Analysis of the interaction and offensive network of the Portuguese national team at the 2016 European Football Championship
Análisis de la interacción y red ofensiva de la selección portuguesa en la Eurocopa de Fútbol 2016

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Abstract. The aim of this study was to analyse the offensive actions preceding shots, using a combination of pass sequences and *network analysis* of the Portuguese national football team in the European Championships. The sample consisted in the observation and analysis of 118 collective offensive actions that ended in a shot based on seven European Championships matches (e.g., 3 x group stage matches, 1 x round of 16, 1 x quarter-finals, 1 x semi-finals and 1 x final). The results indicated that 488 intra-team interactions were performed, and the highest level of interactions occurred between player number 10 (midfielder) and player number 7 (forward), with a total of 11 interactions. More passes were made during the group phase (97.3 ± 50.1 passes), compared with the knockout phase (49 ± 23.6 passes), assuming that the team adapted to their rivals during the last phase of the competition. The *In-Stat©* platform was used to access the matches in a video file format and consequently coded through the VideObserver® and Upato® software's. This study demonstrates important trends in relation to passing sequences and adds key insights into interactional context within and between players during a European Championships. On a practical level with this type of analysis, coaches can characterise the standard actions of a team, as well as identify key players. This may allow coaches to realize what players contribute in the dynamics of their team as well as the opponent.
Keywords: Network, Football, Match Analysis, VideObserver®, UPato®.

Resumen. El objetivo del estudio fue analisar las acciones ofensivas que preceden a los tiros, utilizando una combinación de secuencias de pases y análisis de redes de la selección portuguesa de fútbol en los Campeonatos de Europa. La muestra consistió en 118 acciones ofensivas colectivas que terminaron en un tiro basado en siete partidos del Campeonato de Europa (por ejemplo, 3 partidos de la fase de grupos, 1 de octavos de final, 1 de cuartos de final, 1 de semifinales y 1 de final) . Los resultados indicaron que se realizaron 488 interacciones intra-equipo, y el mayor nivel de interacciones se dio entre el jugador número 10 (centrocampista) y el jugador número 7 (delantero), con un total de 11 interacciones. La mayor parte del número de pases se realizaron durante la fase de grupos (97,3 ± 50,1 pases), frente a la fase eliminatoria (49 ± 23,6 pases), suponiendo que el equipo se adaptó a sus rivales durante la última fase de la competición. Se utilizó la plataforma InStat© para acceder a los partidos en formato de archivo de video y, en consecuencia, se codificó a través de los software VideObserver® y Upato®. Este estudio demuestra tendencias importantes en relación con las secuencias de pases y agrega información clave sobre el contexto interactivo dentro y entre los jugadores durante un Campeonato de Europa. A nivel práctico con este tipo de análisis los entrenadores pueden tener una caracterización de las acciones estándar de un equipo, así como, la identificación del jugador clave les permite a los entrenadores darse cuenta de lo que los jugadores aportan en la dinámica de su equipo y del rival.
Palabras Clave: Rede, Fútbol, Analisis de Juego, VideObserver®, UPato®.

Introduction

Match analysis has grown exponentially in recent years and is an important given the technological advances that have occurred in the match (Araújo, Freire, Folgado, Fernandes and Davids, 2012; McHale and Relton, 2018). In this sense, video analysis software's has played a key role in this transformation with some pertinent case studies at the elite level of sport such as Oakland Athletics in Major League Baseball (cf. McHale and Relton, 2018).

Coaches, analysts and researchers use match analysis to identify team's match patterns during key moments of the match. Using network analysis, it is possible to identify what patterns exist among the players of the team (Passos, Davids, Araújo, Paz, Minguéns and Mendes, 2011; Clemente, José, Oliveira, Martins, Mendes, Figueiredo, Wong and Kalamaras, 2016b). Hence, Passos et al. (2011) analyzed the network trends in water polo, and quantified the various interactions between players and how they

contribute to the success of the team.

