UNIVERSIDADE TÉCNICA DE LISBOA

FACULDADE DE MOTRICIDADE HUMANA

# Capturing Interpersonal Coordination Processes in Association Football: from Dyads to Collectives

*Dissertation submitted in order to obtain the degree of Ph.D. in the branch of Human Kinetics, specialty in Sport Sciences*

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*All the effort devoted to this work is dedicated to my ultimate little treasure, Madalena.*

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***Não sei quantas almas tenho.***

*Cada momento mudei.*
*Continuamente me estranho.*
*Nunca me vi nem acabei.*
*De tanto ser, só tenho alma.*
*Quem tem alma não tem calma.*
*Quem vê é só o que vê,*
*Quem sente não é quem é,*
*Atento ao que sou e vejo,*
*Torno-me eles e não eu.*
*Cada meu sonho ou desejo*
*É do que nasce e não meu.*
*Sou minha própria paisagem;*
*Assisto à minha passagem,*
*Diverso, móbil e só,*
*Não sei sentir-me onde estou.*
*Por isso, alheio, vou lendo*
*Como páginas, meu ser.*
*O que segue não prevendo,*
*O que passou a esquecer.*
*Noto à margem do que li*
*O que julguei que senti.*
*Releio e digo: "Fui eu?"*
*Deus sabe, porque o escreveu.*

Fernando Pessoa

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## Abstract

The purpose of this thesis was to investigate how football performers coordinate their behaviours in different levels of social organisation. We began with a position paper proposing the re-conceptualisation of sport teams as functional integrated superorganisms to frame a deeper understanding of the interpersonal coordination processes emerging between team players. Time-motion analysis procedures and innovative tools were developed and presented in order to capture the superorganismic properties of sports teams and the interpersonal coordination tendencies developed by players. These tendencies were captured and analysed in representative 1vs1 and 3vs3 sub-phases, as well as in the 11-a-side game format. Data showed higher levels of variability at the individual level compared to the team level. This finding suggested that micro-variability may contribute to stabilise the behavioural dynamics at the collective level. Moreover, the specificities of the interpersonal coordination tendencies displayed within attacking-defending dyads demonstrated to have influenced the performance outcome. Attacking players tend to succeed when they were more synchronised in space and time with the defenders, and their interaction were more unpredictable/irregular. Besides, the time-evolving dynamics of the collective behaviours (i.e., at 11-a-side level) during competitive football performance indicated a tendency for an increase in the predictability (i.e., more regularity). These data were interpreted as evidencing co-adaptation processes between opponent players, which suggest that team players may shift from prevalent explorative and irregular behaviours to more predictable behaviours emerging due changes in their functional movement possibilities. However, some game events such as goals scored, halftime and stoppages in play seemed to break this continuum and acted as relevant performance constraints.

**Keywords:** Interpersonal interactions; spatial-temporal coordination; social neurobiological system; system complexity; degrees of freedom; degeneracy; performance constraints; variability; time-evolving behavioural dynamics; synchrony; superorganism; association football.

# Resumo

O objetivo desta dissertação foi investigar a coordenação interpessoal dos jogadores de futebol em diferentes níveis de análise. Começamos por propor a reconceptualização das equipas como superorganismos como forma de aprofundar o entendimento dos processos de coordenação interpessoal que emergem entre os jogadores e que são funcionalmente integrados no seio da equipa. Foram desenvolvidos procedimentos de análise do movimento e ferramentas que permitem captar as propriedades super-organísmicas e as tendências de coordenação interpessoal dos jogadores. Estas tendências foram captadas e analisadas em situações de 1x1 a 3x3 representativas do jogo, tal como na própria situação de jogo formal. Os resultados demonstraram maiores valores de variabilidade ao nível individual do que ao nível da equipa. Estes resultados sugeriram que a variabilidade ao nível micro parece contribuir para a estabilização da dinâmica comportamental ao nível coletivo. As tendências particulares de coordenação interpessoal exibidas pelos jogadores em díades atacante-defensor demonstraram influenciar o sucesso nesta subfase do jogo. Os atacantes tenderam a alcançar o sucesso quando se sincronizaram mais com o movimento dos defensores, e demonstraram maior imprevisibilidade nessa relação. Ao nível coletivo, a evolução temporal dos comportamentos analisados na situação de jogo formal indicou uma tendência para um aumento da previsibilidade (i.e., mais regularidade no modo de variação desses comportamentos). Estes resultados parecem evidenciar processos de co-adaptação entre as equipas, sugerindo que os jogadores iniciam o jogo com comportamentos predominantemente exploratórios e irregulares que progressivamente mudam para comportamentos mais estáveis e previsíveis. Contudo, alguns eventos críticos do jogo como os golos, a interrupção para o intervalo e paragens momentâneas no jogo pareceram influenciar esta tendência e atuar como importantes constrangimentos ao desempenho.

**Palavras-chave:** Relações interpessoais; coordenação espácio-temporal; sistema neurobiológico social; complexidade do sistema; graus de liberdade; degenerescência; constrangimentos; variabilidade; dinâmica comportamental; sincronia; superorganismo; futebol.

## List of Publications and Communications

During the developmental stages of this thesis, some work has been published, accepted or submitted for publication in peer-reviewed journals, as well as presented at scientific meetings originating some publications in proceedings and abstract books. Next we present a selection of the publications and communications specifically related with the work developed in this thesis.

### Peer-reviewed papers in international journals (ISI)

**Duarte, R.**, Araújo, D., Folgado, H., Esteves, P., Marques, P., & Davids, K. (submitted). Capturing complex, non-linear team behaviours during competitive football performance. (Journal of System Science and Complexity)

**Duarte, R.**, Araújo, D., Correia, V., Davids, K., Marques, P., & Richardson, M. (submitted). Competing together: Assessing the dynamics of *team-team* and *player-team* synchrony in professional football. (Human Movement Science)

**Duarte, R.**, Araújo, D., Freire, L., Folgado, H., Fernandes, O., & Davids, K. (under review). Intra- and inter-group coordination patterns reveal collective behaviours of football players near the scoring zone. (Human Movement Science)

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

**Duarte, R.**, Araújo, D., Travassos, B., Davids, K., Gazimba, V., & Sampaio, J. (in press). Interpersonal coordination tendencies shape 1vs1 sub-phase performance outcomes in youth soccer. *Journal of Sports Sciences*.

**Duarte, R.**, Araújo, D., Fernandes, O., Fonseca, C., Correia, V., Gazimba, V., Travassos, B., Esteves, P., Vilar, L., & Lopes, J. (2010). Capturing complex human behaviors in representative sports contexts with a single camera. *Medicina-Lithuania*, 46(6), 408-414.

## Peer-reviewed papers in international journals (not indexed in ISI)

**Duarte, R.**, Araújo, D., Gazimba, V., Fernandes, O., Folgado, H., Marmeleira, J. & Davids, K. (2010). The ecological dynamics of 1v1 sub-phases in association football. *The Open Sports Sciences Journal*, 3, 16-18.

## Book chapters

**Duarte, R.**, Araújo, D., Davids, K., & Travassos, B. (submitted). How group motion dynamics create instabilities and goal-scoring opportunities in association football. In H. Nunome & B. Dawson (Eds.). *Science and Football VII – The Proceedings of the Seventh World Congress on Science and Football*. Routledge.

**Duarte, R.**, Fernandes, O., Folgado, H., & Araújo, D. (submitted). Single camera analyses in studying pattern forming dynamics of player interactions in team sports. In K. Davids, R. Hristovski, D. Araújo, N. Balague, C. Button, & P. Passos (Eds.). *Complex Systems in Sport*. Routledge.

## Papers in proceedings of scientific meetings

**Duarte**, **R.**, Araújo, D., Gazimba, V., & Fernandes, O. (2010). A time-motion analysis method to study people interaction in human movement science. *Conference Proceedings of the 3rd Mathematical Methods in Engineering International Symposium* (pp. 408-415), Polytechnic Institute of Coimbra, Coimbra, Portugal.

**Duarte, R.**, Freire, L., Gazimba, V., Araújo, D. (2010). A Emergência da Tomada de Decisão no Futebol: da Decisão Individual para a Colectiva [The emergence of decision making in football: from individual to the team]. In C. Nogueira, I. Silva, L. Lima, A. T. Almeida, R. Cabecinhas, R. Gomes, C. Machado, A. Maia, A. Sampaio & M. C. Taveira (Eds.) *Livro de Actas do VII Simpósio Nacional de Investigação em Psicologia [Proceedings of the VII National Symposium on Research in Psychology]* (pp. 1829-1839), Universidade do Minho, Braga, Portugal.

## Communications at scientific meetings

### *Oral Communications*

**Duarte, R.**, Araújo, D., Richardson, M.J., Correia, V., Marques, P. (2011). Assessing player-team synchrony in top level professional football. II Simpósio Internacional da Performance Desportiva [2nd International Symposium of Sports Performance], CIDESD, 8-9 October, Covilhã, Portugal.

**Duarte, R.**, Araújo, D., Folgado, H., Marques, P., & Davids, K. (2011). Do professional football teams behave like *Superorganisms*? 13th European Congress of Sport Psychology. 12-17 Julho 2011, Funchal, Madeira, Portugal.

**Duarte, R.**, Araújo, D., Davids, K., Folgado, H., Marques, P., & Ferreira, A. (2011). In search for dynamical patterns of teams' tactical behaviours during the match. VIIth World Congress on Science & Football, 26-30 May, Nagoya, Japan.

**Duarte**, R., Araújo, D., Gazimba, V., & Fernandes, O. (2010). A time-motion analysis method to study people interaction in human movement science. 3rd Mathematical Methods in Engineering International Symposium, Coimbra, Portugal.

**Duarte, R.**, Araújo, D., Gazimba, V., Travassos, B., Fonseca, S., & Davids, K. (2010). Predictability of spatiotemporal coordination and performance outcomes in 1 v 1 dyads in association football. 3rd International Congress of Complex Systems in Medicine and Sport, 15-18 September, Kaunas, Lithuania.

**Duarte, R.**, Freire, L., Gazimba, V., Araújo, D. (2010). A Emergência da Tomada de Decisão no Futebol: da Decisão Individual para a Colectiva [The emergence of decision making in football: from individual to the team]. VII Simpósio Nacional de Investigação em Psicologia [VII National Symposium on Research in Psychology], 2-4 February, Braga, Portugal.

### *Poster Presentations*

**Duarte, R.**, Travassos, B., Taki, T., Marques, P., & Araújo, D. (2011). Using dominant region method to analyze individual and collective spatial interactions in football. II Simpósio

Internacional da Performance Desportiva [2nd International Symposium of Sports Performance], CIDESD, 8-9 October, Covilhã, Portugal.

**Duarte, R.**, Araújo, D., Correia, V., Travassos, B., Vilar, L., Davids, K. (2011). Footballers' decision making behaviours in creating goal-scoring opportunities. 13th European Congress of Sport Psychology. 12-17 Julho 2011, Funchal, Madeira, Portugal.

**Duarte, R.**, Araújo, D., Travassos, B., Davids, K., Vilar, L., & Sampaio, J. (2011). Interpersonal coordination tendencies explain 1v1 outcomes in football. VIIth World Congress on Science & Football, 26-30 May, Nagoya, Japan.

**Duarte, R.**, Araújo, D., Davids, K., Vilar, L., & Travassos, B. (2011). How group motion dynamics create instabilities and goal-scoring opportunities in association football. VIIth World Congress on Science & Football, 26-30 May, Nagoya, Japan.

**Duarte, R.**, Araújo, D., Travassos, B., Vilar, L., Fonseca, S., & Davids, K. (2010). Team sports performance assessment using autocorrelation function and approximate entropy. 3rd International Congress of Complex Systems in Medicine and Sport, 15-18 September, Kaunas, Lithuania.

**Duarte, R.**, Araújo, D., Rosado, D., Fernandes, O., & Davids, K. (2010). Collective decision-making as an emergent property in association football. 11th European Workshop on Ecological Psychology (EWEP), 9-12 June, Fréjus, France.

**Duarte, R.**, Araújo, D., Gazimba, V., Fernandes, O., Folgado, H., Marmeleira, J. & Davids, K. (2009). The ecological dynamics of 1v1 sub-systems in association football. First International Symposium of Sports Performance, 4-5 July, Vila Real, Portugal.

## Visiting research

During the course of this thesis, an important research visit was made to the **Perceptual-Motor Dynamics Laboratory** in the Department of Psychology at the University of Cincinnati (United States): from the $15^{th}$ to the $25^{th}$ June 2011.

The work presented in Chapter 7 was partially developed during this stage. We are grateful to Professors Michael Riley and Michael Richardson for have received and worked with me.

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# 1. General Introduction

*"The aim of science is not things themselves, as the dogmatists in their simplicity assume, but the relations among things; outside these relations there is no reality knowable"*

(Henri Poincaré, 1905, p. 24)

## 1.1 Introductory note

This chapter provides an overview on the current understanding of Interpersonal Coordination. The literature discussed bellow supported the research studies of the present dissertation, which together contribute to answer the question: *how football performers mutually interact in different levels of social neurobiological organisation*? From the first insights on individual human body-level coordination, understanding is extended to the analysis of other levels of organisation where people (i.e., footballers) interact to coordinate their actions during goal-directed behaviour (Davids, Araújo, & Button, 2011). The main differences concerning the referred levels of analysis are the type of connectivity or linkages between the system components. Whilst individual body-level coordination is sustained essentially by mechanical linkages (e.g., muscles, joints and tendons), interpersonal coordination is based on informational couplings between individuals (Turvey, 1990). Scientific support for a multi-level approach on interpersonal coordination in association football is provided in the next sections.

## 1.2 Defining Coordination

In human movement systems, coordination can be defined as "the process of mastering redundant degrees of freedom of the moving organ, in other words its conversion to a controllable system" (Bernstein, 1967, p. 127). The Russian physiologist Nikolai Bernstein addressed valuable insights on how system components or degrees of freedom are assembled and brought into proper functional relationships, shaping specific movement patterns. Those patterns have been called *coordinative structures* (Turvey, 1977), which can be conceived as a temporarily and flexibly assemblage of many micro-components, so that a single micro-component may participate in many different coordinative structures on different occasions (see also Kay, 1988). At the individual level, coordinative structures are functional synergies that emerge between parts of the body used to achieve specific movement goals such as running, kicking, or passing a ball. However, groups of performers functioning in a team game need to coordinate their actions with respect to each other as well as key task constraints such as rules, performance area dimensions, and shared goals. This process involves social coordination between agents considered as degrees of freedom of a social neurobiological system such an association football team (Davids et al., 2011). Independently of the level of analysis, the concepts of coordinative structures *or* functional synergies explain how any change in one system component is automatically adjusted for, in other system components, without jeopardizing the achievement of the task goal (Turvey, 1990; Davids et al., 2011).

### 1.2.1 Degrees of freedom and degeneracy

The initial formulation of Bernstein's degrees of freedom problem questioned how complex neurobiological systems organize, maintain, and disaggregate the large-scale (or macroscopic) patterned connections which occur between their components (Davids et al., 2011). As Figure 1.1 shows, two possible explanations can be introduced.

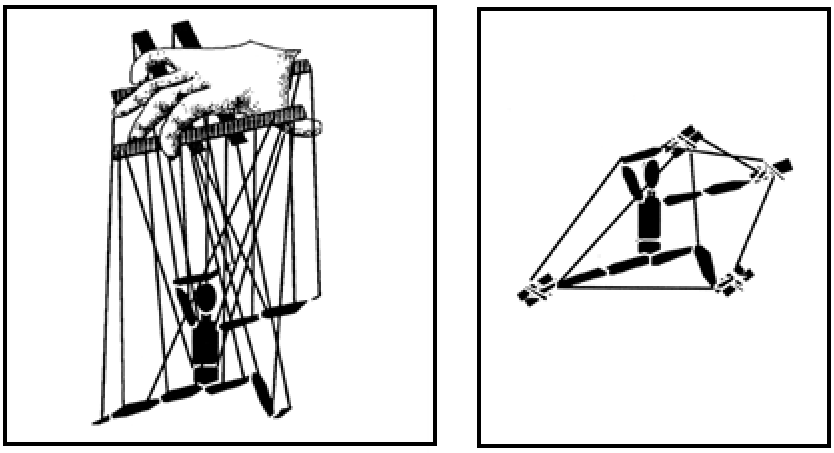

Figure 1.1. Coordination explained by the marionette metaphor. The ordinary hand-controlled marionette (left panel) exemplifies centralised and sequential control of each degree of freedom as acting independently. The other marionette (right panel) is an example of self-organised coordination control. It conveys the idea that a self-organising system of very many interacting degrees of freedom and very many dimensions may be governable by principles describable in few dimensions: The self-organising marionette has fewer strings for the same number of parts as the other-organised marionette (adapted from Turvey, 1990).

On one side (left panel of Figure 1.1), coordination can be considered as a problem in organisation, with each part behaving in a well-defined way according to instructions from an outside source. This independence between component parts would imply that the regulation of coordinative structures is achieved through centralised and sequential computation, which especially sharpens the problem of coordination. Alternatively, Bernstein (1967) proposed that coordination could be considered as a problem of self-organisation (right panel of Figure 1.1). There are neither external instructions nor a single centralised controller. As Michael Turvey (1990) pointed out, the parts spontaneously cooperate through ‘some kind of mutual understanding’ in order to achieve a common goal. Thus, task goals are the meaning by which components parts self-assemble into stable and ordered movement patterns or coordinative structures. This proposal entails a ubiquitous property of biological systems – *degeneracy*.

*Degeneracy* can be defined as the ability of elements that are structurally different to perform the same function or yield the same output (Edelman, & Gally, 2001). Therefore, degeneracy can form the basis for the emergence of equivalent coordinative structures under varying contexts, which ensures an adaptive and robust system. This explanation has been gaining ground in the last years, over the initial proposal of Bernstein (1967). He suggested that human movement systems were governed by redundant motor degrees of freedom. However, strong criticisms led some scientists to favour ‘motor abundance’ in place of motor redundancy. That is, it was argued that motor redundancy is only a property of mechanical or electronic systems (Tononi, Sporns, & Edelman, 1999) inapplicable to human voluntary movements since biological systems cannot completely freeze joints’ range of motion (Latash, 2000). Thus, degeneracy is considered a better descriptor of the human movement system compared to redundancy and it has been considered the natural answer for the degrees of freedom problem (Davids, Araújo, Button, & Renshaw, 2007). As proposed by Edelman and Gally (2001), degeneracy is present in all levels of biological organisation, from the genetic code to behavioural and even social levels. For example, social behaviours, such as interactions among team players during a football match, can be performed in different ways and by different individuals, while maintaining the same playing pattern or a stable output. Therefore, this property is of relevant interest for the study of interpersonal coordination in team sports.

### 1.2.2 Absolute and relative coordination

Nature is rich in providing degenerative solutions for the coordinative problems of living things. Different modes of coordination can be encountered in biological systems. The seminal works of Eric von Holst (1973) introduced the notion of *absolute* and *relative coordination* as the explanation for the different coordination patterns observed in nature. Figure 1.2 exemplifies von Holst's mechanical model of independent and coupled biological rhythm generators.

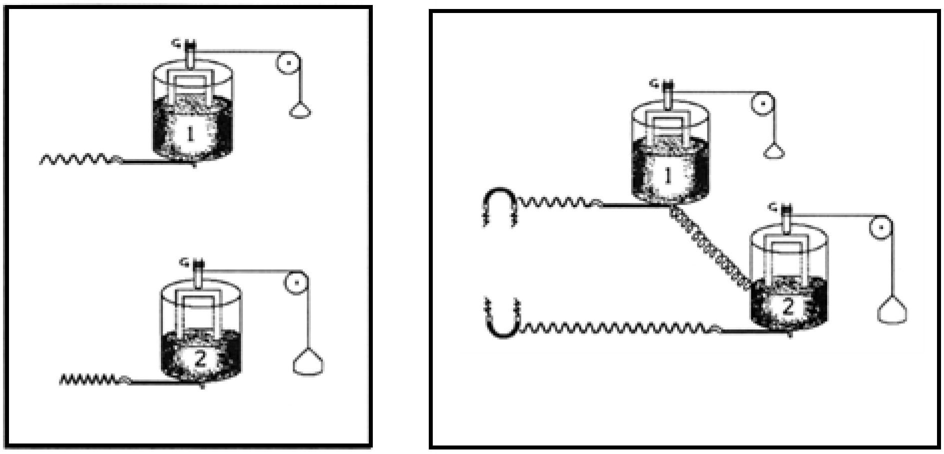

Figure 1.2. Von Holst's mechanical model of biological rhythms generators (adapted from Turvey, 1990).

The von Holst's mechanical model used an oscillator given by a paddle rotating in a liquid under the force produced by a descending weight. This model served to illustrate certain facts of rhythmic movement units. Differences in amounts of liquid and weight mean that the two oscillators have different characteristic frequencies (see left panel). In this case, each oscillator moved independently at its own tempo, thereby satisfying its intrinsic dynamics. Von Holst called this preference, the *maintenance tendency*. However, if the two oscillators were to be coupled by a spring (see right panel), then they would progressively share oscillatory vibrations and would eventually be coupled on the same frequency. Von Holst (1973) called the tendency of a rhythmic unit to attract another to its tempo the *magnet effect*. He proposed that as both oscillators are attracted to the extrinsic dynamics of the other, and that the resultant single tempo is likely to occur between the preferred tempos of the two oscillators. However, Kugler and Turvey (1987) showed that this single tempo does not necessarily collapse into an intermediate frequency. Using swinging pendulums experiments, these authors concluded that this tempo is constrained by the preferred frequencies of oscillation of the system in a high-dimensional space.

Generalising these ideas for coordination of rhythmical biological movements, von Holst (1973) saw the *maintenance tendency* (i.e., to move at one's own pace) and the *magnet effect* (i.e., to move at the pace of the other) as working in direct opposition. If the maintenance tendency dominates, then the *coordination is relative* (i.e., multiple rhythms and wandering phase relations). On the other hand, if the magnet effect dominates, then the *coordination is absolute,* showing a single rhythm and a single phase relation. As Kelso and Engstrøm (2006) pointed out, the complementary relation between absolute and relative coordination encompasses all the possible forms of coordination that are feasible and found in nature. However, as Kugler and Turvey (1987) showed, the modes of relation between the component parts of a system can be constrained by the features of the system itself in a high level of organisation. This point can be particularly important in studying social systems such as the playing interactions developed within sports teams. Therefore, the relation between different levels of organisation could be thus hypothesised as a key point to deep understanding on the interpersonal coordination processes developed by football players during competition.

## 1.3. Extending the picture

In this section we argue that the coordination processes previously introduced embrace also phenomena at the social level of biological organisation such as in association football competition. Left panel of Figure 1.3 presents an analogy with Figure 1.1 to illustrate how each team player can be seen as a system component interacting together with his team-mates. The strings portray the connectedness between players and the potential degrees of freedom of the whole system. Degenerative patterns of coordination between system components (i.e., the players) should be equally observable at this level of biological organisation, as a property allowing the stability of performance outcome and the functional behaviour of the team.

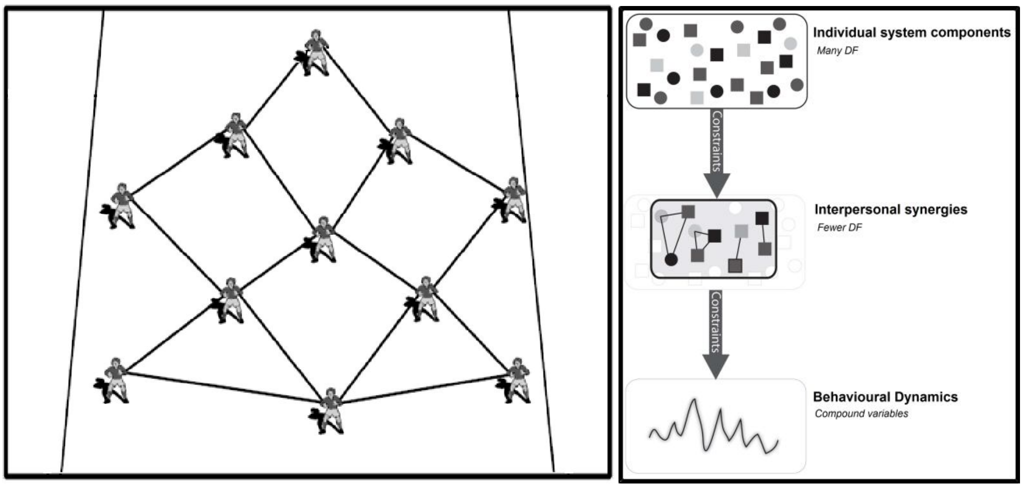


Figure 1.3. Social connectedness and interpersonal synergies within a football team. Imaginary strings link players and constrain the degrees of freedom of the whole team (left panel) allowing the emergence of functional interpersonal synergies which reveal their low-dimensional behavioural dynamics (right panel, adapted from Riley et al., 2011).

