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Network analysis and intra-team activity in attacking phases of professional football

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Abstract

In this study we sought to verify whether network analyses could be used to identify key players in attacking phases of a professional football match and establish the main interactions and preferential linkages between attacking teammates during competitive performance. For this purpose, we examined circulation of the ball on field during randomly selected attacking phases of play in a video-taped Portuguese Premier League match. We observed six matches and notated 1488 collective attacking actions, including: passes completed, passes received, and crosses involving a total of 4126 intra-team interactions (e.g., 2063 passes and crosses performed and 2063 passes and crosses received). We used Amisco® software to perform quantitative and qualitative analyses of the attacking actions. Results indicated how key individual players are instrumental in orchestrating team performance, exerting a powerful influence in creating attacking patterns of play. Our findings may help coaches and sports scientists quantify the contributions and interactions of individual team members through analysis of their relevant actions in team sports like football.

Keywords: *interpersonal interactions, association football, network analysis, attacking phases of play.*

1. Introduction

In the past decades it has been proposed that association football is a sport in which two teams interact as components of a dynamical system in which the players move the ball around the field in order to score a goal (McGarry *et al.*, 2002; Grund, 2012; Sargent and Bedford, 2013). Due to the nature of the players' interactive behaviors (involving teammates and opponents), football has been characterized as a team sport involving great variability and unpredictability of actions, leading researchers to investigate the network of interactions that emerge between professional football players within teams (Vilar *et al.*,2014). For example, in the study of Grund (2012), interpersonal interactions within 23 football teams from the English Premier League (EPL) were analysed. An important issue in conducting such network analyses to study interactive behaviors of team games players is the significance of highlighting the actions of an orchestrating player who is embedded within a team's collective behaviors (Duch *et al.*, 2010). Network analyses might be useful to shed light on a key individual performer's contributions to team performance and provide insights on how creative and organizing individuals might act to orchestrate team strategies.

Recently, Yamamoto and Yokoyama (2011) demonstrated that networks resulting from players' interpersonal interactions within a football match can frame the collective behaviors of team members, revealed by typologies such as *small-world networks* and *scale-free networks*. These concepts have attained significant theoretical support within social science research, for example, in analyses of networks that emerge in different social systems (Weelman, 1985, Wasserman and Faust, 1999; Enemark *et al.*, 2014), as well as in the study of biological system functions. In this approach the world around us has been described through a global network of contacts that emerge during the continuous functional interactions between living organisms (Barabasi and Oltvai, 2004; Klipp *et al.*, 2005).

Social communities are networks in which the nodes are people between whom there are many different types of possible interactions (Mitchell, 2009). A sports team can be considered a small world network with relatively few long-distance connections between nodes (e.g., the players). But due to a large number of close-distance connections, this collective system displays a small average path-length relative to the total number of nodes, a feature of small world networks. Moreover, small-world networks in team sports also typically exhibit a high degree of clustering (e.g., grouping tendencies) which means that for specific nodes (e.g., players) A, B, and C, if node A is connected to nodes B and C, then B and C are also likely to be connected to one another.

A particular kind of small-world networks that more closely resemble networks in the real world are scale-free networks which are based on the distribution of the amount of interactions across nodes. Scale free networks are characterized by many nodes with few connections and few nodes with large number of connections. This network property obeys a power law distribution which is a general feature of self-organizing, complex systems

(Mitchell, 2009). This property can help us better understand how complexity and self-organization emerge in intra-team activity in professional football, revealed by network analysis. Based on previous research we assumed that players' interactive behaviours within a football match support the existence of a scale free network (Yamamoto and Yokoyama, 2011). A general feature of this type of network is that a few players (vertices or nodes) will tend to exhibit more links than other players. Consequently, because a football team has been conceptualized as a complex, self-organising system, the number of links between players tends to display a power law statistical distribution (Passos *et al.*, 2011; Barabasi and Oltvai, 2004).

Passos *et al.* (2011, p. 170) described the relevance of conducting network analyses in team sport sciences as follows: *"In team sports, functional performance is assured by a complex network of interpersonal relationships among the players (a social network)."* (…) *"The network nodes are system agents (i.e. the players), and the interconnecting lines among players represent the ways that those players interact, through verbal or non-verbal communications skills"*. Network analyses are important to sports science research for mapping the technical and tactical actions of individual performers in the team. This approach can reveal the interpersonal interactions involving creative and influential performers in team sports and how their interactive behaviours might change from match to match. It is also useful for identifying specificities in a team's strategical planning between competitive matches (Grund, 2012).

In summary, network analyses can support investigations of continuous interactions between players and teams during competitive performance. This methodology can be used to characterize the collective behaviors that emerge through cooperation and competition between players during competitive football matches (Passos *et al.*, 2009, 2011; Duch *et al.*, 2010).

The methodology of network analysis can be implemented so that coaches and sport scientists can**:** i) record intra-team patterns of play that result from competitive actions and adjust a strategic game model and establish specificity of training programmes focused on major tactical and technical needs of a team; ii) analyse intra-team patterns of play that emerge during both training and competitive interpersonal interactions of players; iii) verify who the most interactive players (key players) are and assess how their interactions with other individuals change across matches during a competitive season; iv) verify the preferential linkages between team members and the changes within preferential linkages across matches during a competitive season; and v) record the main interactions that emerge (using frequency analyses) from the players' averaged field positions.

