

Using of Network Motifs on Basketball Tactical Analysis

Halil Orbay Çobanoğlu

Correspondence: Halil Orbay Çobanoğlu, Muzaffer Çil Anadolu High School, Ministry of National Education, Eskişehir, Turkey.

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Abstract

In the specific case of team sports there are a particular interest to recognize the cooperation tendencies between team-members. There are several ways to extend the investigation of pass motifs to reveal finergrained details of teams and players. The aim of this study was to solve the game strategies of basketball teams by using network science through motifs. The study sample consists of 6 matches of Turkish National Basketball Team in the EuroBasket2015 tournament. 6 matches were analyzed with e-analysis basketball program, the pass actions obtained from the analysis were transferred into Excel files. The Excel pass files were processed with the open-source program Gephi to obtain the network of the matches and the measurements of networks' motifs. And then using R and R package igraph 3-nodes and 4-nodes pass motifs were found. As a result, for 3-nodes Type 9 has been seen as mode 2 times. With the help of network science approach and by using motifs the most influential players can be found, the most compatible squad for future games can be selected and the opponent's key players can be analyzed. If coaches want to disrupt the opponent's game format, they must first be aware of the pass motifs that the team often uses. Determining how to break these motifs will make an important contribution to the success of a team.

Keywords: network science, motifs, basketball, tactics

1. Introduction

Complex networks have been studied in many disciplines (Milo, Shen-Orr, Itzkovitz, Kashtan, Chklovskii & Alon, 2002). Many complex networks share global features such as power-law degree distribution and the small world property. Nowadays, observations of biological networks revealed the existence of network motifs: small connected subgraphs occurring significantly higher than in randomized networks with the same degree sequence (Heinlein, 2019). The motifs in a network are small connected subnets formed at much higher frequencies than random networks (Li, Xiao, Zhou & Yang, 2012). Recently, they have received a lot of attention as a useful concept to reveal the structural design principles of complex networks (Kashtan, Itzkovitz, Milo & Alon, 2004; Wernicke, 2005). A network is a set of vertices, sometimes called nodes, with links between them, called edges. A complex network is a network characterized by a large number of vertices and edges that follow some pattern, like the formation of clusters or highly connected vertices, called hubs. While in a simple network, with at most hundreds of vertices, the human eye is an analytic tool of remarkable power, in a complex network, this approach is useless. Therefore, to examine complex networks, we need to use statistical methods to tell us how the network looks (Vaz de Melo, Almeida & Loureiro, 2008). Capturing the interaction between individuals within a group is a central purpose of network analysis. Useful illustrations of the network structure should provide information about the purpose and functionality of networks (Fewel, Armbruster, Ingraham, Petersen & Waters, 2012). Network science gives information about the cliques and motifs that dominate the game. For example, with closeness centrality, how well connected a player to the team can be calculated. Out-degree of a player can be used as a metric to measure the passes he has given. The clustering coefficient can be used as a sign of "possession" in the pass network. And, betweenness, which naturally capture the hubs and essential associations in the distribution of the ball, has crucial importance to analyze network metrics (Cotta, Mora, Merelo-Molina & Merelo, 2011).

Nowadays, sport is now considered as a complex networks often display network motifs and these can be described as subgraphs that recur in the network much more often than in randomized networks (Gürsakar, Yılmaz, Çobanoğlu & Çağlıyor, 2018). Performance analysis in team sports aims to measure and process data from training sessions and competitions with a view to use the information to improve future performances (Sampaio, Leser, Baca, Calleja-Gonzalez, Coutinho, Gonçalves & Leite, 2016). Different computer-based approaches have been attempting to extract and analyse tactical patterns in team sports (Clemente, Couceiro, Martins & Mendes, 2015). Basketball is a complex and dynamic

system based on interactions. These interactions within a team can be considered as a collaborative process based on the strategic plan, the state variables and contextual constraints for the team (Clemente, Martins, Kalamaras, Oliveira, Oliveira & Mendes (2015). The use of data mining techniques provides information about the individual qualities and habits of players in both attack and defense; therefore, it is easier to predict where the advantages of problems will occur in individual offense or defense situations. With this in mind, a coach can pay more or less attention to a particular part of a game, reduce the number of information, and give all players of the team an explicit and identical idea of how to play this game (Markoski, Ivkovic & Ivkovic, 2012).

