



## **Modelling Players' Interactions in Football:** A Multilevel Hypernetworks Approach

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Porto, 2019





## **Modelling Players' Interactions in Football:**

### **A Multilevel Hypernetworks Approach**

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To my family, with Love!



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## **Resumo**

Na presente tese procura-se avançar com fundamentação teórica e prática, assim como com demonstrações empíricas referentes à reconceptualização das equipas de futebol enquanto redes sociais complexas. Estas redes evidenciam comportamentos sinérgicos emergentes e auto-organizados cuja complexidade, enraizada nas redes de interações dos jogadores, pode ser discernida através da análise de redes sociais. Não obstante, as técnicas tradicionais de rede exibem algumas limitações que podem levar a dados imprecisos e falaciosos. Essas limitações estão relacionadas com a exagerada ênfase que é colocada nos comportamentos de ataque das equipas, negligenciando-se as ações defensivas. Tal leva a que: a troca de informações incida maioritariamente nos comportamentos de passe; a variabilidade do comportamento dos jogadores seja, na maioria dos casos, desconsiderada; e a maioria das métricas usadas para modelar as interações dos jogadores se baseiem em distâncias geodésicas. Assim, as hiperredes multiníveis são aqui propostas enquanto nova abordagem metodológica capaz de superar aquelas limitações. Esta abordagem multinível caracteriza-se por um conjunto de conceitos e ferramentas metodológicas coerentes com a análise da dinâmica relacional subjacente aos processos sinérgicos evidenciados durante a competição. Por um lado, estes processos foram capturados na dinâmica de alteração das configurações táticas exibidas pelas equipas durante a competição, pela quantificação do tipo de simplices (interações de grupos de jogadores, e.g., 2vs.1) atendendo à localização da bola, e na dinâmica de interação, transformação dos simplices em determinados eventos do jogo. Por outro lado, a aplicação das hiperredes multiníveis permitiu, de igual modo, capturar as tendências de sincronização local (nível meso) emergentes em contextos de prática. Esta tese destacou o valor da adoção de uma abordagem de hiperredes multiníveis para melhorar a compreensão sobre os processos sinérgicos dos jogadores e equipas de futebol emergentes durante a prática e a competição. Estas poderão vir a revelar-se ferramentas promissoras na análise da performance desportiva, tendo igualmente um papel relevante na monitorização e controlo do treino.

**PALAVRAS-CHAVE:** FUTEBOL, CIÊNCIA DAS REDES, HIPERREDES MULTINÍVEL, DINÂMICA DA EQUIPA, ANÁLISE DA PERFORMANCE



## **Abstract**

This thesis aims to advance practical and theoretical understanding, as well as empirical evidence regarding the re-conceptualisation of Football teams as complex social networks. These networks display synergetic, emergent and self-organised behaviour and the complexity rooted in the networks of players' interactions can be discerned through analysis of social networks. Notwithstanding, traditional network techniques display some limitations that can lead to inaccurate and misleading data. Such limitations are related with an over-emphasis on network attacking behaviours thus neglecting the defensive actions of the opposing team. This leads to: information exchange mainly analysed through passing behaviours; the variability of players' performance is in most cases disregarded; most metrics used to model players' interactions are based on geodesic distances. Thus, multilevel hypernetworks are proposed as a novel methodological approach capable of overriding such limitations. This multilevel approach is characterised by a set of conceptual and methodological tools consistent with analysis of the relational dynamics underlying the synergistic processes evidenced during competition. On the one hand, these processes were captured in the changing dynamics of tactical configurations of teams during competition, by the quantification of the type of simplices (interactions between sub-groups of players, e.g., 2vs.1) in relation to ball location, and in the dynamics of simplices' interactions and transformations in certain game events. On the other hand, the application of multilevel hypernetworks allowed to capture local (meso level) synchronisation tendencies in practice contexts. This thesis highlighted the value of adopting a multilevel hypernetworks approach for enhancing understanding about the synergistic processes of players and football teams emerging during practice and competition. These tools may prove to be promising in the analysis of sports performance, also having an important role in the monitoring and control of training.

**KEYWORDS:** FOOTBALL, NETWORK SCIENCE, MULTILEVEL HYPERNETWORKS, TEAM DYNAMICS, PERFORMANCE ANALYSIS.



## **List of Abbreviations**

CAS - Complex adaptive systems

Dofs – Degrees of freedom

SNA – Social network analysis

GK – Goalkeeper

CRD - Central right defender

CLD - Central left defender

LD - Left defender

RD - Right defender

DM - Defensive midfielder

LM - Left midfielder

RM - Right midfielder

LW - Left wing

RW - Right wing

FW - Forward

CSS - Complex social systems

BM –Ball manipulation

LC – Left corridor

CC – Central corridor

RC – Right corridor

B – Ball

A – Attacking

D – Defending

P – Pass

BR – Ball reception

DB – Dribbling

H – Header

BH – Ball holder

G – Goal

RPE – Borg rating of perceived exertion

P-S – Player-simplice

CPM – Cluster phase method





## List of Formulas

Cluster phase time series of the group in complex form:  
 $\dot{r}_j(t_i) \frac{1}{n_j} \sum_{k \in \Gamma_j} \exp(i\theta_k(t_i)) \dots\dots\dots 90$

Cluster phase time series of the group in radian form:  
 $\bar{\varphi}_j(t_i) \text{atan2}(\dot{r}_j(t_i)) \dots\dots\dots 90$

Continuous degree of synchronisation of the group:  
 $\rho_{\Gamma_j}(t_i) \left| \frac{1}{n_j} \sum_{k \in \Gamma_j} \exp(i(\theta_k(t_i) - \bar{\varphi}_j(t_i))) \right| \dots\dots\dots 90$

Temporal mean degree of group synchronisation:  $\rho_{\Gamma_j} = \frac{1}{T} \sum_{i=1}^T \rho_{\Gamma_j}(t_i) \dots\dots\dots 90$



## Chapter 1

### General Introduction



## **1.1 Introductory note**

This chapter provides an overview on the current understanding of team communication. Moreover, it briefly discusses the processes that govern the formation of communication networks among players within teams, while highlights the relevance of social networks to investigate the properties underlying such communication processes. Social network analysis encompasses a set of theoretical constructs and analytic tools that shed light on important topological properties (e.g., density of interactions within teams) underlying team organisation and performance. Although important insights have been acquired in previous research through implementation of such traditional network techniques, still some important issues related with the current application of social networks urge to be addressed. Moreover, the communication processes emerging within teams occur through numerous networks of players' interactions that cohere to form patterns at a multilevel (micro-meso-macro) scale through exploiting processes of synergy formation. Scientific support for a multilevel approach capable of adequately analysing team communication processes is appraised in the next sections.

## **1.2 Team communication**

A highly relevant topic of concern in sports science, and, more specifically, in performance analysis, is to understand how team sport games composed by multiple and interrelated individuals communicate among themselves in order to achieve shared performance goals. In this regard, previous research (e.g., Silva et al., 2016) has allowed to conceptualise team sport games as complex adaptive systems (CAS) composed by individual elements or degrees of freedom (dofs) of the system (team) that can be coordinated and regulated to produce functional movement behaviour. Transposing such ideas to the realm of team sport performance implies viewing each player as an individual dof of a team that needs to coordinate and regulate his actions with others to attain organised coherent patterns of play. Previous insights of Bernstein (1967) regarding on how independently controllable movement system dofs could be coupled into functional synergies without needing control of each single dof separately (Bernstein, 1967; Newell & Vaillancourt, 2001; Turvey, 1990), were extrapolated

to team sports performance analysis to explain how coordination and communication processes emerged within and between players and teams.

This thesis will focus solely on analysis of the synergetic behaviours underlying the communication processes of association football (soccer) teams. Football teams are composed of numerous heterogeneous individuals whom have been assigned differentiated roles and/or functions to perform collectively during competitive performance. Despite this differentiation of roles within teams, satisfying task demands during competition requires from players the ability to perform coordinated and functional behaviours, by communicating and interacting dynamically, interdependently, and adaptively to achieve shared performance goals (Duarte et al., 2012). Coordination of actions among team players during competition depends on information communicated effectively and efficiently to support networks of interactions between individual players or sub-groups.

In general, communication may be regarded as some form of transaction between performers (i.e., teammates in sports teams) whereby all parties involved are continually and simultaneously sending and receiving information (e.g., communicating through ball-passing actions) (Harris & Sherblom, 1999). Like other social activities, in sports teams (e.g., football), there are two main mechanisms through which information can be diffused, namely: i) explicit or verbal communication, and (ii), implicit or non-verbal communication (Lausic et al., 2009).

While both communicative systems can be used simultaneously to develop human communication and coordination in sports teams, during competition, they may be expressed differently in terms of magnitude of use. Explicit or verbal communication is costly with respect to both time and cognitive load (Eccles & Tenenbaum, 2004). During sports performance, it is crucial for players to coordinate and communicate without relying on overt use of extended discussion, due to time constraints (Eccles & Tenenbaum, 2004; Reimer et al., 2006). Therefore, due to the ongoing dynamic nature of interactions that characterise sports performance, players must have the capacity to effectively coordinate behaviours by implicitly communicating (e.g., rotating positions) with each other. This thesis describes a programme of work that exclusively focuses

on analysis of the social networks that are implicitly created by players' interactions during competitive performance.

### **1.3 Establishing interpersonal synergies for team communication**

Among the properties that characterise CAS, self-organisation and emergence, are two intertwined and fundamental concepts that enable researchers to explain how collective patterns of behaviour emerge from local interactions of players. Self-organisation tendencies emerging through both local-to-global and global-to-local processes allow players and teams to attain newly formed structures (patterns of collective behaviour). Such structures, called synergies or coordinative structures (Davids et al., 2006; Kelso, 1998), allow players to reduce the number of feasible interpersonal linkages that can be used in a given task-specific circumstance (e.g., scoring a goal) for engaging in effective communication during goal-directed behaviours (Marsh et al., 2009; Passos et al., 2009; Riley et al., 2012;). Moreover, synergies are time-evolving dynamical systems (Thelen & Smith, 1994) meaning that they are not static but rather they may vary over time according to the circumstances of the competition. Therefore, when formed, synergies allow players in a team to behave as a collective social unit (Kelso, 2012; Riley et al., 2011), through establishment of complex networks. The complexity rooted in the network of interpersonal relationships emerging in competition is paramount since it constitutes a sentient, non-verbal communication system that supports functional performance (Passos et al., 2011). Importantly, during competitive performance, players may establish networks of interactions, allowing them to form multilevel structures (Johnson & Iravani, 2007). These multilevel structures may be expressed at micro-levels coupled with dynamics at macro-levels (Johnson & Iravani, 2007). This feature signifies that, for example, players interact locally (micro-scale level) with their nearest teammates (e.g., retrieving the ball from the pressure zone after recovering it) to produce more complex set of behaviours manifested at higher levels (macro-scale level), with players behaving as a collective social unit (e.g., increases in team width and length through increases of players' interpersonal distance values after recovering the ball).

Several studies have provided evidence that team synergies emerge from physical and informational constraints presented in competitive environments, with players being perceptually connected mainly by informational constraints (Araújo & Davids, 2016). Informational constraints can be exemplified, for example, by the positioning of teammates and opponents, motion directions and changes in motion, or by approaching velocities of teammates and opponents that can afford specific behaviours. These information sources can thus be used by players and teams to govern coordination and communication tendencies (Duarte et al., 2012; Passos et al., 2008). For instance, during competitive performance, the ball holder might perceive an empty space to be explored in the opposition defensive structure, while, at the same time, another teammate also perceives it and starts running into that space aiming to receive the ball and/or to shot at goal. The ball holder perceives this move from his teammate and intentionally passes him the ball. This is a clear example where team communication can be underpinned by the perception of collective information sources that specify certain behaviours.

Hence, the establishment of collective synergies through perception of informational and physical constraints permit players to effectively coordinate and communicate with each other, through a complex networking of behaviours and actions. The development of such networks of interaction between players, within and between teams, is of chief importance since, when formed, they provide a communication platform through which information continuously flows. However, understanding how individual and collective patterns self-organise into collective synergies through development of social networks of interactions remains elusive. Nevertheless, researchers and sports scientists have already started to investigate the properties underlying the networks of interactions established by players and teams during competition through implementation of social network techniques.

#### **1.4 A social network perspective for capturing team synergies**

The synergistic processes established between teammates in football underlie the organisation and functioning of teams in competitive performance environments (Passos et al., 2011). Such synergetic, interactional processes



present properties that are key for understanding team coordination and communication within teams, providing clear insights on team collective behaviour. These properties of synergies are well documented in the literature (e.g., Araújo & Davids, 2016). They include: (i) reciprocal compensation (Latash, 2008; Riley et al., 2011); (ii) dimensional compression (Riley et al., 2011); interpersonal linkages also known as division of labour (Araújo et al., 2015; Duarte et al., 2012;) or sharing patterns (Latash, 2008) and; (iv) degeneracy (Davids et al., 2006; Seifert et al., 2016). In brief, reciprocal compensation refers to the ability of one element of the synergy (a player) to react to changes in others (teammates), while dimensional compression highlights that players' actions are coupled to produce collective movement behaviour (Riley et al., 2011). Interpersonal linkages refer to the level of contribution of each player to the team (Araújo & Davids, 2016), whilst degeneracy refers to the functional variability displayed by players and teams during competitive performance (Araújo & Davids, 2016; Seifert et al., 2016).

Traditionally, social networks have been used to ascertain the functional variability (degeneracy) evidenced by teams during attacking sub-phases of play (Passos et al., 2011). For instance, these techniques facilitate the identification of players who most frequently intervene in team passing networks, i.e., those players who receive and/or perform more or fewer passes within a team during competitive performance.

A social network consists of a social structure composed by a set of social actors (e.g., players in sports teams) interacting through sets of dyadic ties. The network approach is necessarily relational and provides a set of methods and analytic tools that permit to uncover hidden patterns of social interactions established by teams during performance, enabling the analysis of the communication networks developed by teammates (Ramos et al., 2018; Rice & Yoshioka-Maxwell, 2015) under different performance conditions. In addition, the implementation of such approach is extremely useful in describing the activity of complex systems (i.e., football teams), their components (i.e., team players) and respective networks of interactions, providing knowledge over the topology (i.e., structure and dynamics) of teams (Ramos et al., 2018). Usually, SNA utilises a specific terminology for modelling social interactions, where players are typically framed as nodes or vertices of the network (i.e., team) interconnected through

several relational ties (e.g., ball-passing networks), through which information continuously flows (Gudmundsson & Horton, 2016; Lusher et al., 2010; Ramos et al., 2018; Wasserman & Galaskiewicz, 1994). Additionally, the utilisation of visual/graphical representations depicting the network of interactional links formed by team players in specific competitions enables easy and quick interpretations regarding team communication. The SNA typically represents players in fixed positions on field with their interactions being represented by directed and/or oriented edges or links. The width of the arrows represents the intensity of interactions achieved between dyads of players. In this particular context, thicker arrows represent higher number of passes, for example, accomplished between players while thin arrows represent fewer number of passes. Most research conducted on social networks have been concentrated in investigating the local dynamics of networks by measuring specific centrality-based indicators (i.e., assessed through measurement of the strength and number of links, e.g., passes, received from and sent to other individuals in a social network) in network structures. On the other hand, some studies have addressed the global dynamics of networks by considering, for example, how well-connected team members in a social network are, while others have confirmed that decentralised networks (e.g., interactions are equally distributed among players) obtained more successful team results when compared with centralised networks (e.g., interactions are unequally distributed among players).

### **1.5 Modelling team communication networks: Preview of the Problem**

Understanding the network properties of synergetic behaviour that underlie the complex dependencies established among players during competition, which, in turn, support the organisation and functioning of complex networks is of chief importance for coaches, performance analysts and practitioners. Indeed, current research have provided evidence of the relatedness of network properties with team performance (e.g., Grund, 2012). Thus, enlightening and understanding the relational properties that characterise players' interdependencies within teams might provide an excellent body of knowledge for coaches and performance analysts that can be helpful for developing novel interventions, coaching methods and/or practice tasks that may

optimise team performance (Passos et al., 2017), or for monitoring team training and performance. Typically, models for social networks include additional features relevant to the network such as actors (i.e., the players), attributes (e.g., number of passes), as well as their degree of prominence (e.g., the player's levels of involvement in which regards the ball flux control) within a social structure (i.e., a team).

However, incorrect inferences can be made through implementation of current social network techniques if networks are to be viewed in such an overly simplistic manner. Moreover, in its current state, the network approach applied to sports performance data lacks a strong theoretical and practical framework explaining the applicability of concepts and tools utilised by the network approach in describing individual and team performance. It needs to be referred the benefits of implementing such a network approach to investigate players and teams' interactions. Additionally, some important conceptual and methodological limitations of traditional network techniques still require some attention and need to be discussed.

In this regard, a major concern of traditional network techniques applied to the study of interpersonal relations in football is related to the concept of binary links, typically utilised for modelling players' interactions. Indeed, current network techniques only allow representation of 2-ary (dyadic) relations established among players during competition, which signifies that other types of relations, be it cooperative and/or competitive, are not considered. Beyond that, network tools have failed in capturing and understanding the multilevel dynamics (micro-to-meso-to-macro levels) that underlie the formation of interpersonal synergies emerging within and between teams at higher complexity levels. These and other limitations associated with the application of traditional network techniques if not well identified and scrutinised may eventually compromise the achievement of an uppermost understanding regarding the analysis of the communication networks formed by competing teams, thus limiting the real potential of such an approach in capturing and explaining team dynamics and performance. Above all, research is needed on how such practical frameworks can be aligned with powerful theoretical approaches to enhance understanding concerning team performance. Hence, there is a need for continuing research aiming to explore and develop

novel conceptual and methodological tools capable of reinforcing the network approach in analysing team performance data.

#### *1.5.1 Hypergraphs and hypernetworks as novel research opportunities for modelling players and teams' interactions in football*

Network science provides a wide range of methods and tools that can be applied for modelling players and teams' interactions. In this regard, according to the network theory, different types of graphs can be classified according to the relational properties and structures that they represent. In general, a graph consists of mathematical structures that are used to model pairwise relationships (edges) between certain objects (nodes or vertices). A key property of graphs is that edges allow connecting two nodes. However, a major issue here is that in team sports, more particularly, in football, the synergetic processes underlying team communication may involve more than two nodes (i.e., the players). Hence, such relations are not coherent with employment of such traditional graph edges. Alternatively, hypergraphs comprise a natural generalisation of graphs, whose edges, known as hyperedges, allow connecting groups of more than two nodes. This means that, in hypergraphs, a hyperedge, which depicts some form of relation, either cooperative and/or competitive, can connect an arbitrary number of players. Hence, hypergraphs can be generalised to represent complex networks in what will be called hypernetworks (Johnson & Iravani, 2007; Ramos et al., 2017).

These increasingly sophisticated models of hypernetworks can thus provide novel and valuable insights regarding team communication, as such types of networks enable consideration of multiple kinds of n-ary relations established between players during competition. Therefore, they may be more adequate for implementation in further studies of network analysis to understand team performance and dynamics. Importantly, such a fine-grained approach may be key to operationally relating different properties manifested in synergetic behaviour of teams, thus enabling a coherent (theoretical) understanding of team collective behaviour.

Interestingly, although there is apparent relevance of hypergraphs and hypernetworks as promising methodological tools for modelling players'

interactions during competition, with clear implications for better understanding team game performance, there is much less known about them than graphs. Indeed, there is a clear lack of literature investigating the usefulness of hypergraphs and hypernetworks in overcoming major limitations observed in traditional networks techniques, when applied to analysis of sports performance data. Furthermore, it still needs to be tested if such an approach allows the capture of the synergetic properties of teams manifested during practice and competition.

## **1.6 Structure and aims**

Given the aforementioned, the overall purpose of this thesis is to reconceptualise sports teams as complex social networks by investigating the benefits of adopting social network techniques to capture and study interpersonal relations in football performance, and to report the most common limitations associated with such an analysis. After that, a theoretical and practical explanation is provided on how hypernetworks may be helpful in overcoming limitations of traditional network analyses, and how they can provide a coherent theoretical understanding about multilevel team behaviours through examining synergy processes. Finally, the multilevel hypernetworks approach is applied to test its usefulness in capturing properties of team synergies during practice of both simulated and 11-a-side matches. If it proves to be useful this body of research can clarify important issues, concerning team collective behaviour based on principles of team synergy formation. Moreover, findings might be extrapolated to coach education programmes with insightful information reframed by novel and relevant concepts of graph theory and networks. This would help heighten coaches, performance analysts and practitioners about the potential of considering network techniques in modelling social interactions latent in communication networks of teams.

While social network methods and tools are employed to capture the properties of complex networks (here exemplified by football teams), a theoretical explanatory model framed by sub-disciplines pertaining to the field of complexity sciences (e.g., ecological dynamics approach and dynamical systems theory) is used to explain the establishment of interpersonal synergies underlying the

formation of communication networks between players and teams during competition.

This thesis encloses a compilation of four original research articles published and/or under-review in peer-review journals. All data were collected as kinematic time series of players' displacements during performance in matches, obtained through positioning tracking devices (GPS). In addition, a fixed camera (GoPro) was used for recording the performance of players and teams in two conditioned matches. Further notational analysis was employed for registration of technical actions performed by players.

Chapter II ("*Team Sports Performance Analysed Through the Lens of Social Network Theory: Implications for Research and Practice*") presents a position statement where sports teams are reconceptualised as complex social networks. By doing so, the network approach can furnish novel insights regarding the synergistic processes that govern the organisation and functioning of teams in specific performance environments. Notwithstanding its utility in addressing the emergent patterns of interactions of players and teams during competition, in its current state, the application of social network techniques presents some limitations that can weaken its true potential when applied in team sports performance analysis, which require attention in future researches.

Hence, in Chapter III ("*The Role of Hypernetworks as a Multilevel Methodology for Modelling and Understanding Dynamics of Team Sports Performance*") is highlighted multilevel hypernetworks as novel and potent methodological tools having the potential for revealing key properties of sports teams as complex social systems.

Chapter IV ("*A multilevel hypernetworks approach to capture properties of team synergies at higher complexity levels*") comprises an experimental study that sought to test whether different properties of synergies, often measured in the current literature through implementation of different methods, can be operationally related using a hypernetworks approach, thus revealing task dependence. Therefore, three levels of analysis (from N toward N+2) were formally elaborated aiming to: (i) address changes in tactical configurations of teams over match (Level N); (ii) investigate the frequency and types of simplices that emerge behind and ahead of the ball line, for each team (Team A vs. Team B) and for each 15-minute period of both game halves (First vs. Second), and

(iii), ascertain the level of contribution and/or prominence of players, while analysing the dynamics of simplices' interactions before a goal is scored.

Chapter V ("*A multilevel hypernetworks approach to capture meso-level synchronisation processes in football*") consists of an experimental study in which the synchronisation processes of within and between teams was captured through multilevel hypernetworks. More specifically, the hypernetworks approach is applied along with the cluster phase method to assess meso-local (player-simplice) synchronisation during performance in two conditioned matches in which the number, size and location of goals are manipulated. Furthermore, this study aims to analyse how such synchronisation processes change in the two game conditions, particularly as a function of ball-possession (Attacking vs. Defending), field-direction (Longitudinal vs. Lateral) and individual teams (Team A vs. Team B).

## 1.7 References

Araújo, D., & Davids, K. (2016). Team synergies in sport: Theory and measures. *Frontiers in Psychology*, 7, 1449.

Araújo, D., Silva, P., & Davids, K. (2015). Capturing group tactical behaviours in expert team players. In J. Baker & D. Farrow (Eds.), *Routledge Handbook of Sport Expertise* (pp. 209-220). London: Routledge.

Bernstein, N. (1967). *The coordination and regulation of movement*. New York: Pergamon.

Davids, K., Button, C., Araújo, D., Renshaw, I., & Hristovski, R. (2006). Movement models from sports provide representative task constraints for studying adaptive behavior in human movement studies. *Adaptive Behavior*, 14, 73-94.

Duarte, R., Araújo, D., Correia, V., & Davids, K. (2012). Sport teams as superorganisms: Implications of biological models for research and

- practice in team sports performance analysis. *Sports Medicine*, 42(8), 633–42.
- Eccles, D., & Tenenbaum, G. (2004). Why an expert team is more than a team of experts: A social cognitive conceptualisation of team coordination and communication in sport. *Journal of Sport & Exercise Psychology*, 26, 542-560.
- Grund, T. (2012). Network structure and team performance: The case of English Premier League soccer teams. *Social Networks*, 34(4), 682–690.
- Gudmundsson, J., & Horton, M. (2016). Spatial-temporal analysis of team sports—a survey. arXiv:1602.06994v1[cs.OH].
- Harris, T., & Sherblom, J. (1999). *Small group and team communication*. Allyn & Bacon: Boston.
- Johnson, J., & Iravani, P. (2007). The multilevel hypernetwork dynamics of complex systems of robot soccer agents. *ACM Transactions on Autonomous and Adaptive Systems*, 2, 1–23.
- Kelso, J. (1998). From Bernstein's physiology of activity to coordination dynamics. In M. Latash (Ed.), *Progress in motor control. Bernstein's traditions in movement studies* (pp. 203-219). Champaign, IL: Human Kinetics.
- Kelso, J. (2012). Multistability and metastability: Understanding dynamic coordination in the brain. *Philosophical Transactions of the Royal Society of London. Series B, Biological Sciences*, 367, 906-918.
- Latash, M. (2008). *Synergy*. New York, NY: Oxford University Press.



- Lausic, D., Tenenbaum, G., Eccles, D., Jeong, A., & Johnson, T. (2009). Intrateam communication and performance in doubles tennis. *Research quarterly for exercise and sport*, 80(2), 281-290.
- Lusher, D., Robins, G., & Kremer, P. (2010). The application of social network analysis to team sports. *Measurement in Physical Education and Exercise Science*, 4, 211–224.
- Marsh, K., Richardson, M., & Schmidt, R. (2009). Social connection through joint action and interpersonal coordination. *Topics in Cognitive Science*, 1, 320-339.
- Newell, K., & Vaillancourt, D. (2001). Dimensional change in motor learning. *Human Movement Science*, 20(4-5), 695-715.
- Passos, P., Araújo, D., Davids, K., Gouveia, L., Milho, J., & Serpa, S. (2008). Information-governing dynamics of attacker-defender interactions in youth Rugby Union. *Journal of Sports Sciences*, 26(13), 1421–1429.
- Passos, P., Araújo, D., Davids, K., Gouveia, L., Serpa, S., & Milho, J. (2009). Interpersonal pattern dynamics and adaptative behavior in multiagent neurobiological systems: Conceptual model and data. *Journal of Motor Behavior*, 41(5), 445-449.
- Passos, P., Davids, K., Araújo, D., Paz, N., Minguéns, J., & Mendes, J. (2011). Networks as a novel tool for studying team ball sports as complex social systems. *Journal of Science and Medicine in Sport*, 14(2), 170–6.
- Passos, P., Milho, J., & Button, C. (2017). Quantifying synergies in two-versus-one situations in team sports: An example of Rugby Union. *Behavior Research Methods*, 50(2), 620-629.

- Ramos, J., Lopes, R., & Araújo, D. (2018). What's next in complex networks? Capturing the concept of attacking play in invasive team sports. *Sports Medicine*, 48(1), 17-28.
- Ramos, J., Lopes, R., Marques, P., & Araújo, D. (2017). Hypernetworks reveal compound variables that capture cooperative and competitive interactions in a soccer match. *Frontiers in Psychology*, 8, 1379.
- Reimer, T., Park, E., & Hinsz, V. (2006). Shared and coordinated cognition in competitive and dynamic task environments: An information-processing perspective for team sports. *International Journal of Sport and Exercise Psychology*, 4(4), 376-400.
- Rice, E., & Yoshioka-Maxwell, A. (2015). Social network analysis as a toolkit for the science of social work. *Journal of the Society for Social Work and Research*, 6(3), 369-383.
- Riley, M., Richardson, M., Shockley, K., & Ramenzoni, V. (2011). Interpersonal synergies. *Frontiers in Psychology*, 2, 1-7.
- Riley, M., Shockley, K., & Orden, G. (2012). Learning from the body about the mind. *Topics in Cognitive Science*, 4, 21-34.
- Seifert, L., Komar, J., Araújo, D., & Davids, K. (2016). Neurobiological degeneracy: A key property for functional adaptations of perception and action to constraints. *Neuroscience & Biobehavioral Reviews*, 69, 159-165.
- Silva, P., Vilar, L., Davids, K., Araújo, D., & Garganta, J. (2016). Sports teams as complex adaptive systems: Manipulating player numbers shapes behaviors during football small-sided games. *SpringerPlus*, 5(1), 191.
- Turvey, M. (1990). Coordination. *American Psychologist*, 45(8), 938-953.

