Journal of Physical Education and Sport ® (JPES), 15(2), Art 33, pp. 212 - 217, 2015
online ISSN: 2247 - 806X; p-ISSN: 2247 – 8051; ISSN - L = 2247 - 8051 © JPES

Original Article

Network analysis in basketball: inspecting the prominent players using centrality metrics

FILIPE MANUEL CLEMENTE[1], FERNANDO MANUEL LOURENÇO MARTINS[2], DIMITRIS KALAMARAS[3], RUI SOUSA MENDES[4]
[1,2,4] Polytechnic Institute of Coimbra, Coimbra College of Education, Department of Education, PORTUGAL
[1,2,4] Polytechnic Institute of Coimbra, IIA, RoboCorp, ASSERT, PORTUGAL
[1]Faculty of Sport Sciences and Physical Education, University of Coimbra, PORTUGAL
[2]Instituto de Telecomunicações, Delegação da Covilhã, PORTUGAL
[4]New Media Network Synapsis S.A.

Published online: June 26,2015
(Accepted for publication April 26, 2015)
DOI:10.7752/jpes.2015.02033;

Abstract:
The aim of this study was to analyse the team-members cooperation in basketball by using centrality metrics of network. Different ages were compared in this study. Forty players (10 players of under-14; 10 players of under-16; 10 players of under-18 and 10 players in amateurs with more than 20 years) voluntarily participated in this study. A total of 326 units of attack were generated based on the team-members interactions and then converted in final graphs. The one-way ANOVA for the factor tactical position found statistical differences in the dependent variables of %DCentrality ($F(4,15) = 13.622$; p-value = 0.001; $n^2= 0.784$; Large Effect Size) and %DPrestige ($F(4,15) = 20.590$; p-value = 0.001; $n^2= 0.846$; Large Effect Size). In conclusion this study showed that point guard was the prominent position during the attacking organization and that social network analysis it is a useful approach to identify the patterns of interactions in the game of basketball.
Key words: collective behaviour; match analysis; network; metrics; technical performance; basketball.

Introduction

The organization between team-members it is one of the main challenges in team-sports games (Gréhaigne, Bouthier, & David, 1997). The dynamic properties of the game, the cooperation-opposition relationship and the contextual factors constraints the cooperation process of the team-members (Balague, Torrents, Hristovski, Davids, & Araújo, 2013). For those reasons the tendencies and patterns of relationship between team-members it is not always the same or repetitive (Gréhaigne, Godbout, & Zerai, 2011). In fact, the ability to be variable and improve the dynamic of cooperation may improve the possibility to overcome the opponent and decrease the chance to be blocked by the opponent (Couceiro, Clemente, Martins, & Machado, 2014).

In the specific case of team sports there are a particular interest to recognize the cooperation tendencies between team-members (Peña & Touchette, 2012). In fact, such systematic knowledge may augment the perception of coaches to understand the dynamic of their team and to identify the weakness and strong points of opponent's team (Clemente, Martins, Couceiro, Mendes, & Figueiredo, 2014). This specific process of analyse the performance in match it is designated as match analysis in sports (Carling, Williams, & Reilly, 2005). In the field of match analysis there are different approaches to process the observation and the analysis. One of the most common is the traditional notational analysis based on codification of events (actions) or behaviours (Franks & McGarry, 1996). This analysis leads with a tendency to analyse the technical events and reduce the outputs about the inter-relationship between team-members, organization, and tactical behaviour (Clemente, Couceiro, Martins, Mendes, & Figueiredo, 2014). In other hand, recently there are been suggested some computational metrics that integrates the bi-dimensional position of players (using GPS devices, multi-cameras tracking systems, or RFID) to compute the geometric organization of teams and the coordination tendencies between team-members (Bartlett, Button, Robins, Dutt-Mazumder, & Kennedy, 2012; Duarte, Araújo, Correia, & Davids, 2012). These computational metrics shows relevant information about organizational level but do not identify the cooperation of team-members in the passing sequence (Clemente, Couceiro, Martins, Mendes, et al., 2014).