Regarding football, Gama, Passos, Davids, Relvas, Ribeiro, Vaz and Dias (2014); Gama, Dias, Couceiro, Sousa and Vaz (2016) found that the offensive actions mainly occur, in the offensive midfield area and also concluded that this mode of analysis could give an insight into the interpersonal and intrapersonal relationships within football match play. Garrat, Murphy and Bower (2017) analyzed the passing sequences that resulted in a goal by analysing a total of 36,397 ball possessions. The authors concluded that more goals were scored in sequences of five or more passes, with a conversion rate of 13 goals per 1000 possessions compared to shorter passing sequences with a total of 6 goals per 1000 possessions.

In football, the use of network analysis has gained attention in the last years, and it's been used to breakdown patterns of play and tactics (Ribeiro, Silva, Duarte, Davids and Garganta, 2017). The nodes are represented as players and are connect to each other by links and in the case of

football they are connected through passes. The number of connections is represented by an adjacency matrix where researchers can characterize the team collectively and individually (Passos et al., 2011).

Using network analysis enables coaches to identify key players who have greater prominence in the offensive process of a team in order to prime further their own teams offensive threat or to nullify an opposition teams threat. This type of analysis has been used effectively for recruitment purposes as McHale and Relton (2018) used this to justify the purchases of Luis Suarez in 2014 and Gareth Bale in 2013 from FC Barcelona and Real Madrid respectively, for high transfer fees. Following in same line, Yu, Gai, Gong, Gómez and Cui (2020), aimed to compare the passing performance between foreign and domestic players in the Chinese Super League, and they found out that foreign players had an important role in the offensive contribution of the team, especially midfielder. They had higher values in outdegree and closeness centrality.

Network analysts use a variety of metrics to characterize the organization of a team and the role of each player to understand their contribution inside the team (Clemente, Martins, Kalamaras, Wong and Mendes, 2015b; Martinez, Garrido, Herrera-Diestra, Busquets, Sevilla-Escoboza, and Buldu, 2020). In this case, e.g., metrics like degree centrality can give information about the overall contribution of a player in the ball possession of the team.

Aquino, Carling, Vieira, Martins, Jabor, Machado, Santiago, Garganta and Puggina (2020), studied the impact situational variables, team formation and playing position on match running performance and social network analysis of Brazilian professional football players, and they found out in the network analysis that central and external midfielders had greater values in closeness centrality, betweenness centrality, outdegree and eigenvector centrality compared with central and external defenders, and forwards. This is because midfielders control the team organization and in most of the cases, they are the key-players of the team.
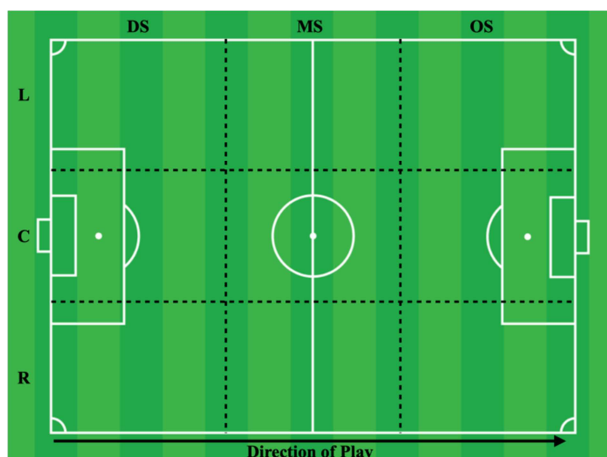

Figure 1. Match field chart (adapted from the one used by Alves et al., 2016). Sectors: DS - Defensive Sector, MS - Medium Sector; OS - Offensive sector; Side Corridors:L - Left, C - Central, R - Right.

In a study about the network centrality variations be-

tween playing positions in the 2018 FIFA World Cup, it was concluded that defensive midfielders and central defenders had greater values of degree centrality, indicating that they were the ones who contributed more to the ball possession of the team (Clemente, Sarmento and Aquino, 2020).

Given the above, this study analysed the offensive actions preceding shots, using the passing sequences and *network analysis* of the Portuguese national football team in the 2016 European Football Championships. In addition, through the network, we will be able to identify who the key players are and how they contribute to team dynamics.

