Developing a two-dimensional landscape model of opportunities for penetrative passing in association football–Stage I

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Developing a two-dimensional landscape model of opportunities for penetrative passing in Association Football – Stage I

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Abstract

This study investigated a method for modeling a landscape of opportunities for penetrative passing completed on the ground by ball carriers in association football. Analysis of video footage of competitive, professional football performance was undertaken, identifying a sample (n=20) of attacking sub-phases of game play which ended in a penetrative pass being made between defenders to a receiver. Players' relative co-positioning during performance was modelled using bi-dimensional x and y coordinates of each player recorded at 25 fps. Data on player movements during competitive interactions were captured using an automatic video tracking system, recording player co-locations emerging over time, as well as current and estimated running velocities. Results revealed that the half-spaces between the midfield and both side lines were the key locations on field providing most affordances for penetrating passes in the competitive performance sample analysed. Due to the dynamics of players' co-adaptive performance behaviours, it was expected that opportunities for penetrative passing by ball carriers would not display a homogeneous space-time spread across the entire field. Results agreed with these expectations, showing how a landscape of opportunities for penetrative passing might be specified by information emerging from continuous player interactions in competitive performance.

Key words: Penetrative passing; Affordances; Team sports; Emergent behaviours; Co-adaptation

1. Introduction

Interactive behaviours in social settings are governed by local interaction rules which specify how each agent in a collective self-organises (i.e., coordinates activities) with other individuals nearby in the environment, for example when herding to confuse predators or nesting in colonies to enhance security (Couzin & Franks, 2003; Couzin, Krause, Franks, & Levin, 2005; Sumpter, Buhl, Biro, & Couzin, 2008). Self-organising collective behaviours in competitive team sports requires each individual to continuously adjust his/her own decisions and actions influenced by the behaviours of others (i.e., nearby teammates or opponents) (Araujo, Diniz, Passos, & Davids, 2014; Ribeiro et al., 2019). Known as co-adaptation (Kauffman, 1993), interactive behaviours with others in a collective system demand continuous decisions and actions from each individual, constrained by information which specifies what has been previously planned (e.g., in practising of set pieces), and by emergent local information which emerges during performance, (i.e., information with a space-time specificity) (Passos, Araujo, & Davids, 2016; Ribeiro et al., in press). This conceptualisation of self-organisation in human behaviour, as being continuously informationally coupled with environmental constraints, raises the issue of 'what' actions could be performed by each individual in team sports (e.g., decisions and actions of a ball carrier when constrained by the positioning of the nearest defenders). These decisions are also clearly co-related with 'when' (time related) and 'where' (space related) interactions emerge with others nearby (Fajen, Riley, & Turvey, 2009; Passos, Cordovil, Fernandes, & Barreiros, 2012). These vital sources of information for regulating actions create local interactive rules that sustain the dynamics of each individual's interactive behaviors, characterized as a landscape of affordances or opportunities for action (Rietveld & Kiverstein, 2014; Withagen & Caljouw, 2017; Withagen, de Poel, Araujo, & Pepping, 2012). A landscape can be defined as "all the visible features of an area", referring to perceivable and quantifiable environmental properties. A landscape of opportunities for action modelled in competitive team sports performance must contain perceivable/quantifiable features. These can be related to those opportunities of action that emerge as the game evolves at the timescale of perception and action (e.g., during performance), and at the timescale of a sport's evolution (e.g., as equipment and technology changes are introduced and rules modified). Clearly, research is needed to quantify those features that are perceivable for performers during competition in a given team sport in order to depict an affordance landscape model.

An affordance landscape is a powerful concept for team sports practitioners to understand all the opportunities available for athletes to perform relevant actions to achieve intended task goals such as dribbling with the ball, defending space, restricting the time of opponents to act and, of course, playing penetrative passes through defensive formations to create scoring opportunities. Understanding all the potential decisions and actions available to a team sports performer as an affordance landscape can help sports practitioners to understand how to design practice tasks to highlight information for available affordances (Chow, Davids, Shuttleworth, & Araújo, 2020; Davids, Güllich, Araújo, & Shuttleworth, 2017). These designs can support learners in strengthening the coupling of their decisions and actions with key affordances in specifically-designed landscapes during training and practice (Button, Seifert, Chow, Araújo, & Davids, 2020; Davids et al., 2017).

