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Systemic Mapping of High-Level Women's Volleyball using Social Network Analysis: The Case of Serve (K0), Side-out (KI), Side-out Transition (KII) and Transition (KIII)

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Abstract

Competitive sports are growing in popularity at an exponential rate, with training becoming an almost overwhelming process, demanding an understanding and awareness of the effects of a great number of variables on sport performance. Thus, systemic approaches have emerged as essential for understanding the complex dynamics of performance. In this vein, Social Network Analysis (SNA) acquires particular relevance in comprehending the relationships established between different nodes. Therefore, the purpose of the present study was to analyze performance in high-level women's volleyball using SNA. A systematic mapping of four game complexes of the volleyball game was carried out using Gephi©. The analyzed complexes were: serve (K0), side-out (KI), side-out transition (KII) and transition (KIII). A total of 8 matches from the first Group Stage of the Women's World Grand Prix 2015 were viewed (1,264 rallies), and eigenvector centrality values were calculated. Results showed that most variables presented categories with relatively close eigenvector values, pointing to a diversified distribution of events. However, some categories did exhibit substantially distinct eigenvector centralities. Based on the findings of the present study, it was concluded that it was crucial to develop ways to enhance teams' abilities to play off-system, as it was the most common situation in female high-level volleyball. It was also shown that this enhancement should be carried out by providing diversity to the teams' options, as this diversity would create more uncertainty in the opponent and therefore, a higher chance of success.

Key words: off-system gameplay, performance analysis, social network analysis, volleyball

1. Introduction

Competitive sports are growing at an exponential rate, with training becoming an almost overwhelming process demanding an understanding and awareness of the effects of a great number of variables (Salmon, 2010). During the course of any sports event, critical tasks are performed within a dynamic, complex, collaborative system comprising multiple humans and sometimes artefacts (e.g. the ball), under high-pressure, complex, and rapidly changing conditions (Vickers et al., 1999). Accordingly, physiological markers, tactical and technical performance indicators, as well as psychosocial characteristics have been thoroughly studied in attempting to better understand the factors underlying success in sport (Eliakim et al., 2009; Lac and Maso, 2004; Vingerhoets, Bylsma and Vlam, 2013). In some cases, attempts are made to predict future performances. One such example is the algorithm developed by Blundell (2009) to predict the outcome of American Football matches. It should be kept in mind that, whereas in some individual sports, such as swimming, performance is evaluated mainly through anthropometrical, physiological and biomechanical parameters (Jürimäe et al., 2007), in other sports researchers should use distinct approaches. Specifically in team sports, the choice of performance indicators for analysis is both more complex and more intricate, in as much as there are a greater number of variables at play that can influence the result of the game, and their interactions grow exponentially, thereby making predictive ventures quite risky and volatile (Ruiz et al., 2011; Afonso et al., 2009; Palao, Santos and Ureña, 2004).

Any systemic analysis in sport performance involves undertaking numerous decisions about which performance indicators and/or their relationships may be relevant (O'Donoghue 2008, p. 145). However, Garganta (2009) underlined the fact that most analyses avoid systematic approaches – especially under ecological conditions –, perhaps due to the complexity involved. The amount of data involved, especially when interactions among variables are considered, naturally leads to greater obstacles in analysing and interpreting any findings (Xie et al., 2002; Mroczek et al., 2014). But what does 'systemic analysis' really mean? According to Oxford Dictionaries, a system can be defined as "a set of things working *together* as parts of a mechanism or an *interconnecting network*" (general definition). The use of systems as a theoretical model-building in science – the General System Theory – was first developed in the mid-1900s by scientists originating from a variety of fields, such as Biology (e.g. Bertalanffy, 1950), Economics (e.g. Boulding, 1956), Neurophysiology (e.g. Gerard, 1958), Mathematics (e.g. Rapoport, 1966), Computer Sciences (e.g. Klir, 1972), and Philosophy (e.g. László, 1969), just to refer to a few. According to its founders, General Systems Theory is a logical-mathematical discipline applicable to all sciences concerned with systems (Bertalanffy, 1950) that "lies somewhere between the highly-generalized constructions of pure mathematics and the specific theories of the specialized disciplines" (Boulding 1956, p. 197).