The strings showed in Figure 1.3 were used for illustrative purposes only and to highlight the potential connectedness between team-mates during performance. As proposed by Riley, Richardson, Shockley and Ramenzoni (2011) interpersonal synergies are likely to emerge from individuals sharing common task goals. Individuals intentionally coordinating their movements shape high-dimensional synergies which reduce the degrees of freedom of the whole system (e.g., a team). Its behavioural dynamics may be captured by selecting functional relevant compound variables that describe the synergy's organisational state (see right panel of Figure 1.4).

However, the question is what type of connection might link players allowing them to produce coordinated patterns at group or team level and act as an interpersonal synergy?

### 1.3.1. From intra- to inter-person coordination

Are the individuals actually connected during social activities such as playing football? A clue to answer this question can be found in a landmark study developed by Richard Schmidt and colleagues (Schmidt, Carello, & Turvey, 1990). They demonstrated that patterns of interpersonal coordination between individuals optically connected displayed exactly the same dynamical features that previous studies have shown for intra-person index finger experiments described below (Kelso, Scholz, & Schöner, 1986, illustrated in upper panel of Figure 1.4).

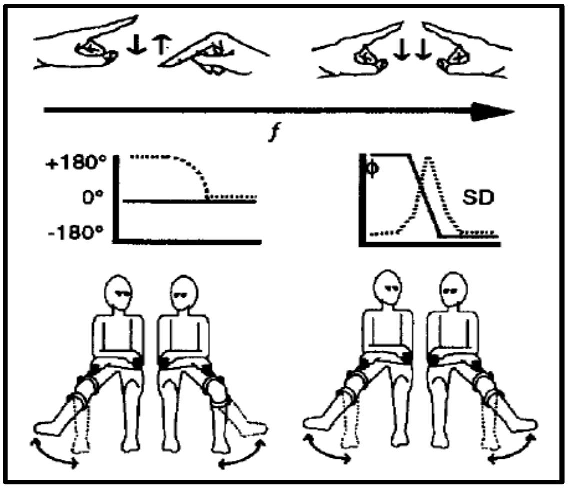


Figure 1.4. As frequency *(f)* is increased, a person coordinating his/her two index fingers in anti-phase absolute coordination (left side) will jump spontaneously to in-phase absolute coordination (right side). The same sudden transition accompanied by critical fluctuations (SD) is seen when two persons who watch and follow each other's leg's motions try to coordinate together (adapted from Kelso et al., 1986 and Schmidt et al., 1990).

In these experiments, two seated persons oscillated a leg with the goal of coordinating the two legs in anti-phase (i.e., syncopation) or in-phase (i.e., synchronisation) as the frequency of the movement oscillations was increased. To satisfy the goal, the two persons watched each other closely. As with the within-person case, the between-person experiment exhibited a sudden behavioural transition from anti-phase to in-phase mode of coordination, but not vice versa. More importantly, if the two persons moved their limbs without watching each other, no spontaneous jumps in coordination occurred, with people swinging their legs independently of the other individual. The two experiments presented in Figure 1.4 differ in the perceptual systems involved (i.e., the visual system in between-person coordination vs. the haptic system in within-person coordination). However, these differences did not affect the emergence of similar coordination patterns in the two cases. The more stable pattern arising when the natural system oscillations were perturbed (e.g., increasing the natural frequency) was synchronising movement coordination to in-phase modes, since system components were connected (whatever physically or informationally).

Summarising, anatomical and optical connectivity between system components appear to be governed by identical underlying principles. However, other means than optical information seems to be equally important for interpersonal coordination processes. For example, Néda and colleagues (2000) showed how people can synchronise their clapping based on auditory information. Therefore, perceptual information (e.g., optical, auditory) can be a crucial mean by which individuals are coupled during social activities, sustaining patterns of interpersonal coordination in goal-directed behaviours.

### 1.3.2. Sports teams as synergistic collectives

The importance of the perceptual information (particularly optical information) for the coordination and control of the behaviour of individuals was firstly suggested by James Gibson (1966, 1979). In its ecological approach to perception and action, Gibson emphasised the mutuality of individual and environment as a central tenet. He argued that the interaction with the surrounding environment occurs by direct physical contact and perception of the physical properties of the ambient energy array. Thus, the optical flow resulting from patterns of light reflection on surfaces and objects of the environment presents individuals with the necessary visual information to guide behaviour. As the top left panel of Figure 1.5 shows, the information-movement couplings are the mode by which individuals explore and interact with environmental properties such as surfaces, objects, events and even other individuals (Gibson, 1979).

Marsh and colleagues (2006) proposed an extension from the individual-environment to group-environment relations based on gibsonian ecological psychology and the principles of dynamical systems (see Figure 1.5).

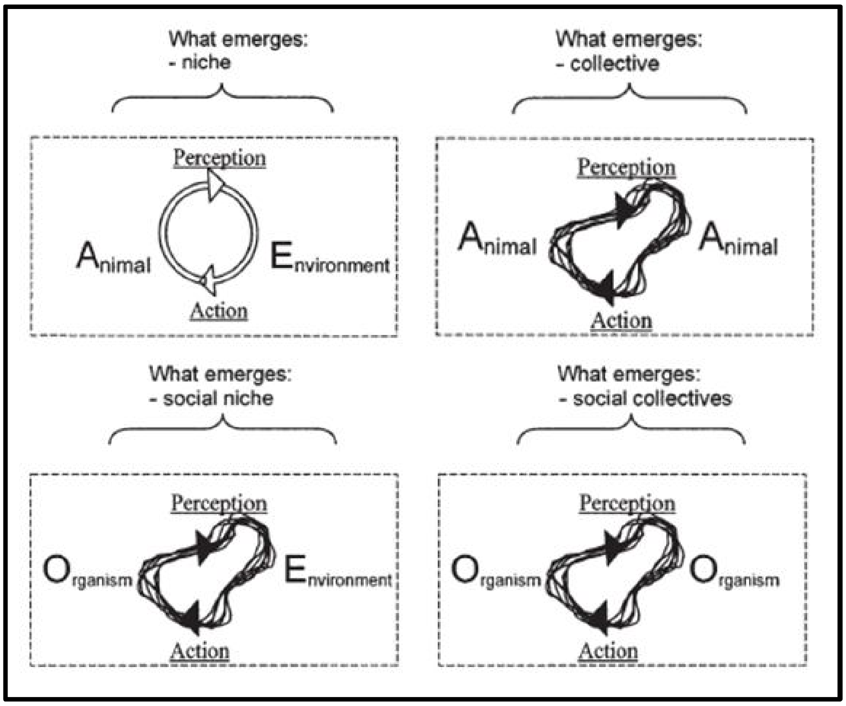


Figure 1.5. Relational properties are defined over an animal–environment system in different levels of systems organisation. Mutuality between two or more individuals yields perceptions and actions that obey time-evolving dynamical principles (based on an image from Marsh et al., 2006).

Top left panel illustrates the perception–action processes viewed as involving mutuality of animal and environment rather than being solely focused on the animal or on the environment itself. When another person becomes a significant aspect of one's environment, mutuality implies the intertwined of one person's perceptions and actions with the other person's perceptions and actions (see top right panel). An implication of this mutuality is the emergence of a 'collective'. This collective is not merely the sum of the individuals, but it is a coordinative structure or synergy, which can be defined as functional groupings of structural elements (e.g., players) that are temporarily constrained to act as a single coherent social unit (Kelso, 2009). Thus, a synergistic collective emerges by the soft-assemble of individuals acting as system degrees of freedom, typically sharing common social goals (Richardson, Marsh, & Schmidt, 2010). As the emergent collective is also mutually linked with the environment, it can then be understood as a new organism (e.g., a team) within the animal–environment system (bottom left panel – Figure 1.5). In the specific case of team sports, two synergistic collectives compete within the team-team-environment system with the laws of the game and field dimensions acting as boundary constraints (bottom right panel – Figure 1.5).

This social synergistic perspective provides a sound theoretical framework to study interpersonal coordination processes in different levels of social organisation of football teams. For example, dyadic systems such as 1vs1 sub-phases, or multi-agent systems such as the whole 11vs11 game can be investigated using the principles underlying the presented framework.

### 1.3.3. Understanding emergent coordination in social neurobiological systems

Nature supports the view that groups of cooperating individuals gain some advantages when working and living together. There are plenty of examples of animal societies that typically display emergent collective behaviours such as schools of fish, flocks of birds, swarms of honeybees, flashing firefly or ant colonies. Examples of emergent social coordination in human systems with large number of interacting individuals reported in scientific literature include panic escape (Helbing, Farkas, & Vicsek, 2000), walking in a busy street (Helbing, & Molnar, 1995), the formation of Mexican waves in football stadiums (Farkas, Helbing, & Vicsek, 2002), the emergence of traffic jams (Helbing, & Huberman, 1998), and audience applause (Néda et al., 2000). These emergent social behaviours have the particular feature of displaying novel properties and new patterns at the group (macro) level, which cannot be observed at the individual (micro) level (Reeve, & Hölldobler, 2007). In recent years, the concept of self-organisation has been used to explain how certain behavioural patterns emerge in complex social neurobiological systems (Sumpter, 2006). Self-organisation can be defined as a process by which complex systems evolve based on spontaneous (no centralised external control) interactions among system components.

A central tenet of self-organisation in biological systems (and not necessarily similar to physical and chemical systems) is that simple repeated interactions between individuals can produce complex adaptive patterns at group level. Inspiration came from Nicolis and Prigogine (1977) general observation that, individuals following simple behavioral rules can produce complex behavioural patterns. Despite the variety of shapes and motions of grouping individuals, it has been suggested that many of the different collective patterns are generated by small variations in the local rules followed by their members (Sumpter, 2006). Indeed, Couzin and colleagues (2002) showed how adjusting simple local rules using computerised simulations grouping animals would lead to emergent patterns such as swarm, torus (i.e., moving in a circle) or dynamic parallel group motion.

Therefore, it seems that individuals base their movement decisions on locally acquired information sources such as the relative positioning, motion direction, or changing motion direction, of their near-neighbours conspecifics (Couzin, 2009). Thus, emergent patterns of movement coordination in social neurobiological systems can arise spontaneously without any centralised homunculus-like control. These social neurobiological models are inspirational in the way individuals manage their local interactions to achieve advantageous forms of emergent coordination. Like in the mentioned examples, team sports players need to develop coordinated relations within its team. In this sense, sports teams can be regarded as functional integrated 'superorganisms' displaying emergent patterns of interpersonal coordination at different levels of analysis. Furthermore, sport contexts embrace also the need to develop competitive relations with the opposing performers. Some recent studies developed in sports contexts have dedicated particular attention to this point. For example, interpersonal coordination between two competing performers was previously investigated in squash (McGarry, 2006), tennis (Palut, & Zanone, 2005), basketball (Bourbousson, Sève, & McGarry, 2010a), rugby union (Passos et al., 2008), and futsal (Travassos, Araújo, Vilar, & McGarry, 2011). All these investigations have shown high levels of task-dependence, highlighting how specific task constraints influence interpersonal coordination patterns. Using compound kinematic measures, some other work was done on group-level coordination in association football (Frencken, Lemmink, Delleman, & Visscher, 2011; Lames, Ertmer, Walter, 2010; Yue, Broich, Seifriz, & Mester, 2008), basketball (Bourbousson, Sève, & McGarry, 2010b) and rugby union (Passos, Milho, Fonseca, Borges, Araújo, Davids, 2011; Correia, Araújo, Davids, Fernandes, Fonseca, 2011). Together, these studies shed new light on the understanding of dyadic and group-level coordination and are the conceptual and experimental basis for the specific research aims presented in the next chapters.

## 1.4. Towards an understanding of interpersonal coordination in football

The purpose of the present thesis was to understand the processes underlying interpersonal coordination on Association Football performance. Distinct studies concerning different levels of organisation were described, ranging from dyads to collectives.

A collection of 6 original research articles, submitted or published on peer-review journals with ISI Impact Factor, constituted the main body of this thesis. Each article was presented as an individual chapter following the format requested by the journal for where it was submitted.

The current chapter (Chapter 1) introduced the general conceptual and scientific fundamentals supporting the research programme on interpersonal coordination.

Chapter 2 presents a position statement (***Sport teams as superorganisms: Implications of biological models for research and practice in team sports performance analysis***) in which current knowledge from socio-biological systems such as animal societies frame a way sports teams can be theoretically re-conceptualised. The concept of ‘superorganism’ was discussed bringing insights on how sport teams could be seen as functionally integrated social complex systems. Methodological tools to capture the superorganismic properties of sports teams were also presented and discussed.

In Chapter 3, a methodological article entitled: ***Capturing complex human behaviors in representative sports contexts with a single camera***, was presented. This work described the conceptual framework and the motion analysis procedures followed in this programme of work. Particularly, concepts related to complex systems research such as order and control parameters, as well as methodological procedures such as the use of TACTO software and the DLT method were discussed and introduced in a step-by-step tutorial fashion.

Chapter 4 presents an experimental research article entitled: ***Interpersonal coordination tendencies shape 1-vs-1 sub-phase performance outcomes in youth football***. This work investigated interpersonal coordination at the dyadic level between opposing players. The coordination tendencies underlying the two possible outcomes (success of the attacker vs. success of the defender) as well as the structure of their variability were presented and discussed.

Chapter 5 introduces another experimental research article entitled: ***Intra- and inter-group coordination patterns reveal collective behaviours of football players near the scoring zone***. The coordination patterns of two competing sub-groups of players were investigated in a 3vs3 sub-phase task. Intra- and inter-group coordination tendencies were described in this study, namely the particular environmental and relational conditions that afford the creation of goal scoring opportunities.

Chapter 6 conveys an experimental research entitled: ***Capturing complex, non-linear team behaviours during competitive football performance***. Assigned to a macro level of analysis, the team level, this work presented the use of compound positional variables to capture the idiosyncratic behaviours of football teams. Trends in the magnitude and structure of variability of the emergent team behaviours were also discussed.

Chapter 7 addresses the study: ***Competing together: Assessing the dynamics of team-team and player-team synchrony in top level professional football***. This study followed a different research strategy by integrating two different levels of organisation in an effort to capture synchronisation processes occurring within each competing team. This was achieved by means of the use of the innovative cluster phase method. Furthermore, non-linear measures assessing the dynamical structure of the whole team and player-team synchronies were also presented.

Finally, Chapter 8 provides a General Discussion where findings of the different investigations were integrated into a single framework in line with the ontological foundations of ecological dynamics. Theoretical and methodological considerations, as well as practical applications were further discussed.

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# 2. Sport teams as superorganisms: Implications of biological models for research and practice in team sports performance analysis

## 2.1. Abstract

Significant criticisms have emerged on the way that collective behaviours in team sports have been traditionally evaluated. A major recommendation has been for future research and practice to focus on the interpersonal relationships developed between team players during performance. Most research has typically investigated team game performance in game sub-phases, rather than considering the interactions of performers within the whole team. In this paper, we propose that team performance analysis could benefit from the adoption of biological models used to explain how repeated interactions between grouping individuals scale to emergent social collective behaviours. We highlight the advantages of conceptualising sports teams as functional integrated ‘superorganisms’ and discuss innovative measurement tools which might be used to capture the superorgamismic properties of sports teams. These tools are suitable for revealing the idiosyncratic collective behaviours of sports teams, particularly their coordination of labour and the most frequent channels of communication and patterns of interaction between team players. The principles and tools presented here can serve as the basis for novel approaches and applications of performance analysis, devoted to understanding sports teams as functioning, high-order organisms exhibiting their own peculiar behavioural patterns.

***Keywords*****:** Social neurobiological systems, collective behaviours, team sports, performance analysis, superorganisms.

## 2.2. Introduction

Nature provides evidence that groups of cooperating individuals can gain many functional advantages when working and living together. Research has demonstrated the superior performance of groups over single organisms in a wide range of human social phenomena.[1] Sports teams are equally composed of different interacting individuals who develop cooperative relations to achieve successful performance outcomes. The collective performance of sports teams has been extensively analysed by a range of analytical performance indicators.[2,3] For example, it has been demonstrated that the percentage of ball possession of association football teams changes as a function of the evolving match status, game location, and level of opposition,[4] and that the percentage of ball possession in the opposition penalty box remained high when teams used a counterattacking style[5]. However, the view that some game events are more important than others, and that the method of notating discrete actions or events fails to provide information about the performance context, is challenging sports scientists to re-think their research strategies.[6]

With reference to tracked positional data, recent studies have begun to reveal how players and teams *continuously* interact during competition. For example, teams tend to be tightly synchronised in their lateral and longitudinal movements[7], with a counterphase relation regarding their expansion and contraction movement patterns[8] commonly caused by changes in ball possession[9]. This type of investigatory approach shares some conceptual similarities with models of behaviour in biological systems, which have revealed the emergent social collective behaviours of human groups and animal societies.[10] Here, we argue that sports teams also exhibit emergent collective behaviours that differ from the sum of individual aggregated performances. Analysis of patterns of behaviour at the collective system level in team sports requires a reformation of notational analysis methods used to study performance.

As in other collective systems, sports team performers often need to make decisions about where to move and which actions to perform, in uncertain and shifting environmental conditions. It has been suggested both in biology[11] and in team sports analyses[12] that individuals base their movement decisions on locally acquired information sources such as the relative positioning, motion direction, or changing motion direction, of significant others operating in a system, making a collective response all the more remarkable. This finding implies that the actions of individuals functioning in a complex biological system need to be intimately coordinated. Next we discuss the potential advantages of integrating biological models to study emergent collective behaviours of performers in team sports.

## 2.3. A brief incursion into sociobiology

Studies in biology have shown how the repeated interactions among grouping animals (including humans) scale to global collective system behaviours.[10] These social interactive behaviours within a group lead to the emergence of a 'collective', which can be understood as a 'new organism' within the animal–environment system.[13,14] In this sense, the actions of individual organisms (e.g., team players) constrain and are constrained by the actions of neighbouring organisms toward the implicit and mutually exclusive goals of the 'collective'. The coordination and re-organization of these ongoing interactions occur via externally controlled feedback processes sustained by the continuous exchange of information between the grouping individuals.[15] For example, when an ant finds a food source it deposits a pheromone so that other members of the colony can locate it, or when a fish swims in a specific direction, its nearest neighbours in a school soon follow. As such recruitment behaviour continues, the number of individuals engaged in a goal-directed activity increases.[10] Evidence is beginning to reveal that similar processes seem to emerge during competitive performance in team games in which a player's motions can functionally influence the spatial-temporal characteristics of movements in team mates and opponents, creating a purposeful aggregation during specific performance sub-phases.[16,17]

What does a commitment to viewing sports teams as complex superorganismic systems imply? The sensitivity of biological systems to information provided in feedback loops can help us to better understand the postulate that 'a system is more than the sum of its parts'. The *functional integration* of individuals in highly-related grouping organisms, such as social insects (e.g., ants, bees, wasps), is a central aspect to consider. This feature has been attributed to natural multilevel selection mechanisms acting at the level of between-group colonies and not just at the level of genetic selection.[18] The evolutionary advantages of functional (re)-organisation through cooperative activities have led some animal societies to develop tightly coordinated and complementary behaviours among group members, which improve the likelihood of the entire group to be selected, or to attain some beneficial adaptations.[19] In the performance context of team sports, these advantages act to promote functional group adaptations as a means of symbolic group 'selection'. Here, the term 'selection' can be equated with a team succeeding when competing against another group of individuals in sport, even though the outcomes of performance might differ from those pursued by a biological system like a colony, flock or school. Despite the need for *functional integration*, each individual in a group is different in terms of genetic heritage, previous experience and specific roles in the group. It is widely accepted that *inter-individual variation* is a valuable process that can yield a continual supply of new solutions to the behavioural challenges that groups face [10]. Therefore, complex biological systems face a complementary interplay between *functional specialization* (based on inter-individual variation) and *functional integration*.[20] These properties have led some scientists to advocate that highly-coordinated groups behave like 'superorganisms',[18,21-23] since individuals possessing high levels of inter-individual variability can cooperate together to perform as a single social entity in order to achieve specific task goals.

### 2.3.1 Viewing teams as 'superorganisms'

The 'superorganism' concept was first proposed by William Morton Wheeler to describe the degree to which ant colony members appear to operate as a single functional unit.[24] The concept has been extensively used in sociobiology although some criticism has pointed to the absence of experimental and mathematical support for this notion .[25] Recent formal descriptions of group adaptation[19] and intergroup competition[26] have proved its utility and tempered the criticisms. An example of successful collective system behaviours was demonstrated by fire ants self-assembling waterproof rafts as an adaptive evolutionary strategy to survive floods.[27] The cooperative complementary relations of the conspecific individuals allowed the emergence of superorganismic behaviours based on the trapping of ants at the raft edge by their neighbours. These data suggested that the 'superorganism' concept can be defined as "a group of individuals self-organized by *division of labour* and united by a closed *system of communication*".[28, p.84, *in italics our emphasis*] These two main features of highly-coordinated grouping organisms – *division of labour* and *system of communication* – might also be of interest for performance analysis in sports teams, functioning as integrated organisms/entities.

*Division of labour* has been considered in studies of team sports as a key aspect expressing the functional integration, complementarity of behaviour and coordination among teammates.[29] The existence of a *communication system* is another central issue also present in team sports research. Coaches, performance analysts and researchers have begun to enhance understanding of the communication channels used by players to support the effectiveness of teamwork.[30] Common actions in team games, such as passing the ball or switching positions with teammates, are founded on a platform of communication or information exchange. Such actions imply the existence of informational links between players which allow them to detect the appropriate environmental conditions to successfully cooperate during performance.[31] Extending understanding from other social neurobiological systems, we argue that considering sports teams as functional integrated 'superorganisms' might allow us to capture the self-organised dynamics of complex social interactions that shape collective behaviours in teams. In order to progress understanding of sports teams as superorganisms, sport science needs to develop specific analysis methods that provide insights into the functional collective behaviours of such social neurobiological systems. How has recent work developed methodological tools that can capture the superorganismic properties of sports teams?

## 2.4. Capturing the *superorganismic* properties of sports teams

The interactions of agents in sports teams, defined as collective social systems, reveal common underlying principles. In this respect, emergent interactions between team players are sustained by informational flow fields that specify each individual's opportunities for action.[32,33] For example, in the team sport of rugby union, Passos and colleagues[16] showed that an attacking sub-group with a ball, generated information for each individual to decrease interpersonal distances with other players and act as a single cohesive social unit, during its approach to a sub-group of defenders. However, each performer possessed different characteristics that influenced his/her action capabilities[34], which constrained each individual to display his/her own idiosyncratic behaviours. Thus, conceptualizing sports teams as superorganisms requires dedicated methodological tools suitable for capturing the *division of labour* and the *communication systems* of each collective during the interplay between *inter-individual variation* and *functional integration* processes.

### 2.4.1. Tools to assess 'division of labour' and 'communication systems'

One approach to characterise the division of labour amongst individual agents in sports teams involves measuring the area of a performer's interventions on field (known as the major range).[8] The predominant area of each individual's interventions during performance is defined by an ellipse centred at the 2D mean location of each performer, with semi-axes being the standard deviations in X- and Y-directions, respectively. Figure 2.1 displays the major ranges for four backs (left panel) and three forward players (right panel) of a GK+4+3+3 team formation during a football match, classified by defending and attacking phases (as a function of ball possession).

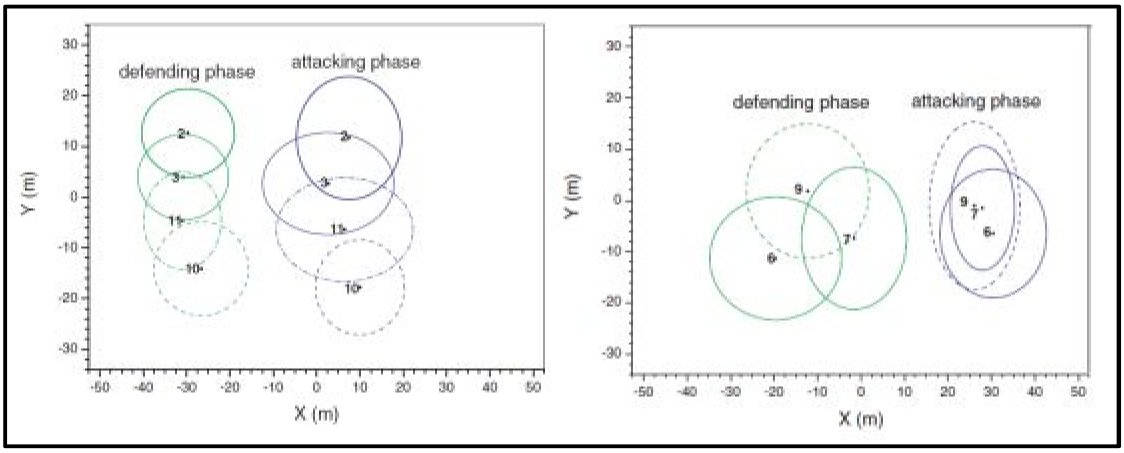



Figure 2.1. Major ranges for two sub-groups of football players in defending and attacking phases. Left panel shows the four back players; right panel shows the three forward players of the same team. Reproduced with permission from the authors.[8]

These spatial data revealed an inverse trend between the two sub-groups of players. While backs increased their individual covered area (i.e., range of displacement trajectories) in attacking phases, the forwards enlarged their covered areas in the defending phases. This tool can also be used to assess the coordination of labour during performance as the game unfolds. Figure 2.2 presents exemplar data from a change in the global trend of team performance, from smaller and more proportional individual areas of intervention (left panel) in the first 5-mins of the match, to highly narrow and elongated ranges (right panel) in the next 5-mins of the game.