Previous research, conceptualising team sports as a complex, dynamical system, has revealed how the landscape of local information is continuously changing, both in time and space, due to the dynamics of individuals' relative co-positioning, values of distances to field boundaries, nearest active defender and/or proximity to the scoring area (e.g., basket, goal, try line) (Headrick et al., 2012; Orth, Davids, Araujo, Renshaw, & Passos, 2014; Passos et al., 2012). Underpinned by Ecological Psychology and Dynamical Systems Theory (Ecological Dynamics) (Davids, Handford, & Williams, 1994; McGarry, Anderson, Wallace, Hughes, & Franks, 2002), this body of work has identified a broad set of collective variables that describe the interactive behaviours emerging between two or more players which characterize their affordances or opportunities for action.

It has revealed that every performer has the ability to detect specific emergent information sources specifying behaviours to uitlise specific affordances *inviting* potential actions of him/her, and *others* (e.g., teammates and opponents). Perceptual information constrains each performer’s own opportunities to act reciprocally, demanding continuous, ongoing adaptations of actions in space and time (Gibson, 1979; Passos et al., 2012; Passos & Davids, 2015; Stoffregen, Gorday, Sheng, & Flynn, 1999).

For example, evidence has implicated the attacker-defender interpersonal angles emerging in team games like Basketball, Futsal and Rugby Union (Correa, Vilar, Davids, & Renshaw, 2014; Esteves et al., 2015; Passos et al., 2009), or attacker-defender interpersonal angle regarding the centre of the goal in Football (Vilar, Araujo, Davids, & Travassos, 2012). Despite this large body of work seeking to establish a set of collective variables that could characterize interactive behaviours of performers in various team sports, there is a need to enhance the methodological approaches that depict a landscape of opportunities for action in sport performance contexts. Calculated over time, values of relevant collective variables could illustrate the dynamics of individuals' relative co-positioning (incorporating changes in space and time), characterizing the affordance landscape for actions, like passing, during competitive performance.

In a team sport like football, for example, intending to pass the ball to a support player located nearer the opposing goal (i.e., located in half spaces in between defensive lines of opposing players), will constrain a ball carrier to actively explore (i.e., through his/her actions) opportunities for performing a penetrative pass. Here, we define a ‘penetrative pass’ as one made longitudinally up the field (within a range angle) to a supporting teammate located in a defensive gap, nearer the opposition scoring area, which will increase the possibilities of a team creating an opportunity to shoot at goal. However, due to the continuous co-adjustments in the relative positioning of defenders, these affordances or opportunities to perform a penetrative pass to a support player are continuously becoming available or disappearing (Passos & Davids, 2015). This is because individuals' opportunities for action in an affordance landscape (Rietveld & Kiverstein, 2014) can change over very short time scales, e.g., in team sports gaps in a defensive formation (which may provide an opportunity to pass the ball to a support player) appear and dissolve in fractions of a second.

This affordance landscape is dynamic since opportunities for action are available in a limited space-time window. On the one hand, there are opportunities to perform a pass which remain available during the period in which the ball carrier retains possession of the ball. On the other hand, there are other opportunities for action that vanish due to changes in the relative positioning of opponent players (Passos & Davids, 2015).

Modifications in the co-positioning of competing performers is strongly influenced by immediate technical and tactical performance constraints. Due to tactical defensive formations used to deny space in critical scoring regions, there are some areas of a football field which has a ‘high density’ in terms of penetrative passing opportunities, compared to others, suggesting that opportunities for a ball carrier to perform such a pass in football may not have a homogeneous space-time spread across the entire field. To examine this idea during competitive performance, one can depict a varying landscape of passing opportunities, regarding areas onfield where they emerge, as well as for how long these affordances last. Thus, the aim of this study at the initial verification stage of this research programme was to present an exploratory method to investigate how a two-dimensional landscape of opportunities for penetrative passing might continuously change in time and space during competitive football performance. Specifically, the study's aim was to verify the construction of the display of the 2D landscape of penetrative passing opportunities for a ball carrier, emerging from the co-positioning of competing players in different attacking sub-phases in competitive football.