1.1 Number of Motifs and Network Types

Motifs are small, local, patterns of interconnections that occur throughout a network with significantly higher probability than in random networks. In other words, network motifs are small connected subnetworks within a larger network that occur in statistically significant quantities and may indicate functional regions of the network. Network motif software tools employ algorithms that compare a network to randomly generated networks in order to identify subnetworks that occur in frequencies higher than would be expected by random chance (Luciano, 2009). Network motif identification is significant in that motifs generally reflect functionalities. However, the task is greatly challenging due to diverse patterns of motifs possibly existent in a network and high computation complexity for large scale networks (Zhang & Xue, 2013). These basic structural elements are the building blocks that make up the network and are crucial for understanding how the network functions (Huang, Murray, Shen, Song, Wu & Zheng, 2005). Owing to their small size, motifs can be explicitly identified and enumerated in various networks, each network being characterized by its own set of distinct motifs (Dobrin, Beg, Barabási & Oltvai, 2004).

Table 1. Number of motifs according to network types

Network type	3 nodes	4 nodes	5 nodes
Undirected	2	6	21
Directed	13	199	9364

As it can be seen from Table 1, for undirected networks, number of 3-nodes motifs are 2 (Figure 1) (Gürsakar et al., 2018).



Figure 1. 2 undirected 3-nodes motifs

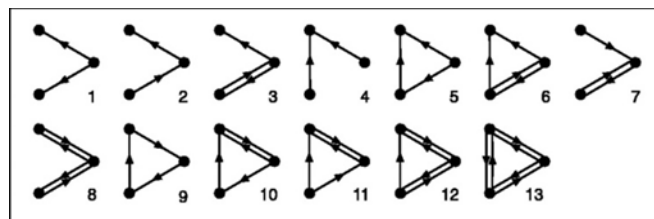


Figure 2. 13 directed 3-nodes motifs

Also 13 directed 3-nodes motifs can be seen in Figure 2 above (Gürsakar et al., 2018).

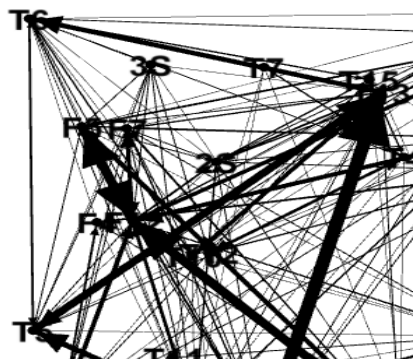


Figure 3. Motifs from France-Turkey Match (12-09-2015)

Figure 3 shows us that 3-node motifs like T5-T6-T15 (This is 13th motif in Figure 2).

2. Methods

The study sample consists of 6 matches of Turkish National Basketball Team in the EuroBasket2015 tournament. 6 matches were analyzed with e-analysis basketball program, the pass actions obtained from the analysis were transferred into Excel files. The Excel pass files were processed with the open-source program Gephi to obtain the network of the matches and the measurements of networks' motifs.

3. Results

3.1 Basketball Motifs

In this study 6 National Teams matches' data were used and these matches can be seen in Table 3. Using R and R package igraph 3-nodes and 4-nodes pass motifs were found. As an example let's take a match between France and Turkey and apply the codes below for the Turkish team.

```
> View(fratur2ags)
> library(readxl)
> fratur2ags1 <- read_excel("C:/Users/LENOVO/Desktop/basketbolyeniveri/fratur2ags1.xlsx")
> View(fratur2ags1)
> View(fratur2ags1)
> library('igraph')
> network <- graph_from_data_frame(d=fratur2ags1, directed=T)
> plot(network)
```