Material and methods

Sample

The sample consisted of the analysis of 118 collective offensive actions that ended in shot/finishing, resulting from the observation of seven matches of the Portuguese football team (e.g., 3 group stage matches, 1 match of the round of 16, 1 quarter-final match, 1 semi-final match and 1 final match), during the 2016 European Football Championship, held in France 2016, with a level of opponent «Medium-High».

Procedures

Through the Instat platform we had access to the video matches and the match data was obtained through the Software VideObserver®, allowing to analyze all collective offensive sequences that resulted in finishing. To this end, in the course of each collective offensive action, originated from the recovery of the team's possession until the moment of completion, all contacts with the ball from the team were made on the field (e.g., passes, reception of the ball, crosses, shots, recoveries and losses of the ball) (Alves, Dias, Gama, Vaz and Couceiro, 2016) were recorded. In order to analyze the level of intra-team interaction, the technical actions were selected: passing and receiving the ball, with a view to mapping the network of interactions that took place among the players of the selection. Thus, an adjacency matrix was generated (Passos et al., 2011). So, it was possible to measure the key players who interacted most with each other. Across the board, players from the same selection were identified and coded according to their tactical positions in the match.

In order to identify the areas of greatest intervention of the team in the match(s), the VideObserver software®, which considered the sub-division of the field adopted by Alves et al., 2016), being operationalized for this specific program (Figure 1). This field had a division of 9 areas of play, consisting of 3 sectors (defensive, medium and offensive) and 3 lateral areas (left, central and right).

After this procedure, we exported the data from the team's interaction matrix (Table 4) into the UPato Software® (Clemente, Silva, Martins, Kalamaras and Mendes, 2016a), in order to apply a set of centrality metrics associ-

ated with the social network analysis, namely: *Network Density, Degree Centrality* and *Degree Prestige* described by some authors (Borgatti, Mehra, Brass and Labianca, 2009; Gama, Dias, Couceiro and Vaz, 2017; Peña and Touchette, 2012), which were adapted in the present study.

According to some authors we define the following metrics: i) Density: characterize the amount of cooperation between teammates; ii) Degree Centrality: consists in the level of connection of a player with his teammates; iii) Degree Prestige: consists in the number of links a player receives from his teammates (Grund, 2012; Peña and Touchette, 2012; Clemente, Sarmento and Aquino, 2020; Sarmento, Clemente, Gonçalves, Harper, Dias and Figueiredo, 2020; Ichinose, Tsuchiya and Watanabe, 2021).

For statistical analysis were used SPSS (version 26, IBM Corporation, Armonk, NY, USA). For the total number of passes made, independent samples t-test were used to determine differences between the group and knockout phase. Data is presented as total, mean, standard deviation (SD), coefficient of variation (CV%) and the level of significance was set at $p < 0.05$.

Results

Table 1 shows the notational analysis during the course of the competition in each of matches observed.

Table 1.
Notational analysis of the passes in the 7 matches played.

Variables	Total	Mean	SD	CV%	P value
Passes from all matches	488	69.7	42.2	60.6	
Passes from the group phase	292	97.3	50.1	51.5	0.144
Passes from the knockout phase	196	49	23.6	48.2	

The notational analysis indicated that the overall number of passes made during the group in the actions that ended with finishing were higher (292 passes) compare with the knockout phase (196 passes). Although there were more matches in the knockout phase (n=4 matches), the average number of passes were greater in the group phase (97.3 ± 50.1 passes), compared with the knockout phase (49 ± 23.6 passes). Despite that, there was no significant differences ($p > 0.05$) in the total number of passes in the actions that ended in finishing between the group and knockout phase.

Table 2 shows the number of the offensive sequences that resulted in finishing in each of matches observed.

Table 2.
Offensive actions that resulted in finishing over the 7 matches played.