2. Materials and Methods

Data acquisition

Data used in this study were captured from a recording of an official competitive football match from the Dutch Eredivisie which is the highest echelon of professional football in the Netherlands. In the match, the attacking team adopted a 4-3-3 tactical configuration and the defending team adopted a 4-4-2 tactical configuration and the match recording was kindly provided by the company who collected the data. Due to the impossibility of addressing all the performance details, and for ease of simplicity, the method for characterising an affordance landscape for penetrative passes, presented here, is only supported by each player's positional data. For this reason, it was decided not to include other types of data related to, for example, technical, tactical, physiological or psychological variables, although these performance aspects can be addressed in further iterations of the model. This study received institutional ethics approval. We analyzed performance that did not require identification of individual performers. This initial analysis only required that we studied the opportunities for in-depth passing of one of the competing teams. The team selected for performance analysis was the home team. Bi-dimensional coordinates (*x* and *y*) of each performer were recorded at 25 fps, using an automatic video tracking system (spatial accuracy was calculated with Root Mean Square Error (RMSE), and achieved a positional error value of 0.73m (Siegle, Stevens, & Lames, 2013)).

Procedure

In this study our aim was to deliberately characterise the properties of a two-dimensional landscape model of opportunities of action for a ball carrier limited to passing opportunities on the ground. Not limiting the passing opportunities to those made at ground level, demands a three-dimensional analysis which involves previous studies to support the variables to be used in the 3D construction of the landscape.

After converting the original data into speed and acceleration records, both noise and outliers (in some cases due to the presence of noise itself) were identified. Although not quantified, noise in the data was revealed to be random (i.e., white noise) and negligible for purposes of identifying player positioning. However, for speed and acceleration calculations, data sensitivity to noise increased with its frequency.

Thus, to correct these issues, a method of data preprocessing was applied. First, the outliers were identified according to the following criteria: i) instances where a player's speed was exactly 0 m/s, since data noise prevents a player from being recorded at exactly the same position for two consecutive moments and, for this data set, these situations corresponded to sudden anomalous drops in speed; ii) spikes (>5 m/s^2) in acceleration which were followed by another spike with an opposing sign in less than 0.5 seconds, since these values are likely to be related to sudden abnormal changes in speed (similar to a sprint, but in a shorter time window); iii) the top 0.01% speed records of every player (corresponding to 1.8 seconds of measurements), since, by removing such a reduced fraction of data resulted in changing the players' estimated maximum speed from 37-115 $km.h^{-1}$ to 25-33 $km.h^{-1}$.

Detected outliers were then removed and replaced using a linear interpolation method (adopting the average of the nearest two points). Afterwards, a 3-point centered moving average value was applied in order to remove most of the noise in the data. Lastly, the data were resampled to 5 Hz frequency in order to reduce the algorithm computational loading, retaining relevant information and removing some more noise from the data.

The first 20 organized attacking situations, using the criterion that *a player in possession of the ball (defined as a ball carrier) needed to enter the opposition's midfield area*, were identified by visual inspection. Next, support players identified by the algorithm were defined as those located closest to the opposing team's goal line (hereinafter defined as *receivers*). Moreoever, to add to the model an estimation of the location of: (i) the potential pass receiver, and (ii) the closest defenders at the next moment in time, displacement vectors was calculated to provide information regarding the direction and veloctiy of each player's running line (black arrows in Figure 1). Each displacement vector was calculated based on the velocity vectors in the x and y axes. Next, based on positioning of the ball carrier and receivers, two potential penetrative passing lines (PPL) were constructed. One for the *potential receiver's current position* connecting the ball carrier to the beginning of the potential receiver's displacement vector (please see PPL1 in Figure 1). The second passing line connected the *potential receiver's estimated position*, from the ball carrier to the endpoint of the potential receiver's displacement vector (please see PPL2 on Figure 1).

The attacking situations selected for analysis contained several possibilities of penetrative passes, depending on the number of receivers that we sought to consider (the number of receivers is a variable that the model allows to customize according to the aim of the analysis). Penetrative passes were defined as those passes which were played upfield in the longitudinal direction (i.e., towards the pass receivers located closest to the opposing goal line) to exploit space between and behind defenders. These actions did not include passes played backwards or sidewards onfield which typically had a key aim of maintaining ball possession.