Thus, a new approach based on Social Network Analysis has been used in the last few years to identify the cooperation process of players in the attacking moments (in the moments with possession of the ball) (Duch, Waitzman, & Amaral, 2010; Grund, 2012). The Social Network Analysis provide an opportunity to analyse the general level of cooperation of the team and also to identify the centrality levels of players for the overall

Corresponding Author: FILIPE MANUEL CLEMENTE, E-mail: filipe.clemente5@gmail.com

cooperation (Clemente, Couceiro, Martins, & Mendes, 2014). Thus, the network focus more in the collective than in the individuals (Wasserman & Faust, 1994).

In the specific case of team sports, the majority of reported studies have been in soccer (Clemente, Couceiro, Martins, & Mendes, 2014; Duch et al., 2010; Peña & Touchette, 2012). In the case of European Cup 2008 it was found that the midfielder of Spain was the centrality player of the winning team (Duch et al., 2010). After, in a study on FIFA World Cup 2010 it was possible to identify that the centrality players in the winning team were the midfielders and in the case of the opponent team in the final the biggest centrality levels were found in defenders and midfielders (Peña & Touchette, 2012). In the case of general cooperation, it was found in the Premier League case that the greatest levels of density and smallest levels of heterogeneity were associated with the teams that had best performance in matches (Grund, 2012). In a more recent study it was found that in a top team in Portuguese Premier League the centrality players in the attacking process were the external defenders and the midfielders (Clemente, Couceiro, Martins, & Mendes, 2014). Briefly, it is possible to identify that soccer have been well studied by using network approach. Nevertheless, such situation it is not similar in other team sports such as basketball (Bourbousson, Poizat, Saury, & Seve, 2010; Fewell, Armbruster, Ingraham, Petersen, & Waters, 2012). In the case of under-18 French basketball players it was found small mutual forms of interactions and suggested that the coordination networks of the team were built on local coordination's chaining together in such a way as to not necessarily form a single unit (Bourbousson et al., 2010). By other hand, in a study that used data from NBA first round play-offs, it was showed a star pattern in the Bulls team who inbound only to the Point Guard at 60% and for which most passes were between the Point Guard and other players (Fewell et al., 2012).

The small investigation in basketball and the reduced analysis to the contribution of each tactical position to build the attacking process are the main motivation in this study. Thus, the aim of this study was to analyse the general properties of different competitive levels of basketball and to identify the centrality levels of different strategic positions in basketball.

Method

Sample

Forty players (10 players of under-14; 10 players of under-16; 10 players of under-18 and 10 players in amateurs with more than 20 years) voluntarily participated in this study. One match per each team were observed and codified by an expert observer. A total of four adjacency matrices corresponding to 326 units of attack (79 in U14; 84 in U16; 83 in U18; 80 in Amateurs) were generated based on the team-members interactions and then converted in final graphs. Per each player it was also computed the technical indexes.

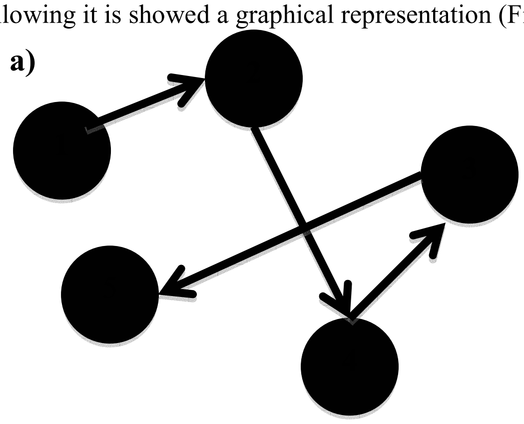
Experimental Procedures

Two main categories of analysis were processed in this study. The first used the social network analysis to identify the general properties of the team-members cooperation and also to identify the centrality levels of cooperation of players. In a second level of analysis it was codified the technical performance of players in the match and then computed four performance indexes based on an instrument of analysis.