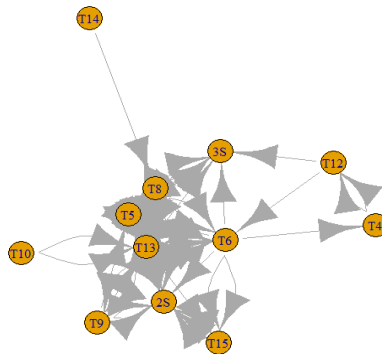


Figure 4. Pass network of the Turkish National Basketball Team

```
> motif=graph.motifs(network,size=3)
> motif
[1] NA NA 10 NA 13 8 11 8 0 5 2 1 1 10 31
> plot(graph.isocreate(size=3,number = 2))
```

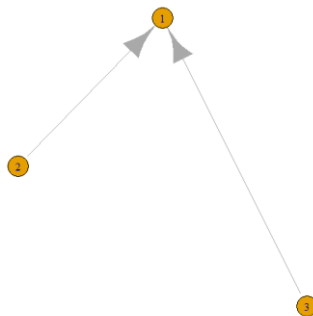


Figure 5. The 3 node motif of The Turkish team

```
> motif=graph.motifs(network,size=4)
> motif
```

```
[1] NANANA 1 NANANA 1 0 NANANA 11 11 3 NA 3 2 0 0 2 0 NANANA 5 4
[27] 2 NANANA 2 1 2 1 NANANA 5 1 15 3 NA 0 0 0 0 0 1 2 6 0 0 0 1
[53] 0 0 0 0 4 1 2 0 2 0 NA 0 2 2 0 0 0 0 0 0 0 0 0 0 3 6
[79] 1 0 0 0 2 0 0 0 0 0 0 0 0 0 1 1 0 3 0 0 0 1 1 0 0 6
[105] 1 0 0 3 1 0 0 0 0 0 0 3 0 2 1 0 NA 0 0 2 1 0 0 0 0 0
[131] 0 0 0 0 0 0 0 0 1 1 0 0 0 1 0 0 0 0 0 0 0 0 2 0 0 0
[157] 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 2 0 0 5 1 0 0 0 0
[183] 0 0 1 0 5 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
[209] 0 0 0 0 1 2 0 0 0 0
> plot(graph.isocreate(size=4,number = 22))
```

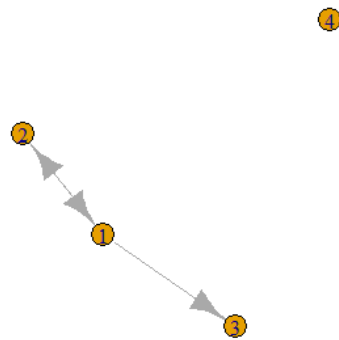


Figure 6. The 4 node motif of The Turkish team

Table 2. Matches and Turkey Networks

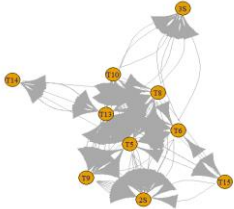
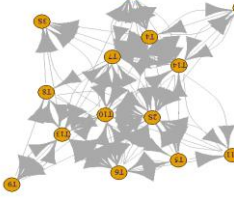
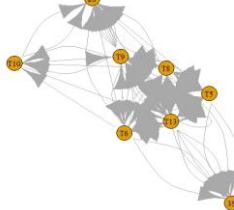