VARIABLES UNDER STUDY	MATCH 1 GROUP	MATCH 2 GROUP	MATCH 3 GROUP	MATCH 4 8th FINAL	MATCH 5 4er FINAL	MATCH 6 SEMI FINAL	MATCH 7 FINAL	TOTAL
Offensive Actions with finishing	27	23	19	5	17	16	11	118
Shots Saved by opponents GK	9	6	3	1	4	3	4	30
Missed Shots	8	10	11	3	3	8	6	49
Intercepted Shots	9	7	2	0	9	3	0	30
Goals during ball in play	1	0	2	1	1	1	1	7
Goals through set pieces	0	0	1	0	0	1	0	2
Total goals in the match	1	0	3	1	1	2	1	9
Total of passes during the sequences that ended with finishing	154	59	79	17	70	63	46	488

The results indicated that the Portuguese National Football Team carried out a total of 118 collective offensive actions, which resulted in finishing, and only 9 were achieved in goal. In this follow-up, a total of 30 shots were defended by the goalkeeper and another 30 shots were intercepted and 49 missed shots. We can observe that most of the offensive actions occurred in the group phase compare with the knockout phase, not only in the number of passes (Table 1) but as well in the number of actions with finishing and in the number of shots.

Table 3 shows the passing sequences that occurred during offensive actions that resulted in finishing

Table 3.
Example of data structure of passing sequences (PS) that resulted in finishing (G=goals) over the 7 matches played.

PS	MATCH 1 GROUP		MATCH 2 GROUP		MATCH 3 GROUP		MATCH 4 8th FINAL		MATCH 5 4er FINAL		MATCH 6 SEMI FINAL		MATCH 7 FINAL		TOTAL	
	PS	G	PS	G	PS	G	PS	G	PS	G	PS	G	PS	G	PS	G
1	3	0	7	0	2	0	2	0	1	0	3	0	2	0	20	0
2	3	0	2	0	2	1	0	0	3	0	1	1	1	0	12	2
3	5	0	0	0	3	1	0	0	1	0	1	0	0	0	10	1
4	2	0	0	0	0	0	1	0	4	1	3	0	1	1	11	2
5	1	0	0	0	2	0	0	0	2	0	1	0	0	0	6	0
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
30	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
Total	21	1	14	0	13	2	4	0	15	1	13	2	7	1	87	7

The team made a total of 87 passing sequences from the moment they regained possession until finishing their offensive process. Thus, a total of 53 short passing sequences (e.g. less than 5 passes) were performed in actions that resulted in finishing, unlike longer passing sequences, with a total of 34 passing sequences. In this sense most of the attacks made by the Portuguese national team can by fast and counter attacks. The goals scored resulted mostly

in shorter passing sequences (e.g., 5 goals). This type of data can give information about the type of attacks a team made during a match, helping to identify their game model.

Table 4 indicated the interactions established between players in the sum of the 7 matches observed.

Table 4.
Example of data structure of interactions established between players during the offensive actions that resulted in finishing.

From/To	1	3	5	6	7	8	10	11	13	15	16	17	20	14	4	19	21	2	23	9	Total
1	-	5	0	2	1	0	0	0	1	0	0	0	0	2	1	0	0	0	0	0	12
3	0	-	1	10	3	2	3	4	2	2	0	1	1	1	1	1	1	0	0	0	33
5	0	1	-	2	7	3	7	0	6	5	2	3	1	1	0	0	0	1	2	0	41
6	2	3	6	-	0	2	0	0	4	3	1	0	0	2	0	1	0	0	0	0	24
7	0	0	3	0	-	1	7	2	3	2	4	8	0	3	0	2	1	0	2	0	38
8	0	3	6	3	3	-	3	1	1	5	0	7	0	2	0	0	2	0	0	1	37
10	0	3	4	1	11	3	-	2	1	1	4	7	3	1	4	1	0	0	0	0	46
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
Total Received	3	27	37	24	65	30	44	21	29	27	28	52	17	26	10	13	15	4	14	2	488
Total Completed	12	33	41	24	38	37	46	29	29	26	24	37	21	27	9	16	19	5	15	0	488
Intervention	15	60	78	48	103	67	90	50	58	53	52	89	38	53	19	29	34	9	29	2	976

The results show that 488 intra-team interactions were performed, and the highest level of interactions occurred between player number 10 (midfielder) and player number 7 (forward), with a total of 11 interactions, followed by player number 3 (defender) and player number 6 (defender), with a total of 10 interactions.

