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Original Article

Identifying the centrality levels of futsal players: A network approach

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Abstract:
The aim of this study it was verify the differences of prominence levels between tactical positions in futsal (indoor football). For that reason, it was performed an analysis of variance between competitive levels and tactical positions for the centrality metrics computed by using network analysis. Forty-six futsal players from different competitive levels (U12, U14, U16 and Amateurs) it were analysed during three official futsal matches. Results revealed no differences in centrality metrics between competitive levels ($p = 1.00$; $\eta_p^2 = 0.001$; *very small effect size*) had no significant statistical differences in the centrality metrics. Nevertheless, tactical position ($p = 0.001$; $\eta_p^2 = 0.593$; *moderate effect size*) had significant main effects on the centrality metrics. Centrality metrics revealed that defenders are the most prominent players in to receive the ball. By the other hand, defenders and wings are the positions with greater centralities in to pass the ball for the teammates.
Keywords: Graph Theory; Adjacency Matrices; Network analysis; Performance; Passes.

Introduction

Futsal or indoor football it is a team sport with a great dynamic properties between teammates (Travassos, Araújo, Vilar, & McGarry, 2011). As a team sport, the cooperation between teammates it is a crucial factor to improve the patterns of play and the possibilities to win (Gréhaigne, Godbout, & Bouthier, 1999). For that reason, the study of cooperative process in sports must be carefully cogitated in order to identify how coaches may adjust the sports training to improve the collective performance (Clemente, Couceiro, Martins, & Mendes, 2014).

The cooperative process in sports can be understood in many ways. In fact, there are different cooperative processes from social cooperation until the cooperation in match based on actions or behaviours (Johnson & Johnson, 1989). Knowing the importance of each cooperative process for the overall result, one of the prominent cooperation occurs in the field and during the match. The interaction among teammates to conclude the attack process can be considered a specific kind of cooperation that integrates the notion of match analysis (Grund, 2012; Peña & Touchette, 2012). In the specific case, the passes between teammates can be considered as the linkage indicator (Passos et al., 2011).

There are different possibilities to study the interaction in attacking process, such as traditional notational analysis (Hughes & Franks, 2005), temporal patterns (Bloomfield, Jonsson, Houlahan, & Donoghue, 2005), artificial neural networks (Grunz, Memmert, & Perl, 2012), spatiotemporal coordination (Travassos, Araújo, Duarte, & McGarry, 2012), or the Social Network Analysis (SNA) based on graph theory (Bourbousson, Poizat, Saury, & Seve, 2010; Clemente, Martins, Kalamaras, Wong, & Mendes, 2015; Grund, 2012). Despite of the importance of each approach, the SNA provided a multiple range of possibilities to analyse the interaction, based on the multiple network metrics for centrality analysis (Clemente, Couceiro, et al., 2014) and for general analysis (Clemente, Couceiro, Martins, & Mendes, 2015).

The majority of studies of SNA in team sports have been made in football (Clemente, Martins, et al., 2015; Duch, Waitzman, & Amaral, 2010; Grund, 2012; Malta & Travassos, 2014; Peña & Touchette, 2012). The studies distribute their analysis in general properties of the team and in the centrality levels of players. In the case of general properties, the results revealed that teams with greater levels of density and cohesion increases their performance in matches and competitions (Clemente, Martins, et al., 2015; Grund, 2012). In the case of centrality levels, the teams that tends to act in attacking building or indirect attacking style has as the prominent players the external defenders and midfielders (Clemente, Couceiro, et al., 2014; Peña & Touchette, 2012). In other hand, during offensive transition (or counter-attack) the prominent players tend to be the external midfielders and the forwards (Malta & Travassos, 2014).

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If in the case of football, the SNA produced some findings in the last years, the same evidence it is not verified in futsal. In fact, the patterns of play and the intrinsic dynamics of futsal are quite different from football. For that reason, it is necessary to analyse how teammates' cooperates in attacking process during futsal matches. Based on that, this study aimed to analyse the centrality levels of cooperation of futsal players during official matches. The objective it is analyse the variance of network centrality measures between different tactical positions and competitive levels.

Methods

Sample

Forty-six futsal players (11 players of under-11; 9 players of under-14; 13 players of under-16 and 11 players in amateurs with more than 20 years) it were analysed in three official matches. A total of twelve adjacency matrices corresponding to 3128 passes were recorded based on the team-members interactions and then converted in final graphs. The study complied the ethical standards for the study in humans according to the Declaration of Helsinki.

Data Collecting

Three official matches per team it were recorded and then treated. The matches it were analysed in the home of the analysed team in order to ensure similar conditions of observation. The observation it was made by the same expert observer with previous experience in network analysis in team sports. In order to ensure the reliability of study the Cohen's kappa was tested with a 15-day interval between test and retest (Robinson & O'Donoghue, 2007). A total of 10% of the overall data was used. The value of 0.91 it was obtained from Kappa test and for that reason it was considered achieved the reliability.