In this vein, the interest in network systems research can be found in such diverse areas as Computer Systems (e.g., Milner, 1996) or Sociology (Carrington, Scott and Wasserman, 2005). In the latter, concerns about the information flow and its structure gave rise in the first half of the 20th century to Social Network Analysis (SNA) that was a tenet of urban research in North-American (see Whyte, 1943) and African (see Mitchell,

1969) metropolises. Although in existence for over five decades, SNA is still finding a relevant role in a more widespread set of scientific areas, such as Sports Sciences (Lusher, Robins and Kremer, 2010). Writing in 2010, Lusher, Robins and Kremer reported that "recent developments in the overlap of fields, such as Sociology, Economics, Anthropology, Mathematics, Political Science, History, and Social Psychology, have seen the emergence of a new approach to analysis of complex intra-group relations" (2010, p. 213). The first applications of complex intra-group relations in Sports Science can be traced back to the 1990s in the area of Sports Sociology. These first studies in the area of Sports Science reflect the influence of the major development in the 1980s of SNA within the Social Sciences. The work of Harris (1989) on 'suited up' and 'stripped down' approaches to sport studies, and that of Nixon (1992, 1993) on the willingness of athletes to play with injuries and/or pain constitute early examples. Studies using SNA as a tool have been aiming to understand how variables affecting intra-team relationships such as norms, hierarchies (and other informal social structures), and cohesion, are related to sports performance (Lusher, Robins and Kremer, 2010).

In light of the above, and recognizing that Sports Sciences are just starting to scratch the surface regarding the potential of SNA, the specific case of women's volleyball from a systemic point of view was analysed in the present study. For the purpose, we applied SNA by taking into consideration a set of game behaviours that extend beyond the traditional performance indicators, namely those concerned with efficacy of terminal or intermediate actions. More specifically, behavioural variables and their interactions were considered. The establishment of a systemic behaviour, even if specific to a certain competition and/or team(s), would likely improve our comprehension of the intricacies of sports performance, as well as provide guidelines for coaches to deliver better guidance (Clemente et al., 2015). As such, we explored systematic mappings of four game complexes of the volleyball game, namely, serve (K0), side-out (KI), side-out transition (KII) and transition (KIII). Muñoz (2003, 2007) suggested a separation of the volleyball game in six complexes. First, K0, which consists only of the serve - the sole action of the game that does not depend on previous actions – and is the start of the play. Second, KI, which consists on receiving the serve and constructing the play after the serve (reception, set and attack); KII is considered the response to KI, and consists of block, defence, set and attack. KIII has the same elements of KII, and the same way KII is the response to KI, KIII is the response to KII. Although KI and KII are two of the most studied complexes in volleyball (Laporta and Afonso, 2015, p.14), there are few studies that focus on interrelationships between behavioural variables, such as the relative position of the setter (net or back row) and setting zone (interfering with the number and type of attack organizations that can be deployed).

2. Materials and methods

2.1. Sample

A total of eight matches from the first Group Stage of the Women's World Grand Prix 2015 were analysed. Specifically, Groups A (Brazil: 3rd place in the competition and 3rd place on the Fédération Internationale de Volleyball - FIVB ranking; Japan: 6th place in the competition and 5th on the FIVB ranking; Serbia: 8th place in the competition and 6th place on the FIVB ranking; Thailand: 9th place in the competition and 13th on the FIVB ranking) and B (Russia: 2nd place in the competition and 4th on the FIVB ranking; China: 4th place in the competition and 2nd on the FIVB ranking; Germany 7th place in the competition and 11th on the FIVB ranking Dominican Republic: 12th place in the competition and 7th on the FIVB ranking;) were observed. The observation was made on all the sets of the referred to games, but the register of the data was aggregated per game complex: overall, 29 sets and 1,264 rallies were analysed.

Instruments

The video recordings of the matches were obtained from the public domain site *youtube.com,* which offered both a lateralized view (aligned with the net) and an overview of the court.

The observers were trained in advance in order to attain proficiency and consistency on the coding data criteria register, both for intra- and inter-observer reliability calculations. For training purposes, each observer analyzed a minimum of eight games from different high-level competitions (men and women). Reliability was established with Cohen's Kappa above 0.80 for all the considered variables.