Thelen, E., & Smith, L. (1994). *A Dynamic Systems Approach to the Development of Cognition and Action*. Cambridge, MA: MIT press.

Wasserman, S., & Galaskiewicz, J. (1994). *Advances in social network analysis: research from the social and behavioural sciences*. Newbury Park: Sage Publications.



## Chapter 2

### Team Sports Performance Analysed Through the Lens of Social Network Theory: Implications for Research and Practice<sup>2</sup>

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JÚLIO GARGANTA

#### Abstract

This paper discusses how social network analyses and graph theory can be implemented in team sports performance analyses to evaluate individual (micro) and collective (macro) performance data, and how to use this information for designing practice tasks. Moreover, we briefly outline possible limitations of social network studies and provide suggestions for future research. Instead of cataloguing discrete events or player actions, it has been argued that researchers need to consider the synergistic interpersonal processes emerging between teammates in competitive performance environments. Theoretical assumptions on team coordination prompted the emergence of innovative, theoretically driven methods for assessing collective team sport behaviours. Here, we contribute to this theoretical and practical debate by re-conceptualising sports teams as complex social networks. From this perspective, players are viewed as network nodes, connected through relevant information variables (e.g., a ball-passing action), sustaining complex patterns of interaction between teammates (e.g., a ball-passing network). Specialised tools and metrics related to graph theory could be applied to evaluate structural and topological properties of interpersonal interactions of teammates, complementing more traditional analysis methods. This innovative methodology moves beyond the use of common notation analysis methods, providing a richer understanding of the complexity of interpersonal interactions sustaining collective team sports performance. The proposed approach provides practical applications for coaches, performance analysts, practitioners and researchers by establishing social network analyses as a useful approach for capturing the emergent properties of interactions between players in sports teams.

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<sup>2</sup> Ribeiro, J., Silva, P., Duarte, R., Davids, K., & Garganta, J. (2017). Team sports performance analysed through the lens of social network theory: Implications for research and practice. *Sports Medicine*, 47, 1689-1696.



## 2.1 Introduction

Investigating cooperative and competitive interaction tendencies between performers is a major theme of research and practice in team sports performance analysis. Cooperation refers to the purposive contribution of individual efforts in achieving performance sub-goals (Wagner, 1995). High levels of cooperation allow collectives to increase their competitive performance. Biological characteristics of competition and cooperation are ubiquitous in nature, with groups of organisms tending to display both in many interactions. They are also present in human societies (Wu et al., 2010). Sports teams are a microcosm of human societies, i.e. a group of individuals who develop cooperative interactions, bounded by specific spatial-temporal constraints, to achieve successful competitive performance outcomes (Duarte et al., 2012). Although composed of individual members, sports teams typically function as an integrated whole, displaying an intricate and complex set of behaviours impossible to predict at an individual level of analysis (Duarte et al., 2012; Parrish & Edelstein-Keshet, 1999). These emergent patterns are not merely the sum of individual aggregated performances per se but arise through continuous interactions among group members (Duarte et al., 2012).

Despite providing meaningful information about performance in some dimensions (e.g., technical), traditional notational analysis methods struggle to cope with the complex competitive and cooperative interactions emerging between individuals at different spatial and temporal scales (Balague et al., 2013; Sarmiento et al., 2014). Beyond discrete indicators provided by traditional methods, team sports performance analysis needs to consider theoretical and practical frameworks that support evaluation of emergent structural and topological properties that underlie team functionality. Recent work has highlighted the value of re-conceptualising research and practice in team sports performance analysis, proposing new investigative methods, more coherent with principles of dynamical systems and complexity sciences (Couceiro et al., 2016; Glazier, 2010; Glazier, 2015; Vilar et al., 2012). Additionally, a body of empirical studies has begun to analyse interpersonal interactions emerging within and between sport teams utilising social network analyses (Clemente et al., 2014a; Grund, 2012; Mukherjee, 2013). Like other collective social systems, sports

teams can be conceptualised as complex social networks in which structural and topological properties of interpersonal interactions emerge between teammates and opponents under the ecological constraints of competitive performance environments. Here, we re-conceptualise sports teams as complex social networks, highlighting the applicability of graph theory for modelling social interactions in team sports performance. There are some potential advantages of considering concepts and tools of social network theory to evaluate the web of interpersonal interactions shaping collective team sports performance. Possible limitations are associated with these techniques and new insights offered by social network analyses can elucidate research on interpersonal interactions in team sports.

## **2.2 Sports teams as complex social networks**

A social collective can be conceived as a network composed of individuals called nodes, connected by specific types of relational ties (Wellman & Wasserman, 2000). Like other complex social systems (e.g., organisations), team sports are composed of different system agents (e.g., players), interacting in various ways, revealing emergent and self-organising behaviours during team coordination (Aguiar et al., 2015). Emergence of coordinative behaviours in social networks is based on formation of interpersonal synergies between players (Silva et al., 2014). Synergies or coordinative structures in an individual athlete have been defined as functional groupings of structural elements (e.g., neurons, joints, etc.), temporarily constrained to act as a single and coherent unit (Kelso, 2009) enabling team members to act as collective sub-systems (Kelso, 2012). In competitive sport, a team can be characterised as a group of performers who interact in a dynamic, interdependent and adaptive way, managing efforts towards achieving common goals (Salas et al., 1992). Teamwork can be interpreted as the functional behaviours emerging from performers within groups, resulting from coordination requirements imposed by interdependent tasks (Brannick et al., 1995). One example of such requirements was reported by Silva et al. (2016), who verified that emergent synergies (entirely novel perception-action relations) established by teammates were formed and dissolved swiftly, resulting from locally-created information, specifying shared affordances for



synergy formation. Shared affordances constitute collective environmental resources that exist independently of individuals who might learn to perceive and use them (Silva et al., 2013). These shared affordances may constitute network opportunities for enhancing team coordination (Silva et al., 2013).

In performance, competing teams reveal specific structural and dynamical properties, pivotal for the organisation and function of these complex social systems, discerned through analysis of collective behaviours. Behaviours of complex systems (e.g., organisations/teams), emerge from the orchestrated local, pairwise interactions of system components (Barabási & Oltvai, 2004). This process foments the development and maintenance of system goals for teammates, operating together as a single unit. They need to continually seek, explore and establish effective ways of creating and maintaining the flow of interactional patterns, while coordinating decision-making and actions (Henttonen, 2010).

#### *2.2.1 Social network analysis: An interdisciplinary perspective on collective performance in team sports*

Social network research seeks to uncover patterns of behavioural interactions characterising relations between actors (components of a social system), and to ascertain constraints that promote pattern formation (Quatman & Chelladurai, 2008). Freeman (2004) highlighted four properties of social network analysis: (1) importance of interactions between social actors; (2) significance of data collection and analysis sustained by social interactions; (3) revelation and display of interaction patterns through graphic imagery; and (4) description of interaction patterns of between system agents, using computational and mathematical modelling. Nodes or vertices represent individual actors within networks, in which ties (also called edges or links) represent types of interactions that bind actors (Rice & Yoshioka-Maxwell, 2015; Wasserman & Galaskiewicz, 1994; Wellman & Wasserman, 2000). This approach in team sports research raises pertinent questions, including: What differentiates this approach from others applied in team sports performance analyses? And, how can team sports performance analyses benefit from implementation of this approach? Social network analysis addresses the nature of interdependencies in team structures, where intra-group

interactions are important for development and maintenance of collaborative behaviours, including aspects like cohesiveness, roles and hierarchies among players (Lusher et al., 2010). Network analysis investigates patterns of interactions from whole to part, from system structure to individual relations, and from behaviours to attitudes (Wellman & Wasserman, 2000). Network analysis bridges the gap between the micro (e.g., dyads, triads and small groups) and macro (e.g., the whole structure) levels of analysis (Wasserman & Galaskiewicz, 1994). Team sports environments are well suited for social network investigations, being composed of a number of well-defined elements. Competitive games contain clear rules and the strength of interaction patterns within and between teams, relative to performance, can be objectively assessed (Grund, 2012). Support for social network analysis requires elaboration of adjacency matrices (e.g., using simple spreadsheet tables), and manipulation of social network analysis software (e.g., NodeXL, Social Media Research Foundation: Belmont, CA, USA), permitting representation, analysis, visualisation or simulation of nodes (e.g., players) and edges (e.g., passes). These software packages provide mathematical and statistical routines that can elucidate graph properties.

Social network analysis research (Clemente et al., 2014a; Gama et al., 2014; Grund, 2012; Malta & Travassos, 2014; Mukherjee, 2013) has begun to reveal relational patterns (communication systems) emerging from interpersonal interactions in team sports. For example, a network approach, and application of its measures, has characterised cooperation between players in a football (soccer) team during competitive performance (Clemente et al., 2015; Clemente et al., 2014a). Other studies have reported a power law degree distribution (scale-free invariant) capturing emergence of passing behaviours (Yamamoto & Yokoyama, 2011). Research has shown that game momentum can be represented by the number of triangles (triangular passing in groups of three players) attained in attacking sequences of play (Yamamoto & Yokoyama, 2011). Other studies have confirmed the validity of network approaches to quantification of contributions by different individuals to overall team performance (Duch et al., 2010). The impact of network structure on team performance has also been examined, showing that higher density levels, and low centralisation of

interactions, are associated with more successful performance outcomes (Grund, 2012).

Regardless, there is still a need for more performance analyses in team sports using a network approach, with a powerful theoretical framework that can sustain a network approach lacking. The elaboration of such a theoretical framework might heighten sport scientists' awareness of the main concepts and tools when studying individual and team performance. Extrapolation of this framework to coach education programmes is also important to consider with practical interpretations reframed by relevant concepts like nodes and edges. In addition to complementing other pedagogical tools in modelling social interactions, use of concepts and tools derived from graph theory needs to be clearly extrapolated to sports performance contexts, without compromising data interpretation. Here, we propose the adoption of a network approach in verifying the importance and complexity of social interactions in studies of team sports dynamics.

### **2.3 Graph theory as a tool for modelling and analysing social interactions in team sports**

In team sports, functional performance is predicated on a complex network of social interactions established among teammates (Passos et al., 2011). Many of its principles have emerged from graph theory, and social network analysis uses algorithms and procedures that map social structures within collectives (Warner et al., 2012). Several disciplines have used graphs to model specific types of interactions and processes emerging in many complex systems, especially those with biological, physical and social characteristics. A graph  $G = (V, E)$  consists of a non-empty vertex set  $V(G)$  and a finite family  $E(G)$  of unordered pairs of elements of  $V(G)$  called edges, such that an edge  $\{v, w\}$  joins the vertices  $v$  and  $w$ , being abbreviated to  $vw$  (Bondy & Murty, 1976; Zhu, 2011).

Different types of graphs are exemplified in Figure 1. Weighted graphs have edges that contain associated weights, characterised by a real number (Bondy & Murty, 1976). Directed graphs or digraphs are composed of a set of vertices connected by edges which assign a direction from one vertex to another (Bondy & Murty, 1976; Ruohonen, 2008).

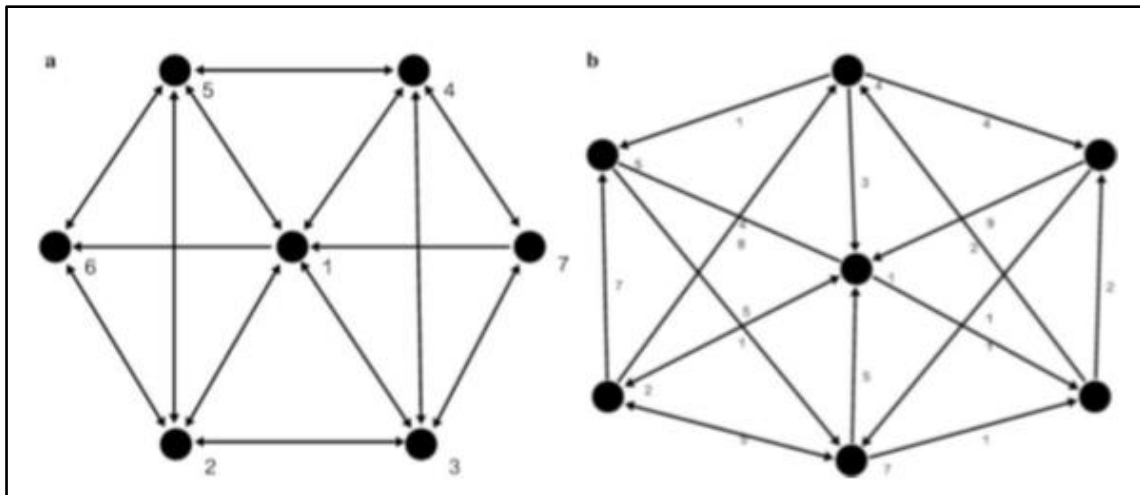


Figure 1. Schematic representation of types of graphs: a) digraph composed of a set of vertices (black circles) connected by directed edges (black arrows); b) directed weighted graph in which the edges (black lines) connect the vertices (black circles) through associated weights (number of times that vertices interact with each other).

In team sports, weighted graphs indicate the strength of interactions between teammates, for example, in passing behaviours or in rotating positions on field/on court. They also show directedness, since in team sports players pass the ball in a specific direction from one player to another (Figure 2a). When recording graph information, computer scientists and mathematicians utilise the adjacency list, adjacency matrix and incidence matrix. The most commonly used tool to build graphs in team sports performance analysis is the adjacency matrix, which represents which vertices in a graph are adjacent to other vertices (Voloshin, 2009).

Previous studies have used adjacency matrices to characterise interpersonal interactions of teammates, in team sports like water polo (Passos et al., 2011) and football (Clemente et al., 2015; Clemente et al., 2014a; Clemente et al., 2014b). These matrices have been used to build a finite  $n \times n$  network, where entries coded by number '1', for example, represent ways that players interact (e.g., when GK passed the ball to CRD), and code number "0" represents those players who do not interact (Figure 2b).

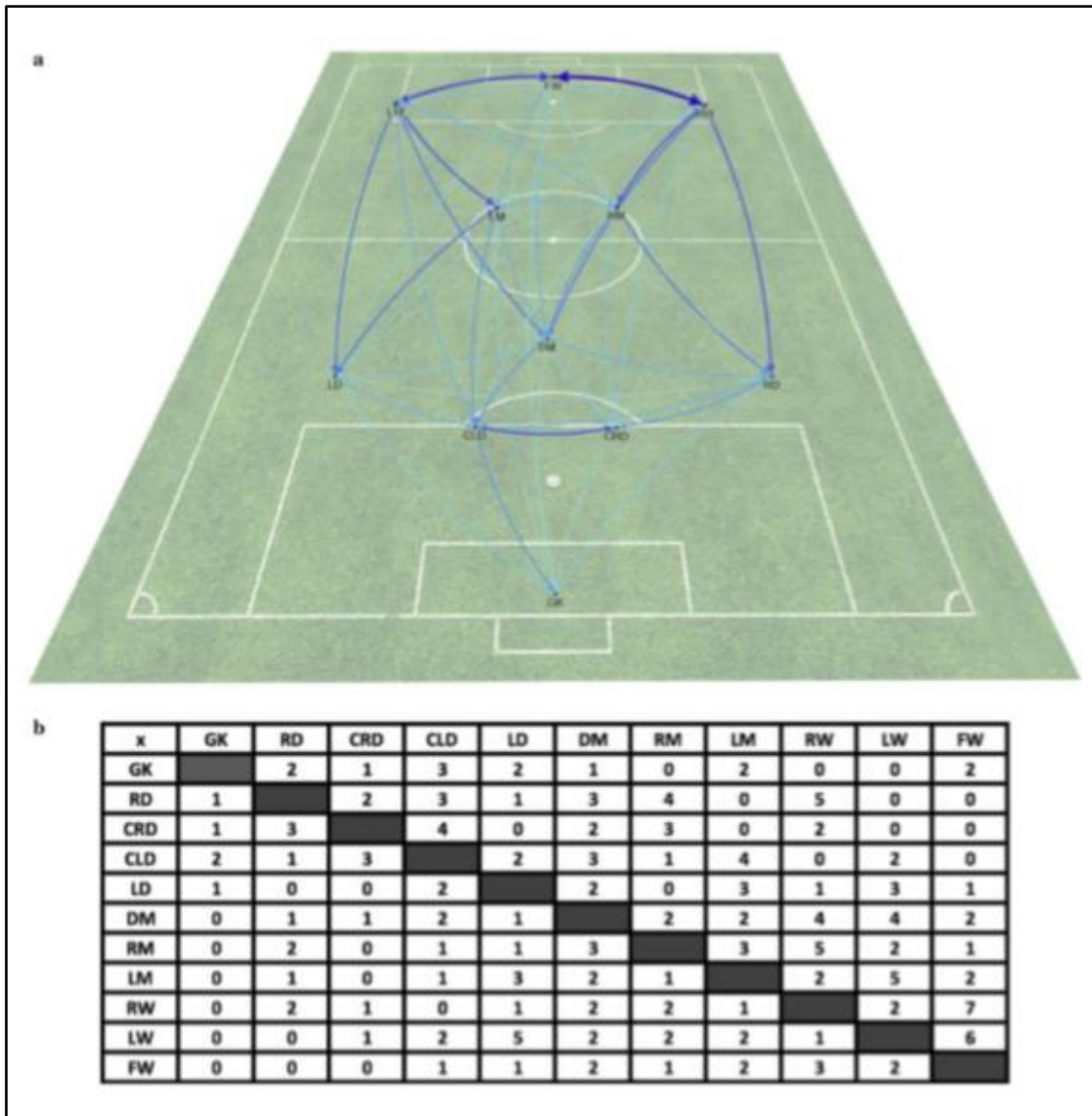


Figure 2. Representation of interpersonal interactions between teammates: a) network of interpersonal interactions displayed in a 1-4-3-3 tactical formation, obtained from adjacency matrix processing in NodeXL (Social Media Research Foundation: Belmont, CA, USA). Black circles represent players; blue arrows indicate pass direction. The origin of the arrow indicates the player who passed the ball and the arrowhead indicates the player who received the ball. The width and colour of each arrow represents the quantity of passes completed between players during performance (thicker arrows represent a greater quantity of passes between players), whereas circle size represents players who participate more frequently in attacking phases (bigger circles represent players who receive and perform more passes); b) adjacency matrix representing interpersonal interactions between teammates. GK goalkeeper, CRD central right defender, CLD central left defender, LD left defender, RD right defender, DM defensive midfielder, LM left midfielder, RM right midfielder, LW left wing, RW right wing, FW forward.

## **2.4 Social network properties and collective team performance: A novel set of team sports performance indicators?**

Increasing evidence on other collective social system (e.g., organisations) behaviours suggests that structural properties of networks (e.g., centrality) characterising interactions of individuals within a collective, are related to performance, here regarded as a goal-oriented process of sharing information (non-material-verbal or other, through explicit communication) (Balkundi & Harrison, 2006; Borgatti & Foster, 2003; Cummings & Cross, 2003; Molm, 1994; Sparrowe et al., 2001). Orchestration of behaviours within teams, and interpersonal interactions that bind teammates, are essential for team performance (Grund, 2012). To achieve complex task goals, multi-agent systems (e.g., sports teams) should exhibit relational structures that privilege interdependency of behaviours and coordination to solve problems that emerge within competitive performance contexts and to achieve common performance goals (Gaston & DesJardins, 2008). Social network analysis provides information on their purpose and functionality through analysis of network structures (Fewell et al., 2012).

Studies of team sports have demonstrated that the emergence of such network properties can be related to team performance (goal-oriented process of sharing information through implicit communication like passing the ball) (Clemente et al., 2014a; Duch et al., 2010; Grund, 2012; Mukherjee, 2013), with others showing that team sports contain properties related to small-world (Passos et al., 2011) and scale-free networks (Yamamoto & Yokoyama, 2011). The small-world concept implies that, despite their often large size, most networks have a relatively short path between any two nodes, with distance defined as the number of edges along the shortest path connecting them (Watts & Strogatz, 1998). Scale-free networks have a distribution with a power-law tail. The fraction  $P(k)$  of nodes in the network has connections to other nodes with large values of  $k$  as  $P(k) \sim k^{-\gamma}$  (Albert & Barabási, 2002). There are several network properties that can elucidate the structure and function of complex systems, helping sport scientists to characterise the continuous interactions of teammates in sports teams. For instance, a characteristic path length measures the separation between two vertices (e.g., players in team games) in a graph (global property).

A clustering coefficient measures the cliquishness of a network neighbourhood (local property) (Watts & Strogatz, 1998). Characteristic path length can reveal how many passes are needed for the ball to traverse from one particular player to another. Clustering coefficients provide coaches and performance analysts with knowledge about subgroups of players who coordinate their actions more frequently (Passos et al., 2014). This idea is exemplified in football when two players coordinate their actions with each other more frequently than with other teammates, forming a cluster. Globally, high values of a clustering coefficient might indicate a team disposition to form functional clusters (Passos et al., 2014), with players tending to create tightly knit groups comprising high-density ties. Graph theory provides four measures of centrality which indicate the importance of a vertex (e.g., a team player) in a graph, including degree, 'betweenness', closeness and eigenvector centrality (Gudmundsson & Horton, 2016; Freeman, 1979). Degree centrality consists of the number of ties incident upon a node (Borgatti, 2005). Since in team sports players pass the ball in a specific direction from one player to another, the degree of a vertex can be defined according to two types of centrality: 'Indegree' (number of passes directed to the player) and 'Outdegree' (number of passes that the player directs to others). These metrics move beyond simplistic frequency counts of passes made, providing insights on how many passes each player receives and how often he/she passes the ball effectively. Betweenness centrality is defined as the number of times that a vertex connects two other vertices through their shortest paths (Borgatti, 2005; Gudmundsson & Horton, 2016; Freeman, 1979). These data provide insights on the amount of network 'flow' that a given player 'controls' (e.g., player(s) responsible for connecting the defensive sector within a midfield area in football). Closeness centrality of a vertex is defined as the sum of distances from all other vertices presented in a graph, with this distance defined as the length of the shortest paths from one vertex to another (Borgatti, 2005; Gudmundsson & Horton, 2016; Freeman, 1979). This network metric provides information on adjacency of one player to others, where players with low closeness scores are adjacent to others, providing conditions for receiving flows (e.g., receive a pass or rotate with the nearest player) more rapidly. Eigenvector centrality measures the influence of a vertex in a graph (Borgatti, 2005). Density and centralisation consist of two network structural properties characterising global interaction

patterns of a team. Density describes the overall level of cooperation/coordination between teammates, whereas centralisation reflects the extent to which interactions are unequally distributed among team members (Cummings & Cross, 2003). Analysis of these data can inform coaches and performance analysts about: (1) the functionality of team organisation where all players interact with similar proportionality, and (2), whether team organisation relies on a heterogeneous system level, characterised by unequal proportionality of interactions, depending on the input of specific 'key players'. With this information, coaches can manipulate different practice task constraints to facilitate emergence of specific team dynamics. For example, team dynamics could emerge from implementing a conditioned activity involving prominent players, facilitating self-organisation tendencies in a team, or team dynamics could be manipulated to promote/inhibit emergence of influence of different player subgroups during competition.

Regardless, researchers may face some problems when applying such techniques, with four limitations reported in social network studies: (1) the majority of studies employing social network analysis have observed information exchange between players mainly through passing behaviours; (2) the variability of player's performance outcomes, associated with specific match events (e.g., match location) is in most cases disregarded; (3) overemphasis on network attacking behaviours, thus not considering the influence of defensive behaviours on network functionality and adaptability; (4) most of the metrics used to model social interactions are based on paths, which can be inappropriate for sports contexts. Undoubtedly in team sports (e.g., football), information flows between players beyond passing behaviours, with the pass being only one essential technical action (e.g., dribble) that players perform. Variability of player performance should also be carefully evaluated since his/her performance may be affected by several factors (e.g., fatigue) throughout the game. 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. The adoption of dynamic network analysis (Yamamoto & Yokoyama, 2011) can reveal more accurate and relevant information about the dynamics of individual and team performance. It is crucial for further investigations to conduct analyses of team defensive behaviours, providing pivotal information on team functionality



and adaptability. Here, both teams are connected through a feedback loop (competition), where the behaviours of a given network A will be regarded as external input by network B, and vice-versa, influencing its global topology and local dynamics (Yamamoto & Yokoyama, 2011). Finally, the use of geodesic paths as a tool to model social interactions can exert a negative impact on interpretation of results, since the use of paths suggests that whatever flows through the network only moves along the shortest possible paths (Borgatti, 2005). This may not be appropriate when applied to sporting contexts, since for example in football, players do not necessarily pass the ball uniquely to a player with the shortest path. Thus, the more appropriate approach is to use walks instead of paths, since walks model interactions assuming that trajectories can not only be circuitous, and also revisit nodes and lines multiple times along the way (Borgatti, 2005). A key next step is to develop relevant analytical solutions (e.g., formulas) for analysing specific topological structures of team sports, or seek metrics that use walks to model interactions.

## **2.5 Conclusions and practical implications**

We highlighted how sports teams can be re-conceptualised as complex social networks composed of different individuals who develop and adapt cooperative and coordinative relations to achieve common performance goals. When evaluating collective performance in training or competition, the adoption of social network analyses, not replacing but complementing other pedagogical methods, can provide novel insights on the complexity of interpersonal interactions that shape team behaviours. Such information may be utilised by coaches and/or performance analysts for designing practice-learning environments. These techniques furnish an adequate approach for team sports performance analysis, consistent with the assumptions of complexity sciences and dynamical systems theory, capturing the emergent properties presented in the interactions of players in sports teams.

## 2.6 References

- Albert, R., & Barabási, A. (2002). Statistical mechanics of complex networks. *Reviews of Modern Physics*, 74(1), 47–97.
- Aguiar, M., Gonçalves, B., Botelho, G., Lemmink, K., & Sampaio, J. (2015). Footballers' movement behaviour during 2-,3-,4- and 5-a-side small-sided games. *Journal of Sports Sciences*, 33(12), 1259–66.
- Balague, N., Torrents, C., Hristovski, R., Davids, K., & Araújo, D. (2013). Overview of complex systems in sport. *Journal of Systems Science and Complexity*, 26(1), 4–13.
- Balkundi, P., & Harrison, D. (2006). Ties, leaders, and time in teams: Strong inference about network structure's effects on team viability and performance. *The Academy of Management Journal*, 49(1), 49–68.
- Barabási, A., & Oltvai, Z. (2004). Network biology: Understanding the cell's functional organization. *Nature Reviews Genetics*, 5, 101-113.
- Bondy, J., & Murty, U. (1976). *Graph theory with applications*. Elsevier Science Ltd: North-Holland.
- Borgatti, S. (2005). Centrality and network flow. *Social Networks*, 27, 55–71.
- Borgatti, S., & Foster, P. (2003). The network paradigm in organizational research: A review and typology. *Journal of Management*, 29(6), 991–1013.
- Brannick, M., Prince, A., Prince, C., & Salas, E. (1995). The measurement of team processes. *Human Factors*, 37, 641–51.

