Available online at www.sciencedirect.com
ScienceDirect
Journal of Science and Medicine in Sport 14 (2011) 170–176
Journal of Science and Medicine in Sport
www.elsevier.com/locate/jsams

Original paper

Networks as a novel tool for studying team ball sports as complex social systems

P. Passos [a,*], K. Davids [b], D. Araújo [a], N. Paz [c], J. Minguéns [d], J. Mendes [d]

[a] *Faculty of Human Kinetics/Technical University of Lisbon, Portugal*
[b] *Queensland University of Technology, Australia*
[c] *Lusófona University of Humanities and Technologies, Portugal*
[d] *University of Aveiro, Portugal*

Received 27 April 2010; received in revised form 4 October 2010; accepted 17 October 2010

Abstract

This paper describes and evaluates the novel utility of network methods for understanding human interpersonal interactions within social neurobiological systems such as sports teams. We show how collective system networks are supported by the sum of interpersonal interactions that emerge from the activity of system agents (such as players in a sports team). To test this idea we trialled the methodology in analyses of intra-team collective behaviours in the team sport of water polo. We observed that the number of interactions between team members resulted in varied intra-team coordination patterns of play, differentiating between successful and unsuccessful performance outcomes. Future research on small-world networks methodologies needs to formalize measures of node connections in analyses of collective behaviours in sports teams, to verify whether a high frequency of interactions is needed between players in order to achieve competitive performance outcomes.

Keywords: Interpersonal coordination; Collective neurobiological systems; Pattern forming dynamics; Water polo

1. Introduction

An important challenge in the social sciences is to understand the structure and dynamics of the web of interpersonal interactions that contribute to the organisation and function of complex social systems (exemplified by team sports and other collective networks). The behaviour of most complex systems such as cells, social institutions, flocks of pigeons or the internet, emerges from the orchestrated activity of many system components that interact through pairwise local interactions.[1] A common feature of such complex, social neurobiological networks is that any two nodes or system agents can become interconnected for action through a path of a few links only.[1] This feature of complex systems has been termed the *small-world effect*, which was originally observed in studies of collective systems. An interesting question is whether the *small-world effect* can be observed in the interactions of small units formed by system agents in performance subphases of team games (i.e. interactions of attacker or defender subunits with more than two players such as 2 vs. 1 or 3 vs. 2 situations).

The complexity of numerous social (e.g. team sports, traffic jams), biological (e.g. cells, fish schools, flocks of pigeons), or communication systems (e.g. World Wide Web) is rooted in the web of interactions of system agents/components. For example, in team sports, function performance is assured by a complex network of interpersonal relationships among the players (i.e. a social network). The network nodes are system agents (i.e. the players), and the interconnecting lines among players represent the ways that those players interact, through verbal or non-verbal communications skills.[2]

Studies in other scientific sub-disciplines [e.g. 3] have provided a strong conceptual basis to clarify how agents might

* Corresponding author.
E-mail addresses: ppassos@fmh.utl.pt, passos.p@gmail.com (P. Passos).

1440-2440/$ – see front matter
doi:10.1016/j.jsams.2010.10.459

interact in social neurobiological systems. For example, a key observation in the biochemical activity of metabolic and genetic networks is the existence of *hot links*, or preferential component attachments, characterized by a high frequency of node interactions observed within a network of less active interactions. The origin of this property is nested in network topology. It seems that metabolic fluxes in biological systems and the weights of links in non-biological systems are determined by the scale-free nature of the network topology affording the emergence of *hot links*.[3] Consequently, the existence of high frequency nodes of interactions in social neurobiological networks has been proposed.[1] Such theoretical advances have implications for sport performance analysis and it is worth examining whether small-world network topologies might be observed in the study of player interactions in team sports.