Regarding the number of interactions performed, player number 10 (midfielder) was the player who performed the most passes in the offensive actions that resulted in finishing with a total of 46 interactions performed.

On the other hand, the player who received the most interactions was player number 7 (forward), with a total of 65 interactions received. Finally, at the level of interventions (sum of interactions made and received (Gama et al., 2014; Alves et al., 2016), the players with the highest values were player number 7 (forward), with a total of 103 interventions, followed by player number 10 (midfielder), with a total of 90 interventions, and finally player number 17 (number), with a total of 89 interventions.
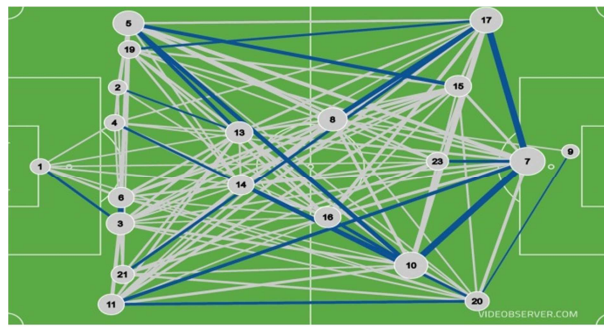

Figure 2. *Network* established among players, resulting from the offensive actions that ended in finishing.
Caption: The team's direction of attack is displayed through the black arrow displayed along the playing field charts. N*etwork*: the increase in the level of interaction between players is represented by the increase of thickness in the arrows, while the preference of interaction is presented by the color blue. On the other hand, players with the highest rate of intervention in the team are represented by the increase of the circle.
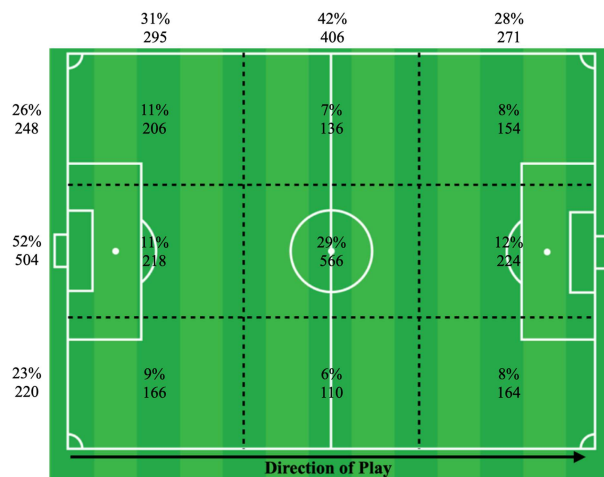

Figure 4. Team interaction areas resulting from offensive actions that ended in finishing. The direction of attack is represented through the black arrow displayed along the field chart.

Through the *network,* we were able to realize that the team tried to play in a tactical system 1-4-3-3, trying to play in the entire width and depth of the field, and through the passing sequences, we can identify that there were a greater number of shorter passing sequences, leading us to state that the team tried to use with some frequency the offensive methods of play, the quick attack and the counter attack.

The areas of greatest interaction occurred in particular in the central corridor, mainly in the middle sector center (29%) and in the offensive sector center (12%).

Table 5 represents the network's metrics, and through them we can see how players contribute to the team.

Table 5. Metrics applied to *network analysis* in offensive actions that resulted in completion.

PLAYERS	DEGREE CENTRALITY	DEGREE PRESTIGE
1	0.024590	0.006148
3	0.067623	0.055328
5	0.084016	0.075820
6	0.049180	0.049180
7	0.077869	0.133197
8	0.075820	0.061475
10	0.094262	0.090164
11	0.059426	0.043033
13	0.059426	0.059426
15	0.053279	0.055328
16	0.049180	0.057377
17	0.075820	0.106557
20	0.043033	0.034836
14	0.055328	0.053279
4	0.018443	0.020492
19	0.032787	0.026639
21	0.038934	0.030738
2	0.010246	0.008197
23	0.030738	0.028689
9	0.000000	0.004098
Density : 0.11675		

The analysis of networks metrics helps to understand the contribution of a given player in the overall performance of the team.