- Clemente, F., Couceiro, M., Martins, F., & Mendes, R. (2014b). Using network metrics to investigate football team players' connections: A pilot study. *Motriz*, 20(3), 262–71.
- Clemente, F., Couceiro, M., Martins, F., & Mendes, R. (2015). Using network metrics in soccer: A macro-analysis. *Journal of Human Kinetics*, 45, 123–34.
- Clemente, F., Martins, F., Couceiro, M., Mendes, R., & Figueiredo, A. (2014a). A network approach to characterize the teammates' interactions on football: A single match analysis. *Cuadernos de Psicología del Deporte*, 14(3), 141–8.
- Couceiro, M., Dias, G., Araújo, D., & Davids, K. (2016). The ARCANE project: How an ecological dynamics framework can enhance performance assessment and prediction in football. *Sports Medicine*, 46(12), 1781-1786.
- Cummings, J., & Cross, R. (2003). Structural properties of work groups and their consequences for performance. *Social Networks*, 25(3), 197–210.
- Duarte, R., Araújo, D., Correia, V., & Davids, K. (2012). Sport teams as superorganisms: Implications of biological models for research and practice in team sports performance analysis. *Sports Medicine*, 42(8), 633–42.
- Duch, J., Waitzman, J., & Amaral, L. (2010). Quantifying the performance of individual players in a team activity. *PLoS One*. doi: 10.1371/journal.pone.0010937.
- Fewell, J., Armbruster, D., Ingraham, J., Petersen, A., & Waters, J. (2012). Basketball teams as strategic networks. *PLoS One*. doi: 10.1371/journal.pone.0047445.

- Freeman, L. (1979). Centrality in social networks: Conceptual clarification. *Social Networks*, 1, 215–39.
- Freeman, L. (2004). *The development of social network analysis: A study in the sociology of science*. Vancouver: Empirical Press.
- Gama, J., Passos, P., Davids, K., Relvas, H., Ribeiro, J., Vaz, V., & Dias, G. (2014). Network analysis and intra-team activity in attacking phases of professional football. *International Journal of Performance Analysis in Sport*, 14(3), 692–708.
- Gaston, M., & DesJardins, M. (2008). The effect of network structure on dynamic team formation in multi-agent systems. *Computational Intelligence*, 24(2), 122–57.
- Glazier, P. (2010). Game, set and match? Substantive issues and future directions in performance analysis. *Sports Medicine*, 40(8), 625–34.
- Glazier, P. (2015). Towards a grand unified theory of sports performance. *Human Movement Science*, 139-156. doi: 10.1016/j.humov.2015.08.001.
- Grund, T. (2012). Network structure and team performance: The case of English Premier League soccer teams. *Social Networks*, 34(4), 682–90.
- Gudmundsson, J., & Horton, M. (2016). Spatial-temporal analysis of team sports—a survey. *arXiv:1602.06994v1[cs.OH]*.
- Henttonen, K. (2010). Exploring social networks on the team level: A review of the empirical literature. *Journal of Engineering and Technology Management*, 27(1-2), 74–109.
- Kelso, J. (2009). Synergies: Atoms of brain and behaviour. *Advances in Experimental Medicine and Biology*, 629, 83–91.

- Kelso, J. (2012). Multistability and metastability: Understanding dynamic coordination in the brain. *Philosophical Transactions of the Royal Society of London. Series B, Biological Sciences*, 367, 906–18.
- Lusher, D., Robins, G., & Kremer, P. (2010). The application of social network analysis to team sports. *Measurement in Physical Education and Exercise Science*, 14(4), 211–24.
- Malta, P., & Travassos, B. (2014). Characterization of the defense-attack transition of a soccer team. *Motricidade*, 10(1), 27–37.
- Molm, L. (1994). Dependence and risk: Transforming and structure of social exchange. *Social Psychology Quarterly*, 57(3), 163–76.
- Mukherjee, S. (2013). Complex network analysis in cricket: Community structure, player's role and performance index. *Advances in Complex Systems*, 16(8). doi:10.1142/S0219525913500318.
- Parrish, J., & Edelstein-Keshet, L. (1999). Complexity, pattern, and evolutionary trade-offs in animal aggregations. *Science*, 284(2), 99–101.
- Passos, P., Araújo, D., Travassos, B., Vilar, L., & Duarte, R. (2014). Interpersonal coordination tendencies induce functional synergies through co-adaptation processes in team sports. In K. Davids, R. Hristovski, D. Araújo, N. Serre, C. Button & P. Passos (Eds.), *Complex systems in sport* (pp. 117-121). London: Routledge.
- Passos, P., Davids, K., Araújo, D., Paz, N., Minguéns, J., & Mendes, J. (2011). Networks as a novel tool for studying team ball sports as complex social systems. *Journal of Science and Medicine in Sport*, 14(2), 170–6.
- Quatman, C., & Chelladurai, P. (2008). Social network theory and analysis: A complementary lens for inquiry. *Journal of Sport Management*, 22, 338–60.

- Rice, E., & Yoshioka-Maxwell, A. (2015). Social network analysis as a toolkit for the science of social work. *Journal of the Society for Social Work and Research*, 6(3). doi:10.1086/682723.
- Ruohonen, K. (2008). *Graph theory*. Tampere: Tampere University of Technology.
- Salas, E., Dickinson, T., Converse, S., & Tannenbaum, S. (1992). Toward an understanding of team performance and training. In R. Swezey & E. Salas (Eds.), *Teams: Their training and performance* (pp. 3-29). Norwood, NJ: Ablex.
- Sarmento, H., Marcelino, R., Anguera, M., Campaniço, J., Matos, N., & Leitão, J. (2014). Match analysis in football: A systematic review. *Journal of Sports Sciences*, 32(20). doi:10.1080/ 02640414.2014.898852.
- Silva, P., Chung, D., Carvalho, T., Cardoso, T., Davids, K., Araújo, D., & Garganta, J. (2016). Practice effects on intra-team synergies in football teams. *Human Movement Science*, 46, 39-51
- Silva, P., Travassos, B., Vilar, L., Aguiar, P., Davids, K., Araújo, D., & Garganta, J. (2014). Numerical relations and skill level constrain co-adaptive behaviours of agents in sports teams. *PLoS One*. doi:10.1371/journal.pone.010711
- Silva, P., Garganta, J., Araújo, D., Davids, K., & Aguiar, P. (2013). Shared knowledge or shared affordances? Insights from an ecological dynamics approach to team coordination in sports. *Sports Medicine*, 43, 765–72.
- Sparrowe, R., Liden, R., Wayne, S., & Kraimer, M. (2001). Social networks and the performance of individuals and groups. *The Academy of Management Journal*, 44(2), 316–25.

- Vilar, L., Araújo, D., Davids, K., & Button, C. (2012). The role of ecological dynamics in analysing performance in team sports. *Sports Medicine*, 42(1), 1–10.
- Voloshin, V. (2009). *Introduction to graph theory*. New York: Nova Science Publishers Inc.
- Wagner, J. (1995). Studies of individualism-collectivism: Effects on cooperation in groups. *The Academy of Management Journal*, 38(1), 152–72.
- Warner, S., Bowers, M., & Dixon, M. (2012). Team dynamics: A social network perspective. *Journal of Sport Management*, 26, 53–66.
- Wasserman, S., & Galaskiewicz, J. (1994). *Advances in social network analysis: Research from the social and behavioural sciences*. Newbury Park: Sage Publications.
- Watts, D., & Strogatz, S. (1998). Collective dynamics of ‘small-world’ networks. *Nature*, 393(6684), 440–2.
- Wellman, B., & Wasserman, S. (2000). Social networks. In A. Kazdin (Ed.), *Encyclopedia of psychology* (pp. 351-353). New York: American Psychological Association and Oxford University Press.
- Wu, B., Zhou, D., Fu, F., Luo, Q., Wang, L., & Traulsen, A. (2010). Evolution of cooperation on stochastic dynamical networks. *PLoS One*. doi:10.1371/journal.pone.001187.
- Yamamoto, Y., & Yokoyama, K. (2011). Common and unique network dynamics in football games. *PLoS One*, 6(12), 1–6.
- Zhu, J. (2011). *Power systems applications of graph theory*. New York: Nova Science Publishers Inc.





## Chapter 3

### The Role of Hypernetworks as a Multilevel Methodology for Modelling and Understanding Dynamics of Team Sports Performance<sup>3</sup>

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#### Abstract

Despite its importance in many academic fields, traditional scientific methodologies struggle to cope with analysis of interactions in many complex adaptive systems, including team sports. 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 their natural environments. Multilevel networks and hypernetworks comprise novel and potent methodological tools for assessing team dynamics at more sophisticated levels of analysis, increasing their potential to impact on competitive performance in team sports. Here, we discuss how concepts and tools derived from studies of multilevel networks and hypernetworks have the potential 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 the dynamics of relational structures of sports teams during practice and competition. Specifically, we explore the benefits of implementing multilevel networks, in contrast to traditional network techniques, highlighting future research possibilities. We conclude by recommending methods for enhancing the applicability of hypernetworks in analysing team dynamics at multiple levels.

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<sup>3</sup> Ribeiro, J., Davids, K., Araújo, D., Silva, P., Ramos, J., Lopes, R., & Garganta, J. (2019). The Role of Hypernetworks as a Multilevel Methodology for Modelling and Understanding Dynamics of Team Sports Performance. *Sports Medicine*, 1-8.



### 3.1 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, in which behaviour is commonly depicted as resulting from the aggregate of individual actions within the system (Passos et al., 2006). This line of thinking is aligned with simple models of information processing, resulting from linear input-transformation-output processes (Davids et al., 2001). 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 (CAS), such as schools of fish, colonies of insects and sports teams (Araújo et al., 2014). 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 (Araújo & Davids, 2016; Duarte et al., 2012; Parrish & Edelstein, 1999). Contrary to postulates of linear models, complexity sciences have emerged as a holistic approach to understanding behaviours of CAS. Within the field of network sciences, an emergent methodological approach is hypernetworks (Johnson & Iravani, 2007) that investigate *n*-ary group dynamics at *multiple levels* of analysis (Ramos et al., 2017). In this Current Opinion article, we outline the benefits of utilising a multilevel hypernetwork approach, in contrast to traditional network techniques, in analysing team dynamics during competitive performance. We start by briefly reviewing the importance of complexity sciences for studying complex social systems (CSS) in the realm of team sports performance. Next, we discuss the relevance of social network analysis (SNA) 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 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 and hypernetwork approach.

### **3.2 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., Araújo et al., 2006; Balague et al., 2013; Davids et al., 1994; Silva et al., 2016; Vilar et al., 2013), effective methods for analysing behaviours of non-linear systems. An important point to note is that high-dimensional complex systems have *many interacting* parts with a large number of different possible states captured, for example, through analysis of the variable of team dispersion, or by the number and heterogeneity of player interactions (Efatmaneshnik & Ryan, 2016). However, due to their high dimensionality, such systems are less amenable to linear, reductionist analyses. Previous studies have revealed that the complexity sciences can provide profound insights into sports-related phenomena that are inherently complex and multidimensional by nature (Araújo et al., 2015).

Complexity sciences investigations of behaviours in CAS have revealed many *interacting* elements, the behaviour of which is difficult to ascertain due to continuous interactions and interdependencies between system components, and co-relations with their surrounding environments. 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. In addition, self-organisation, adaptive behaviours and complex networking constitute other key properties of such systems (Araújo & Davids, 2016; Davids et al., 2013).

Current research on team sports performance analysis has witnessed a progressive increase in investigations of performance behaviours based on positional data (see, for example, Agras et al. (2016) and Sarmento et al. (2018) for detailed reviews). Applications of novel techniques using non-linear mathematical 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 (networks underpinning ball-passing sequences) and sequential patterns (predicting future passing sequences) (Sarmento et al., 2018). Lately, there has been increasing interest in research on networks (e.g., Dey et al., 2017; Jarvie, 2018; Sargent & Bedford, 2013).

Sports teams are composed of players interacting through communication networks, revealing specific relational ties (e.g., ball-passing actions). Typically, players represent the nodes of the network, and the links reflect their interactions on the field (Jarvie, 2018; Passos et al., 2011; Ribeiro et al., 2017; Yamamoto & Yokoyama, 2011). Network approaches are extremely useful, since application of their concepts and methods can illuminate dynamic properties in individual and team sports (Clemente et al., 2014; Clemente et al., 2015; Gama et al., 2014; Mukherjee, 2013), contributing to a specialised body of knowledge for understanding the functioning of such complex adaptive social systems.

### **3.3 Social network analysis as a paradigm for modelling complex social systems**

Theories and methods underpinning SNA include 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 (Duch et al., 2010; Fewell et al., 2012; Gonçalves et al., 2017; Jarvie, 2018; Passos et al., 2011; Travassos et al., 2016) 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 (Pina et al., 2017; Yamamoto & Yokoyama, 2011). Indeed, re-conceptualisation of sports teams as complex social networks (Ramos et al.,

2018; Ribeiro et al., 2017) has revealed novel research opportunities for sports scientists and performance analysts to investigate the structural properties of teams during competition linked to successful performance outcomes (see, for example, Grund (2012), for detailed information on the relatedness of network properties to successful performance).

Beyond the unique terminology (e.g., nodes/vertices) used for modelling social interactions within collectives, such an approach utilises specific conceptual and methodological tools for understanding team performance. Despite being a promising methodological approach, more coherent with the principles of complexity sciences in analysing CSS, traditional network techniques contain specific limitations that can hinder or even conceal important information regarding team functioning during competition. Such limitations have been carefully scrutinised in the works of Ribeiro et al. (2017) and Ramos et al. (2018), 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.

### **3.4 Hypernetworks as innovative and potent methodological tools for analysing dynamic relational structures of sports teams**

Multilevel analysis and representing relations via hypernetworks were originally introduced by Johnson and Iravani (2007) for analysing the dynamics of complex systems of robot football agents. They used multilevel hypernetworks to reconstruct dynamics in multi-agent systems emerging at different levels of complexity (from micro–meso–macro). Recently, such an approach was extrapolated to investigate the dynamics of human football players during competition (Ramos et al., 2017). Indeed, Johnson and Iravani (2007) 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 performers. 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 dyadic relations between two players (Johnson, 2006). 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 (called simplex, plural-simplices) (Boccaletti et al., 2014; Johnson, 2006; Johnson, 2008; Johnson, 2013; Johnson, 2016). Hyperedges shed light on physical links (e.g., notation of who passes the ball to whom) established between players which facilitate information exchange, but also informational links (e.g., values of interpersonal distances, velocity) that bound players' interactions. This is particularly important because researchers can analyse emergent interactions (by verifying changes in the velocity and direction of each player's vectors) that led to the aggregation and/or disaggregation 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. (2017)) 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. (2017) confirmed the relevance of hypernetworks for extracting important information from game performance data. They applied the hypernetworks approach to a set of five competitive football matches in the English Premier League 2010–2011 season, and verified: (1) the most frequently occurring simplices configurations during the match; (2) dynamics of simplices' transformations (variations of players' speed and direction) near the goal that led to the creation of goal-scoring opportunities; and (3) 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. (2017).

### **3.5 Application of multilevel hypernetworks to understanding sport performance**

#### *3.5.1 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) (Johnson, 2016) composed of a given number of players in a sports team. When considering spatial proximity relationships, 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 and applied to each time frame of the match. Such a proximity criterion (non-parametric) 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 directional speed variables (Ramos et al., 2017). This signifies that each player is connected to his/her nearest player (or goal, for goalkeepers), and simplices can be linked to their closest simplices (Ramos et al., 2017).

To exemplify (Figure 3), imagine a first simplex identified by  $\sigma_1$  and represented by the following set  $\sigma_1 \{a_{16}, a_{23}, a_{24}, d_9, d_{13}\}$ , 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  $R_1$  (Ramos et al., 2017), which, basically, identifies the relationships (microstructures of play) within the set  $R_1 = (3 \text{ vs. } 2)$ . These elements  $R$  are highlighted in the hypernetworks model, and are obtained via a computational hypernetwork analysis procedure. The second simplex  $\sigma_2$  represents the following set  $\sigma_2 \{a_{16}, a_{24}, d_9\}$  identified by  $R_2 = (2 \text{ vs. } 1)$ , composed of two attackers and one defender. Finally, the third simplex  $\sigma_3$  is represented by  $\sigma_3 \{a_{23}, d_{13}\}$  identified by  $R_3 = (1 \text{ vs. } 1)$ , composed of one attacker and one defender. Hence, the respective microstructures of play are  $R_1 = (3 \text{ vs. } 2)$ ,  $R_2 = (2 \text{ vs. } 1)$  and  $R_3 = (1 \text{ vs. } 1)$ , and the corresponding simplices are  $\sigma_1 \{a_{16}, a_{23}, a_{24}, d_9, d_{13}; (3 \text{ vs. } 2)\}$ ,  $\sigma_2 \{a_{16}, a_{24}, d_9; (2 \text{ vs. } 1)\}$  and  $\sigma_3 \{a_{23}, d_{13}; (1 \text{ vs. } 1)\}$ . Let us say that these simplices' transformation (from  $\sigma_1$  to  $\sigma_3$ ) 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  $\sigma_1$  to  $\sigma_3$  was provoked by a movement of



player  $a_{23}$  from simplex  $\sigma_1$  that ran with the ball at speed (BM) further away from simplex  $\sigma_1$ . This action performed by player  $a_{23}$  allowed him to disaggregate along with  $d_{13}$  (geographical proximity criteria) from previous simplex  $\sigma_1$ , thus originating the formation of simplices  $\sigma_2$  and  $\sigma_3$ .

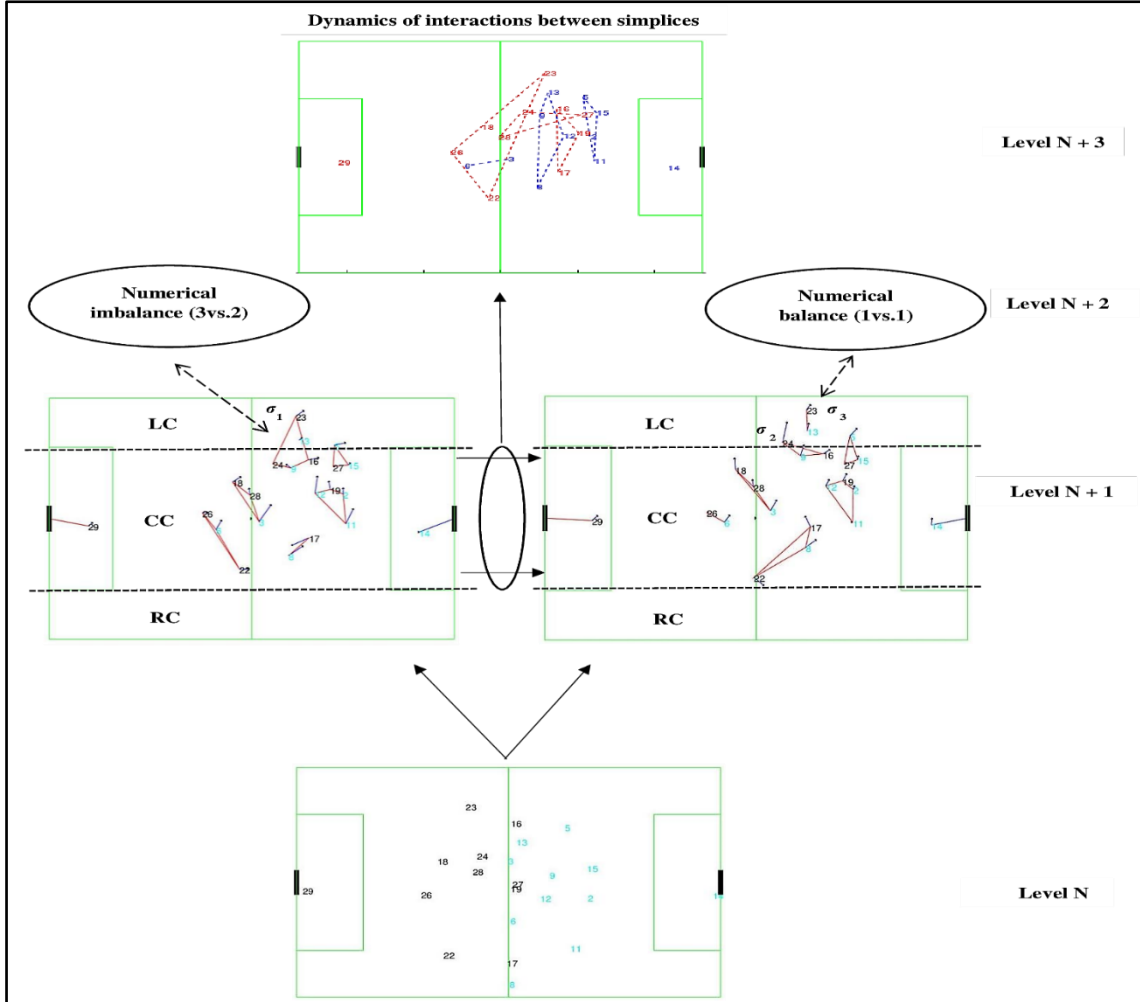


Figure 3. Example of a multilevel hypernetwork representation (from bottom to top): all players are tagged by numbers and those pertaining to the black team play from left to right while players from the blue team play from right to left. Goalkeepers are attached to their respective goals and the simplices' formation is based on players' proximity on field with the arrows depicting players' direction of displacement. Level  $N$  is the simplest and represents the disposition of players on field [the 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 the proximity-based simplex interactions. These interactions are the foundations for defining the simplex sets identified for the two time frames. Level  $N+2$  represents emerging microstructures of play showing both numerical imbalance (3 vs. 2) and numerical balance (1 vs. 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, for example, 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.

We can add BM ( $BM_{a23-d13}$ ) to  $\sigma_1 \{a_{16}, a_{23}, a_{24}, d_9, d_{13}; (3 \text{ vs. } 2); BM_{a23-d13}\}$  as an extra layer to complete the description of the set. Hence, the sequence of the following sets of simplices is:  $\sigma_1 \{a_{16}, a_{23}, a_{24}, d_9, d_{13}; (3 \text{ vs. } 2); BM_{a23-d13}\} \rightarrow \sigma_2 \{a_{16}, a_{24}, d_9; (2 \text{ vs. } 1)\} + \sigma_3 \{a_{23}, d_{13}; (1 \text{ vs. } 1)\}$ . 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 numerical balance on the field (e.g., when an attacker performs an overload action to aggregate to a simplex leading to a 3 vs. 2 situation) or for re-stabilising numerical imbalance (e.g., when a defender moves to that simplex to initiate a 3 vs. 3 situation) of a given simplex, without focusing solely on ball-passing statistics.

However, beyond providing qualitative information regarding team performance, other relevant information can be included to quantify 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 1 vs. 1) emerging during practice (Ramos et al., 2017), and the frequency of other technical actions (acquired through video analysis) performed by players during competition. The conceptualisation of team sports performance with a hypernetworks methodology might help sports scientists develop novel performance metrics (Ramos et al., 2017), capable of capturing team synergies (how individual players combine actions to function as a single coherent unit) emerging between players. By using positional coordinates of players and the ball, we can analyse, for example, how players pertaining to a specific simplex synchronise their movement with other players pertaining to another simplex. 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. Alternatively, we may ascertain how far simplices 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.

### 3.5.2 *Variability of player performance outcomes is associated with specific events in competitive performance*

Ribeiro et al. (2017) 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 ( $t_1, t_2, \dots, t_n$ ) (Ramos et al., 2017). Furthermore, Johnson (2013) introduced the concepts of *backcloth* and *traffic* to emphasise the study of dynamics in multilevel analysis. Typically, the network structure is the *backcloth* involving structures that are less dynamic, while the *traffic* relates to the network flows, thus considering higher rates of change emerging within the *backcloth* (Johnson, 2013).

Application of these novel ideas to team sports performance analysis might consider, for example, the disposition of players on field in football (e.g., players organised according to positions in a 1-4-3-3 formation with one goalkeeper, four defenders, three midfielders and three forwards), with its typical adjustments as being the *backcloth*, and the players’ displacements on field (both off- and on-the-ball) as 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, as the former has only three midfielders and one central forward, and the latter has four midfielders and two forwards. These and other team properties, here considered as *backcloth*, might constrain team dynamics, and thus promote specific individual and team behaviours, that is, favour particular types of *traffic*.

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 (Araújo & Davids, 2016; Ramos et al., 2017), allowing investigation of higher complexity levels inherent to team sports competition (Figure 3).

### *3.5.3 Research over-emphasises analysis of attacking behaviours in team sports performance analysis, rather than defensive behaviours*

A major advance, compared to traditional network analysis, is that use of hypernetwork simplices can capture interactions of sets of players that may involve an arbitrary number of teammates and opponents (Ramos et al., 2017). 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 can furnish novel and rich insights regarding functional dynamics of both competing teams. Arguably, ball location constitutes a major constraint that 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 (Figure 4), researchers can identify the player with the ball (B) in a given simplex  $n$  ( $\sigma_n \{a_{24B}, a_{23}, d_9, d_{13}\}$ ), while investigating the number and types of simplices formation (e.g., 2 vs. 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.

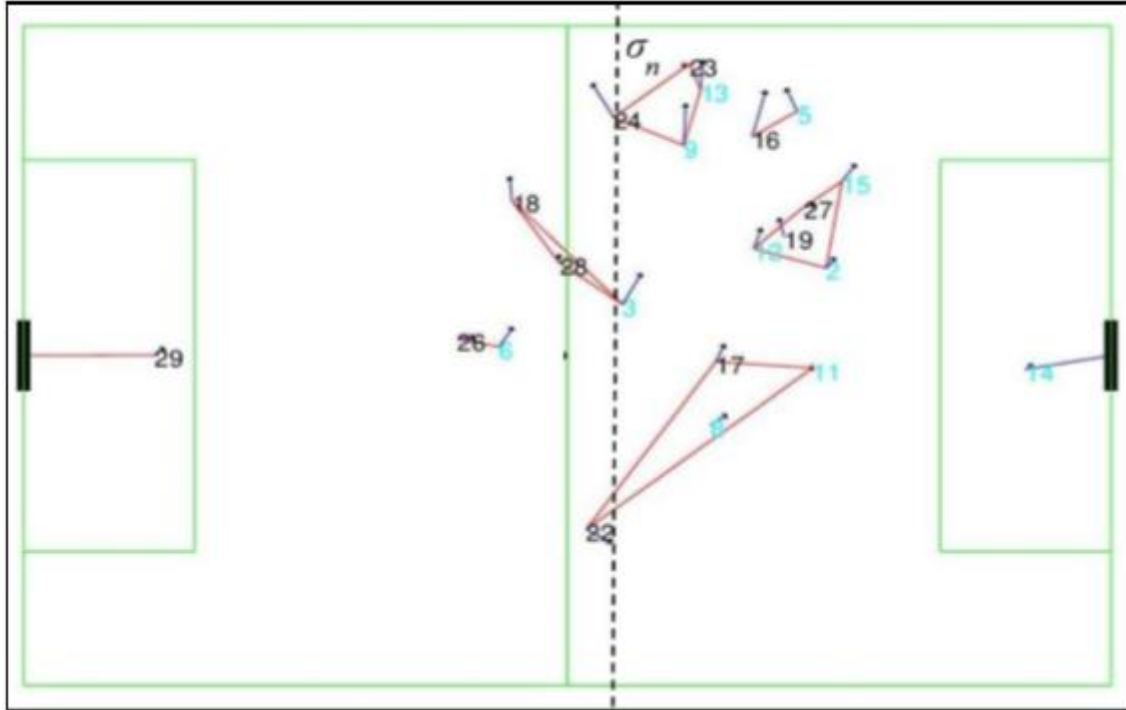


Figure 4. Schematic representation of players' simplices and the ball line (black dashed line). Players composing the black team play from left to right, while players from the blue team play from right to left. Simplice formation is based on geographical proximity between players, with goalkeepers being attached to their goals. The player tagged with number 24 has the ball (B) and is involved in a simplex of 2 vs. 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 (1 vs. 1 composed of players 26 and 6; 2 vs. 1 composed of 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 (1 vs. 1 composed of players 16 and 5; 3 vs. 2 with players 15, 2, 12 from the blue team and players 19 and 27 from the black team; 2 vs. 2 composed of 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.