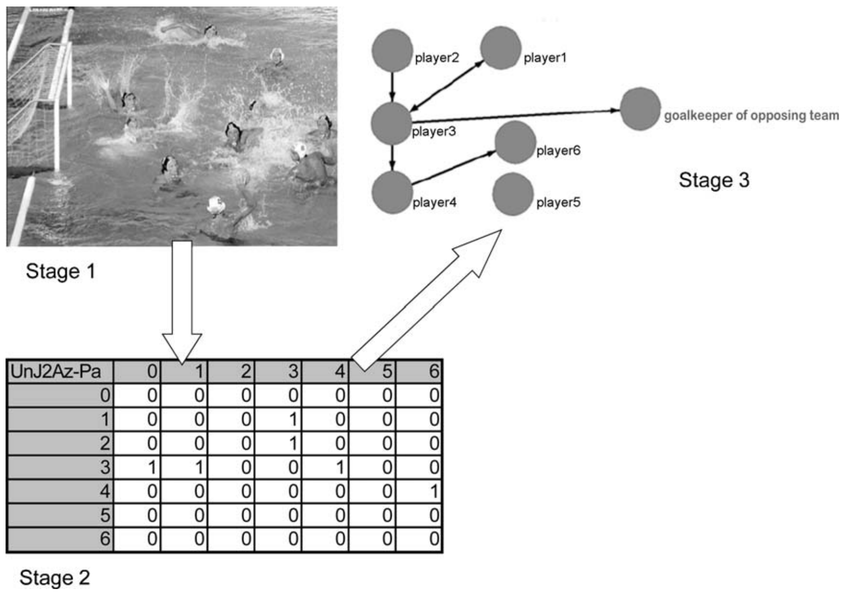
How to perform collectively in competition is an issue that is highly topical in sport science and performance analysis; thus it is important to attempt to identify whether network topologies can characterize successful or unsuccessful performance. In team sports it is fundamental that players coordinate their actions to achieve dynamic patterns of collective behaviours that allow them to satisfy game task constraints. In sport science, interpersonal coordination tendencies (inter-team and intra-team) have been shown to emerge from the couplings of players as social system agents.[4,5] These interactive tendencies are influenced by multiple causes that produce multiple effects and are, thus, defined as complex.[6] For example, if observed, this type of conceptualisation could provide a viable basis for future notational analysis research.

The limited number of agents in team sports bound opportunities for interactions among players. Owing to this feature, a team game might be conceptualised as a small-world, social neurobiological system, in which system behaviour might evolve from the interpersonal interactions among system agents. In the present study of team sport collectives we hypothesised that the creation of nodes of interactions among players might be an emergent property and may, thus, be time- and space-specific. These ideas illustrate how a set of players can be linked to form a sub-unit in a team to perform collective actions that enhance the probability of successful performance outcomes. Using networks methodology in an intra-team analysis, it may be possible to identify the players who most frequently interact with neighbouring team-mates and contribute to successful and unsuccessful collective actions. There are two main characteristics that make network approaches potentially more useful than traditional performance analysis methods (i.e. notational analysis). The first is the availability of network theory for developing understanding of how social networks are constructed. This knowledge conceptualises how agents in a complex system might interact to form a network. The second feature concerns the possibility of plotting a pattern of play with an observable network structure and topology. These network features allow us to identify the players engaged in more and less frequent interactions within a team, a useful method for comparing outcomes of successful and less successful patterns of play during performance.

In this paper our aim was to observe whether small-world networks could capture the rich interactions among players in a sports team. To achieve this aim, in the following sections, we introduce network methodology and analyse the levels of interaction among players that emerged during a competitive water polo match, as a task vehicle. We also evaluate the capacity of network methodology to characterize successful and unsuccessful patterns of play in team games. In the next section we describe the development of small world networks methodologies to analyse patterns of play in team games. The couplings that characterize how performers are linked incur structural changes over time, and are thus dynamic. In developing data collection methods to study collective system behaviours in sport, a key issue concerns how information is captured from competitive performance environments. This challenging aim requires the establishment of valid and reliable measures to describe and explain player interactions during team game performance.[1]