Network Analysis

To compute the network it is necessary to build an adjacency matrix. The adjacency matrix represents the connections (arrows) between team-members (nodes) (Clemente, Martins, et al., 2014). The linkage indicator was the pass between team-members as considered in previous studies on team sports (Cotta, Mora, Merelo, & Merelo-Molina, 2013; Passos et al., 2011). Each passing sequence without losing the possession of the ball resulted in one unit of attack and then in an individual matrix. The number of passes in the same direction (player A to player B) was considered in the adjacency matrix. To make easier the understanding about the concept, following it is showed a graphical representation (Figure1).

a)



b)

	1	2	3	4	5
1	0	1	0	0	0
2	0	0	0	1	0
3	0	0	0	0	1
4	0	0	1	0	0
5	0	0	0	0	0

Figure 1. a) Passing sequence of team-members; b) respective adjacency matrix.

As observed in Figure 1 the connections were codified with 1 (because no more than 1 pass in the same direction was verified in this specific case) and no connections with 0 (zero). This passing sequence only represents one unit of attack and one subsequent adjacency matrix. In the end of each match it was computed the sum of all generated adjacency matrices.

The players were codified with numbers in order to process the data. The numbers corresponded to a given tactical position: Player 1 - Shooting Guard; Player 2 - Point Guard; Player 3 - Small Forward; Player 4 - Power Forward; and Player 5 -Post. The same researcher that had more than 5 years of experience in match analysis undertook the data collecting and codification. In order to ensure the reliability of study the Cohen's kappa was performed with a 25-day interval between the first and the second data collecting (Robinson & O'Donoghue, 2007). A total of 15% of the overall data was tested for the reliability procedure. The Kappa value was 0.81, thus ensuring the accomplishment of reliability.

Network Metrics

From the network codification it was possible to compute some metrics that identifies the prominent players during the cooperation. To run such metrics it was used the *Social Network Visualizer* software (version 1.5.). This software allows to visualize the graphical representation of team-members cooperation and also provide valuable outputs about the network metrics (Kalamaras, 2014). Two centrality (prestige and centralization) network metrics were computed.

Degree Prestige

Degree prestige (in-degree measure, IDC) represents the prominence level of each player to be the target of his teammates to pass the ball. Therefore, greater values suggest that the player is the priority player to receive the ball and smallest values suggest that the player is not one of the targets to pass the ball.

The IDC can be computed for valued graphs and digraphs as well. In these cases, the IDC of each node is the sum of weights of all inbound arcs to that node from its neighbors

$$IDC'_u = \sum_{v=1, u \neq v}^{g} a_{vu} \quad (1)$$

where a_{vu} is the weight of $e_{vu} \in E$.

Degree Centrality

Degree centrality (out-degree measure, ODC) represents the prominence level of each player to build the attacking process. Greater values suggest that the player has a great participation to build the attack with their passes for other players.

For both valued and unvalued graphs, the ODC score of a node can be easily computed by summing the elements of the corresponding row of the adjacency matrix.

$$ODC_u = \sum_{v=1, u \neq v}^{g} A(u, v) \quad (2)$$

where $A(u, v)$ is (u, v) element of the adjacency matrix A.

Statistical Procedures

The influences of tactical position and level of competition (under-14, under-16, under-18 and amateurs) were analysed using two one-way ANOVA due the impossibility to use the MANOVA by the lack number of degrees of freedom. The assumption of normality for each univariate dependent variable was examined using Kolmogorov-Smirnov tests (p-value < 0.05). The assumption of the homogeneity of each group's variance/covariance matrix was examined with the Box's M Test. No homogeneity was shown. Ultimately, the Bonferroni post-hoc test was made. All statistical analyses were performed using IBM SPSS Statistics (version 21) at a significance level of $p<0.05$. The following scale was used to classify the effect size (partial eta square) of the test (Pierce, Block, & Aguinis, 2004): small, 0.14–0.36; moderate, 0.37–0.50; large, 0.51–1.