Accordingly, we sought to record and characterize the attacking effectiveness of professional football teams using network analyses. Identification of attacking patterns required that we identified, first, who the key players in each professional team were and how the amount of interactions of each key player changed between competitive matches. Second, we characterized the preferential linkages between team members, and also described changes in emerging preferential linkages from match to match. Third, we recorded the positions of key players in a professional football team during competitive performance. In existing work, it has been established that the probability of a new node being connected to an existing node depends on the connectivity of the latter (Duch *et al.*, 2010; Yamamoto and Yokoyama, 2011). For this reason we analysed the preferential connectivity levels of specific players (especially key players) in relation to their team mates, highlighting those who had the greatest influence on ball movement as well as their interactions in the collective dynamics of competitive football (Barabasi and Oltvai, 2004; Duch *et al.*, 2010; Yamamoto and Yokoyama, 2011; Yamamoto *et al.*, 2013).

2. Methods

We observed a randomly selected sample of six matches and analysed by notation 1488 collective attacking actions, including: passes completed, passes received, and crosses involving a total of 4126 intra-team interactions (e.g., 2063 passes and crosses performed and 2063 passes and crosses received) from one single team during competitive matches in the Portuguese Premier League. Concerning the context of performance for the notation analyses, the six competitive matches were played in an alternating sequence beginning with away and home games. The team observed was in first place in the league and their last game was against a direct opponent competing for the title.

Performance data were analysed using the *Match Analysis Software –Amisco®* (version 3.3.7.25), a specialized program that allowed us to characterize activity profiles in the team (Carling *et al.*, 2005). This system allowed us to follow the movements of every player simultaneously over the course of the match, on digital video footage obtained from fixed multiple cameras positioned strategically to cover the entire pitch. Simultaneously, a trained operator coded each technical action involving the ball, providing *a posteriori* information on various types of actions performed in the game (Di Salvo *et al.*, 2007; Carling, 2010; Zubillaga *et al.*, 2009 and Randers *et al.*, 2010).

To identify intra-team interactions, we analysed performance by players of the relevant actions typically used during attacking game phases, including: passes to team mates, crosses into the penalty box and ball receptions. Each time a pass, cross or ball reception occurred during attacking performance, we recorded the event as an interaction between attacking players. In this way networks were constructed with nodes representing players and arrows graphically connecting players representing the links which were weighted according to number of emergent interactions (Duch *et al.*, 2010).

2.1. Procedures

First, aiming to quantify the frequency of relevant events, such as collective actions like passes, crosses and passes received, we performed a notational analysis of competitive performance of the team during attacking phases of play on each game. Next, we quantified players' interactions, beginning by setting criteria to characterise successful performance.

We defined that an interaction was established whenever a pass or a cross was performed by a player with the successful reception of the ball by a teammate. In our analysis, we discounted actions emerging from random events in the game, such as undercuts or awkward ball rebounds on the turf, followed by subsequent ball reception by a player.

Using Amisco® software, we constructed the networks and intra-team connectivity matrices, displaying and measuring the interpersonal relationships established by players on each game. A major focus of this study was to analyze which areas of the field were usually occupied by key players during the football match.