#### 3.5.4 *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) (Johnson, 2008; Johnson, 2016). In previous research (Ramos et al., 2017), and in the running examples of the

current paper, a major concern with such an analysis is player geographical coordinates and proximity currently utilised for defining the simplice sets and modelling team dynamics in hypernetworks. The definition of such criteria will considerably limit all data analyses and interpretations of team sport performance. Nonetheless, the fundamental tools provided by multilayer hypernetworks ( $n$ -ary sets, and relationships) and their applications do not depend on the particular features and criteria used for defining simplice sets and their relations. Indeed, different micro-meso-macro relations and emergent properties under investigation require adequate features and criteria selected for the definition of the simplices set and their intra- and inter-relationships. Thus, it is a 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 (2005)) have presented examples where using metrics based on shortest paths may not be adequate. Using walks instead of paths (Borgatti, 2005) or even applying random walk Monte Carlo methods (e.g., Cheng et al. (2017)) for modelling social interactions may be worth considering.

### **3.6 Conclusions and practical applications**

In this Current Opinion article, 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 dynamic 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.

### 3.7 References

Agras, H., Ferragut, C., & Abrales, J. (2016). Match analysis in futsal: A systematic review. *International Journal of Performance Analysis in Sport*, 16(2), 652-686.

Araújo, D., & Davids, K. (2016). Team synergies in sport: Theory and measures. *Frontiers in Psychology*, 7, 1449.

Araújo, D., Davids, K., & Hristovski, R. (2006). The ecological dynamics of decision making in sport. *Psychology of Sport and Exercise*, 7(6), 653-676.

Araújo, D., Diniz, A., Passos, P., & Davids, K. (2014). Decision making in social neurobiological systems modelled as transitions in dynamic pattern formation. *Adaptive Behavior*, 22(1), 21-30.

Araújo, D., Passos, P., Esteves, P., Duarte, R., Lopes, J., Hristovski, R., & Davids, K. (2015). The micro-macro link in understanding sport tactical behaviors: Integrating information and action at different levels of system analysis in sport. *Movement & Sport Sciences – Science & Motricité*, 89, 53-63.

Balague, N., Torrents, C., Hristovski, R., Davids, K., & Araújo, D. (2013). Overview of complex systems in sport. *Journal of Systems Science and Complexity*, 26(1), 4–13.

Boccaletti, S., Bianconi, G., Criado, R., del Genio, C., Gómez-Gardeñes, J., Romance, M., Sendiña-Nadal, I., Wang, Z., & Zanin, M. (2014). The structure and dynamics of multilayer networks. *Physics Reports*, 544(1), 1–122.

- Borgatti, S. (2005). Centrality and network flow. *Social Networks*, 27(1), 55–71.
- Cheng, W., Cox, J., & Whitlock, P. (2017). Random walks on graphs and Monte Carlo methods. *Mathematics and Computers in Simulation*, 135, 86-94.
- Clemente, F., Couceiro, M., Martins, F., & Mendes, R. (2014). Using network metrics to investigate football team players' connections: A pilot study. *Motriz*, 20(3), 262-271.
- Clemente, F., Couceiro, M., Martins, F., & Mendes, R. (2015). Using network metrics in soccer: A macro-analysis. *Journal of Human Kinetics*, 45, 123-134.
- Davids, K., Araújo, D., Vilar, L., Renshaw, I., & Pinder, R. (2013). An ecological dynamics approach to skill acquisition: Implications for development of talent in sport. *Talent Development and Excellence*, 5(1), 21-34.
- Davids, K., Handford, C., & Williams, M. (1994). The natural physical alternative to cognitive theories of motor behaviour: An invitation for interdisciplinary research in sports science? *Journal of Sports Sciences*, 12, 495-528.
- Davids, K., Kingsbury, D., Bennett, S., & Handford, C. (2001). Information-movement coupling: Implications for the organisation of research and practice during acquisition of self-paced extrinsic timing skills. *Journal of Sports Sciences*, 19(2), 117-127.
- Dey, P., Ganguly, M., & Roy, S. (2017). Network centrality based team formation: A case study on T-20 cricket. *Applied Computing and Informatics*, 13(2), 161-168.
- Duarte, R., Araújo, D., Correia, V., & Davids, K. (2012). Sport teams as superorganisms: Implications of biological models for research and practice in team sports performance analysis. *Sports Medicine*, 42(8), 633–42.



- Duch, J., Waitzman, J., & Amaral, L. (2010). Quantifying the performance of individual players in a team activity. *PLoS One*. doi:10.1371/journal.pone.0010937.
- Efatmaneshnik, M., & Ryan, M. (2016). A general framework for measuring system complexity. *Complexity*, 21(1), 533-546.
- Fewell, J., Armbruster, D., Ingraham, J., Petersen, A., & Waters, J. (2012). Basketball teams as strategic networks. *PLoS One*. doi:10.1371/journal.pone.0047445.
- Gama, J., Passos, P., Davids, K., Relvas, H., Ribeiro, J., Vaz, V., & Dias, G. (2014). Network analysis and intra-team activity in attacking phases of professional football. *International Journal of Performance Analysis in Sport*, 14(3), 692-708.
- Gonçalves, B., Coutinho, D., Santos, S., Lago-Peñas, C., Jiménez, S., & Sampaio, J. (2017). Exploring team passing networks and player movement dynamics in youth association football. *Plos One*, 12(1):e0171156.
- Grund, T. (2012). Network structure and team performance: The case of English Premier League soccer teams. *Social Network*, 34(4), 682-690.
- Jarvie, D. (2018). Do long-time team-mates lead to better team performance? A social network analysis of data from Major League Baseball. *Sports Medicine*, 48(11), 2659-2669.
- Johnson, J. (2006). *Hypernetworks for reconstructing the dynamics of multilevel systems*. In: European Conference on Complex Systems. Oxford, U.K.
- Johnson, J. (2008). Multidimensional events in multilevel systems. In S. Albeverio, D. Andrey, P. Giordano & A. Vancheri (Eds.), *The Dynamics of*

*Complex Urban Systems: An Interdisciplinary Approach* (pp. 311-334).  
Heidelberg: Physica-Verlag HD.

Johnson, J. (2013). *Hypernetworks in the science of complex systems*. London:  
Imperial College Press.

Johnson, J. (2016). Hypernetworks: multidimensional relationships in multilevel  
systems. *European Physical Journal Special Topics*, 225(6), 1037–1052.

Johnson, J. & Iravani, P. (2007). The multilevel hypernetwork dynamics of  
complex systems of robot soccer agents. *ACM Transactions on  
Autonomous Adaptive Systems*, 2,1–23.

Mukherjee, S. (2013). Complex network analysis in cricket: Community structure,  
player's role and performance index. *Advances in Complex Systems*,  
16(8):1350031

Parrish, J., & Edelstein-Keshet, L. (1999). Complexity, pattern, and evolutionary  
trade-offs in animal aggregations. *Science*, 284(2), 99–101.

Passos, P., Araújo, D., Davids, K., Gouveia, L., & Serpa, S. (2006). Interpersonal  
dynamics in sport: The role of artificial neural networks and three-  
dimensional analysis. *Behavior Research Methods*, 38(4), 683–691.

Passos, P., Davids, K., Araújo, D., Paz, N., Minguéns, J., & Mendes, J. (2011).  
Networks as a novel tool for studying team ball sports as complex social  
systems. *Journal of Science and Medicine in Sport*, 14(2), 170–176.

Pina, T., Paulo, A., & Araújo, D. (2017). Network characteristics of successful  
performance in Association Football: A study on the UEFA Champions  
League. *Frontiers in Psychology*, 8, 1173.

- Ramos, J., Lopes, R., & Araújo, D. (2018). What's next in complex networks? Capturing the concept of attacking play in invasive team sports. *Sports Medicine*, 48(1), 17-28.
- Ramos, J., Lopes, R., Marques, P., & Araújo, D. (2017). Hypernetworks reveal compound variables that capture cooperative and competitive interactions in a soccer match. *Frontiers in Psychology*, 8, 1379.
- Ribeiro, J., Silva, P., Duarte, R., Davids, K., & Garganta, J. (2017). Team sports performance analysed through the lens of social network theory: Implications for research and practice. *Sports Medicine*, 47(9), 1689-1696.
- Sargent, J., & Bedford, A. (2013). Evaluating Australian football league player contributions using interactive network simulation. *Journal of Sports Science and Medicine*, 12, 116-121.
- Sarmiento, H., Clemente, F., Araújo, D., Davids, K., McRobert, A., & Figueiredo, A. (2018). What performance analysts need to know about research trends in Association Football (2012-2016): A systematic review. *Sports Medicine*, 48(4), 799-836.
- Silva, P., Chung, D., Carvalho, T., Cardoso, T., Davids, K., Araújo, D., & Garganta, J. (2016). Practice effects on intra-team synergies in football teams. *Human Movement Science*, 46, 39–51.
- Travassos, B., Bourbousson, J., Esteves, PT., Marcelino, R., Pacheco, M., & Davids, K. (2016). Adaptive behaviours of attacking futsal teams to opposition defensive formations. *Human Movement Science*, 47, 98-105.
- Vilar, L., Araújo, D., Davids, K., & Bar-Yam, Y. (2013). Science of winning soccer: Emergent pattern-forming dynamics in association football. *Journal of Systems Science and Complexity*, 26, 73-84.

Yamamoto, Y., & Yokoyama, K. (2011). Common and unique network dynamics in football games. *PLoS One*, 6(12), 1–6.

## Chapter 4

A multilevel hypernetworks approach to capture properties of team synergies at higher complexity levels<sup>4</sup>

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### Abstract

Research conducted over past years has sought to explain team collective behaviours using insights from theories of synergy formation in collective systems. Under this theoretical rationale, players are viewed as independent degrees of freedom (dofs) which can become coupled, during continuous interactions, to produce coherent patterns of behaviour (team synergies) guided by shared affordances (invitations for action in the environment). Previous conceptualisation has identified key properties of synergies whose measurement can reveal important aspects of team dynamics. A major issue is that some of these properties have typically been measured through implementation of a variety of methods, while others have only loosely been addressed. Here, we show how multilevel hypernetworks comprise an innovative methodological framework that can successfully capture key properties of synergies, clarifying conceptual issues concerning team collective behaviours based on team synergy formation. Therefore, this study investigated whether different synergy properties, typically examined using a variety of methods, could be operationally related (utilising hypernetworks), exhibiting task dependence. Thus, we represented a multilevel model composed of three levels of analysis. Level N captured changes in tactical configurations of teams during competitive performance. Level N+1 analysed the most frequently emerging simplices, both behind and ahead of the ball line for both competing teams. Finally, Level N+2 analysed the level of prominence of individual players and their interactions within and between simplices before a goal was scored. Altogether, our findings showed that different synergy properties can be assessed through hypernetworks, which can provide a coherent theoretical understanding of competitive team performance.

**Keywords:** Multilevel Hypernetworks, Dynamics, Team Synergies, Team Collective Behaviour, Performance Analysis, Association Football.

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## 4.1 Introduction

Current research on team sports performance has contributed with a rich theoretical rationale for conceptualising how collective team behaviours emerge from players' continuous interactions within competing teams during performance (e.g., Araújo & Davids, 2016; Silva et al., 2013). In this way, competing players and teams have been conceptualised as co-evolving dynamical sub-systems who have the capacity to self-organise into newly formed structures (Johnson, 2013) by forming team synergies for the purposes of functioning in performance (Araújo & Davids, 2016).

According to Turvey (2007) a synergy comprises a group of relatively independent dofs (i.e., the players) that combines actions to behave as a single, functioning coherent unit (i.e., a team). Araújo and Davids (2016) highlighted four properties of a synergy, including: (1) dimensional compression (Riley et al., 2011); reciprocal compensation (Latash, 2008; Riley et al., 2011); (3) interpersonal linkages (Araújo & Davids, 2016), and (4), degeneracy (Davids et al., 2006; Latash, 2008; Seifert et al., 2016). Briefly, dimensional compression highlights how players (dofs) can influence each other to produce collective movement patterns. Reciprocal compensation refers to the ability of one element of the synergy to react and adapt the system to changes in others. Interpersonal linkages refers to the individual contribution of the elements comprising a synergy. Finally, system degeneracy is defined as the capacity of elements that are structurally different to attain similar, but not necessarily identical, functions with respect to a specific behavioural context (Edelman & Gally, 2001), thus expressing functional variability (Araújo & Davids, 2016).

Most of these synergetic properties have begun to be investigated in the literature through application of different methods for analysing different variables (see Araújo et al., 2015 and Araújo & Davids, 2016, for detailed reviews on the methods and variables used for identifying properties of synergies). One of such methods is networks which comprise a valuable tool to analyse functional variability (system degeneracy) during sub-phases of play in team sports (e.g., Passos et al., 2011). Degeneracy in sports teams would be expressed by players combining and interacting in different ways to achieve similar performance outcomes, such as maintaining possession of the ball, penetrating the

opposition's critical scoring space and providing defensive cover in a critical scoring region. Regardless, identifying properties of synergies goes far beyond analysing the number of links (typically observed through ball-passing actions) of a given node (i.e., a player) to its neighbors (i.e., other players).

However, other sophisticated methods and techniques are beginning to appear in the literature such as *multilevel hypernetworks* (Ramos et al., 2017; Ribeiro et al., 2019). In hypernetworks, hyperedges allow connecting more than two nodes thus it generalises the concept of two-edge vertex (used in traditional network techniques) toward  $n$ -ary ( $n > 2$ ) relations between many agents (i.e., subgroups of players, e.g., 3vs.2) (Johnson, 2008). Moreover, there are two key concepts that support dynamics assessments in multilevel systems: the *backcloth* and the *traffic* (Johnson, 2006; Johnson, 2013; Johnson, 2016). The former involves structures that are less dynamic (e.g., tactical configurations of play such as 1-4-4-2), while the latter implies higher rates of change emerging within the backcloth (e.g., interpersonal synergies afforded by such tactical configurations) (Johnson, 2008).

On the other hand, the mathematical formalisms underlying hypernetworks can provide a fruitful template for addressing, in more principled way, relevant properties of synergies. Importantly, this fine-grained framework can be used for clarifying conceptual issues concerning collective behaviour based on team synergies theory (Araújo & Davids, 2016).

In this study, we sought to test whether different properties of synergies, usually investigated using different methods, can be operationally (by means of hypernetworks) related. For this purpose, we elaborated a model encompassing three levels of analysis, where each level shed light on synergetic properties. For each level, we sought to consider the following questions:

i) Level N: Has the backcloth changed during competitive performance, as expressed by changes in tactical configurations (degeneracy) of both competing teams? The visual representation of multilevel hypernetworks allows us to answer this question.



ii) Level N+1: What are the most frequently emerging simplices in the match, with respect to the position of the ball? Ball data were included as ball location and possession are major constraints influencing team dynamics. Basically, we investigated the frequency of types of simplices emerging behind and ahead of the ball line (degeneracy) for each team (Team A vs. Team B), and for each 15-minute time period of the first and second halves of the match.

iii) Level N+2: Which were the most prominent players in the attacking play, whose dynamics provoked a disruption in the opposition defensive structure before a goal was scored? What kind of actions did they perform? Here, we conducted a frame-by-frame analysis for the first goal to describe the players' interactions within and between simplices (degeneracy). Moreover, the inclusion of other important technical actions as additional terms in the set of simplices allowed us to describe the individual contribution of players (interpersonal linkages) in the sequence of play, thus helping to ascertain their level of prominence.

## **4.2 Methods and Procedures**

Twenty-eight male professional football players (22 starting players and 6 substitutes) competed in a single match in the Russian Premier League season 2015-2016. The final score was 0-2 in favour of the visiting team. Positional raw data (2D) of players' movement displacements and the ball was provided by STATS. These data were obtained by a multiple-camera match analysis system whereby the movements of all 28 players performed during the match were recorded with the cameras positioned at the top of the stadium. The raw data of the displacements of the 14 (11 players and 3 substitutes) on-field players of each team (Team A and Team B), as well as the ball coordinates, were divided by each game half. Furthermore, when a player was substituted by a teammate, the 2D positional data of his colleague was added to his data columns with a timestamp corresponding to the moment of substitution.

The frames were processed at 1Hz using an automated system that synchronised the video files. The effective playing area was 68 m wide and 105 m long. A computer procedure for computing the simplices' hyperedges, set with

the proximity-based criteria, was performed using GNU Octave version 4.4.1 and applied to each frame. Each simplex was represented graphically by the convex hull calculation (i.e., the minimum convex area containing all players in the simplex). They included the velocity of each player (i.e., vector velocity represented by an arrow that considered the instant  $t-1$  and  $t$ ), beyond the velocity of the geometric center of the simplices.

Positional data from the ball was used to trace a line perpendicular to the pitch (through a computer procedure established in GNU Octave), thus enabling further analysis of the number and types of simplices emerging behind and ahead of the ball line.

Regarding the analysis of specific time points of the sequence that resulted in a goal scored (Level N+2), the simplices were represented with two different colours: for players in team A, vertices are in red, and for players composing team B, vertices are in blue.

### 4.3 Results

At Level N, we observed that both Team A and Team B started the match organised in a 1-4-3-3 (one goalkeeper, four defenders, three midfielders, and three forwards) tactical configuration. However, as the match evolved, both teams altered their tactical configurations, with Team A exhibiting more pronounced changes compared to Team B. Thus, Team A changed from an earlier 1-4-3-3 (one goalkeeper (29), four defenders (23-18-26-22), three midfielders (24-28-19), three forwards (16-27-17)) to a 1-4-4-2 (one goalkeeper (29), four defenders (23-18-26-22), four midfielders (24-28-17-16(later substituted by player 25 as verified in line d)), and two forwards (27-21)) tactical configuration, approximately at instant 1380'' of the second half (see lines a) and c) of Figure 5). Team B, although maintaining an initial 1-4-3-3 (one goalkeeper (14), four defenders (5-15-2-11), three midfielders (9-12-6), and three forwards (13-3-8)) configuration, on the other hand displayed changes in the dynamics of the three midfielders, approximately at instant 1980'' of the second half. Initially, the three midfielders were organised in a triangle with two players composing its base (9 and 12) and another one, operating in a more offensive role (6), played as a vertice just behind the central forward. Then, they inverted the triangle and

started playing with only one back midfielder (7) and two front (right-12 and left-9) midfielders (see lines b) and d) of Figure 5).

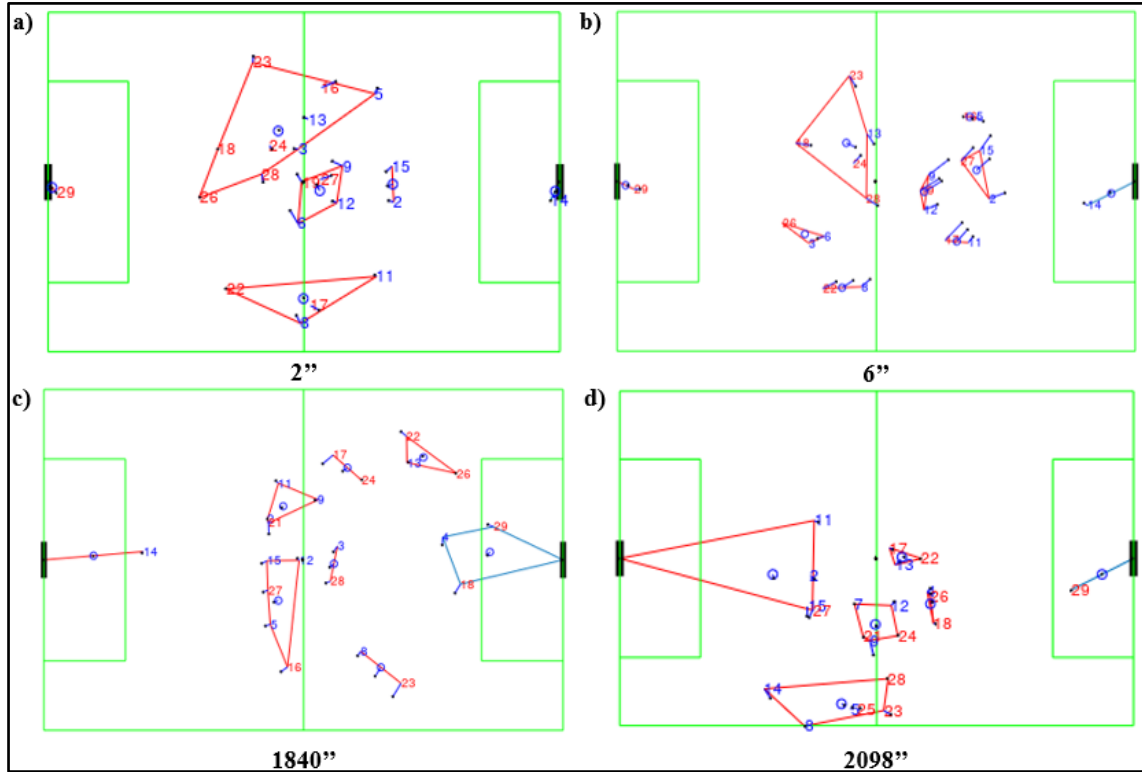


Figure 5. Schematic representation of hypernetworks representing simplices' interactions extracted from a set of four different time periods of the match. Lines a) and b) refer to the first 2'' and 6'' of the first half, respectively, while lines c) and d) refer to the 1840'' and 2098'' of the second half of the match, respectively. In the first half, Team A (represented in red) is attacking from left to right and Team B (represented in blue) is attacking from right to left. In the second half, Team A is attacking from left to right whilst Team B is attacking from right to left. Each simplex is represented by the polygon (or a line when it involves only two players) defining the convex hull that links the nodes (i.e., players –identified by numbers, or goals – identified by black boxes). A velocity vector for each player as well as the geometric center of each simplex is also represented.

Moreover, Level N+1 allowed us to describe and quantify the most frequently emerging simplices in the match with respect to the position of the ball, as displayed in Figure 6 and Figure 7. All histograms contain the most frequent simplex structures that emerged in each 15-minute time period of the match, both ahead and behind of the ball line. The simplex structure 1vs.0 (or 0vs.1) refers to the goalkeeper (with the exception of 0vs.1 (76'-90') in line b)) connected to his own goal. Nevertheless, this simplex was not highlighted during analysis of

the structures that reached the highest frequency values, because they obviously appear behind the ball line when a team has ball possession and in front of the ball line when a team is attacking. To help clarify the interpretation of the following histograms, we take as an example line a) (simplices emerging behind of the ball line) and line b) (simplices emerging ahead of the ball line) of Figure 6, referring to the 0'-15' time period. So, in line a), for the first 15 minutes of the first half when Team A had the ball, behind the ball line appeared the 0vs.1 (goalkeeper linked to the goal) simplice structure (n=156), the 0vs.2 (n=13), 1vs.1 (n=113), and so on. Team B attained numerical advantage in the form of 2vs.1 (n=23), while numerical balance was accomplished in the simplices' structures of 1vs.1 (n=113) and 2vs.2 (n=15). In line b), when Team A had the ball, ahead of the ball line appeared the 1vs.0 (n=164; corresponds to the opposing goalkeeper attached to his own goal), the 1vs.1 (n=323), and so on.

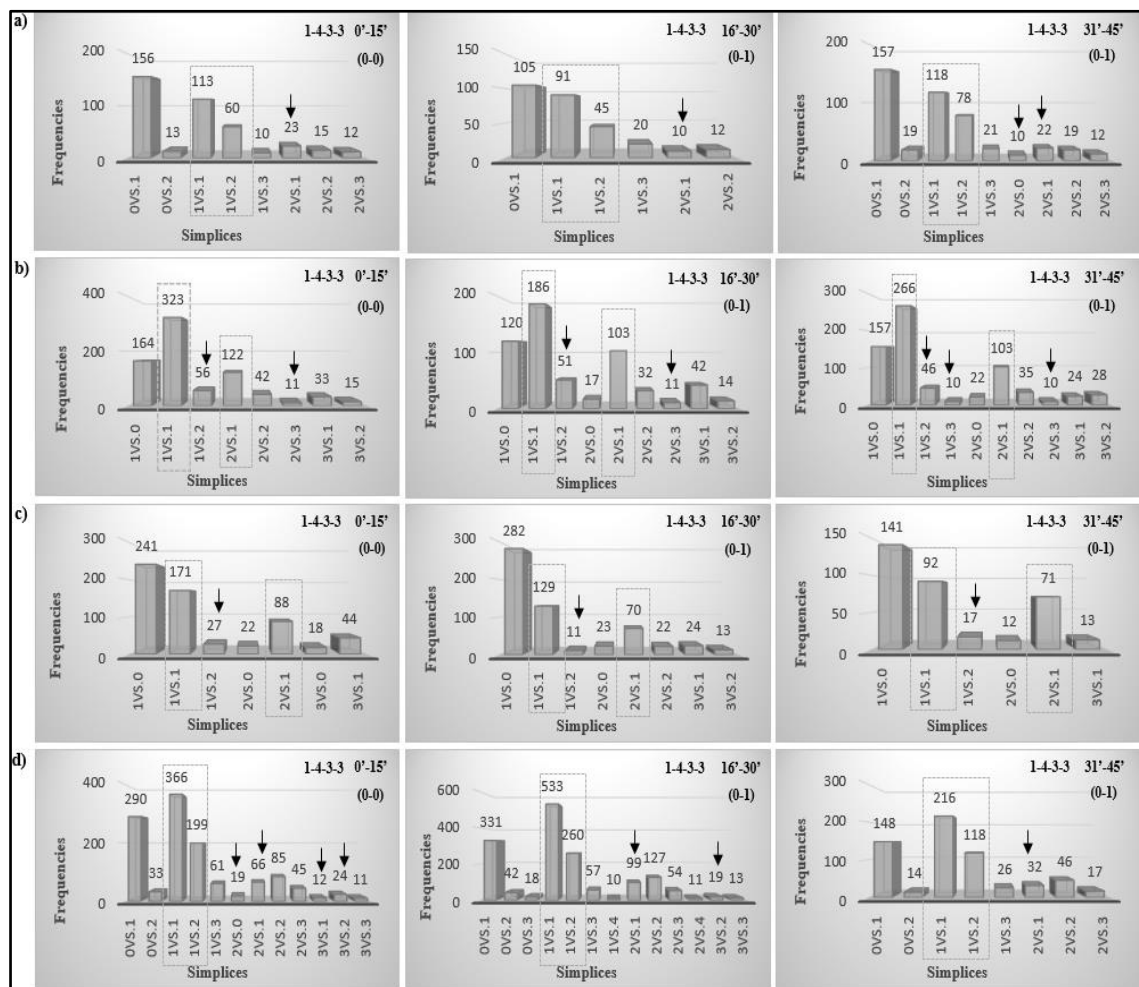


Figure 6. Histograms representing the most frequently emerging simplices' structures behind and ahead of the ball line for the 45 minutes of the first half.

Lines a) and b) represent the frequencies of simplices emerging behind and ahead of the ball line, respectively, for each time period of the match (located at the upper right corner) when Team A has the ball. Lines c) and d) represent the frequencies of simplices emerging behind and ahead of the ball line, respectively, for each time period of the match when Team B has the ball. Grey dashed lines identify the simplices' structures with the highest frequencies, while black arrows identify the simplices' structure with unbalanced number of players favouring the opposing team. The tactical disposition of each team as well as the game result (between brackets) are also shown in the upper right corner.

The results presented in Figure 6 revealed that the two most frequently emerging simplices (identified by the grey dashed lines), located both behind and ahead of the ball line, were the 1vs.1 and 1vs.2 (or 2vs.1) for both teams, although with different frequency values.