Results

The one-way ANOVA for the factor tactical position found statistical differences in the dependent variables of %DCentrality ($F_{(4,15)} = 13.622$; *p-value* = 0.001; $\eta^2 = 0.784$; *Large Effect Size*) and %DPrestige ($F_{(4,15)} = 20.590$; *p-value* = 0.001; $\eta^2 = 0.846$; *Large Effect Size*). The post hoc results can be found in the following table 1.

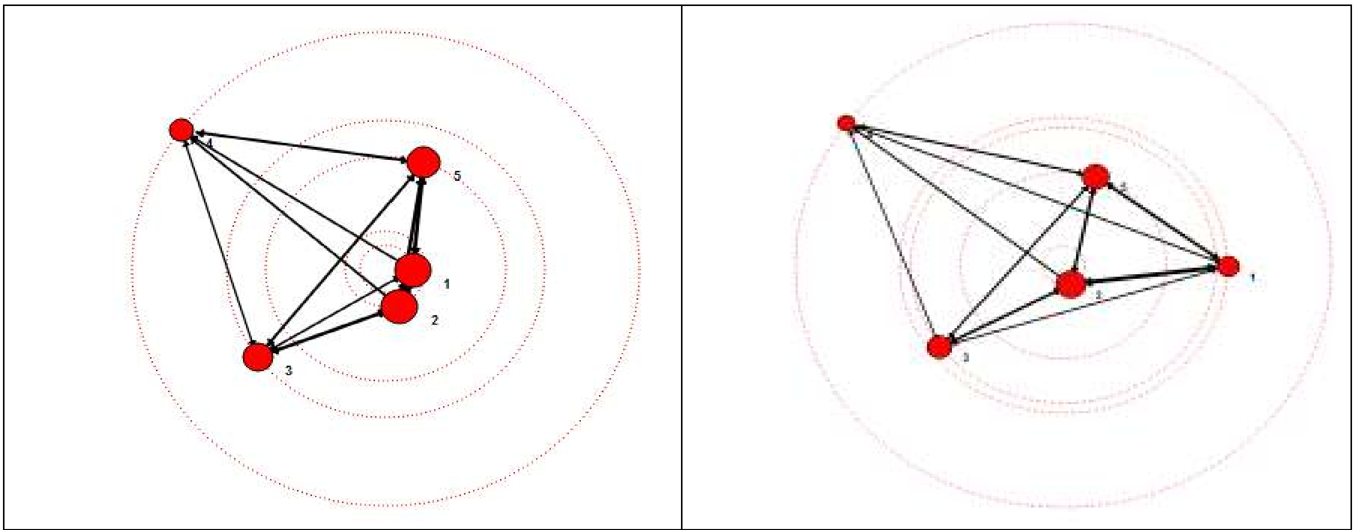
Table 1. Descriptive statistics and post-hoc results for the Tactical Position.

	Shooting Guard	Point Guard	Small Forward	Power Forward	Post
%DCentrality	23.83 (3.46)^{d,e}	28.65 (4.37)^{c,d,e}	16.63 (1.24)^{b}	15.55 (2.68)^{a,b}	15.40 (3.50)^{a,b}
%DPrestige	19.53 (3.27)^{b}	32.90 (2.01)^{a,c,d,e}	15.90 (2.20)^{b}	13.80 (3.89)^{b}	17.88 (4.50)^{b}

Statistically different of Shooting Guard^{a}; Point Guard^{b}; Small Forward^{c}; Power Forward^{d}; and Post^{e} for a *p-value* < 0,05

The one-way ANOVA for the factor competition level not found statistical differences in the dependent variables of %DCentrality ($F_{(3,16)}$ = 0.001; *p-value* = 1.000; η^2 = 0.001; *Very Small Effect Size*) and %DPrestige ($F_{(3,16)}$ = 0.001; *p-value* = 1.000; η^2 = 0.001; *Very Small Effect Size*).

