A multilevel hypernetworks approach to capture properties of team synergies at higher complexity levels.

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Title: A multilevel hypernetworks approach to capture properties of team synergies at higher complexity levels

Running title: Applicability of Multilevel Networks in Team Sports Performance Analysis

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Fig. 1 Example of a multilevel hypernetwork representation (from bottom to top): All players are tagged by numbers: Those of the black team play from left to right: Players from the blue team play from right to left. Goalkeepers are attached to their respective goals and the simplices' formation is based on players' proximity on field with the arrows depicting their direction of displacement. Level N is the simplest and represents player location on field (black team is organised according to a 1-4-3-3 configuration (one goalkeeper, four defenders, three midfielders and three forwards) and the blue team in a 1-4-4-2 configuration (one goalkeeper, four defenders, four midfielders and two forwards)). Level N + 1 depicts two consecutive time frames of the match (from left to right) and refers to proximity-based simplice interactions, which are are foundations for defining the simplice sets identified for the two time frames. Level N + 2 represents emerging microstructures of play showing both numerical imbalance (3vs.2) and numerical balance (1vs.1), with respect to field location (LC – left corridor; CC – central corridor; RC – right corridor). Level N + 3 represents the dynamic interaction between simplices, here exemplified by the interaction between players that form the simplex of the defensive line sector with players that form the simplex of the midfield line sector of the blue team, without resorting to geographical proximity criteria.

Fig. 2 Schematic representation of players' simplices and the ball line (black dashed line). Players composing the black team play from left to right, while players from the blue team play from right to left. Simplice formation is based on geographical proximity between players with goalkeepers being attached to their goals. The player tagged with number 24 has the ball (B) and is involved in a simplex of 2vs.2 along with player 23 from the black team, and players 9 and 13 from the blue team. Behind the ball line are located the goalkeeper (29), and two types of simplices (1vs.1 composed by players 26 and 6; 2vs.1 composed by players 18 and 28 from the black team and player 3 from the blue team). Ahead of the ball line are located three types of simplices (1vs.1 composed by players 16 and 5; 3vs.2 with players 15, 2, 12 from the blue team and players 19 and 27 from the black team; 2vs.2 composed by players 22 and 17 from the black team and players 8 and 11 from the blue team), and the goalkeeper from the blue team coded by number 14.

Abstract Despite its importance in many academic fields, traditional scientific methodologies struggle to cope with analysis of interactions in many complex adaptive systems, including sports teams. Inherent features of such systems (e.g., emergent behaviours) require a more holistic approach to measurement and analysis for understanding system properties. Complexity sciences encompass a holistic approach to research on collective adaptive systems, which integrates concepts and tools from other theories and methods (e.g., ecological dynamics and social network analysis) to explain functioning of such systems in natural performance environments. Multilevel networks, such as hypernetworks, comprise novel and potent methodological tools for assessing team dynamics at more sophisticated levels of analysis, increasing their potential to impact on understanding of competitive performance. Here, we discuss the potential of concepts and tools derived from studies of multilevel networks for revealing key properties of sports teams as complex, adaptive social systems. This type of analysis can provide valuable information on team performance, which can be used by coaches, sport scientists and performance analysts for enhancing practice and training. We examine the relevance of network sciences, as a sub-discipline of complexity sciences, for studying dynamics of relational structures in sports teams during practice and competition. We explore benefits of implementing multilevel networks, in contrast to traditional network techniques, highlighting future research opportunities. We conclude by recommending methods for enhancing applicability of hypernetworks in analysing collective dynamics at multiple levels.

Key Points:

- Inherent properties of complex social systems require more holistic methodological approaches for studying adaptive system functioning.
- Complexity sciences provide a holistic and comprehensive approach for understanding continuous interactions that emerge between individual competing athletes to explain team dynamics.
- Use of multilevel networks such as hypernetworks, circumscribed in the complexity sciences paradigm, has the potential to overcome major limitations that exist in traditional network analyses, enabling a more sophisticated and accurate method of understanding relational structures underlying team functioning at multiple levels.