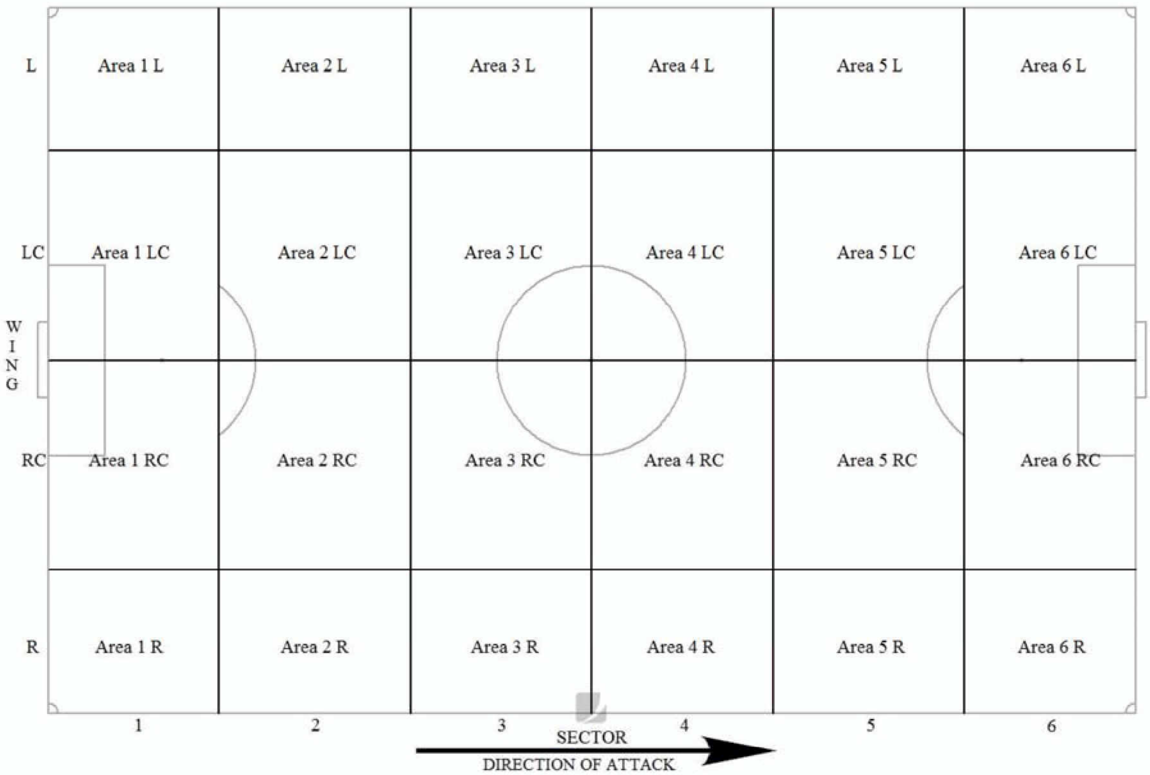

Figure 1.The football field divided into 24 areas (adapted from Amisco).

This football field was validated using Amisco® software which automatically divided the football field into 24 areas, composed of 4 corridors and 6 sectors (Figure 1). Each player's position on field, within the network, was calculated by averaging his positioning during the entire game.

The average positioning was calculated through recording the total number of ball contacts achieved by each player (a player's position was calculated each time he touched the ball). Thus each player's average positioning was related to the number of times and field location where he contacted the ball (Duch *et al*., 2010; Grund, 2012).

Additionally each player's probability of interaction was measured using the *relative frequency odds method* (Peebles, 2001). This method calculates the probability that each player has of interacting with any teammate using the following formula (1):

$$P = \Pr(X, Y) = \frac{\text{number of interactions Player "X" with "Player Y"}}{\text{Total number of interactions Player X}} \qquad (1)$$

A probability of interaction that is unlikely to be achieved is recorded as a 0, and the likelihood of an achieved interaction is rated as 1.

3. Results

The networks we observed depicted the interactions established between players of the same team through their distribution on field during an attacking phase of play across the selected sample of six matches. Thus, to each player was assigned an arrow attaching to another player, with whom they engaged in an interaction, allowing us to record the total number of interactions performed between the two players across all six matches (Duch *et al.*, 2010; Passos *et al.*, 2011). Table 1 shows that during the six games a total of 4126 intra-team interactions were registered (successful passes and crosses) between players of the football team.

Table 1. Number of interactions between players, identifying passes made or crosses performed with reception of the ball by a teammate, as a function of different periods of playing time for each individual.

To/Of	**Players**																			
Players	**1**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**12**	**13**	**14**	**17**	**18**	**19**	**21**	**23**	**25**	**28**	**30**	**Passes and crosses receive**
1	-	11	13	1	0	1	0	0	1	3	24	0	0	0	5	1	5	2	3	70
4	30	-	24	5	1	7	1	0	0	1	14	1	0	0	5	0	9	2	0	100
5	32	37	-	9	12	38	7	10	11	0	4	29	0	2	1	4	22	21	8	247
6	2	5	9	-	6	3	1	0	4	2	5	5	0	0	6	0	3	6	0	57
7	1	2	16	5	-	17	11	1	22	17	7	7	0	0	8	1	17	2	6	140
8	0	16	27	7	18	-	17	2	13	15	24	29	0	0	6	1	32	10	4	221
9	0	1	23	6	10	23	-	1	22	5	8	8	1	1	6	0	16	2	2	135
10	0	0	7	2	2	3	1	-	0	1	0	0	0	0	1	0	6	0	0	23
12	1	0	27	8	34	19	18	1	-	30	12	8	0	1	30	2	4	9	3	207
13	11	9	0	0	10	16	3	0	8	-	11	13	3	1	0	2	9	7	0	103
14	14	12	9	5	8	19	2	0	4	13	-	1	0	2	14	4	24	6	11	148
17	1	2	46	2	11	43	14	0	7	21	8	-	0	0	4	2	14	3	4	182
18	0	0	2	0	0	0	0	0	0	3	0	0	-	1	0	1	2	1	0	10
19	0	1	5	0	0	0	2	0	0	2	2	0	0	-	0	0	0	5	0	17
21	4	0	1	2	10	6	4	1	8	0	19	2	0	0	-	3	3	1	1	65
23	0	2	4	0	0	1	1	0	1	5	1	0	0	2	3	-	3	1	0	24
25	1	16	22	5	13	18	11	1	9	12	19	13	3	0	7	2	-	5	9	166
28	1	16	19	0	0	10	8	1	2	11	5	4	0	3	2	0	11	-	1	94
30	8	0	10	0	9	6	0	0	1	1	7	3	0	0	0	2	6	1	-	54
Passes and crosses performed	106	130	264	57	144	230	101	18	113	142	170	123	7	13	98	25	186	84	52	2063
Total of interactions	176	230	511	114	284	451	236	41	320	245	318	305	17	30	163	49	352	178	106	4126

Legend: *To* – interaction received by player; *Of*– interaction made by player. The lines display the number of passes and crosses received by each player; The columns display the number of passes or crosses performed by each player.