Previous research on interpersonal coordination in neurobiology has typically focused on the emergence of inter-limb coordination patterns between individual participants.[7,8] These studies revealed that the emergence of perception-action couplings underpinned coordinated activity between individuals. More recent work has attempted to study intentional and unintentional coordinated activity among individuals engaged in tasks with limited system degrees of freedom, such as rocking in a chair.[9] Some previous work has attempted to study the interpersonal interactions between agents in social neurobiological systems such as athletes in sub-phases of team games. Previous work on team games (e.g. rugby union, basketball, futsal) has conceptualised players' actions in competitive team sport performance as specific 'perception-action couplings' that emerge in specific game sub-phases, such as 1 vs. 1 attacker–defender dyads.[4,5,10]

Indeed, data from our programme of work[4,5] has suggested that the myriad of interactions that emerge among team players during competitive performance might lead to the emergence of distinct patterns of play. Some of these patterns will lead to successful performance outcomes and others will not. Nevertheless, an important goal for future research in sport science is to understand how the *structure* of the player interactions within teams might differ during performance. In this investigation we used networks methodology to analyze the structure of successful and unsuccessful patterns of play in sub-phases of water polo, evaluating the intra-team interactions that occurred in competitive matches. With the present state of development in networks methodology in mind, two main questions were addressed: (i) How can the number of intra-team interactions that emerge among team-mates during performance be displayed?; and (ii) What are the most successful types of intra-team interactions: those with a larger number of interactions or those with a smaller number of interactions between players?.[11]



UnJ2Az-Pa	0	1	2	3	4	5	6
0	0	0	0	0	0	0	0
1	0	0	0	1	0	0	0
2	0	0	0	1	0	0	0
3	1	1	0	0	1	0	0
4	0	0	0	0	0	0	1
5	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0

Fig. 1. A methodology to collect data using the complex networks approach. Stage 1 describes how images of a water polo match were captured for data analysis. Stage 2 displays an example of an adjacency matrix with the numbers 1–6 representing the players involved in a unit of attack. The number 0 (zero) is used when no linkages exist among players and the number 1 represents an event linking players (i.e. a pass between players; or players exchanging positions). Stage 3 provides an exemplar network of a unit of attack with the black arrows representing the level of linkages among players.

2. Methods

To characterize a team sport as a network, an important step is to define the criteria by which the players are linked. Only after that step can progress be made to build an *adjacency matrix* for each unit of attack to identify the proximity of interacting players. An adjacency matrix is a means of representing which vertices (e.g. players) in a network are adjacent to other vertices (e.g. players). The adjacency matrix is used to build a finite $n \times n$ network where the entries represent the linkages between players (e.g. when player A passes the ball to player B). A 'unit of attack' can be defined as the moment a team gained ball possession until the moment that ball possession was recovered by the opposition. In water polo, to build the adjacency matrix for each unit of attack, two linkage levels were established: (i) identification when a player passed the ball to a team-mate; or (ii) identification when players changed position in the performance area due to a team-mate's displacement. In water polo the players' positions in the performance area are defined by numbers from 1 to 6, allowing positional interchanges to be objectively observed in a straightforward manner (see Fig. 1). The criteria for choosing these two levels of linkage included: (i) an expression of a level of interaction between two system agents (e.g. a pass always involves a passer and a receiver; changing position in the performance area signifies that player A takes the place of player B and vice versa); and (ii) being easily observable for the purposes of objective analysis.

In Fig. 1 the method to convert patterns of collective team behaviours into networks is displayed. For example, the first stage was to record the images of the water polo game using a MiniDv camcorder at 25 Hz. The second stage was to analyze the images to collect data to build the adjacency matrix. In this study, the adjacency matrix displayed the numeric code "1" every time the ball was passed from one player to another, and "zero" was used to identify the players who were not directly involved in a specific sub-phase of attack (i.e. players who were not directly involved in the move). The third stage was to build the network, based on this adjacency matrix, so that we could plot the structure of the players' interactions in this attacking sub-phase. Since we set two levels of linkage an additional matrix was constructed to identify when the players changed position. Again, the numeric code "1" was used to identify a position change, and "zero" signified that a player remained in the same location. Those procedures were carried out on recordings of 11 units of attack for each team during a water polo match as a task vehicle to test the network methodology.

