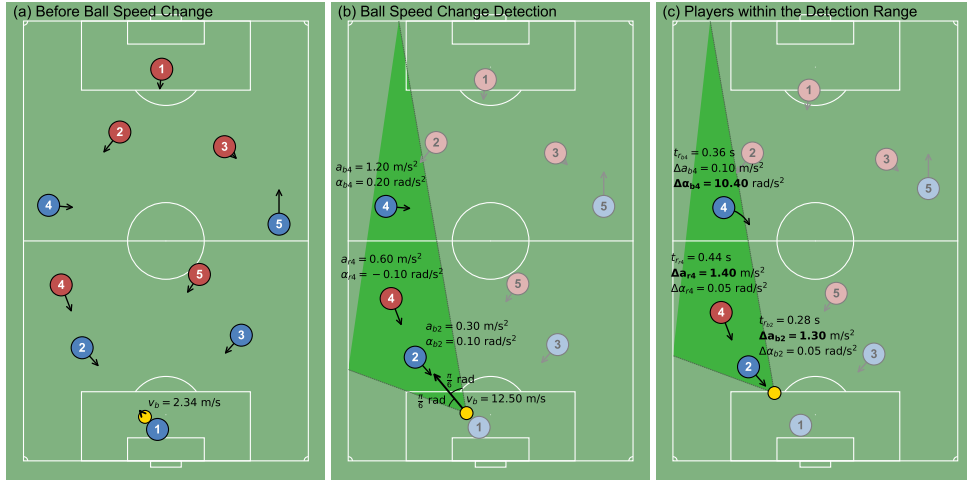


Fig. 2 Example of the individualized reaction time estimation procedure. A simplified 5-versus-5 scenario is shown, where blue and red markers represent players and the yellow marker represents the ball. Players are identified by team color and jersey number (e.g., b2 denotes blue player 2 and r4 denotes red player 4). **(a)** Player positions and movement vectors 0.5 s before the ball undergoes a velocity change. **(b)** The ball changes velocity by more than 10 m/s, identifying candidate responders within $\pm\pi/6$ radians of the ball's direction of motion. **(c)** Linear and angular accelerations are monitored for each candidate player until the first threshold is exceeded, defining the player's reaction time.

Once the player's reaction time has been estimated, the remaining task is to estimate the arrival time from the player's updated position to the target region z , as illustrated in an example in Figure 3a. During the reaction period, the player continues

153 to move according to their current movement without responding to the new objective.
 154 The reaction interval is divided into ten equal subintervals, and the player's trajectory
 155 is simulated by assuming constant linear and angular accelerations throughout each
 156 subinterval. At every update, the player's linear and angular velocities are recalculated
 157 accordingly, followed by their position. This finer temporal resolution provides a
 158 more accurate estimate of the player's trajectory during the reaction period. During
 159 this simulated trajectory, the player may unintentionally pass through one or more
 160 regions, including the target region itself. Every traversed region is therefore assigned
 161 its corresponding arrival time and is considered dominated by that player if no other
 162 player reaches it sooner.

163 After the reaction period, both movement models begin by entering a turning
 164 step, during which the player adjusts their direction toward the target region. The
 165 desired orientation is determined from the five reference points that define the region
 166 z , namely its centroid and the four midpoints of the edges. The second closest point
 167 in the angular distance defines the chosen direction (d_{chosen}), while the fourth closest
 168 point defines the check direction (d_{check}). Because the player's position changes
 169 throughout the simulation, both d_{chosen} and d_{check} are recomputed at every simulation
 170 step using the updated player position. Their corresponding angular separations
 171 from the player's current direction are denoted by θ_{chosen} and θ_{check} , respectively,
 172 and the player is considered aligned whenever their direction of movement lies within
 173 the angular interval bounded by these two angles, as illustrated in Fig. 3a. During
 174 this turning step, both models update the player's angular velocity and angular
 175 acceleration every 0.04 s using the individualized angular movement profile. To avoid
 176 overshooting the target direction, angular deceleration is initiated whenever the braking
 177 angle, $\theta_{brake} = \frac{\omega_i^2}{2|\alpha_{i,\Delta-}|}$, exceeds the remaining angle θ_{chosen} . This iterative process
 178 continues until the turning step is complete.

179 In *CAM*, the player remains in motion throughout the turning step and exits
 180 aligned with the target after a turning time $t_{t_{CAM,i}}$, as illustrated in Fig. 3b. In contrast,
 181 *SRM* simultaneously turns while reducing linear speed during a stopping step
 182 lasting $t_{s,i}$, shown in Fig. 3c. Depending on the remaining angular displacement when
 183 the player's linear velocity reaches zero, the player may already be aligned or may
 184 require an additional turn in place before continuing toward the target region.