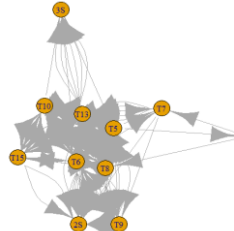
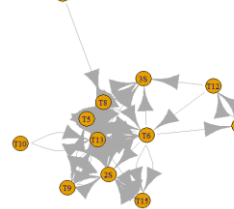
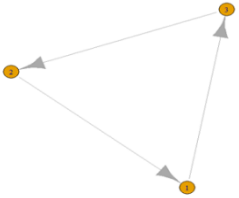
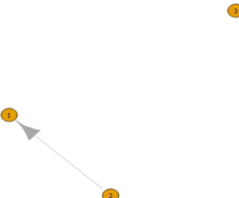
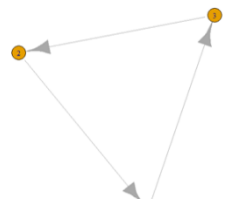
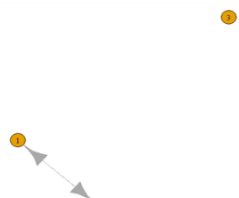
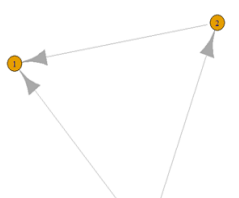
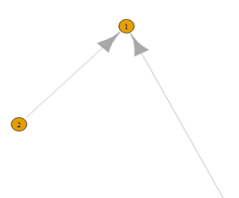
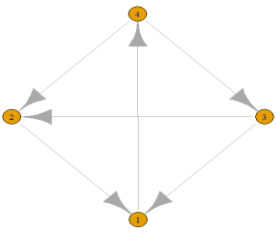
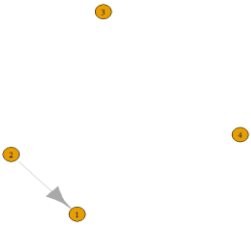
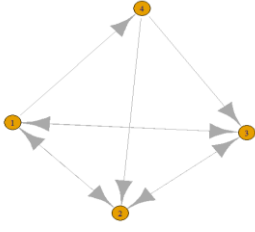
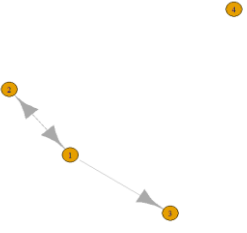
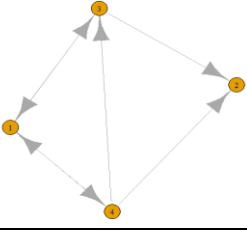
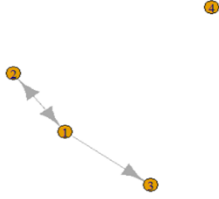
Matches	Turkey Networks
Italy-Turkey (05.09.2015)	 <p>A network diagram showing 22 nodes (numbered 1-22) connected by directed edges. The nodes are arranged in a roughly circular pattern with a central cluster. Node 1 is at the top, and node 22 is at the bottom. The network is dense with many connections between nodes.</p>
Turkey-Spain (06.09.2015)	 <p>A network diagram showing 22 nodes (numbered 1-22) connected by directed edges. The nodes are arranged in a roughly circular pattern with a central cluster. Node 1 is at the top, and node 22 is at the bottom. The network is dense with many connections between nodes.</p>
Germany-Turkey (08.09.2015)	 <p>A network diagram showing 22 nodes (numbered 1-22) connected by directed edges. The nodes are arranged in a roughly circular pattern with a central cluster. Node 1 is at the top, and node 22 is at the bottom. The network is dense with many connections between nodes.</p>
Turkey-Serbia (09.09.2015)	 <p>A network diagram showing 22 nodes (numbered 1-22) connected by directed edges. The nodes are arranged in a roughly circular pattern with a central cluster. Node 1 is at the top, and node 22 is at the bottom. The network is dense with many connections between nodes.</p>
Turkey-Iceland (10.09.2015)	 <p>A network diagram showing 22 nodes (numbered 1-22) connected by directed edges. The nodes are arranged in a roughly circular pattern with a central cluster. Node 1 is at the top, and node 22 is at the bottom. The network is dense with many connections between nodes.</p>
France-Turkey (12.09.2015)	 <p>A network diagram showing 22 nodes (numbered 1-22) connected by directed edges. The nodes are arranged in a roughly circular pattern with a central cluster. Node 1 is at the top, and node 22 is at the bottom. The network is dense with many connections between nodes.</p>

Table 3. 3-nodes motifs results

Matches	Team	Number of passes	Mode motif 1
Italy-Turkey (05.09.2015)	Turkey	135	
Turkey-Spain (06.09.2015)	Turkey	117	
Germany-Turkey (08.09.2015)	Turkey	128	
Turkey-Serbia (09.09.2015)	Turkey	148	
Turkey-Iceland (10.09.2015)	Turkey	174	
France-Turkey (12.09.2015)	Turkey	71	

As a result, in Table 3 for 3-nodes considering Figure 2, type 9 has been seen as mode 2 times.

