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Original Article

The social network analysis of Switzerland football team on FIFA World Cup 2014

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Abstract:
The aim of this study was to apply the social network analysis approach to the football match analysis case. For such, it was analyzed the Switzerland national football team during the FIFA World Cup 2014 tournament. Two general network metrics (total links and network density) and two centrality metrics (degree centrality and degree prestige) were computed. Four matches from Switzerland in FIFA World Cup 2014 were analysed in this study. A total of 334 adjacency matrices corresponding to 334 units of attack were generated based on the teammates' interactions and then converted in 4 network graphs. A total of 1129 passes were analysed. The greatest value of total links and network density was achieved in the first match (88 total links and 0.80 of density value). Degree centrality revealed that the defenders and midfielders were the players with greatest prominent values in the attacking building. Degree prestige showed that midfielders were the main targets of the team to pass the ball in the attacking process. In summary, this study showed that centrality metrics can be an important tool in match analysis to identify the style of play of football teams, revealing the most prominent tactical roles in the attacking process.
Key words: match analysis; football; network; cooperation; performance.

Introduction

The football is a complex and dynamic system that depends from the interactions of many agents (Gréhaigne, Bouthier, & David, 1997). Such interactions within a team can be considered as a cooperation process that emerges based on the strategic plan for the team, the situational variables and the contextual constraints (Davids, Araújo, & Shuttleworth, 2005). Despite of many dynamic factors that can change the strategic master plan for the team, usually there are some intrinsic patterns of cooperation that comes from weekly daily training sessions (Jonsson et al., 2006). Such patterns of play aims to provide some stability to the team's performance and organize the cooperation process of different teammates (Couceiro, Clemente, Martins, & Machado, 2014). In fact, the organization of different players is one of the main challenges for the coach in the game of football.

Besides to organize the team for different matches during a season, another interesting main role of coaches and their staff is to observe, analyze and understand the interactional process of players during the match trying to identify the strength and weakness points of the team (Filipe M Clemente, Couceiro, Fernando, Mendes, & Figueiredo, 2013). In that sense, the match analysis on football is one of the fundamental processes to provide relevant feedback for the coach in order to identify the team and players' properties (Carling, Williams, & Reilly, 2005; Hughes & Bartlett, 2002). The usual match analysis provides relevant information about time-motion profiles of players and the individual efficacy of football actions (Carling, Bloomfield, Nelsen, & Reilly, 2008; Hughes & Bartlett, 2002). Despite of these important indicators, the tactical information seems to be the weakest parameter of the regular match analysis systems (Vilar, Araújo, Davids, & Bar-Yam, 2013). In fact, such evidence can be explained by the complexity of analysis and by the difficulty to produce quantitative information about human behaviors.

Lately, new methodological approaches have been proposing new quantitative solutions to quantify the tactical behavior of teams (Travassos, Davids, Araújo, & Esteves, 2013). Some approaches use the Cartesian information of players' locations in the field to compute the spatio-temporal relationships. Such tactical metrics provides very interesting collective information in a online or offline fashion (Filipe M Clemente, Couceiro, Martins, Mendes, & Figueiredo, 2013). Nevertheless, those metrics depend from the information about players' position in the field, thus depending of multi-camera tracking systems or GPS (Global Positioning System) to

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work (Filipe Manuel Clemente, Couceiro, Martins, Mendes, & Figueiredo, 2014). Due to very expensive costs, this alternative is not an immediate solution for all clubs and contexts.

A different approach is a semi-computational solution that crosses the individual observation of some indicators (as passes between players) and then processes such data using specific algorithms to provide information about the collective interaction and reveal some interactional tendencies within the team (Lusher, Robins, & Kremer, 2010). Such approach is called by Social Network Analysis and is based on graph theory (Wasserman & Faust, 1994). By now the use of network approach for the study of football dynamics is only beginning (Grund, 2012). One of the first network applications used some individual metrics to determine the prominence of players during European Cup 2008 (Duch, Waitzman, & Amaral, 2010). Later, a crossed approach using individual and general metrics identified the most prominent player within the most successful teams in FIFA World Cup 2010 (Peña & Touchette, 2012). A similar analysis was also performed in such competition but with a greater focus on general teams properties (Cotta, Mora, Merelo, & Merelo-Molina, 2013). Lately, a pilot study used some network metrics to analyze the inter-dependency between teammates in a specific football team of Portuguese premier league (Filipe Manuel Clemente, Couceiro, Martins, & Mendes, 2014). Briefly, the studies reveals that there are two main group of network metrics: i) network metrics to identify the graph properties and that provide a unique value for the network; and ii) centrality metrics that identify the prominence levels of each player for the overall network of a team.