1 Introduction

Traditionally, team interactions in sports performance contexts have been conceived as the aggregation of individual performances. Typically, in an attempt to identify relevant properties of such collective systems, sports scientists have applied a set of methodological tools that recursively decompose the parts of the system into individual units. Once gaining insights into how individual units (players) behave within the system, sport practitioners recombine them again into a collective/whole system. Such a reductionist approach is based on linear thinking and models, consonant with analysis of reducible, linear systems, whose behaviour is commonly depicted as resulting from the aggregate of individual actios within the system [1]. This line of thinking is aligned with simple models of information processing, resulting from linear input-transformation-output processes [2]. However, what happens when such systems display dynamic, complex, non-linear, interdependent behaviours? Indeed, traditional science has been challenged to describe and explain how novel coordination patterns spontaneously emerge within complex adaptive systems, such as schools of fish, colonies of insects and sports teams [3]. Despite being composed of individual members, sports teams operate as an integrated whole, producing an intertwined and complex set of behaviours that are not entirely predictable at an individual level of analysis [4, 5]. Such behavioural patterns are emergent and not merely an accumulation of individual performances per se; instead, they arise from continuous, ongoing interactions amongst group members [6, 4]. Contrary to postulates of linear models, complexity sciences have emerged as a holistic approach to understanding behaviours of complex adaptive systems. Within the field of network sciences, an emergent methodological approach is hypernetworks [7] that investigate group dynamics at *multiple levels* of analysis [8]. In this position paper, we outline the benefits of utilising a multilevel approach, in contrast to traditional network techniques, in analysing team dynamics during practice and competitive performance. We start by briefly reviewing the importance of complexity sciences for studying complex social systems in the realm of team sports performance. Next, we discuss the relevance of social network analysis (SNA) (a sub-discipline utilised by complexity sciences) as a suitable framework for ascertaining the relational structures exhibited by interactions between agents in sports teams during competition. We discuss the adoption of multilevel networks, in contrast to traditional network techniques, as novel and potent methodological tools for overcoming some of the limitations encountered in previous analysis of social networks. Finally, we propose future research possibilities and methodological alternatives for enhancing the multilevel approach.

2 Complexity sciences: A multidisciplinary approach for studying social interactions in team sports

A major question considered here is: Are theories and methods in complexity sciences relevant for describing and analysing collective phenomena in sports? Complexity sciences have already demonstrated, over past years [e.g., 9-13], effective methods for analysing behaviours of non-linear systems. An important point to note is that, the more complex a system is (i.e. having *many interacting* parts), the less amenable to linear, reductionist analyses it becomes. Previous studies have revealed that the complexity sciences can provide profound insights on sports-related phenomena which are inherently complex and multidimensional by nature.

Complexity sciences investigations of behaviours in complex adaptive systems have revealed many *interacting* elements, whose behaviour is difficult to ascertain due to continuous interactions and interdependencies between system components, and co-relations with their surrounding environments. The delimitations of such open systems tend to be based on operational definitions (e.g., skin as a barrier between organism and environment), which is not theoretically driven. Such systems display properties underpinning integrated behaviours, significantly differing from properties and behaviours of their individual elements. A fundamental property of complex systems is emergence. Emergent behaviours cannot be simply irreducible to the behaviours of system elements. Rather, behaviour must be contextualised according to how the elements interact within the system and environment within which they are embedded. Moreover, self-organisation, adaptive behaviours, variability, nonlinearity, and complex networking, constitute other key properties of such systems [14, 6].

The key challenges when analysing behaviours of such systems are related to their formal modelling and simulation. Current research on team sports performance analysis has witnessed a progressive increase on investigations of performance behaviours based on positional data (see, for example, Agras et al. [15] and Sarmento et al. [16] for detailed reviews). Applications of novel and sophisticated techniques, using non-linear statistical tools have supported capture of collective behaviours, identified by variables such as team centroids (geometric centre of a group of players) and team dispersion (how far players are apart), as well as team communication (e.g., networks underpinning ball-passing sequences) and sequential patterns (predicting future passing sequences) [16]. Lately, there has been increasing interest in research on team communication networks [e.g., 17-19].
Sports teams are composed of players interacting through several communicational channels, revealing specific relational ties (e.g., through ball-passing actions). These interactions can be depicted by a

complex network with players representing the nodes of the network, and the links reflecting their interactions on field [18, 20-22]. Network approaches are extremely useful, since application of their concepts and methods can illuminate dynamical properties in individual and team sports [23-26], contributing to a specialised body of knowledge for understanding the functioning of such complex adaptive social systems.

3 Social network analysis (SNA) as a paradigm for modelling complex social systems

Theories and methods underpinning SNA include, for example, graph theory (mathematical structures utilised for modelling pairwise relations between objects) and social structure analysis pertaining to the field of sociology. Lately, SNA has extensively focused on sports performance data [18, 20, 27-30] as a means of analysing complex relational/structural interactions. The applicability of such an approach is predicated on insights regarding interactions of structures that ultimately lead to emergent complex phenomena [21, 31]. Indeed, re-conceptualisation of sports teams as complex social networks [22, 32] has revealed novel research opportunities for researchers, sports scientists and performance analysts to investigate the structural properties of teams during practice and competition linked to successful performance outcomes.