Algorithm description

Having determined the ball carrier as the closest player in the attacking team to the ball (with a maximum distance threshold of 1,5 m), *N* potential penetrative passing lines were defined, where *N* was the number of support players closest to the opposition goal (i.e., the model allow customization from one up to ten receivers). To evaluate availability of penetrative passing opportunities for a ball carrier, the defenders who were best positioned for a potential interception were identified as the closest players to a potential passing line (PPL). For a more accurate estimation of a potential pass interception, instead of simply considering the defenders' positioning, the model also estimated where each defender could be in the next second based on the value of current velocity (black arrows which represent players' displacement vectors in Figure 1).

Insert Figure 1 about here

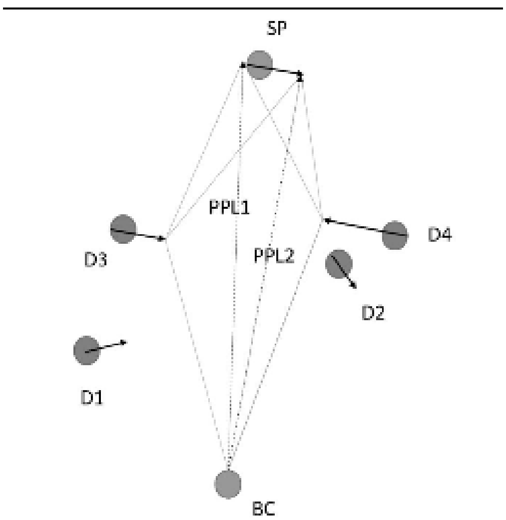

Figure 1. Depiction of the polygon that specifies opportunities for penetrating passes. Grey circles represent the ball carrier (BC), the receiver/support player (SP) and the defenders (D1, D2, D3 and D4) closest to the potential passing line (PPL1 and PPL2). The black dashed arrows are the potential passing lines. The grey filled lines represent the polygon boundaries. Finally the black arrows represent the players displacement vectors.

A penetrative passing opportunity was created when the defenders' end vectors did not intercept a potential passing line, or if only one of the potential passing lines was intercepted. Additionally, by forming a polygon where both extremities of the potential passing lines linked the ball carrier with the receiver's initial and end vector (i.e., PPL1 and PPL2 respectively on Figure 1), the model is able to illustrate this part of a landscape of opportunities of penetrative passing (in terms of space temporary availability), continually updating the landscape of opportunities for penetrative passing every 0.2 seconds. In the absence of adequately positioned opposing players, the algorithm assumed that the coordinates (*x*, *y*) along the sideline, closest to the hypothetical passing line, was a reference marker to create the polygon.

This polygon was updated every 0.2 s and it can either: i) slightly change its shape (as the involved players are moving); ii) be completely redefined due to changes in ball carrier identity, and/or which defenders were most suited to intercept the potential penetrating pass; or iii), cease to exist as both passing opportunities (to the potential receiver current and estimated position) in the landscape dissolved.

Data analysis

As mentioned, the polygon's shape can be quite dynamic due to its sensitivity to changes in the emergence of player co-positioning. By keeping track over time and overlaying formed polygons, a model of a 2D landscape of opportunities for penetrating passes could be depicted by a heatmap, where a gradient of colours differentiated regions with more/fewer passing opportunities. However, this methodological logic can also be applied to evaluate performance contexts where penetrative passing lines disappear, defining a polygon and building an emergent landscape in which opportunities for penetrating passes were most effectively ‘blocked’ by the positioning of defenders. A blocked line implies an interception with at least one defender’s vector.

Landscapes of opportunities for action can be customized considering the number of simultaneous potential pass receivers, as well as the angle from which a penetrative pass was considered to be played. The present model was limited to the three pass receivers closest to the opposing goal line. Therefore, there was no need to set an angle from which a penetrative pass was considered.

Additionally, three other types of data could be calculated with this method: i) to provide information regarding the time that each opportunity for a penetrative pass was available, the time duration of the emergence of each polygon was calculated in seconds; ii) the total duration that each player has to perform a penetrative pass; iii) the total duration that each player has to receive a penetrative pass; iv) the mean time that each player has to perform a penetrative pass; v) the mean time that each player has to receive a penetrative pass; and vi), distribution of the possibilities to perform a penetrative pass in each longitudinal corridor upfield field towards the opposition goal (left, central, right).