Variables

Six *game complexes* were considered, as proposed by Muñoz (2003, 2007): K0 (serve), KI (side-out), KII (side-out transition), KIII (transition), KIV (attack coverage) and KV (freeball and downball). Although only the first four complexes were fully included in this investigation, KIV and KV as a whole were reported to denote general connections with the remaining complexes. While some variables occur in several different complexes (thereby under distinct sets of constraints), others are specific to certain complexes. The K0 is an exception in as much as it has no variables in common with any of the other complexes. It is important to underline that, whenever a game action did not occur, the observer would register that moment as a non-occurring action. Therefore, categories such as *reception zone* (no first touch given in KI), *defence zone* (no first touch given in KII or KIII), *setting zone* (no second touch given in KI, KII or KIII), *attack zone* (no attack performed, or an attack gesture but with no jump, in KI, KII or KIII) and *attack tempo* (both conditions used in attack zone, plus ball sent to the opponent in another form of contact, in KI, KII or KIII) could be registered within the parameter non-occurring (NO) for any complex of the game.

For K0, the analysed variables were *serve type* (jump, jump-float or standing float) and *serve zone* (zone 1, zone 5 or zone 6) (Quiroga et al., 2010). The analysis of KI considered: *reception zone* (official zones 1 to 6); *setting zone* (following Laporta et al., 2015, and Esteves and Mesquita, 2007): A – all attack options available; B – quick attacks are possible but more difficult to deploy, and some attack combinations are inhibited; C – only slow, outside settings are possible; *attack zone* (official zones 1 to 6), and *attack tempo* (adapted from Afonso and Mesquita, 2007 and Costa et al., 2012): 1 - the attacker is in the air or jumping during or rapidly after the set; 2 - the attacker takes two steps after the set; 3 - the attacker takes three or more steps after the set. Regarding KII and KIII, the variables analyzed were: *number of blockers* (triple, double, single, or no block); *defense zone* (official zones 1 to 6, plus Other - when the dig occurs outside the court due to ball deflection by the block); *setting zone*; *attack zone*; and *attack tempo*. KIV and KV were merely registered as a whole, to denote when the previous complexes directly transitioned to attack coverage or freeball. When any variable did not occur it was catalogued as NO.

Statistical analysis
The data was registered on a worksheet created using the program Microsoft® Excel® 2015 for Windows, and was later analysed trough the statistical program IBM® SPSS® Statistics for Windows (Version 21, U.S.A.) for data quality control and exploratory cross table statistics. Finally, Social Network Analysis was performed using the software Gephi© 0.8.2-beta (Version 10.10.3, France). For this study, the eigenvector centrality on the software Gephi© was used. The insertion of the collected data in this software produced a total of 82 nodes and 808 bridges. In SNA studies different centrality measures are used. As Ruhnau (2000, p.358) stated "[t]he description of actors in social networks is often done in terms of some 'structural features' like the degree, closeness or betweenness of an actor. These structural features have been used to create measures of centrality for single nodes in a graph". An additional measure of centrality that is often used is the *eigenvector centrality* (Bonacich, 1972). This concept is based on the idea that a node is more central if it is related with nodes that are themselves central. As such, the centrality of a node does not depend solely on the number of its adjacent nodes but also on their characteristics.

Despite previous testing of the instrument, we performed reliability testing specific for the set of data that was used in this investigation. For purposes of inter-observer reliability of analysis of the current sample, 28.9% (n = 365) of the rallies were reanalyzed (above the 10% suggested by Tabachnick and Fidell, 2000). Cohen's Kappa values respected the minimum value of 0.75 suggested in specialized literature (Fleiss, 2003), having ranged from 0.81 to 1.

3. Results

The overall Social Network Analysis' mapping is presented in Figure 1.

