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SMALL-WORLD NETWORKS IN PROFESSIONAL FOOTBALL: CONCEPTUAL MODEL AND DATA

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ABSTRACT

The aim of this study was to verify whether interactions taking place between professional football players are compatible with the concept of small world networks. We observed 30 matches and analysed 7.583 collective offensive actions, since the beginning of possession of the ball to their loss, including: passes completed, passes received and crosses, involving a total of 22.518 intra-team interactions in the Portuguese Premier League, corresponding to all 2010/2011 season. The players were classified based on their tactical intervention region and movements, through four sectors: 1) goalkeepers; 2) defenders; 3) midfielders, and 4) forwards. Performance data was analysed using the Match Analysis Software Amisco® (version 3.3.7.25). We analysed the relevant actions typically used during offensive phases, including: passes to teammates, crosses into the penalty box and ball receptions. The results suggest that players' interactive behaviours within a football match support the existence of a scale free network. Defenders and midfielders are the athletes presenting the highest level of connectivity with their teammates. It was concluded that network analysis might be useful to shed some light on the individual contributions to the collective team performance and provide insights on how creative and organizing individuals might act to orchestrate team strategies. This suggests that the proposed methodology can be used to characterize the collective behaviours that emerge through cooperation and competition between players during football matches.

Key Words: football, interactive behaviours, interpersonal interactions, scaled connectivity, centroid conformity

RESUMEN

El objetivo principal de este estudio era verificar si las interacciones que tienen lugar entre los futbolistas profesionales son compatibles con el concepto de las redes de mundo pequeño. Se observaron 30 partidos y se analizaron 7.583 acciones ofensivas colectivas, desde el inicio de la posesión del balón hasta la pérdida del mismo incluyendo: pases completados, pases recibidos y cruces, incluyendo un total de 22.518 interacciones intraequipo en la Primera División Portuguesa, correspondiente a la temporada 2010/2011. Los jugadores fueron clasificados basándose en su área de intervención táctica y sus movimientos en estos cuatro sectores: 1) porteros; 2) defensores; 3) centrocampistas y 4) atacantes. Los datos de rendimiento fueron analizados mediante la herramienta Match Analysis Software Amisco® (version 3.3.7.25). Se analizaron las acciones relevantes típicas empleadas durante las etapas ofensivas, incluyendo: pases a compañeros, cruces en el área y recepciones de balón. Los resultados sugieren que los comportamientos interactivos de los jugadores en un partido de fútbol apoyan la existencia de una red libre de escala. Defensas y centrocampistas son los atletas que presentan el mayor nivel de conectividad con sus compañeros. Se concluyó que el análisis de la red debe ser útil para arrojar alguna luz en las contribuciones individuales al rendimiento colectivo del equipo y proporcionar conocimientos sobre como la creatividad y la organización individual puede actuar para orquestar estrategias de equipo. Esto sugiere que la metodología propuesta puede ser usada para caracterizar los comportamientos colectivos que emergen a través de la cooperación y la competición entre jugadores durante los partidos de futbol.

Palabras clave: fútbol, comportamientos interactivos, interacciones interpersonales, conectividad a escala, conformidad centroide

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INTRODUCTION

Recent studies have shown that football can be considered a small-world network with relatively few long-distance connections between nodes (*i.e.,* players). Yet, 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 innate to small-world networks (*e.g.,* Sargent & Bedford, 2013; Gama *et al.,* 2014; Folgado *et al.,* 2014). Under these properties, Peña & Touchette (2012) highlighted that networks arise in a variety of problems, ranging from technological and transport issues, to social phenomena and biological problems. For these authors (2012), team sports that involves interactions between players, like football, present themselves as interesting examples of such networks. Hence, the network can also be used by a team to detect under-performing players, fix weak spots, detect potential problems amongst teammates, as well as to detect weaknesses in the opposing team. Generally speaking, this methodology can be used to characterize the collective behaviors emerging through cooperation and competition between players during football matches (Duch *et al*., 2010; Sargent & Bedford, 2013).

Regarding the analysis of interpersonal connections in small-world networks' perspective, a network analysis method was proposed to identify regularities of teams' collective behaviour, based on the interactions generated by the ball's motion among players (Passos *et al.,* 2011). By analysing two teams of water polo, the authors concluded that a larger number of connections between the various players corresponded to a greater likelihood of success. The team with the highest number of connections depicted a higher success rate (Passos *et al.,* 2011). Similarly, applying the same methodology to football, network analysis allowed to evaluate the performance of individual players and their influence on the collective performance of the team (*cf.* Duch *et al.,* 2010; Gama *et al*., 2014). These authors conducted a 'flow' analysis, where flow patterns of the ball that resulted in completion were identified.

Small world networks in team sports typically exhibit a high degree of clustering (Duch *et al.,* 2010; Passos *et al.,* 2011; Yamamoto *et al*., 2013). For instance, in every team game, there are players with whom teammates might prefer to be linked with (*e.g.,* illustrated through passing the ball). These groups of 'actors' are known, in complex networks' language, as preferential attachments. From this perspective, identifying the preferential attachments within a small world network can be a very useful way to accurately identify the key decision-makers during important phases of competitive performance. As a result, the network nodes (*e.g.,* players) are system agents, and the interconnecting lines among players represent the ways that those athletes interact, through verbal or non-verbal communications skills (*e.g.,* ball-passing).

More recently, Folgado *et al*. (2014) described the football as a team sport where two opposing teams dynamically interact to gain advantage over the other team. These authors argued that the overall performance should be understood in terms of space-time interaction dynamics, and not only in terms of the players' individual time-motion demands. In spite of this, network concepts can support the study of the continuous interactions between players and teams during competitive performance. Hence, based on previous research (*e.g.,* Yamamoto & Yokoyama, 2011; Grund, 2012; Folgado *et al.,* 2014), we assumed that players interactive behaviours within a football match support the existence of a scale free network. A general feature of this type of network is that a few players will tend to exhibit more links between themselves than other players will (Gama *et al.,* 2014). 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 distribution (Duch *et al.,* 2010).