3. Results

Visual inspection of the data revealed areas between the midfield and both side lines (yellow areas in Figure 2.a, 2.b, 2.c) as those with most opportunities for penetrative passes to be played. Additionally, the areas between the midfield and both sidelines were the regions where the defending team was most frequently able to block penetrative passing opportunities (Figure 2.d, 2.e, 2.f).

Insert Figure 2 about here

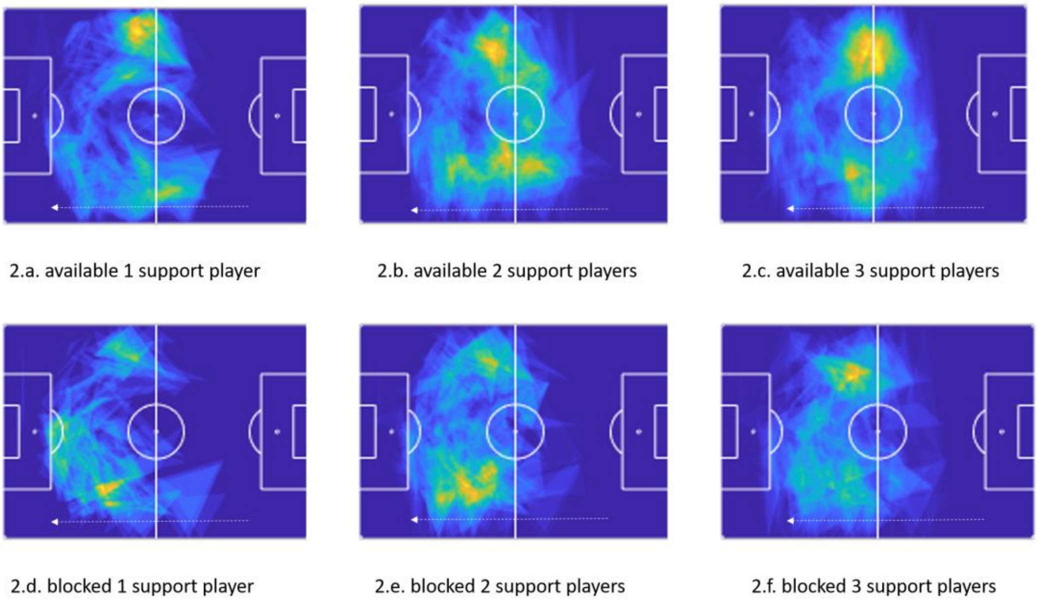

Figure 2. Depiction of the landscape model of opportunites for penetrative passes; a), b) and c) depict the landscape of opportunites to play penetrative passes for one to three available receivers; d), e) and f) depict landscapes of blocked passing lines. Dark (blue) areas represent the zones with less frequent events (available passing opportunities or blocked passing opportunities); yellow areas represent zones with the

highest frequency of events (available passing opportunities or blocked passing opportunities). The dashed white arrows indicate the direction of the attack.

The time dimension associated with this landscape model of penetrative passing opportunities was calculated for up to three receivers. Data displayed in Table 1 concerning the descriptive statistics of the polygon duration exemplify the kind of analysis that could be undertaken with this method.

Insert table 1 about here

Table 1. Descriptive statistics of polygon duration (s). Note that the minimum duration is conditioning by the polygon's update rate.

Nº_receivers	Nº polygons	Min	Mean	Med	max	IQ range
1	45	0,2	0,73	0,4	3,4	0,8
2	84	0,2	0,67	0,4	3,4	0,6
3	125	0,2	0,74	0,6	3,4	0,8

Data in Table 1 displayed an increase in the number of polygons emerging whenever a receiver was added to the computation. However, the amount of time that the opportunities for a penetrative pass became available did not reveal relevant changes. Despite being calculated for one, two or three receivers, the ball carrier's opportunities to play a penetrative pass were available for very short periods of time, 0.2 s, but also for longer periods, lasting for 3.4 s.

Figure 3 displays the time windows of the opportunities for performing a penetrative pass, where it is displayed, and how long each opportunity remained available (Figure 3).