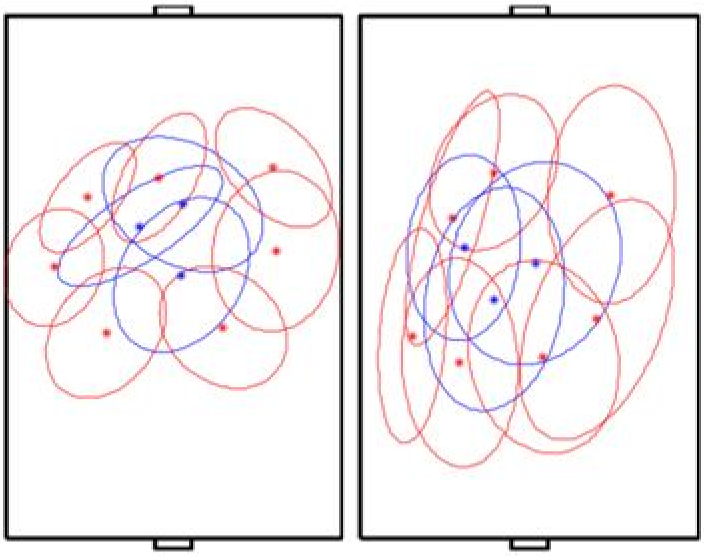


Figure 2.2. Major ranges of 10 outfield players from a football team. Left panel shows values from the first 5 mins of the game; right panel displays values from the next 5-min segment. A blue colour was used to distinguish the midfielders from the backs and forwards (data from [38]).

Data from Figure 2.2 exemplify how the coordination of labour can change during performance under the influence of natural variations in competitive constraints such as, for instance, the opposition's style of play[5] or the dynamics of ball displacement on-field[35].

Concerning the communication system of teams, an approach to capture the tendencies in the relationships of team players is provided by small-world networks.[36] A ball passing action exemplifies a functional relationship between teammates and trends of passing relations can reveal preferred channels of communication within a team. Figure 2.3 shows an application of network analysis to passing trends during a water polo competition, based on simple notational data.[31]

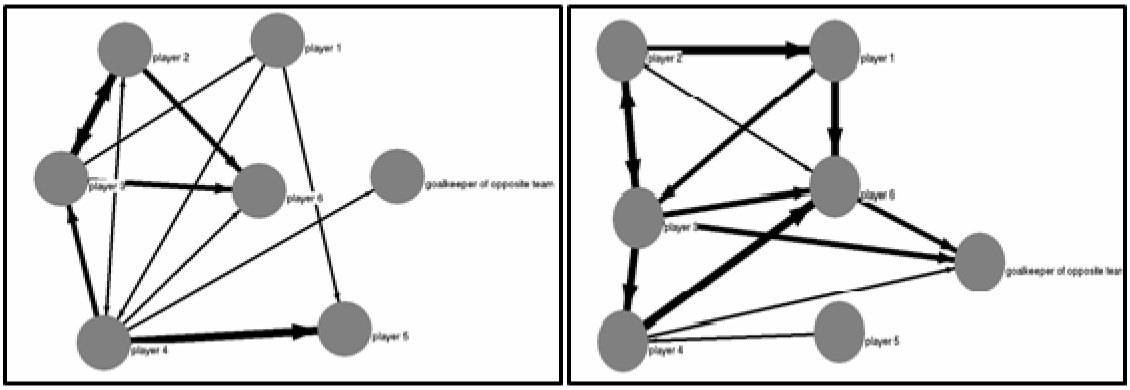



Figure 2.3. Grey circles represent players involved in the units of attack. Orientation of the black arrows indicates pass direction. Origin of the arrow represents the player who passed the ball and the arrowhead represents the player who received the ball. Width of the black arrows denotes quantity of passes from one player to another during performance (i.e., the thicker the arrows the more passes occurred between specific players). Each panel displays trends for each team. Reproduced with permission of the authors.[31]

The strength of the relationships between pairs of players was expressed by the width of the arrows. Dominant relations and probabilities of interaction among teammates can be assessed using this method. Deeper understanding of teamwork effectiveness can be obtained by constructing networks according to passing accuracy.[30] Other actions, such as switching positions between two players, if understood as communication processes, can also be studied in these analyses. Thus, networks provide a useful method to qualitatively and quantitatively describe the communication-based interactions that emerge among players in team sports.

### 2.4.2. Compound positional variables

Based on individual positional data, other variables have been proposed to assess specific functional collective behaviours of sports teams. These have been termed ‘compound positional variables’ because they integrate the individual positions of each team player into a meaningful description of a collective team pattern.

Examples of such *compound positional variables* include:

i) the *surface area* occupied by teams,[37] which represents the covered area of the field by the whole team in each time frame;

ii) the *geometrical centre* of teams,[7,8] which represents a kind of "centre of mass" of a team;

iii) the *stretch index* of teams[9] (also known as *radius*[8]), which represents the mean dispersion value of the players around the centre of each team (i.e., the *geometrical centre*);

iv) the *team ranges* (also known as *length and width* of the team[7]), which represent the size of the team in the longitudinal and lateral field directions.

These innovative compound measures of team performance reveal meaningful collective behaviours from a practical perspective and can be used to assess the idiosyncratic performance values of each team.[38] Supplementary material illustrating these *compound positional variables* from two competing teams[39] can be found in supplementary materials section. These collective measures can assist understanding of interactions between agents in sports teams as 'superorganismic' qualities. Observing their changes on different timescales, due to variations in performance constraints such as the evolving scoreline or different offensive playing styles, is an important aspect to consider in future performance evaluations. Another important issue to consider when measuring team performance behaviours is to discriminate values for compound positional variables during defending and attacking performance phases. Measurement functions to discriminate data between these phases have been reported previously in the literature.[8] Despite the merits and potential of these collective measures, they are based on the assumption that each individual agent's behaviour equally contributes to functional collective performance. However, team players may not always have the same weight in the emergence of the social collective system behaviours.[40] The weighting of the contribution of each player may change as a function of the evolving game context (e.g., the place where the ball is located on-field) and the action capabilities of each individual (e.g., maximum movement displacement speed). The next section proposes alternative methods that account for the weighted contribution of each team player during competitive performance.

## 2.5. Emerging alternative approaches and future directions

### 2.5.1. Cluster phase

The cluster phase method was recently proposed in order to analyse synchrony within systems with a small number of oscillating components.[41] This method is based on the Kuramoto order parameter,[42] which has been used to investigate phase synchronization in systems with large number of oscillating components (e.g., emergence of collective clapping in theatre audiences)[43]. The Kuramoto model describes the synchronisation of oscillatory movement components (e.g. team players) in a single collective parameter. Investigators have adapted this model and showed its applicability using a rocking chair paradigm with only six oscillatory units (i.e., six individuals coordinating rocking chair movements).[41] Specific measures of individual-group and whole group synchrony can be obtained, which can be a useful means to quantify the contribution of each team player to the global behaviour of a team, as well as changes in the global synchronisation tendencies within a team.

### 2.5.2. Dominant region

The dominant region is a method for group motion analysis proposed to analyse the spatial interactions in team sports.[44] The dominant region of a team player is defined as a region of the field space where a particular performer is likely to arrive earlier than other players.[45] This method determines a high functional and dynamic sphere of influence around each individual by integrating data on position, speed, direction, and acceleration. Comparing those kinematic data of all the performers, this method specifies their movement possibilities and the functional area of intervention behind the control of each specific player. The weighted contribution of each player interacting together with his/her teammates and opponents originating a purposeful aggregation (*functional integration*), can collectively express the space-time relations between teams. Dominance diagrams integrating the sphere of influence of all players can be visualised in a frame-by-frame manner depending on the sampling rate of the positional data.[46] Figure 2.4 presents an illustration of the dominant region method for a single frame. The measures provided are time-series of individual and collective dominant region areas, time occupancy rate per specific zones and number of links with near neighbours of each team.

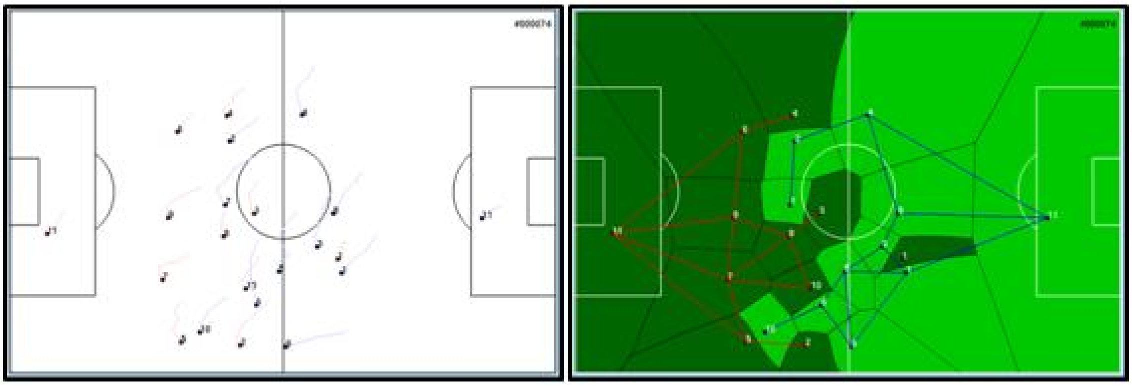


Figure 2.4. Visualisation of the dominant region method in a single frame. Left panel shows players' on-field positions with tracked courses. Right panel displays individual (boundary lines) and team's dominant regions (colour contrasts), as well as intra-team links among players sharing direct/immediate space. Exemplar unpublished data provided by Tsuyoshi Taki.

### 2.5.3. Modelling

Common underlying principles of team sports and animal collectives can form the basis for a formal description (mathematical modelling) of the collective behavioural dynamics of sports teams, allowing scientists and practitioners to make accurate predictions about team behaviours. More than 30 years ago, biologists[47] developed computer simulations, known as self-propelled particle (SPP) models, that captured the collective behaviours of animal groups in terms of local interactions developed[10]. For example, Couzin and colleagues[48] proposed a model in which individual animals follow only three simple rules of thumb: (i) move away from very nearby neighbours; (ii) adopt the same direction as those that are close by and (iii), avoid becoming isolated. Biological systems such as schools of fish are able to produce different complex patterns due to small changes in these simple localized rules. SPP models have also been used to formalise phenomena in human crowds. Treating humans as particles that interact according to a set of 'social forces', these models have been successful in predicting specific collective behaviours such as escape panic, walking in a busy street, the formation of Mexican waves in football stadiums, and the emergence of traffic jams.[10] It is likely that adaptations of these models can be successfully applied to capture the time-evolving dynamics of sports teams as functional integrated entities or ‘superorganisms’. For example, these models could help coaches predict how attacking and defensive formations change during the course of a match as specific individuals become fatigued, if weather conditions deteriorate or if the competitive performance constraints of a game changes from beginning to end.[49] This might be an important advance for sports performance analysis given the recent criticism that it is overly concerned with documenting discrete performance statistics, often in specific sub-phases.[50] These innovative collective system analysis methods may support simulations and accurate theoretically principled predictions about the collective behaviours of whole teams.[51]

## 2.6. Concluding remarks

This paper has considered conceptualisation of sports teams as functionally integrated ‘superorganisms’, as an explanation of how highly-coordinated grouping players might collectively operate as a single social unit. Coordination tendencies underlying the emergence of team behaviours seem to be governed by locally generated information sources from the relative positioning of other team players, motion directions and changes in motion. The ‘superorganism’ proposal, more than focusing attention on compiling discrete action frequencies, suggests the need to regard the meaningful and synergistic (inter)actions within sports teams as the appropriate focus of analysis. The present framework suggests the re-conceptualisation of research approaches dedicated to team sport collectives, as well as performance analysis applications. For instance, simple notation data typically collected by performance analysts can be interpreted in reference to small-world networks. Notational variables should also contain contextual information regarding the performance constraints surrounding the players’ behaviours, such as their relative position on the pitch, numerical relations between players in opposing teams and relative dispersion between teams. The growing development of player tracking systems, such as electronic portable devices or multi-player video-based systems[51,52] offer a novel opportunity to improve research and sports performance analyses. The innovative tools presented here might support these novel approaches to performance analysis, devoted to the understanding of sports teams as functionally integrated high-order organisms that exhibit their own idiosyncratic features.

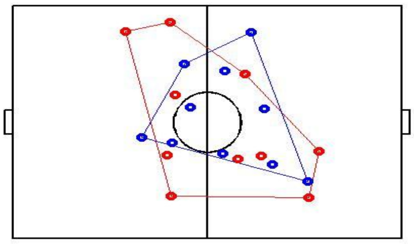
The conceptual approach presented here might have also some important applications concerning learning and training design. Changing the local available information that guides players, coaches can manipulate the local rules governing interactions between neighbour teammates, inducing the emergence of new patterns of collective movement solutions. For example, changing the numbers of players involved in different team game practices is likely to promote adaptations in the way team players coordinate their labours and explore different channels of communication, which should lead to the emergence of a distinct pattern of collective behaviour.[53] A challenging future task for researchers and practitioners is the formal description of social collective behaviours of sports teams. Mathematical models adapted from other biological systems, such as SPP models, may provide computer simulations to undertake performance predictions without the need to experimentally test a whole range of team patterns on-field.

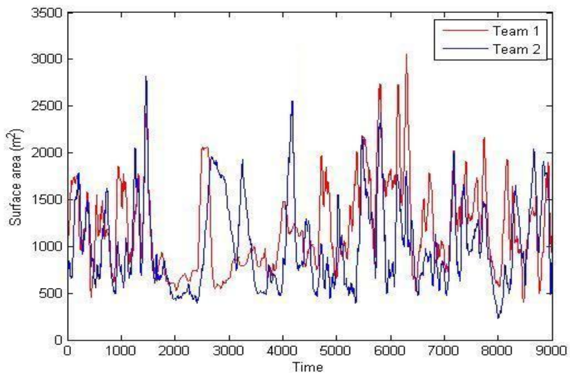
## 2.7. Supplementary materials

Table 2.1. Exemplar data on *compound positional variables* from two competing teams during the first 15-mins of an association football match[39] calculated with a specifically conceived software application – TeamSense.[38] Tutorial examples of computations: left panel shows a photogram of each variable for a single time frame extracted from the 2D video animations; right panel displays time plots of each variable.

| Variables illustration | Time-series plots |
|---|---|

*Surface area*

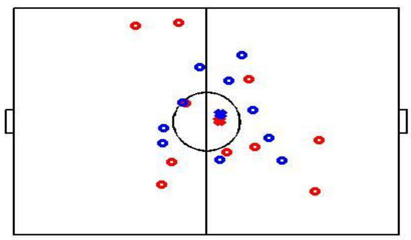


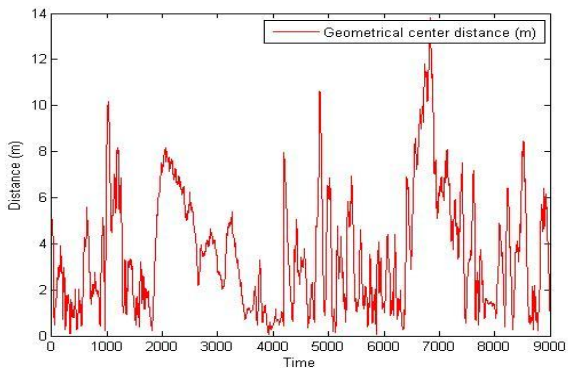



**Computation details:** calculated as the area of a polygon drawn by linking the externally positioned players in each team's formation. These values were computed using Matlab functions (convhull) employing the rule of a convex polygonal area (see left panel).

**Meaning:** This compound variable expresses the relation between the shapes and the occupied spaces of the two teams, and how they change over time. Overlapped areas can also be obtained.

*Team centre*

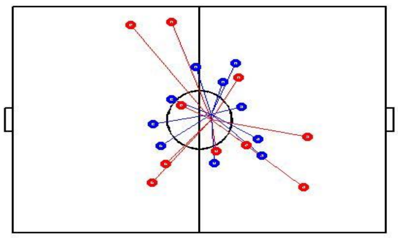


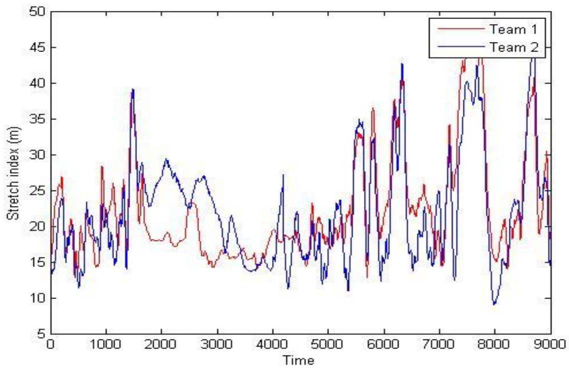



**Computation details:** calculated as the mean position of all team players over time in each axis of motion. Distance between team centres can also be measured (right panel).

**Meaning:** Based on the mean point or "centre of mass" of a team, this variable captures its global oscillatory movements such as movements towards or away from the goals or the sidelines. Distance between the team centres can also be used as an indicator of the closeness of teams.

*Stretch index*

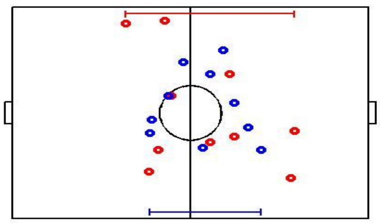


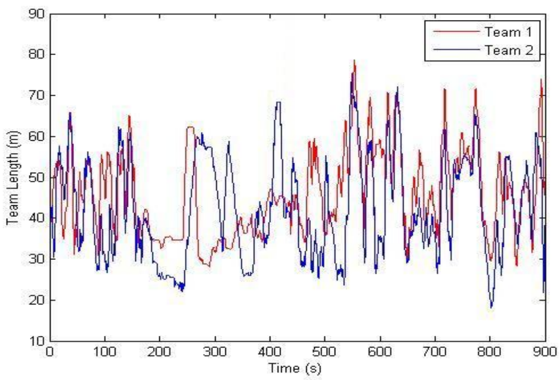



**Computation details:** computed as the average of the vectorial distance of each player to the corresponding team's centre [8] (it can be alternatively calculated decomposing positions in x- and y-axis of motion [9]).

**Meaning:** This compound variable captures the synergistic counter-phase relation of contraction and expansion behaviours of teams as a function of exchanges in ball possession [9]. First derivative of this measure may also evidence the speed at which teams stretch or shorten their dispersion on the field.

*Team length*

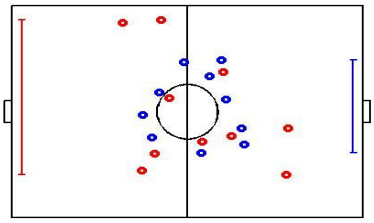


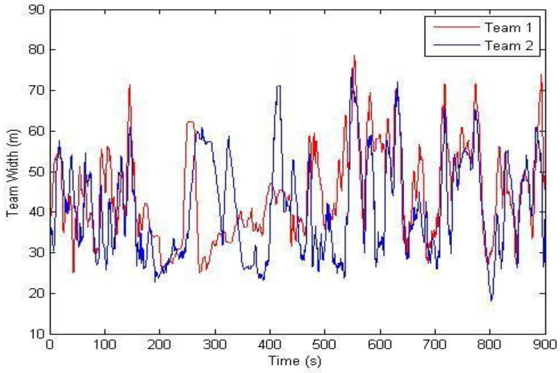



**Computation details:** calculated as the difference between the maximum and minimum positions of players in the field's longitudinal dimension in each time frame.

**Meaning:** This variable captures the compactness of the whole team and its variation as a function of changes in performance constraints. It can be used in the monitoring of specific reference values for team length, or to evaluate depth differences between teams.

*Team width*






**Computation details:** calculated as the difference between the maximum and minimum positions of players in the field's lateral dimension in each time frame.

**Meaning:** When in defence, the width of a team may reveal the potential for the opponents to find inner or outer spaces to penetrate. When attacking, it may indicate the lateral spread of the team.

## 2.8. Acknowledgments

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# 3. Capturing complex human behaviours in representative sports contexts with a single camera

## 3.1. Summary

**Background and objective:** In the last years, several motion analysis methods have been developed without considering representative contexts for sport performance. The purpose of this paper was to explain and underscore a straightforward method to measure human behavior in these contexts.

**Material and Methods:** Procedures combining manual video tracking (with TACTO device) and bi-dimensional reconstruction (through direct linear transformation) using a single camera, were used in order to capture kinematic data required to compute collective variable(s) and control parameter(s). These procedures were applied to a 1vs1 association football task as an illustrative sub-phase of team sports and will be presented in a tutorial fashion.

**Results:** Preliminary analysis of distance and velocity data identified a collective variable (difference between the distance of the attacker and the defender to a target defensive area) and two nested control parameters (interpersonal distance and relative velocity).

**Conclusions:** Findings demonstrated that the complementary use of TACTO software and direct linear transformation permits to capture and reconstruct complex human actions in their context in a low dimensional space (information reduction).

***Keywords*:** TACTO device, Direct Linear Transformation, Representative Sports Contexts, Complex Behavior.

## 3.2. Introduction

In the last years, theoretical and experimental evidence from sport performance literature have emphasized the need for a complex systems approach to sport behaviors [1-4]. In fact, athletes perform in a complex environment within which they exchange energy, matter and information [5]. This mutuality between the performer and his/her surrounding is the basis for the study of behavioral dynamics in sport contexts [6,7]. Accordingly, the dynamics of the environment-athlete system should be captured by context-dependent variables [8]. For example, Passos and colleagues [4] demonstrated how the angle formed between the defender-attacker vector and an imaginary horizontal line parallel to the try line captured the dynamics of attacker-defender interactions in youth rugby union. These types of variables that synthesize several degrees of freedom and describe the dynamics of the sport system sub-phase are called collective variables (or order parameters) [9,10]. The collective variables (i.e., the system's state of order) may change qualitatively by the continuous scaling of other type of variables known as control parameters [9,10] (for an example in sailing see [11]). At critical values, these parameters may abruptly change the state of the system [9,10]. For instance, Passos and colleagues [12] showed how specific values of interpersonal distance and relative velocity (i.e., the control parameters) influenced the dynamics of the attacker-defender interactions in rugby union near the try line, prompting qualitative changes in the previously mentioned angle (i.e., the order parameter).

One way to capture the collective dynamics of team sports at the level of individual-environment system is by means of players' kinematic data collection [13]. In this sense, the selection of procedures to capture and reconstruct players' movement in their context of action comprises one of the most important issues for studying collective behavior in team sports. In the last years, several motion analysis methods have been developed, as well as different mathematical procedures used to reconstruct players' spatial coordinates [14]. Moreover, when analyzing movement with video-system analysis, a critical issue is the transformation of the virtual world data (i.e., what is seen on the computer screen) into real world data (i.e., what occurs in the real frame of reference), minimizing the error [15]. To adequately deal with this problem, the direct linear transformation (DLT) method has been one of the algorithms mostly used for camera calibration and reconstruction [16].

In this methodological paper we will present procedures that joint manual video tracking and bi-dimensional reconstruction (2D-DLT), using a single camera. These procedures will allow the capturing of the kinematic data required to compute candidate order and control parameters to study complex behavior in team sports.

## 3.3. Material and Methods

For illustrating the conceptual and motion analysis procedures used in this line of research, the 1vs1 football sub-phase was selected. This task was previously used by Duarte and colleagues [17] to investigate the interpersonal dynamics between youth football players. A detailed description of the representative task design, data collection, image treatment, camera calibration and 2D-reconstruction, signal filtering, reliability analysis, and data computation is presented.

### 3.3.1. Representative task design

With the purpose of generalizing performers' behavior from the research context (the experimental setting) to the performance context (the football game) [18,19] we created an in situ experimental task. The designed task allowed performers to explore available informational variables and use them to achieve specific mutually exclusive goals (see Figure 3.1).