However, despite the results already achieved in previous studies around network theory applied in team sports, it is considered that the information retrieved from such analysis may contain greater relevance to the coach when adequately contextualised in terms of space and time, and considering the relationships established among players of the opposing team (Malta & Travassos, 2014). Therefore, to better understand football, it is essential to assess the interpersonal relationships between players, taking into account the different phases of the match, the location where these occur, as well as the type of relationships established (Vilar *et al,* 2012; Travassos *et al.,* 2011; Malta & Travassos, 2014). So, football can be regarded, from the network perspective, as a competitive relationship between two cooperative networks (Zhang & Zhang, 2009; Yamamoto & Yokoyama, 2011; Balague *et al*., 2013).

Given the above, we hypothesised that the creation of interaction nodes among players might be an emergent property and may, therefore, be time and space specific. These ideas illustrate how a set of players can be related to form a sub-unit in a team to perform collective actions that enhance the probability of successful performance outcomes (Passos *et al.,* 2011; Gama *et al.,* 2014). Likewise, using the proposed methodology in an intra and inter-team analysis, it may be possible to identify the players who interact the most with their neighbouring teammates and that contribute the most to successful and unsuccessful collective actions.

Bearing these ideas in mind, the aim of this study was to verify whether interactions taking place between professional football players are compatible with the concept of small world networks.

METHOD

Participants

We observed 30 matches and analysed 7 583 collective offensive actions, since the beginning of possession of the ball to their loss, including: passes completed, passes received and crosses, involving a total of 22 518 intra-team interactions (*e.g.,* 11 259 passes and crosses performed and 11 259 passes and crosses received) in the Portuguese Premier League, corresponding to all 2010/2011 season. The team observed was the winner of the championship. Over all the matches, 25 players of the same team were analyzed. Each player was encoded to identify individual characteristics, maintaining the same code for all matches. Despite the different playing times per player, this study aimed at keeping the real characteristics of an official football game, thus respecting the substitutions and the different options for each match. The position the players in the soccer field was classified based on the routines and actions performed by individual players during the league. The players were classified based on their tactical intervention region and movements, through four sectors: 1) goalkeepers; 2) defenders; 3) midfielders, and 4) forwards.

The data was analysed using the *Match Analysis Software Amisco®* (version 3.3.7.25); a specialized program designed to characterize activity profiles in the team. This system allows to follow the movements of every player, simultaneously, over the course of the match, on digital video footages obtained from multiple cameras strategically positioned to cover the entire pitch. At the same time, a trained operator identifies each technical action involving the ball, providing *a posteriori* information on the actions performed during the match (Di Salvo *et al*., 2007; Carling, 2010; Zubillaga *et al*., 2009; Randers *et al*., 2010; Gama *et al.,* 2014). In order to identify intra and inter-team interactions, we analysed players' performance, focusing on the relevant actions typically used during offensive phases, namely: passes to teammates, crosses into the penalty box and ball receptions. Each time a pass, cross or ball reception occurred during the offensive phases, we recorded the event as an interaction between players. The networks were then built with nodes representing players and arrows, or edges, representing the links which were weighted according to number of emergent interactions (Gama *et al.,* 2014). In this sense, three metrics were suggested for the football analysis: 1) scaled connectivity; 2) clustering coefficient, and 3) global rank.

Method for creating a network in football

Many kinds of networks (*e.g.,* biological, sociological) share some topological properties. To identify and describe such properties, most potentially useful network concepts are known from graph theory (Couceiro *et al.,* 2014). In the context off football, we can divide network concepts into: 1) intra-players network analysis (*i.e.,* network properties of a node); 2) inter-players network analysis (*i.e.,* network relationship between two or more vertices), and 3) team network analysis. To allow using most of the network analysis (Couceiro *et al.,* 2014), one can create a new relative weighted adjacency matrix $A_r = [r_{ij}] \in \mathbb{R}^{n \times n}$, defined as:

$$r_{ij} = \begin{cases} \dfrac{w_{ij}}{\max\limits_{i \neq j} A_w} & , i \neq j \\ w_{ij} & , i = j \end{cases} \tag{1}$$

where $0 \leq r_{ij} \leq 1$ for $i \neq j$, with $i, j = 1, \ldots, n$. The denominator $\max_{i \neq j} A_w$ corresponds to all offensive collective actions (*i.e.,*whenever a team has ball possession), which will give rise to one network comprising all passes and crosses performed by players, and another network comprising all ball receptions (Gama *et al.*, 2014). It is noteworthy that the diagonals of A_r represent the number of offensive plays in which a given player participated. This value is only considered for visualization purposes, in which the size of vertices is proportional to the number of offensive plays a given player participated.

A network analysis approach was proposed to identify regularities of teams' collective behaviour within a small-world networks' perspective (Passos *et al.,* 2011). A set of metrics was computed based on the weighted matrix, considering both inter-player and intra-player network analysis. Each metric is a statistical method designed for network analysis. Therefore, more than being just a visual representation, these metrics represent the individual contribution of each player in a given context. Likewise, by using networks methodology in an intra and inter-team analysis, it may be possible to identify the players who interact the most with their neighbouring teammates and that contribute the most to successful and unsuccessful collective actions. Hence, this method is appropriate to determine the individual's contribution to the team's network (Couceiro *et al.,* 2014; Gama *et al.,* 2014).

Inter-player network analysis

For the football case, the collective offensive actions correspond to the moment of recovery/beginning of ball possession, to its loss (Vaz *et al.,* 2014; Gama *et al.,* 2014). Therefore, it is important to understand how the team breaks its homogeneity level. Moreover, it is also important to understand the connectivity levels between teammates.

Scaled connectivity

The first analysis and one of the widely used in the literature for distinguishing a vertex of a network (Horvath, 2011) is the connectivity (also known as degree). In the situation herein presented, *i.e.*, players' networks, the connectivity ki equal the sum of connection weights between player i and the other players. The most cooperative player, or players, can be found by computing the index/indices of the maximum connectivity.

$$k_{max} = \max_{j} k_j \tag{2}$$

One can then define a relative connectivity, known as scaled connectivity, of player i as:

$$s_i = \frac{k_i}{k_{max}} \tag{3}$$

such that $s = [s_i] \in \mathbb{R}^{1\times n}$ is the vector of the relative connectivity of players. In football context, one could interpret the scaled connectivity as a measure of cooperation level of a given player in which high values of s_i (*i.e.,* as s_i tends to) indicate that the i^{th} player participate with most of the other players from the team (Couceiro *et al.,* 2014).