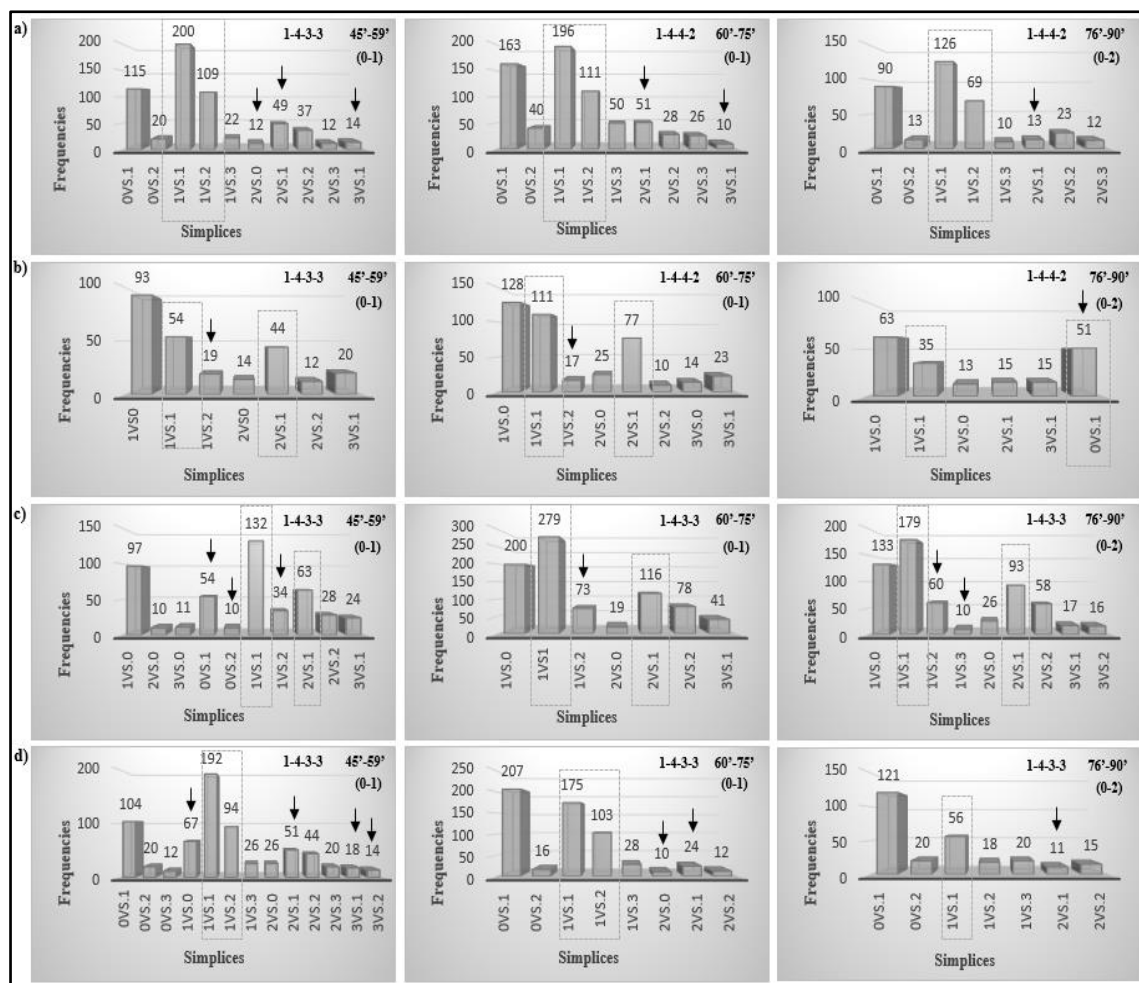


Figure 7. Histograms representing the most frequently emerging simplices' structures behind and ahead of the ball line for the second 45 minutes of the second half. Lines a) and b) represent the frequencies of simplices emerging

behind and ahead of the ball line, respectively, for each time period of the match (located at the upper right corner) when Team A has the ball. Lines c) and d) represent the frequencies of simplices emerging behind and ahead of the ball line, respectively, for each time period of the match when Team B has the ball. Grey dashed lines identify the simplices' structures with the highest frequencies, while black arrows identify the simplices' structure with unbalanced number of players favouring the opposing team.

Similar to Figure 6, Figure 7 displays the 1vs.1 and 1vs.2 (or 2vs.1) as the two most predominant simplices' structures emerging behind and ahead of the ball line, with the exception of 0vs.1 (76'-90') in line b)).

Finally, Level N+2 captured simplex interactions seconds before a goal was scored by Team B (Figure 8). Herein, we presented a hypernetworks model where analysis of simplices' interactions of Team B occurred on the defensive midfield of Team A (offensive midfield of Team B). The sequence of play was analysed in eight consecutive time frames of the match prior to the goal. Furthermore, a velocity vector was computed for each player and for each of the eight time frames.

Figure 8 shows a visual representation of the set of simplices ( $\sigma$ ) and their respective evolution during the 8-second period (see the sequence of letters from a-h) that preceded a goal scored by Team B at instant 29' 36". These simplices were formed based on a proximity criterion, which signifies that a player is linked to his nearest player (a teammate and/or an opponent), or the case of a goalkeeper linked to his goal (G). Each simplex is completed with an element R that describes the relationships established in each set.

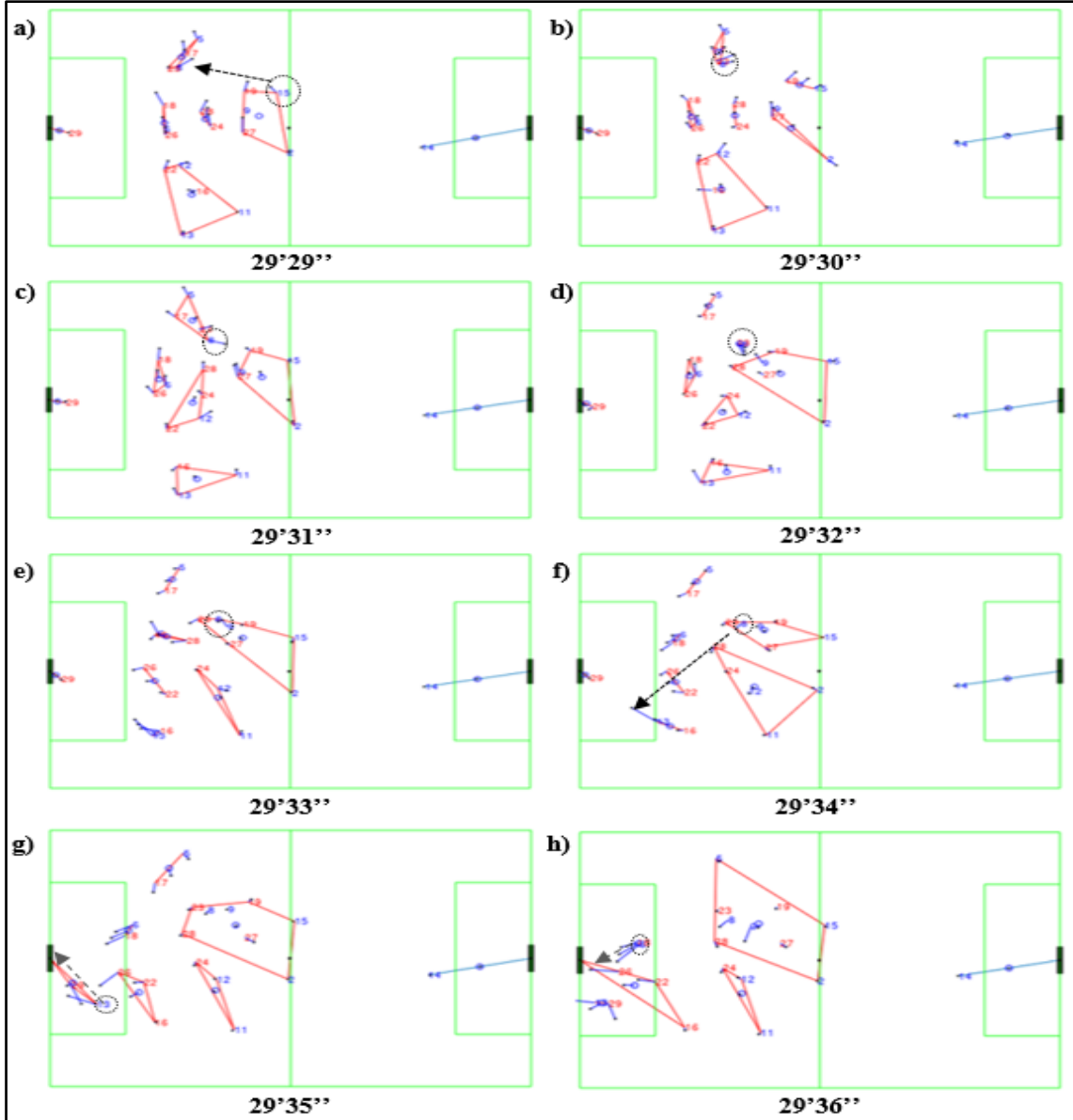


Figure 8. Simplices' interactions in a sequence composed by eight frames (29'29'' to 29'36'') resulting in a goal to Team B. Team B is attacking from right to left (represented in blue), while Team A is attacking from left to right (represented in red). Each player is coded by a number (red for Team A and blue for Team B). A simplex is represented by the polygon (or a line when there are only two players) defining the convex hull that connects the nodes (players or goal). A velocity vector, represented by an arrow, is also displayed for each player.

Beyond the visual representation, we can describe the sequence of the set of simplices for each time frame as follows:

$$\begin{aligned} \mathbf{a)} \quad & \sigma_1 \{a_{14}, G\} + \sigma_2 \{a_2, a_9, a_{15}, d_{19}, d_{27}; (3vs.2); a_{15bh/p}\} + \sigma_3 \{a_5, a_8, d_{17}, d_{23}; (2vs.2)\} + \sigma_4 \\ & \{a_6, d_{18}, d_{26}; (1vs.2)\} + \sigma_5 \{a_{11}, a_{12}, a_{13}, d_{16}, d_{22}; (3vs.2)\} + \sigma_6 \{d_{24}, d_{28}; (0vs.2)\} + \sigma_7 \\ & \{d_{29}, G\}; \end{aligned}$$

**b)**  $\sigma_1 \{a_{14}, G\} + \sigma_2 \{a_2, a_9, d_{27}; (2vs.1)\} + \sigma_3 \{a_5, a_8, d_{17}, d_{23}; (2vs.2); a_{8br}\} + \sigma_4 \{a_6, d_{18}, d_{26}; (1vs.2)\} + \sigma_5 \{a_{11}, a_{12}, a_{13}, d_{16}, d_{22}; (3vs.2)\} + \sigma_6 \{a_{15}, d_{19}; (1vs.1)\} + \sigma_7 \{d_{24}, d_{28}; (0vs.2)\} + \sigma_8 \{d_{29}, G\};$

**c)**  $\sigma_1 \{a_{14}, G\} + \sigma_2 \{a_5, a_8, d_{17}, d_{23}; (2vs.2); a_{8bh/db}\} + \sigma_3 \{a_6, d_{18}, d_{26}; (1vs.2)\} + \sigma_4 \{a_{11}, a_{13}, d_{16}; (2vs.1)\} + \sigma_5 \{a_{12}, d_{22}, d_{24}, d_{28}; (1vs.3)\} + \sigma_6 \{a_2, a_9, a_{15}, d_{19}, d_{27}; (3vs.2)\} + \sigma_7 \{d_{29}, G\};$

**d)**  $\sigma_1 \{a_{14}, G\} + \sigma_2 \{a_2, a_9, a_{15}, d_{19}, d_{27}, d_{28}; (3vs.3)\} + \sigma_3 \{a_5, d_{17}; (1vs.1)\} + \sigma_4 \{a_6, d_{18}, d_{26}; (1vs.2)\} + \sigma_5 \{a_8, d_{23}; (1vs.1); a_{8bh/db}\} + \sigma_6 \{a_{11}, a_{13}, d_{16}; (2vs.1)\} + \sigma_7 \{a_{12}, d_{24}, d_{22}; (1vs.2)\} + \sigma_8 \{d_{29}, G\};$

**e)**  $\sigma_1 \{a_{14}, G\} + \sigma_2 \{a_2, a_8, a_9, a_{15}, d_{19}, d_{23}, d_{27}; (4vs.3); a_{8bh/db}\} + \sigma_3 \{a_5, d_{17}; (1vs.1)\} + \sigma_4 \{a_6, d_{18}, d_{28}; (1vs.2)\} + \sigma_5 \{a_{11}, a_{12}, d_{24}; (2vs.1)\} + \sigma_6 \{a_{13}, d_{16}; (1vs.1)\} + \sigma_7 \{d_{22}, d_{26}; (0vs.2)\} + \sigma_8 \{d_{29}, G\};$

**f)**  $\sigma_1 \{a_{14}, G\} + \sigma_2 \{a_2, a_{11}, a_{12}, d_{24}, d_{28}; (3vs.2)\} + \sigma_3 \{a_5, d_{17}; (1vs.1)\} + \sigma_4 \{a_6, d_{18}; (1vs.1)\} + \sigma_5 \{a_{13}, d_{16}; (1vs.1); a_{13rm}\} + \sigma_6 \{a_8, a_9, a_{15}, d_{19}, d_{23}, d_{27}; (3vs.3); a_{8p}\} + \sigma_7 \{d_{22}, d_{26}; (0vs.2)\} + \sigma_8 \{d_{29}, G\};$

**g)**  $\sigma_1 \{a_{14}, G\} + \sigma_2 \{a_2, a_8, a_9, a_{15}, d_{19}, d_{23}, d_{27}, d_{28}; (4vs.4)\} + \sigma_3 \{a_5, d_{17}; (1vs.1)\} + \sigma_4 \{a_6, d_{18}; (1vs.1)\} + \sigma_5 \{a_{11}, a_{12}, d_{24}; (2vs.1)\} + \sigma_6 \{a_{13}, d_{29}, G; (1vs.1+G); a_{13sh}\} + \sigma_7 \{d_{16}, d_{22}, d_{26}; (0vs.3)\};$

**h)**  $\sigma_1 \{a_{14}, G\} + \sigma_2 \{a_2, a_5, a_8, a_9, a_{15}, d_{19}, d_{23}, d_{27}, d_{28}; (5vs.4)\} + \sigma_3 \{a_6, d_{18}; (1vs.1); a_{6g/h}\} + \sigma_4 \{a_{11}, a_{12}, d_{24}; (2vs.1)\} + \sigma_5 \{a_{13}, d_{29}; (1vs.1)\} + \sigma_6 \{d_{16}, d_{22}, d_{26}, G; (0vs.3+G)\}.$

All letters (a) and (d) coded by a number refer to players from the attacking (Team B) and defending team (Team A), respectively. The goalkeepers from Team B and Team A are coded by the number 14 ( $a_{14}$ ) and 29 ( $d_{29}$ ), respectively, being attached to their respective goals, coded with (G). Nevertheless, due to the proximity-based criteria utilised to model players' interactions, the goalkeepers can also be linked to other players (see g) and h)). Moreover, other technical actions performed by players were codified including the pass (p), ball reception (br), dribbling (db), shooting (sh), and header (h), as well as other off-the-ball movements such as running movements (rm). Finally, the ball holder was codified by (bh). The arrows in lines a) and f) depict ball-passing actions between



simplices, while arrows in lines g) and h) represent shooting actions. As an example, we will describe the set of simplices presented in line a).

Therefore, the simplex  $\sigma_1$  is composed of the goalkeeper ( $a_{14}$ ) attached to his own goal (G). The simplex  $\sigma_2$  is composed of three attackers ( $a_2, a_9, a_{15}$ ) and two defenders ( $d_{19}, d_{27}$ ), identified by  $R_2 = (3\text{vs}.2)$ . This simplex contains the ball holder who performs the pass ( $a_{15\text{bh/p}}$ ). The simplex  $\sigma_3$  is composed of two attackers ( $a_5, a_8$ ) and two defenders ( $d_{17}, d_{23}$ ) identified by  $R_3 = (2\text{vs}.2)$ . The simplex  $\sigma_4$  includes one attacker ( $a_6$ ) and two defenders ( $d_{18}, d_{26}$ ) identified by  $R_4 = (1\text{vs}.2)$ . The simplex  $\sigma_5$  contains three attackers ( $a_{11}, a_{12}, a_{13}$ ) and two defenders ( $d_{16}, d_{22}$ ) identified by  $R_5 = (3\text{vs}.2)$ , while the simplex  $\sigma_6$  has two defenders ( $d_{24}, d_{28}$ ) and is identified by  $R_6 = (0\text{vs}.2)$ . Finally, the simplex  $\sigma_7$  contains the goalkeeper ( $d_{29}$ ) attached to his own goal (G).

#### 4.4 Discussion

In this study, a hypernetworks model composed of three levels of analysis (Level N to Level N+2) was elaborated aiming to: (i) capture changes in tactical configurations (backcloth) of teams as the match evolved; (ii) ascertain the most frequently emerging simplices in relation to the position of the ball, and (iii), analyse the level of prominence of players and their interactions within and between simplices before a goal was scored.

At Level N, we were able to identify changes in tactical configurations of both teams. The visual representation derived from the hypernetworks model provided an informative basis for identifying variations of players' positioning on field, emphasising how their interactions varied across space and time. Therefore, unlike previous applications of network approaches (Ribeiro et al., 2017), multilevel hypernetworks use positional data to describe and analyse the spatial-temporal dynamics of players.

As stated before, the advantage of such analysis to understand team synergies is that changes in the backcloth (tactical configurations) of teams may encompass changes in the traffic (interpersonal dynamics). Both teams have presented changes in their tactical configurations that influenced interpersonal dynamics. For example, in line b) of Figure 7, is observed the emergence of a novel simplex structure 0vs.1 ( $n=51$ ), when Team A was playing in a 1-4-4-2

tactical configuration. However, we did not verify whether such changes had an impact on the development of specific team synergies, as the presence of other variables (e.g., game result, fatigue) may have influenced the dynamics of players on field, and we did not conduct an analysis to examine their potentially confounding effect. Nevertheless, in future research, it would be interesting to verify which simplices' structures emerge more often as a result of the tactical dispositions employed by teams during a whole competitive season.

Interactions at Level N+1 allowed us to quantify the types of simplices emerging behind and ahead of the ball line (re-organisation of team synergies through exploiting degeneracy) for each team and for each 15-minute period of both game halves. Generally, our data revealed that the two most frequently occurring simplices, both ahead of and behind the ball line for the two teams, were the 1vs.1 and 1vs.2 (or 2vs.1). These results are somewhat aligned with data verified by Ramos et al. (2017). Apparently, both teams tried to secure their goals by maintaining at least a numerical balance with competing players (e.g., 1vs.1), or by playing more conservatively by employing a numerical overload as confirmed by the emergence of other types of simplices (e.g., 3vs.2, 3vs.1). The same happens ahead of the ball line with teams trying to create numerical balance (e.g., 1vs.1) which may favour players with high technical skills, or numerical overload (e.g., 2vs.1) to surpass the opposition defensive structure.

In this study, we did not consider the 1vs0 (or 0vs.1) simplices' structures involving the goalkeepers and their respective goals when highlighting the simplices with highest frequencies. However, it is worth mentioning that the analysis of variations in the number of these simplices may provide important information regarding individual and team competitive performance. Indeed, as verified in Figure 6 and Figure 7, these simplices often change between both halves of a game. Changes in the frequencies of 1vs.0 (or 0vs.1) simplices may be related, for example, with a momentary movement of the goalkeeper away from his own goal. This action consequently induced a covering movement towards the goal by another teammate and/or opponent (geographical-proximity) as verified in Figure 8, and exemplified by the set of the simplex h. In this case, the goalkeeper intentionally increased his speed leaving the goal behind (causing the simplex goalkeeper-goal to disaggregate), thus moving towards to his nearest opponent, in an attempt to tackle the ball.

Nevertheless, it is important to highlight that these results do not consider the position of the ball line across the pitch. Essentially, we verified the frequencies of types of simplices regardless of the pitch position of the ball. Therefore, future studies should consider, for example, how the distribution of frequencies of types of simplices varies when the ball is located in the defensive and/or offensive areas of the midfield of each team. Additionally, using heat-maps to verify the zones of the field where such types of simplices emerge more often would be valuable. However, the analysis of such interpersonal dynamics (simplice structures), emerging both ahead and behind the ball line, can provide meaningful insights regarding the emergent organisational and structural aspects of team behavioural dynamics.

At Level N+2, our model of hypernetworks successfully captured players' interactions within and between simplices, and their corresponding transformations in an attacking sequence of play that led to a goal scored by Team B. Of particular importance is the fact that hypernetworks approach allow to conduct a concurrent analysis of both dynamics *of* the networks (through analyses of changes in teams' configurations, e.g., tactical disposition on field and/or simplices configurations), and dynamics *on* networks (players' interactions within and between simplices).

Moreover, the ball-passing actions performed by players within simplices, as verified in lines a) and f), allowed us to introduce the concept of directed hypergraphs in team ball sports. Essentially, a directed hypergraph refers to a hypergraph with directed hyperedges (Gallo et al., 1993). For example, in line a) there was a pass from player  $a_{15}$  located in simplex  $\sigma_2$  to player  $a_8$  located in simplex  $\sigma_3$ . Including this information on the hypernetworks model is important since it allows observers to ascertain teams' preferred communication channels, and the player(s) that are most commonly involved in moves.

Typically, when attacking, players seek to expand their area of spatial connection on field by increasing values of interpersonal distance to best explore the width and length of the pitch aiming to create goal-scoring opportunities. Indeed, as shown in Figure 8 a), both players  $a_5$  and  $a_{13}$  from the attacking team (Team B) provided width on both the right- and left-hand sides of the pitch. These players were trying to destabilise the opposition defensive structure of Team A by stretching the defensive block seeking to create spaces in between defending

lines to afford movement of the ball towards the opponent's goal (either by passing the ball through opening gaps or by creating opportunities for dribblers to move through spaces). Alternatively, the defensive team tries to reduce space by increasing team compactness through decreasing of interpersonal distances between players as shown, for example, in Figure 8 c). Here the defending players  $d_{19}$ ,  $d_{27}$ ,  $d_{28}$ , and  $d_{23}$ , seek to pressurise the ball holder  $a_8$  by reducing spaces (reflected by the direction of players' arrows).

On the other hand, as referred to by Ramos et al. (2017), changes in players' speed may lead to the disaggregation and/or aggregation of a specific simplex structure, when moving away or toward the simplex geometric centre, respectively. Such moves are represented in Figure 8, and provided insights regarding the co-adaptation processes emerging within and between teams, with players interacting with each other's through continuous aggregations and/or disaggregations between sets of simplices (re-organisation of team synergies). Moreover, these moves of players within and between simplices represent an essential feature of synergies called degeneracy. Indeed, degeneracy can be inspected through examination of simplices' transformations (i.e., how one particular simplex transform into another at specific moments and/or in specific spatial orientations).

For example, we verified changes in simplex configurations (e.g., from a) to b) in simplices  $\sigma_2$  and  $\sigma_6$ ). Of particular interest is the move of the attacking player  $a_{12}$  that allowed him to attract the nearest defender  $d_{22}$ , depicted by the direction of both players' arrows. At the same time, in c) the defender  $d_{16}$  has failed to secure the space left by  $d_{22}$ , and apparently was attracted by player  $a_{13}$  (as indicated by the direction of his arrow), thus increasing team width, instead of closing down the space in the central corridor of the field, between him and  $d_{26}$ . In d), apparently  $d_{16}$  tried to move towards a more central position letting  $a_{13}$  at his back gaining territorial advantage, while increasing his speed towards an open space left at the back of the defence. This combination of possibilities for acting (open space left in the back of the defensive opposition structure of Team A and the running move from player  $a_{13}$  into that space) was perceived by player  $a_8$  who passed the ball in between defending lines towards player  $a_{13}$ . Simultaneously, the goalkeeper  $d_{29}$  sought to anticipate this move by intentionally increasing his speed trying to block the shot from player  $a_{13}$ .

Theoretically interpreted, these actions represent a clear situation where shared team affordances have been perceived by a communication network established between cooperating and competing players (Silva et al., 2013). Shared team affordances can be specified by surrounding information sources emerging from co-positioning of teammates, motion directions, and changes in motion, utilised to govern a team's coordination and communication tendencies (Araújo & Davids, 2016; Duarte et al., 2012; Passos et al., 2008). Therefore, players can communicate by presenting each other with affordances (Vilar et al., 2012). In this example, player  $a_8$  performed the action of passing the ball, while perceiving the running move from player  $a_{13}$  into the open space, with player  $a_{13}$  simultaneously perceiving and even anticipating the passing action from  $a_8$ . Hence, the perception of such shared team affordances allowed players to establish effective interpersonal synergies to attain shared performance goals (i.e., score a goal).

Finally, the inclusion of other relevant technical actions in the multilevel analysis provided a more comprehensive description regarding the individual contribution of each player during the sequence of play that resulted in the goal being scored, allowing us to identify possible key players. Therefore, players  $a_{12}$ ,  $a_{13}$ ,  $a_8$ , and  $a_6$  were identified as having a prominent role in the sequence of play, although with different contributions.

This is another property of synergies called interpersonal linkages, also known in the literature as sharing patterns (Latash, 2008) or division of labour (Duarte et al., 2012). Interpersonal linkages thus refer to the specific contribution of each player to a given task (e.g., scoring a goal) (Latash, 2008). Here, the off-the-ball movement from player  $a_{12}$  allowed him to attract the nearest opponent ( $d_{22}$ ), thus creating an empty space to be explored, while player  $a_8$  perceived that empty space and performed the pass. Player  $a_{13}$  recognised that possibility and ran into that space to receive the ball and shot at goal, while player  $a_6$  anticipated his move towards the nearest defenders to score a goal through a header. Moreover, the analysis revealed that player  $d_{22}$  and  $d_{16}$  performed some individual mistakes that led the opposing team to score. While player  $d_{22}$  was attracted by player  $a_{12}$ , leaving an open space to be explored within the defensive block of Team A, player  $d_{16}$  did not cover that space. Instead, he was attracted by the move of player  $a_{13}$  and then let himself anticipate by the running move of

player  $a_{13}$ . Araújo and Davids (2016) highlighted that this property of interpersonal linkages claims for the uniqueness of each element composing a team.

Therefore, each team can be viewed simultaneously as a new entity with properties that exceed the individual performance of each performer (i.e., a superorganism, please see Duarte et al., 2012), and at the same time, by considering the individuality of each element which contributes with their unique skills (Araújo & Davids, 2016). Thus, a sport team is not merely a hinge of independent components (the players) that disregards the unique skills of individuals (Araújo & Davids, 2016): instead, individuals do not lose their identity.

It is worth mentioning that, although not analysed here, multilevel hypernetworks also provide a fine-grained tool to measure other key properties of team synergies, namely reciprocal compensation and dimensional compression. For instance, a clear example of reciprocal compensation is provided in c) when the defender  $d_{16}$  has failed to secure the space left by  $d_{22}$ , i.e., player  $d_{16}$  did not perceived that space left by his teammate  $d_{22}$  therefore was not able to cover his back. Regarding dimensional compression, such property can be examined by analysing how the team, collectively, (re)organises on field when, for example, a player reacts to pressurise an opponent in the first phase of the attack of the opposition (e.g., when the ball is passed from the goalkeeper to a defender).

Altogether, this analysis provides a clear example on how a simple visual representation of multilevel hypernetworks, completed with an element R reporting the microstructures of play contained in each set, along with relevant information regarding other technical actions (e.g., dribble) performed by players, can provide meaningful insights, which can be organised in a coherent (theoretical) understanding of the game.

## **4.5 Conclusions**

This study highlighted how a model of hypernetworks allowed to verify how team self-organisation (through assemble and/or disassemble of synergies captured in simplices' transformations), guided by shared affordances manifest its properties and how a concurrent (mathematically related) view of such properties reveal important aspects of match dynamics. Moreover, multilevel hypernetworks prove

their utility, as they were able to capture key properties of synergies, thus clarifying conceptual issues concerning team collective behaviour based on team synergy formation.

#### 4.6 References

Araújo, D., & Davids, K. (2016). Team synergies in sport: Theory and measures. *Frontiers in Psychology, 7*, 1449.

Araújo, D., Silva, P., & Davids, K. (2015). Capturing group tactical behaviors in expert team players. In J. Baker & D. Farrow (Eds.), *Routledge handbook of sport expertise* (pp. 209-220). London: Routledge.