Beyond the unique terminology (e.g., nodes/vertices, links/edges) used for modelling social interactions within collectives, such an approach utilises specific conceptual and methodological tools for understanding and predicting team performance. Despite being a promising methodological approach, more coherent with the principles of complexity sciences in analysing complex social systems, traditional network techniques contain specific limitations that may eventually hinder or even conceal important information regarding team functioning during competition. Such limitations have been carefully scrutinised in the works of Ribeiro et al. [22] and Ramos et al. [32], and researchers have proposed possible alternatives and/or methodological tools that can ultimately reinforce the network approach for adequately analysing the relational properties of sports teams.

4 Hypernetworks as innovative and potent methodological tools for analysing dynamic relational structures of sports teams

Hypernetworks have recently emerged as a major hot topic of research for many branches of science, including sports science. Multilevel analysis and representing relations via hypernetworks were originally introduced by Johnson and Iravani [7] for analysing the dynamics of complex systems of robot football agents. More recently, such an approach was extrapolated to investigate the dynamics of human football players during competition [8]. Indeed, Johnson and Iravani [7] have proposed that a multilevel approach can be extended to analyses of other multiagent systems (e.g., football teams) where dynamics emerge from interactions between the agents. Research on hypernetworks is still fresh and much work is needed to continue development of multilevel analytics. Its potential is enormous since it can override most of the limitations found in traditional network techniques.

For example, a major limitation of traditional methods is that they only focus on binary relations between two players [33]. Potentially, multilevel hypernetworks are not restricted to analysis of dyadic relations; rather they support representation of simultaneous *n-ary* relations (n > 2) among sets of nodes/vertices (i.e., team players). Their properties are represented by a hyperedge supporting connections between more than two players (within and between teams) at the same time (called simplex, plural - simplices) [33-37]. Hyperedges shed light on physical links (e.g., notation of who passes the ball to whom) established between players which facilitate information exchanges. Also informational links (e.g., values of interpersonal distances, velocity and acceleration) bound players' interactions. This is particularly important because, for instance, researchers can analyse emergent interactions (by verifying changes in the velocity and direction of each player's vectors) that led to the assembly and/or dissolution of a specific simplex structure (e.g., to balance and/or unbalance the simplex). These interactions are important because previous research (e.g. Ramos et al. [8]) has suggested that changes in velocity near the goal allowed players to improve their positioning to score goals and/or to unbalance opposition defensive structures.

Ramos et al. [8] confirmed the relevance of hypernetworks for extracting important information from game performance data. Their data verified: i) the most frequently occurring simplices configurations during the match; ii) dynamics of simplices' transformations (variations of players' speed and direction) near the goal that led to the creation of goal-scoring opportunities, and: iii), dynamics of interactions at higher complexity levels, i.e., interactions between simplices of simplices.

Next, we provide a detailed analysis of the conceptual and methodological implications of applying multilevel hypernetworks in sport, addressing the main limitations of traditional network techniques, as discussed in the article by Ribeiro et al. [22].

5 Application of multilevel hypernetworks to understanding sport performance

5.1 The majority of studies employing social network analysis have observed information exchange between players mainly through passing behaviours

Hypernetworks can include an element *R* that describes relationships emerging within the set (simplex) [36] composed by a given number of players in a sports team. Each simplex can be represented by a convex hull computation (the minimum convex area containing all players in the simplex) and includes the velocity of each player (vector velocity regarding the instant t-1 and t), as well as the velocity of the geometric centre of the simplices. The simplices can be completed with information describing other types of technical actions (e.g., ball manipulation (BM)) undertaken by players during performance. Additionally, a computer procedure for calculating the simplices' hyperedges, defined with a proximity criterion, can be implemented using GNU Octave and applied to each time frame of the match. Such a proximity criterion implies that interactions between players, as well as sets of these interactions (simplices), are assessed based on interpersonal distance values, especially spatial proximity and instant speed relational variables [8]. This signifies that each player is connected to his/her nearest player (or goal, for goalkeepers), while the same is verified at higher levels, where simplices can be linked to their closest simplices [8].