Clustering coefficient

The *clustering coefficient* of player i offers a measure of the degree of interconnectivity in the neighborhood of player i, being defined as:

$$c_i = \frac{\sum_{j\neq i}\sum_{l\neq i,j} r_{ij} r_{jl} r_{ki}}{\left(\sum_{j\neq i} r_{ij}\right)^2 - \sum_{j\neq i}\left(r_{ij}\right)^2} \tag{4}$$

such that $c = [c_i] \in \mathbb{R}^{1\times n}$ is the vector of the clustering coefficient of players.

The higher the clustering coefficient of a player, the higher is the cooperation among its teammates. If the clustering coefficient tends to zero than the teammates do not cooperate much each other. The relationship between the clustering coefficient and the connectivity has been used to describe structural (hierarchical) properties of networks (Ravasz *et al.,* 2002). Thus, is it possible identify which players have a higher level of cooperation in terms of its positioning field and established by the coach tactics. For example, it is expected that the players playing in midfield and attacking players use a higher trend of cooperation/interaction relative to their peers (*e.g.*, goalkeeper).

However, we must not forget that football is a dynamic game, nonlinear, which is subject to great variability (Gama *et al.,* 2014).

Global Rank

A weighting distribution of the cluster coefficient and the connectivity between players should be taken into account. At the same time, it also considers that the cluster coefficient of a player is relevant to the team since it is necessary to produce interaction in order to create relationships, thus increasing the collective productivity (Couceiro *et al.,* 2014; Belli *et al.,* in press). Therefore, a weighting function, denoted as *global rank*, was defined as:

$$g_i = \rho_s s_i + \rho_c c_i \tag{5}$$

where $\rho_s + \rho_c = 1$, such that $g = [g_i] \in \mathbb{R}^{1\times n}$ is the vector of the global rank of players.

Note that the scaled connectivity s_i was chosen over the unscaled one k_i since it lies between 0 and 1 as the clustering coefficient, thus resulting in $0 \leq g_i \leq 1$. Taking into account that the main objective of players is to give priority to the collective performance (*i.e.*, the overall interaction between players), one can ponder a balanced consideration of $\rho_k = \rho_c = 0.5$. The top-ranked player, *i.e.*, the one presenting the higher g_i, will then be denoted as the player centroid. Within football team context, the player centroid could be considered as a hierarchically superior member (*e.g.*, key player). It is noteworthy that the key player for performed passes may be different from the key player for received passes.

Intra-player network analysis

To further understand team's performance, one should be able to characterize the individual contribution of each player. Moreover, it is quite important to identify the players that contribute the most for the teams' process and how players cooperate with each other (Couceiro *et al.,* 2014; Belli *et al.,* in press).

Centroid significance and centroid conformity

The network centroid can define the centrally located node (Horvath, 2011). For the football case, the centroid can be defined as one of the most highly connected node(s) in the network. The first one arises from the centroid player(s) in which one can express its connectivity strength to all other teammates as:

$$cc_{i,centroid} = \begin{cases} r_{i,centroid}, i \neq j \\ 1 \qquad\qquad , i = j \end{cases} \tag{6}$$

This inter-player analysis is denoted as *centroid conformity* and corresponds to the adjacency between the centroid player and the *i^th^* player, such that $cc = [cc_i] \in \mathbb{R}^{1\times n}$ is the vector of the centroid conformity of players. In other words, $cc_{i,centroid}$ presents the cooperation level of the *i^th^* player with the top-ranked player.

The intra-player network analysis is based on the topological overlap presented in several works such as Ravasz *et al*. (2002) and Horvath (2011) which represents the pair of players that cooperates with the same players. This measure may also represent the overlap between two players even if they do not participate in the same offensive plays with one another. In other words, the topological overlap between the *i^th^* player and the *j^th^* player depends on the number of offensive plays with the same shared players but it does not take into account the number of offensive plays between them. Moreover, the topological overlap is represented by a symmetric matrix, thus presenting the overlap between players but neglecting the most independent player of the pair. Therefore, by using the concepts inherent to the clustering coefficient (equation 4), one should consider not only the shared offensive plays, but also the influence of the conjoint offensive plays among players *i* and *j*.

In other words, if two players participate in offensive plays with the same other players, then the cooperation between both of them allows building triangular relations between the other players. However, the *i^th^* player may be more dependable from the *j^th^* player if he only participates in offensive plays with the same player than player *j^th^* which, in turn, is able to participate in offensive plays with other players. As a result, similarly to Ravasz *et al.* (2002) and Horvath (2011), one can define a *topological dependency* $T_d = [td_{ij}] \in \mathbb{R}^{n\times n}$ as:

$$td_{ij} = \begin{cases} \dfrac{\sum_{l\neq i,j} r_{il} r_{lj}\, r_{ij}}{\sum_{l\neq i} r_{il}} & , i < j \\ \dfrac{\sum_{l\neq i,j} r_{il} r_{lj}\, r_{ij}}{\sum_{l\neq j} r_{lj}} & , i > j \\ 1 & , i = j \end{cases} \tag{7}$$

with $i, j, l = 1,2, \dots, n$.

As a consequence, two players have a high topological dependency, *i.e.*, $td_{ij} = 1$, if they participate in offensive plays with same player and with one another. In other words, the more players are shared between two players that highly participate in offensive plays with one another, the stronger their cooperation are and more likely they will both represent a small cluster. However, since T_d corresponds to a square matrix with the size equal the number of players and since that contrarily to the adjacency matrix or topological overlap (Horvath, 2011), T_d is not symmetric, *i.e.*, $td_{ij} \neq td_{ji}$, it makes it difficult to compare the td_{ij} and td_{ji} pairs (Couceiro *et al.,* 2014).

To complement the previous analysis, a new 'inter-player' metric denoted as *topological inter-dependency* $T_{id} = \left[ti_{ij}\right] \in \mathbb{R}^{n \times n}$ is introduced as:

$$T_{id} = T_d - {T_d}^T \qquad (8)$$

wherein ${T_d}^T$ is the transpose of matrix T_d and T_{id} corresponds to an antisymmetric square matrix, *i.e.*, $ti_{ij} = -ti_{ji}$. In players' networks, one can easily observe dependencies between players, such that if $ti_{ij} > 0$, then the i^{th} player depends on the j^{th} player to play with his teammates. Moreover, when associated to other network analysis (*e.g.*, centroid player), the relative topological dependency allows identifying possible dependencies between players and even hierarchical relations (Couceiro *et al.,* 2014).