The data clearly indicate that player 5 was the individual who most interacted with other players, engaged in a total of 511 interactions (264 passes and crosses; 247 passes received), followed by player 8 with 451 interactions (230 passes and crosses; 221 passes received) and player 25 with a total of 352 interactions with the others (186 passes and crosses; 166 passes received). These data suggest that in the sample of six matches, players number 5, 8 and 25 were most influential performers during the attacking phases of play.

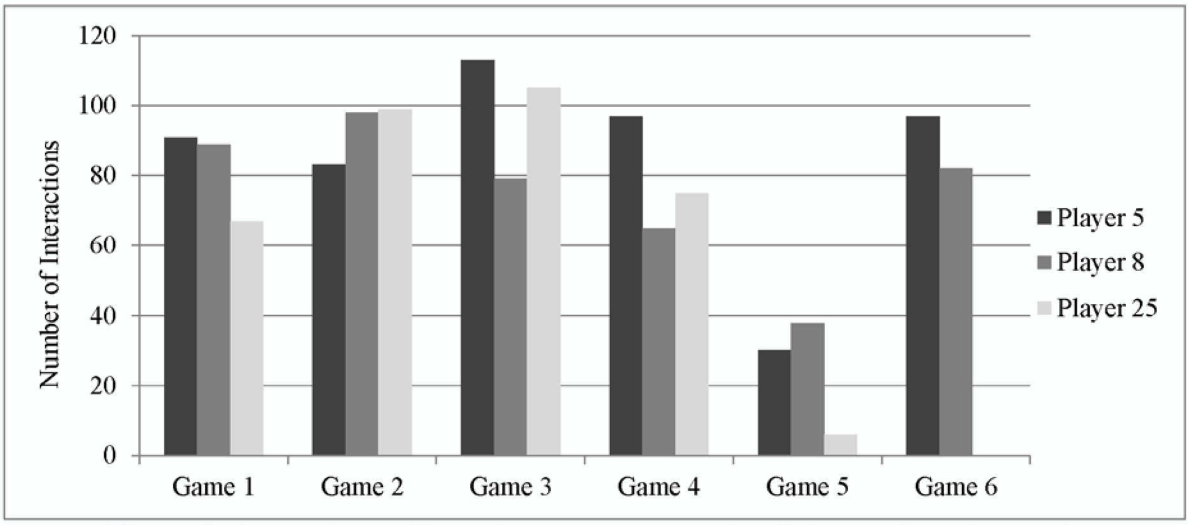

Figure 2. Interactions of key players in the sample of six matches observed.

Figure 2 provides a longitudinal analysis of the key players' interactions, highlighting the emergent interacting tendencies in the sample of six matches under analysis. We observed that player 5 was the main key player (with the highest amount of interactions with teammates) in four out of the six games. The exceptions were in game two, where player 25 achieved the greatest number of interactions and game five where player 8 was the key player with the highest number of interactions with other players in the team.

These data reveal that key players may replace each other, making it harder for opponents to negate the influence of a key performer. For instance if key player 5 performed fewer interactions (e.g., due to a task constraint like the proximity of a marking defender), other players (player 8 or 25) may emerge to replace a key player (e.g., player 25 was the key player on game 2). This may be identified as a form of system redundancy which is a general feature of any complex system, in which components can be interchangeable in their functions.

These data imply that performance activity in team sports like football can be described as a scale free network, where a small number of players are involved in a great amount of interactions, and many players involved in a small number of interactions, a common feature at different scales of analysis. In this study, this typical feature of scale free networks emerged in every match (short timescale of analysis) and also across matches (longer timescale of analysis) in our selected sample, independently of individuals who were identified as the pivotal player.

Beyond quantification of the number of passes and crosses performed, it is worth noting where on field (on average) important interpersonal interactions emerged. Figure 3 displays the network providing a qualitative analysis of the main interactions performed (at which field location and between whom the passes were performed), based on the players' averaged field positions across the sample of six matches.