Network Analysis

Each network analysis based on Graph Theory requires an adjacency matrix. This matrix represents the connections (arrows) among teammates (nodes) (Clemente, Martins, Couceiro, Mendes, & Figueiredo, 2014). As previous described, the linkage indicator between teammates it was the pass (Cotta, Mora, Merelo, & Merelo-Molina, 2013; Passos et al., 2011). Per each passing sequence without interruption (lose the ball) it were generated an individual adjacency matrix. The direction of the passes and the volume of passes it were considered to build the adjacency matrix. This process complies with similar studies in other team sports (Clemente, Couceiro, et al., 2015; Clemente, Martins, et al., 2015).

As described in the objective of the study, the aim it was compare different tactical positions. For that reason, the players were codified with the specific code of position in order to process the data. All the teams lined up with the traditional 1-1-2-1 and the codification of players' positions was: Player 1 – Goalkeeper (GK); Player 2 – Defender (D); Player 3 – Wing (W); Player 4 – Wing (W); and Player 5 – Forward (F). The graphical representation of the line up and codification can be observed in the following Fig 1.

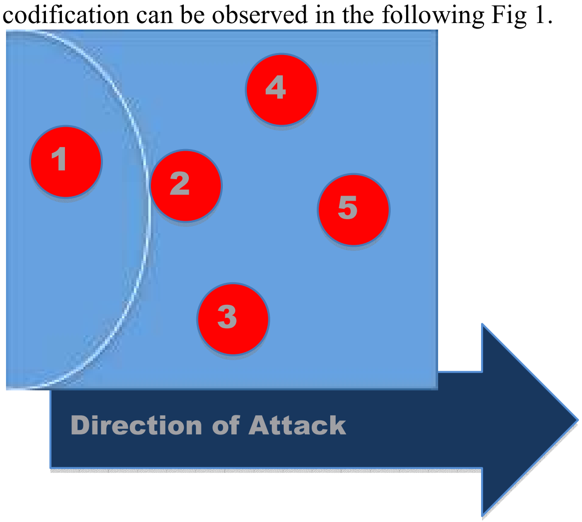

Fig 1. Tactical line-up and players' positions during the matches.

Network Metrics

Using the adjacency matrices from the observational analysis, it were computed the network metrics based on SNA. For such computation it was executed 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 (%InDegree and %OutDegree) network metrics were computed.

InDegree

The InDegree represents the prominent player in the team in to receive the ball from teammates. The following algorithm it was used in order to standardize the group size n (Opsahl, Agneessens, & Skvoretz, 2010):

$$P'^{w}{}_{D}(n_i) = \frac{k_i^{w^{in}}}{\sum_{i=1}^{n}\sum_{\substack{j=1 \\ j \neq i}}^{n} a_{ij}}, \quad (1)$$

that is the proportion of weights of nodes that are adjacent to n_i.

OutDegree

The OutDegree measures the centrality level of players in to pass the ball for the remaining teammates. The following algorithm it was used for the case of weighted digraphs (directed graphs), as a standard measure (Opsahl et al., 2010):

$$C'^{w}{}_{(D-out)}(n_i) = \frac{k_i^{w^{out}}}{\sum_{i=1}^{n}\sum_{\substack{j=1 \\ j \neq i}}^{n} a_{ij}}, \quad (2)$$

that is the proportion of weights of nodes that are adjacent to n_i.

Statistical procedures

The influences of Competitive Level and Tactical Position factors on the %InDegree and %OutDegree were analyzed using two-way MANOVA after validating normality and homogeneity assumptions. The assumption of normality for each univariate dependent variable was examined using Kolmogorov-Smirnov tests. The assumption of the homogeneity of each group's variance/covariance matrix was examined with the Box's M Test. When the MANOVA detected significant statistical differences between the two factors, we proceeded to the two-way ANOVA for each dependent variable, followed by Tukey's HSD post-hoc test (O'Donoghue, 2012). When the two-way ANOVA showed an interaction between factors, it also generated a new variable that crossed the two factors (e.g., U12*GK; U12*D) for each dependent variable to identify statistical significance (Maroco, 2012). Ultimately, the statistical procedures used were one-way ANOVA and Tukey HSD post-hoc. If no interactions were detected in two-away ANOVA, a one-way ANOVA was used for each independent variable. 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) (Lakens, 2013): small, 0.2-0.49; moderate, 0.50–0.79; large, 0.80–1.

Results

The two-way MANOVA revealed that the competitive level (p = 1.00; η_p^2 = 0.001; *very small effect size*) had no significant statistical differences in the centrality metrics. In other hand, tactical position (p = 0.001; η_p^2 = 0.593; *moderate effect size*) had significant main effects on the centrality metrics. There was significant interaction (Pillai's Trace = 1.111; F = 4.164; p = 0.001; η_p^2 = 0.555; *moderate effect size*) between competitive level and tactical position on centrality metrics. As previously indicated in the statistical procedures, a two-way ANOVA was conducted for each dependent variable after the confirmation of the interaction (O'Donoghue, 2012, p. 243). Interaction was found between factors for %InDegree (F = 4.909; p = 0.001; η_p^2 = 0.596; *moderate effect size*) and %OutDegree (F = 3.429; p = 0.002; η_p^2 = 0.507; *moderate effect size*). The one-way ANOVA tested the crossing between factors for %InDegree revealed statistical differences (F = 25.476; p = 0.001; η_p^2 = 0.924; *large effect size*), The post-hoc results observed are shown in table 1.