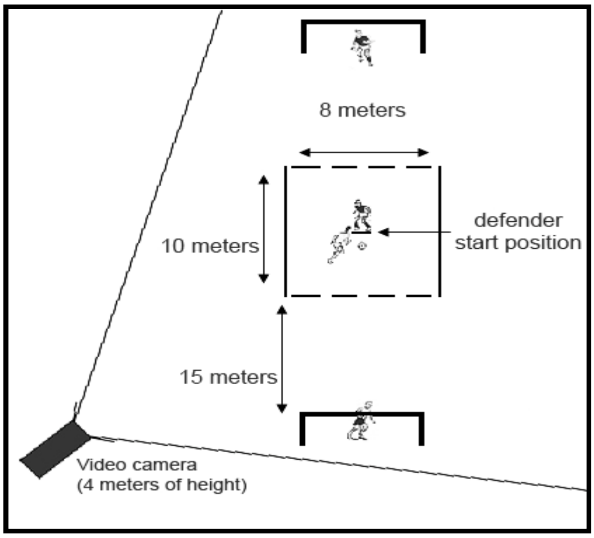


Figure 3.1. Experimental task schematic representation, with the video camera fixed at 4 meters of height and approximately 45 degrees.

### 3.3.2. Data collection

The first step for motion analysis procedures consisted in recording performers' behavior using a regular digital video camera. In the study of 1vs1 football sub-phase taken as a task vehicle, a fixed digital camera was set in an elevated plane (4 meters of height) using a tripod placed on the bleachers of a football stadium. In order to capture the movement of all players participating in each trial, the video camera formed approximately 45 degrees with the longitudinal dimension of the task (see Figure 3.1). The (x,y) coordinates of several non-collinear control points' candidates were also taken for subsequent calibration procedures (see camera calibration and 2D-reconstruction sub-section). Video recorded images of every trial were transferred to digital support, coded and saved as .avi format.

### 3.3.3. Image treatment

For image treatment, we used the TACTO 8.0 software [15] originally created by Fernandes in Microsoft Visual Basic 6.0 programming language. This device has been continuously improved since its original version. It was created to collect and analyze the physical performance of football players [20]. TACTO has been adapted to different goals in several studies, ranging from the measurement of the physical performance

[20,21], to measuring players' behavioral patterns in many sports [6,22], or to the codification of certain action categories [21].

TACTO screen is illustrated in the Figure 3.2. The procedures for digitization consisted in following the selected working point with a mouse cursor. For this study, the working point selected was the middle point between the feet of each player, as this point somehow represents the projection of the player's center of gravity on the ground. The film was played in slow motion (1/2 normal velocity) and virtual coordinates were obtained at 25 Hz. The desktop resolution was 1280x800 pixels and the device window didn't move during the procedures.

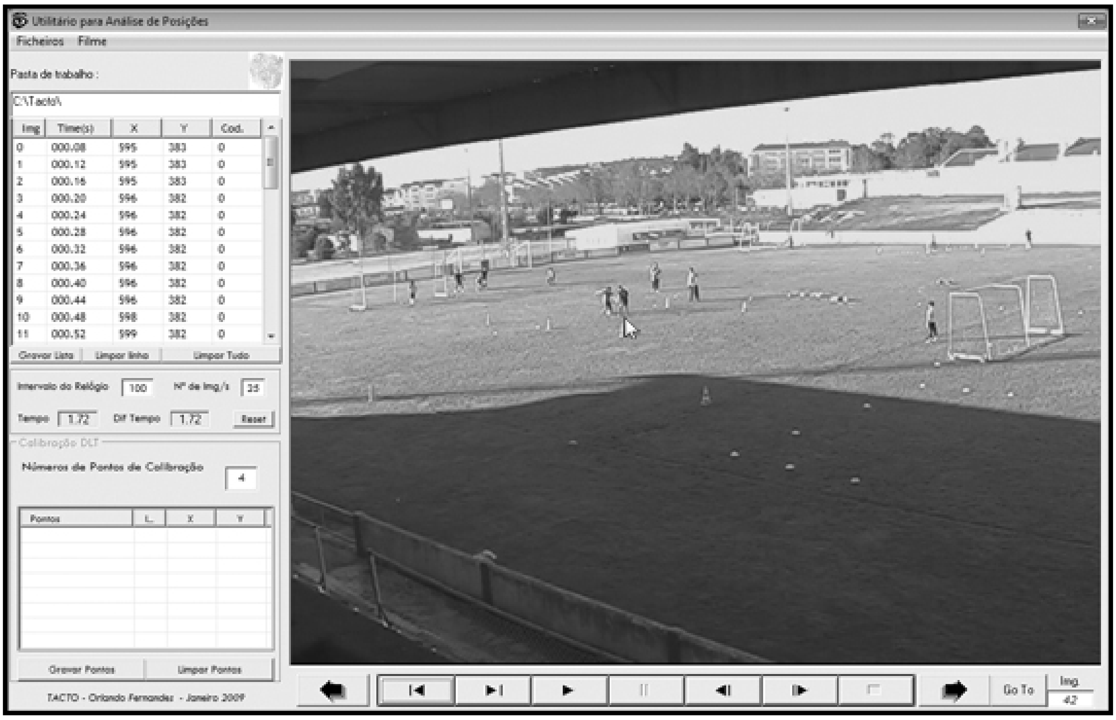


Figure 3.2. The TACTO 8.0 device window. By following a selected working point with the mouse cursor, the software computes over time the virtual coordinates for the tracked object (see up left side of the window).

### 3.3.4. Camera calibration and 2D-reconstruction

In the study of Duarte and colleagues [17], the authors utilized a planar analysis using the 2D-DLT method [16,23] for calibration and object-plane reconstruction. This two-dimensional method uses the same DLT algorithms employed in tri-dimensional analysis, but considers the z-coordinates always equal to zero. DLT method directly relates an object point located in the object space/plane and the corresponding image point on the image plane (see Figure 3.3).

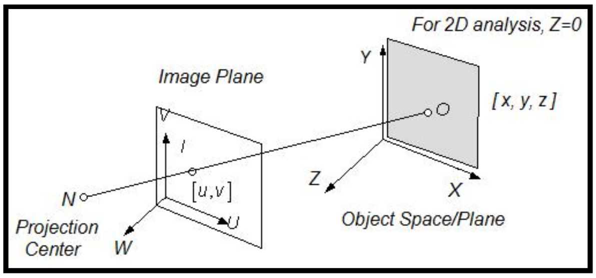


Figure 3.3. Mapping in imaging and reconstruction: Object-space/plane and image-plane reference frames.

Object O is mapped directly to the projected image I. The projection plane is called image plane, while point N is the new node or projection center. Hence, the object point (O), the image point (I), and the projection centre (N) are collinear. This is the so-called collinearity condition, the basis of the DLT method. Two reference frames are defined in Figure 3.3: object-space reference frame (the XYZ-system) and image-plane reference frame (the UV-system). The [x, y, z] is the object-space coordinates of point O, while [u, v] is the image-plane coordinates of the image point I. There is a direct relationship between the object space coordinates, [x,y,z], and the image plane coordinates, [u,v] [16,23], as it is shown in equations (1) and (2) :

$$u_i - u_o - \Delta u_i = -\lambda_u w_o \cdot \frac{t_{21}(x_i - x_o) + t_{22}(y_i - y_o) + t_{23}(z_i - z_o)}{t_{11}(x_i - x_o) + t_{12}(y_i - y_o) + t_{13}(z_i - z_o)} \quad (1)$$

$$v_i - v_o - \Delta v_i = -\lambda_v w_o \cdot \frac{t_{31}(x_i - x_o) + t_{32}(y_i - y_o) + t_{33}(z_i - z_o)}{t_{11}(x_i - x_o) + t_{12}(y_i - y_o) + t_{13}(z_i - z_o)} \quad (2)$$

where i is the control point number, [0,ui,vi] and [wo,uo,vo] are the image plane coordinates of the image point (I) and the projection centre (N), respectively, [xi, yi, zi] and [xo, yo, zo] are the object space/plane coordinates of the object point (O) and the projection centre (N), respectively, [Δui, Δvi] are the optical errors (optical distortion and de-centring distortion [24]) involved in the image coordinates, and [λu, λv] are the scaling factors for the unit conversion from the real-life unit to the digitizer unit (DU).

The t11 – t33 in equations (1) and (2) are the elements of a 3 x 3 transformation matrix from the object-space/plane reference frame to the image-plane reference frame.

Successive rearrangements of equations (1) and (2) resulted in 11 DLT parameters that reflect the relationships between the object-space/plane reference frame and the image-plane reference frame. In the current study, due to the utilization of planar analysis, DLT parameters were reduced to 8 (for mathematical details see [25]).

To study the 1vs1 football sub-phase, several non-collinear control points were tested. The use of 6 points was sufficient for accurate camera calibration and 2D-reconstruction procedures. Figure 3.4 shows control point's location, as well as the bi-dimensional reference frame for this task. In order to ensure the proper calculation of kinematic variables, zero-zero coordinates (0,0) were assigned with 2m of safety margin (see Figure 3.4).

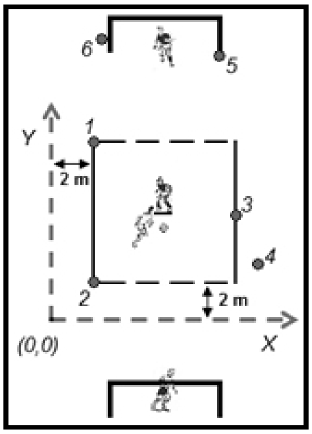


Figure 3.4. Control points and zero-zero coordinates identification.

Table 3.1 displays the real coordinates (x,y) measured in the field and the virtual coordinates obtained from TACTO software.

Table 3.1. Real (m) and virtual (pixels) coordinates of the control points measured.

| Control Point | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| Real X-coordinate | 2 | 2 | 10 | 11 | 9 | 2.9 |
| Real Y-coordinate | 12 | 2 | 7 | 3 | 27 | 28.2 |
| Virtual X-coordinate | 461 | 597 | 642 | 726 | 420 | 325 |
| Virtual Y-coordinate | 339 | 327 | 356 | 362 | 366 | 354 |

These coordinates (i.e., the virtual and the real coordinates) were the starting point to calculate the DLT parameters used in calibration and reconstruction procedures. MATLAB files were then created with 2D-DLT algorithms to create the DLT parameters. These parameters were firstly used for camera calibration, and afterward for image reconstruction.

### 3.3.5. Filtering

Some data fluctuations may be due to lack of accuracy in digitization and calibration processes. Failure to treat these errors properly results in amplified and noisy velocity and acceleration data [16]. However, due to the inherent variability of human movement data, it is difficult to distinguish it from instrumentation noise. In order to adequately deal with instrumentation error, it was used a Butterworth low-pass filter [26]. The original data set was compared with different cut-off frequencies. Figure 3.5 concerns an illustration of this comparison made between a 3Hz and 6Hz filtering cut-off frequency on the x-coordinates of an attacker displacement, in the 1vs1 football sub-phase. The percentage of variance accounted for (VAF), computed as the normalized error between the original and filtered signal, was used to assess the adequate cut-off frequency [27]. Results demonstrated less variation using a 6 Hz's than 3Hz's cut-off frequency. This similarity between unfiltered and filtered data was taken as criterion to use the cut-off frequency of 6Hz for all trials [26].

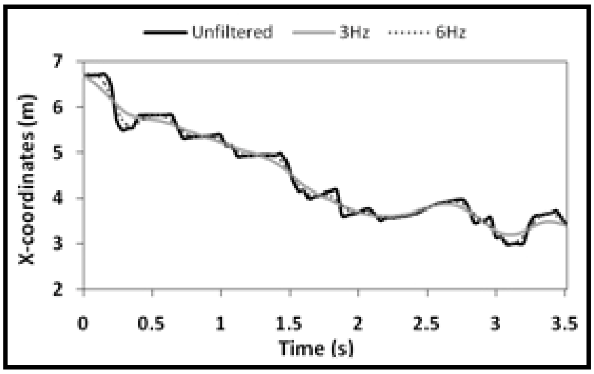


Figure 3.5. Effect of filtering on the x-coordinates of player displacements.

### 3.3.6. Reliability analysis

To obtain data with minimal error we developed a digitization training program during 7 consecutive days. On the first day, the tracking operator (i.e., the observer) completed 5 trials for two times as a pre-test. In the next five days, the operator made 30 trials per day (15 trials x 2 times). On the seventh day, he completed the same pre-test protocol as post-test measures.

For the reliability measurements between trials in pre- and post-test we used Pearson correlation coefficients and variation accounted for (VAF) [27]. Results showed high R values for both pre- and post-tests (pre-test: R=.997±0.004 for x-component and R=.875±.173 for y-component; post-test: R=.996±0.003 for x component and R=.894±.178 for y component). VAF results also demonstrated high percentage of reliability for x- and y-component of the two players both in pre- and post-tests (VAF always > 99.99%).

### 3.3.7. Data computation

After the correct implementation of the aforementioned procedures, the kinematic variables that capture the collective behavior of the system under analysis were calculated. The running distance of any moving object in a t (time) interval was calculated as the sum of partial displacements between each frame. By computing the derivative of the positions in each frame instantaneous velocity data along time was obtained. Specifically created MATLAB files (MATLAB 2008a, MathWorksTM) were used to compute these time-series of kinematic variables. At a dyadic system level, as the one studied, the literature suggests the calculated kinematic variables as potential order and control parameters (for details see [4,6,12]).

## 3.4. Results and Discussion

A graphical example of kinematic variables such as the distance to the defensive line and the velocity data of both players, in a random selected trial, are presented on Figure 3.6.

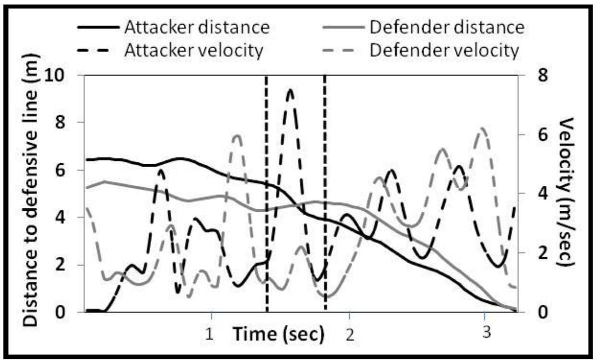


Figure 3.6. Distance to defensive line and velocity data for each player.

Figure 3.6 displays the time-series of the player's distance to defensive line, as well as player's velocity. Vertical dashed lines highlighted the moment where the attacker crossed the defender (i.e., when the projection of attacker's center of gravity on the ground was closer to the defensive line than the defender). At this point, it can be observed the differential velocity between the two players, in favor of the attacker. These preliminary observations help to identify a relevant collective variable that synthesizes the relational quantities between system components (see Figure 3.7).

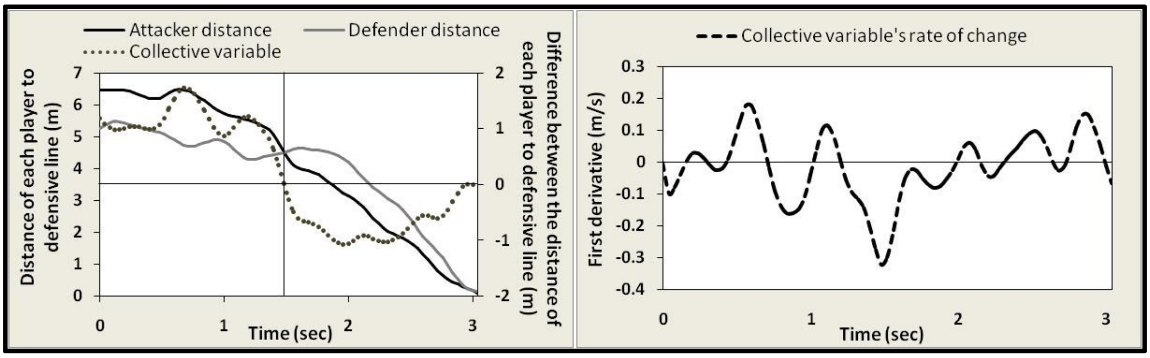


Figure 3.7. Left panel: collective variable of the 1vs1 association football sub-phase and the phase transition between the two different qualitative states of order. Right panel: collective variable's rate of change (first derivative).

The left panel of Figure 3.7 shows how the difference between the distance of the attacker and the defender to defensive line synthesized and described the dynamics of this dyadic system. Near 1.5 seconds, when the attacker over passed the defender player, the collective variable changed qualitatively from positive to negative values. In the right panel, it is observed an increase in the rate of change (maximum absolute peak value) of the collective variable, near 1.5 seconds, associated to a phase transition. The negative rate of change at this moment indicated that attacker's distance to the defensive line decreased faster than the defender's distance.

The moment of phase transition (Figure 3.6, dashed vertical lines) was related to the difference between the velocities of each player. Thus, the relative velocity (i.e., the difference between the velocity of the attacker and the velocity of the defender) was tested as a potential control parameter of this dyadic system. Left panel of Figure 3.8 displays the relative velocity time-series. This variable seems to be related to the phase transitions. This may indicate that the qualitative change of the collective variable was influenced by the increase in the velocity difference between both players. As previous demonstrated [17], a closed examination showed that high relative velocity values promoted phase transitions only when interpersonal distance displayed low values (right panel of Figure 3.8). In fact, the organizational state of the 1vs1 association football sub-phase only jumped to another order state due to the nested influence of the two control parameters (i.e., relative velocity and interpersonal distance).

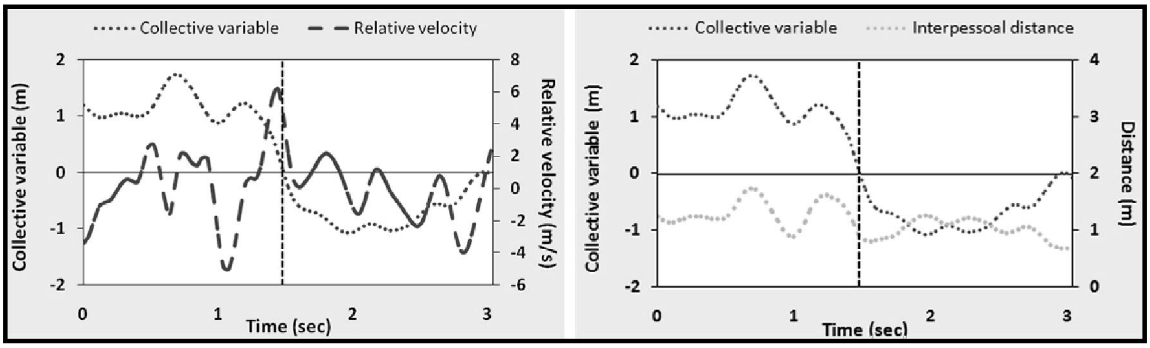


Figure 3.8. Example of the complementarities of relative velocity (left panel) and interpersonal distance (right panel) acting as control parameters of the 1vs1 football sub-phase.

## 3.5. Conclusions

The presented time-motion analysis procedures revealed consistency to reconstruct the players' movement in the performance context, with intra-observer reliability. As demonstrated in this paper, the combination between TACTO device and DLT method provides real kinematic data with minimal error [15,20], allowing to identify relevant order and control parameters. Conceptualized as complex systems [4], the internal and external constraints on players' behaviors can be studied by analyzing the qualitative changes of the order parameter along time [10]. As suggested by Passos and colleagues [4], the rate of change of the order parameter (i.e., its first derivative) seems to be a relevant way to understand this phenomenon.

The presented method captured and contributed to the understanding of the inherent complexity of team ball sport behaviors. The used time-motion analysis procedures can be carried out using a single camera. As a major limitation, manual tracking of each object, one by one, is very time consuming. However, the ongoing improvement of the TACTO device towards more automatic tracking procedures will overcome this limitation. It is worth outlining that these procedures captured the complexity of human movement systems, as the example provided at a team sports' dyadic level. Using the concepts of order and control parameters applied to kinematic data, it is possible to study the collective behavior of the teams at different levels of analysis [3].

## 3.6. Acknowledgments

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# 4. Interpersonal coordination tendencies shape 1-vs-1 sub-phase performance outcomes in youth football

## 4.1. Abstract

This study investigated the influence of interpersonal coordination tendencies on performance outcomes of 1-vs-1 sub-phases in youth soccer. Eight male developing soccer players (11.8±0.4 yrs; training experience: 3.6±1.1 yrs) performed an in situ simulation of 1-vs-1 sub-phase of soccer. Data from 82 trials were obtained with motion-analysis techniques, and relative phase used to measure the space-time coordination tendencies of attacker-defender dyads. Approximate entropy (ApEn) was then used to quantify the unpredictability of interpersonal interactions over trials. Results revealed how different modes of interpersonal coordination emerging from attacker-defender dyads influenced the 1-vs-1 performance outcomes. High levels of space-time synchronisation (47%) and unpredictability in interpersonal coordination processes (ApEn: 0.91±0.34) were identified as key features of an attacking player's success. A lead-lag relation attributed to a defending player (34% in -30º bin) and a more predictable coordination mode (ApEn: 0.65±0.27, $p < .001$), demonstrated the coordination tendencies underlying the success of defending players in 1-vs-1 sub-phases. These findings revealed how the mutual influence of each player on the behaviour of dyadic systems shaped emergent performance outcomes.

***Keywords*****:** performance analysis, interpersonal coordination tendencies, relative phase, approximate entropy, association football.

## 4.2. Introduction

For some time, it has been known that the interpersonal interactions between two players during team game performance can occur in both physical (e.g., when players form a defensive wall in free-kicks or dispute ball possession) and non-physical processes of coordination (Schmidt, O'Brien, & Sysko, 1999). Previous research on coordination in social neurobiological systems has shown that non-physical interpersonal coordination occurs as individuals subtly adapt movement variables such as movement displacement trajectories and personal velocity levels to create space and time. Non-physical interpersonal coordination tendencies are based on the establishment of information-based links between individuals in pursuing specific performance goals (Marsh, Richardson, Baron, & Schmidt, 2006; Richardson, Marsh, & Schmidt, 2005), such as penetration or defence of critical scoring areas.

An extensive body of work has attempted to investigate the interpersonal coordination tendencies that emerge within attacker-defender dyads in team sports (e.g., a competing pair of athletes with opposing aims to score or prevent goals or points). Dyadic systems have been studied in different sport performance contexts like tennis (Lames, 2006; Palut, & Zanone, 2005), squash (McGarry, 2006; McGarry, Khan, & Franks, 1999), 1-vs-1 sub-phases in rugby union (Passos et al., 2008), basketball (Bourbousson, Sève, & McGarry, 2010), and also in Association Football (known as soccer around the globe) (Duarte et al., 2010a). Results from these studies have revealed that different patterns of interpersonal coordination emerge in different sports, due the nature of the specific task constraints shaping these processes in different performance contexts. At the same time, identified spatiotemporal patterns of coordination have been in line with the universal principles of dynamical self-organising systems (McGarry, 2009; Glazier, 2010). McGarry et al. (2002) considered that competing performers in team sports forged and broke interpersonal relations that emerged in space and time in the pursuit of mutually exclusive performance goals. From this perspective, analysis of dynamical patterns of interpersonal relationships between individuals is an important research task that can reveal the preferred modes of coordination that characterise dyadic system interactions in sport (Araújo, Davids, & Hristovski, 2006).

For example, previously, Passos et al. (2008) and Duarte et al. (2010a) have reported how initial dyadic system stability was broken by interpersonal coordination patterns influenced by specific values of key variables like interpersonal distance and relative velocity of attackers and defenders. Consequently, different performance outcomes emerged in 1-vs-1 sub-phases of team sports. Furthermore, Bourbousson et al. (2010) used relative phase analyses to assess dyadic relations between performers during a basketball game. They observed in-phase attractions between players in longitudinal (basket-to-basket) directions, especially for attacker-defender dyads, and both in-phase and anti-phase coordination patterns in lateral (side-to-side) directions. Further research that characterises the relation between performance behaviours and performance outcomes in specific game settings has been called for (McGarry, 2009). Specifically, an understanding of the modes of relations that characterise different performance outcomes in team sports under different task constraints, such as 1-vs-1 sub-phases of soccer, needs to be developed.

The purpose of this study was to investigate whether interpersonal coordination tendencies emerging between opposing players influenced the performance outcomes of 1-vs-1 sub-phases of soccer. In this process, the emergence of two possible performance outcomes was studied: (i) the attacker's success in de-stabilising the dyadic system, and (ii) the defender's success in stabilising the system and recovering ball possession. Specifically, we investigated how different patterns of interpersonal coordination might influence the emergence of the different performance outcomes in this sub-phase of play, with a special emphasis on its variability. We hypothesised that different patterns of interpersonal coordination should characterise distinct performance outcomes.

## 4.3. Methods

### 4.3.1. Participants

Eight male, developing soccer players (age: 11.8±0.4 yrs; weight: 39.3±4.5 kg; height: 1.46±0.1 m) participated in the study. They were deliberately selected to participate in this study due their intermediate level of skill (training experience:

3.6±1.1 yrs; weekly training volume: 90 mins x 3, in addition to competitive experience), to avoid too experienced soccer players with idiosyncratic behaviours, or inexperienced individuals who could not execute actions skilfully. All players and their parents were informed about the procedures, according to the guidelines of the local university ethics committee. All parents signed an informed consent attesting the voluntary participation of their children in the study.