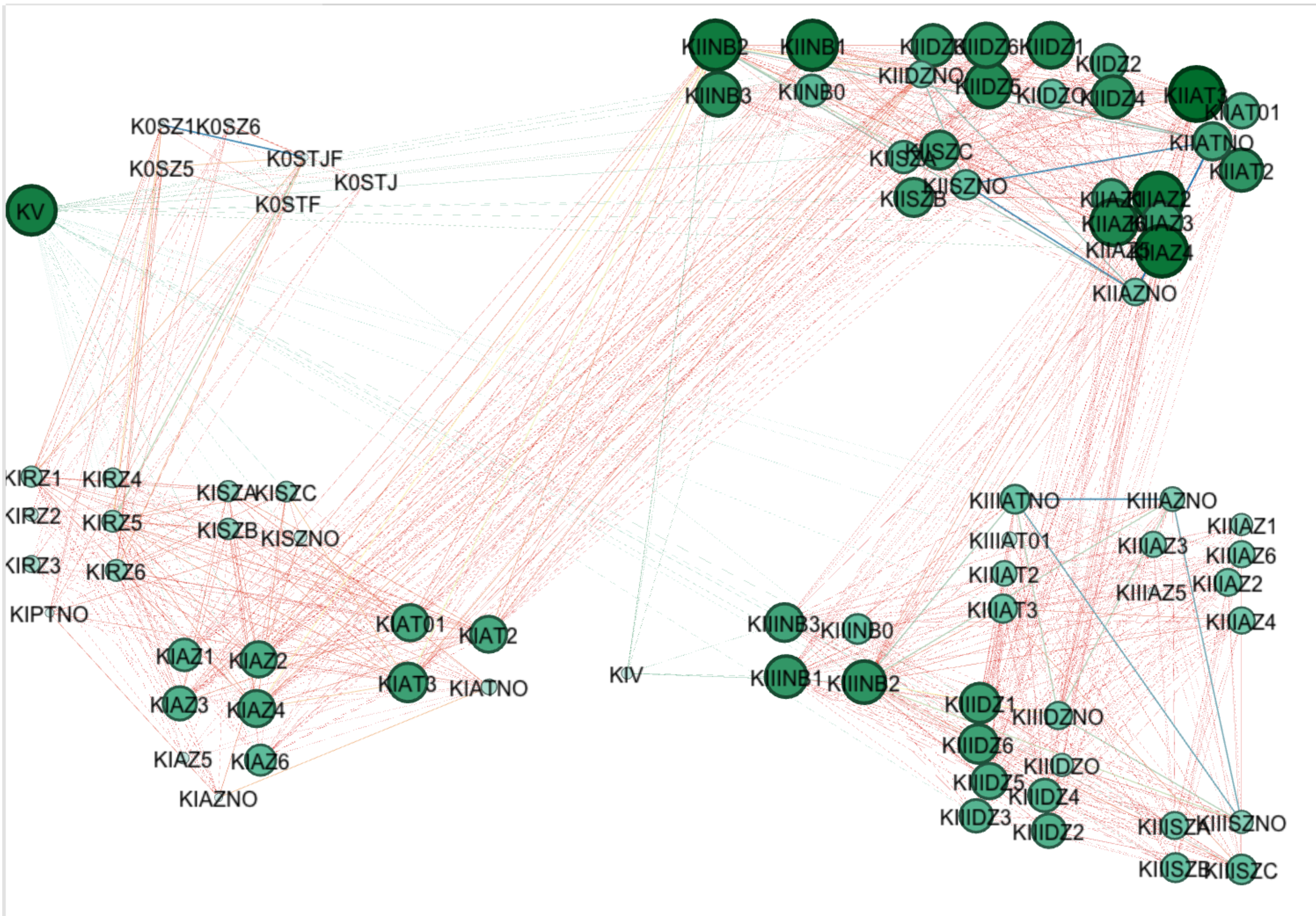

Figure 1 - K0, KI, KII and KIII Social Network Analysis' mapping (Gephi).

Concerning the first game complex, K0, the highest eigenvector value for serve type was registered in *standing float* (0.14), closely followed by *jump-float* (0.12), while the lowest value was observed in the *jump serve* (0.08). Regarding serving zones, the highest value was obtained in *zone 1* (0.12). However, both *zones 5* and *6* presented a value close to the latter (0.11) (Table 1).