Team network analysis

Although both inter and intra-players analysis are useful to identify properties between players, team network concepts also need to be considered to achieve properties of the full football team. In that sense, the inter-player connectivity allows retrieving several other team network analysis, such as the *network density*, which can be defined as:

$$D = \sqrt{\frac{\sum k_i}{n(n-1)^2}} \qquad (9)$$

Within players'networks, the density measures the overall cooperation among athletes. A density that tends to 1 indicates that all players strongly interact with each other.

Another network analysis based on the connectivity of players is the *network heterogeneity* which is closely related to the variation of connectivity across players (Albert *et al*., 2000; Watts, 2002). As Horvath's work (2011), it is herein defined as the coefficient of variation of the connectivity distribution:

$$H = \sqrt{\frac{n \sum k_i^2 - (\sum k_i)^2}{(\sum k_i)^2}} \qquad (10)$$

Since the heterogeneity measure is invariant with respect to multiplying the connectivity by a scalar, one could use the scaled connectivity instead of the connectivity. Many complex networks have been found to exhibit an approximate scale-free topology, which implies that these networks are very heterogeneous. In other words, a high heterogeneity of the football network means that the players exhibit a high level of performance and there is, collectively, a low level of cooperation between players (Couceiro *et al.,* 2014; Belli *et al.,* in press). Finally, to further analyze the football network, a widely used measure denoted as *network centralization* was used. The network centrality (or degree centralization as Freeman, 1978: addresses) can be defined as:

$$C = \frac{n}{n-2}\left(\frac{\max k}{n-1} - D\right) \tag{11}$$

A centralization close to 1 means that one player strongly cooperates with all other players which, in turn, present a small (or inexistent) cooperation with each other. In contrast, a centralization of 0 indicates that all players cooperates equally between each other.

RESULTS

The networks we observed depicted the interactions established between players of the same team during an attacking phase of play across the selected sample of 30 matches, corresponding to a sports season. 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 thirty matches (Gama *et al.,* 2014).

Thus, Figure 1 displays the network hierarchical providing a qualitative analysis of the interactions performed and received.

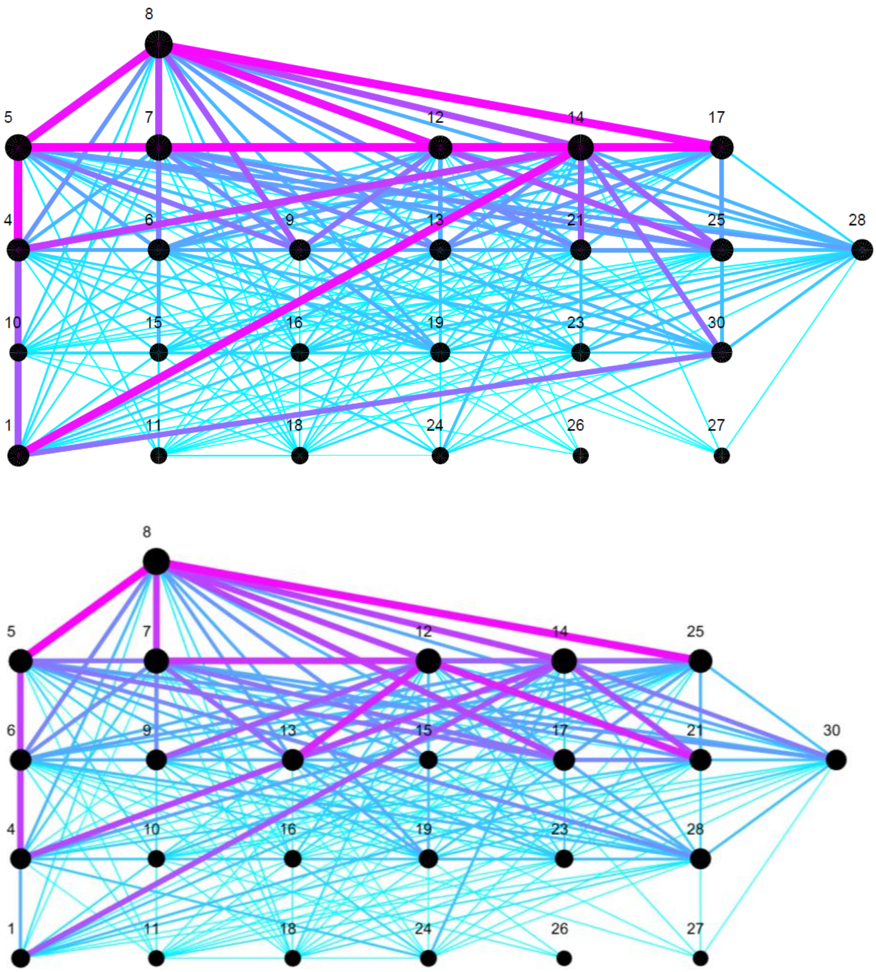

FIGURE 1: Representative network of all interactions between players that occurred in the league: performed (top) and received (bottom).

The network of interactions performed indicates that the player 8 (1 191) was the player who has promoted the greatest number of passes and crosses performed, followed by player 4 (1 011) and player 5 (922). Moreover, we verified that player 8 (1 138) was the player who developed the largest number of ball receptions, followed by player 12 (1 014) and player 7 (7 981). Finally, there is a similar hierarchy both as the passes and crosses performed as the ball receptions, since the vast majority maintains its hierarchical classification.

Table 1 shows that during the thirty games a total of 22518 intra-team interactions were registered between players of the football team and the scaled connectivity for passes and crosses performed and ball receptions.

TABLE 1
Intra-team interactions and scaled connectivity for passes and crosses performed and ball receptions.