#### 4.3.2. Experimental task

The experimental setting consisted of a simulation of a 1-vs-1 sub-phase of soccer performance on a grass surface, where the attacker tried to destabilize a dyad formed with a defender to move into the free space behind him and create shooting opportunities. Conversely, the defender tried to maintain dyadic stability, recover the ball and attack the opposite goal. Based on expert knowledge of experienced coaches in soccer and in a pilot study, the experimental task was performed in a space of 10x8 m beyond which there was a 15m scoring zone in which players could shoot at a goalkeeper positioned in goal to ensure a representative task design (see Figure 4.1, left panel) (Davids, Button, Araújo, et al., 2006). Each participant performed 4 series of 5 trials as an attacking player, while the other five participants took turns to act in 1 trial as a defender. The experiment resulted in a total of 120 trials. Only 82 trials (n=55 successful attacks and n=27 successful defensive trials), in which one of the players successfully crossed the end line of the central square and got into the scoring/target zone with the ball, were selected for further analysis.

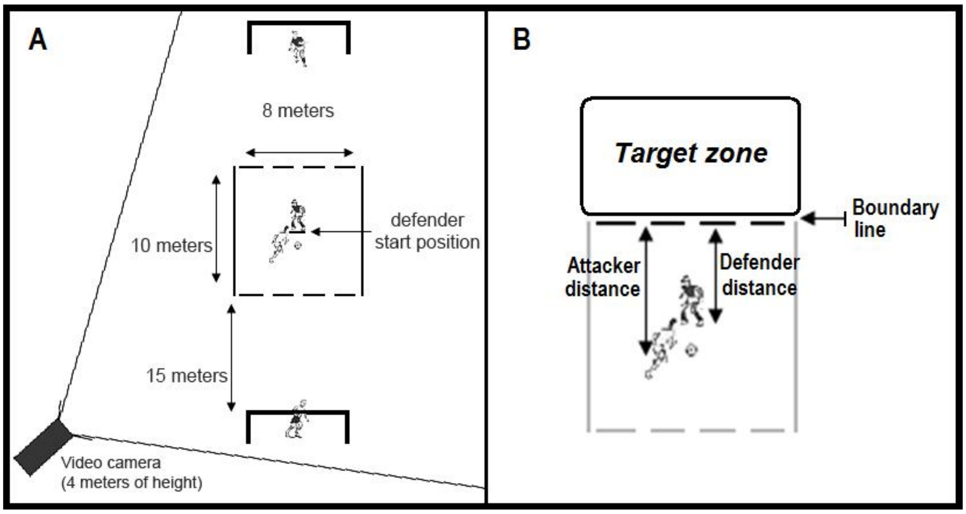


Figure 4.1. Experimental task: Left panel shows the entire experimental setting, including the camera positioning (reprinted with permission from Medicina journal); Right panel highlights the aims and variables used to capture the interaction between players.

### 4.3.3. Procedures

Participants' movement displacement trajectories were captured by a digital video camera placed in an elevated plane (4 m of height), forming an angle of approximately 45º with the longitudinal axis of the performance area. Video recordings were transferred and divided into 82 video files (.avi format), corresponding to the plays selected for further analysis. For image processing and to obtain positional data from players' displacement trajectories, we used a dedicated software package - TACTO 8.0 - with validity reported as superior to 95% (see Fernandes, Folgado, Duarte, & Malta, 2010). The procedure consisted of following with a computer mouse cursor a working point located between the feet of each participant. This working point was used because it represents the projection of the player's centre of gravity on the ground. Camera calibration was made by comparing virtual (pixels units) and real measures (metric units) of six control points. Next, the x and y virtual coordinates of the players were extracted with a data sampling rate of 25 Hz. To transform the virtual into real coordinates we used the bi-dimensional Direct Linear Transformation method (2D-DLT) (Abdel-Aziz & Karara, 1971). The x and y coordinates were subsequently filtered with a Butterworth low pass filter of 3 Hz cut-off frequency (Winter, 2005). To ensure appropriate quality control of measurements, the digitising researcher undertook seven days of a digitisation-training programme. Intra-digitiser reliability was assessed using the 'variation accounted for' measure (VAF) (Moorhouse & Granata, 2007), which revealed high consistence both for x- and y-component of motion (VAF always >99.98%) (for further details about these time-motion analysis procedures see Duarte et al., 2010b).

Considering a 1-vs-1 sub-phase of team sports as a dyadic system, the players can be regarded as two components oscillating in relation to a target zone (i.e., the offensive space which an attacker intends to penetrate, see right panel of Figure 4.1). Thus, to capture the different modes of relations between players in approaching/protecting the target zone, time-series data of the minimum distance of each player to the end line of the central square was calculated for all trials. Matlab® R2008a software (The MathWorks Inc, Natick, MA, USA) was used for all computing procedures.

#### 4.3.4. Statistical analysis of the data

Relative phase calculations with Hilbert transform (Palut, & Zanone, 2005; Rosenblum & Kurths, 1998) were used to measure the phase relations of the minimum distance of each player to the end line over the entire duration of each trial. These measurements were used to capture the interpersonal coordination tendencies established between the players. The relative phase data were then forced into – 180º and 180º limits for frequency analysis using histograms.

Variability of interpersonal coordination tendencies was assessed using standard deviation (SD) of the mean relative phase value (Schmidt, Richardson, Arsenault, & Galantucci, 2007), and approximate entropy (ApEn) (Harbourne & Stergiou, 2009). Whilst SD measured the magnitude of the deviation around the mean tendency, ApEn evaluated the structure of coordination variability (i.e., examining the regularity with which certain patterns of coordination varied over time) (Pincus & Goldberger, 1994). Values of ApEn typically range from 0 to 2, with values closer to 0 indicating greater regularity (i.e., periodicity), values from 0.5 to 1.5 representing chaotic behaviours, and values nearing 2 corresponding to greater irregularity (i.e., more randomness) in pattern variations within a time-series (Harbourne & Stergiou, 2009). Due to the different length of the time-series from each trial, ApEn random ratio values were computed using the Matlab. These normalised values comprised a ratio calculated from the ApEn value for the original time-series divided by the average of the ApEn values calculated from 100 normally distributed random time-series (Fonseca, Milho, & Passos, 2009; Passos et al., 2009). The m (i.e., the length of the vector to be compared) and r (i.e., the tolerance factor) input parameters were set at 2 and 0.2 standard deviations, respectively (Stergiou, Buzzi, Kurz, & Heidel, 2004). In order to compare mean values of ApEn for successful outcomes for both attackers and defenders, a Mann-Whitney U test was performed, while comparison of SD values was made using an F-test. Both analyses were performed in MedCalc® 11.5.1 software (MedCalc Software bvba, Belgium). Alpha levels were maintained at $p < .05$ for both statistical procedures.

## 4.4. Results

### 4.4.1. Interpersonal coordination tendencies

A strong in-phase mode of coordination (47%) was observed for the plays ending in attacking success (see left panels of Figure 4.2). For the plays ending in success for the defending player, the values of preferred mode of coordination decreased and shifted to negative values (34% in -30º bin, see right panels of Figure 4.2).

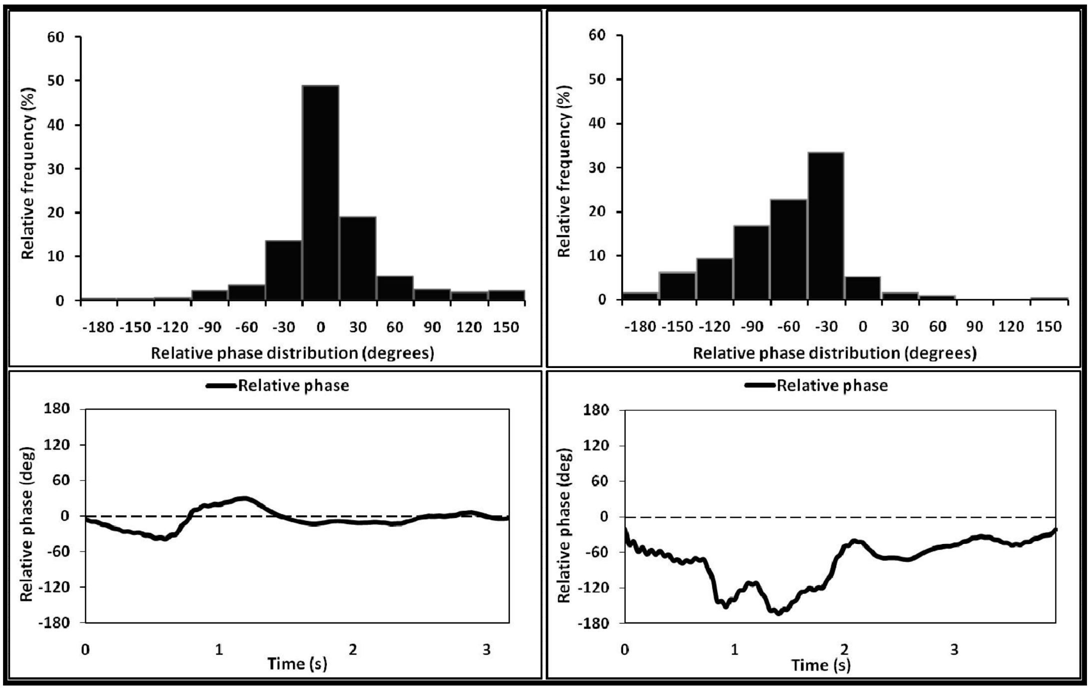


Figure 4.2. Interpersonal coordination tendencies of 1vs1 sub-phases. Upper panels show the overall relative phase histograms for successful trials of attackers (left panel, n=55) and defenders (right panel, n=27). Bottom panels display exemplar trials of relative phase time-series for each of the corresponding performance outcomes.

In order to improve understanding of the lagged relationships for successful outcomes in defending, the plays with clearly demarcated performance success for the defending player were selected and subjected to further analysis. Figure 4.3 displays the relative phase frequencies for the plays with only one crossover between players (i.e., only one reversal in the relative positioning of players), which ended in a successful outcome for a defender.

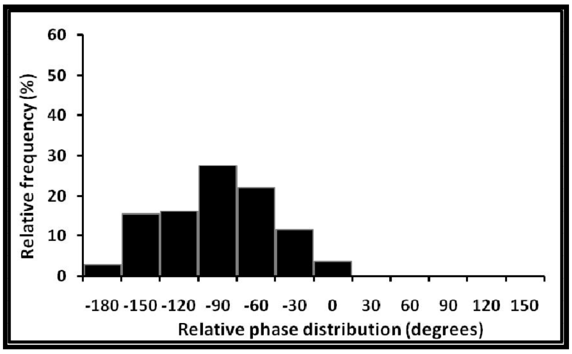


Figure 4.3. Relative phase of the special case of plays with only one crossover between players, ending in successful outcomes for the defenders (n=11 of 27).

In this type of play, the lead-lag phase relations observed in the right panel of Figure 4.2 were emphasized for a -90º mode of coordination (near 28% of the time) with an increase in negative modes of coordination. Negative values showed that, in these types of plays, defenders clearly led the interpersonal interactions.

### 4.4.2. Variability of interpersonal coordination tendencies

In order to assess the variability that underlies interpersonal coordination tendencies between players, measures of SD and ApEn were calculated for the two possible performance outcomes (see Figure 4.4).

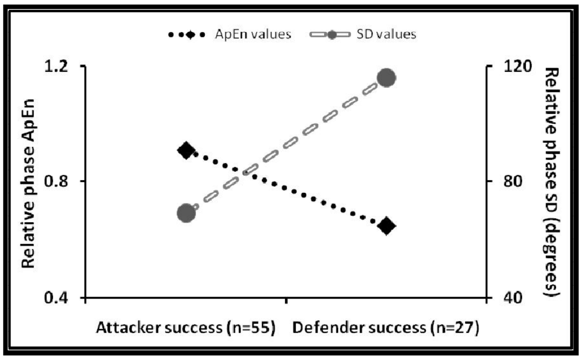


Figure 4.4. Mean data of ApEn and SD of the relative phase.

No differences in SD values were identified between successful outcomes of attackers and defenders ($F(26,54) = 1.5$, $p = .18$). However, values of ApEn were different between the trials in which attackers and defenders succeeded (0.91±0.34 and 0.65±0.27, $U(80) = 3.6$, $p < .001$, $\eta 2 = 0.92$). Data showed that interpersonal coordination tendencies observed in successful outcomes for attacking players displayed significant higher levels of irregularity (less periodicity) over time.

## 4.5. Discussion

The specific purpose of this study was to investigate the influence of interpersonal coordination tendencies on the performance outcomes of 1-vs-1 sub-phases in youth soccer. Results clearly revealed different trends in interpersonal coordination between players in the two performance outcomes, indicating that different mode relations within a dyad tended to influence the final outcome of this sub-phase of play. While successful outcomes for attackers were related to a high level of spatiotemporal synchronisation between players, the success of the defenders was distinctly associated with their ability to lead the relationship (i.e., the to-and-fro movement displacements of defenders preceded the moves of the attacking player).

McGarry (2006) also reported the existence of a lead-lag phase relation (of 135º) within dyads of opposing squash players for radial distances to the T-position (i.e., the central point of the court), with the lag phase being attributed to the movements of the serving player. This type of lagged phase relations evidenced time delays between players' movements. In the successful outcomes for the defending players, the predominant lead-lag phase relations were observed as near in-phase (-30º) for 34% of the time in all trials. These outcomes also depicted a more distributed frequency of values over the entire spectrum of relative phase. In the coordination dynamics literature this phenomenon has been termed 'relative coordination' (Kelso, & Engstrom, 2008). These findings suggest that a higher number of coordination modes were associated with performance success of defending players. Additionally, in plays with clearly demarcated performance success of the defending player, the predominant mode of coordination involved a shift in the phase relations lag to a quarter phase (-90º). This type of change in mode relations was observed in trials where the defender maintained system stability, and recovered ball possession to move past the opponent. Thus, the present findings suggest that trials in which performance was controlled by the defending players were associated with larger time delays in the phase relations led by these players.

On the other hand, for successful attacking outcomes, the preferred mode of coordination did not reveal predominant lagged phase relations. A high level of synchrony between players was observed for 49% of the performance time. Thus, it seems the success of attacking players in destabilising dyads was based on creating a tightly coupling with the defender. Bourbousson et al. (2010) have also reported strong in-phase relations for playing dyads in a longitudinal (basket-to-basket) direction during performance. However, these authors did not report the performance outcomes associated with these dyadic system relations. It is worth noting that, in the present study, the movements of the soccer players were not decomposed into lateral and longitudinal components of motion as in some previous work (e.g., Bourbousson et al., 2010; Palut, & Zanone, 2005). In keeping with the idea of studying phase synchronisation of coupled chaotic oscillators (Rosenblum, Pikovsky, & Kurths, 1996), a single measure was used to express the movement oscillations of each player in the approaching to the scoring zone. This measure consisted of the minimum distance of each player to the line that bounded the scoring zone and was similar to the radial distance measure used by McGarry (2006). This type of measure that integrates relevant task constraints such as target zones and/or goal locations, for instance, seems to more meaningfully capture the coordination tendencies that underlie goal-directed behaviours in team sports (Davids, Vilar, Araújo, & Travassos, 2010; Travassos, Araújo, Vilar, & McGarry, 2011).

Concerning the stability of the interpersonal coordination tendencies that emerged from the interactions of the players, we examined the magnitude (SD) and structure (ApEn) of system variability. While SD measured the magnitude, or 'amount', of deviations around the mean tendency of interpersonal coordination values, ApEn revealed the predictability, or regularity, of the relative phase fluctuations over time (Harbourne, & Stergiou, 2009). In the present study, only ApEn values significantly differed between performance outcomes. That is, the success of the attacker was associated with high ApEn values, while defensive success showed the opposite trend. This finding implies that the dyadic interpersonal coordination tendencies emerging in relation to the attacking player's successful outcomes were characterised by a higher level of irregularity (less periodicity). This higher level of unpredictability seemed to be a key feature related to successful attacking performance in the 1-vs-1 sub-phases of play. In contrast, the success of the defenders seemed to be associated with higher levels of regularity and predictability in the interpersonal coordination tendencies that emerged. These data contrasted with the findings of Passos et al. (2009) who observed that successful performance outcomes for the attacking players in 1-vs-1 sub-phases of rugby union were related to lower values of ApEn, than observed in successful tackles by defending players. These differing results can be attributed to the different nature of the task constraints in both studies, especially the higher levels of physical contact between players allowed in the team sport of rugby union compared to soccer.

This study advanced understanding of 1-vs-1 sub-phases of soccer presented in earlier work by Duarte et al. (2010a), by demonstrating how different modes of interpersonal coordination emerged from attacker-defender dyads to influence performance outcomes in sequences of competitive play. High levels of space-time synchronisation and unpredictability in interpersonal coordination processes were identified as key features of an attacking player's success in 1-vs-1 sub-phases of soccer. A lead-lag relation attributed to a defending player and a predictable coordination mode demonstrated the coordination tendencies underlying the success of defending players in 1-vs-1 sub-phases of soccer. These findings have important implications for learning and practice designs. Attacking players can be constrained and encouraged to develop a highly irregular and creative space-time synchrony with defenders which could abruptly change to atypical, creative and unpredictable behaviours. For instance, attacking players might perform explorative actions such as changing speed, direction and using deception to alter the interpersonal relations in their favour. These explorative actions can be promoted by manipulating some task constraints such as limiting the time to shot on goal, decreasing the area of play, or using additional goals. On the other hand, defenders need to adopt postures and movements suitable for actively influencing an opponent's actions in spaces advantageous for recovering ball possession (e.g., channel the attacker to the side line or move closer to a defending teammate to ensure spatial and numerical advantage). Finally, it is possible that the particular values for dependent variables found in this study were related to specific characteristics of this sample. There is a need for additional work to examine the generality of the data to different samples such as older players or elite performers. The current data imply that interpersonal coordination tendencies may vary within specific ranges according to different levels of skill and experience in participants, but probably maintaining the same general trends observed in this study. It might be expected that skilled players would present small differences in interpersonal patterns of coordination for different outcomes but with larger values of ApEn (Davids, et al. 2003). Therefore, the use of longitudinal designs to assess intervention effectiveness in 1-vs-1 sub-phases of team sports remains a challenging, but important, task for future research.

## 4.6. Acknowledgments

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# 5. Intra- and inter-group coordination patterns reveal collective behaviours of football players near the scoring zone

## 5.1. Abstract

This study examined emergent coordination processes in collective patterns of behaviour in 3vs3 sub-phases of the team sport of association football near the scoring zone. We identified coordination tendencies for the centroid (i.e., team centre) and surface area (i.e., occupied space) of each sub-group of performers (n=20 plays). We also compared these kinematic variables at three key moments of play using mixed-model ANOVAs. The centroids demonstrated a strong symmetric relation that described the coordinated attacking/defending actions of performers in this sub-phase of play. Conversely, analysis of the surface area of each team did not reveal a clear coordination pattern between sub-groups. But the difference in the occupied area between the attacking and defending sub-groups significantly increased over time. Findings emphasised that major changes in sub-group behaviours occurred just before an assisted pass was made (i.e., leading to a loss of stability in the 3vs3 sub-phases).

***Keywords*****:** Group performance; Geometrical centre; Surface area; Coordination tendencies; Association Football.

## 5.2. Introduction

The study of collective system behaviours in nature has contributed to understanding of how large populations of organisms interact together and adapt their actions to achieve common goals (e.g., Deneubourg & Goss, 1989). For example, initial studies of biological systems have revealed spontaneous (i.e., non-externally controlled), emergent collective behaviours in schools of fish (Partridge & Pitcher, 1979; Partridge, 1982), swarms of honeybees (Visscher & Camazine, 1999) and ant colonies (Mallon, Pratt & Franks, 2001; Pratt, Mallon, Sumpter & Franks, 2002). Similar lawful processes have been revealed in studies of human social systems such as waves produced by crowds' at large sporting events, pedestrian escape panic (Farkas & Vicsek, 2005) or traffic flows (Yuan, Wang, Xu & Li, 2005). In line with these findings, previous research has suggested that sports teams can also be regarded as complex, open systems (Gréhaigne, Bouthier & David, 1997; Davids, Araújo & Shuttleworth, 2005; McGarry, 2005), constituted of many degrees of freedom that result from the variety of possible interactions among system components (e.g., the attacker and defender interactions in a team game) (McGarry, Anderson, Wallace, Hughes & Franks, 2002; Davids, Button & Bennett, 2008). In these systems, collective behaviours emerge from the patterns of interpersonal coordination between agents (Bar-Yam, 2004; Passos et al., 2009), as a result of exchanges in energy, matter and information between them (e.g., team players) and their environment (e.g., the performance surroundings that constrain the behaviours of the performers) (Kugler, Kelso & Turvey, 1980; Beek, Peper & Stegeman, 1995).

Previous research on movement coordination has tended to emphasise the analysis of bivariate signals at the within-individual level (e.g., the movement oscillations of two index fingers, Kelso, 1984). In this regard, relative phase was the most prevalent coordinative variable used to assess coordination (also, for an application to interpersonal coordination in racket sports see Palut, & Zanone, 2005). However, the measurement of coordination processes in systems composed of three or more individuals (multivariate data) implies the need for a different strategy to capture and synthesize the state of a complex system.

From a coordination dynamics perspective, Schöllhorn (2003) has proposed some group-motion (kinematic) variables for analysing team sports, such as the surface area occupied by players, the geometrical shape and geometrical centre/or centroid of particular sub-groups of teams. This type of compound physical variables may be useful to synthesise and capture a system's low dimensional dynamics, including social emergent collective behaviours. At this time, few studies have investigated coordination processes when more than two athletes interact over time during team sport performance. Lames, Erdmann and Walter (2010) calculated the centroid and the ranges (in depth and width dimensions) of sports teams to study the spatiotemporal interactions of individuals during competitive performance. They observed a stable synchronisation between performers in opposing teams with few and small perturbations throughout the game. They concluded that the tight spatiotemporal coupling observed between opposing performers evidenced the dependency and mutuality between the two teams studied, and that further work was needed to identify key events that disrupted stability of the coordination between teams. Frencken and colleagues (Frencken & Lemmink, 2008, Frencken, Lemmink, Delleman & Visscher, 2011) analysed centroid and surface area measures to capture the collective behaviours of teams in 4vs4 small-sided football games. They confirmed that measurement of team centroids accurately captured the synchronised tendencies between opposing teams. These investigators reported that the variable occupied surface area did not seem to adequately describe the interaction between opposing teams during competition. However, in some performance contexts there may be some intra-team coordination trends for surface area in these sub-group relations over time. In other words, observed variations in surface area may express intra-team coordination processes as a consequence of cooperative goal-directed behaviours (e.g. a number of teammates coordinating together to create a goal-scoring opportunity). A deeper understanding about the potential utility of these group-motion variables to establish the properties of social complex systems, such as sports teams, is needed. This work might contribute to the later identification of coordination variables in team sports and also in a wide range of other social collectives (Beek, Verschoor, & Kelso, 1997).

Apart from these few studies of intra- and inter-team coordination processes in team sports, notational analysis research has revealed that 75-80% of shots at goal in elite international football competitions emerge from short passing sequences (Hughes, & Franks, 2005). These passing sequences typically involve a reduced number of players acting in localised sub-units trying to break the stability of interactions with the opposing team. Together, these data emphasise the need to investigate the collective behaviours of particular sub-groups of players involved in the creation/prevention of goal-scoring opportunities in the team sport of association football. However, an apparent lack of data in performance contexts other than elite competitions exists. Therefore, the purpose of this paper was to investigate how collective behaviours emerge in 3vs3 sub-phases of intermediate-level youth football near the scoring zone. To achieve this purpose we identified coordination tendencies for the centroid and surface area of each team. Then, we compared these group-motion variables in three key moments of play, to understand their temporal evolution and clarify the intra- and inter-group coordination tendencies developed by the two sub-groups of performers.

## 5.3. Method

### 5.3.1 Participants

Fourteen, male football players (age: M = 11.8, S = 0.4 yrs; training experience: M = 3.6, S = 1.1 yrs) participated in the study. These participants were recruited from the same U13 team, that according to Association Football rules usually play competitively in a 7-a-side game format. Participants were selected due their intermediate level of skill, to avoid too experienced and idiosyncratic footballers, or inexperienced individuals who could not execute actions skilfully. All players and their parents were informed about the procedures and voluntarily agreed to participate in the study.