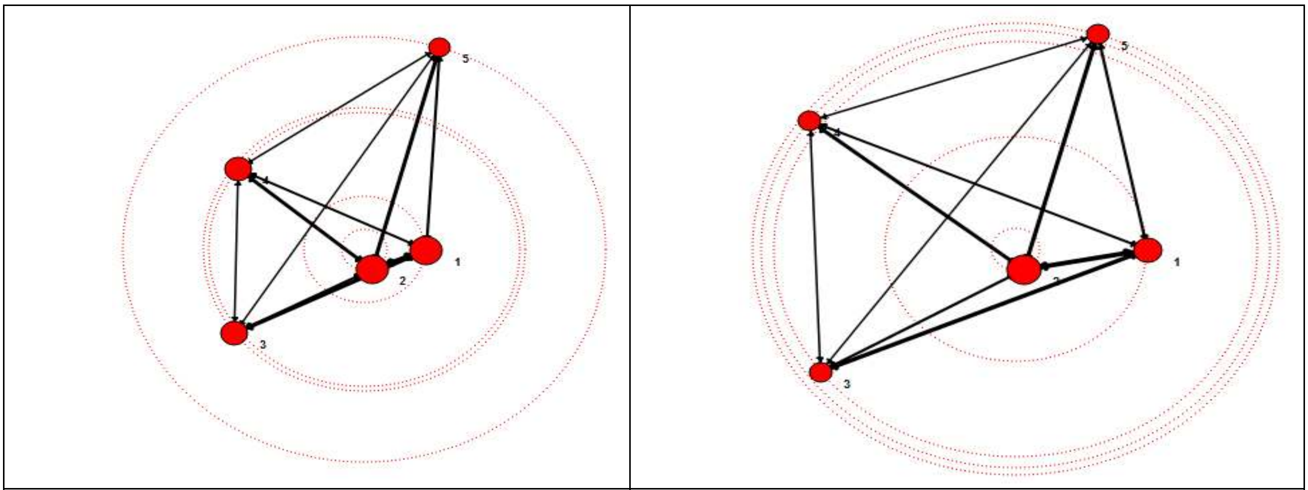
As observed before, no statistically differences were found in different competition levels but large statistical differences were found in tactical position. Thus, using the SocNetV it was possible to visualize the centrality players in a circular layout type as shown in the following Figure 2.



Degree Centrality	Degree Prestige

Fig. 2. Visualization of centrality levels achieved by tactical positions in under-14. Player 1: Shooting Guard; Player 2: Point Guard; Player 3: Small Forward; Player 4: Power Forward; and Player 5: Post.

As possible to observe in the Figure 2, the prominent player in both centrality levels is the point guard that are in the middle of the circular layout. Also in both case the power forward is the team-member with smallest values of degree centrality and degree prestige. As illustrative example the following Figure 3 represents the competition level of amateurs with more than 20 years old.



Degree Centrality	Degree Prestige

Fig 3. Visualization of centrality levels achieved by tactical positions in amateurs. Player 1: Shooting Guard; Player 2: Point Guard; Player 3: Small Forward; Player 4: Power Forward; and Player 5: Post.

As possible to observe in the figure 3, the point guard is also the prominent player in both centrality levels. The same situation is in line with the analysis of variance from ANOVA. In the case of amateurs it is possible to observe that the post is the player with small prominence in circular layout.

Discussion

The cooperation between team-members and the individual contribution of each player to the organization process it is extremely relevant in team sports (Vilar, Araújo, Davids, & Bar-Yam, 2013). For that reason the aim of this study was to identify the network properties of basketball teams and the individual contribution of each tactical position for the attacking process.

This study was conducted in competition levels of under-14, under-16, under-18 and amateurs with more than 20 years old. No differences in the prominent tactical position were found between competitive levels. Nevertheless, the statistical analysis found statistical differences in centrality levels between different tactical positions.