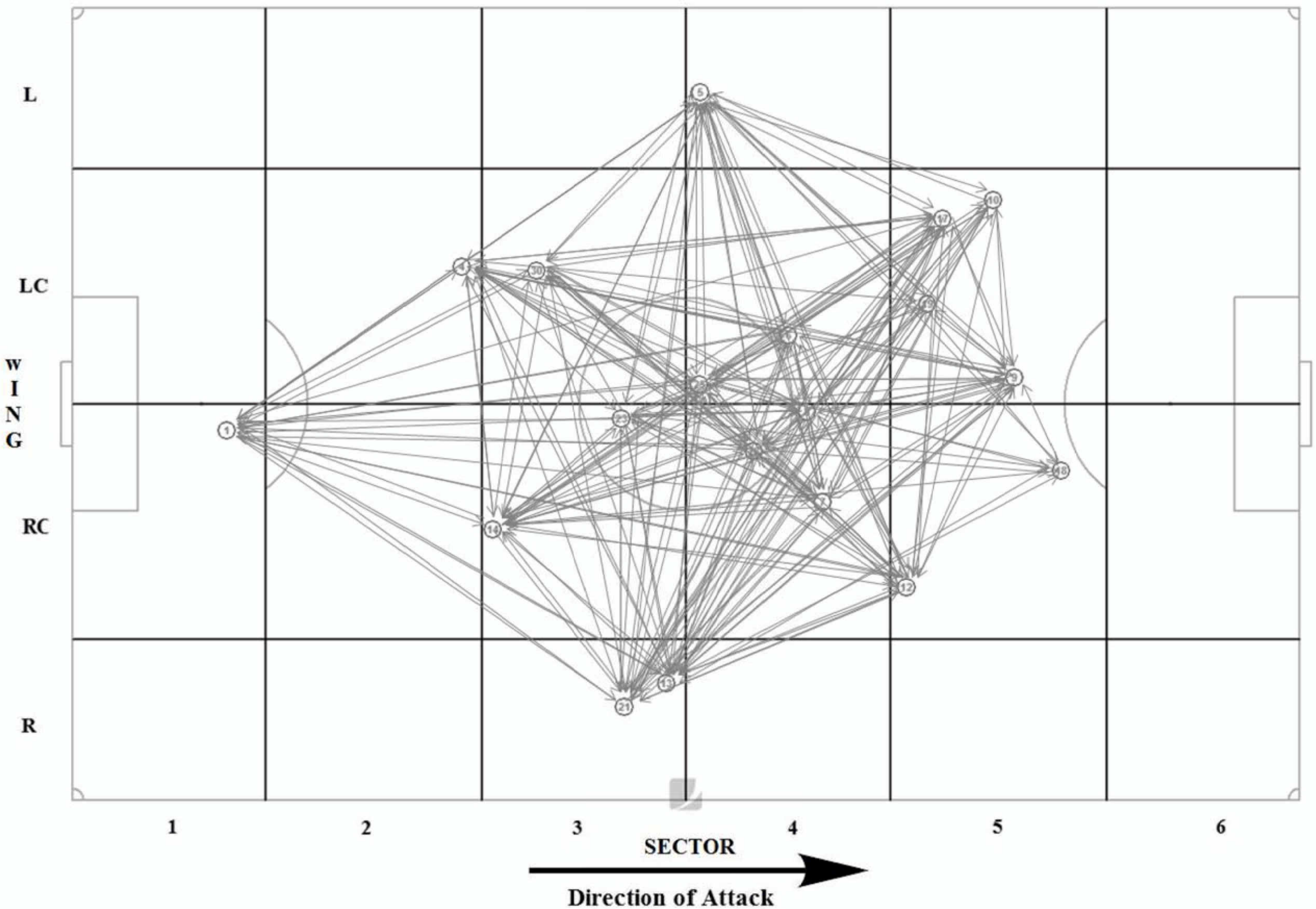

Figure 3. Representative network of all interactions (performed and received) between players that occurred across the sample of six matches, according to field location.

3.1. Identifying players' preferential linkages and connections

During competitive performance, we were able to depict each player's emergent preferential linkages with teammates supported by analysis of successful passes and crosses performed and received in the sample of six matches. The highest number of interactions (passes and crosses performed and received) between players, was indicative of the players' preferential linkages across six matches. The greatest number of passes and crosses performed between teammates emerged between player 5 and player 17. There were a total of 46 interactions, signifying that player 5 performed 46 passes or crosses that received by player 17. The next such preferential linkage emerged between player 8 and player 17, resulting in 43 interactions. Between players 8 and 5 there were 38 such interactions (Figure 4).

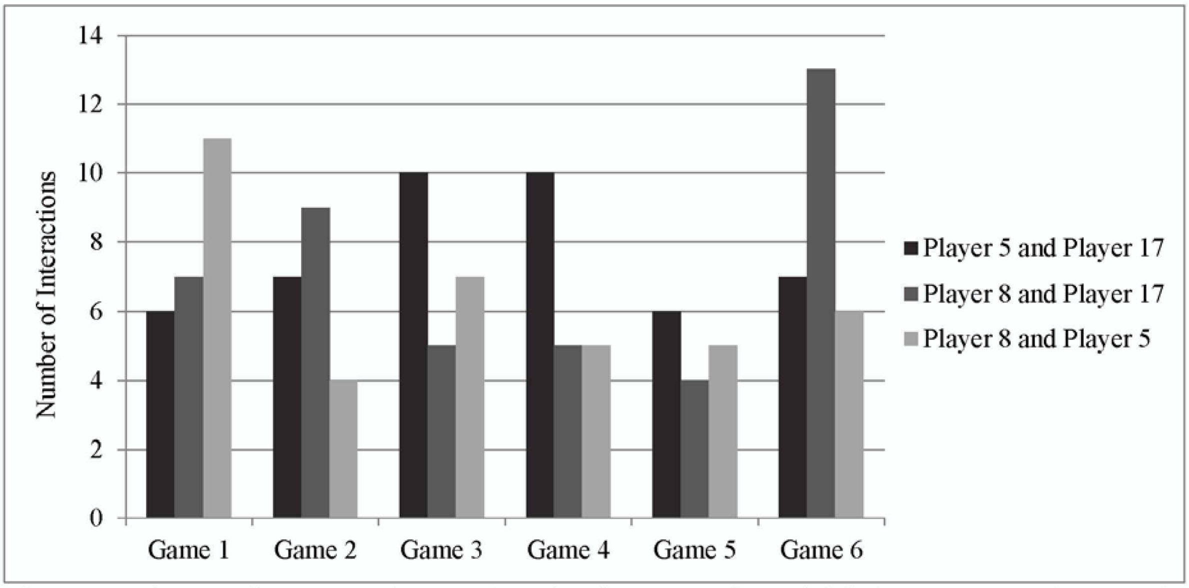

Figure 4. History of emergent interactions leading to preferential linkages across the sample of six games.

