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Original Article

Who is the prominent tactical position in rink-hockey? A network approach based on centrality metrics

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Abstract:
The aim of this study was to verify the prominence levels of rink-hockey players in different competitive levels. For that reason, it was analysed the variance of network centrality metrics between competitive levels and tactical positions. Fifty-four rink-hockey players from five different levels (U12, U14, U16, U18 and Elite) were analysed during three official matches. The results did not found statistical differences in centrality levels of players between competitive levels (*p-value* = 1.00; *partial eta square* = 0.001; *very small effect size*). Nevertheless, tactical position (*p-value* = 0.001; *partial eta square* = 0.534; *moderate effect size*) had significant main effects on the centrality metrics. In this study it was found that defender and forward are the positions that most receive balls from the teammates. In other hand, the forward is the position that most passes performed until the U16 and in older levels the defender assumes the centrality in passes performed.
Keywords: Graph Theory; Adjacency Matrices; Network Analysis; Performance; Passes.

Introduction
The rink-hockey it is specific invasion team sport where players' uses quad skate with four wheels set in two side-by-side pairs (Brázio, 2006). Each player uses a stick to drive the ball. The dynamics of rink-hockey it is very similar to any invasion team, despite the possibility to be possible to play in the back of goals. As every invasion team, the internal logic of rink-hockey deal with strategy and tactical behaviour based a cooperation-opposition relationship during all match (Griffin & Butler, 2005). As a sport that depends from the cooperation between teammates, it is very relevant to identify how the patterns of play occur (Clemente, Martins, Kalamaras, Wong, & Mendes, 2015). This specific information can be retrieved from the process of match analysis (Travassos, Davids, Araújo, & Esteves, 2013). In this scientific field there are many approaches that can provide outcomes to understand the specific dynamics of a team (Coutts, 2014).
In the sport of rink-hockey, there is a lack of match analysis studies (Brázio, 2006; Morujão & Ferreira, 2009). In the study that analysed five official matches of the U20 Portuguese Team in the European Cup, it was found that in offensive process the team generated 408 units of attacks distributed by the five matches (Brázio, 2006). From these units of attack, the majority it was based on positional attack (in circulation – indirect attack), followed by counter-attack and quick transition. Another found it was that during attacking process the majority of units of attack cover both lateral sides of the field and the central zone. Following this line of analysis, it was found in another study that central zone it is determinant in the attacking move based on the greater amount of shooting (Morujão & Ferreira, 2009). Considering the time-motion profile of rink-hockey players, it was found that rink-hockey players performs between 418 and 422 displacements per match and 43.5% of such displacements in low intensity (Tantiña, Vidal, & López, 2014). Finally, in the case of teammates interactions it was found that per each unit of attack it was made 2.73 passes in average (Brázio, 2006).
As possible to identify in the previous studies, the approach to analyse rink-hockey sport is based on traditional notational analysis that's depends from observational methodologies. In fact, the observational process it is the most common in every team sports so far (Barreira, Garganta, Castellano, & Anguera, 2013). Nevertheless, recent technological advances (in the field of tracking players) have allowing to apply some mathematical algorithms to determine the collective performance such as temporal-patterns (Jonsson et al., 2006), spatio-temporal and tactical metrics (Clemente, Couceiro, Martins, Mendes, & Figueiredo, 2014) and network analysis based on graph theory (Duch, Waitzman, & Amaral, 2010; Peña & Touchette, 2012).
This last approach (network analysis) it has been growing in the last years as an alternative approach to traditional notational analysis (Clemente, Martins, et al., 2015; Cotta, Mora, Merelo, & Merelo-Molina, 2013; Grund, 2012). No study in rink-hockey it was found. Nevertheless, in the football analysis it has been possible to

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identify that the prominent players in the attacking building are the external defenders and the midfielders (Clemente, Couceiro, Martins, & Mendes, 2014). During counter-attacks or offensive transitions the prominent players are external midfielders and forwards (Malta & Travassos, 2014). Besides this individual analysis to the centrality level of each player, it was found that teams that shows greater cooperation between teammates ensures betters results in competitions (Clemente et al., 2015; Grund, 2012).