In the case of degree centrality that measures the prominence level of each player to build the attacking process, it was possible to found in all competitive levels that the point guard is the prominent player that originates the passes for the team-members. Such results are in line with previous studies (Fewell et al., 2012). In fact, the point guard position in basketball as the role to link the team-members and organize the attacking process (Sampaio, Janeira, Ibáñez, & Lorenzo, 2006). Thus, the greatest values of degree centrality are justified by the specific role of guard position. In the other hand, the post position had the smallest value of degree centrality. In fact, the post are always farthest from the point guard and the main participation is to receive the ball and shot and not organize the attacking process. For that reason, it is justified the small value of degree centrality.

The degree prestige it was also analysed in this study. This metric represents the prominence level of each player to be the target of his teammates to pass the ball. In this case, the post position had greater values than forwards. In fact, the post is the player that is closest to the target and for that reasons it is a reference to pass the ball. Despite of this change in results in comparison with degree centrality, the point guard had once again the greatest values. Actually, only statistical differences were found between point guard and the remaining tactical positions. The specific properties and roles of point guard may lead with greater values of centrality in- and out-degree. All the attacking process depends from the participation of this tactical role, thus it is understandable that had great values of balls received and passed.

Using the centrality metrics of social network analysis it was possible to conclude that point guard is the prominent player during the attacking organization in basketball. Such evidence is common to all competition levels, thus may characterize the collective organization in this team sport. This study had as main limitation the small sample used. In fact a more extended sample in the future will allow generalizing the conclusion of this study. Moreover, the conditioning levels of players were not inspected and may be important to associate with the participation level in next studies. Finally, the technical efficiency must be associated in next studies with the tactical prominence.

Although those limitations, it was possible to apply the social network approach to identify the prominent tactical position in the field. In fact, the use of such approach for match analysis may lead with a quickly understanding of overall participation of each player in match. Moreover, it is also possible to identify the patterns of play of a given team and to anticipate the collective organization, thus providing useful information for coaches and analysts.

Conclusion

The aim of this study was to identify the centrality tactical positions in basketball. Using the social network analysis metrics was possible to conclude that point guard is the prominent tactical position that links the remaining team-members during the attacking process. Moreover, it was observed no differences between different competitive leagues considering the centrality levels. In summary, the social network analysis can be considered a useful approach to match analysis in basketball providing relevant information about the organizational process of team-members during the game.

Acknowledgments

This study was carried out in the scope of R&D Unit 50008, financed by UID/EEA/50008/2013.

References

Balague, N., Torrents, C., Hristovski, R., Davids, K., & Araújo, D. (2013). Overview of complex systems in sport. *Journal of Systems Science and Complexity*, *26*(1), 4–13. doi:10.1007/s11424-013-2285-0

Bartlett, R., Button, C., Robins, M., Dutt-Mazumder, A., & Kennedy, G. (2012). Analysing Team Coordination Patterns from Player Movement Trajectories in Football: Methodological Considerations. *International Journal of Performance Analysis in Sport*, *12*(2), 398–424.

Bourbousson, J., Poizat, G., Saury, J., & Seve, C. (2010). Team Coordination in Basketball: Description of the Cognitive Connections Among Teammates. *Journal of Applied Sport Psychology*, *22*(2), 150–166.

Carling, C., Williams, A. M., & Reilly, T. (2005). *Handbook of Soccer Match Analysis: A Systematic Approach to Improving Performance*. London & New York: Taylor & Francis Group.

Clemente, F. M., Couceiro, M. S., Martins, F. M. L., & Mendes, R. S. (2014). Using network metrics to investigate football team players ' connections: A pilot study. *Motriz*, *20*(3), 262–271. doi:dx.doi.org/10.1590/S1980-65742014000300004

Clemente, F. M., Couceiro, M. S., Martins, F. M. L., Mendes, R. S., & Figueiredo, A. J. (2014). Practical Implementation of Computational Tactical Metrics for the Football Game: Towards an Augmenting Perception of Coaches and Sport Analysts. In Murgante, Misra, Rocha, Torre, Falcão, Taniar, … Gervasi (Eds.), *Computational Science and Its Applications* (pp. 712–727). Springer.