Data revealed that in three out of six matches (game 3 to 5) the preferential linkage between players 5 and 17 displayed the highest number of interactions. Next, preferential linkages between players 8 and 17displayed the highest number of interactions (game 2 and 6). Finally, the preferential linkage between players 8 and 5 revealed the highest amount of passes and crosses performed in game 1. These results reveal the variability in preferential linkages expressing the emergent adaptive behaviours between players across the sample of six matches.

3.2. Networks of interactions

Figure 5 provides the intrateam networks structure of attacking subphases of play obtained in each of the six games under analysis (Figure 5).

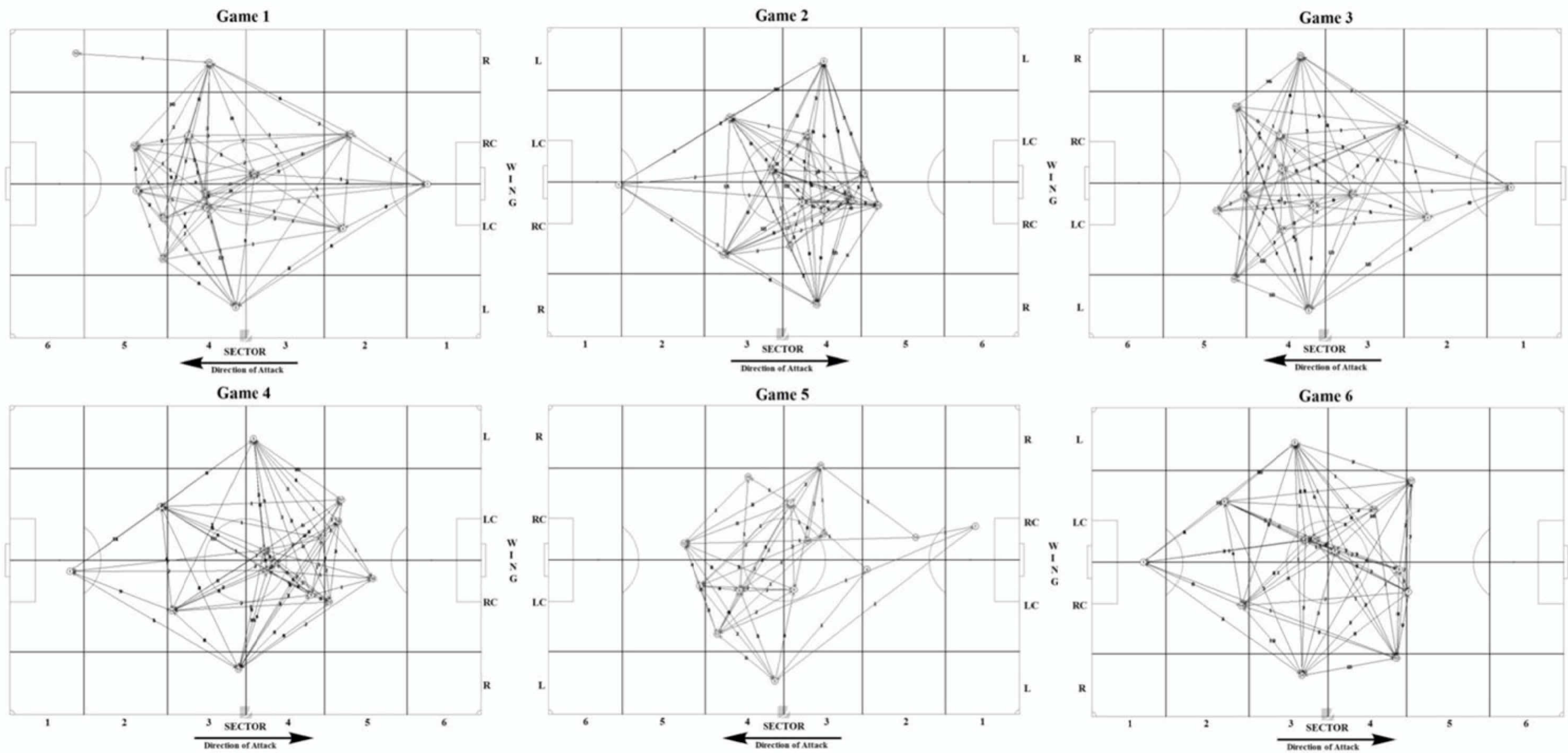

Figure 5. Networks of interactions obtained in each of the game observed.

In games played at home, the team observed is shown from left to right. In contrast, the away games, the team presentation is performed from right to left.

The data display the collective behavioral tendencies manifested by the team in each of the six games. Throughout these game sequences we observed some similarities at the interaction level. It is worth noting that game 5 depicted some differences, for instance corridor ‘r’ and column 5 were rarely (or sparsely) occupied by the players suggesting that the team did not seek to use the entire width of the pitch.