3. Results

In the remaining sections of this paper we analyse and discuss exemplar data on player interactions during an attacking sub-phase of water polo, to provide some insight on intra-team pattern-forming dynamics in sport. The findings highlighted two parameters that seemed to lead to successful patterns of play: (i) the number of interactions between team members; and (ii) the probability of each player within a team interacting with each team-mate in subsequent phases of attack.

The results suggested that networks provide a useful method to qualitatively describe the interactions that occur

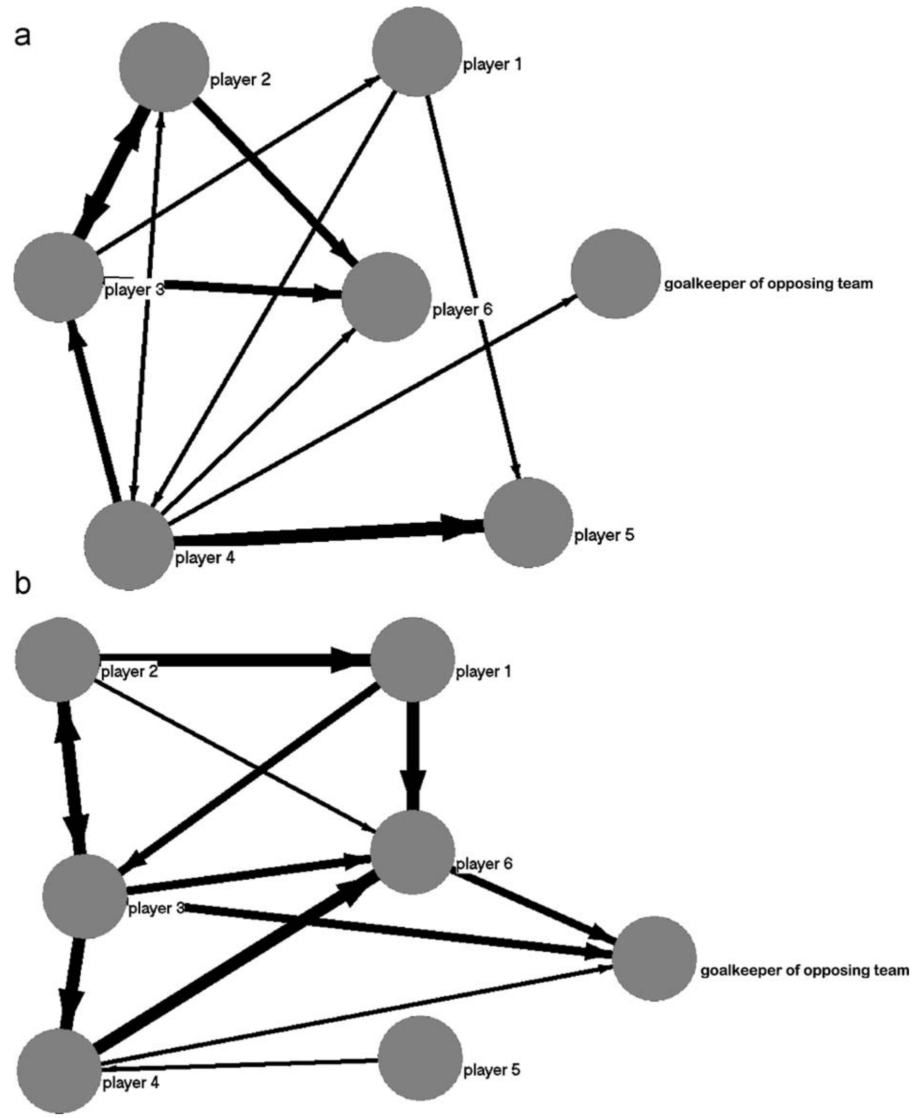


Fig. 2. (a and b) The grey circles represent the players involved in the units of attack. The direction of the black arrows indicates pass direction. The origin of the arrow represents the player who passes the ball and the arrowhead represents the player who received the ball. The width of the black arrows denotes the quantity of passes from one player to another during performance (i.e. thicker arrows illustrate more passes occurring between specific players and thinner arrows represent fewer passes taking place among players).

among players in the water polo game. In Fig. 2a and b the direction and level of interactions within each team are displayed. The black arrows identify the pass direction (i.e. between the player who passed the ball and the player who received the ball). The width of arrows in the figures characterizes the number of interactions (i.e. passes or positional changes) among players, with larger arrows signifying more inter-player interactions, and smaller arrows indicating fewer interactions among team-mates.