### 5.3.2 Experimental task

The experimental task was designed to be representative of a sub-phase of play involving creation of scoring opportunities near the scoring zone, typical of a 7-a-side competitive match for this age group. In this performance context, many shooting opportunities are created by disrupting the stability of the relative positioning between attacking and defending players in a 3vs3 sub-phase of performance near a scoring zone (McAvoy, 1998). Therefore, the experimental task consisted of a 3vs3 game, where in order to shoot at goal, the attacking performers needed to make a penetrating pass into the defensive space behind the defending players (see Figure 5.1). The central space in the field of play was 20x20 m, and both defensive spaces were 14.5 m to simulate the goalkeeper's area. The defensive line was used to simulate the task constraints of the 7-a-side off-side rule for this age level. The twelve outfield players were divided into four separate teams. Four games of 5 mins each were performed by the participants, with 3 mins of passive recovery between games (Rampinini et al., 2007).

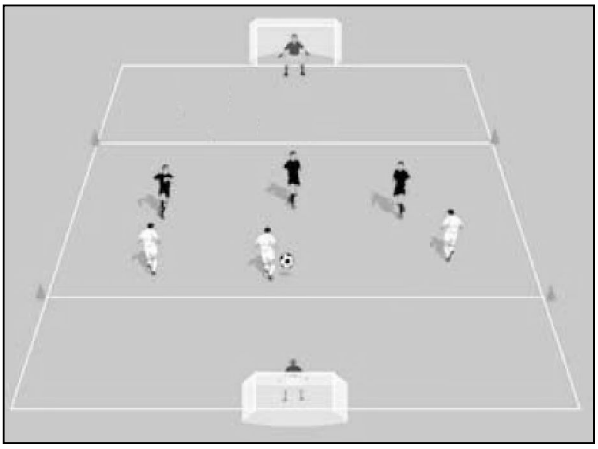

Figure 5.1. Experimental task schematic representation.

### 5.3.3 Procedures

Participants' movement displacement trajectories were captured by a statically positioned digital video camera. For detailed analysis, we randomly selected 20 plays: (i) that ended in shots at goal, (ii) in which the ball did not displace in an aerial trajectory, and (iii), which did not involve changes in ball possession between teams.

These passages of performance represent short sequences in which the attacking team rapidly got into the scoring area after recovering ball possession. Video recordings were transferred and divided into 20 .avi files, corresponding to the selected plays. The beginning of the plays corresponded to the first touch of the attacking player who recovered ball possession. The end of the play corresponded to the moment where the player who entered the scoring area touched the ball. For image treatment and to extract positional data from participants' movement displacement trajectories, we used a dedicated software package, TACTO 8.0, with accuracy levels reported as superior to 95% (Fernandes, Folgado, Duarte & Malta, 2010). Camera calibration was made by comparing virtual (pixels units) and real measures (metric units) of seven control points. Next, the x and y virtual coordinates of the players were extracted with a data sampling rate of 25 Hz. To transform the virtual into real coordinates we used the bi-dimensional Direct Linear Transformation method (2D-DLT) (Abdel-Aziz & Karara, 1971). Detailed information about these time-motion analysis procedures is presented in Appendix section. The x and y coordinates were subsequently filtered with a Butterworth low pass filter (6 Hz) (Winter, 2005). To ensure appropriate quality control of measurements, the digitising researcher undertook seven days of a digitisation training programme, consisting of digitising two random plays per day (i.e., six outfield players involved in each play). On the seventh day, the researcher digitised the same play twice, interspersed by a break of five hours. In order to assess the intra-digitiser reliability we used the 'variation accounted for' measure (VAF) (Morhouse, & Granata, 2007). Results showed high levels of reliability in calculating the displacements of the six digitised players in the x- and y-component of motion (VAF always >99.98%) (for further details about these time-motion analysis procedures see Duarte et al., 2010). Subsequently, the centroid and surface areas of both teams in each play were computed using MATLAB software R2008a (The MathWorks, Inc., Natick, MA). The centroid of each team was calculated as the mean position of the three players over time in the x- and y-component of motion. Next, we determined the smallest distance of the centroid to the defensive line using x-component motion values. The surface area of each team was calculated as the area of a triangle with the following formula for Cartesian coordinates:

Area(A,B,C) = abs((xB*yA-xA*yB)+(xC*yB-xB*yC)+(xA*yC-xC*yA))/2 (equation 1).

### 5.3.4 Data Analysis

To analyse the spatiotemporal interactions between participants in attacking and defending teams, we used a running correlation technique (Corbetta, & Thelen, 1996; Meador, Ray, Echauz, Loring, & Vachtsevanos, 2002; Araújo, Davids, & Hristovski, 2006) that was applied along the entire data time-series recorded for each kinematic variable (i.e., the centroids and surface areas). We used a 0.4-s sliding window (i.e., a 10 data-point window) that was shifted frame by frame (i.e., every 0.04-s). At every shift of the window, a correlation value was calculated, that resulted in a continuous correlation function that described the coordination of both teams, independently, for the centroid and surface area measurements over time (for a detailed description of this technique see Meador et al., 2002). With running correlations we were able to identify three types of coordination tendencies (Corbetta & Thelen, 1996): (i) symmetric patterns when the kinematic variables were predominantly correlated around high positive values; (ii) anti-symmetric patterns when kinematic variables displayed prevalent correlation frequencies around low negative values; and (iii), no correlated patterns when the values did not show a clear tendency for high or low associations.

In order to compare mean values of centroid and surface area of both sub-groups of performers (between-teams factor) at key moments of plays (within-teams factor), we used mixed-model ANOVA. Based on expert coaching knowledge (McAvoy, 1998) we identified three key moments in all the plays: (i) first touch of ball control by the player making the final pass in the move, (ii) last touch in the assisted pass made by the same player, and (iii), time of ball crossing the defensive line. Tukey's HSD test was used to discriminate mean differences in multiple comparisons. Data analyses were conducted using SPSS 17.0 (SPSS, Inc., Chicago, IL). Alpha levels were maintained at $p < .05$ for all statistical procedures.

## 5.4. Results

The average duration of plays was 4.7±2.0 s, with a mean of 2.9±1.8 touches per player and 3.4±2.0 passes per play. Exemplar data from these sequences of play were selected in order to illustrate the relation between the three key moments identified and the evolution over time of the group-motion variables (i.e., centroid and surface area). Thereafter, the correlation landscapes of all trials show how the centroid and surface areas of both teams evolved and interacted across time. Finally, we provide additional results from mixed-model ANOVAs that compared the kinematic variables within- and between-teams during the plays.

### 5.4.1 Coordination Tendencies in 3vs3 Sub-Phases

The upper panel of Figure 5.2 describes the distance of the centroid of each team to the defensive line in a random selected play, as the game evolved in the playing field over time. The time of the three key events has been highlighted. A uniform decrease in the distance of the centroid to the defensive line was observed as a function of time. The bottom left panel shows the very stable corresponding correlation function that indicated a predominance of a symmetric pattern of coordination between the two sub-groups of performers. This observation signifies that both sub-groups moved forward and backward in a highly synchronised spatiotemporal manner. The bottom right panel displays the frequency histogram that strengthens the predominance of high correlation values during this play.

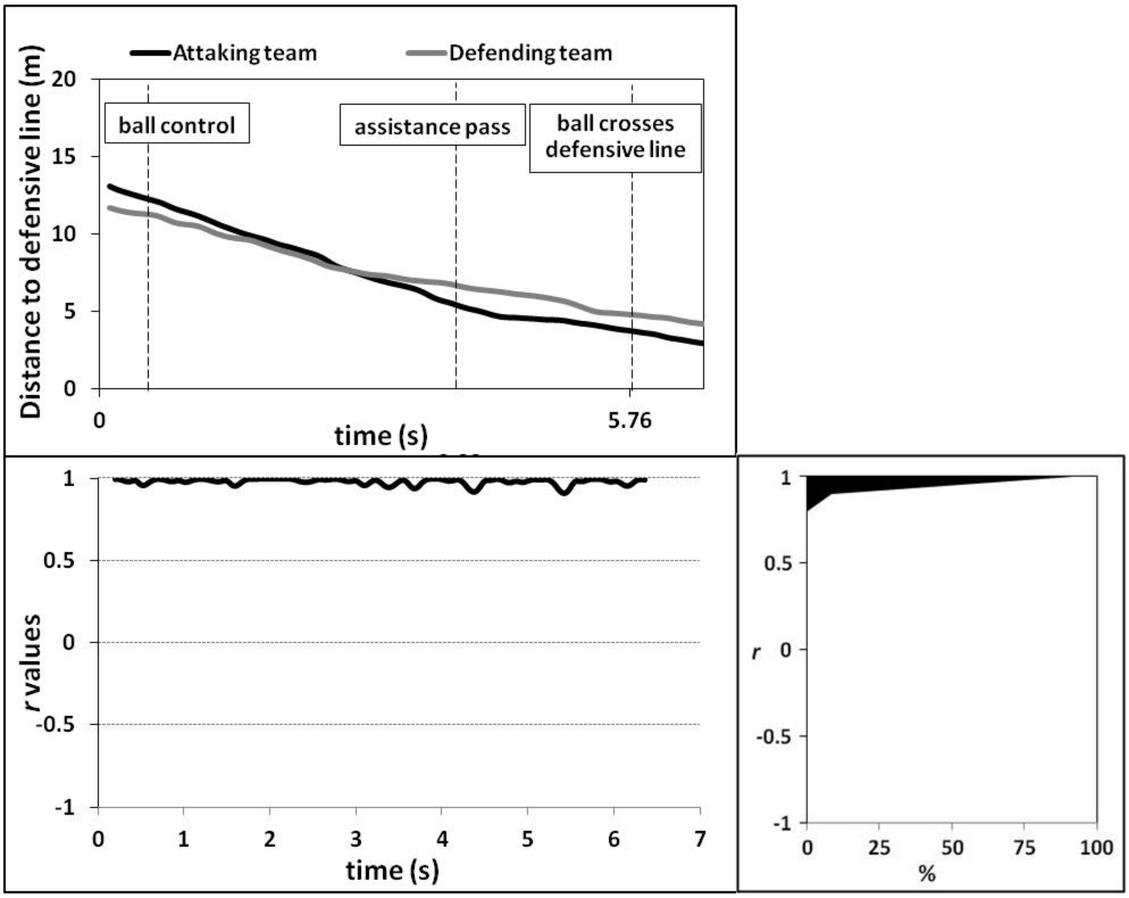


Figure 5.2. Exemplar data of coordination tendencies between both teams for centroids during 7 s of motion in an exemplar play. Top: Variation in the distance of each centroid to the defensive line. Bottom: Respective running correlation function and frequency histogram. The tendency of the correlation function to be predominantly positive is captured by the asymmetrical distribution of frequency histogram (bottom right panel).

Figure 5.3 depicts the correlation landscape for the centroids of both teams in all trials. This view of the data highlighted the global coordination tendencies between the centroids of the two teams.

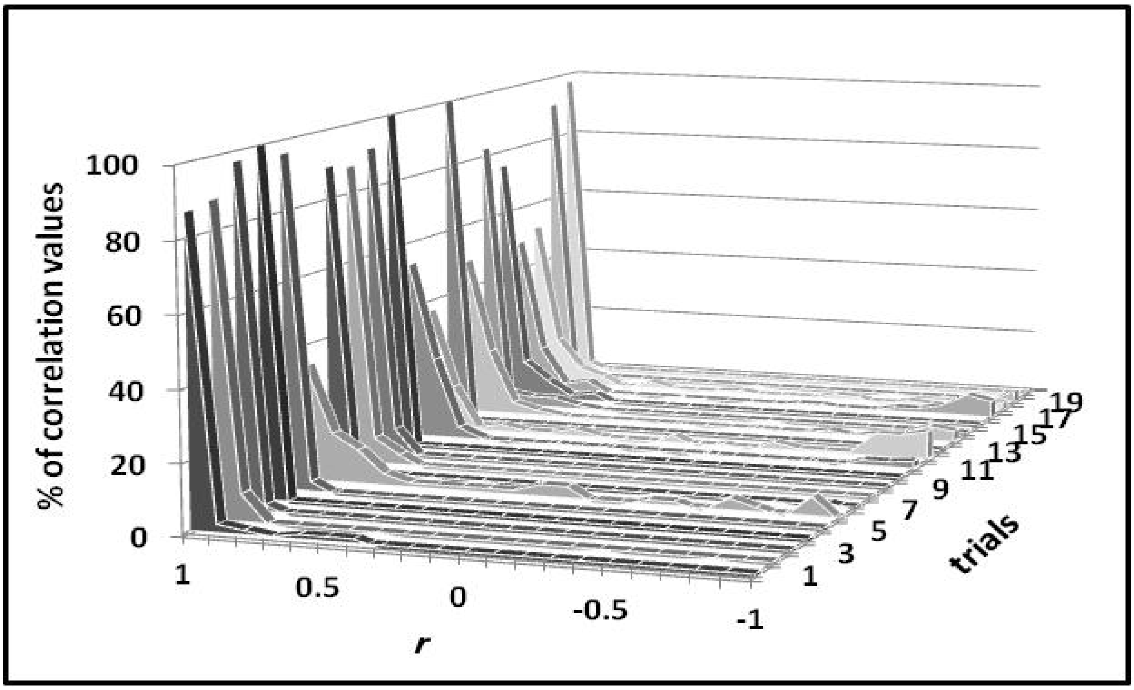


Figure 5.3. Correlation landscape for the distance of each centroid to defensive line in all trials (n=20).

The centroid showed predominantly higher correlation values (i.e., values of *r* near 1) for all trials, confirming that the average position of both teams moved consistently at the same time, in the same direction in all the plays.

Figure 5.4 presents the variations in surface area of each team in the same random selected play presented in Figure 5.2, also evidencing the three key events (upper panel), the corresponding correlation function (bottom left panel) and, frequency histogram (bottom right panel). The data showed that the surface area of each sub-group displayed some fluctuations during the play. Continuous correlation functions also showed high variations between -1 and 1 *r* values, indicating the absence of a clear mode of coordination between the covered areas of the two sub-groups in this play (also observable in the frequency histogram – bottom right panel).

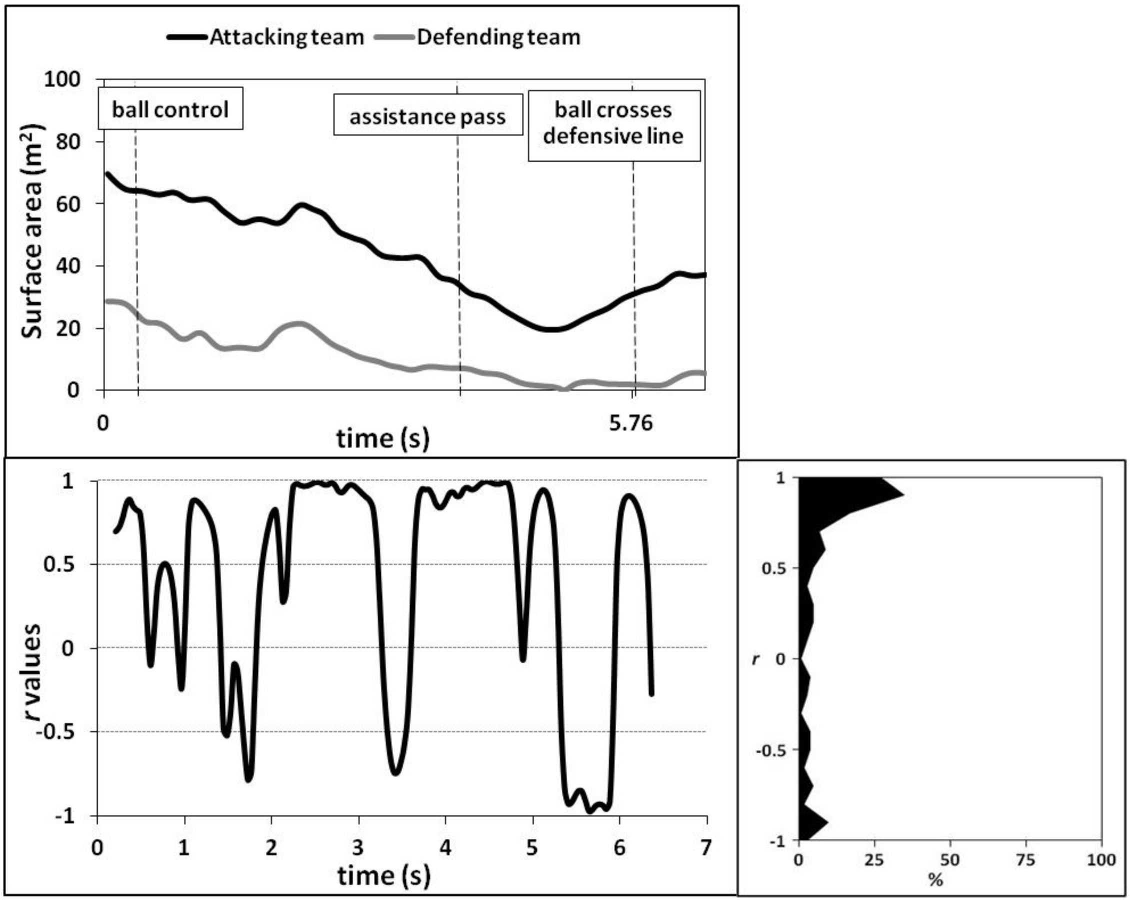


Figure 5.4. Exemplar data of coordination tendencies between both teams for surface area during 7 s of motion. Top: Variation in surface area for both teams. Bottom: Corresponding correlation function and frequency histogram. The fluctuations of the correlation function between positive and negative correlation values resulted in a more equally distributed frequency histogram (bottom right panel).

Figure 5.5 shows the correlation landscape for the surface areas of both sub-groups in all the plays, evidencing their global coordination tendencies between the two teams.

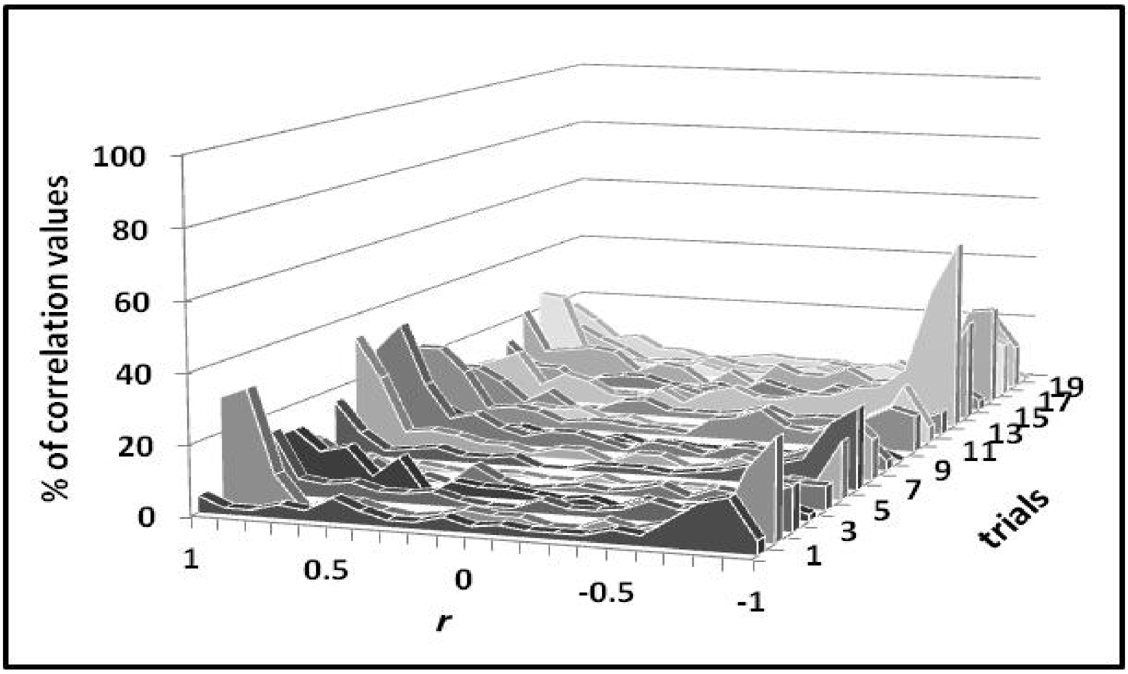


Figure 5.5. Correlation landscape for surface area of each team in all trials (n=20).

The continuous correlation function of the surface areas showed fluctuations between the three possible coordinative states (i.e., symmetric, anti-symmetric and uncorrelated states) with no clear predominant coordination tendencies.

### 5.4.2 Sub-group Relations at Key Moments of the Plays

A mixed-model ANOVA revealed that there were differences in the centroid values of both sub-groups of performers at the three key moments of the plays (see Figures 6), $F$ (1,38) = 21.841, $p$ < .001. Tukey's HSD comparisons revealed that for the attacking team, significant differences were noted between moments of ball control ($M$=9.46, $S$=3.8) and the assisted pass ($M$=6.98, $S$=2.9), and between the moment of ball control and the moment the ball crossed the defensive line ($M$=5.27, $S$=3.2), $p$=.001. For the defending team, Tukey's HSD tests discriminated significant differences between the same moments: ball control ($M$=9.01, $S$=4.0) and assisted pass ($M$=7.08, $S$=3.4), $p$=.001, and ball control and ball crossing the defensive line ($M$=5.72, $S$=3.4), $p$=.003. No differences were observed between the centroids of the attacking and defending sub-groups at any time ($F$ (1,38) = 0.002, $p$ > .05). However, as noted in Figure 5.6, mean results showed a trend for a crossing of the centroids between the moments of ball control and the assisted pass (i.e., the centroid of the attacking team showed a greater decrease of the distance to the defensive line than the centroid of the defending team). This tendency was confirmed by visual inspection in 13 of 20 trials. In the other seven trials we found a tendency for a decrease in the distance between the centroids of both sub-groups.

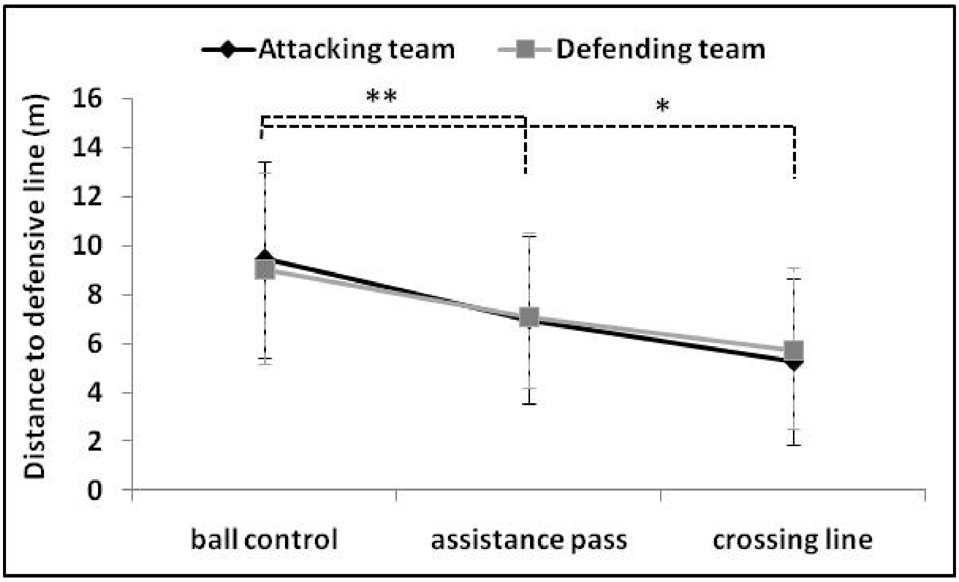


Figure 5.6. Distance of the centroid to defensive line for both teams in the three key moments of play. ** - showed statistical differences between ball control and assistance pass moments ($p < .001$) for both teams; * - showed statistical differences between assistance pass and crossing line moments ($p < .01$) for both teams. Error bars shows standard deviation.

A mixed-model ANOVA revealed that there were differences in the surface area between attacking and defending sub-groups across the three defined moments (see Figure 5.7), $F(1,38) = 10.086$, $p \leq .003$. Tukey's HSD comparisons revealed that the differences were only for the moment of the assisted pass (attacking team: $M$=24.75, $S$=20.0, defending team: $M$=12.55, $S$=10.6, $p = .018$) and for the moment when the ball crossed the defensive line (attacking team: $M$=32.32; $S$=18.8; defending team: $M$=13.18; $S$=11.6; $p = .001$). No differences in surface area were observed at the three key moments of performance ($F(1,38) = 1.345$, $p > .05$.