Table 1- Eigenvector centrality values for K0

Serve (K0)				
Serve Type	Jump	Jump-float	Standing Float	**Range**
	0.08	0.12	0.14	0.08 – 0.14
Serving Zone	Zone 1	Zone 5	Zone 6	**Range**
	0.12	0.11	0.11	0.11 – 0.12

Regarding KI (Table 2), the *reception zones* with the highest eigenvector values were *zones 5* and *6* (both with a value of 0.40), followed closely by *zone 1* (0.39). The lowest score was registered for the node concerning *failure to receive* (KIRZNO: 0.16). The *setting zones A* and *B* displayed a common value (0.39). Although *setting zone C* was not at the top of the values for this category, it was very close (0.38), while *failure to set* (KISZNO) had the lowest value (0.24).

Still in KI, the attack zone with the highest value for eigenvector was *zone 4* (0.68), followed closely by *zone 2* (0.66) and *zone 3* (0.63). The lowest values were registered for *zone 5* (0.21) and *failure to attack* (KIAZNO: 0.15). The three main categories within attack tempo exhibited neighboring values: *tempo 1* and *tempo 3* presented values of 0.68 and 0.72, respectively. *Non-occurring attack tempos* (KIATNO) scored the lowest value (0.29).

Table 2 - Eigenvector centrality values for KI

Side-out (KI)								
Reception Zone	Zone 1	Zone 2	Zone 3	Zone 4	Zone 5	Zone 6	Zone Not Occurring	**Range**
	0.39	0.25	0.31	0.36	0.40	0.40	0.16	0.16 – 0.40
Setting Zone	Zone A	Zone B	Zone C	Zone Not Occurring	**Range**			
	0.39	0.39	0.38	0.24	0.24 – 0.39			
Attack Zone	Zone 1	Zone 2	Zone 3	Zone 4	Zone 5	Zone 6	Zone Not Occurring	**Range**
	0.60	0.66	0.63	0.68	0.21	0.57	0.15	0.15 – 0.68
Attack Tempo	Tempo 1	Tempo 2	Tempo 3	Tempo Not Occurring	**Range**			
	0.68	0.67	0.72	0.29	0.29 – 0.72			

Within KII (Table 3), *double* and *single blocks* had the highest eigenvector values (0.93 and 0.92, respectively), while the lowest value was scored by the *no block* variable (0.59). The defense zones with a higher eigenvector centrality value were *zones 1* and *5* (0.85). The lowest values belonged to *other defense zones* (0.53) and *failure to dig* (KIIDFNO:

0.49).Regarding the setting zone, there was a common value of 0.71 between *setting zones B* and *C*. The lowest registered value for setting zone was for *KIISZNO* (0.55). With respect to the attack, the higher eigenvector value was obtained by *attack zone 4* (0.95) while the lowest value was found in *attack zone 5* (0.13). Within attack tempo, *tempo 3* scored the highest (1.00), while *tempo 1* scored the lowest (0.65).

Table 3 - Eigenvector centrality values for KII

Side-out transition (KII)									
Number of Blockers	Triple	Double	Single	No block			**Range**		
	0.82	0.93	0.92	0.59			0.59 – 0.93		
Defence Zone	Zone 1	Zone 2	Zone 3	Zone 4	Zone 5	Zone 6	Other	Zone Not Occurring	**Range**
	0.85	0.67	0.77	0.79	0.85	0.82	0.53	0.49	0.49 – 0.85
Setting Zone	Zone A	Zone B	Zone C	Zone Not Occurring			**Range**		
	0.60	0.71	0.71	0.55			0.55 – 0.71		
Attack Zone	Zone 1	Zone 2	Zone 3	Zone 4	Zone 5	Zone 6	Zone Not Occurring	**Range**	
	0.70	0.94	0.74	0.95	0.13	0.86	0.50	0.13 – 0.95	
Attack Tempo	Tempo 1	Tempo 2	Tempo 3	Tempo Not Occurring			**Range**		
	0.65	0.79	1.00	0.70			0.65 – 1.00		

Regarding transition (KIII) (see Table 4), the most common number of blockers was *two* (KIIINB2), followed by *single block* (KIIINB1), with values of 0.79 and 0.77, respectively. Concerning the defence zone, *zones 1* (0.73) and *6* (0.72) were the highest scoring zones, with the lowest value being found for *other defence zones* (0.42). The setting zone with a higher value was *C* (0.55), while the lowest value was observed within *failure to set* (KIIISZNO: 0.42). Considering the KIII attack (zone and tempo), the highest eigenvector value registered was 0.50 (for *zone 2*), and the lowest was 0.14 (*zone 5*). Regarding attack tempo, the lowest value for eigenvector centrality was found in *attack tempo 1* (0.28), and the highest value (0.54) was registered when *attack tempo did not occur* (KIIIATNO).