The network analysis allows to understand how teammates cooperate and identify the prominent players in the team. Despite of such possibilities no studies it were conducted in rink-hockey. For that reason, this study aims to analyse the cooperation process of rink-hockey players in attack process and identify the most prominent players. More specifically, an analysis of variance it will be conducted to analysis the variance of centrality levels between tactical positions and competitive levels.

Methods

Sample

Fifty-four rink-hockey players from five different levels (10 players of under-12; 11 players of under-14; 10 players of under-16, 12 players of under-18 and 11 players in elite players with more than 20 years) it were analysed in three official matches. A total of fifteen adjacency matrices corresponding to 3450 passes were recorded based on the teammates 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 it were analysed per each competitive level. Only home matches it were considered in order to ensure similar conditions in the analysis. In order to guarantee the reliability of the data, the same observer perform a test-retest analysis of the 10% of the full data. The Cohen's kappa was tested with a 15-day interval between test and retest (Robinson & O'Donoghue, 2007) and the result 0.87 from Kappa test showed the conditions to carried out the analysis.

Network Analysis

The network analysis carried out in this study it was made in two steps. In the first step it was codified each tactical position. All the teams lined up with 1-1-2-1 formation (in the majority of the time) and the codification of players' positions was: Player 1 – Goalkeeper (GK); Player 2 – Defender (D); Player 3 – Right Wing (W); Player 4 – Left Wing (W); and Player 5 – Forward (F). The graphical representation of the line up and codification can be observed in the following Figure 1.

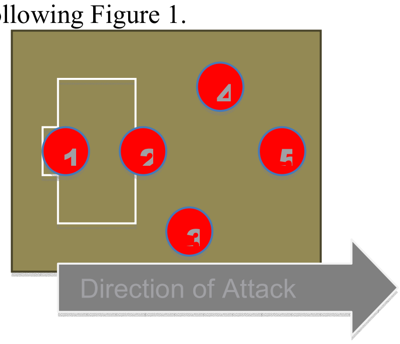

Figure 1. Tactical line-up and rink hockey players' positions during the matches.

To perform the network analysis it was required an adjacency matrix. This matrix represents the numeric relationship (arrows) between teammates connections (nodes) (Clemente, Martins, Couceiro, Mendes, & Figueiredo, 2014)). The linkage indicator it was the pass between two players (Cotta et al., 2013; Passos et al., 2011). Each unit of attack (passing sequence) resulted in an adjacency matrix. As a team sport, it were considered the direction of the passes (player A to player B or player B to player A) and the weight (number of passes in the same direction) to build the adjacency matrix. This process follows previous protocols in other team sports (Clemente, Couceiro, Martins, & Mendes, 2015; Clemente, Martins, et al., 2015).

Network Metrics

The social network analysis (SNA) approach it was followed to analyse the centrality levels of the players. The computation of network metrics it were executed in the *Social Network Visualizer* software (version 1.5.). This software allows to visualize the graphical representation of teammates cooperation and also provide valuable outputs about the network metrics (Kalamaras, 2014). Two centrality (%InDegree and %OutDegree) network metrics were computed.

OutDegree

The OutDegree metric identify the centrality level a player in to pass the ball. The following algorithm it was used for the case of weighted digraphs (directed graphs), as a standard measure (Opsahl, Agneessens, & Skvoretz, 2010):

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

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

InDegree

The InDegree represents the centrality level of a player in the team. Specifically, identifies the most recruited players to receive the ball. The following algorithm it was used in order to standardize the group size *n* (Opsahl et al., 2010):

$$P^{rw}{}_{D}(n_i) = \frac{k_i^{w^{in}}}{\sum_{i=1}^{n} \sum_{\substack{j=1 \\ j \neq i}}^{n} a_{ij}}, \tag{2}$$

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; *partial eta square* = 0.001; *very small effect size*) had no significant statistical differences in the centrality metrics. In other hand, tactical position (*p-value* = 0.001; *partial eta square* = 0.534; *moderate effect size*) had significant main effects on the centrality metrics. There was significant interaction (Pillai's Trace = 0.994; F = 14.338; *p-value* = 0.001; *partial eta square* = 0.497; *small 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 = 4.531; *p-value* = 0.001; *partial eta square* = 0.592; *moderate effect size*). No differences were found between factors for %OutDegree (F = 1.402; *p-value* = 0.180; *partial eta square* = 0.310; *small effect size*).