Scaled Connectivity (*s*)																
Passes and Crosses Performed																
	Game 1	**Game 2**	**Game 3**	**Game 4**	**Game 5**	**Game 6**	**Game 7**	**Game 8**	**Game 9**	**Game 10**	**Game 11**	**Game 12**	**Game 13**	**Game 14**	**Game 15**	
Player	5	5	25	5	5	30	5	13	7	5	6	25	8	7	8	
Value	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	
	Game 16	**Game 17**	**Game 18**	**Game 19**	**Game 20**	**Game 21**	**Game 22**	**Game 23**	**Game 24**	**Game 25**	**Game 26**	**Game 27**	**Game 28**	**Game 29**	**Game 30**	**Overall**
Player	30	8	8	30	7	8	5	8	14	8	28	5	7	23	28	7
Value	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Ball Receptions																
	Game 1	**Game 2**	**Game 3**	**Game 4**	**Game 5**	**Game 6**	**Game 7**	**Game 8**	**Game 9**	**Game 10**	**Game 11**	**Game 12**	**Game 13**	**Game 14**	**Game 15**	
Player	12	5	12	5	8	30	25	28	8/17	21	30	25	8/15	7	8	
Value	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	
	Game 16	**Game 17**	**Game 18**	**Game 19**	**Game 20**	**Game 21**	**Game 22**	**Game 23**	**Game 24**	**Game 25**	**Game 26**	**Game 27**	**Game 28**	**Game 29**	**Game 30**	**Overall**
Player	8	8	25	12	8	25	8/25	8	13	8	28	5	15	14	28	8
Value	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

The data clearly indicate that player 8 (midfielder) was the individual who interacted the most, with other players, engaged in a total of 2329 interactions (1 191 passes and crosses performed; 1 138 ball receptions), followed by player 14 (defender), with 1 914 interactions (1 011 passes and crosses performed; 903 ball receptions) and player 7 (midfielder), with a total of 1 897 interactions with the others (916 passes and crosses performed; 981 ball receptions). This data suggests that players' 8, 14 and 7 were most influential performers during the attacking phases of play. Beyond quantification of the number of passes and crosses performed, it is worth noting where on field (on average) those interactions were performed.

This metric reveals the indices of the scaled connectivity level of each player. Therefore, for the football analysis, the scaled connectivity can be defined as a measure of cooperation level of a given player (Clemente *et al.,* 2014; Belli *et al., in press*). In this case, the highest values (1.00) suggest that player participate with most of the other players from the team. On the other hand, the opposite (0.00) suggest the player had specific preferences to participate with some players within the team.

We verified that the values of the scaled connectivity vary between 0.00 and 1.00, to generalize the cooperation in attacking phases of play. For this measure, the high values of *Si* indicate that the players participate with most of the other players from the team (Couceiro *et al.,* 2014). In that sense, an analyzing match by match, we consider that the strongest values vary from player to player throughout every one of the different games. Interestingly, in each game, the highest value of scaled connectivity is always 1.00. For example, in game 1 and game 2, the player 5 (1.00) was the one who had the highest value of scaled connectivity for passes and crosses in both games, while in game 3, the highest value was represented by player 25 (1.00).

The data also reveal that the player 7 (midfielder – 1.00), player 4 (defender – .8758) and player 13 (defender – .8178) were those with the highest values of scaled connectivity for passes and crosses, during the champioship. In contrast, results indicate that player 12 (1.00) showed the highest value of scaled connectivity (game 1 and game 3). Howevear, in game 2, the highest value was more expressed by the player 5 (1.00). In that sense, player 7 (midfielder – 1.00) was the athlete who showed the best values of scaled connectivity along the championship, followed by player 13 (defender – .6549) and player 11 (forward – .6467).

On the other hand, the clustering coefficient of a given player measures the degree of interconnectivity in the neighborhood of the player, and reveals whether or not the player promotes connectivity between teammates. This metric allows to analyze if one player can involve all teammates in the offensive phases, fostering a global cooperation among the team. In that sense, highest values of clustering coefficient suggest that the teammates of a given player frequently cooperate with each other (Table 2). The clustering coefficient for each player was considered to analyze if one player can involve all teammates in the offensive phase (*i.e.*, enabling a global cooperation). This metric reveal the emergence of clusters within the team. The higher the clustering coefficient of a player, the higher is the cooperation among its teammates. If the clustering coefficient tends to zero, then the teammates do not cooperate much with each other (Table 2).

TABLE 2
Clustering coefficient values.

Clustering Coefficient (c)																
Passes and Crosses Performed																
	Game 1	**Game 2**	**Game 3**	**Game 4**	**Game 5**	**Game 6**	**Game 7**	**Game 8**	**Game 9**	**Game 10**	**Game 11**	**Game 12**	**Game 13**	**Game 14**	**Game 15**	
Player	6	1	10	1	17	9	4	1	1	19	27	1	9	23	11	
Value	0.4266	0.4173	0.4722	0.4800	0.5539	0.5858	0.4433	0.4549	0.7500	0.4615	0.6021	0.3851	0.4573	0.4478	0.5455	
	Game 16	**Game 17**	**Game 18**	**Game 19**	**Game 20**	**Game 21**	**Game 22**	**Game 23**	**Game 24**	**Game 25**	**Game 26**	**Game 27**	**Game 28**	**Game 29**	**Game 30**	**Overall**
Player	9	17	11	1	25	30	1	17	24	7	7	9	1	28	18	9
Value	0.2634	0.4509	0.4259	0.5279	0.4956	0.4345	0.5510	0.5677	0.4746	0.5052	0.5326	0.3915	0.4931	0.3840	0.4056	0.4929
Ball Receptions																
	Game 1	**Game 2**	**Game 3**	**Game 4**	**Game 5**	**Game 6**	**Game 7**	**Game 8**	**Game 9**	**Game 10**	**Game 11**	**Game 12**	**Game 13**	**Game 14**	**Game 15**	
Player	1	8	9	1	17	1	10	9	30	1	17	17	10	9	19	
Value	0.5714	0.4051	0.4579	0.3442	0.4762	0.6961	0.4572	0.5754	0.9900	0.2968	0.6039	0.3381	0.3344	0.3003	0.4618	
	Game 16	**Game 17**	**Game 18**	**Game 19**	**Game 20**	**Game 21**	**Game 22**	**Game 23**	**Game 24**	**Game 25**	**Game 26**	**Game 27**	**Game 28**	**Game 29**	**Game 30**	**Overall**
Player	17	25	16	19	18	17	1	17	17	7	24	18	1	24	30	1
Value	0.4398	0.2452	0.4117	0.4381	0.6333	0.5043	0.4066	0.5860	0.4986	0.4534	0.4050	0.5000	0.4545	0.4812	0.4560	0.4163

The data clearly indicates that the strongest value of clustering coefficient for passes and crosses performed, displayed in the game 9 by the player 1 (goalkeeper – .75). Then, emerge player 27 (forward – .6021) in game 11 and player 9 (forward – .5858) in game 6, were those with the highest values of clustering coefficient. In a general analysis, the best performance of clustering coefficient during a total of thirty matches occurred by player 9 (forward – .4929), followed by player 17 (forward – .4039) and player 16 (defender – .4034) for passes and crosses performed.