To exemplify (Fig. 1), imagine a first simplex identified by σ_1 and represented by the following set σ_1 {a_{16}, a_{23}, a_{24}, d_9, d_{13}}, where a_{16}, a_{23}, and a_{24} represent three attacking players, while d_9 and d_{13} represent defending players. The simplex set can be enhanced by an element R_1 [8] which, basically, identifies the relationships (microstructures of play) within the set R_1=(3vs.2). The second simplex σ_2 represents the following set σ_2 {a_{16}, a_{24}, d_9} identified by R_2=(2vs.1), composed of two attackers and one defender. Finally, the third simplex σ_3 is represented by σ_3 {a_{23}, d_{13}} identified by R_3=(1vs.1), composed of one attacker and one defender. Hence, the respective microstructures of play are R_1=(3vs.2), R_2=(2vs.1) and R_3=(1vs.1), and the corresponding simplices are σ_1 {a_{16}, a_{23}, a_{24}, d_9, d_{13}; (3vs.2)}, σ_2 {a_{16}, a_{24}, d_9; (2vs.1)} and σ_3 {a_{23}, d_{13}; (1vs.1)}. Let us say that these simplices' transformation (from σ_1 to σ_3) was observed during two consecutive time frames (t_1-t_2) of the match in an attacking sequence that resulted in a goal-scoring opportunity. Now, let us suppose that the configuration of the simplices' transformation from σ_1 to σ_3 was provoked by a movement of player a_{23} from simplex σ_1 which ran with the ball at speed (BM) further away from simplex σ_1. This action performed by player a_{23} allowed him to dissociate along with d_{13} (geographical proximity criteria) from previous simplex σ_1, thus originating the formation of simplices σ_2 and σ_3.

We can add BM ($BM_{a23\text{-}d13}$) to σ_1 {a_{16}, a_{23}, a_{24}, d_9, d_{13}; (3vs.2); $BM_{a23\text{-}d13}$} as an extra layer to complete the description of the set. Hence, the sequence of the following sets of simplices is: σ_1 {a_{16}, a_{23}, a_{24}, d_9, d_{13}; (3vs.2); $BM_{a23\text{-}d13}$} -> σ_2 {a_{16}, a_{24}, d_9; (2vs.1)} + $\sigma 3$ {a_{23}, d_{13}; (1vs.1)}. This example provides a more complete description of the behaviours of both teams and how they evolve over time, which now includes relevant information on other technical actions realized by the players. These actions might be crucial for destabilising the numerical balance/imbalance of a given simplex, without focusing solely on ball-passing events.

However, beyond providing qualitative information regarding team performance, other relevant information can be included to quantitatively express relational dynamics of competing teams. This could be exemplified by counting the number and types of microstructures of play (e.g., sub phases such as 1vs.1) emerging during practice [8], and also the frequency of other technical actions performed by players during competition. The conceptualisation of team sports performance with a hypernetworks methodology might help sports scientists and researchers develop novel performance metrics [8], capable of capturing team synergies emerging between players. By using positional coordinates of players from both teams and the ball, we can analyse, for example, how players pertaining to a specific simplex (the defensive line sector) synchronise their movements with other players pertaining to another simplex (the midfield line sector). This can be done, for example, by computing the mean relative phase of each player to his/her corresponding simplices with which players interact throughout the match. Or, we may ascertain how far both simplices (the defensive and midfield line sectors) are separated from each other (e.g., through measurement of the simplices' geometric centre), providing insights into team compactness and/or spread. Here, hypernetworks support the provision of detailed information on the players composing each simplex and how synchronised or far/near simplices are.

5.2 Variability of player performance outcomes is associated with specific events in competitive performance

Ribeiro et al. [22] highlighted the over-emphasis on frequency counts of actions in performance analysis, suggesting that *"Most studies analyse results according to the total number of interactions* *displayed by the adjacency matrix, which does not reflect the inherent dynamics of team games" (pp. 1694).* Implementation of multilevel hypernetworks can consider both space and time in analysis of team dynamics since, for example, it can use geographical proximity criteria (if previously defined for creating the simplices' sets of nodes) and capture temporal changes by considering players' geographical positions over time (t_1, t_2,…..,t_n) [8]. Furthermore, Johnson [35] introduced the concepts of *backcloth* and *traffic* to emphasise the study of dynamics in multilevel analysis. The network is the backcloth involving fewer dynamic structures, while the traffic relates to the network flows, thus considering higher rates of change emerging within the backcloth [35]. Application of these novel ideas to team sports performance analysis, might consider, for example, the disposition of players on field in football. Pplayers organised according to positions in a 1-4-3-3 formation with one goalkeeper, four defenders, three midfielders and three forwards, for example), with typical adjustments, can be the *backcloth*, and player displacements on field (both off- an on-the-ball) is the *traffic*. Hence, each pre-defined team disposition on field may afford the emergence of certain relational dynamics specific to that configuration. Playing in a configuration of 1-4-3-3 is not the same as playing in a 1-4-4-2 configuration. Relational dynamics of players in both systems may differ significantly. For example, the first configuration has only three midfielders and one central forward, the latter has four midfielders and two forwards. These and other team properties might constrain team dynamics, and thus promote specific individual and team behaviours.