These studies provided some relevant information about the possibilities of network approach for the match analysis. Nevertheless, the massive use of these techniques is not a reality by now. Besides of that, the practical applications for the coaches are not a main priority in those studies. Therefore, the aim of this study was to apply general and centrality network metrics to identify the style of play and some patterns of interactions of Switzerland football team during the FIFA World Cup 2014. This is a case study that aims to identify the variation of general properties of cooperation in Switzerland team and also identify which tactical roles have a greater prominence for the overall teammates' cooperation.

Methods

Sample

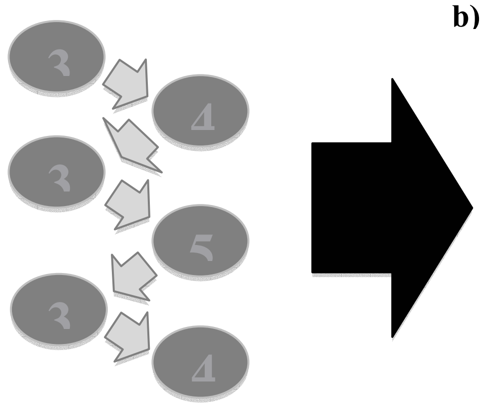
Four official matches from Switzerland in FIFA World Cup 2014 tournament were analysed in this study. A total of 334 adjacency matrices corresponding to 334 units of attack were generated based on the teammates' interactions and then converted in 4 network graphs. A total of 1129 passes were analysed.

Experimental Procedures

To perform a network analysis based on graph theory it is necessary to build an adjacency matrix that represents the connections (arrows) between a node n (player) and their neighbour y (teammate). In the case of this study it was considered the pass between two players as the indicator to generate the connection (Passos et al., 2011). Thus, only the attacking moments were observed.

To make easier generate the matrix it was built an individual adjacency matrix per each unit of attack. The unit of attack can be considered as the moment that team recovers the ball from the opponent and performs a passing sequence until lose the ball again (Passos et al., 2011). During each unit of attack the interactions between teammates were codified with 1 (one) for a pass from player n to player y and with 0 (zero) for none pass between such dyad. In the case of more than 1 pass in the same direction between teammates, the number of passes was codified. Please consider the example of coding in Figure 1.

a)



b)

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11
P1	0	0	0	0	0	0	0	0	0	0	0
P2	0	0	0	0	0	0	0	0	0	0	0
P3	0	0	0	2	1	0	0	0	0	0	0
P4	0	0	1	0	0	0	0	0	0	0	0
P5	0	0	1	0	0	0	0	0	0	0	0
P6	0	0	0	0	0	0	0	0	0	0	0
P7	0	0	0	0	0	0	0	0	0	0	0
P8	0	0	0	0	0	0	0	0	0	0	0
P9	0	0	0	0	0	0	0	0	0	0	0
P10	0	0	0	0	0	0	0	0	0	0	0
P11	0	0	0	0	0	0	0	0	0	0	0

Fig. 1. Example of data collecting and coding: a) Passing sequence between players 3, 4 and 5; and b) corresponding adjacency matrix of the passing sequence.

As is possible to observe in the previous Figure 1, the 0 code is for no passes between teammates. In the specific case of player 3 the connection code for player 4 was 2 that correspond to the number of passes in same direction (from player 3 to player 4). This procedure was undertaken per each unit of attack and in the end of each match it was generated the overall adjacency matrix that corresponds to the sum of all individual adjacency matrices generated in the match.

The observational process focused in the tactical role of each player. This methodological option follows the most recent works (Filipe Manuel Clemente, Couceiro, Martins, & Mendes, 2014; Malta & Travassos, 2014) and aimed to provide more useful tactical information about the specific style of play. The positional referential followed the Di Salvo et al. (Di Salvo et al., 2007) recommendation: i) goalkeeper; ii) external defenders; iii) central defenders; iv) midfielders; v) external midfielders; and vi) forwards. In the case that one player permanently changed their tactical position in the field a new code was attributed.

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 20-day interval between the first and the second data collecting (Robinson & O'Donoghue, 2007). A total of 10% of general data was tested for the reliability procedure. The Kappa value was 0.76, thus ensuring the accomplishment of reliability.

Network Metrics

Per each of 4 global graphs obtained from the social network analysis of Switzerland national team it was computed a set of general and centrality network metrics. The data computing was carried out using the software *SocNetV* (version 1.4.) (Kalamaras, 2014). This software is a graphical application to analyse and visualize the social networks and to compute the general metrics and identify the centrality levels of players. Two general network metrics (total links and density) and two centrality metrics (degree prestige and degree centrality) were carried out to analyse the interactional process of

Switzerland team.