Nonetheless, for ball receptions, this value is most evident in the game 9, for player 30 (defender – .99). Following, player 1 (goalkeeper – .6961) in game 6, and player 17 (forward – .4163) in game 11, showed the best values of clustering coefficient. Moreover, we found that the best performance of clustering cooefficient for ball receptions occurred by player 1 (goalkeeper– .1704), followed player 19 (forward – .4088) and player 17 (forward – .3995).

Table 3 shows the global rank of each player for passes and crosses performed and ball receptions. The global rank merges the cluster coefficient and the connectivity between players, giving an overview of the player who might balance his ability to interact with the team, with his ability to foster interactions among the teammates he cooperates with.

TABLE 3
Global rank of each player for passes and crosses performed and ball receptions.

Global Rank (g)																
Passes and Crosses Performed																
	Game 1	**Game 2**	**Game 3**	**Game 4**	**Game 5**	**Game 6**	**Game 7**	**Game 8**	**Game 9**	**Game 10**	**Game 11**	**Game 12**	**Game 13**	**Game 14**	**Game 15**	
Player	5	5	25	5	5	30	5	13	12	5	6	25	8	7	8	
Value	0.5530	0.5613	0.6159	0.5855	0.6240	0.5906	0.6015	0.6100		0.5866	0.7094	1.00	0.6295	0.5965	0.6017	
	Game 16	**Game 17**	**Game 18**	**Game 19**	**Game 20**	**Game 21**	**Game 22**	**Game 23**	**Game 24**	**Game 25**	**Game 26**	**Game 27**	**Game 28**	**Game 29**	**Game 30**	**Overall**
Player	30	8	8	7	7	8	8	8	14	8	28	5	7	23	28	7
Value	0.5786	0.6378	0.6014	0.5778	0.6014	0.6228	0.6199	0.6295	0.6132	0.6135	0.6305	0.5871	0.6212	0.6201	0.6153	0.6387
Ball Receptions																
	Game 1	**Game 2**	**Game 3**	**Game 4**	**Game 5**	**Game 6**	**Game 7**	**Game 8**	**Game 9**	**Game 10**	**Game 11**	**Game 12**	**Game 13**	**Game 14**	**Game 15**	
Player	12	5	12	5	8	25	25	28	30	21	30	25	15	7	8	
Value	0.6553	0.6260	0.5814	0.5956	0.6225	0.6735	0.5770	0.6214	0.9900	0.5697	0.6320	0.5840	0.5883	0.6092	0.6185	
	Game 16	**Game 17**	**Game 18**	**Game 19**	**Game 20**	**Game 21**	**Game 22**	**Game 23**	**Game 24**	**Game 25**	**Game 26**	**Game 27**	**Game 28**	**Game 29**	**Game 30**	**Overall**
Player	8	8	25	12	17	25	8	8	13	8	28	28	15	14	28	8
Value	0.6039	0.5999	0.6100	0.6423	0.6571	0.6460	0.6274	0.6159	0.6537	0.5863	0.5979	0.6039	0.6143	0.6080	0.6180	0.6410

The data suggests that player 25 (midfielder – 1.00, game 12), player 6 (midfielder – .7094, game 11) and player 8 (midfilder – .6368, game 11) showed the best global rank for passes and crosses performed. Moreover, for ball receptions, data suggest that player 30 (defender – .99, game 9), player 25 (midfielder – .6735, game 6) and player 17 (forward – .6571, game 20) showed the best global rank. These results are very interesting since these players belong to three different sectors of soccerfield (*i.e.*, defensive, midfielder and attack).

The centroid conformity allows us to understand the level of cooperation that the remaining players in the team have with the centroid player (Table 4).

TABLE 4
Centroid conformity and level of cooperation.

Centroid Conformity (cc)																
Passes and Crosses Performed																
	Game 1	**Game 2**	**Game 3**	**Game 4**	**Game 5**	**Game 6**	**Game 7**	**Game 8**	**Game 9**	**Game 10**	**Game 11**	**Game 12**	**Game 13**	**Game 14**	**Game 15**	
Player	5/17	4/5	25	5	4/5/12	30	4/5/17	13	7/12	5	6	4/25	8/15	5/7	8	
Value	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	
	Game 16	**Game 17**	**Game 18**	**Game 19**	**Game 20**	**Game 21**	**Game 22**	**Game 23**	**Game 24**	**Game 25**	**Game 26**	**Game 27**	**Game 28**	**Game 29**	**Game 30**	**Overall**
Player	1/30	8/17	8/21	7	7	8/25	8	7/8	4/14	8/13	23/28	5/17	7	23/28	28	7
Value	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Ball Receptions																
	Game 1	**Game 2**	**Game 3**	**Game 4**	**Game 5**	**Game 6**	**Game 7**	**Game 8**	**Game 9**	**Game 10**	**Game 11**	**Game 12**	**Game 13**	**Game 14**	**Game 15**	
Player	8/12	4/5	12	5/25	5/8	25	25	28	30	12/21	5/30	15/25	8/15	7	8	
Value	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	
	Game 16	**Game 17**	**Game 18**	**Game 19**	**Game 20**	**Game 21**	**Game 22**	**Game 23**	**Game 24**	**Game 25**	**Game 26**	**Game 27**	**Game 28**	**Game 29**	**Game 30**	**Overall**
Player	8	8	8/25	12/13	17	7/8/25	8/25	5/8	13	8	28	28	10/15	14	5/28	8/28
Value	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

The data indicate, for passes and crosses performed, that player 4 (defender – .9259) and player 12 (forward – .9259) were the most cooperative players with centroid player (player 7, midfielder) during the championship. On the other hand, for the ball receptions, player 28 (midfielder) was the player who most interacted (1.00) with the centroid player (player 8, midfielder).

Table 5 shows the team network analysis for passes and crosses performed and ball receptions.

TABLE 5
Network analysis for passes and crosses performed and ball receptions.