Developing mathematical formalisms underlying the hypernetworks approach enables the representation of a multilevel model for describing team behaviour dynamics, where micro–to–meso–to-macro levels of relational structures are considered in a holistic analysis [8, 38], allowing us to investigate higher complexity levels inherent to team sports competition (Fig. 1).

Please insert Figure 1 near here

5.3 Research over-emphasises analysis of attacking behaviours in performance analysis, rather than defensive behaviours

A major advance, compared to traditional network analysis, is that use of simplices can capture interactions of sets of players that may involve an arbitrary number of teammates and opponents [8]. Such an advance signifies permits analysis of both cooperative and competitive interactions emerging between players simultaneously. This approach ensures that both attacking and defending patterns of coordination are considered in analysis of team dynamics, providing insights regarding team functionality and adaptability during competitive performance. Adding information about ball location (e.g., position coordinates acquired though match analysis statistical reports, such as Opta Sports (London, United Kingdom) can furnish novel and rich insights regarding functional dynamics of both attacking and defending teams. Arguably, ball location on field constitutes a major constraint which continually shapes how players from both teams continuously co-adapt their positioning on field. This could affect individual and team dynamics, which should be addressed in future investigations of hypernetworks. For example, by including information from ball location in hypernetworks analysis (Fig. 2) researchers are able to identify the player with the ball (B) in a given simplex n (σ_n {a_{24B}, a_{23}, d_9, d_{13}}), while investigating the number and types of simplices formation (e.g., 2vs.1), as well as the attacking and defending players located behind and ahead of the ball line. Such an analysis may provide coaches and performance analysts with relevant information regarding offensive and defensive patterns of team play.

Please insert Figure 2 near here

5.4 Most of the metrics used to model social interactions are based on paths, which can be inappropriate for sports contexts

An imperative step of the hypernetworks approach is to define, at each level of analysis, the significant relations that govern dynamics of competitive performance, and represent them utilising different criteria (e.g., modelling team dynamics through values of players' interpersonal distances) for selecting the players in each set (i.e., linked by a hyperedge) [34, 36]. A major concern with such an analysis is geographical proximity currently utilised for modelling team dynamics in hypernetworks. The definition of such criteria will considerably limit all data analyses and interpretations of team sport performance. It is an arduous and challenging task for researchers and sports scientists to seek and explore novel ways of conceptualising and (re)defining such criteria, theoretically and mathematically, based on characteristics of each team sport subjected to a multilevel approach. Another relevant issue is the use of metrics that consider more than single relationships (either dyadic or hyperedges). Previous studies (e.g. Borgatti [39]) have presented examples where using metrics based on shortest paths may not be adequate. Using walks instead of paths [39] or even applying random walk Monte Carlo methods (e.g. Cheng et al. [40]) for modelling social interactions may be worth considering.

6 Conclusions and practical applications

In this position paper, we highlighted how the multidisciplinary nature of complexity sciences, in contrast to traditional sciences, supports explanations of complex phenomena emerging in sports performance contexts. Under the umbrella of complexity sciences, and particularly SNA, multilevel hypernetworks constitute promising frameworks for scrutinising the dynamical relations emerging in collective interactions of competitive sport performance at several levels of analysis. Multilevel networks can overcome major limitations of traditional network techniques, having the potential for expanding the scope of analysis for studying team dynamics. They could provide more accurate information by representing and understanding multilevel team behaviour dynamics, including micro (e.g., interactions between players), meso (e.g., dynamics of a given critical event, e.g., a goal being scored), and macro (e.g., interaction between sets of players) levels.

Compliance with Ethical Standards

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Conflict of interest João Ribeiro, Keith Davids, Duarte Araújo, Pedro Silva, João Ramos, Rui Lopes, and Júlio Garganta declare that they have no conflicts of interest relevant to the content of this article.

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