3.3. Changes in the average positioning of key players during the matches

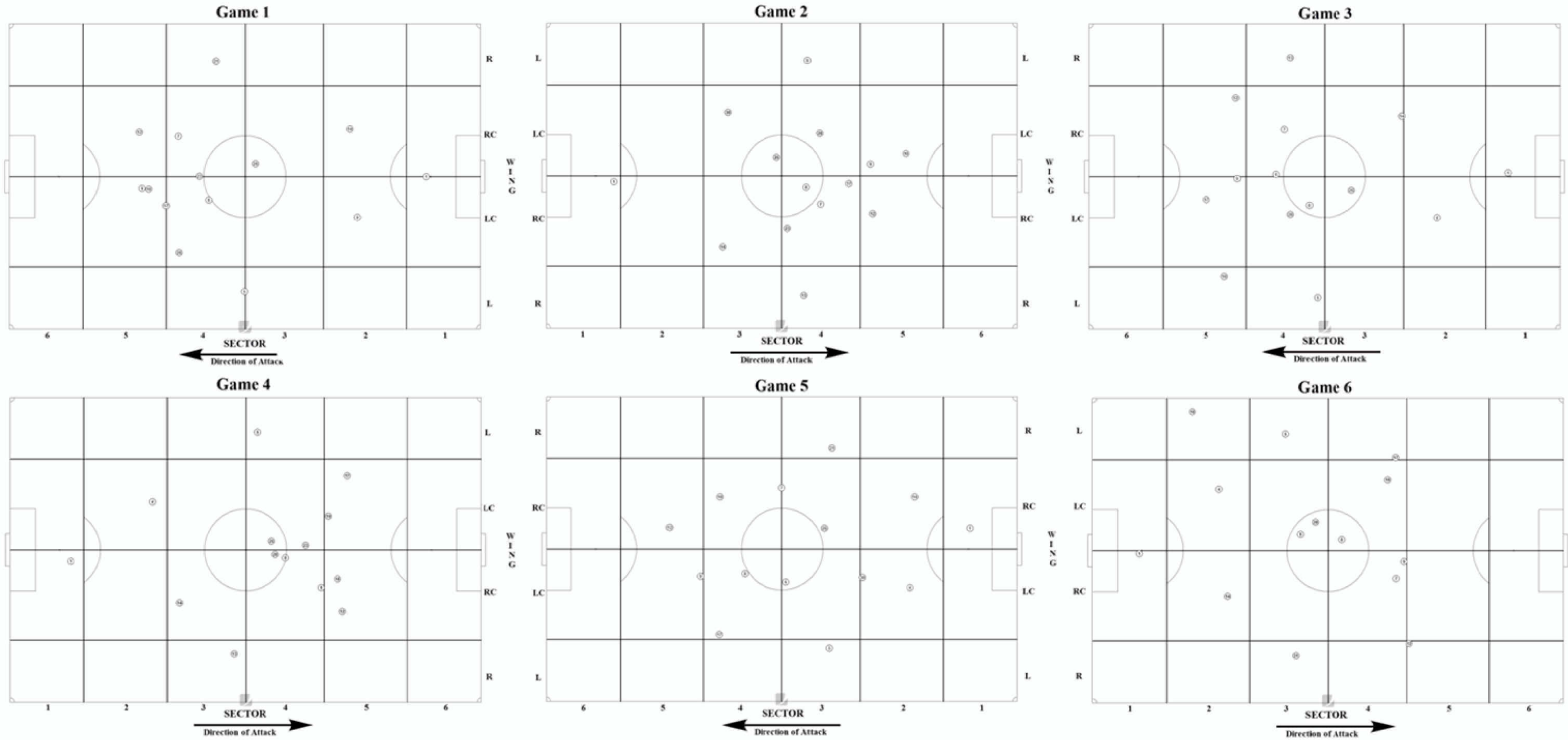

Figure 6. Preferred pitch location of key players.

Data in Figure 6 reveal how the average positioning of key players changed across the sample of six competitive matches. For example, Player 5 (left defender), tended to occupy area 3L and 4L during the first match, and then switched between the second and fourth game to another preferred area (4L). For the fifth and sixth match, Player 5 sought to re-occupy 3L as a preferred area. Regarding other key players in the team, player 8 (a central midfielder) preferentially occupied area 4LC in the first, third, fifth and sixth match, whereas in the second and fourth match, he used area 4RC as a preferred pitch location. Finally player 25 (defensive midfielder), preferentially occupied area 4RC in the first and in fifth match, whereas in the second, third and fourth match, that player, was preferentially located in the area 4LC. This player did not participate in the last match sampled.

3.4. Intra-team interaction probabilities

Table 2 shows the interaction probabilities between players in offensive game phase.

Table 2. Interaction probability between players in offensive game phase.