Clemente, F. M., Martins, F. M. L., Couceiro, M. S., Mendes, R. S., & Figueiredo, A. J. (2014). A network approach to characterize the teammates' interactions on football: A single match analysis. *Cuadernos de Psicología Del Deporte*, *14*(3), 141–148.

Cotta, C., Mora, A. M., Merelo, J. J., & Merelo-Molina, C. (2013). A network analysis of the 2010 FIFA world cup champion team play. *Journal of Systems Science and Complexity*, *26*(1), 21–42.

Couceiro, M. S., Clemente, F. M., Martins, F. M. L., & Machado, J. A. T. (2014). Dynamical Stability and Predictability of Football Players: The Study of One Match. *Entropy*, *16*(2), 645–674. doi:10.3390/e16020645

Duarte, R., Araújo, D., Correia, V., & Davids, K. (2012). Sports Teams as Superorganisms: Implications of Sociobiological Models of Behaviour for Research and Practice in Team Sports Performance Analysis. *Sports Medicine*, *42*(8), 633–642.

Duch, J., Waitzman, J. S., & Amaral, L. A. (2010). Quantifying the performance of individual players in a team activity. *PloS One*, *5*(6), e10937.

Fewell, J. H., Armbruster, D., Ingraham, J., Petersen, A., & Waters, J. S. (2012). Basketball teams as strategic networks. *PloS One*, *7*(11), e47445.

Franks, I. M., & McGarry, T. (1996). The science of match analysis. In T. Reilly (Ed.), *Science and Football* (pp. 363–375). Oxon: Spon Press Taylor & Francis Group.

Gréhaigne, J. F., Bouthier, D., & David, B. (1997). Dynamic-system analysis of opponent relationship in collective actions in football. *Journal of Sports Sciences*, *15*(2), 137–149.

Gréhaigne, J. F., Godbout, P., & Zerai, Z. (2011). How the "rapport de forces" evolves in a football match: the dynamics of collective decisions in a complex system. *Revista de Psicología Del Deporte*, *20*(2), 747–765.

Grund, T. U. (2012). Network structure and team performance: The case of English Premier League soccer teams. *Social Networks*, *34*(4), 682–690.

Kalamaras, D. (2014). Social Networks Visualizer (SocNetV): Social network analysis and visualization software. *Social Networks Visualizer*. Homepage: http://socnetv.sourceforge.net .

Passos, P., Davids, K., Araújo, D., Paz, N., Minguéns, J., & Mendes, J. (2011). Networks as a novel tool for studying team ball sports as complex social systems. *Journal of Science and Medicine in Sport*, *14*(2), 170–176.

Peña, J. L., & Touchette, H. (2012). A network theory analysis of football strategies. In *arXiv preprint arXiv* (p. 1206.6904).

Pierce, C. A., Block, R. A., & Aguinis, H. (2004). Cautionary Note on Reporting Eta-Squared Values from Multifactor ANOVA Designs. *Educational and Psychological Measurement*, *64*(6), 916–924. doi:10.1177/0013164404264848

Robinson, G., & O'Donoghue, P. (2007). A weighted kappa statistic for reliability testing in performance analysis of sport. *International Journal of Performance Analysis in Sport*, *7*(1), 12–19.

Sampaio, J., Janeira, M., Ibáñez, S., & Lorenzo, A. (2006). Discriminant analysis of game-related statistics between basketball guards, forwards and centres in three professional leagues. *European Journal of Sport Science*, *6*(3), 173–178. doi:10.1080/17461390600676200

Vilar, L., Araújo, D., Davids, K., & Bar-Yam, Y. (2013). Science of winning football: emergent pattern-forming dynamics in association football. *Journal of Systems Science and Complexity*, *26*, 73–84.

Wasserman, S., & Faust, K. (1994). *Social network analysis: Methods and applications*. New York, USA: Cambridge University Press.