185 Following the turning step, *CAM* immediately advances towards the target region
 186 in a straight line for a duration $t_{\ell_{CAM,i}}$, as illustrated in Fig. 3d. In *SRM*, if the player
 187 is not yet aligned after the stopping step, the remaining rotation is completed while
 188 stationary during a turn in place step of duration $t_{t_{SRM,i}}$. The player then accelerates
 189 in a straight line towards the target region for a duration $t_{\ell_{SRM,i}}$, as shown in Fig. 3e.
 190 The total estimated arrival time for each movement model is obtained by summing
 191 the durations of its corresponding movement steps together with the individualized
 192 reaction time, and the minimum of the two estimates is retained. Figure 3f compares
 193 both trajectories for the representative player.

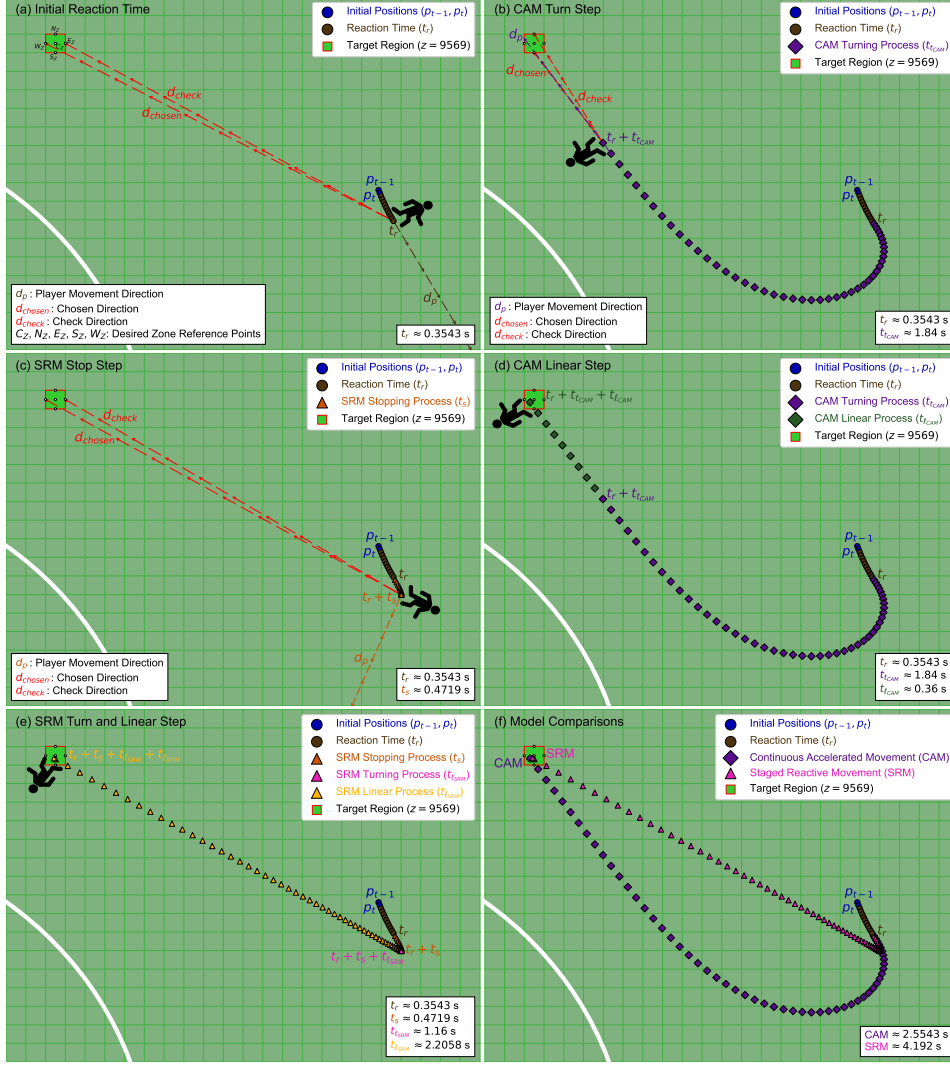


Fig. 3 Example of the movement simulation for player i toward target region $z = 9569$. (a) Initial reaction time trajectory and the reference directions used to determine alignment with the target region. (b) *CAM* turning step, during which the player remains in motion until becoming aligned, while the chosen and check directions are updated at every simulation step. (c) *SRM* stopping step, where the player reduces linear speed while turning but does not necessarily become aligned. (d) *CAM* linear advance to the target region. (e) *SRM* turn in place, when required, followed by linear advance to the target region. (f) Comparison of the complete *CAM* and *SRM* trajectories, illustrating that, for this example, *CAM* reaches the target region faster than *SRM*.