Duarte, R., Araújo, D., Correia, V., & Davids, K. (2012). Sport teams as superorganisms: Implications of biological models for research and practice in team sports performance analysis. *Sports Medicine, 42*(8), 633–42.

Davids, K., Button, C., Araújo, D., Renshaw, I., & Hristovski, R. (2006). Movement models from sports provide representative task constraints for studying adaptive behavior in human movement studies. *Adaptive Behavior, 14*, 73-94.

Edelman, G., & Gally, J. (2001). Degeneracy and complexity in biological systems. *Proceedings of the National Academy of Sciences, 98*, 13763-13768.

Gallo, G., Longo, G., & Pallottino, S. (1993). Directed hypergraphs and applications. *Discrete Applied Mathematics, 42*, 177-201.

Johnson, J. (2006). Hypernetworks for reconstructing the dynamics of multilevel systems. In: *European Conference on Complex Systems*. Oxford, U.K.

- Johnson, J. (2008). Multidimensional events in multilevel systems. In S. Albeverio, D. Andrey, P. Giordano & A. Vancheri (Eds.), *The Dynamics of Complex Urban Systems: An Interdisciplinary Approach* (pp. 311-334). Heidelberg: Physica-Verlag HD.
- Johnson, J. (2013). *Hypernetworks in the Science of Complex Systems*. London: Imperial College Press.
- Johnson, J. (2016). Hypernetworks: Multidimensional relationships in multilevel systems. *The European Physical Journal Special Topics*, 225, 1037–1052;. doi: 10.1140/epjst/e2016-02653-4.
- Latash, M. (2008). *Synergy*. New York, NY: Oxford University Press.
- Passos, P., Araújo, D., Davids, K., Gouveia, L., Milho, J., & Serpa, S. (2008). Information-governing dynamics of attacker-defender interactions in youth rugby union. *Journal of Sports Sciences*, 26(13), 1421-1429.
- Passos, P., Davids, K., Araújo, D., Paz, N., Minguéns, J., & Mendes, J. (2011). Networks as a novel tool for studying team ball sports as complex social networks. *Journal of Science and Medicine in Sport*, 14(2), 170-176.
- Ramos, J., Lopes, R., Marques, P., & Araújo, D. (2017). Hypernetworks reveal compound variables that capture cooperative and competitive interactions in a soccer match. *Frontiers in Psychology*, 8, 1379.
- Ribeiro, J., Davids, K., Araújo, D., Silva, P., Ramos, J., Lopes, R., & Garganta, J. (2019). The role of hypernetworks as a multilevel methodology for modelling and understanding dynamics of team sports performance. *Sports Medicine*, 1-8.
- Ribeiro, J., Silva, P., Duarte, R., Davids, K., & Garganta, J. (2017). Team sports performance analysed through the lens of social network theory: Implications for research and practice. *Sports Medicine*, 47(9), 1689-1696.



- Riley, M., Richardson, M., Shockley, K., & Ramenzoni, V. (2011). Interpersonal synergies. *Frontiers in Psychology*, 2, 1-7.
- Seifert, L., Komar, J., Araújo, D., & Davids, K. (2016). Neurobiological degeneracy: A key property for functional adaptations of perception and action to constraints. *Neuroscience & Biobehavioral Reviews*, 69, 159-165.
- Silva, P., Garganta, J., Araújo, D., Davids, K., & Aguiar, P (2013). Shared knowledge or shared affordances? Insights from an ecological dynamics approach to team coordination in sports. *Sports Medicine*, 43, 765–72.
- Turvey, M. (2007). Action and perception at the level of synergies. *Human Movement Science*, 26, 657–697. doi: 10.1016/j.humov.2007.04.002
- Vilar, L., Araújo, D., Davids, K., & Button, C. (2012). The role of ecological dynamics in analysing performance in team sports. *Sports Medicine*, 42(1), 1-10.



## Chapter 5

A multilevel hypernetworks approach to capture meso-level synchronisation processes in football<sup>5</sup>

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### Abstract

Understanding team behaviour in sports settings requires an adequate knowledge on the interdependencies established between their levels of complexity (micro-meso-macro). Apparently, most studies looked at interactions emerging at micro- and macro-levels, thus neglecting those emerging at a meso-level. We addressed this issue using the multilevel hypernetworks approach, along with a cluster phase method, to measure player-simplice local synchronies in two game conditions where the number, size and location of goals were manipulated (1<sup>st</sup> – condition: 6x6+4 mini-goals; 2<sup>nd</sup> – condition: Gk+6x6+Gk), and as a function of ball-possession (attacking/defending), field-direction (longitudinal/lateral) and teams (Team A/Team B). Generally, large synergistic relations and more stable patterns were observed in the longitudinal direction of the field than the lateral direction for both teams, and for both game phases in the first condition. The second condition displayed higher synchronies and more stable patterns in the lateral direction than the longitudinal plane for both teams, and for both attacking and defending phases. These results suggest: (i) the usefulness of hypernetworks in assessing synchronisation of teams at a meso-level; (ii) coaches may consider manipulating the number, location and size of goals to develop levels of local synchronies emerging within teams.

**Keywords:** Multilevel Hypernetworks, Synchronisation Processes, Team Sports, Association Football.

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## 5.1 Introduction

Living in social settings often requires from individuals the need to coordinate their actions to achieve simple and/or complex task goals. Such actions/activities can go from walking and dialoguing with another person to performing a piano duet, or playing in team sports. Sports teams consist of social entities composed of individual agents who correlate and coordinate actions to establish effective team communication networks (Ribeiro et al., 2017). The synergetic behaviours (i.e., players combine actions to produce goal-oriented behaviours) that underlie the formation and development of such communication networks can be expressed at different levels of complexity.

Typically, there are three general levels of complexity into which networks may typically fall: the micro- the meso- and macro-levels. The micro-level focuses essentially on the relationships that each player has to other players in a team, while the meso-level sheds light on the interpersonal synergies emerging between small groups of players during performance. Finally, the macro-level tends to consider the whole structure of social interactions emerging within a team and how it relates to team performance outcomes.

The interdependence of team players' behaviours and actions suggests that all three levels are interconnected. For example, players at a micro-level might interact with their nearest team members (at a meso-level) under  $n$ -ary interpersonal relations to produce more complex set of behaviours or patterns exhibited at a macro-level. In essence, players interact to form multi-level structures at higher complexity levels (from micro-to-meso-to-macro) (Johnson & Iravani, 2007).

Usually, the majority of previous studies have tended to focus on the relations established at a micro-level (dyads, i.e., relations established between pairs of individuals), or at a macro level of team organisation (whole team behaviour). On the other hand, other studies (e.g., Duarte et al., 2013) have focused on the link between micro and macro relations, by measuring the synchronisation processes between such levels. Indeed, the article by Duarte et al. (2013) aimed to analyse the movement synchronies evidenced at player-team and team-team levels. These investigators tried to understand how such synchronisation tendencies varied as a function of transitions in ball possession

(attacking/defending), halves of the match (first/second), team status (home/visiting) and field direction (longitudinal/lateral), by means of a cluster phase method (see Frank and Richardson, 2010, for detailed descriptions on this method). Although this and other studies have contributed meaningful theoretical and empirical insights regarding team game performance, they have not captured the synchronisation tendencies emerging at a meso-level scale. These processes should not be neglected as they fall between the micro and macro levels and can provide relevant information regarding the connections established between such levels (e.g., how players interact locally with their nearest teammates to produce regular patterns of behaviour).

Given the interdependency between levels in a complex system, there is a need for integrating all scales of analysis (micro-to-meso-to-macro) in research on team sports performance (Bar-Yam, 2003; Bar-Yam, 2004). However, there is a clear paucity of studies seeking to propose methods for measuring and providing insights on the processes underlying the establishment of such synchronisation processes of players within and between teams at a meso-level scale. An exception is the study of López-Felip et al. (2018) which used the cluster phase method (CPM) to capture team coordination by means of players' behavioural variables (players' orientation-to and distance-to goal).

On the other hand, recent developments in the study of network approaches applied to team sports performance analysis have led to the introduction of a novel methodology: *multilevel hypernetworks* (Ramos et al., 2017; Ribeiro et al., 2019). This approach might be helpful in ascertaining the complexity rooted at such levels of team interdependencies.

Therefore, in this study, we sought to extend the previous analysis of Duarte et al. (2013) by proposing a multilevel hypernetworks approach for capturing the movement synchronies of players at a meso-level scale. Moreover, we aimed to analyse whether such synchronisation tendencies changed between game conditions (1<sup>st</sup> condition – 6x6+4 mini-goals; 2<sup>nd</sup> condition – Gk+6x6+Gk) where the location, number and size of goals were manipulated, and as a function of ball-possession (attacking/defending), field direction (longitudinal/lateral) and teams (Team A/Team B).

## **5.2 Participants**

Fourteen male youth football (soccer) players pertaining to an U19 squad (mean age  $17,9 \pm 0,7$  years, mean height  $175,6 \pm 5,7$  cm, mean weight  $69,7 \pm 9,9$  Kg, and training experience:  $9,2 \pm 2,9$  years), competing at a regional level, were recruited to participate in this study. All participants gave prior informed consent before initiating the experiment. All procedures followed the guidelines of the Declaration of Helsinki and were in accordance with the ethical standards of the lead institution.

## **5.3 Task and procedures**

This study was conducted over a two-week period during the 2017/2018 competitive season. Participants performed in two game conditions in which the number, location and size of goals were manipulated. Each game was preceded by a 10-minute standardised warm-up composed of low-intensity running, ball-passing actions and dynamic stretches. All these activities were part of the regular training sessions that players were involved with. The first game condition (conducted in the first week) consisted of two 6-a-side (6vs.6) games without Goalkeepers (Gk), where players from opposing teams were solicited to attack/defend two mini-goals sized  $0,90 \times 0,90$  m (height x width) located in both right- and left-hand sides of the pitch (Figure 9a). The second game condition (conducted in the second week) comprised two 6-a-side plus Gk (Gk+6vs.6+Gk) games with two football goals sized  $6 \times 2$  m (height x width) centered on the end line of the pitch (Figure 9b). The players were split by the team coaches into two technically-balanced teams. In the first condition, players were organised on field according to a 2-3-1 tactical disposition, with 1 right central defender (RCD), 1 left central defender (LCD), 1 left midfielder (LM), 1 right midfielder (RM), 1 central midfielder (CM), and 1 forward (FW). In the second condition, the organisation of players on field was similar to the first condition, but now with the inclusion of a goalkeeper (Gk) (1-2-3-1). The objective of teams in both game conditions was to score as many goals as possible while preventing the opposing team from scoring. The respective field dimensions of the playing area in both conditions ( $63,6 \times 40,7$  m, height x width) were obtained based on the minimum dimensions

permitted by the *International Football Association Board* (100x64 m, height x width), and the number of players involved in each game (Hughes, 1994).

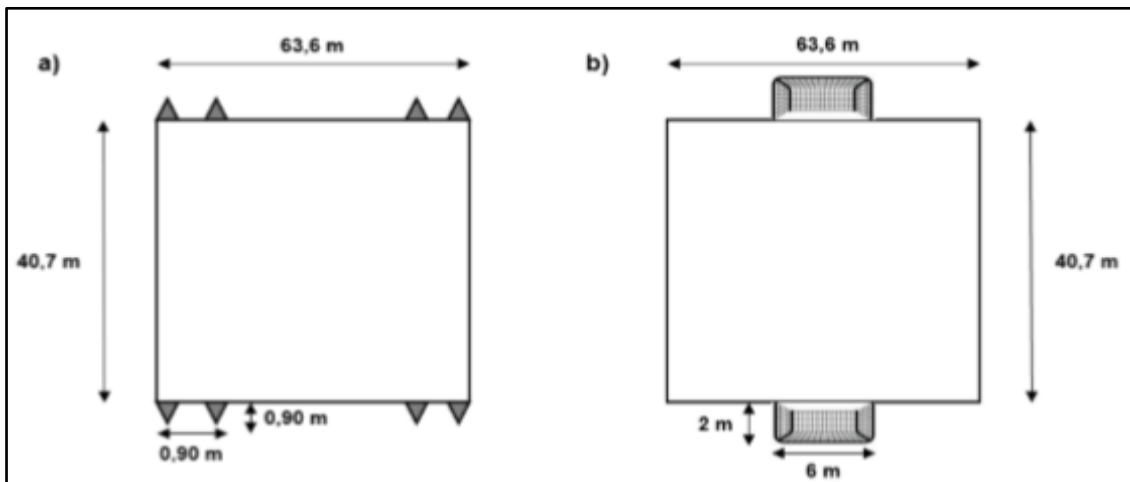


Figure 9. Experimental task schematic representation: a) 6x6+4 mini-goals condition; b) Gk+6x6+GK condition.

Each match had a duration of 15 minutes interspersed by a recovery interval of 7 minutes to minimise the influence of fatigue on participants. During recovery periods, players could recovery at will and rehydrate. Additionally, during this period, players were asked to respond to the Borg Rating of Perceived Exertion (RPE) Scale (Borg, 1982). The RPE was utilised with verbal anchors, which comprehended a 15-grade scale ranging from 6 (minimum effort) to 20 (maximum effort) (Borg, 1982), with players being asked the following: *“how do you classify the physical effort in the task from 6 (minimum effort) to 20 (maximum effort)?”* Moreover, all matches were undertaken at the same hour of the day (19:00 pm) in order to prevent possible circadian effects on performance (Cappaert, 1999). Several balls were placed around the pitch to prevent trial stoppages. Additionally, coaches were instructed to not provide any sort of encouragement and/or feedback to the players, before and during practice, since it can influence levels of practice intensity in individual participants, thus affecting performance (Rampinini et al., 2007).



### 5.3.1 Data collection

Positional data (x, y) were acquired through utilisation of global positioning tracking devices (Qstarz, Model: BT – Q1000Ex) at 10Hz, placed on the upper back of each player. Previous studies have confirmed the usefulness and reliability of such GPS devices (e.g., Silva et al., 2016). All pitches were calibrated using the coordinates of four GPS devices stationed at each corner of the pitch for about 4 min. The absolute coordinates of each corner were calculated as the median of the recorded time series, yielding measurements that were robust to the typical fluctuations of the GPS signals. These absolute positions were used to set the Cartesian coordinate systems for each pitch, with the origin placed at the pitch center. Longitudinal and latitudinal (spherical) coordinates were converted to Euclidean (planar) coordinates using the Haversine formula (Sinnott, 1984). A GoPro Rollei Ac415 actioncam (Rollei GmbH & Co. KG, Norderstedt, Germany) was utilised to record and capture players' interactions on field, which encompassed the following characteristics: (i) resolution: FullHD; (ii) processing capacity of 30Hz; (iii) maximum lens aperture:  $F=2.4$ ; (iv) sensor type: CMOS; (v) capture angle:  $140^\circ$ . The Gopro was stationed on a higher level above the pitch (approximately 4 m high) to ensure an optimal viewing angle (allowing views of the entire field) during the games.

### 5.3.2 Hypernetworks approach

Hypernetworks utilise the concept of hypergraphs to model interactions of a set of elements (e.g., the players) that make up a given system (e.g., a football team). In mathematics, a hypergraph consists of a generalisation of a graph (a structure composed by a set of elements that may share some type of relation) in which an edge can connect any number of nodes. Therefore, a hypergraph  $H$  corresponds to a pair  $H=(X, E)$  where  $X$  encompasses a set of elements called nodes/vertices, while  $E$  comprises a set of non-empty subsets of  $X$  named hyperedges (Johnson, 2009). Hyperedges can connect more than two nodes (i.e., the players), thus they support representation of simultaneous  $n$ -ary relations ( $n>2$ ), be it cooperative and/or competitive, established between a given set of players (called simplex, plural-simplices) (Johnson & Iravani, 2007; Ramos et al., 2017). Thus, by

adopting the hypernetworks approach we were able to assess how players synchronise their movements in relation to the simplices (intra and inter relationships) that they interacted with during competition (see Figure 10). The criteria chosen for selecting the set of nodes was based on the geographical proximity (non-parametric) between players (i.e., a player does interact with his nearest player and/or goal for goalkeepers (2<sup>nd</sup> condition) and mini-goals for players (1<sup>st</sup> condition)) and directional speed of players that enable them to interact (through disaggregation and/or aggregation) with other simplices (Ramos et al., 2017). In short, the hypernetworks approach allowed us to assess the synchronies evidenced in intra- and inter-team relationships between players during competition.

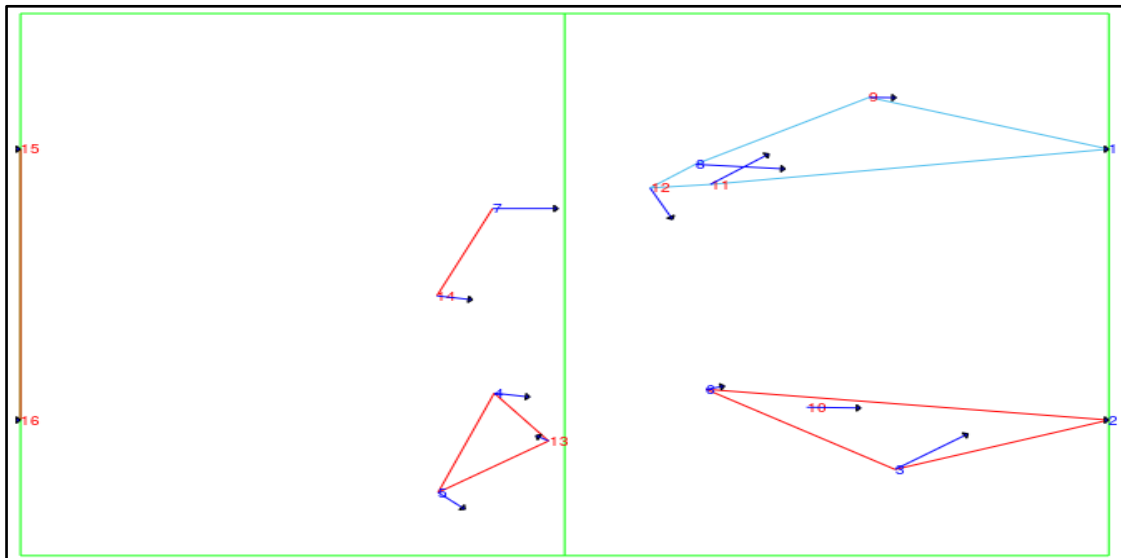


Figure 10. Example of an illustration of hypernetworks representing simplices' interactions in an association football pitch, retrieved from performance in the first game condition (6x6+4 mini-goals). The 4 mini-goals (1 and 2 for Team A; 15 and 16 for Team B) are represented by black dots. Team A (represented in blue) is attacking from left to right and Team B (represented in red) is attacking from right to left. Each simplex is represented by the polygon (or a line when only two players are involved, e.g., players 7 and 14) defining the convex hull that connects the players (identified by numbers, or goals – identified by black points). Players can also be linked to the goals due to the proximity-based criteria (e.g., player 6 and 3 from the blue team and player 10 from the red team are connected to the mini-goal number 2). A velocity vector for each player is also represented.

### 5.3.3 Cluster phase method

Frank and Richardson (2010) proposed the CPM by adapting the model from the Kuramoto order parameter (Kuramoto & Nishikawa, 1987). Such a model was originally developed for analysing systems whose oscillatory unit's number tended to infinity (Strogatz, 2000). Frank and Richardson (2010) decided to test the applicability of the same model in analysing systems composed by a small number of oscillatory units (a multiple-rocking chair experiment with only six oscillatory units).

Basically, the CPM allow calculating the mean and continuous group synchrony,  $\rho_{group}$  and  $\rho_{group}(t_i)$ , as well as the individual's relative phase,  $\theta_k$ , in regard to the group measure (Richardson et al., 2012). This method has been used in a study by Duarte et al. (2013) to assess whole team synchrony (at a macro-scale level) and player-team synchrony (at a micro-scale level) in a professional football match. Implementation of this method allowed them to calculate a global measure, the cluster amplitude  $\rho_{group}(t_i)$ , depicting the team synchronisation at every instant time of the match. It also supported use of a relative phase measure reporting the level of individual player's synchronisation with respect to the team,  $\phi_k(t_i)$ .

A major advance proposed in the present study, compared to that of Duarte et al. (2013), is that we introduced a multilevel hypernetworks approach to assess the synchronisation processes emerging at a micro-to-meso level depicted through measurement of player-simplices (P-S) synchronisation. To achieve that aim, we assessed how each player synchronises his movements with the corresponding simplices into which he is inserted.

The extension to other groups, i.e. player sets, beyond teams is supported by the following generalisations to the definitions and equations presented by Duarte et al. (2013).

These procedures starts with the phase time-series acquired through Hilbert transformation,  $\theta_k(t_i)$ , for the  $k^{th}$  player movements measured in radians  $[-\pi \pi]$ , where  $k = 1, \dots, N$  and  $i = 1, \dots, T$  time steps. In the generalisation proposed in the current study we use the definition of group,  $\Gamma_j$ . These groups

correspond to the different hypernetworks' player sets. For each group,  $\Gamma_j$  its size,  $n_j$ , is defined by the number of players that compose that group (i.e., simplex).

Using this generalisation, the group cluster phase time-series,  $\bar{\phi}_j(t_i)$ , can be calculated as:

$$\dot{r}_j(t_i) = \frac{1}{n_j} \sum_{k \in \Gamma_j} \exp(i\theta_k(t_i)) \dots \dots \dots (1)$$

and:

$$\bar{\phi}_j(t_i) = \text{atan2}(\dot{r}_j(t_i)) \dots \dots \dots (2)$$

where  $i = \sqrt{-1}$  (when not used as a time step index),  $\dot{r}_j(t_i)$  and  $\bar{\phi}_j(t_i)$  comprise the resulting cluster phase in complex and radian form, respectively.

Finally, the continuous degree of synchronisation of the group  $\rho_{\Gamma_j}(t_i) \in [0, 1]$ , i.e., the cluster amplitude  $\rho_{\Gamma_j}(t_i)$  at each time step  $t_i$  can be calculated as:

$$\rho_{\Gamma_j}(t_i) = \left| \frac{1}{n_j} \sum_{k \in \Gamma_j} \exp(i(\theta_k(t_i) - \bar{\phi}_j(t_i))) \right| \dots \dots \dots (3)$$

and the temporal mean degree of group synchronisation,  $\rho_{\Gamma_j} \in [0, 1]$ , is computed as:

$$\rho_{\Gamma_j} = \frac{1}{T} \sum_{i=1}^T \rho_{\Gamma_j}(t_i) \dots \dots \dots (4)$$

The cluster amplitude corresponds to the inverse of the circular variance of  $\phi_k(t_i)$ . Therefore, on the one hand, if  $\rho_{\Gamma_j} = 1$ , the group is in complete intrinsic synchronisation. On the other hand, if  $\rho_{\Gamma_j} = 0$ , the group is completely unsynchronised. Therefore, the larger the value of  $\rho_{\Gamma_j}$  (i.e., close to 1), the larger the degree of group synchronisation. The same expressions can be applied to teams by replacing the simplice sets  $\Gamma_j$  by the set of players of each team  $\Gamma_A$  and  $\Gamma_B$ , respectively.

All the computations were conducted by using dedicated routines implemented in GNU Octave software v4.4.1.

#### 5.3.4 Data analysis

Sample entropy (SampEn) was used to evaluate the regularity of cluster amplitude for each group (P-S) during performance in the two conditioned matches. This nonlinear statistical tool was introduced by Richman and Moorman (2000) and presents the following characteristics: (i) greater consistency with regards to different choices of input parameters; (ii) lower sensitivity to data series length (data length independence), and; (iii) less propensity to statistical bias by eschewing self-matches when compared with traditional approximate entropy (ApEn – Pincus, 1991). SampEn comprises a modification of ApEn and evaluates the existence of similar patterns in a time-series, thus unveiling the nature of their intrinsic structure of variability (Duarte et al., 2013). Thus, given a series  $Y(t)$  of  $T$  points ( $t=1, \dots, T$ ), SampEn calculates the logarithmic probability that two similar sequences of  $m$  points retrieved from  $Y(t)$  remain similar. Or, in other words, it evaluates whether the sequences are kept within tolerance bounds given by  $r$ , in the next incremental comparison (i.e., for  $m+1$  sequences) (Duarte et al., 2013).

In the current study, input parameters were established as  $m=1$   $r=0.2$  standard deviations for entropy estimations, as suggested in other investigations of neurobiological system behaviour (e.g., Preatoni et al., 2010; Richman & Moorman, 2000). Values close to zero indicated the presence of regular/near-periodic evolving behaviours for the cluster amplitude regarding the P-S interactions. Higher values of SampEn indicated more unpredictable patterns of synchronisation (Preatoni et al., 2010). A 2 (game condition) x 2 (ball-possession) x 2 (field direction) x 2 (teams) univariate ANOVA was used to ascertain the cluster amplitude mean values between game conditions, and as a function of ball possession (attacking/defending), field direction (longitudinal/lateral) and teams (Team A/Team B). The repeated measures ANOVA's possible violation of sphericity assumption for the within-participant factors was checked using the Mauchly's test of sphericity. Effect size values were calculated as partial eta square ( $\eta^2$ ) (Levine & Hullett, 2002). All statistical comparisons were conducted

by using the IBM SPSS 24.0 software (IBM, Inc., Chicago, IL); Significance level was set at 5%.

## 5.4 Results

### 5.4.1 Player-simplice synchronisation

Mean, SD, and SampEn values of P-S cluster amplitude are presented in Table 1. Significant main effects were found for teams, ball-possession, and field direction between game conditions.

Table 1. Mean, SD, and SampEn values of P-S cluster amplitude as a function of teams (Team A/Team B), ball-possession (Attacking/Defending), and field direction (Longitudinal/Lateral) for each game condition.

Condition 1 (6x6+4 mini-goals)								
	Team A				Team B			
	Attacking		Defending		Attacking		Defending	
	Long	Lat	Long	Lat	Long	Lat	Long	Lat
Mean	0,74	0,66	0,69	0,69	0,7	0,61	0,68	0,61
SD	0,17	0,16	0,19	0,17	0,17	0,20	0,18	0,20
SampEn	2,08	2,20	2,02	2,10	2,11	2,18	2,16	2,19
Condition 2 (GK+6x6+GK)								
	Team A				Team B			
	Attacking		Defending		Attacking		Defending	
	Long	Lat	Long	Lat	Long	Lat	Long	Lat
Mean	0,59	0,82	0,6	0,77	0,61	0,78	0,61	0,81
SD	0,17	0,14	0,20	0,17	0,20	0,16	0,17	0,14
SampEn	2,19	2,08	2,18	2,02	2,18	2,11	2,18	2,16

### 5.4.2 Between game conditions

Higher mean values of cluster amplitude were found for the longitudinal direction of the field in the attacking phase of the first condition for both Team A ( $F(1,48224) = 1055,960$ ;  $p < 0,001$ ,  $\eta^2 = 0,021$ ) and Team B ( $F(1,48224) = 387,406$ ,  $p < 0,001$ ,  $\eta^2 = 0,008$ ), compared to the second condition. Moreover, we observed higher mean values in the lateral direction when attacking in the second condition, for Team A ( $F(1,48224) = 1271,121$ ,  $p < 0,001$ ,  $\eta^2 = 0,026$ ) and Team B ( $F(1,48224) = 1352,441$ ,  $p < 0,001$ ,  $\eta^2 = 0,027$ ), compared to the first condition.

Significant differences for the longitudinal direction of the field when defending were verified in the first condition, for both Team A ( $F(1,48224) = 418,547$ ,  $p < 0,001$ ,  $\eta^2 = 0,009$ ) and Team B ( $F(1,48224) = 226,151$ ,  $p < 0,001$ ,  $\eta^2 = 0,005$ ), when compared to the second condition. Furthermore, we observed higher mean values for the lateral direction for both Team A ( $F(1,48224) = 295,393$ ,  $p < 0,001$ ,  $\eta^2 = 0,006$ ) and Team B ( $F(1,48224) = 2087,341$ ,  $p < 0,001$ ,  $\eta^2 = 0,041$ ) when defending in the second condition compared to the first condition.