To/Of	**Players**																		
Players	**1**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**12**	**13**	**14**	**17**	**18**	**19**	**21**	**23**	**25**	**28**	**30**
1	-	0.08	0.05	0.02					0.01	0.02	0.14				0.05	0.04	0.03	0.02	0.06
4	0.28	-	0.09	0.09	0.01	0.03	0.01			0.01	0.08	0.01			0.05		0.05	0.02	
5	0.30	0.28	-	0.16	0.08	0.17	0.07	0.56	0.10		0.02	0.24		0.15	0.01	0.16	0.12	0.25	0.15
6	0.02	0.04	0.03	-	0.04	0.01	0.01		0.04	0.01	0.03	0.04			0.06		0.02	0.07	
7	0.01	0.02	0.06	0.09	-	0.07	0.11	0.06	0.19	0.12	0.04	0.06			0.08	0.04	0.09	0.02	0.12
8		0.12	0.10	0.12	0.13	-	0.17	0.11	0.12	0.11	0.14	0.24			0.06	0.04	0.17	0.12	0.08
9		0.01	0.09	0.11	0.07	0.10	-	0.06	0.19	0.04	0.05	0.07	0.14	0.08	0.06		0.09	0.02	0.04
10			0.03	0.04	0.01	0.01	0.01	-		0.01					0.01		0.03		
12	0.01		0.10	0.14	0.24	0.08	0.18	0.06	-	0.21	0.07	0.07		0.08	0.31	0.08	0.02	0.11	0.06
13	0.10	0.07			0.07	0.07	0.03		0.07	-	0.06	0.11	0.43	0.08		0.08	0.05	0.08	
14	0.13	0.09	0.03	0.09	0.06	0.08	0.02		0.04	0.09	-	0.01		0.15	0.14	0.16	0.13	0.07	0.21
17	0.01	0.02	0.17	0.04	0.08	0.19	0.14		0.06	0.15	0.05	-			0.04	0.08	0.08	0.04	0.08
18			0.01							0.02			-	0.08		0.04	0.01	0.01	
19		0.01	0.02				0.02			0.01	0.01			-				0.06	
21	0.04			0.04	0.07	0.03	0.04	0.06	0.07		0.11	0.02			-	0.12	0.02	0.01	0.02
23		0.02	0.02				0.01		0.01	0.04	0.01			0.15	0.03	-	0.02	0.01	
25	0.01	0.12	0.08	0.09	0.09	0.08	0.11	0.06	0.08	0.08	0.11	0.11	0.43		0.07	0.08	-	0.06	0.17
28	0.01	0.12	0.07			0.04	0.08	0.06	0.02	0.08	0.03	0.03		0.23	0.02		0.06	-	0.02
30	0.08		0.04		0.06	0.03			0.01	0.01	0.04	0.02				0.08	0.03	0.01	-

Legend: *To* – interaction received by player; *Of*– interaction performed by player.

Assuming that a probability of an interaction that was unlikely to be achieved was assigned a value of 0, and that an achievable interaction corresponded to a value 1 (100%), the results showed that there is a greater probability of interaction between the following players: player 10 had a 56% of probability of interaction (to perform a pass or a cross) with player 5; player 18 had a 43% of probability of performing a pass or a cross to player 13 and player 25; player 5 had a 30% of probability of receiving a pass from player 1, and performance of a pass or a cross by player 5 to player 1 had a 28% probability.

4. Discussion

The obtained interactions between players in our network analysis allowed us to identify the key players involved in coordinating the attacking performance of a professional football team and to describe their predominance of linkages with other specific teammates. Therefore, comparing the intra-team level of interactions, results revealed that player 5 (left defender) made and received the greatest number of interactions in the team. Accordingly, the network analysis revealed that player 5 intervened most often in the attacking phases of the game, being characterized as a key player for the team investigated. It would be interesting to compare these objective data from the network analysis to the coaches' subjective perspectives on performance of individuals related to the team strategic model (Duch *et al.*, 2010; Yamamoto and Yokoyama, 2011).

With regard to key players, our data verified that the highest number of interactions undertaken by players 5, 8 and 25 had a significant influence on ball movement by the team when attacking. These data clarified how network analysis could be used to accurately identify the key performers who assume an important role in the collective dynamics of a team, during a competitive game and across a sample of matches (and training if required) (Duch *et al.*, 2010; Grund, 2012).

The data also enabled us to highlight that key players, on average, occupied different but closely related areas of the pitch during the competitive match but also that these preferred occupied areas also changed from match to match. This is a relevant pedagogical tool, useful for mapping the technical and tactical actions of individual performers in the team (Garganta, 2005, 2006; Davids *et al.*, 2006; Sargent and Bedford, 2013).

Due to specific task constraints, such as allocated tactical roles and coaches' instructional constraints, some players tended to establish preferential linkages with others. This feature, characterizing team collective behaviors (e.g., paired or groups of players), was also captured by our network analysis. We noted that preferential linkages between specific individuals tended to emerge on the same side of the pitch. These results from the network analysis may be useful for identifying specificities in a team's strategical planning.

It is also important to note that, during the analysed games, plenty of nonlinear interactions emerged between players, revealing the great variability of actions that characterized this football match, indicating how interpersonal interactions might change from match to match (Yamamoto and Yokoyama, 2011; Sargent and Bedford, 2013; Perl and Weber, 2004; Carling, 2005; Perl and Dauscher, 2006). The study also captured intra-team interactions during different competitive performances, which allowed us to verify whether trends in patterns of play remained across several matches. This longitudinal approach was relevant since previous work has indicated that players' performance behaviours, especially the interaction probabilities between specific players, cannot be determined at the outset of a competitive match. Rather, they emerge through the interaction of various constraints, including the athlete, environment and task (Newell, 1986; Araújo *et al.*, 2006; Davids *et al.*, 2008).

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