Table 4. 4-nodes motifs results

Matches	Team	Number of passes	Mode motif 1
Italy-Turkey (05.09.2015)	Turkey	135	
Turkey-Spain (06.09.2015)	Turkey	117	
Germany-Turkey (08.09.2015)	Turkey	128	
Turkey-Serbia (09.09.2015)	Turkey	148	
Turkey-Iceland (10.09.2015)	Turkey	174	
France-Turkey (12.09.2015)	Turkey	71	

As a result, in Table 4 for 4-nodes considering Figure 6 has been repeated 2 times between 6 motifs.

4. Discussion and Conclusion

The aim of this study was to solve the game strategies of basketball teams by using network science through motifs. In this research, it was determined that which 3-nodes and 4-nodes motif types were the mod motif types within the framework of a 6-match data set. As a result, in Table 3 for 3-nodes considering Figure 2, type 9 has been seen as mode 2 times and in Table 4 for 4-nodes considering Figure 6 has been repeated 2 times between 6 motifs. Clemente, Martins, Kalamaras & Mendes (2015) in their study which aim was to identify the centrality tactical positions in basketball they emphasized that 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 and it was observed no differences between different competitive leagues considering the centrality levels. Clemente, Martins & Mendes (2015) in their study which aim was to analyze the variance of general network metrics between different team sports and competitive levels and they found that team sports with greater number of players increased the values of total arcs and team sports with smaller players increases the density values and the clustering coefficient, thus suggesting the better values of cohesion emerges in smaller formats. Vaz de Melo et al., (2008) in their study they examined that the evolution of the NBA using complex network metrics, calculated from a graph in which the vertices are the players and the teams, and the edges identify labor relationships among them. And they estimated that in their study they showed the evolution and growth of the NBA social network, constructed from data obtained in the NBA database and showed the NBA network structure can be characterized as a small-world network. They also predicted that complex network metrics could be used to analyze social relationships between NBA players and discover new information in the NBA database. In addition, this new kind of information derived from network relationships has been improved in understanding team behavior (Vaz de Melo et al., 2008). Fewel et al. (2012) in their study asked that how team dynamics can be captured in relation to function by considering games as networks. They defined players as nodes and ball movements as links, they analyzed the network properties of degree centrality, clustering, entropy and flow centrality across teams and positions, to characterize the game from a network perspective and to determine whether they could assessed differences in team offensive strategy by their network properties. Their analysis showed the utility of network approaches in quantifying team strategy and showed that testable hypotheses could be evaluated using this approach and also highlight the richness of basketball networks as a dataset for exploring the relationships between network structure and dynamics with team organization and effectiveness (Fewel et al., 2012). In the other study authors used a graph theory to analyse the relationship between basketball players in each unit of attack crossing this quantitative analysis with a qualitative one to explain social interactions. They found the rise of a specific network regarding each team. These results suggest that the networks' coordinations were built on local interactions that do not necessarily require all players to achieve the team's goal (Bourbousson, Poizat, Saury & Carole, 2010). Kooij, Jamakovic, Kesteren, Koning, Theisler & Veldhoven (2009) in their study emphasized that by using network science coaches could be determined the optimal line-up for matches. In other study Piette, Pham & Anand (2011) studied on network science in sports and they emphasized that to the importance of how two teammates perform together. And in this way they performed the same type of performance evaluation on pairs of teammates, which could highlight players who while not successful individually, work great as a couple. Gürsakal, Çobanoğlu & Çağlıyor (2017) in their study emphasized that with the help of network science approach, the most influential players can be found, the most compatible squad for future games can be selected and the opponent's key players can be analyzed.

If coaches want to disrupt the opponent's game format, they must first be aware of the pass motifs that the team often uses. Determining how to break these motifs will make an important contribution to the success of a team. Examination of the mode pass types of the teams that are very successful and consistently winning is important for the other teams who want to achieve this success. The most important deficiency of the pass network analysis method is that this analysis does not take into account the position of the players in the field in any way.

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