#### *5.4.3 Magnitude and structure of synchrony*

Our data also revealed that in the first condition, Team A displayed a slightly lower magnitude of variation (SD) value in the lateral direction of the field compared to the longitudinal direction. However, they exhibited greater regularity (SampEn) in the longitudinal direction in both attacking and defending game phases. Team B displayed a lower magnitude of variation and greater regularity in the longitudinal direction, compared to the lateral direction of the field, in both attacking and defending phases. In the second condition, we verified a lower magnitude of variation and greater regularity in the lateral direction of the field compared to the longitudinal plane for both teams, in attacking and defending phases.

Thus, when comparing values of the magnitude of variation (SD) and regularity (SampEn) between game conditions we observed greater stability in the longitudinal direction of the field in the first condition (although Team A presented lower SD values in the lateral direction). The second condition presented more stability in the lateral direction of the field for both teams, and in both attacking and defending game phases.

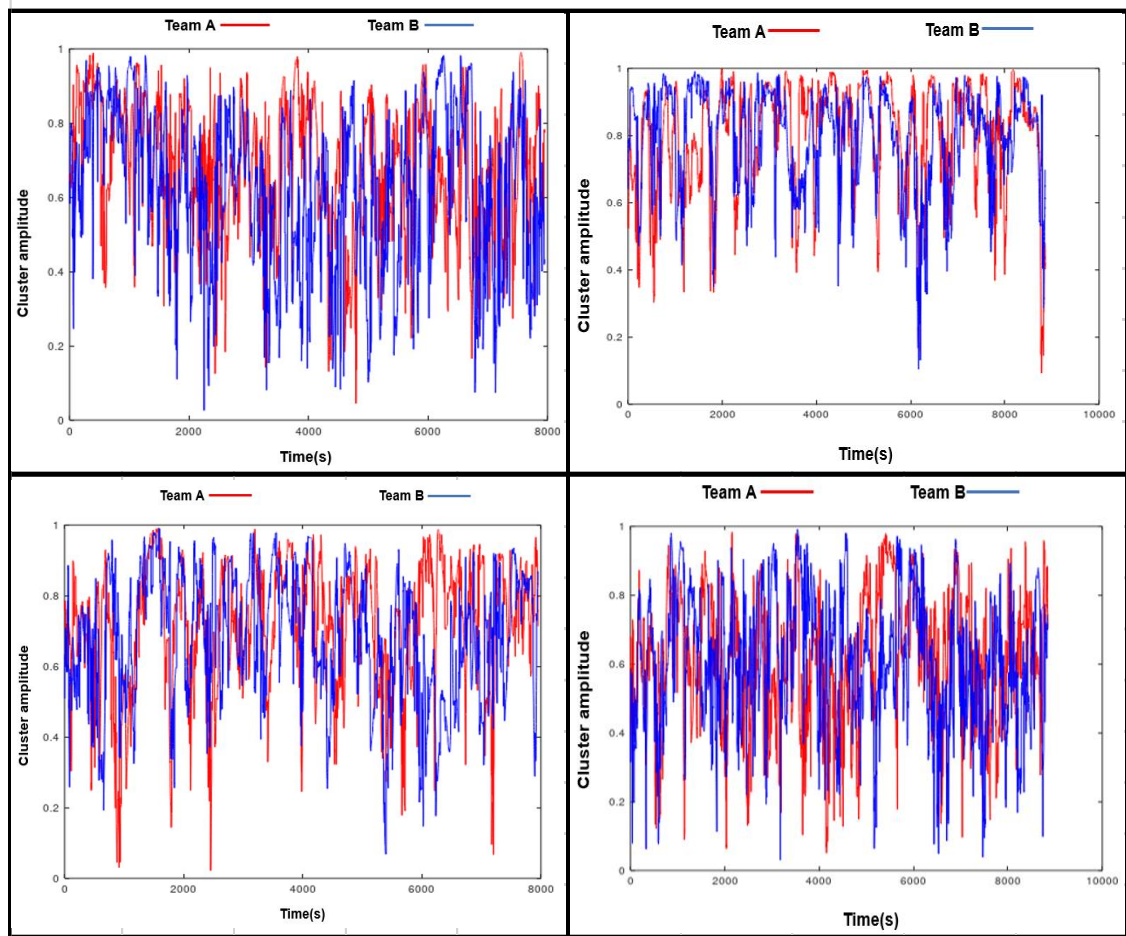


Figure 11. Example of the time-series representing the P-S synchronisation for both teams using the cluster amplitude, as a function of field direction and game condition. Cluster amplitude values range from 0 (no synchrony) to 1 (complete synchrony). Left and right panels display values for the first and second condition, respectively. Upper and bottom panels display values for the lateral and longitudinal direction, respectively.

## 5.5 Discussion

To the best of our knowledge, this is the first study that sought to investigate synchronisation processes emerging at a micro-to-meso (P-S) level of analysis. To fulfil this purpose, the multilevel hypernetworks approach along with the cluster phase method, previously used in the study of Duarte et al. (2013), was applied to capture the P-S synchronies formed within and between competing players. Moreover, we were also able to observe that local synchronisation tendencies changed when the number, location and size of goals were altered between game conditions, and as a function of ball-possession, field direction and teams.



This is particularly interesting, as previous studies (e.g., Duarte et al., 2013; Pinto, 2014) have reported that synchrony does not change as a function of ball possession. However, a study by López-Felip et al. (2018) identified changes in team synchrony according to ball possession. The results of that study reported higher mean values of team synchrony in defensive sub-phases of play. However, it is worth mentioning that our study analysed differences in ball-possession according to game conditions, and not between attacking and defending phases.

Moreover, a common finding reported in the current literature (e.g., Bourbousson et al., 2010; Duarte et al., 2012a; Duarte et al., 2012b) is that longitudinal displacements present higher levels of synchrony than lateral displacements. Indeed, typical displacements of players on field tend to unfold more frequently in the longitudinal direction of the field, as the attacking team advances upfield seeking to create goal-scoring opportunities. Simultaneously the defending team moves backward trying to prevent the opposing team from creating goal-scoring opportunities in the critical scoring region of the field (Frencken et al., 2011). Both the location of goals and the offside rule has been proposed as two plausible reasons for explaining such results (e.g., Duarte et al., 2012b; Travassos et al., 2012).

It is worth noting that, unlike analyses reported in previous studies of performance in 11-a-side football matches, in the current study the two game conditions consisted of conditioned matches with manipulations of the number, location and size of goals, which did not consider the effects of the offside rule. By not considering the offside rule players were given the opportunity to freely explore the space left behind the opponent's defensive line whenever they wanted. This task constraint led teams to explore more in-depth attacking movements with- and without ball-possession, in the longitudinal direction of the field when performing in the first condition.

Travassos et al. (2014) observed that teams reduced their distances to each other (evaluated through measurement of teams' centroids) when the number of goal targets were manipulated (from two official goals to six mini-goals). The absence of a goalkeeper, in combination with an increased number of possibilities for scoring (due to increased number of goals/targets), possibly led teams to utilise affordances for more forward-backward movements on field

(Araújo & Davids, 2016, after Gibson, 1979). The attacking team tried to perform more long passes to get behind the opposition's defence, thus exploiting the absence of the offside law. The defending team tried to prevent this behaviour by reducing distances (approaching defending lines) to the attacking team in the longitudinal direction of the field, seeking to pressurise opponents, while not conceding suitable passing and/or shooting opportunities.

In the second condition, the location of goals at the centre of the field might have constrained players without ball-possession to tightly defend the centre corridor of the field. This tactical approach offered behavioural invitations for the attacking team to circulate the ball to both left and right-hand sides of the pitch (outside riskier zones), thus increasing chances for the defensive team to recover ball-possession. By passing the ball from one side of the field to the other, the attacking team tried to pull the defenders out of the central corridor of the field. This approach caused the opposing team to stretch on field and created possible empty spaces left between defenders to exploit. Such synergetic, collective movements, manifested by both attacking and defending teams might have increased the synchronisation tendencies in the lateral direction of the field. However, like the study of Duarte et al. (2013), the differences reported in this study revealed small effect sizes, suggesting the need for further empirical clarification.

Nonetheless, these results suggested how players needed to continually reorganise and adjust their functional behavioural patterns (re-organisation of team synergies) to surrounding informational constraints (number, location and size of goals). These constant adaptations produced goal-oriented behaviours coherent with the fulfilment of performance goals (Bernstein, 1967; Davids, 2015). These results imply the sensitivity of inherent synergy formation tendencies to changing performance constraints (Riley et al., 2012), with players temporarily (re)assembling into collective synergies to achieve specific task goals (Silva et al., 2013).

By participating in two conditioned competitive matches with different performance objectives, the participants needed to engage in exploratory behaviours to search for functional movement solutions aiming to satisfy the changing task demands (Davids et al., 2012). They needed to co-adapt their behaviours to changing performance constraints to attain competitive goals

(Passos et al., 2016; Passos et al., 2009). The emergence of different behavioural solutions, as evidenced in both game conditions, may signify, for example, that previous preferred coordination tendencies, i.e., higher synchronisation levels verified in the longitudinal direction of the field in the first condition, may no longer have been functional under the constraints of the second condition.

In the first condition, Team B exhibited lower values of SD and SampEn in the longitudinal direction of the field compared to the lateral direction in both game phases. This finding suggested that players displayed greater stability in their coordination tendencies in the simplices with which they interacted in the longitudinal direction of the field. However, Team A showed slightly higher values of SD and lower values of SampEn in the longitudinal, rather than lateral direction of the field in both game phases. In the second condition, we observed lower values of SD and SampEn for both teams in the lateral field direction than longitudinally in both attacking and defending phases. This finding signified that players coordinated their actions in a more regular and stable phase with reference to the simplices they were involved with in the lateral direction of the field.

## **5.6 Conclusions and practical applications**

The multilevel hypernetworks approach, along with a CPM, successfully captured the synchronisation processes emerging at a meso-level scale through measurement of P-S synchronies. Altogether, the preliminary findings of this study suggested how the manipulation during practice, of the number, location and size of goals, can influence the local synchronisation processes of teams. Therefore, coaches may consider these task manipulations in their training settings to foment the development of such local synchronisation tendencies. Multilevel hypernetworks seem to constitute a set of suitable and promising tools for measuring the meso-local synchronisation processes emerging in teams during competition.

## **5.7 References**

Araújo, D., & Davids, K. (2016). Team synergies in sport: Theory and measures. *Frontiers in Psychology*, 7, 1449.

- Bar-Yam, I. (2003). Complex systems insights to building effective teams. *International Journal of Computer Sciences in Sport*, 2, 8-15.
- Bar-Yam, I. (2004). *Making things work: Solving complex problems in a complex world*. Cambridge, MA: New England Complex Systems Institute, Knowledge Press.
- Bernstein, N. (1967). *The coordination and regulation of movement*. New York: Pergamon.
- Borg, G. (1982). Psychophysical bases of perceived exertion. *Medicine and Science in Sports and Exercise*, 14(5), 377-381.
- Bourbousson, G., Sève, C., & McGarry, T. (2010). Space-time coordination dynamics in basketball: Part 1. Intra- and inter-couplings among player dyads. *Journal of Sports Sciences*, 28, 339-347.
- Cappaert, T. (1999). Time of day effect on athletic performance. An update. *Journal of Strength and Conditioning Research*, 13(4), 412–421.
- Davids, K. (2015). Athletes and sports teams as complex adaptive system: A review of implications for learning design. *Revista Internacional de Ciências del Deporte*, 39, 48-61.
- Davids, K., Araújo, D., Hristovski, R., Passos, P., & Chow, J. Y. (2012). Ecological dynamics and motor learning design in sport. In M. Williams & N. Hodges (Eds.), *Skill Acquisition in Sport: Research, Theory & Practice* (pp. 112-130). London: Routledge.
- Duarte, R., Araújo, D., Correia, V., & Davids, K. (2012b). Sports teams as superorganisms: Implications of sociobiological models of behavior for research and practice in team sports performance analysis. *Sports Medicine*, 42, 633-642.

- Duarte, R., Araújo, D., Correia, V., Davids, K., Marques, R., & Richardson, M. (2013). Competing together: Assessing the dynamics of team-team and player-team synchrony in professional association football. *Human Movement Science*, 32(4), 555-566.
- Duarte, R., Araújo, D., Freire, L., Folgado, H., Fernandes, O., & Davids, K. (2012a). Intra- and inter-group coordination patterns reveal collective behaviors of football players near the scoring zone. *Human Movement Science*. 31, 1639-1651.
- Frank, T., & Richardson, M. (2010). On a test statistic for the Kuramoto order parameter of synchronisation: An illustration for group synchronisation during rocking chairs. *Physica D*, 239, 2084-2092.
- Frencken, W., Lemmink, K., Delleman, N., & Visscher, C. (2011). Oscillations of centroid position and surface area of soccer teams in small-sided games. *European Journal of Sport Science*, 11(4), 215-223.
- Gibson, J. (1979). *The Ecological Approach to Visual Perception*. Hillsdale, NJ: Lawrence Erlbaum Associates.
- Hughes, C. (1994). *The football association coaching book of soccer tactics and skills*. Harpenden: Queen Anne Press.
- Johnson, J., & Iravani, P. (2007). The multilevel hypernetwork dynamics of complex systems of robot soccer agents. *ACM Transactions on Autonomous and Adaptive Systems*, 2, 1–23.
- Levine, T., & Hullett, C. (2002). Eta square, partial eta square, and misreporting of effect size in communication research. *Human Communication Research*, 28, 612-625.

- López-Felip, M., Davis, T., Frank, T., & Dixon, J. (2018). A cluster phase analysis for collective behavior in team sports. *Human Movement Science*, 59, 96-111.
- Kuramoto, Y., & Nishikawa, I. (1987). Statistical macrodynamics of large dynamical systems: Case of a phase transition in oscillator communities. *Journal of Statistical Physics*, 49, 569-605.
- Passos, P., Araújo, D., & Davids, K. (2016). Competitiveness and the process of co-adaptation in team sport performance. *Frontiers in Psychology*, 7, 1562.
- Passos, P., Araújo, D., Davids, K., Gouveia, L., Serpa, S., Milho, J., & Fonseca, S. (2009). Interpersonal pattern dynamics and adaptive behavior in multiagent neurobiological systems: Conceptual model and data. *Journal of Motor Behaviour*, 41, 445–459.
- Pincus, S. (1991). Approximate entropy as a measure of system complexity. *Proceedings of the National Academy of Sciences of the United States of America*, 88, 2297-2301.
- Pinto, C. (2014). The emergence of team synchronisation during the soccer match: Understanding the influence of the level of opposition, game phase and field zone. Universidade de Lisboa. Faculdade de Motricidade Humana. Dissertação de Mestrado.
- Preatoni, E., Ferrario, M., Donà, G., Hamill, J., & Rodano, R. (2010). Motor variability in sports: A non-linear analysis of race walking. *Journal of Sports Sciences*, 28, 1327-1336.
- Ramos, J., Lopes, R., Marques, P., & Araújo, D. (2017). Hypernetworks reveal compound variables that capture cooperative and competitive interactions in a soccer match. *Frontiers in Psychology*, 8, 1379.

- Rampinini, E., Impellizzeri, F., Castagna, C., Abt, G., Chamari, K., Sassi, A., & Marcora, S. (2007). Factors influencing physiological responses to small-sided soccer games. *Journal of Sports Sciences*, 25(6), 659-666.
- Ribeiro, J., Silva, P., Duarte, R., Davids, K., & Garganta, J. (2017). Team sports performance analysed through the lens of social network theory: Implications for research and practice. *Sports Medicine*, 47(9), 1689-1696.
- Ribeiro, J., Davids, K., Araújo, D., Silva, P., Ramos, J., Lopes, R., & Garganta, J. (2019). The role of hypernetworks as a multilevel methodology for modelling and understanding dynamics of team sports performance. *Sports Medicine*, 1-8.
- Richardson, M., Garcia, A., Frank, T., Gergor, M., & Marsh, K. (2012). Measuring group synchrony: A cluster-phase method for analysing multivariate movement time-series. *Frontiers in Psychology*, 3. <http://dx.doi.org/10.3389/fphys.2012.00405>.
- Richman, J., & Moorman, J. (2000). Physiological time-series analysis using approximate entropy and sample entropy. *AJP-Heart and Circulatory Physiology*, 278, 2039-2049.
- Riley, M., Shockley, K., & Van Orden, G. (2012). Learning from the body about the mind. *Topics in Cognitive Science*, 4, 21-34.
- Silva, P., Garganta, J., Araújo, D., Davids, K., & Aguiar, P. (2013). Shared knowledge or shared affordances? Insights from an ecological dynamics approach to team coordination in sports. *Sports Medicine*, 43(9), 765-772.
- Silva, P., Chung, D., Carvalho, T., Cardoso, T., Davids, K., Araújo, D., & Garganta, J. (2016). Practice effects on intra-team synergies in football teams. *Human Movement Science*, 46, 39-51.
- Sinnott, R. (1984). Virtues of the Haversine. *Sky and Telescope*, 68(2), 159.

Strogatz, S. (2000). From Kuramoto to Crawford: Exploring the onset of synchronisation in populations of coupled oscillators. *Physica D*, 143, 1-20.

Travassos, B., Araújo, D., Duarte, R., & McGarry, T. (2012). Spatiotemporal coordination behaviors in futsal (indoor football) are guided by informational game constraints. *Human Movement Science*, 31, 932-945.

Travassos, B., Gonçalves, B., Marcelino, R., Monteiro, R., & Sampaio, J. (2014). How perceiving additional targets modifies teams' tactical behavior during football small-sided games. *Human Movement Science*, 38, 241-250.



## Chapter 6

### Final Considerations



The main aims of this thesis were threefold: (i) to re-conceptualise sports teams as complex social networks highlighting the potential of the network approach in capturing the synergistic processes underlying team performance, to outline limitations associated with such analysis and to propose alternative methodological solutions; (ii) to propose multilevel hypernetworks as novel and potent methodological tools for analysing synergetic relations underlying team dynamics and performance, and (iii), to verify the usefulness of the multilevel hypernetworks approach in capturing synergetic relations and their key properties when applied to a set of competitive and practice football games. To fulfil these purposes, two position statement manuscripts were realised, and two experimental studies were conducted. In this chapter, the main findings of this thesis are discussed with an outline of conclusions as well as theoretical and practical implications, and future researchers.

## **6.1 Synthesis of main findings**

The present thesis encompassed four original research articles. The first two comprised a theoretical rationale regarding the application of network approaches in the realm of team sports performance analysis, while the following two presented experimental designs that allowed the study of team communication networks emerging during competitive performance. The major findings of each study will be briefly discussed here in order to achieve an integrated perspective of the overall thesis.

In chapter II an argument was presented that traditional scientific methodologies grounded on linear thinking models have struggled to cope with analysis of synergetic behaviour displayed in many complex adaptive systems, including sports teams (e.g., football teams). Inherent features manifested by such systems (e.g., self-organisation, emergent behaviour, formation and dissolution of synergies, non-linearity of behaviours, complex networking) demand more holistic-based approaches rooted in complexity sciences and dynamical systems theory (e.g., Davids et al., 2005; Davids et al., 2008; Kelso, 1995; McGarry et al., 2002; Silva et al., 2016). Network sciences have roots in complexity sciences and provide a theoretical and practical framework for the study of the synergetic behaviour underlying the establishment of team

communication networks. Regardless of its recognisable potential in capturing and analysing the relational patterns of teams (e.g., Buldú et al., 2018), we have outlined some limitations associated with the application of traditional network techniques that can conceal important network (team) properties and ultimately lead to misleading and inaccurate data. Such limitations are related to: i) observation of information exchange mainly through passing behaviours; ii) variability of players' performance outcomes (in which regards the spatial-temporal dynamics); iii) over-emphasis on network attacking behaviours, and iv), the fact that most network metrics used to model social interactions are based on paths (the so-called shortest path or geodesic distance).

Hence, in chapter III, multilevel hypernetworks were highlighted as novel and potent methodological tools for analysing team performance and dynamics, having the potential to overcome the limitations discussed in chapter I. In contrast to traditional network techniques, hypernetworks comprise a natural extension of networks with two-vertex edges (Johnson, 2008). A major advance is that in hypernetworks a hyperedge (more commonly known as a simplex) can connect more than two nodes (i.e., players) (Johnson & Iravani, 2007). Therefore, simplices can thus capture the interactions formed between sets of players (Ramos et al., 2017; Ribeiro et al., 2019), thus allowing simultaneous analysis of both cooperative and competitive interactions emerging within and between opposing teams. Additionally, such multilevel approach considers space by using geographical proximity criteria for connecting simplices and captures temporal changes by ascertaining players' geographical positions over time ( $t_1, t_2, \dots, t_n$ ) in analysis of simplices' interactions (Ramos et al., 2017; Ribeiro et al., 2019). Moreover, the inclusion of an element  $R$  allows describing the relationships emerging within each set of players (Johnson & Iravani, 2007).

Chapter IV aimed to test whether different properties of synergies, normally analysed through implementation of different methods and/or techniques, could be operationally related by means of a hypernetworks approach. Therefore, given the mathematical formalisms of hypernetworks, a multilevel model composed by three levels of analysis (from Level N towards Level N+2) was elaborated to assess team synergies during an elite competitive football match. Thus, Level N allowed verification of changes in the backcloth of teams expressed by changes in teams' tactical configurations (degeneracy) from

the first to the second half of the match. Furthermore, Level N+1 permitted to describe and quantify the types of simplices (degeneracy) emerging more frequently both behind and ahead of the ball line. In general, the results showed that the two most predominant simplices' structures were the 1vs.1 and 2vs.1 (or 1vs.2) for both teams. Finally, Level N+2 provided an opportunity to ascertain the individual level of the contribution and/or prominence of players (interpersonal linkages), as well as their interactions within and between simplices (degeneracy) during a sequence of play that ended with a goal scored by Team B.

In chapter V, the multilevel hypernetworks approach along with a cluster phase method were applied to capture and analyse team synergies emerging at a meso-local scale (P-S) in two game conditions where the number, size and location of goals were manipulated. The combination of these two relevant and sophisticated methods allowed embedding, for the first time, interpersonal synchronisation in network analysis. In general, both teams displayed stronger and more regular/stable synchronisation tendencies in the longitudinal (goal-to-goal) direction of the pitch compared with the lateral (side-to-side) direction, in both attacking and defending phases, when the goals were placed each one on the right- and left-hand sides of the pitch. However, when the goals were located at the centre of the pitch, both teams presented higher and more regular/stable levels of synchronisation in the lateral side of the pitch, compared to the longitudinal side in both attacking and defending phases.

## **6.2 Future theoretical and methodological considerations**

As the overall findings of our studies have suggested, sports teams, and more particularly football teams, can be viewed as complex social networks. Teams regarded as complex social networks are self-organising and adaptive by nature, displaying intertwined and emergent behaviours during team coordination and communication. They can self-organise into newly formed structures (new patterns of collective behaviour) expressed at multiple and higher complexity levels through inherent tendencies for synergy formation (Johnson, 2006; Johnson, 2008; Johnson, 2013; Johnson, 2016). In short, players establish local interpersonal synergies with their nearest teammates and/or opponents at a

lower level (micro-meso scale) to produce more complex set of patterns of behaviour at a higher level (macro scale) to attain competitive performance goals.

Moreover, the complexity underlying such systems relates to their multilevel structure and the dynamics at lower levels (e.g., at the level of individual athletes' behaviours) constrains and are constrained by the dynamics of higher-levels (e.g., the dynamics of whole team behaviour). The behaviour of a system can thus be understood by considering how the individual components that make up the system interrelate to form the whole, that is, when the attention is shifted from individual system components (without disregarding the relevance of individuality of each component composing the system) to the *networks* of interactions established among them (Hatch, 1997).

Another essential feature of networks is the interplay between dynamics *of* the network (i.e., network topology or structure) and dynamics *on* networks (i.e., each node or player represents a dynamical system). In the former, a clear emphasis is placed on the structure of the network, which is viewed as a dynamical system that changes over time as a function of specific, often local, rules. In the latter, the network is composed by an ensemble of dynamical systems (i.e., the players), to whom is assigned a dynamical state (i.e., players' behaviour changes across time based on local rules such as, for example, interpersonal distances, approaching velocities of teammates and/or opponents, etc).

These two lines of research on networks described above have been conducted nearly independently in the realm of team sports performance analysis. However, a major issue here is related to the interdependence of both types of network processes, i.e., the evolution of the topology or network structure is invariably associated to the state of the network nodes (the players). From this standpoint, the topology of each network, i.e., the global pattern of cooperation displayed by each team, influences the local dynamics (e.g., the movement of players), which conversely, influences the team's pattern of cooperation at a global scale (Yamamoto & Yokoyama, 2011). Such a feedback loop gives rise to a complex mutual interaction between a time-varying global topology (dynamics of collective behaviour) and the nodes (players) dynamics (Gross & Blasius, 2008; Meisel & Gross, 2009). Networks that display such a feedback loop are called *coevolutionary* or *adaptive networks* (Gross & Blasius, 2008) Therefore,

adaptive networks comprise evolving, dynamic networks, in which the topology changes in relation to the dynamic state; while the dynamics of the nodes depends on the topology (see Figure 12). Evolving networks mean that the network topology, e.g., the number of players' configurations changes as a function of time, while dynamic implies that the state of the nodes or players' behaviours also changes dynamically in time.

Such bi-directional self-organisation processes emerging at higher complexity levels (from micro-to-meso-to-macro levels) involve continuous and simultaneous changes in global topologies and local dynamics (through players' (re)organisation of team synergies). Therefore, a key step is to bring these two strands (both dynamics *of* and dynamics *on* the network) back together and to investigate the dynamics of adaptive networks, which amalgamate the time evolution of the topology with that of the states of nodes (i.e., the players).

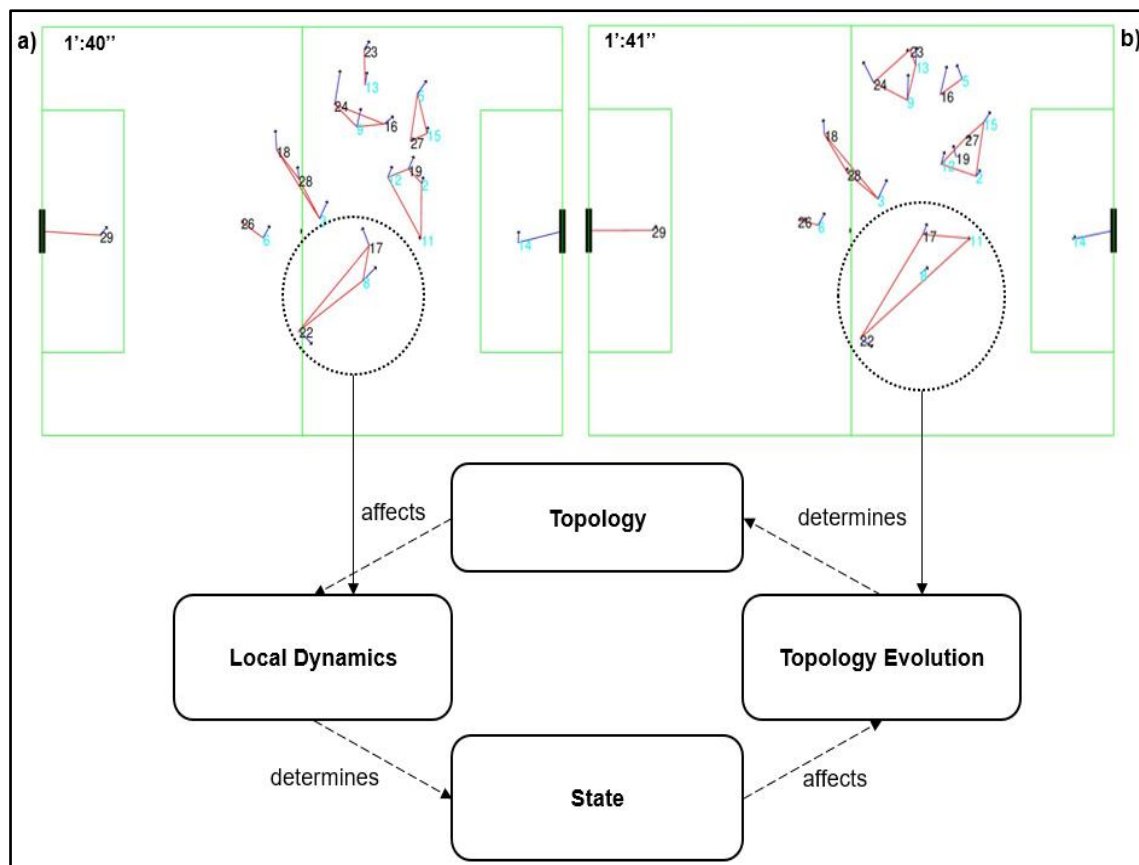


Figure 12. In a) and b) is displayed a schematic representation of multilevel hypernetworks concerning two consecutive time frames of a match. A mutual and complex interaction is observed between a time-varying topology or network structure and the local dynamics of players contained in each simplex.