Finally, the eigenvector values of the two complexes that will not be developed in this paper are presented in Table 5. As it can be seen by the table presented below, KV has a much higher eigenvector value than KIV.

Table 4 - Eigenvector centrality values for KIII

	Transition (KIII)								
Number of Blockers	Triple	Double	Single	No block			**Range**		
	0.70	0.79	0.77	0.55			0.55 – 0.79		
Defence Zone	Zone 1	Zone 2	Zone 3	Zone 4	Zone 5	Zone 6	Other Zone	Zone Not Occurring	**Range**
	0.73	0.63	0.61	0.61	0.66	0.72	0.42	0.51	0.42 – 0.73
Setting Zone	Zone A	Zone B	Zone C	Zone Not Occurring			**Range**		
	0.50	0.54	0.55	0.42			0.42 – 0.55		
Attack Zone	Zone 1	Zone 2	Zone 3	Zone 4	Zone 5	Zone 6	Zone Not Occurring	**Range**	
	0.40	0.50	0.47	0.49	0.14	0.49	0.45	0.14 – 0.50	
Attack Tempo	Tempo 1	Tempo 2	Tempo 3	Tempo Not Occurring			**Range**		
	0.28	0.46	0.53	0.54			0.28 – 0.54		

Table 5 - Eigenvector centrality values for KIV and KV

Attack coverage (KIV)	***Freeball or downball (KV)***
0.12	0.91

4. Discussion

Because competitive sports' training is increasingly demanding an understanding and awareness of the effects of a great number of variables on sport performance, systemic approaches have emerged as essential for understanding the complex dynamics of performance. As such, the purpose of the present study was to analyze performance per game complex in high-level women's volleyball, using Social Network Analysis. This was made by measuring the eigenvector centrality values while exploring systematic mappings of four game complexes of the volleyball game, namely the serve (K0), side-out (KI), side-out transition (KII) and transition (KIII). Results showed that most variables presented categories with relatively close eigenvector values, pointing to a diversified distribution of events. However, some categories did exhibit substantially distinct eigenvector centralities.

Performance analysis allows researchers to more fully understand the complexities surrounding performance, and therefore, to better conceptualize our teaching and training structures and guidelines (e.g. Walter, Lames and McGarry, 2007; Ericsson, 2013). It further provides coaches and athletes with an edge in improving their practices and enhancing their strengths, be it more individually (i.e., physical characteristics) or collectively (e.g., team tactics). Multidimensional variables interact within a complex and hopefully coherent system: the team (e.g. Silva et al., 2013). Understanding its interactions and systematic patterns is the purpose of a wide body of research (e.g. Travassos et al., 2013). Because using SNA as a tool allows understanding the intricate relationships established between such variables, while also allowing comprehending the impact they might have on the overall performance and outcome, in this work we sought to investigate its potential applications while studying high-level women's volleyball.

The data collected for K0 showed that the highest eigenvector value belonged to the standing float serve. It is generally known that women's teams tend to make more use of the standing float serve while men's teams make more use of the jump serve (e.g., Palao, Manzanares and Ortega, 2009), and this preference seems to develop as early as the youth level (Costa et al., 2012). It is clear that jump serves are not a part of female volleyball culture. Biologically, female athletes are on average less powerful than male athletes, therefore benefitting to a lesser extent from powerful jump serves (Palao, Manzanares and Ortega, 2009). However, it would be interesting to analyze if this is actually being produced due to cultural differences, i.e., whether there really is a relative biological disadvantage (as the net is also lower than in men's game) or a consequence of not sufficiently developing that action during the career of female athletes. The K0 data further showed that all serving zones were fairly equally distributed. We can reasonably expect that this might happen because players tend to choose their serving zone according to their starting defense location (Quiroga et al., 2010). This relation might be the reason behind the registered even distribution of serving zones.