Total Links

This metrics allows quantifying the total number of connections between all teammates. Such metric considers that one teammate is connected to another if a pass at least has been occurred during the match. Greater values reveal that more connections emerged between the teammates.

Network Density

Density metric is a relative index that measure the overall affection between teammates (Horvath, 2011). In the case of ordered relationships the possibility of directed connections in a diagraph of n nodes is $n(n-1)$, thus the density can be computed as (Wasserman & Faust, 1994):

$$D = \frac{L}{n(n-1)} \tag{1}$$

In that sense, the density is a fraction that has a minimum of zero (without arrows) and a maximum of 1 (all arrows). Values closer to 1 suggest a greater general affection between teammates and smallest values suggest a star-graph tendency.

Degree Centrality

Degree centrality (out-degree measure) 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.

Degree Prestige

Degree prestige (in-degree measure) 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.

Results

The general properties of Switzerland team graph were inspected using the total links and density metrics. The results per each match can be observed in the following Table 1.

Table 1. Descriptive statistics for total links and density values achieved by Switzerland team during FIFA World Cup 2014.

	Total Links	Density
Switzerland 2 vs. 1 Ecuador	88.00	0.80
Switzerland 2 vs. 5 France	82.00	0.75
Honduras 0 vs. 3 Switzerland	67.00	0.61
Argentina 1 vs. 0 Switzerland	69.00	0.63
Average	76.50	0.70
Standard Deviation	10.15	0.09
Coefficient of Variation	13.27	13.27

As is possible to observe in the previous Table 1 the greatest values of total links and density were achieved in the first match (88 total links and 0.80 density value). In the other hand, the smallest values were achieved in the third match of round of qualification (67 total links and 0.61 density value). In a general way the level of overall connection it was decreasing from the first until the third match.

Besides the general properties of Switzerland team graph, the centrality levels of tactical roles it were computed based on degree centrality and degree prestige. The descriptive statistics can be found in the following Table 2 and Table 3.

Table 2. Degree centrality of Switzerland players during FIFA World Cup 2014.

Degree Centrality	Match 1	Match 2	Match 3	Match 4	Average	Stan. Dev.	%CV
Goalkeeper	5.66	2.73	2.90	2.98	3.57	1.40	39.27
Lateral Defender	12.74	11.21	14.01	7.74	11.42	2.71	23.72
Lateral Defender	9.67	10.91	10.14	15.48	11.55	2.67	23.09
Central Defender	12.03	13.64	5.80	5.95	9.35	4.07	43.52
Central Defender	7.08	13.33	7.25	7.14	8.70	3.09	35.52
Midfielder	15.57	13.03	9.18	8.33	11.53	3.38	29.33
Midfielder	12.03	11.82	15.94	16.67	14.11	2.55	18.05
Midfielder	8.49	9.70	10.63	13.10	10.48	1.95	18.63
Wing Midfielder	8.73	5.45	10.14	10.12	8.61	2.21	25.62
Wing Midfielder	4.95	4.55	7.25	9.52	6.57	2.30	35.05
Striker	3.07	3.64	6.76	2.98	4.11	1.79	43.61

Table 2 reveals that the midfielders and defenders achieved the greatest values of degree centrality. In fact, in three of the four matches the lateral defenders achieved the greatest values (range between 12.74% and 15.48%) and midfielders as well (range between 15.57% and 16.67%). Excluding the goalkeeper, the striker had the smallest values of degree centrality in the majority of matches (range between 2.98% and 6.76%). Such values suggest that the lateral defenders and midfielders had a greater participation in the ball circulation and building attack. Moreover, the midfielders had the lowest values of coefficient of variation (around 18%), thus suggesting a greater stabilization of the prominence in all matches.

Table 3. Degree prestige of Switzerland players during FIFA World Cup 2014.

Degree Prestige	Match 1	Match 2	Match 3	Match 4	Average	Stan. Dev.	%CV
Goalkeeper	2.36	1.21	1.45	1.79	1.70	0.50	29.23
Lateral Defender	11.79	10.00	8.21	7.14	9.29	2.04	22.01
Lateral Defender	6.84	10.61	9.18	10.71	9.33	1.80	19.33
Central Defender	9.91	10.91	3.86	4.17	7.21	3.71	51.51
Central Defender	6.84	11.82	4.83	4.17	6.91	3.46	50.06
Midfielder	14.86	13.33	6.76	7.74	10.67	4.02	37.67
Midfielder	13.44	11.21	15.94	16.67	14.32	2.49	17.38
Midfielder	11.08	11.52	19.32	14.29	14.05	3.79	26.97
Wing Midfielder	11.08	6.67	12.08	11.90	10.43	2.55	24.42
Wing Midfielder	6.84	6.67	8.21	13.69	8.85	3.30	37.26
Striker	4.95	6.06	10.14	7.74	7.22	2.26	31.27

The degree prestige values (Table 3) reveals that midfielders had the greatest values in the majority of matches (range between 13.33% and 19.32%). In fact, only in one match another tactical role had the second greatest value (central defender – 11.82%). In other hand and excluding the goalkeeper, the forward had the smallest value in the majority of matches (range between 4.95% and 10.14%). The midfielder had also the smallest coefficient of variation (17.38%), thus suggesting a greater prominence during all matches. The overall results suggest that midfielders were the targets of the teammates to pass the ball during the passing sequences.