The one-way ANOVA tested the crossing between factors for %InDegree revealed statistical differences (F = 25.367; *p-value* = 0.001; *partial eta square* = 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)	Right Wing (TP3)	Left Wing (TP4)	Forward (TP5)
U12					
%IdC	0.01 (0.01)	**30.27 (5.32)**	21.80 (1.10)	17.97 (3.06)	29.93 (1.25)
U14					
%IdC	0.01 (0.01)	21.47 (1.40)	24.73 (1.68)	26.63 (2.71)	**27.20 (2.19)**
U16					
%IdC	0.01 (0.01)	23.17 (1.80)	23.30 (3.80)	24.20 (2.29)	**29.30 (4.29)**
U18					
%IdC	0.01 (0.01)	**27.13 (4.05)**	25.13 (0.71)	26.50 (5.39)	21.30 (2.21)
Elite					
%IdC	0.01 (0.01)	27.40 (2.76)	21.73 (2.47)	22.03 (1.48)	**28.87 (1.27)**

One-way ANOVA was used as no interaction between factors was found. The results for %OdC (Table 2) showed no statistical differences in the GK (F = 1.38; *p-value* = 0.31; *partial eta square* = 0.36; moderate effect size), D (F = 0.581; *p-value* = 0.68; *partial eta square* = 0.19; *small effect size*), RW (F = 1.43; *p-value* = 0.29; *partial eta square* = 0.36; *small effect size*), LW (F = 0.57; *p-value* = 0.69; *partial eta square* = 0.19; *small effect size*) and F (F = 1.75; *p-value* = 0.22; *partial eta square* = 0.41; *small effect size*) positions.

Table 2. One-way ANOVA values in competitive level in each tactical position in %OdC.

		M(SD)	F	*p-value*	*partial eta square*
GK	U12	3.70 (2.83)	1.384	0.307	0.356
	U14	1.01 (1.32)			
	U16	2.11 (2.03)			
	U18	0.63 (0.60)			
	EL	1.31 (1.36)			
D	U12	26.37 (1.31)	0.581	0.683	0.189
	U14	26.93 (2.90)			
	U16	24.03 (2.80)			
	U18	27.00 (2.08)			
	EL	26.57 (4.08)			
RW	U12	18.17 (1.75)	1.432	0.293	0.364
	U14	22.33 (1.80)			
	U16	24.53 (6.55)			
	U18	23.60 (3.21)			
	EL	24.83 (4.18)			
LW	U12	23.37 (1.79)	0.567	0.693	0.185
	U14	22.33 (2.14)			
	U16	23.27 (3.71)			
	U18	26.87 (5.95)			
	EL	23.50 (4.80)			
F	U12	28.43 (1.37)	1.751	0.215	0.412
	U14	27.40 (5.86)			
	U16	26.03 (2.54)			
	U18	21.97 (2.90)			
	EL	23.87 (2.85)			

One-way ANOVA was used as no interaction between factors was found. The results for %OdC (Table 3) showed no statistical differences in the U12 (F = 82.35; *p-value* = 0.00; *partial eta square* = 0.97; *large effect size*), U14 (F = 34.00; *p-value* = 0.00; *partial eta square* = 0.93; *large effect size*), U16 (F = 20.18; *p-value* = 0.00; *partial eta square* = 0.89; *large effect size*), U18 (F = 31.13; *p-value* = 0.00; *partial eta square* = 0.93; *large effect size*) and Elite (F = 24.74; *p-value* = 0.00; *partial eta square* = 0.91; *large effect size*) competitive levels.

Table 3. One-way ANOVA values in tactical position in each competitive level in %OdC.