To reduce computational cost, all player-region combinations are evaluated simultaneously using vectorized operations. For each region, players are first ordered according to their Euclidean distance to the target, allowing the closest candidates to be evaluated first. The shortest arrival time found so far is continuously updated,

and simulations that can no longer improve this value are discarded. This procedure is repeated simultaneously for every region of the field, substantially reducing the computational cost of estimating *PSO* while producing the same result as the complete simulation.

The complete sequence of operations described throughout this section is summarized in Fig. 4. The workflow highlights the main computational stages of the proposed methodology, from processing optical tracking data to assigning spatial ownership across all field regions.

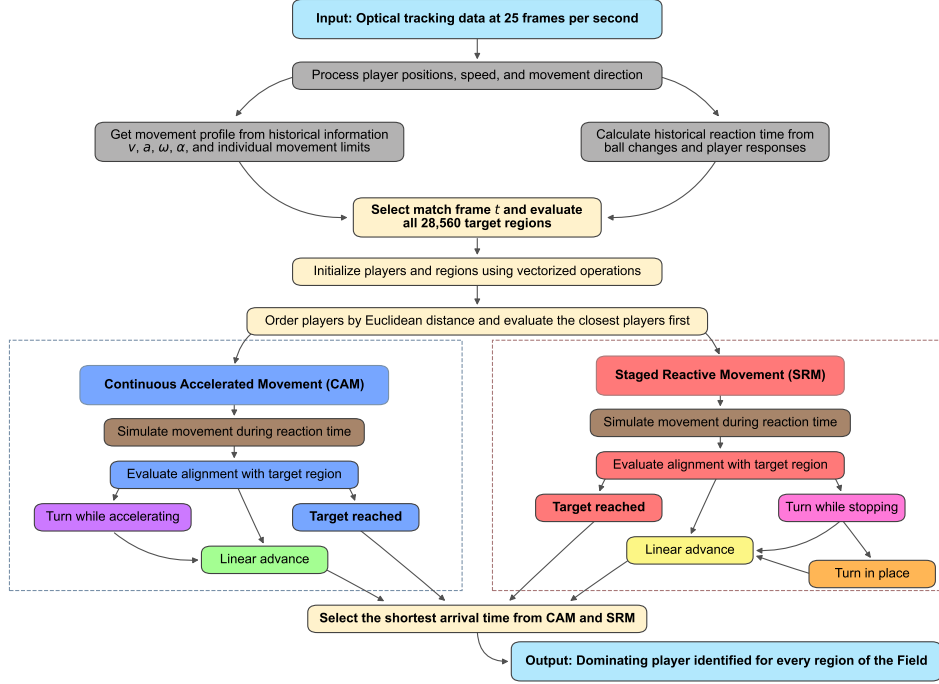


Fig. 4 Overall workflow of the proposed *Player Spatial Ownership (PSO)* methodology. The colors used for the *Continuous Accelerated Movement (CAM)* and *Staged Reactive Movement (SRM)* models are consistent with those introduced in Fig. 3.

3 Discussion

Compared with existing dominant region models, *PSO* estimates spatial control as an individualized and dynamic process rather than a purely geometric one. Unlike previous approaches that assume identical player movement, simplified turning behavior, fixed reaction times, or non-parametric movement representations [1, 2, 4–10], the proposed methodology combines individualized linear and angular movement profiles with player-specific reaction times in a fully reproducible framework estimated directly from historical tracking data. Because it relies exclusively on optical tracking data

and a computationally efficient implementation, the framework can be readily applied across competitions and has the potential to operate in real time without wearable sensors or manual parameter tuning. Current limitations include estimating reaction times from tracking data rather than experimental measurements and modeling player movement only in the two-dimensional plane.

Player Spatial Ownership also provides a foundation for future analyses of player and team behavior. Since every region is assigned an individualized arrival time, the framework can be extended to study passing opportunities, off ball movement, spatial occupation, and decision making under different match situations, including real-time match analysis. Because it relies only on player tracking data and individualized movement profiles, the methodology can also be adapted to other invasion sports with minimal modifications. Player specific characteristics, such as fatigue, can also be incorporated by allowing movement capabilities to vary throughout the match rather than remaining fixed. Consequently, *PSO* should not be viewed as a final performance metric but as a general spatial representation upon which more advanced tactical and performance analyses can be built.

4 Conclusion

This work presents a novel, reproducible methodology for estimating Player Spatial Ownership in football from optical tracking data. By incorporating individualized movement capabilities and reaction time, the proposed framework provides a realistic estimate of player spatial control while remaining computationally efficient, fully reproducible, and capable of operating in real time environments. We envision *PSO* as a fundamental spatial representation that will support the development of future metrics and analytical models to better understand player behavior, tactical strategies, and team performance.

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