Beyond qualitative analyses, networks also afford opportunities for quantitative analyses to interpret differences between successful and unsuccessful patterns of play. Fig. 3a and b illustrates the probability that players A and B interact together (i.e. passing the ball to each other or exchanging positions). The more interactions that occurred among players, the lighter is the colour displayed in the grid, as displayed in the reference scale on the right hand side of each grid. In Fig. 3a and b it can be observed that the light team (Fig. 3b) displayed more interactions among its players than the dark team (Fig. 3a). In both figures, players coded number "seven" are the goalkeepers. When analyzing the data from the dark team (Fig. 3a), it can be observed that the player coded number "1" had a low probability (between 0.06 and 0.13) of interacting with other players in the team. Additionally, it can be observed that player number "6" had a high probability of interacting only with the players numbered "2" and "3" (0.48). With other team-mates, the probability of interaction was very low (between 0.06 and 0.13). In contrast, in the light team (Fig. 3b), all the players displayed a reasonable (above 0.22; a value classified as "reasonable" because it is

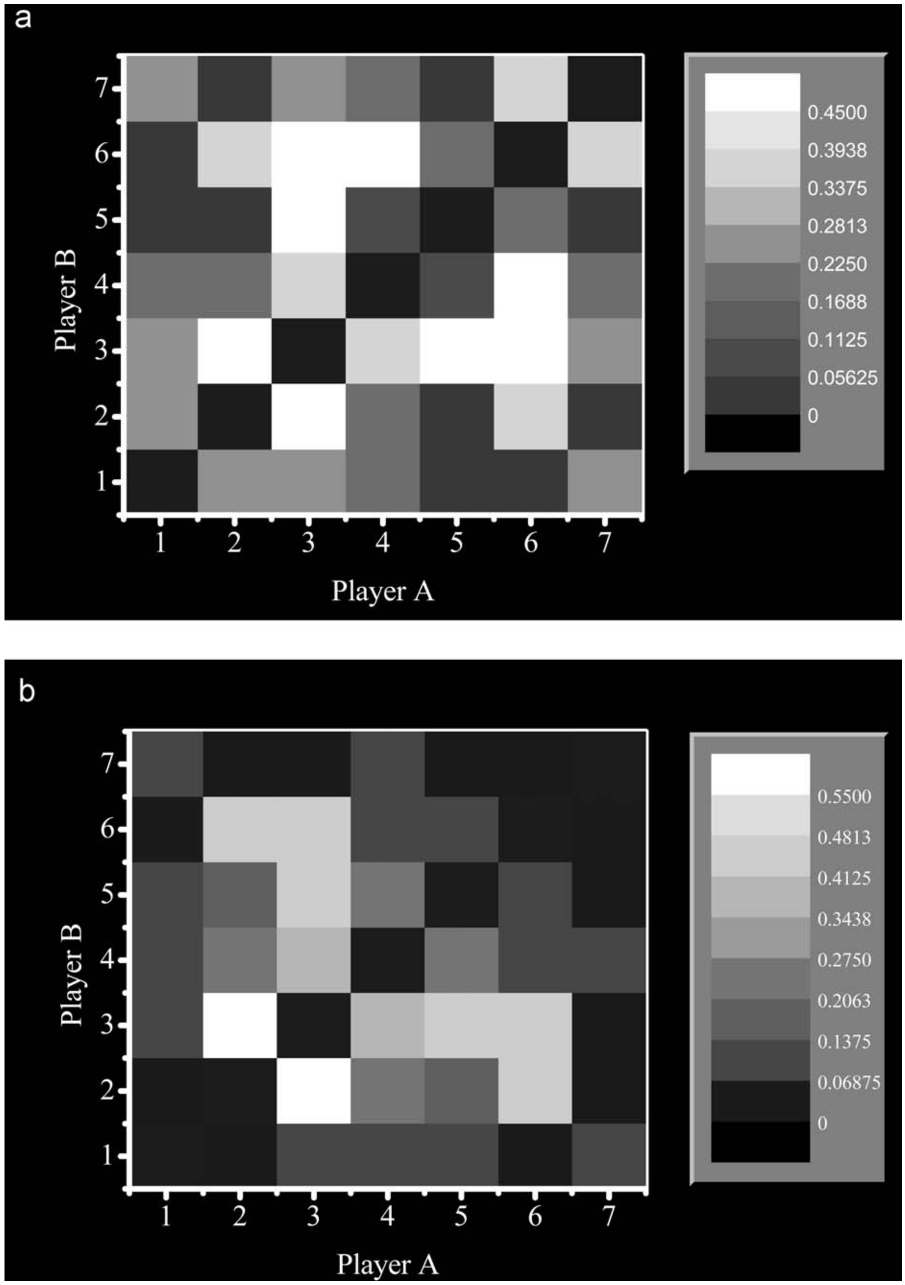


Fig. 3. (a and b) The scale on the right-hand side of each figure displays the probability that player A will interact with player B.

situated near the middle of the scale) to high level of probability of interacting with each other. The only exception to this observation was the probability of interaction among player number "1" and players number "5" and "6" (values below 0.06).

From the data visualisations, it appears that the pattern of play displayed by the light team was characterized by a higher number of interactions (Fig. 2), as well as a higher probability of interactions among players (Fig. 3) in subsequent units of attack. It was observed that this pattern of interactions among team-mates tended to lead to more successful collective performance outcomes. It was also observed that the players of the dark team interacted less frequently than the players of the light team. This observation can be sustained by the higher number of thinner arrows ($k = 6$) displayed for the dark team (Fig. 2a), signifying single interactions among players. In contrast, the light team (Fig. 2b) exhibited a higher number of interactions