The *Density* level of the network that occurred during the offensive sequences that resulted in finishing is 0.11675. In the *Degree Centrality,* player number 10 (midfielder), was the player who presented himself as the most central player on the network. And in the *Degree Prestige*, player number 7 (forward), was the player more engaged by his teammates.

Discussion

This study analysed the offensive actions preceding shots, using the passing sequences and *network analysis* of the Portuguese national football team in the European Championships. In addition, through the network, we will be able to identify who the key players are and how they contribute to team dynamics. In the context of the analyzed matches, the present data demonstrates that most of the offensive actions that resulted in shots were more frequent in the group stages than the knockout phase of the competition. This is due to the team's strategic approach as well as the level of the opponent as the competition

progressed. This finding is line with Couceiro, Dias, Silva and Araújo (2018) as they demonstrated that in the group phase, teams made a greater number of passes in contrast to the opponent, but that in the knockout phase, the *network analysis* highlighted different characteristics compared to the group phase, despite there were no significant differences between the total number of passes in the actions that ended in finishing between the group and knockout phase.

The passing sequences results are in accordance with the studies of Reep and Benjamin (1968), Hughes and Franks (2005) and Alves et al. (2016) where most of the actions and goals scored occurred in shorter passing sequences. The data are also in agreement with McLean, Salmon, Gorman, Naughton and Solomon (2017a), who compared the Euro 2016 and American Cup 2016 and found that most of the goals scored occurred from shorter passing sequences. In addition to these authors, the results are in accordance with McLean, Salmon, Gorman, Stevens and Solomon (2017b), where all networks that resulted in goals scored in the 2016 European Football Championship were analyzed, having identified that most goals occur in fast and direct attacks, containing a *network* of fewer passes. In a study that analysed specifically the performance of a Spanish club playing in the Spanish first division, it was concluded that most of the goals conceded by that team came by passing sequences with three (3) or less passes (Aguado-Méndez, Gonzálex-Jurado and Otero-Saborido, 2020). McLean et al. (2017b) also verified that the variation of passes was from 1 to 29 passes, which is in accordance with the 1 to 30 passes found in the present study. This leads us to think that the team in the group stage has obtained a greater number of passing sequences in relation to the knockout phase. This may be due to the strategy adopted by the team in each stage or match of the competition, taking into account the level of the opponent. Moreover, Clemente, Martins and Mendes (2016c), states that the teams in the knockout stage, when they are in advantage, seek to have more a defensive structure and then exploit the counter attack.

The results are not in line with Clemente, Martins, Kalamaras, Wong and Mendes (2015a), in which it states that the teams that qualify for the final stages of the competition are the ones with the highest values in terms of interactions with teammates. This fact is something interesting because the team under study was the winner of this competition. Which leads us to point out that to score the team has to have possession, but in some cases the percentage of possession may not be a good indicator that the team is playing well (Lago-Peñas and Dellal, 2010). Which leads us to say that the team in question has adapted to the level of the opponents and the stage of the competition, and that can be observed in the average number of passes made during the group (97.3 passes) and knockout phase (49 passes).

Regarding the *network,* the data show that the player number 10 (midfielder) performed more interactions with

the player number 7 (forward), in a total of 11 interactions, being the player who received the most interactions. It is important to note that player number 10 (midfielder) was the player who made the most interactions, with a total of 46 interactions. This is due to the fact that this player played in a position that allowed him to manage the organization of the team's match, on the other hand, player number 7 (forward) was the player who received the most interactions throughout the matches in a total of 65 interactions, being the reference of the team (Alves et al, 2016). These values make sense because it is usually the midfielders who seek to organize the team match and the forwards seek to receive the ball in the more advanced sectors of the field in order to finish the team's passing sequences (Peña and Touchette, 2012; Clemente et al., 2016b).