Concerning KI, *reception zone* showed a predominance of solicitation of zones associated with longer serving trajectories (zones 1, 5 and 6). The lower values of the front row zones are likely related to both its small area (each front row zone has half the area of backcourt zones) and its closeness to the net (thereby increasing the risk of serve failure when attempting such trajectories). According to Elftmann (2012, p. 2) "[t]hough studies have been conducted in an attempt to quantify the effectiveness of serves based on speed, rotational and angular velocity, and mode of serve, the effectiveness of serving location strategies remains unknown". One interesting case obtained in these data is that of zone 4 (0.36). This case could be related with an attempt to force the opposing attacking player (for example, an outside hitter) to pass in difficult conditions and possibly impair her attack movements (Afonso et al., 2010; Lithio and Webb, 2006; López, 2013). Still in KI, *setting zone* also produced balanced eigenvector values, meaning that women's teams need to be able to build their side-out attack independently of the quality of the second contact, translating in frequent off-system play. With regard to *attack zone* in KI, front row zones expectedly presented the greatest eigenvector centrality values, while zone 5 had the lowest value, which could be explained by the usual presence of a non-attacking player (the libero) in the aforementioned zone. However, and since crossings are permitted, perhaps a greater utilization of zone 5 to attack would increase uncertainty in the opponent, expanding on the possibilities of scoring a point. The high values of zones 2 (0.66) and 1 (0.60) can probably be related to the importance attributed to the opposite hitter in scoring points (Mesquita and César, 2007; Marcelino et al., 2009), but also to the use of middle-blockers in combined attack moves (such as the 'one-foot take off'). Although studies have shown preferences in attack tempo (see Afonso et al., 2005; Mesquita et al., 2007; Castro and Mesquita, 2010), the *attack tempo* categories in this study presented instead similar values, implying that there is a relatively homogeneous distribution of their frequencies. This is consistent with the values obtained for the setting zone, and this level of values also hint at a need for women's teams to display diversity in their attacking strategies.

As in KI, the collected data in KII was fairly equally distributed within its categories, namely the *defense zone*, meaning the side-out attack uses a wide array of trajectories.

Within the front row zones, there are lower eigenvector values (compared to back row values) and it is important to underline zone 2 (0.67), as it is significantly lower than zone 3 (0.77) and zone 4 (0.79). As women's teams have several technical resources to compensate for the generally less powerful form of play when compared to men's teams (Kountouris et al., 2015), it is striking that this zone is not more explored in KII. We can assume that, usually, the opposite hitter and/or the setter are responsible for zone 2, and so it would be an advantage to try to undermine both of these players' roles by putting the ball in this zone more often. The latter would work because firstly, if the setter had to carry out the first touch she would no longer be able to perform her main purpose (setting); as such, the whole team would have to adapt their attack build-up in an off-system situation. Secondly, if the opposite hitter had to make a defense, she might not be able to promptly be available for a quick attack. The eigenvector values for the *number of blockers* showed that it is rare to have a side-out transition where there is no block formation (KIINB0). The almost certain presence of block opposition presents itself as a structural characteristic of the game and is consistent with other research (Castro and Mesquita, 2008; Araújo et al., 2010). The awareness of a certain structure in the game allows for two options: a) research and development of new ways to force an off-system play (this is, KIINB0); or b) improve the already existing side-out tactics/techniques so that this structure (block) becomes less effective.