among players as displayed by the higher number ($k = 8$) of broader arrows. In Fig. 3a (dark team), a low probability of player interaction was displayed, suggesting that this team was more reliant on individual efforts and initiatives of players, rather than collective behaviours. In contrast, the light team displayed a greater probability for players to interact in collective behaviours which is an important feature for successful outcomes in team games.

4. Discussion

In this paper we outlined how the structure and specific topology of a network might provide useful insights about collective behaviours in team sports, which can be used in tactical and strategic decision making for competition. From the results it was possible to visually identify emergent patterns of play that were different (Fig. 2a and b). Thus, it can be suggested that team games, such as water polo, are systems with the capacity for small-world networks to form among system agents. This methodological approach provides the opportunity to assess the relative success of a specific team formation or tactical pattern over others, a notion that requires further investigation.

Collective behaviours are paramount for success in attacking sub-phases of team games and are strongly dependent on how players are coupled in emerging intra-team coordination patterns. The quantification and visualisation of those intra-team coordination patterns afford coaches useful knowledge to assess which players are most and least involved (i.e. displayed in the highest and lowest number of interactions with the team-mates) in each attacking subphase. Measurement of temporal or spatial distribution of the high frequency nodes of interaction in team sports is an important issue for further research in this approach to performance analysis. The data illustrated how team games can be characterized as small-world networks with peaks of high activity interactions among agents that occur with different spatio-temporal relations. We hypothesised that, at each moment of the game, not all the players would demonstrate an equal level of interaction with team-mates. In other words, some players might have greater involvement in high frequency activity regions (i.e. regions where the ball is located), whereas other players may be located far from those areas. This performance feature led to the emergence of specific topologies that were captured by the small-world networks.