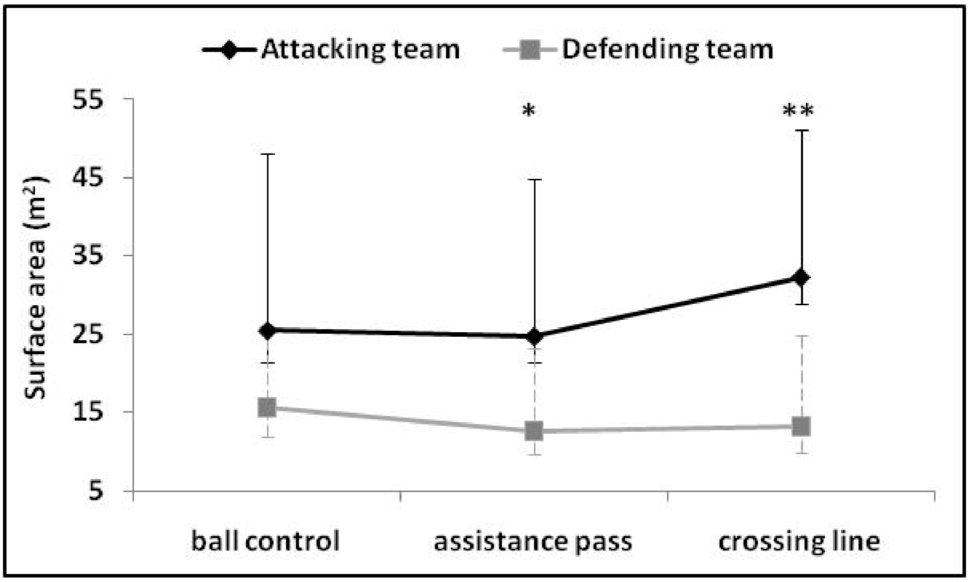


Figure 5.7. Surface area for both teams at the three key moments of performance. * - showed statistical differences between attacking and defending teams at the passing moment ($p$ = .018); ** - showed statistical differences between attacking and defending teams at the moment that the ball crossed the defensive line ($p$ = .001). Error bars shows standard deviation.

## 5.5. Discussion

The main goal of this study was to identify how coordination tendencies between team players emerged from collective system behaviours in 3vs3 sub-phases of performance near the scoring zone in the team sport of football. To achieve this aim, the group-motion variables ‘centroid’ and ‘surface area’ were analysed to capture the interactions within and between two sub-groups of players. We found that the emerging coordination tendencies exhibited a predominantly symmetric pattern between the centroid of the teams in all trials. Despite the fluctuations in centroid displacement time-series, results showed that the average position of both teams approached and moved away from a defensive line in a highly coupled fashion as demonstrated by high positive correlation values. This compound physical variable elegantly captured the rhythmic flow of attacking and defending patterns of play in 3vs3 sub-phases near the scoring zone, in which all the players seemed to move collectively. These results are in agreement with the findings of Frencken and colleagues (2008, 2011) in the team sport of football, and Bourbousson, Sève and McGarry (2010) in basketball, who observed a high synchronisation between team centres in the longitudinal plane of the pitch. However, in the present study, we used a representative practice task that allowed us to capture the coordination dynamics of opposing sub-groups in a specific performance setting where performers tried to create/prevent shooting opportunities (Davids, Button, Araújo, Renshaw, & Hristovski, 2006; Araújo, Davids, & Passos, 2007; Dicks, Davids, & Araújo, 2008).

Results from the statistical analyses showed significantly superior centroid mean values at the moment of ball control by the passing player, compared with the moment of the assisted pass and the moment of the ball crossing the defensive line in both teams. Statistical analyses also showed no significant differences between the distance from the attacking and defending sub-groups' centroids to the defensive line. This finding implies that both teams progressively approached the scoring zone, with high proximity between the centres of the teams at almost all times during competitive performance. Curiously, as Figure 5.6 shows, there is a mean tendency for a crossing, or at least a decrease in the distance, of the centroids of the teams in the immediate instants before the time of the assisted pass. This mean tendency for centroids to cross or, at least, to approach each other, was confirmed by individual inspection for all trials. In an 11-a-side game format, Lames et al. (2010) found an almost perfect synchrony between the centroids of the two teams during the entire match studied. Relating the findings of that study to our data, it may be suggested that the approaching of the centroids reported in the present study might be evidence that transitions at this level of system organization (e.g., as a 3vs3 sub-phase nears a scoring zone) are fundamental for a loss of system stability during collective competitive performance (i.e., 11vs11). This may be one of the main perturbations (McGarry et al., 2002) that might change the organizational state of a competitive match. However, literature suggests that there was not a linear relationship between these transitions at a micro- and macro-level analysis of the system (Grehaigne et al., 1997). These non-linear relationships between different levels of analysis demonstrate the functional role of (micro)variability in (macro)system dynamics (Davids et al., 2005; Davids et al., 2008). This feature of teams' centroid measures to approach each other before the final pass in the move was a consequence of the high rate of change in the distance of the attacking team to the defensive line. This outcome was achieved as a result of stable tendencies in coordination between players within and between each team. Despite the high variability in the individual behaviours of attacking players (e.g., creating support, running along the pitch or creating space for teammates), and defending players (e.g., marking an opponent, covering a teammate, controlling space), the collective patterns of behaviour were very stable among all the trials. As reported by Frencken and colleagues (2008, 2011), these data might suggest that the loss of stability in the 3vs3 sub-phases seems to be related with a previous crossing in the centroids of the teams, or at least, with an approaching between them. In the present study we found that the emergence of the moment of the assisted pass was related to specific spatiotemporal relations between the two sub-groups of players.

For the surface area measure, there were no clear tendencies in running correlation values observed in all trials. The very unstable mode of coordination was characterised by the highly variable fluctuations in correlation functions over time. This feature of performance was indicative of no prevalent pattern of coordination between teams for this compound group-motion variable. In 3vs3 football sub-phases of play, it seems that teams increase or decrease their surface area independently of the behaviours of the opposing team. These data showed that the surface area had limited capacity to capture the coordination dynamics between these two sub-groups of players near the scoring zone, and confirmed the proposals of Frencken and colleagues (2008, 2011) with regards to this variable. However, it may be hypothesised that variations in surface area of each team are the result of coordination tendencies emerging within each team, constrained by the functional relations between their own players during the approach to the scoring zone. Results from a mixed-model ANOVA confirmed these expectations, by showing that differences between teams progressively increased along the three key moments of performance (i.e., ball control, assisted pass and crossing line), despite the absence of prevalent patterns of coordination between teams in the correlation landscape. This finding can be indicative of within-group coordination processes, in which attacking players coordinated their actions in order to increase team space to move into the scoring zone, with some degree of independence from the opposing group of performers. Focusing on the post hoc tests results, we found that the differences were observed only at the moments of the assisted pass and when the ball crossed the defensive line. These findings might suggest the importance of increasing the surface area to the attacking sub-groups in order to destabilise the opposing team and to create shooting opportunities (Grehaigne et al., 1997), but only immediately before the moment of the assisted pass. However, in this study we did not compare successful and unsuccessful plays to better support this explanation. This is an issue for further research. The apparent lack of surface area to describe the coordination between the sub-groups near the scoring zone may not be transferable to other sub-phases of play or the context of the full match. For example, it might be argued that sudden changes in surface area of the teams at match level might be indicative of exchanges in ball possession. In this study, we investigated only plays without exchanges in ball possession, and these propositions need to be tested empirically.

To summarise, in this study, we investigated the collective patterns of behaviour in 3vs3 sub-phases of play in a representative context of creation/prevention of goal scoring opportunities. The centroids of the sub-groups demonstrated a strong symmetric relation that described the collective attacking/defending performers' behaviours in this sub-phase near the scoring zone. This relation showed a mean tendency for an approaching (even a crossing) of the centroids immediately before the loss of stability in the system (i.e., the assisted pass). The surface area did not show a clear coordination pattern between teams. However, it revealed that the difference in the occupied area between the attacking and defending teams also significantly increased immediately before the assisted pass was made. The between- and within-team coordination tendencies reported for these compound group-motion variables allowed an understanding of the dynamics of the collective behaviours in this typical competitive performance situation. Results also emphasised that major changes in sub-group behaviours occurred just before an assisted pass was made in the performance sub-phase.

The current study showed how interpersonal coordination processes within and between two small groups of competing football players can be captured by compound physical variables that synthesised the functional relationships between individuals and the performance environment. The time-evolved group behaviours described in this study were related to discrete game events considered as influential in breaking the initial stability of the relative positioning of the two sub-groups. The current investigation used methods and tools that can be applied to develop a deep understanding of interpersonal coordination processes in other team sports and in other social collectives where continuous interactions between people is an important issue and has a crucial meaning.

## 5.6. Appendix

Time-motion analysis procedures used in the current study involved manual video tracking and bi-dimensional reconstruction, using a single video camera. Here, we briefly describe the sequential steps of the method.

*1. Data collection* – The first step consisted of recording the participants' behaviours using a regular digital video camera statically positioned at 30 m from the pitch. It was placed at 5 m of height, perpendicular to the longitudinal component of the pitch and with an angle of elevation of approximately 10º. Before the start of the experiment, several non-collinear control points (corresponding to specific landmarks visible in the video camera) were measured for later calibrations.

*2. Image treatment* – The software package TACTO 8.0 (Fernandes et al., 2010) was used to extract the positional coordinates (pixels units) from participants' movement displacement trajectories. The procedure consisted of following with a computer mouse cursor a working point located between the feet of each participant. This working point was used because it represents the projection of the player's centre of gravity on the ground (Duarte et al., 2010). The TACTO package was also used to assess the virtual coordinates of the seven control points selected that afterwards were used for calibration.

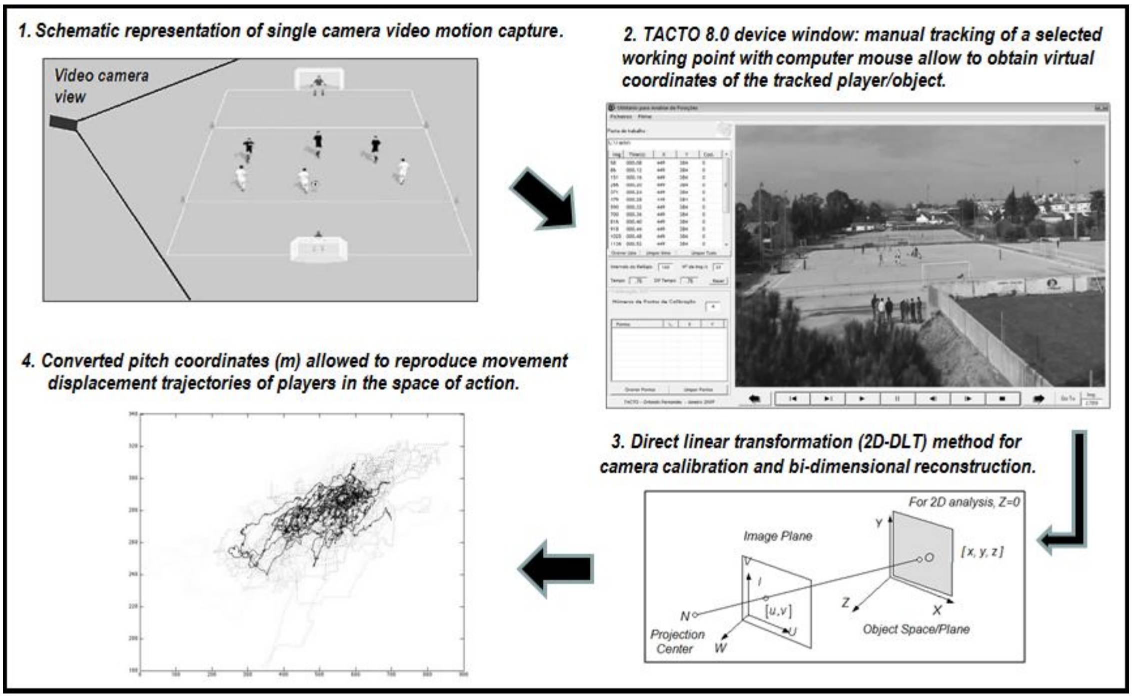


Figure 5.8. Flow chart representation of the time-motion analysis procedures employed.

*3. Camera calibration and bi-dimensional reconstruction* – Camera calibration and object-plane reconstruction were made using bi-dimensional Direct Linear Transformation (2D-DLT) method (Abdel-Aziz & Karara, 1971; Kwon, 2008). This two-dimensional method uses the same DLT algorithms employed in tri-dimensional analysis, but considers the z-coordinates always equal to zero. The DLT method is considered also to deal with some measurement errors reported by other methods such as optical distortion and de-centring distortion (Marzan & Karara, 1975). The DLT method directly relates an object point located in the object space/plane and the corresponding image point on the image plane from the camera. Two reference frames are defined object-space reference frame (the *XYZ*-system) and image-plane reference frame (the *UV*-system) (see bottom left panel of Figure 5.8). The [*x, y, z*] is the object-space coordinates of point *O,* while [*u, v*] is the image-plane coordinates of the image point *I*. There is a direct relationship between the object space coordinates, [*x,y,z*], and the image plane coordinates, [*u,v*], as it is shown in equations (1) and (2) :

$$u_i - u_o - \Delta u_i = -\lambda_u w_o \cdot \frac{t_{21}(x_i - x_o) + t_{22}(y_i - y_o) + t_{23}(z_i - z_o)}{t_{11}(x_i - x_o) + t_{12}(y_i - y_o) + t_{13}(z_i - z_o)} \quad (1)$$

$$v_i - v_o - \Delta v_i = -\lambda_v w_o \cdot \frac{t_{31}(x_i - x_o) + t_{32}(y_i - y_o) + t_{33}(z_i - z_o)}{t_{11}(x_i - x_o) + t_{12}(y_i - y_o) + t_{13}(z_i - z_o)} \quad (2)$$

where *i* is the control point number, $[0,u_i,v_i]$ and $[w_o,u_o,v_o]$ are the image plane coordinates of the image point (*I*) and the projection centre (*N*), respectively, $[x_i, y_i, z_i]$ and $[x_o, y_o, z_o]$ are the object space/plane coordinates of the object point (*O*) and the projection centre (*N*), respectively, $[\Delta u_i, \Delta v_i]$ are the optical errors (optical distortion and de-centring distortion, Marzan & Karara. 1975) involved in the image coordinates, and $[\lambda_u, \lambda_v]$ are the scaling factors for the unit conversion from the real-life unit to the digitiser unit (DU). The $t_{11}$ – $t_{33}$ in equations (1) and (2) are the elements of a 3 x 3 transformation matrix from the object-space/plane reference frame to the image-plane reference frame.

Successive rearrangements of equations (1) and (2) resulted in 11 DLT parameters that reflect the relationships between the object-space/plane reference frame and the image-plane reference frame. In the current study, due to the utilisation of planar analysis, DLT parameters were reduced to 8.

Using the virtual and pitch coordinates of the 7 control points, we calculated the DLT parameters used for camera calibration and image reconstruction procedures according the algorithms presented in Woltring and Huiskes (1990).

## 5.7. Acknowledgments

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# 6. Capturing complex, non-linear team behaviours during competitive football performance

## 6.1. Abstract

This study investigated changes in the complexity (magnitude and structure of variability) of the collective behaviours of association football teams during competitive performance. Raw positional data from an entire competitive match between two professional teams were obtained with the ProZone® tracking system. Five compound positional variables were used to investigate the collective patterns of performance of each team including: surface area, stretch index, team length, team width and geometrical centre. Analyses involved the coefficient of variation (%CV) and approximate entropy (ApEn), as well as the linear association between both parameters. Collective measures successfully captured the idiosyncratic behaviours of each team and their variations across the six time periods of the match. Key events such as goals scored and game breaks (such as half time and full time) seemed to influence the collective patterns of performance. While ApEn values significantly decreased during each half, the %CV increased. Teams seem to become more regular and predictable, but with increased magnitudes of variation in their organisational shape over the natural course of a match.

***Keywords*:** complexity; social collective system; variability; association football.

## 6.2. Introduction

Recently, analysis of the complex social interactions developed within and between sports teams has been developed using 2D positional data[1]. In order to study the emergent collective behaviours of sports teams, these analysis methods require the use of *compound positional variables* to functionally synthesise the high dimensional information emerging from the multiple interactions between players' on-field[2,3]. This methodological approach is harmonious with proposals of team games modelled as self-organising dynamical systems[4], to support the capture of complex team behaviours during competitive performance. These theoretical and empirical advances suggest that sports teams can be studied as social collective systems displaying emergent collective behaviours from complex, non-linear interpersonal interactions of players in space and time[5]. The conception and evaluation of *compound positional variables* that capture emergent behaviours at the team level is an important ongoing task to enhance the understanding of complex non-linear interactions of players in team sports.

Some *compound positional variables* have already been proposed to capture complex group behaviours that express the collective patterns of performance in team sports. These variables include: the *surface area* occupied by teams[6], *geometrical centre* of teams[7], *stretch index* of teams[8] (also known as *radius*[1]), and *team ranges* (also known as *length and width* of the team[7]). These variables are related to the degree of dispersion/aggregation of team players on the field and all have been used to investigate specific performance issues related to team sub-systems or coordination processes during specific game sub-phases. For example, it has been demonstrated that the geometrical centres of competing football teams tend to be tightly coupled in the longitudinal (goal-to-goal) and lateral (side-to-side) directions, during competitive performance[7]. Yue and colleagues[9] showed that longitudinal collective movements of competing teams were tightly coupled with the longitudinal movement of the ball. In contrast, lateral collective movements of both teams displayed a coupling delay of about 2 s with the ball's lateral movement. Analysis of the stretch index measure has shown that the dispersion of teams on-field tend to follow a dynamical counter-phase relation[1]. When a team is contracted, the shape of the opposing team tend to be expanded and vice-versa. These expansion/contraction patterns of collective behaviour typically emerge as a function of changes in ball possession between teams[8]. Despite these findings, research in this domain is in its infancy and a number of relevant applied and theoretical questions concerning the emergent patterns of performance in sports teams remain unanswered, including: How do specific teams tend to behave throughout a competitive match? What sort of events influences the emergence of collective patterns of behaviour during competitive performance? And what kind of system complexity (structure of variability) underlies the performance of teams over the course of a match?

Using approximate entropy analyses, Passos and colleagues[10] showed how the level of physical contact in 1vs1 sub-phases of rugby union (i.e., a tackle) increased the complexity/irregularity of the interactions between the opposing players. However, there have been no attempts to investigate the complexity of collective patterns of performance at the team level throughout a competitive match. Besides, some notational analysis studies have reported a strong influence of situational variables, including: match location, quality of opposition and the evolving scoreline, on key performance indicators such as percentage of ball possession[11] and distances covered by players at different intensities[12].

The current case study aimed to investigate whether key events such as goals scored and game breaks, such as half- and full-time, influenced the emergent patterns of collective behaviours in sport teams. A second aim of this case study was to investigate the complexity of team collective behaviours, in terms of their magnitudes and structures of variability during a competitive match. It was hypothesised that the collective behaviours of teams would change in complexity during a competitive game, constrained by the natural changes associated with evolving time during performance.

## 6.3. Methods

### 6.3.1. Sample and Data Acquisition

Twenty-eight elite, male, professional football players (22 starting players and 6 substitutes) participated in a competitive match in the English Premier League (season

2010-2011). Participants ranged in age from 22 to 34 yrs (average 26 yrs) and included 19 international level performers from 8 different countries. The experimental protocol was approved by the Ethics Committee of the Faculty of the leading author of this study.

### 6.3.2. Procedures

Raw positional data (2D) of player performance was obtained using the ProZone® tracking system (Prozone®, ProZone Holdings Ltd, UK), previously validated[13]. This video-based, multi-player tracking system uses 8 colour cameras (Vicon surveyor 23x cameras dome/SVFT-W23) installed in the stadium to cover every area of the pitch. This coverage prevented possible losses of signal in moments of high aggregation of players during performance. After automatic tracking, quality control procedures consisted in the use of: (i) Kalman filters to predict possible direction of an object, given its current speed[14], (ii) computer vision homography to convert image coordinates into world pitch coordinates[15], (iii), quality control operators verifying (and re-identifying when necessary) that the displacement trajectories identified for each player remained constant to that specific player. Data were obtained at a sampling rate of 10Hz. Raw positional data for each player were provided through individual spreadsheet files. A single file containing the 2D positional raw data of the 22 on-field players was created. Moreover, when a player was substituted, the 2D positional data of his teammate was added to his data columns with a timestamp corresponding to the moment of substitution. This single file contained time-series of 54,000 data points for each player (27,000 data points for each half of the match) corresponding to 90 minutes of the game. Added time played in both halves was excluded.

Five *compound positional variables*, verified in existing literature, were calculated for each team during the entire match. As proposed in other investigations[7], the following collective measures of performance were calculated only for the 10 outfield players of each team, excluding the goal keeper:

i) *surface area*, represents the occupied/covered area of each team[6], calculated as the area of a polygon drawing by linking the externally positioned players in each team's formation in each time frame;

ii) *stretch index*, also known as the *radius*, represents the mean dispersion value of the players around the centre (i.e., the *geometrical centre*) of each team[1,8]. It was computed as the mean of the vectorial distance of each player to the corresponding team's centre;

iii) *team length*, represents the maximum length of a team, calculated as the difference between the maximum and minimum positions of players in the field's longitudinal dimension in each time frame[7];

iv) *team width*, represents the maximum width of a team, calculated as the difference between the maximum and minimum positions of players in the field's lateral dimension in each time frame[7];

v) *geometrical centre*, represents the centre of gravity of the team[9], calculated as the mean position of all team players over time. To capture the teams' oscillations in relation to the goals, only the longitudinal component of motion was used to compute this variable.

All computations were developed using dedicated routines implemented in Matlab® R2008a software (The MathWorks Inc, USA).

### 6.3.3. Data Analysis

Descriptive statistics such as mean (M), standard deviation (SD), percentage of coefficient of variation (%CV), and percentage of root mean-square difference (%RMSD) were used to analyse the magnitude of variations in data[16], along six time periods of 15 mins duration (three in each half, e.g.[17]). See corresponding equations below:

$$\bar{x} = \frac{1}{n} \cdot \sum_{i=1}^{n} x_i \quad \text{(Eq. 1)}$$

$$\sqrt{\sum_{i=1}^{n} (\bar{x} - x_i)^2 / (n-1)} \quad \text{(Eq. 2)}$$

$$100s/\bar{x} \quad \text{(Eq. 3)}$$

$$100\sqrt{\sum_{i=1}^{n}(x_C - x_i)^2/n}\Big/\sqrt{\sum_{i=1}^{n}(x_C)^2/n} \qquad \text{(Eq. 4)}$$

Approximate entropy (ApEn) measures were used to assess the complexity of the particular collective behaviours during the six time periods of the match. ApEn is a non-linear statistical tool which determines system complexity by quantifying the regularity (i.e., periodicity) of a time-series[18]. Its measurements provide information about the structure of variability (i.e., the regularity with which certain patterns of variation occur) in a time-series[19]. The computation of ApEn is based on the construction and comparison of patterns of length *m*. Given *N* data points {*u(i)*} with *i* =1, ... , *N*, the algorithm constructs sequences $x_m(i)$ obtained by taking $x_m(i) = [u(i), . . . , u(i + m - 1)]$, and it computes, for each $i \leq N - m + 1$, the quantity:

$$C_i^m(r) = N^{-1}\{\text{number of } x_m(j) \text{ such that } d[x_m(i), x_m(j) \leq r]\} \qquad \text{(Eq. 5)}$$

where $d[x_m(i), x_m(j)]$ is the distance between the vectors, defined as $\max\{|x(i) - x(j)|, ..., |x(i + m - 1) - x(j + m - 1|\}$.

$C_i^m(r)$ measures, with a tolerance *r*, the regularity patterns by comparing them with a given pattern length *m* (*m* and *r* are fixed values: *m* is the length of the vector to be compared, *r* is a threshold or tolerance factor, which filters out irregularities). Thereafter, $\phi^m(r)$ is defined as the average value of ln $C_i^m(r)$, where ln is the natural logarithm. The estimator of this parameter for an experimental time series of fixed length *N* is given by:

$$ApEn(m, \quad r, \quad N) = [\Phi^m(r) - \Phi^{m+1}(r)] \qquad \text{(Eq. 6)}$$

In the current study, the *m* and *r* input parameters were set at 2 and 0.2 standard deviations, respectively[20,21], and *N* corresponded to the 9,000 data points (i.e., the length of *compound positional variables* time-series for every 15-mins time period analysed). Measures of Analysis of Time Series (MATS) Matlab toolkit[22] was used to calculate ApEn values.

In order to evaluate changes in the complexity/regularity of the collective behaviours across the match (x 6 time periods of 15 mins), distributions of ApEn were analysed using Friedman's rank-test, because it uses pairings of data across moments that are group-independent within each particular moment. Wilcoxon's tests were used also for pairwise comparisons between successive time periods. Statistical analyses were performed using IBM SPSS® 19.0 software (IBM, Inc., Chicago, IL). Alpha levels were maintained at $p < .05$.

## 6.4. Results

### 6.4.1. Variations in the patterns of collective behaviour

Mean data from the five *compound positional variables*, divided in the time periods of 15 mins, are presented in Figure 6.1.