Through the sum of the interactions received and performed, we obtained the total number of interventions performed, thus the player number 7 (forward) obtained a total of 103 interventions, then player number 10 (midfielder) who obtained a total of 90 interventions. Thus, player number 7 is considered the key player of the team, these results are in line with Alves et al. (2016) who states that the central midfielder and the forward were the players who got the most interventions. The key players play an important role in the team dynamics, and the development of the offensive process goes through these (Alves et al., 2016). Through this data we can identify certain patterns of play, which players are most important in the offensive dynamics of the team, so that coaches better understand the idea of the match they want their team to take.

At the level of the interaction zones, these occurred mostly in the middle center sector (29%) and in the offensive sector center (12%), these results are partially in accordance with Alves et al. (2016) where they report that the actions that resulted in finishing occurred in the offensive sector. Through centrality metrics we can see how players have contributed to the team dynamics (Peña and Touchette, 2012). We can perceive the level of interaction between players in the density of the team, because if the value has a tendency to 1.00 is considered a strong interaction (Gama, Couceiro, Dias and Vaz, 2015). Taking into account the amount obtained from 0.11675, leads us to conclude that there was not a very strong relationship between the players throughout the competition (Grund, 2012; Gama et al., 2015). Much for the fact that this study only extracted the data of the actions that ended up in finalization and not the entire match.

In the Metric *Degree Centrality*, the player number 10 (midfielder), was the player who presented himself as the most central player of the network and the one who contributed more during the passing sequences of the team by executing mores passes, being in line with Alves et al. (2016), considering that this was the second player with the highest values for key player. Usually, the players who act in this position are the ones who present the higher values of *degree centrality* because they are fundamental to continue the attack of their team, making the connection of the first phase of attack to the forwards (Clemente, Couceiro, Martins and Mendes, 2014; Clemente et al., 2016b; Duch, Waitzman, Amaral, 2010; Malta and Travassos, 2014; Peña and Touchette, 2012; Clemente et al., 2020; Sarmento et al., 2020). As in metric *Degree Prestige*, player number 7 (forward) presented the greater level of intermediation of the team showing how fundamental this player is in the offensive actions of the team, always looking to be a solution to receive the ball from his teammates, being this to be considered the key player of the team. Usually, midfielders are the ones who had greater levels (Clemente, Sarmento, Praça, Nikolaidis, Rosemann and Knechtle, 2019 and 2020; Sarmento et al. 2020), since forwards are the most advance players of the team, they are usually recruited by their peers to finish the passing sequences, receiving the last pass (Yu et al. 2020). Clemente et al. (2019), states that in unbalances scores, the level of centrality increases in the players playing in this position. However, we need to take account, that this study only considers the offensive actions that ended in finishing, so in a certain way it's understandable the results.

At a practical level the use of network analysis allows coaches and analysts and to have a characterization of the playing patterns of a given team, understanding which players contributed more to the dynamics of the team, the use of centrality metrics like the ones in this study, identify in depth the overall influence of the players in the team. For example, the identification of the key player acknowledges the player who contribute more to the offensive process of the team. When analysing the opponent this can help coaches to create strategies to stop their influence and be more careful.

In terms of the competition, coaches must be aware of the adaptions as well the level of opponent, because we can see that during the knockout phase, teams tend to adapt.

Conclusion

Using specialized programs for match analysis and the network, such as those used in this study, allow analysts and researchers a better management of their time, making their work more practical, only in this study we validated two programs: VideObserver® and UPato®.

The present study revealed that through the analysis of passing sequences and passing network, researchers and coaches can have identified the patterns of play of a given team and the players who contributed more to the attacking process. It was observed that most of the attacks occurred from shorter passing sequences. The player number 10 (midfielder) made the greatest number of interactions, and the player number 7 (forward) was the one who received more interactions. Through the analysis of network metrics, we can observe as well that these two players were considered the most important in the organization of

the team.

This study has some limitations, such as the fact that the network's results were presented in a global way and not from match to match in order to better understand the interactions that were made in those matches. And the data presented focused only on the actions in which there was finishing, because due to the amount of data, which is often not relevant, we wanted to study the plays in which the team was objective, that is, in which there was finishing.

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