		M(SD)	F	*p-value*	*partial eta square*
U12	$GK^{b,c,d,e}$	3.70 (2.83)	82.349	0.001	0.971
	$D^{a,c}$	26.37 (1.31)			
	$RW^{a,b,e}$	18.17 (1.75)			
	LW^{a}	23.37 (1.79)			
	$F^{a,c}$	**28.43 (1.37)**			
U14	$GK^{b,c,d,e}$	1.01 (1.32)	33.996	0.001	0.931
	D^{a}	26.93 (2.90)			
	RW^{a}	22.33 (1.80)			
	LW^{a}	22.33 (2.14)			
	F^{a}	**27.40 (5.86)**			
U16	$GK^{b,c,d,e}$	2.11 (2.03)	20.175	0.001	0.890
	D^{a}	24.03 (2.80)			
	RW^{a}	24.53 (6.55)			
	LW^{a}	23.27 (3.71)			
	F^{a}	**26.03 (2.54)**			
U18	$GK^{b,c,d,e}$	0.63 (0.60)	31.130	0.001	0.926
	D^{a}	**27.00 (2.08)**			
	RW^{a}	23.60 (3.21)			
	LW^{a}	26.87 (5.95)			
	F^{a}	21.97 (2.90)			
Elite	$GK^{b,c,d,e}$	1.31 (1.36)	24.739	0.001	0.908
	D^{a}	**26.57 (4.08)**			
	RW^{a}	24.83 (4.18)			
	LW^{a}	23.50 (4.80)			
	F^{a}	23.87 (2.85)			

Statistical different from GK^{a}; D^{b}; RW^{c}; LW^{d}; and F^{e} for a p-value < 0.05

Discussion

This study aimed to analyse the attacking prominence of rink-hockey players in different competitive levels. The tactical positions were considered and the network analysis it was used to identify the prominence in the cooperation process during attacking building. The results found no statistical differences of centrality levels between different competitive levels. Nevertheless, differences were found between tactical positions in both centrality metrics computed in this study.

The individual participation of each player during attacking moments can be constrained by his tactical position. In previous studies performed in football it was found that midfielders and external defenders are the prominent positions during attacking building (Clemente et al., 2014). In the present study it was verified that defenders and forwards are the players that most ball received from the teammates. Goalkeepers (by their specific position) and wings were the players that received less passes. This specific result can suggest that the team opts to pass for the forward in order to process the attack and to defender in order to ensure the possession of the ball. Wings position may be classified as the position with more pressure to receive the ball and for that reason the team opt or to move back or to quick move forward. This specific result it is not in line with previous studies in football where midfielder assumes the major prominence in attacking building (Cotta et al., 2013; Peña & Touchette, 2012).

Besides the prominence in to receive the ball from teammates, similar results were found in to pass the ball. The OutDegree centrality revealed that defenders and forwards are the players that most passes performs for teammates. Nevertheless, a particular evidence it was found. In U12, U14 and U16 level it was found that forward made more passes that remaining players. By the other hand, in U18 and elite levels it was found that the defender position was the player with greater OutDegree levels. This may be explained by the utilization of the best young player as forward in young levels what allow to this player have more possession of the ball and be more accurate in to move the ball for teammates. In forward competitive levels, the sport may be more tactical and the defender assumes a greater prominence in to be the player that starts the attack and the reference to keep the possession of the ball.

Despite of differences of network centrality levels between tactical positions, no differences were found between competitive levels. In fact, this can be explained by the small number of players what makes the system nature of the game more predictable to generate the prominent players. Moreover, the relative measurements may be not the best algorithms to compare between different competitive levels. For that reason will be recommended to use the algorithm that use the absolute values trying to understand the differences between both.

Besides this limitation, this had a small number of official matches tracked per competitive level. For this reason, will be necessary in future studies to increase the number of matches recorded and try to identify similarities and differences between different teams in the same competitive level. Will be also important to add some contextual variables that can explain the cooperation tendencies such as match status, periods of the match and the level of opponent team. It is also interesting to organize the attacks in different categories such as counter-attack, quick transitions and ball circulation in order to verify if prominence levels and tendencies varies between these categories of attack.

Conclusion

This study it was pioneer to apply the network analysis in rink-hockey sport. The attacking process it was observed based on the cooperation between teammates in order to verify the prominent players. The results did not found statistical differences of network centralities between different competitive levels. Nevertheless, statistical differences were found between tactical positions. It was found that defenders and forwards were the positions that more balls received from the teammates and more passes performed. Wing players are the players with smallest prominence levels. Future studies must organize the attacking process in categories in order to verify if prominence tendencies differs from the specific type of attack.

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