Still in KII, *setting zone* held a strong eigenvector distinction between two sets of categories. In one group setting zone A (0.60) and KIISZNO (0.55); in the other setting zones B and C (both with 0.71 eigenvector). This higher influence of setting zones B and C show that in KII playing off-system is the norm. As the setting is going to be performed under less favorable conditions, it is important to develop not only the setters' ability to do so, but also all of the other players' ability to set. Therefore, data strongly suggests that teams should regularly practice KII under non-ideal conditions, i.e., under off-system scenarios. Data on *attack zone* shows that zones 4 (0.95) and 2 (0.94) have a very high eigenvector value when compared to all other attack zones (Palao et al., 2007; Yuhong et al., 2001; Haiqiang, 2010). This overload of the outer net zones compared to the middle zone (zone 3 = 0.74) proves that the use of KII attacking zones in a more evenly distributed way could work as an advantage. The latter would come about by increasing the opponents' team uncertainty and thus force them to play in off-system situations. Although the number of players available for attack in KII may be a strong influence on the opposing's team block formation, it is important to underline that *attack tempo* could also be significant (Castro and Mesquita, 2010). As attack tempos become faster, block cohesiveness tends to diminish (Afonso and Mesquita, 2009) and therefore there is an improvement of the teams' chances to succeed through forcing an off-system situation. The high value found in attack tempo 3, linked with the highest eigenvector values found on *setting zone* (B and C) and *attack zone* (zone 2 and 4) show that there could be a certain limited, predictable pattern play in KII, improving the chances of the opposing team anticipating the events.

The eigenvector values found in KIII were generally lower than the ones found in KII. Regarding KIII's *number of blockers,* the data suggest the same kind of conclusions that were formulated for KII, namely the strong presence of block (KIIINB0=0.55) (see Table 4). Thus, a stronger presence of triple block in this complex could be an advantage, because in KII teams play with slower attack tempos, using preferentially outer attack zones, making the game more predictable. Regarding KIII *defense zone*, once again there is a fairly even distribution of values between all zones (see Table 4). KIII variable *setting zone* (see Table 4) appears more balanced than in KII (see Table 3). It should be born in mind that not only KIII can correspond to a lengthy period of play, but also female teams tend to play longer rallies (Esper, 2003). As such, the setting zones' even distribution of the eigenvector values might correspond precisely to a high volume of ball in play. The highest value collected for KIII (see Table 4) variable *attack zone* was zone 2 (0.50), followed closely by zone 4 and zone 6 (both with 0.49). It is important to underline that zone 3 also registered an eigenvector value close to the two latter zones (see Table 4). The high eigenvector value of KIIIAZ3 may be a result of a) a more balanced presence of setting zone A (see Table 4), combined with b) a possible tendency for setters to take more risks when in difficult conditions (setting zones B and C high eigenvector), and/or c) a higher availability of middle-blockers to perform an offensive action. The high eigenvector value for KIIIAZNO (0.45) (see Table 4) reflects the high number of ending KIII rallies in female volleyball. The former eigenvector value can then be linked to the *attack tempo* data, specifically KIIIATNO (0.54). The latter attack tempo is in fact the highest value found within this variable (see Table 4), most likely a result of KIII being the last complex of a rally. The data displayed in Table 5, shows that there is a much higher presence of KV (0.91), when compared to KIV (0.12). These values although not developed here, will be explored in an additional study.

5. Conclusions

This study showed that the use of SNA for performance analysis is a powerful tool. Its use in this sports performance-centered study through eigenvector measurement, allowed analyzing a high number of game variables (fifteen altogether) and respective categories (a total of eighty-two) within four game complexes. As stated at the beginning of this paper, high-level sports training is becoming an almost overwhelming process demanding an understanding and awareness of the effects of a great number of variables. This study analysed a high number of elements present in female high-level volleyball through SNA and successfully produced new knowledge on factors of play-game. The findings of this study have underlined the importance of several factors, namely the importance of classifying and analyzing the volleyball game by its complexes. The relevance of proceeding in this manner is supported by the data collected in as much as its analysis showed that different complexes have different characteristics. The study also allowed to realize that future studies of these complexes and their systemic characteristics during play would benefit from including as register variable the match status. Although an analysis that would be based on a higher volume of play/matches/rallies would be able to enlarge the understanding of the systemic features of female volleyball here presented, by collecting the data by complexes and respective variables and categories, the study here presented allowed new understandings of the female volleyball game's dynamics to emerge. Namely, the data showed that it is crucial to develop ways to enhance teams' abilities to play off-system, as it is the most common situation in female high-level volleyball. The data also showed this enhancement should be carried out by providing diversity to the teams' options, as this diversity would create more uncertainty in the opponent and therefore, a higher chance of success.

6. References

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