Team network analysis																
Passes and crosses performed																
	Game 1	**Game 2**	**Game 3**	**Game 4**	**Game 5**	**Game 6**	**Game 7**	**Game 8**	**Game 9**	**Game 10**	**Game 11**	**Game 12**	**Game 13**	**Game 14**	**Game 15**	
D	0.1279	0.1117	0.1825	0.1648	0.2308	0.17	0.2187	0.1915	0.1092	0.1691	0.2670	0.1449	0.1918	0.1395	0.1848	
H	0.6469	0.6617	0.5148	0.5816	0.5581	0.6003	0.5400	0.5402	0.8228	0.5508	0.5451	0.6143	0.5506	0.6551	0.5594	
C	0.2343	0.2127	0.1776	0.1923	0.3253	0.1786	0.3013	0.1908	0.1755	0.2308	0.209	0.1900	0.1622	0.2032	0.2331	
	Game 16	**Game 17**	**Game 18**	**Game 19**	**Game 20**	**Game 21**	**Game 22**	**Game 23**	**Game 24**	**Game 25**	**Game 26**	**Game 27**	**Game 28**	**Game 29**	**Game 30**	**Overall**
D	0.1123	0.1892	0.1868	0.1698	0.2108	0.1857	0.2335	0.1882	0.1685	0.1607	0.2434	0.1832	0.2474	0.1876	0.2154	0.1397
H	0.5277	0.5167	0.5547	0.5530	0.4863	0.5796	0.4236	0.5560	0.4981	0.5610	0.5878	0.5357	0.4451	0.4462	0.4877	0.7385
C	0.0933	0.2408	0.2233	0.1519	0.1865	0.2590	0.1494	0.2236	0.1085	0.1827	0.3532	0.2500	0.2043	0.1529	0.2782	0.2440
Ball receptions																
	Game 1	**Game 2**	**Game 3**	**Game 4**	**Game 5**	**Game 6**	**Game 7**	**Game 8**	**Game 9**	**Game 10**	**Game 11**	**Game 12**	**Game 13**	**Game 14**	**Game 15**	
D	0.2080	0.1703	0.1632	0.1464	0.1638	0.2208	0.1315	0.2387	0.1440	0.1154	0.1839	0.1438	0.1245	0.1543	0.2033	
H	0.5252	0.6034	0.5553	0.5739	0.5575	0.5908	0.5404	0.5216	0.8221	0.5482	0.6185	0.6486	0.5854	0.5550	0.6294	
C	0.1804	0.2081	0.1776	0.1241	0.2086	0.1830	0.1494	0.2699	0.1910	0.1167	0.1997	0.2212	0.1189	0.1626	0.3731	
	Game 16	**Game 17**	**Game 18**	**Game 19**	**Game 20**	**Game 21**	**Game 22**	**Game 23**	**Game 24**	**Game 25**	**Game 26**	**Game 27**	**Game 28**	**Game 29**	**Game 30**	**Overall**
D	0.1868	0.1385	0.1707	0.1901	0.2385	0.2055	0.1750	0.1622	0.2468	0.1126	0.2183	0.1680	0.1850	0.1907	0.1987	0.1436
H	0.5561	0.5741	0.5762	0.5952	0.4724	0.5787	0.5228	0.6110	0.4913	0.6613	0.4529	0.5725	0.4931	0.4677	0.4537	0.7299
C	0.1949	0.1526	0.1662	0.1731	0.1615	0.2628	0.1548	0.2172	0.1772	0.1453	0.2022	0.1704	0.1581	0.1493	0.2318	0.2442

Legend: D – Density; H – Heterogeneity; C– Centralization.

A density that tends to 1.00 indicates that all players strongly interact with each other. Over the thirty games, the density value for passes and crosses performed varies between .1092 and .267. However, in game 11, we verified a density of .267. Also, for the network heterogeneity, the variation is very similar connectivity between players for the team. For ball receptions, the density values vary between .1126 and .2387. This value is most evident in match 8, with a density of .2387.

For the network heterogeneity, the variation is very similar in passes and crosses performed and ball receptions. To analyse the passes and crosses performed, the values vary between .4236 and .8228, being stronger in the game 9. On the other hand, for ball receptions, the data clearly indicates that the values vary between .4529 and .821, being stronger in match 9.

Finally, the network centralization allows to measure the overall level of cooperation between players. Regarding passes and crosses performed, one may observe that the team presents low values of centralization, ranging between .0933 and .3532. Thus, it is in match 26 that this value is higher, with a centralization of .3532. At least, for ball receptions, the values vary between .1167 and .3731. Thus, it is in match 15 that this value is stronger, with a centralization of .3731.

DISCUSSION

In this study we sought to verify whether interactions taking place between professional football players are compatible with the concept of small world networks. When analysing the results of networks and scaled connectivity, the data revealed that players 7 (midfielder – 1.00), 4 (defender – .8758) and 13 (defender – .8178) were the players with the most connectivity with their teammates in terms of passes and crosses performed, and players 7 (midfielder – 1.00), 14 (defender – .8259) and 12 (forward – .8155) for ball receptions. These results are in line with Clemente *et al.* (2014) and Folgado *et al.* (2014), where the data revealed that defensive and midfielders are the athletes with the most connectivity with their teammates.

On the other hand, we have to taken into account the weighting distribution of the cluster coefficient and the connectivity between players, *i.e.,* considering that the cluster coefficient of a player is relevant to the team since it is necessary to produce interaction in order to create relationships. Following this reasoning, our results reveal that, while analysing the clustering coefficient, the players that contributed the most to promote interaction among other teammates were players 9 (forward – .4929), 17 (forward – .4039) and 16 (defender – .4034) for passes and crosses performed, and player 1 (goalkeeper – .4163), 9 (forward – .4088), and 17 (forward – .3995) for ball receptions. These players are crucial for the offensive collective actions because they lead to a large number of teammates interactions (Gama *et al.,* 2014). This data reinforces Clemente *et al*. (2013, 2014) arguments that the majority of players with higher clustering coefficient had a low level of scaled connectivity.

Furthermore, a football game can be considered as a dynamical system in which players interact with each other via one ball (Yamamoto & Yokoyama, 2011). In line with our results, Sargent and Bedford (2013) argue that the analysis based on the behavior of networks interaction of players is extremely important as it provides unbiased answers about their collective and individual behavioral trends over a sports season. When comparing the intra-team level of interactions, our results revealed that player 8 (midfielder) are the most interactive player of the team throughout the league. These results show that this key-player assumes an important role in the collective dynamics of the team (Duch *et al*., 2010; Grund, 2012; Vaz *et al*., 2014; Gama *et al*., 2014).