Table 1. Descriptive table (mean and standard deviation) and statistical comparison between crossing factors for %IdC.

	Goalkeeper (TP1)	Defender (TP2)	Wing (TP3)	Wing (TP4)	Forward (TP5)
			U12		
%IdC	1.53 (0.79)	**33.83 (2.90)**	28.73 (10.06)	21.97 (6.21)	13.93 (3.25)
			U14		
%IdC	0.74 (0.65)	**33.40 (2.69)**	18.17 (0.83)	23.20 (1.92)	24.47 (1.88)
			U16		
%IdC	3.48 (2.50)	**27.63 (3.93)**	25.90 (4.03)	21.30 (1.73)	21.73 (2.63)
			Elite		
%IdC	3.55 (1.89)	22.67 (2.58)	**27.63 (1.86)**	27.53 (0.85)	18.60 (3.24)

The one-way ANOVA tested the crossing between factors for %OutDegree revealed statistical differences (F = 7.552; p = 0.001; η_p^2 = 0.782; *moderate effect size*), The post-hoc results observed are shown in Table 2.

Table 2. Descriptive table (mean and standard deviation) and statistical comparison between crossing factors for %OdC.

	Goalkeeper (TP1)	Defender (TP2)	Wing (TP3)	Wing (TP4)	Forward (TP5)
			U12		
%OdC	9.71 (1.56)	**30.77 (2.73)**	25.50 (5.78)	23.27 (0.78)	10.76 (3.52)
			U14		
%OdC	14.10 (2.01)	23.07 (4.96)	**23.40 (1.44)**	17.37 (3.78)	22.07 (1.10)
			U16		
%OdC	14.18 (7.23)	**27.13 (2.15)**	22.07 (2.67)	18.80 (3.47)	17.87 (0.86)
			Elite		
%OdC	11.74 (5.56)	21.00 (3.95)	**24.47 (2.74)**	23.37 (3.10)	19.40 (3.54)

Discussion

This study aimed to analyse how futsal players' cooperates in attacking moments and with kind of relationship occurs during attacking building. For that reason, a network approach it was used to measure the centrality levels of each tactical position during attacking process. Moreover, it is also aim of this study to analyse the variance between centrality levels between different competitive levels.

In the specific case of competitive levels, no statistical differences were found. These results can be explained be the small number of players of futsal that reduce the possibility of interaction in comparison with sports with greater number of players. Moreover, the specific nature and dynamic of futsal may explain the similar results of centralization during attacking moments in levels between U12 and Amateurs with more than 20 years old. Moreover, the relative analysis of each measurement can deal with a standardization of significances, thus may in future studies may be better not take in account the relative number but the absolute value in order to increase the possibility of analysis.

In other hand, the analysis between tactical positions revealed statistical differences between players. Defenders and wings were the players that more balls received from the remaining teammates. These results can be explained by the specific style of play observed in all games. This style of play it was based on indirect style, thus it was verified a great volume of passing sequences and ball circulation from wing-to-wing. In this specific style of play the intervention of forward player reduces based on the defensive pressure over him. If in futsal no studies have been carried out, in the football it was possible to verify similar results for the case of teams that act in attacking building and indirect style (Clemente et al., 2014). This specific pattern of play increases the participation of defenders and midfielders explained for the lowest defensive pressure over them. Thus, similar explanation can be used for the futsal case. Maybe in the future the attacking moments can be organized in counter-attack, quick transitions and ball circulation in order to verify how prominence levels differs from player-to-player.

In the case of the analysis to the passes made from player to the teammate, the OutDegree measure identified that defenders and wings were also the prominent tactical positions. Nevertheless, if in the case of InDegree the majority of bigger results were found in defenders, in the OutDegree the results are more distributed. In fact, the wings may assume a greater prominence in the passes performed by the reason that should act as links between defence and attack. The same evidence may be verified in studies carried out in football (Cotta et al., 2013; Duch et al., 2010; Peña & Touchette, 2012).

This study had has major limitations the small number of observed matches per competitive level. Moreover, no differences between style of attack where considered. For these reasons, future studies may organize and characterize each unit of attack and to process the comparison between prominence levels from player-to-player considering the specific type of attack. It would be also interesting consider more contextual variables that may justify variances in the network patterns such as match status, the local of the game or even the period of the match.

Conclusion

In this study it was possible to identify that there are no differences in network levels between different competitive levels. Despite of that, it was possible to verify statistical interactions with tactical position factor. Defenders, in the majority of competitive levels, had the greatest levels of centrality. Wings acted as linkage players in the moment of attacking building and defenders received more passes due to the nature of indirect attack. Excluding the goalkeeper, the forwards were typically the players with smallest centralizations in comparison with defenders and wings.

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