Discussion

The social network analysis and their metrics can help new approaches for the study of teammates' interactions. Thus, the aim of this study was to apply some general and centrality metrics based on graph theory to identify the properties of Switzerland team during the FIFA World Cup 2014.

A previous study that analyzed the density levels of English Premier League Teams identified that greatest performance on goals scored are associated with greatest levels of density and, in other hand greatest levels of centralization are associated with lowest performance (Grund, 2012). In fact, the capability to act as one is one of the main priorities of team sports. In the study of Switzerland team it was found the lowest value was achieved in the third match (0.61). The greatest value was achieved in the first match (0.80). The curiosity of these values is that both matches were won by Switzerland. In that sense, it was not possible to associate the lowest values of density with worst scores. The similar findings were observed for the total links achieved by the team. Briefly, the general properties can be not enough to understand the collective organization and provide useful information for coaches, mainly because the values are only general indicators of collective network.

In that sense, the centrality values of each tactical role was inspected in this study. In some previous studies it was found that the champion of European Cup 2008 and FIFA World Cup 2010 based their passing sequence in the midfielder (Xavi – Spanish team) (Duch et al., 2010; Peña & Touchette, 2012). In a recent study it was also found that external defenders and central defenders were the players with greatest values of centralization in the attacking building of a professional Portuguese team from Premier League that won four matches and draw one match (Filipe Manuel Clemente, Couceiro, Martins, & Mendes, 2014). Such study also found that defenders and midfielders were the players with most connectivity levels with overall teammates (Filipe Manuel Clemente, Couceiro, Martins, & Mendes, 2014). In the case of Switzerland team it was found similar results, thus the greatest degree centralization levels were achieved by defenders and midfielders. The type of data collected can be associated with such values. In fact, all passing sequences were considered (from counter-attack until regular building attack). Thus, in teams with a style of play based on ball circulation and possession of the ball it is normal that defenders and midfielders have the greatest values of centralization mainly because the attacking processes starts from behind in a set of passes in the defensive midfield. In other hand, the style of play based on counter-attack and quick attacking transition the greatest values of centralization can be found mainly in the midfielders (Malta & Travassos, 2014).

The degree prestige (in-degree metric) revealed that the midfielders are the main targets to pass the ball. Such values can only be understood by the specific style of play of the team. In fact, it is predictable that in teams that opts to play in counter-attack and recruiting the forward players the greatest values of degree prestige can be found in forwards and external midfielders as found in studies that only analyzed the attacking transition and counter-attack (Malta & Travassos, 2014). In the Switzerland case the attacking building are based in exploit the midfielders and the central offensive midfielder (called by number 10 in football), thus even in the degree prestige the level achieved by the striker/forward is too small. Once again, such results reveals that the Switzerland style of play area based on building attack and short passes in the majority of playing time and not in counter-attack and passes with direction to the forward players.

The results of centrality metrics are very interesting mainly because can provide a useful information about the strategic options of the team and also reveals the style of play that team opts to use in the majority of the time. As in any study, this study had some limitations. One of the main limitations was not use some of computational metrics to identify the collective organization mainly in a geometric point-a-view. In fact the notion of proximity between teammates during the match or the away how teammates performs attacking triangulations can be a very important complementary resource to identify the playing style and to justify the centrality levels. Thus, future works must use both methodologies (network approach and computational metrics based on spatio-temporal analysis) to improve the knowledge about the style of play of the teams during football games. This will be a great contribution for the future of match analysis.

Conclusion

This study aimed to analyze the network behavior of Switzerland national team during FIFA World Cup 2014. The main findings revealed that the passing sequence was based on the defenders and midfielders during the majority of the match. Moreover, it was found that the prominent players to receive the ball were the midfielders, suggesting a style of play based on attacking building and not in counter-attack or quickly attacking transition. In fact, the smallest values of centrality levels were achieved by the goalkeeper and forward player, thus representing that the premier strategy of the team was to build the attack with passes between the defensive and midfield sectors in order to build a network of support and not to exploit the counter-attack and the long passes for the forward players.

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