Multilevel hypernetworks can be a very useful approach to address these and other issues as discussed in chapter II of this thesis. In fact, hypernetworks comprise a multidimensional generalisation of networks, where the assembly of vertices (i.e., the players) into simplices is key for moving between levels in multilevel systems (Johnson, 2006), and allows integrating dynamics between levels of complexity (from micro-to-meso-to-macro). Under this novel framework, a particular emphasis is given to the information variables that underpin the formation of team synergies, i.e., values of interpersonal distances and speed relational variables, and how players manage to coordinate behaviours based on such information sources.

Figure 12 shows how local dynamics (exhibited in a)), often based on local rules, affects the network topology, which in turn, influences local dynamics in a circular causality manner (Kelso, 1995). In this particular example, the approaching move from player 11 of the blue team allowed him to disaggregate from his previous simplex (composed by his teammates, player 12 and 2, and player 19 from the black team) to aggregate in another simplex (composed by his teammate, player 8, and players 22 and 17 from the black team). This move induced a re-organisation of team synergies (degeneracy), leading to a 2vs.2 situation as verified in b).

This body of research provides significant insights on how players, constituting a synergy, can be added (e.g., aggregate to a simplex) according to specific changing game circumstances. These game circumstances may imply providing defensive cover to a teammate, or simply balancing the numerical relation between players (contained in a given simplex) in a certain region of the field. Furthermore, these moves depict behavioural adaptability reflected by players moving away or towards a simplex, thus provoking modifications in simplices' configurations as the match unfolds.

As stated by Seifert et al. (2016), regardless of whether some players are able to perform a specific function independently (e.g., to maintain the structure of a specific simplex stable), other players are available for modification of the simplex (e.g., player 11 move towards the simplex composed by players 22, 17 and 8 to initiate numerical balance 2vs.2, portrayed in Figure 12). This observation means that the perception of shared affordances (e.g., a move from



a teammate or opponent) in a communication network can be stable when the game conditions do not require a change (a simplex maintains its structure) (Araújo & Davids, 2016). Alternatively, it can be flexible when the task demands require changes (a simplex changes its structure through players' aggregations and/or disaggregations) (Araújo & Davids, 2016; Ramos et al., 2017).

Moreover, another key property of synergies is interpersonal linkages, (Araújo & Davids, 2016), which have also been captured by multilevel hypernetworks in chapter IV. Interpersonal linkages refer to the relevance of considering the individuality and/or identity of each player in terms of her/his unique skills that are borrowed from and put at the service of the team (a single entity). Hence, this property of interpersonal linkages implies an understanding of team collective behaviour different from viewing a team as a superorganism (Araújo & Davids, 2016). A superorganism refers to a group of synergetically interacting individuals (players in a sports team), which collaborates in concert to produce functional goal-oriented behaviours (e.g., creating goal-scoring opportunities) (Duarte et al., 2012). However, as stated by Araújo and Davids (2016), despite the exquisite importance of viewing teams as single entities able to produce coherent organised behaviour, it is also relevant to consider how each player contributes with her/his unique skills.

In short, although acting as a composite whole (a team), individual players do not lose their identity. Instead, each player is singular and has her/his own characteristics, which can and should be harnessed and exploited by coaches during practice sessions as they can favour team collective behaviour. Once again, this view calls for coaches' attention concerning the importance of considering individualised training programmes as part of their regular training sessions or as a complement, aimed to enhance particular aspects of individual performance that can benefit the team as a whole.

Typically, some players tend to invest more frequently in technical (superior dribbling abilities) or physical skills (acceleration and/or speed), while others may invest in tactical skills (better decision-making) to augment team competitiveness and performance (Passos et al., 2016). This differentiation of skills and/or expertise within teams may be key to achieve high levels of performance, as they can equip teams with an immense repertoire of performance solutions.

Other properties of synergies such as dimensional compression and reciprocal compensation can also be analysed through hypernetworks. A quick glimpse of such properties was undertaken in chapter IV. For example, dimensional compression can be assessed by examining how a team (re)organises on field after a player has moved to pressurise an opponent in a particular game circumstance. Reciprocal compensation can be observed, for instance, when a player is intentionally attracted by the opponent to leave an empty space to be exploited by the opposition. It emerges when a teammate is capable of recognising that situation and seeks to close down that space (compensates her/his teammate's move by closing down the open space).

Thus, this thesis also illuminates how key properties of synergies can be operationally related using a multilevel hypernetworks approach, and more importantly, how such a body of knowledge can be organised in a coherent theoretical understanding, framed by team synergy formation, to explain team collective behaviour.

#### *6.2.1 A novel set of methodological tools for modelling and understanding team dynamics and performance in football*

The huge boost of current technologies available for application in team sports performance analysis, have allowed technologists, sports engineers and performance analysts to seek and obtain valid and accurate data regarding the spatial-temporal dynamics of players during performance in training and competition. Notwithstanding, the volume and complex characteristics of such big data sets, resulting from application of such tracking systems, have raised some challenges that performance analysts should deal with.

Big data is a term commonly used to describe datasets that are too large and complex to be analysed through application of traditional data-processing software. Instead, the volume (quantity of data), variety (type and nature of data (images, audio, video)) and velocity (the speed at which the data is acquired and processed) demand the utilisation of nonlinear statistical tools to adequately extract from such large datasets relevant information depicting team relationships and dependencies between players during performance.

This research program sheds light on the relevance of combining a powerful theoretical framework framed by complexity sciences, mathematical analysis, modelling approaches as well as the use of large heterogeneous datasets to address important aspects related to the performance of players and the team. Figure 13 presents a conceptual and practical framework regarding a novel set of methodological procedures and tools that were thoroughly scrutinised in this thesis. It shows the progressions of conceptual and analytic techniques used from a traditional application of network approaches towards a multilevel hypernetworks approach.

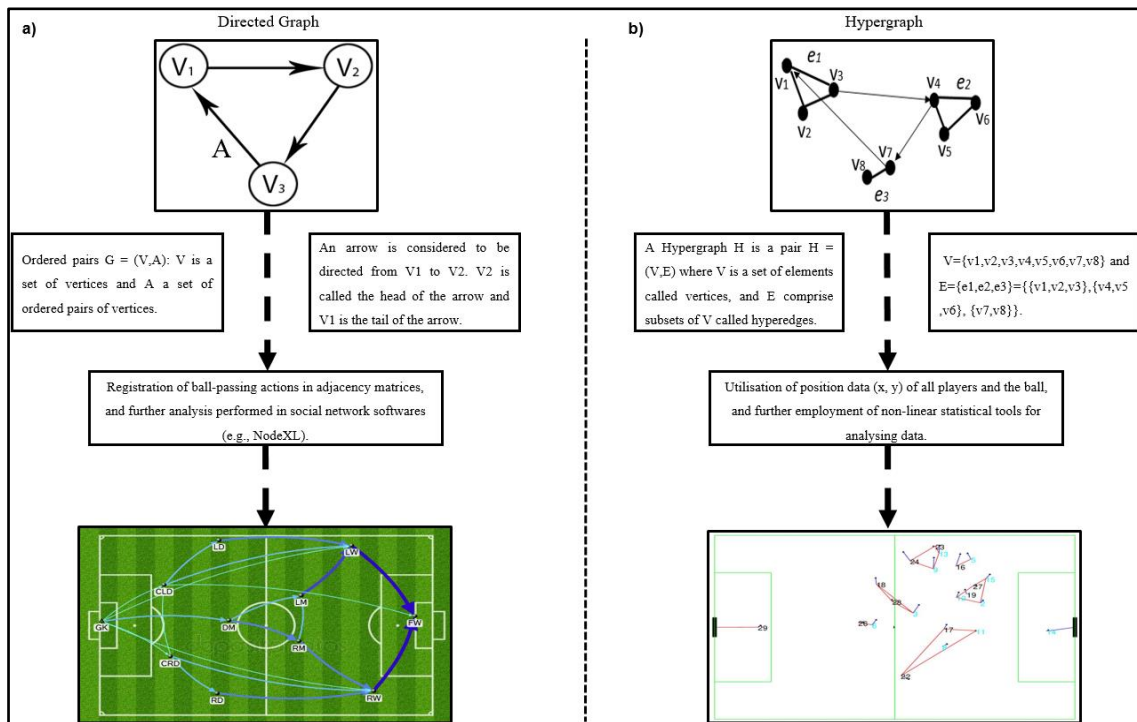


Figure 13. Methodological approaches for analysing game performance data: a) Traditional network techniques; b) Hypernetworks techniques.

Multilevel hypernetworks comprise a set of novel conceptual and methodological tools deeply engrained in complexity sciences that support applications of a set of non-linear statistical tools to assess the time-evolving dynamics underlying behaviours of players and sports teams. Multilevel hypernetworks, used in conjunction with these non-linear tools, provide a fine-grain basis for revealing the complexity rooted in the communication, synergistic processes developed by players within and between teams. The position data of

both the players and the ball, acquired through GPS and/or video-based tracking systems (e.g., STATS), can thus be used to elaborate dynamic hypernetworks of interactions, with insightful information for coaches and performance analysts. Hypernetworks permit understanding of synergetic behaviours displayed in competing teams as players, individually, and teams, collectively, seek to adapt continuously to a variety of spatial-temporal constraints of performance environments. This process allows them to communicate effectively and efficiently in the accomplishment of competitive performance goals. Communication between players is undertaken through perception of relevant contextual information variables (e.g., interpersonal distances and directional speeds of opposing players) that allow them to co-adapt their behaviours (re-organise team synergies) with opponents and teammates during performance.

On the other hand, the results from the experimental studies (chapter IV and V) suggest that the combination of game conceptualisation with the implementation of a hypernetworks approach to performance analysis can open novel and pertinent research opportunities for researchers to elaborate novel performance variables based on position data that can help illuminate the complexity presented in team communication processes.

### **6.3 Practical applications**

This thesis suggests some practical applications that can be extended to the field of performance analysis as well as team training and performance. In this regard, current technologies such as those used in this thesis to obtain players position data like GPS and/or video-based multi-player tracking systems (e.g., STATS) are currently utilised by most of professional football clubs being part of a normal procedure in the analysis of performance (Carling et al., 2009). Additionally, such tools can provide reliable and accurate positional data (Carling et al., 2008), which can be further utilised by coaches and performance analysts for monitoring the ongoing performance of players and teams during training and competition. Moreover, such information can be used for developing individual and team performance through application of specific training tasks.

Nevertheless, despite its huge potential for describing and analysing individual and team behaviours, most of these analyses are mainly based on

physical work rates required for players to perform during competition. Additionally, they have also over-emphasised analysis of frequency counts of skill performance such as, for example, the amount of ball possession, number of crosses, passes completed, and number of corners conceded, etc. Despite the relative importance of such indicators, skill-based measures need to be more informative for performance analysts providing insights on aspects related to team organisation and functioning (e.g., how players adjust defensive lines when attacking and/or defending, or how they interact within and between simplices to destabilise defensive organisation to create goal-scoring opportunities).

However, chapters III, IV and V of this thesis highlighted how position data of both players and the ball can be used for describing and analysing team performance, through analysis of multilevel hypernetworks. Potentially, such a body of knowledge, reframed by concepts like simplices and hyperedges, can provide coaches, performance analysts and practitioners with relevant information for developing (either group-based or individualised for each player) and tailoring training programs aimed for enhancing team dynamics, as well as to monitor team training and performance.

### *6.3.1 Insights for performance analysts and coaches concerning team training and performance*

In chapter IV and V are exemplified types of information derived from game performance data that can inform coaches and performance analysts about individual and team performance. A particular emphasis has been given to the numerical relations (interpersonal synergies), depicted by sets of simplices, that most frequently emerge behind and ahead of the ball line when a team attacks and/or defends. Therefore, despite the diminished power of generalisation of our results (although similar findings have been observed in other studies (e.g., Ramos et al., 2017)) these are fruitful insights that can be used by coaches to enhance team performance. More specifically, coaches can design practice tasks to foment the occurrence of 1vs.1 and 1vs.2 (or 2vs.1) under different performance conditions (e.g., using specific sub-groups of players, manipulating field dimensions through increasing and/or decreasing field dimensions), in both attacking and defending sub-phases of play, so that players can explore a wide

variety of performance solutions in order to fulfil desired performance objectives (e.g., increase velocity to surpass the nearest defender and/or to perform defensive cover to his nearest teammate).

Alternatively, sports performance analysts may use this information to identify individual and team patterns of play. Possibly, this information may provide understanding of how teams perform in specific circumstances of the game. More particularly, coaches and performance analysts may gain knowledge about when teams tend to deliberately use numerical overloads and/or underloads. For example, when winning, teams may adopt more secure patterns of play through numerical overload behind the ball line, while when losing, they may adopt more riskier behaviours through numerical underload. Hence, depending on the context (e.g., current score and match status, strategic plan, fatigue), players may switch between different tactical configurations (e.g., 2vs.1, 3vs.2) through synergy (re)formation processes (observable in simplices transformations through player's interactions over time). Importantly, it allows verifying how specific players (located in each set of simplices) strategically position themselves on certain regions of the pitch (although not analysed in this thesis) when attacking and/or defending, thus providing important insights regarding a team's offensive and defensive strategies.

There are other key information sources regarding team game performance that can be captured through the lens of multilevel hypernetworks. Such information can be used by coaches and performance analysts to design training activities and contexts for practice. For instance, performance analysts may gain understanding concerning where teams tend to create more overloads and/or underloads on field more frequently, or even detect possible opposition weaknesses, e.g., frequent incorrect movements and/or players' positioning on field that commonly destabilise the defensive organisation of the team. On the other hand, hypernetworks allow ascertaining the variety of movements (both off- and on-the-ball) performed by players within and between simplices, as well as the spatial areas of the field preferred in the attack, and those frequently covered by the defence. Moreover, such a multilevel analysis allows verifying the dominant combinations of players achieved during competition. Such combinative actions can be inspected through analysis of ball-passing actions performed between players contained in simplices, or alternatively, by

considering the off-the-ball movements of players to aggregate and/or disaggregate from simplices. In this particular case, the emergence of tightly knit sub-groups of players who interact more often during competitive performance can be assessed (considering the frequency with which some players interact with others in specific simplices).

Chapter V showed how multilevel hypernetworks allow ascertaining the synchronisation processes emerging at a meso-local scale. By analysing these data, performance analysts can detect with more precision which player(s) or sub-groups of players may be failing in adjusting their positions when attacking and/or defending through delays and/or lack of synchronisation in pitch-wide and/or length. In this way, individualised training programmes can be designed to support these players in adapting their positioning more thoughtfully during performance. Furthermore, coaches can verify if the implementation of a specific training task allows the players, individually, as well as the interactions of players with specific sub-groups (sets of simplices) attain desired levels of synchronisation. Thus, although more empirical evidence is still required, these findings can help coaches to consider how to manipulate the number and location of target areas and goals during practice to enhance the synergetic relations of their teams through development of local synchronisation processes. If coaches intend to strengthen the synchronies of specific sub-groups of players in the longitudinal direction of the field, they may consider increasing the number of goals and placing them in the lateral corridors of the field. Contrarily, if coaches plan to develop such synchronisation tendencies in the lateral direction of the field they may consider place the goals at the centre corridor of the field.

### *6.3.2 Contributions for statistical reports regarding team sports performance analysis*

On the other hand, all statistical reports of teams usually display the relationships of players based on the application of traditional social networks. Typically, such reports only provide visual information about the accumulated number of passes that each player performs and receives during the match. Furthermore, such passing-actions are also displayed in an adjacency matrix summing the total number of passes received and performed by players

throughout the match. Such reports can now be updated with information regarding multilevel hypernetworks which involves viewing specific sub-sets of players (simplices) connected through different types of communicative links (e.g., interpersonal distances and directional speed) and not only ball-passing statistics. Indeed, as shown in chapter IV, the hypernetworks approach provides a powerful informative illustration regarding players and teams' performance on field. In addition, other set of variables reported in chapters IV and V can also be incorporated in such reports.

#### **6.4 Concluding remarks**

According to the findings of the studies that compiled this dissertation, the following conclusions can be outlined:

- Team sports performance analysis needs to consider theoretical and practical frameworks more coherent with the assumptions of dynamical systems and complexity sciences, thus granting an adequate support for evaluation of emergent structural and topological properties that underlie team communication networks;
- The social network paradigm has roots in the complexity sciences and provides a set of methods and measures that allow investigating the properties of individual agents (i.e., the players) and the team as a whole;
- Football teams can be viewed as complex social networks, with players being modelled as the nodes or vertices of the network (i.e., team) interconnected through several and relevant informational ties (e.g., ball-passing actions, rotating positions on-field);
- Traditional network approaches present some limitations that may restrict and/or conceal important information regarding team game performance. Such limitations are associated with: (i) observation of information exchange mostly through passing actions; (ii) variability of player's and teams' performance is in most cases neglected; (iii) an over-emphasis on



network attacking behaviours completely disregarding the importance of defensive actions; (iv) most of network metrics used to model players' interactions are based on geodesic distances;

- Multilevel hypernetworks consist of a potent and novel methodological approach that can overcome most of the limitations found in traditional network techniques, enabling an adequate and more accurate analysis of team dynamics and performance;
- Multilevel hypernetworks enable: representation of  $n$ -ary relations ( $n > 2$ ) emerging among sets of nodes (i.e., team players), through the concept of hyperedges, allowing simultaneous analysis of both attacking and defending patterns of behaviour; consideration of both space and time in analysis of team dynamics; the inclusion of an element  $R$  that allows describing the relationships emerging within each set;
- In hypernetworks, each simplex can be completed with information regarding other types of technical actions (e.g., dribble) and other off-the-ball movements (e.g., running into an open space) realised by players during competition, without relying uniquely on ball-passing events;
- The hypernetworks approach has proven successful in capturing team dynamics when applied to a set of both conditioned and official football matches;
- The elaboration of a hypernetworks model containing three levels of analysis allowed to operationally relate different properties of synergy formation emerging during a competitive football match, thus enabling a clear understanding of team collective behaviour based on team synergy formation;
- Level  $N$  revealed changes in tactical configurations of teams from the first to the second half. Level  $N+1$  allowed verifying that 1vs.1 and 2vs.1 (or 1vs.2) were the two most frequently emerging simplices behind and ahead

of the ball line for both teams. Finally, Level N+2 allowed to describe and identify the level of prominence of players based on their individual contributions, as well as to verify players' interactions within and between simplices in the attacking plays that led to a goal scored;

- Application of multilevel hypernetworks along with a cluster phase method allowed to successfully capture the synchronisation processes emerging at a meso-local scale (P-S) during practice in two conditioned matches;
- The P-S synchronies changed from the first (two mini-goals located at both right- and left-hand sides of the pitch) to the second (goals located at the centre of the pitch) game condition and as a function of ball-possession, field-direction and teams. Generally, the first condition displayed higher mean values of cluster amplitude for the P-S synchronisation in the longitudinal (goal-to-goal) direction of the field comparatively with the lateral (side-to-side) direction, for both teams and in both attacking and defending phases. The second condition presented higher mean values of P-S synchronisation for the lateral direction of the field than the longitudinal direction, for both teams and in both attacking and defending phases;
- Generally, players tended to display more regular and stable coordination patterns with their corresponding simplices in the longitudinal than the lateral direction of the field in the first condition, while in the second condition, more regular and stable coordination patterns were verified for the lateral than the longitudinal plane in both attacking and defending phases.

## **6.5 Application of multilevel hypernetworks approach: Limitations and future perspectives**

As confirmed in this thesis, the multilevel hypernetworks approach has a huge potential in addressing the complexity of team dynamics and performance exhibited in both practice and competition, and it could have a powerful impact on team sports performance analysis and training. Notwithstanding, regardless

of the potential of such an approach in analysing complex relational data, yet the multilevel hypernetworks consist of a brand-new topic for sports sciences.

In fact, the existing literature has only provided evidence from one single study (prior to this thesis) applying the hypernetworks approach to assess cooperative and competitive interactions of players during a set of official football matches (Ramos et al., 2017). Therefore, much more work still needs to be done, which is why researchers and sports scientists should continue developing the conceptual and mathematical formalisms required for implementation of such a multilevel approach.

Indeed, there are some issues that still deserve the attention of researchers and sports scientists. In this particular context, continuing to redefine the criteria by which players and teams are connected, theoretically and mathematically, without necessarily relying uniquely on shortest paths and/or geographical proximity-based criteria might be an excellent starting point to begin with. Indeed, our data presented in chapter IV and V were limited to the proximity-based criteria. It is important for further studies to find novel alternatives to model players' interactions.

On the other hand, there are many other conceptual and methodological tools associated with multilevel hypernetworks that can be explored in future studies as they can unravel novel aspects of team dynamics and performance, with insightful information for coaches and performance analysts. For instance, as referred in chapter IV, both the backcloth (e.g., the structure of the network) and the traffic (the flow of information across the backcloth or network) are two intertwine concepts that highlight the dynamics within a specific system (a football team). Here, the tactical disposition of players on field was regarded as the backcloth, however, there are other relevant aspects of the game that can be referred to as the backcloth such as, for example, the strategical/tactical plan and/or players' roles. In this case, a particular strategical/tactical plan advocated by a coach may afford a specific set of behaviours to be accomplished by players during competition, with the same being applied for players' roles. Therefore, it will be important to understand how the dynamics of players, individually, and the team, collectively, are influenced by such pre-defined tactical plans and/or assigned roles.

Moreover, in chapter IV were also analysed the most frequent simplices' structures emerging both ahead and behind the goal line. However, there are some issues here that should be addressed in future studies, namely: (i) to ascertain how the frequency of simplices' structures change both behind and ahead of the ball line as a function of ball location, i.e., when the ball is located, for example, in the offensive and/or defensive side of the midfield of a team; (ii) to verify the zones of the pitch where such simplices' structures occur more often, i.e., their spatial distributions across the pitch in relation to the position of the ball, through application of heat-maps; (iii) to compare how the emergence of such simplices' structures change as a function of the quality of the opposition, fatigue, etc. This research program intended to provide the theoretical background underlying the use of multilevel hypernetworks, and to apply such a methodology to match analysis conducted in both game contexts (training and competition) to ascertain its utility in providing insights on processes of synergy formation. Future studies need to increase the sample size (i.e., the number of matches and/or different competitions) in order to provide a rich body of knowledge.

Finally, a major challenge in future projects is to combine and integrate all the non-linear measurement tools utilised in this thesis, along with others, in a single software capable of: (i) providing an on-the-moment visual representation (i.e., a movie) of players' interactions on field as displayed in chapter III of this thesis, and; (ii) enabling a quick and quasi-automatic generation of outputs containing information from relevant individual and team performance variables (e.g., synchronisation of players with their nearest teammates, etc). The development of such software may assist coaches' decisions, as well as performance analysts in monitoring and analysing team training and performance.

## 6.6 References

Buldú, J., Busquets, J., Martínez, J., Herrera-Diestra, J., Echegoyen, I., Galeano, J., & Luque, J. (2018). Using network science to analyse football passing networks: Dynamics, space, time, and the multilayer nature of the game. *Frontiers in Psychology*, 9, 1900. doi: 10.3389/fpsyg.2018.01900

- Carling, C., Bloomfield, J., Nelson, L., & Reilly, T. (2008). The role of motion analysis in elite soccer: Contemporary performance measurement techniques and work rate data. *Sports Medicine*, 38, 389-862.
- Carling, C., Reilly, T., & Williams, A. (2009). *Performance assessment for field sports*. Routledge: Taylor & Francis LTD.
- Davids, K., Araújo, D., & Shuttleworth, R. (2005). Applications of dynamics systems theory to Football. In T. Reilly, J. Cabri & D. Araújo (Eds.), *Science & Football V* (pp. 556-569). Oxon: Routledge.
- Davids, K., Button, C., & Bennett, S. (2008). *Dynamics of skill acquisition: a constraints-led approach*. Champaign (IL): Human Kinetics.
- Duarte, R., Araújo, D., Correia, V., & Davids, K. (2012). Sport teams as superorganisms: Implications of biological models for research and practice in team sports performance analysis. *Sports Medicine*, 42(8), 633–42.
- Gross, T., & Blasius, B. (2008). Adaptive coevolutionary networks: A review. *Journal of The Royal Society Interface*, 5, 259–271.
- Hatch, M. (1997). *Organization theory: Modern, symbolic, and postmodern perspectives*. Oxford: Oxford University Press.
- Johnson, J. (2006). *Hypernetworks for reconstructing the dynamics of multilevel systems*. In: European Conference on Complex Systems. Oxford: United Kingdom.
- Johnson, J., & Iravani, P. (2007). The multilevel hypernetwork dynamics of complex systems of robot soccer agents. *ACM Transactions on Autonomous and Adaptive Systems*, 2, 1–23.

- Johnson, J. (2008). Multidimensional events in multilevel systems. In S. Albeverio, D. Andrey, P. Giordano & A. Vancheri (Eds.), *The Dynamics of Complex Urban Systems: An Interdisciplinary Approach* (pp. 311-334). Heidelberg: Physica-Verlag HD.
- Johnson, J. (2013). *Hypernetworks in the science of complex systems*. London: Imperial College Press.
- Johnson, J. (2016). Hypernetworks: Multidimensional relationships in multilevel systems. *The European Physical Journal Special Topics*, 225, 1037-1052. doi: 10.1140/epjst/e2016-02653-4
- Kelso, J. (1995). *Dynamic patterns: The self-organising of brain and behavior*. Massachusetts: MIT Press.
- McGarry, T., Anderson, D., Wallace, S., Hughes, M., & Franks, I. (2002). Sport competition as a dynamical self-organizing system. *Journal of Sports Science*, 20, 771–781. doi: 10.1080/026404102320675620
- Meisel, C., & Gross, T. (2009). Adaptive self-organization in a realistic neural network model. *Physical Review E*, 80, 061917.
- Passos, P., Araújo, D., & Davids, K. (2016). Competitiveness and the process of co-adaptation in team sport performance. *Frontiers in Psychology*, 7, 1562.
- Ramos, J., Lopes, R., Marques, P., & Araújo, D. (2017). Hypernetworks reveal compound variables that capture cooperative and competitive interactions in a soccer match. *Frontiers in Psychology*, 8, 1379.
- Ribeiro, J., Davids, K., Araújo, D., Silva, P., Ramos, J., Lopes, R., & Garganta, J. (2019). The role of hypernetworks as a multilevel methodology for modelling and understanding dynamics of team sports performance. *Sports Medicine*, 1-8.

- Seifert, L., Komar, J., Araújo, D., & Davids, K. (2016). Neurobiological degeneracy: A key property for functional adaptations of perception and action to constraints. *Neuroscience & Biobehavioral Reviews*, 69, 159-165.
- Silva, P., Chung, D., Carvalho, T., Cardoso, T., Davids, K., Araújo, D., & Garganta, J. (2016). Practice effects on intra-team synergies in football teams. *Human Movement Science*, 46, 39-51.
- Yamamoto, Y., & Yokoyama, K. (2011). Common and unique network dynamics in football games. *PLoS One*, 6(12), 1-6.