Given the above, the scientific understanding of networks may have a significant impact not only on how we perceive the interaction levels among players, but also our ability to exploit complex networks inherent to the collective behavior (cf. Watts & Strogatz, 1998; Barabasi & Oltvai, 2004; Mitchell, 2009). From this perspective, identifying the preferential attachments within a small world network can provide a very useful way to accurately identify the key decision-makers during important phases of competitive performance (Passos *et al.,* 2011).

Regarding the global connectivity of players, the results suggest that players participate in offensive collective actions with teammates who also have a higher level of interaction with each other. We verified that players 7 (midfielder – 1.00), 4 (defender - .8758) and 13 (defender - .8178) were those with the highest values of scaled connectivity for passes and crosses. For ball receptions, players 7 (midfielder – 1.00), 13 (defender - .6549) and 11 (forward - .6467) were the most highlighted. These players are those withhigher level of cooperation among their peers. In this case, the most cooperative players correspond to each tactical sector's: defense, midfield and attack (Gama *et al.,* 2014; Duarte *et al.,* 2012; Bartlett *et al.,* 2012; Yamamoto *et al*., 2013).

Reinforcing this idea, Clemente *et al.* (2014) indicated that defenders and midfielders are the players that produce offensive plays with more frequency, explaining that this is due to the defensive strategy, *i.e.,* since, typically, after an offensive phase of the opposing team, the ball is recovered by the defenders or midfielders in the defensive zone, thus increasing their participation in the offensive plays. Besides, the second explanation for our results is related to the teams own offensive strategy (Clemente *et al.,* 2014; Belli *et al.,* in press). Thus, we might suggest that if the team opts to build the offensive play around defenders in order to 'attract' the opponents out of their defensive zone, it would be expected that the higher centralization of the game would be with the defenders and midfielders (Gama *et al.,* 2014).

Moreover, the results of centroid conformity revealed that players 4 (defender – .9259) and 12 (forward – .9259) were the players depicting a higher level of interaction with the centroid player (player 7, midfielder), for passes and crosses performed, and player 28 (midielder – 1.00) with the centroid player (player 8, midfielder) for ball receptions. In that sense, the experimental studies on centroid method initiated by Frencken and Lemmink (2008) showed that centroid player performance may be hopeful to describe the collective behavior of the team. Following this idea, Lames *et al.* (2010) indicated that similar principles may underpin the collective organization of teams' centroids in invasion games. These ideas portray the main key players of the connecting nodes, which can be useful in the context of sport sciences, especially in the measurement of intra and inter-individual performance (Duarte *et al.*, 2012; Moura *et al.*, 2012; Folgado, 2014; Belli *et al.,* in press).

In addition, our data suggests that the team presented a network with an overall density of .1397 for passes and crosses performed and .1436 for ball receptions. These reduced density values indicate that players do not interact strongly with each other. So, according to Balkundi & Harrisson (2006) and Grund (2012), high density levels match a higher team performance. In the opposite direction, the team demonstrated a high heterogeneity, with .7385 values for passes and crosses performed and .7299 for ball receptions. Given this result, according to Couceiro *et al.* (2014), a high heterogeneity of the football network means that players exhibit a high level of performance and there is, collectively, a low level of cooperation between players. However, the team showed a good cooperation between players of the team, revealing low levels of centralization; .2440 for passes and crosses performed and .2442 for ball receptions. In that sense, low values of centralization increase the variability and inpredictability of each offensive play, making it a real challenge for the opposing team (Clemente *et al.,* 2014; Belli *et al.,* in press). Therefore, centralization may depend upon the individual and collective tactical options (Clemente *et al.,* 2014; Clemente *et al.,* 2015; Belli *et al.,* in press).

Finally, we verified that some players tended to establish preferential links with others. This feature, characterizing the team collective behaviors (e.g., paired or groups of players), was also captured by our network analysis. In this sense, the great variability of actions characterizing football implies that interpersonal interactions can change from match to match (Perl & Weber, 2004; Carling *et al.,* 2005; Perl & Dauscher, 2006; Yamamoto & Yokoyama, 2011; Sargent & Bedford, 2013). Also, over the 30 matches analyzed, we noted preferential links beetween players 5 (defender) and 17 (forward). These interactions allow, in an objective manner, to portray players' behaviour regarding the opposing goal, measuring the larger success rate in terms of interactions between two or more players (Duch *et al*., 2010; Yamamoto & Yokoyama, 2011; Castellano *et al.,* 2014).

CONCLUSIONS

We conclude that small-world networks can capture the rich interactions among players in professional football. This suggests that network analysis might be useful to shed some light on the key individual contributions to the collective team performance and provide insights on how creative and organizing individuals might act to orchestrate team strategies. Moreover, the proposed methodology, based on network analysis, can be used to characterize the collective behaviours that emerge through cooperation and competition between players during competitive football matches.

Furthermore, it was concluded that centroid players are fundamental in the self-organization process of the team, since they exhibit a higher level of quality during both execution and reception of passes, there by contributing to a high intensity and density of the network established during the match. This is something that can be applied to other team sports, because through this network of interactions, coaches can further understand the team dynamics and optimize its performance to the desired objectives.

On the other hand, we assumed that players' interactive behaviours within a football match support the existence of a scale free network. A general feature of this type of network is that a few players will tend to exhibit more links than other players. Therefore, 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 distribution. These ideas imply that network concepts can lead to an understanding of the continuous interactions between players during competitive performance. So, for a better understanding of the football game, it is essential to assess the interpersonal relationships between players, taking into account the different moments of the match, the region where players' interactions occur, as well as the relationships established. In that sense, football can be regarded, from a network analysis perspective, as a competitive relationship between two cooperative networks.

At last, it can be assumed that many complex networks have been shown to have topological properties in common, based on a small-world network model. Hence, networks may have an important role in describing the collective behaviour, which aroused an effective attention from sports scientists, particularly those that focus on game observation and analysis, and coaches, since those provide a new interpretation of the game dynamics and the collective behavior of the team, perceiving the organization points and improvement needs, transferring this assessment to train and competition.

Given the above, the findings of this study may help coaches in quantifying the contributions and interactions of individual players through the analysis of their relevant actions in a team sport, like football. From this perspective, practical implications for coaches regarding the intra- and inter-individual performance trends, resulting from playing actions, emerge so as to provide some answers about how teams self-organize their behaviour and performance.

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