Insert Figure 3 about here

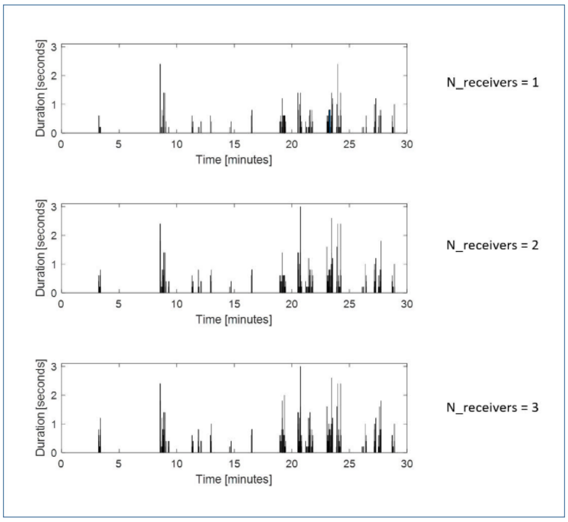

Figure 3. Duration of each polygon along time regarding one, two or three receivers used to create the landscape model. Each black bar reprents a polygon.

Despite the number of receivers (from one to three), between the 8^{th} and the 9^{th} mins a few penetrative passing opportunities emerged and they were available for a period of time between 1.5 s and 2.5 seconds. Additionally, between the 19^{th} and 22^{nd} min, several opportunities to perform a penetrative pass were available, but with a maximum duration close to 3 s for up two or three receivers. Between the 23^{rd} and 24^{th} mins, again, several penetrative passing opportunities were identified, but with durations lasting up to approximately 2.5 seconds. We noted that these time intervals remained, despite the computation of the landscape model being composed for 1, 2 or 3 potential receivers (Figure 3).

For an individual player analysis, Figure 4.a and 4.b display the total duration that each player has for the opportunity to perform or receive a penetrative pass, respectively. Figure 4.c and 4.d display the mean time that each player was available to perform and receive a penetrative pass, respectively.

Insert Figure 4 about here

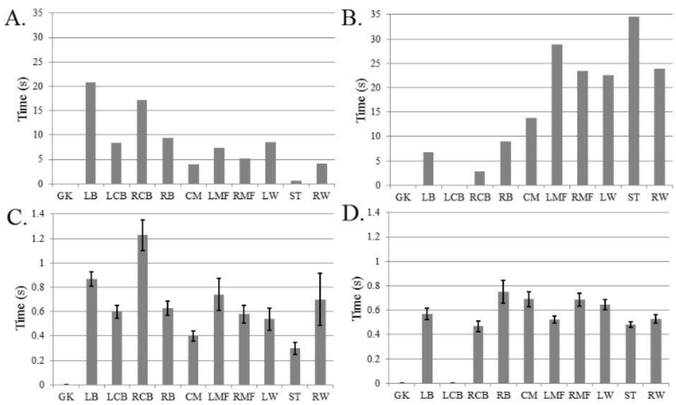

Figure 4. (A) Total time line passes were available for each player in the team when they were carrier; (B) total time line passes were available for each player in the team as with them as receivers; (C) mean time the line passes were available for each player as a carrier; (D) mean time the line passes were available as a receiver. The error bars in the Figures C and D correspond to the standard error of the mean. The total time available is higher for the graph of the receivers than the carrier as a single carrier could have more than one line pass available as a time. Players positions (GK) goalkeeper, (LB) leftback, (LCB) leftcenterback, (RCB) rightcenterback, (RB) right back, (CM) centermidfilder, (LMF) leftmidfilder, (RMF) rightmidfilder, (LW) leftwing, (ST) stricker, and (RW) rightwing.

Analysis of Figure 4 revealed that the leftback (LB) was the ball carrier with more time to perform a penetrative passe (approximately 21 s of the total amount of time available). Each time that he acted as a ball carrier, on average he had 0.8 s to perform a penetrative pass, whereas the right centerback (RCB) had on average 1.2 s to perform a penetrative pass. Concerning the players that ‘create’ more time to receive a penetrative pass, the striker (ST) created opportunities to receive a penetrative pass for 34 s, but on average, each action undertaken to receive a penetrative pass only lasted for 0.5 seconds.

Finally, concerning the distribution of possibilities to perform a penetrative pass, data reveal that 41% of passing opportunities were performed in the left longitudinal corridor; 31% in the central corridor and 28% in the right corridor.