In every team game there are players with whom teammates might prefer to be linked (e.g. illustrated through passing the ball). These players are known in complex networks language as *preferential attachments*. Identifying the *preferential attachments* within a small-world network can be a very useful way to accurately identify the key "decision makers" during important phases of competitive performance. Identifying the ecological constraints that potentiate the decision-making function of players will also advance training methods.[10,12]

A further interesting question for further research is: if we substitute or "erase" a particular *preferential attachment* link, how does the rest of the team re-organise? Are team sport players dependent on the actions of *preferential attachments*, functioning in a hierarchical mode of control, or do they have the ability to collectively display self-organisation in a distributed mode of control? Which one of these modes of control better fits the specificity of demands in different sports? The latter is an open question that has emerged from the initial work of Mendes et al.[11] highlighting the need for further research using small-world networks as a method by which to analyse collective performance in team sports.

5. Conclusions

The present data allowed us to confirm that small-world networks may be a useful method for capturing pattern-forming dynamics in team sports. The results of work indicated that, in theoretical modelling of team game pattern forming dynamics, the most successful collective system behaviours required a high probability of each player interacting with other players in a team (see Fig. 3b). Further research on the nature of *preferential attachments* may add new insights concerning the most useful mode of control to be adopted in different team game performance contexts. More specifically, we were able to conclude that networks analysis is a viable method to represent the several levels of intra-team interactions that emerged during a water polo match.

Practical implications

- Based on empirical observations of the level of interactions among specific players, coaches should adopt training methods to strength specific 'couplings' that emerge among key players in different sub-phases of team games.
- Training methods should increase the number of interactions afforded during each game subphase. Each player in a competitive performance environment must be able to interact with other key players to form successful subunits in teams.
- To potentiate players' couplings, training methods should be sustained on task constraint manipulations (involving changes to the number of opponent players involved in practice; field dimensions; specific task instructions) to design learning environments that are representative of competitive performance contexts.

Disclosures

All procedures used in this study were approved by the Ethics Committee of the Faculty of Human Kinetics, Technical University of Lisbon, following the guidelines of the American Psychological Association for research involving human participants. All participants provided informed consent to take part in this research project.

References

1. Barabasi AL, Oltvai ZN. Network biology: understanding the cell's functional organization. *Nat Rev Genet* 2004;**5**(February (2)):101–13.
2. Albert R, Barabasi AL. Topology of evolving networks: local events and universality. *Phys Rev Lett* 2000;**85**(December (24)):5234–7.
3. de Menezes MA, Barabasi AL. Fluctuations in network dynamics. *Phys Rev Lett* 2004;**92**(January (2)):028701.
4. Passos P, Araujo D, Davids K, et al. Information-governing dynamics of attacker–defender interactions in youth rugby union. *J Sports Sci* 2008;**26**(13):1421–9.
5. Passos P, Araujo D, Davids K, et al. Interpersonal pattern dynamics and adaptive behavior in multiagent neurobiological systems: conceptual model and data. *J Mot Behav* 2009;**41**(October (5)):445–59.
6. Bar-Yam Y. *Making things work. Solving complex problems in a complex world*. NECSI, Knowledge Press; 2004.
7. Schmidt RC, O'Brien B. Evaluating the dynamics of unintended interpersonal coordination. *Ecol Psychol* 1997;**9**(3):189–206.
8. Schmidt RC, O'Brien B, Sysko R. Self-organization of between-persons cooperative tasks and possible applications to sport. *Int J Sport Psychol* 1999;**30**:558–79.
9. Richardson MJ, Marsh KL, Isenhower RW, et al. Rocking together: dynamics of intentional and unintentional interpersonal coordination. *Hum Mov Sci* 2007;**26**(December (6)):867–91.
10. Araujo D, Davids K, Hristovski R. The ecological dynamics of decision making in sport. *Psychol Sport Exerc* 2006;**7**(November (6)):653–76.
11. Mendes J, Passos P, Paz N. Networks as a method to analyze the dynamics of collective behaviors: an exploratory approach with water polo. *Int J Sport Psychol*; in press [2nd ICCSS & 10th EWEP Special Issue].
12. Davids K, Button C, Araujo D, et al. Movement models from sports provide representative task constraints for studying adaptive behavior in human movement systems. *Adapt Behav* 2006;**14**(1):73–95.