4. Discussion

The initial stage of this study provided evidence that it is possible to create a bi-dimensional model to characterize a landscape of opportunities (affordances) for penetrative passing in the team sport of football, constructed from an algorithm recording the dynamics of players’ interactive co-positioning, and their movement velocities.

The algorithm identified the areas of a football field where penetrative passing opportunities are either available or blocked, during elite competitive performance.

By displaying heatmaps frame by frame (i.e., as a movie), we observed how the landscape changed over time and space as a result of emergent dynamical interactions of players’ co-positioning.

Additionally, overlapping the polygons over time, as shown in Figure 2, revealed that penetrative passing opportunities do not have a homogeneous distribution over the entire football field, confirmed by data on the distribution of possibilities to perform a penetrative pass. Integration of information from the dynamics of the landscape of penetrative passing opportunities and blocked passes, suggested that the defending players were seeking to close the passing lines which consequently re-configured the landscape for available penetrative passing opportunities towards the sidelines. This tactic ensured that attackers in a less insecure area of the critical scoring region onfield maintained ball possession, since the penetrative passes through the mid-area are potentially much more dangerous for attackers to shoot at goal compared to the side-areas.

Moreover, the data also revealed the time window (between the 19th and the 24th mins) in which the highest number of penetrative passing opportunities occurred, perhaps an indicator of a time period where the defence had become more vulnerable to attack. Defensive vulnerability may have emerged due to several factors such as: limitations in visual scanning behaviours (Stone, Strafford, North, Toner, & Davids, 2019), physical fatigue (Barte, Nieuwenhuys, Geurts, & Kompier, 2020) or tactical changes (Vilar et al., 2014).

The time that each passing opportunity was available (as a ball carrier and receiver) might be associated with the relative proximity of the opponents. The RCB probably had the opposing players furthest away, while the ST, due to a threatening position in the picth, leads to a close proximity to the opposing defenders.

The verificational aim of this study suggests that some caution is warranted in interpreting these results since they are based on analysis of a model of a 2D landscape, and their generalization is somewhat limited. Factors that might contribute to modifications in the frequency and duration of penetrative passing opportunities is an interesting issue for further research with a larger sample of competitive matches.

Further research is needed to quantify the interactive relationship between individuals' specific abilities and properties of the environment that specify opportunities for action, illustrating an affordance landscape. This initial study exemplified a landscape of opportunities for penetrative passing. To evolve to a landscape of affordances, a weighting must be added to each player related to his/her own individual passing skills, habits and capacities. .

Further stages of research could focus on a three-dimensional landscape, considering not only penetrative passing opportunities for passes made on the ground, but also passes where the ball carrier lifts the ball into the air over defenders into space behind them. Also tactical variations could be evaluated since this method should be sensitive to such changes, suggesting that teams who employ different tactical systems can re-configure the landscape of passing opportunities, depending on the changing performance goals that shape player interactions.

Future modelling might be expected to reveal different performance landscapes to be displayed by: (a) different teams; (b) the same teams against different opposition; (c) the same team playing home and away; (d), the algorithm being adapted to investigate construction of landscapes of opportunities for action in other invasion team sports (e.g., Basketball, Rugby Union, Handball); and (e), considering the addition of variables that require the use of different methods to collect performance data. For instance, the players' gaze behaviours in simulated competitions which require the use of an unobtrusive eye tracker device to assess where each player is currently looking (e.g., the use of 'scanning behaviors' by carriers to locate potential pass receivers) could provide highly relevant information on perceived opportunities for action (Stone et al., 2019).

In summary, a model was developed for assessing professional athletes' engagement with opportunities for penetrative passing in a competitive association football match. Current football analytics research provides a straight linkage between the outputs provided by sports analytic staff, supported by big data, with the needs of a team's technical support staff. The landscapes depicted in this manuscript can be captured in user friendly heatmaps that identify the most vulnerable defensive areas of the pitch and how this vulnerability evolves throughout the match, may provide useful information that fill this gap. Further work is needed, to explore implications for practice designs supported by a deep understanding of the tactical demands on players, predicated on affordances of competitive teams sports environments that emerge through co-adaptative processes.

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Disclosure of interest

The authors report no conflict of interest.

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