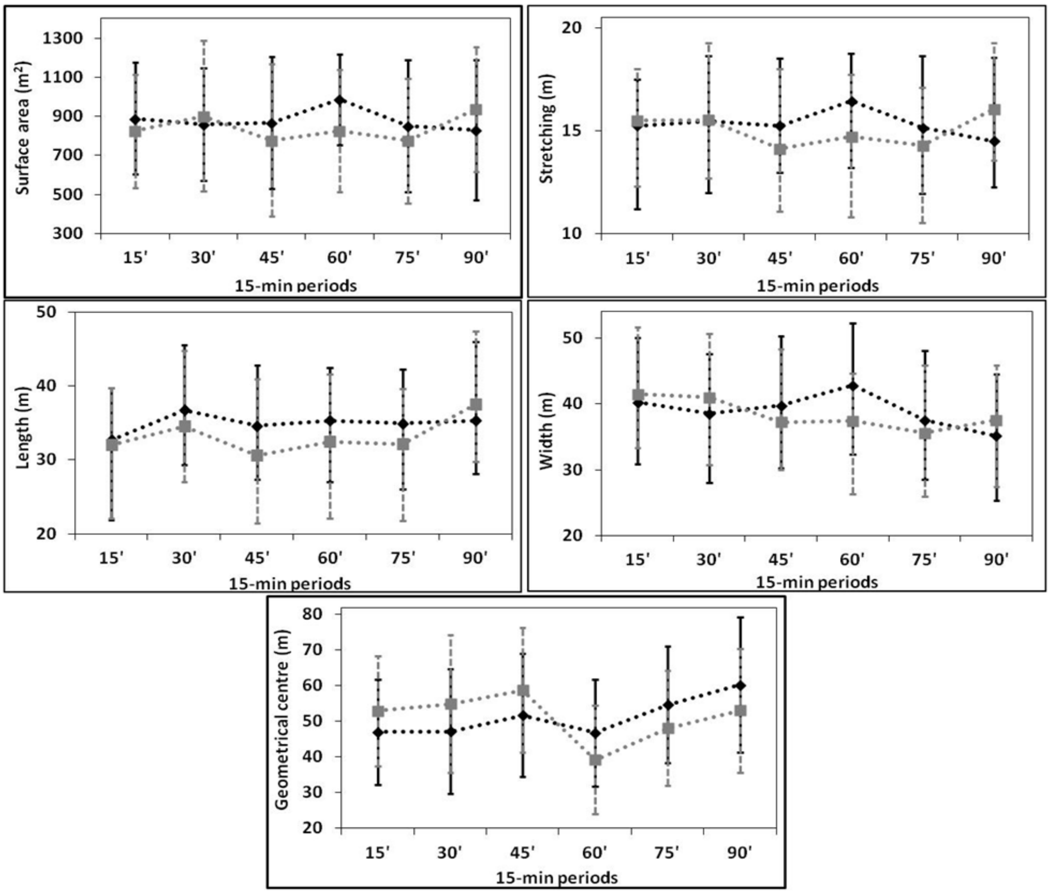


Figure 6.1. Mean and standard deviation data for *surface area* (top left panel), *stretch index* (top right panel), *team length* (middle left panel), *team width* (middle right panel) and *geometrical centre* (bottom panel) of home (♦) and visiting (□) teams presented in time periods of 15 mins.

Descriptive data of the five *compound positional variables* exhibited different patterns across the six time periods analysed, highlighting that each captured different collective behaviours of each team. The surface area and stretch index values obtained by the two teams showed some similarities in their variations. On the other hand, team length tended to be larger in the home team (except for the last period), while the visiting team displayed superior values of width in the first two time periods. In the third, fourth and fifth time periods, right after two successive goals scored during the second time period (minute 18: 1-0; minute 24: 1-1), the home team displayed larger values in all of the compound variables, except the geometrical centre. In the final time period of the match, right after conceding a goal at the 75$^{th}$ minute, the visiting team prominently increased the covered surface area, stretching, length and width, compared with the home team.

#### 6.4.2. Changes in complexity throughout the match

Table 6.1 presents data on the magnitude and structure of variability of the compound variables, which allowed understanding how their complexity evolved over time.

Table 6.1. Measures of magnitude (%CV and %RMSD) and structure (ApEn) of variability utilised to assess the 'quantity of variation' and complexity of the teams' collective behaviours, classified by team and by time periods of 15 mins.

| **Time into the match** | **Compound positional variables** | **Home team** | | | **Visiting team** | | |
|---|---|---|---|---|---|---|---|
| | | *%CV* | *%RMSD* | *ApEn* | *%CV* | *%RMSD* | *ApEn* |
| Time period 1 0-15 mins | *Surface area* | 32.19 | 32.15 | 0.62 | 38.00 | 37.98 | 0.72 |
| | *Stretch index* | 15.44 | 15.41 | 0.63 | 19.19 | 19.18 | 0.70 |
| | *Team length* | 22.68 | 22.65 | 0.68 | 25.14 | 25.13 | 0.79 |
| | *Team width* | 24.36 | 24.36 | 0.61 | 24.43 | 24.41 | 0.55 |
| | *Geometrical centre* | 31.26 | 31.24 | 0.36 | 29.22 | 29.20 | 0.38 |
| Time period 2 15-30 mins | *Surface area* | 33.71 | 33.69 | 0.71 | 41.38 | 41.36 | 0.58 |
| | *Stretch index* | 20.93 | 20.92 | 0.62 | 22.92 | 22.91 | 0.52 |
| | *Team length* | 24.54 | 24.54 | 0.81 | 30.00 | 29.98 | 0.71 |
| | *Team width* | 23.32 | 23.30 | 0.66 | 23.59 | 23.58 | 0.62 |
| | *Geometrical centre* | 37.00 | 36.98 | 0.34 | 35.23 | 35.21 | 0.31 |
| Time period 3 30-45 mins | *Surface area* | 38.76 | 38.73 | 0.56 | 50.03 | 50.00 | 0.45 |
| | *Stretch index* | 21.27 | 21.25 | 0.54 | 27.55 | 27.54 | 0.46 |
| | *Team length* | 23.85 | 23.83 | 0.71 | 33.95 | 33.93 | 0.63 |
| | *Team width* | 26.25 | 26.24 | 0.57 | 29.84 | 29.83 | 0.50 |
| | *Geometrical centre* | 33.53 | 33.51 | 0.30 | 29.72 | 29.70 | 0.31 |
| Time period 4 45-60 mins | *Surface area* | 26.68 | 26.66 | 0.87 | 37.12 | 37.09 | 0.64 |
| | *Stretch index* | 15.67 | 15.66 | 0.80 | 19.51 | 19.50 | 0.63 |
| | *Team length* | 21.43 | 21.41 | 0.94 | 27.71 | 27.70 | 0.77 |
| | *Team width* | 22.25 | 22.24 | 0.71 | 19.25 | 19.24 | 0.78 |
| | *Geometrical centre* | 32.21 | 32.19 | 0.40 | 38.75 | 38.73 | 0.39 |
| Time period 5 60-75 mins | *Surface area* | 40.14 | 40.10 | 0.59 | 42.54 | 42.52 | 0.62 |
| | *Stretch index* | 23.02 | 23.00 | 0.56 | 20.84 | 20.82 | 0.63 |
| | *Team length* | 20.06 | 20.05 | 0.86 | 22.64 | 22.62 | 0.88 |
| | *Team width* | 27.93 | 27.88 | 0.58 | 28.58 | 28.56 | 0.58 |
| | *Geometrical centre* | 30.03 | 30.01 | 0.34 | 33.45 | 33.44 | 0.35 |
| Time period 6 75-90 mins | *Surface area* | 43.48 | 43.37 | 0.54 | 34.09 | 34.08 | 0.65 |
| | *Stretch index* | 28.07 | 27.96 | 0.51 | 20.06 | 20.05 | 0.60 |
| | *Team length* | 30.67 | 30.56 | 0.68 | 26.52 | 26.51 | 0.67 |
| | *Team width* | 26.67 | 26.62 | 0.64 | 21.94 | 21.93 | 0.71 |
| | *Geometrical centre* | 31.31 | 31.29 | 0.36 | 32.71 | 32.69 | 0.40 |

Data from Table 6.1 shows a trend for an inverse relation between the measures of magnitude and structure of variability, namely in the collective behaviours of the home team. This trend was confirmed analysing the linear association between %CV and ApEn which can be observed in Figure 6.2.

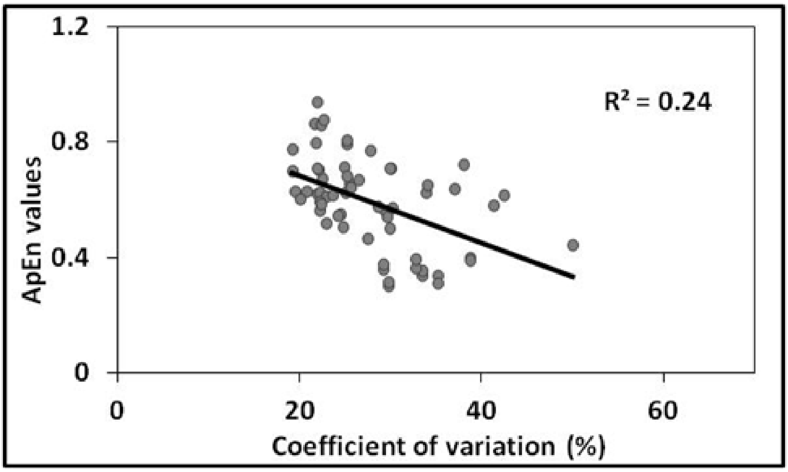


Figure 6.2. Inverse linear association between the coefficient of variation (%CV) and approximate entropy (ApEn) values.

The coefficient of determination ($R^2$) revealed a moderate level of association between the variables (24% of variance explained), demonstrating a trend for an inverse relation (negative slope). That is, larger values of %CV were related with small values of ApEn, and vice-versa.

To provide a deeper understanding on changes in the complexity of teams' collective behaviours during the match, the distribution of ApEn values was also analysed across the six time periods (see Figure 6.3).

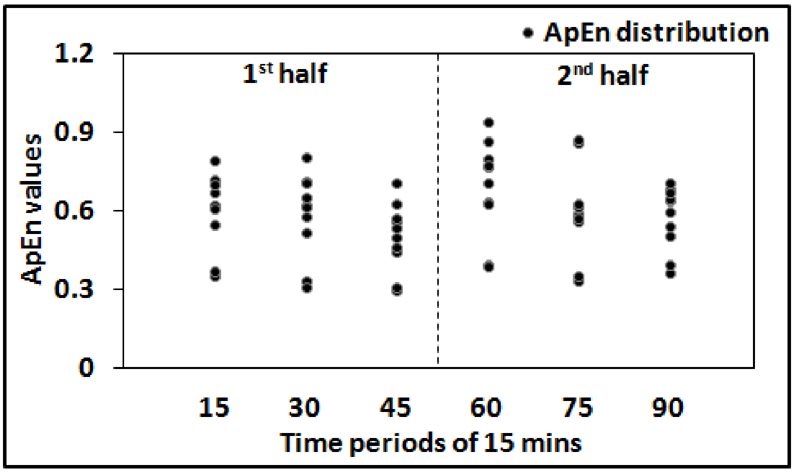


Figure 6.3. Distribution of ApEn values from the five collective behaviours of each team across the 6 time periods of the match.

Non-parametric Friedman's test revealed significant differences in the distribution of ApEn during the 6 time periods of the match, with medium effect size values ($\chi^2$ = 26.629, df = 5, p < .001, $\eta^2$ = .488). Wilcoxon's pairwise comparisons discriminated that significant differences in ApEn values were observed between time periods 2 (0.59±0.16) and 3 (0.50±0.13, p = .017), 3 and 4 (0.69±0.18, p = .005) and, 4 and 5 (0.60±0.18, p = .028). The collective patterns of performance of competing teams became significantly less complex (i.e., more regular and predictable) as each half of the game unfolded.

## 6.5. Discussion

The current case study aimed to investigate the complexity underlying the collective behaviours of two competing sports teams during a competitive match. For that purpose, five measures of collective performance, identified in previous research, were analysed. Data showed that teams clearly changed their behaviours throughout the match, with different patterns of variations observed in each *compound positional variable* for each team.

While the home team tended to show patterns of collective behaviour characterised by high levels of depth, the visiting team exhibited patterns of behaviour in which the lateral spread (width) was predominant in the first two time periods of the match. These data suggest that the visiting team exploited the lateral spaces of the field more greatly, probably aiming for a predominant lateral circulation of the ball (i.e., enhanced possession play). On the contrary, the home team exploited more the spaces created by the increase in depth, and possibly, their passing sequences were short and related with a 'direct playing style'[23]. Hughes and Franks[24] suggested that this style of play is only applicable where the skill of the team is insufficient to sustain possession of the ball. Thus, it seems that the two teams began the match with different strategic behaviours, maybe due differences in the level of skill, which changed due to the evolving dynamics of the game and its emerging key events. The surface area and stretch index measures showed identical patterns in their variations, indicating that both compound variables share a similar nature at the 11vs11 level of analysis. This observation might constitute valuable information to reduce the use of redundant variables in future analyses. Still with regards to the same two compound variables, both teams revealed equivalent values during the two initial time periods, which diverged during all the following game periods. These results can be related to some initial stability in the stretching of the teams (and the corresponded covered surface area) that was altered as a result of two key events: the two successive goals scored during the second time period (min 18: 1-0; min 24: 1-1). In the third, fourth and fifth time periods the home team displayed notably larger values in all of the collective measures, excepting the geometrical centre. That is, the home team players covered a greater area of the pitch, displayed a greater dispersion of players, greater length and width values when compared to the players of the visiting team. These data concur with reports of a superior percentage of ball possession for top football teams playing at home than for visiting teams, when the scoreline showed a draw[11]. According to Bourbousson and colleagues[8], a team having more ball possession should imply a greater stretching in the field than the opposition. In our case study, during the final time period of the match, the visiting team considerably increased all the values of the collective measures, compared to the home team, likely due to a goal conceded in the 75th minute of the game, turning the scoreline in favour of the home team (2-1). So, changes in the scoreline seemed to act as key events perturbing the behaviours of the competing teams, at least in this case study.

Despite some similarities among the *compound positional variables*, the different patterns of variation observed in data highlighted the complementary nature of these variables to capture the peculiar behaviours of each collective. These *compound positional variables* seemed to capture the identity of a team providing the idiosyncratic performance values of each sport team as a competitive match unfolded[25]. The individual behaviours of players can be regarded as contributing to the emergence of higher-order collective behaviours at the collective system level, as suggested in literature[4].

Regarding system complexity, ApEn measures indicated that the collective behaviours of competing teams seemed to become significantly less complex, more regular and predictable as each half of a game unfolds. The size of the effect was also considerable, attesting the influence of the successive time periods on the decrements of system complexity. The distribution of ApEn values showed a trend to decrease in both halves, with the largest change observed after half time. These data may be due to the high level of fatigue collectively accumulated by the players during the course of the game[17]. Fatigue can cause sports teams to stabilise their organisational shape and display less complex collective behaviours (i.e., perform in a highly regular and predictable way). Similar results on the influence of fatigue in high-level water polo performance have been reported[26]. Investigators found a decline in technical performance, but a stabilisation in outcome accuracy and an improvement in decision making as a function of increased levels of fatigue.

It is worth noting that the magnitude (measured by %CV) and structure of variability (measured by ApEn) showed a trend for an inverse linear association as reported in studies of human movement[21]. That is, the analysed collective behaviours demonstrated a decrease in complexity/irregularity during the time periods of the match, accompanied with an increase in the magnitude of deviations from the mean tendency. Despite linear statistical tools used to measure variability (%CV) providing information about increasing quantities in system variations, the time-evolving nature of such variations (indicated by ApEn) tended to become more regular as time progressed in both halves of the game.

These findings can be attributed to the co-adaptation to the specific constraints imposed by opposing teams[27], as well as to changes within the teams (e.g., physiological, tactical). This adaptation pushed the teams to their preferred attractor states, and the more the time evolved the more their behaviours became stabilised. A particular type of adaptation, relevant to explain the present data is harmonious with the concept of ‘freezing system degrees of freedom’ initially suggested by Bernstein[28] with respect to neurobiological coordination. In social collective systems, considering that each individual player is a degree of freedom relevant to the whole team, increasing fatigue might constrain each system component (i.e., the player) to perform conservatively and not explore a wide range of possible playing patterns/movements, due to changes in physical capabilities. Reduced involvement of system degrees of freedom has also been observed in kinematic measurements of batting performance under increasing stress[29]. It seems that fatigue and stress, and even the acquaintance with the opposing team, can act as specific performance constraints influencing coordination processes in complex social systems, by reducing the movement variability of system agents during performance. These data from athletes coordinating their activities in team performance imply the need for further research on the fractal relations that may explain the dynamic patterns of team behaviour.

This study focused on a single competitive game in its entirety with data from *compound positional variables* as the game unfolded. This is a different approach to previous research in which data are typically averaged over several trials, representing different sub-phases of team sports performance. Despite the limited generality of the present findings, the case study approach allowed us to examine how key events such as goals scored or half-time constrained the emergence of collective patterns of performance. The study of the influence of situational/environmental variables such as venue, opposition level, fatigue and strategic substitutions on the dynamics of teams' collective behaviour could benefit from this approach.

## 6.6. Conclusion

This investigation showed how changes in magnitude and structure of performance variability in sports teams tended to occur during competition. Compound positional variables revealed different trends in performance variation, attesting their complementarity for capturing the behaviours of sports teams as complex, dynamical systems during a game. The five collective measures used in the present study, mainly the first four, can be employed to capture the idiosyncratic performance values of each team as competitive performances unfold. In respect to performance variability, data demonstrated that teams tended to become less complex (i.e., more regular and predictable), but with increased magnitudes of variation in their organisational shape over the natural course of a match. Further investigation is needed to verify the power of generalisation of the current findings abroad other professional football teams.

## 6.7. Acknowledgements

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# 7. Competing together: Assessing the dynamics of *team-team* and *player-team* synchrony in professional football

## 7.1. Abstract

This study investigated movement synchronization of players within and between teams during competitive association football performance. The cluster phase method was used to assess synchronies between whole teams and between players with its team as a function of time and field direction. Measures of dispersion (*SD*) and regularity (sample entropy – *SampEn*) were used to quantify the magnitude and structure of synchrony. Large synergistic relations within each professional team sport collective were observed, particularly in the longitudinal direction of the field (0.89±0.01) compared with the lateral direction (0.73±0.03). The coupling between the group measures of the two teams also revealed that changes in the synchrony of each team were intimately related (*Cross-SampEn* values of 0.02±0.01). In player-team synchronization, individuals tended to be coordinated under near in-phase modes with team behaviour (mean ranges between -7 and 5 degrees of relative phase). The magnitudes of variations were low, but more irregular in time, for the longitudinal (*SD*: 18±3 degrees; *SampEn*: 0.07±0.01) compared to the lateral direction (*SD*: 28±5 degrees; *SampEn*: 0.06±0.01, $p < .05$) of the field. Increases in regularity were also observed between the first (*SampEn*: 0.07±0.01) and second half (*SampEn*: 0.06±0.01, $p < 0.05$). Findings provided evidence on the mutual influence of each team's cohesiveness in social competing collective systems, establishing new insights on the measurement of individual contributions to group behavior, as well as unbiased collective measures.

*Keywords*: group synchrony, collective systems, interpersonal dynamics, cluster phase method, sports teams.

## 7.2. Introduction

Competing teams in sports like Association Football are composed of different individuals interacting together to achieve performance goals. In order to succeed, individual teammates develop cooperative relations to achieve common goals and competitive relations to prevent opposing players from achieving theirs. These relations usually underlie emergent collective team behaviors that go beyond the sum of individual performances *per se* (Sumpter, 2006). Indeed, many studies in the fields of psychology and biology have demonstrated the superior performance of grouping individuals over singletons in a wide range of human phenomena (e.g., Krause, James, Faria, Ruxton, & Krause, 2011). In the field of team sports, the nature of cooperative and competitive interaction tendencies constrains players to perform as a group and displays intra- and inter-team couplings between the players (McGarry, Anderson, Wallace, Hughes, & Franks, 2002; Travassos, Araújo, Correia, & Esteves, 2010). Functional groupings of structural elements in complex systems (e.g., players in a sports team), that are temporarily constrained to act as a single coherent unit, have been called *synergies* (Bernstein, 1967; Turvey, 2007). A synergy is a key concept for understanding the process in which individual system components interact to create a single emergent group behavior. Those processes arise from genetic to social levels of organization in neurobiological systems (Kelso, 2009). The interdependency of different scales within a complex system, such as between individual components (e.g., players' movements) and group behaviors (e.g., collective patterns of play in a sports team), can be captured by assessing synchronization processes. The interdependence between levels of a complex system suggests the need to investigate both scales of analysis in team sport performance (Bar-Yam, 2003, 2004), and especially to understand how these tendencies mutually influence each other.

However, previous studies have tended to focus either on coordination between pairs of individuals (i.e., dyads) or at the team level of organization, and not on the relations between the two levels. Some previous research has analyzed team behaviors at the collective level (e.g., as 11-a-side in association football) using compound positional variables to capture specific synchronization tendencies expressed in team behaviors. For example, Lames and colleagues (2010) demonstrated that the *geometrical centers* (i.e., average position of the outfield players) and *team ranges* (i.e., length and width of the teams) of competing football teams tend to be tightly coupled in the longitudinal (goal-to-goal) and lateral (side-to-side) directions on the field of play during competitive performance. Using the *stretch index* measure (i.e., mean players' dispersion around the team center), Yue et al. (2008) showed that the dispersion of teams players on-field tended to follow a dynamical counter-phase relation, that is, when the organization of one team was contracted, the shape of an opposing team tended to be expanded and vice-versa. Bourbousson, Sève, and McGarry (2010b) demonstrated that these expansion/contraction patterns of collective behaviors during performance emerged as a function of changes in ball possession between teams. These types of studies typically assume that individual players contribute equally to the emergence of the collective behaviors of sports teams, which may be a somewhat erroneous proposition. In some instances the compound positional variables that are measured might not include all the players in the computations or may include them with different 'weights' or levels of contributions (McGarry, 2009). However, determining a contribution weighting of an individual player can be a very difficult, if not speculative, task.

In order to enhance understanding of collective behaviors in team sports, another research approach is to analyze sub-unit relations such as the coordination tendencies between pairs of players (dyads from the same team or opposing players). Bourbousson and colleagues (2010a) and Travassos and colleagues (in press) measured the phase differences between all the possible dyadic system relations in team games in order to assess the predominant coordination modes underlying team behaviors, contrasting intra- and inter-team patterns of interpersonal coordination. This methodological strategy regards collective behaviors in teams, not as an upshot of the sum of individual behaviors, but as exhibiting the coordination tendencies between pairs of players.

Although these studies have provided some useful theoretical and empirical insights into team game performance, the measures used have typically failed to fully explain how the actions of different players become synchronized within the collective behaviors of the team. For a deeper understanding of how repeated interactions between teammates can scale to emergent collective team behaviors, one needs to capture the synchronization process of individuals shaping the behavior of the whole team. Such analyzes of synchronization processes may reveal the potential influence of each player in the performance of the whole team, although they have yet to be undertaken.

Recently, Frank and Richardson (2010) proposed a quantitative approach to detect phase synchronization in noisy experimental multivariate data – a *cluster phase method* – by deriving a test statistic based on the Kuramoto order parameter. This method was initially proposed to investigate phase synchronization in systems with a large number of oscillating components (Kuramoto, 1984). The investigators (2010) adapted and successfully showed the applicability of this method using a multiple-rocking chair experiment in which six individuals tried to synchronize their rocking movements. Specific measures of individual and whole group synchrony obtained with this method were able to distinguish intentional from chance level coordination tendencies.

In this study we investigated the utility of the *cluster phase* method for assessing synchronization processes during team sports performance. Specifically, *team-team* and *player-team* synchronization processes were investigated as a function of changes in halves of the game (first/second), team status (home/visiting), and field direction (longitudinal/lateral) during performance in a top level professional association football competition.

## 7.3. Methods

### 7.3.1. Sample and data acquisition

Twenty-eight high level, male, professional football players (22 starting players and 6 substitutes) participated in a competitive match in the English Premier League season 2010-2011. Participants ranged in age from 22 years to 34 years (average 26 years) and included 19 international-level performers from 8 different countries. At the time of data collection, the home team was ranked 4th, and the visiting team was the

10th in league standings. Positional raw data (2D) on player performance was obtained using the ProZone® tracking system (Prozone®, ProZone Holdings Ltd, UK), validated by Di Salvo and colleagues (2006). This video-based, multi-player tracking system uses 8 colour cameras (Vicon surveyor 23x cameras dome/SVFT-W23) installed in the stadium to ensure that every area of the pitch is covered by, at least, two cameras to provide image data. This coverage prevents possible losses of signal during moments of high aggregation of the players during performance. After automatic tracking, quality control procedures consisted in the use of: (i) Kalman filters to predict possible direction of an object, given its current speed (Kalman, 1960), (ii) computer vision homography to convert image coordinates into real world pitch coordinates (Hartley & Zisserman, 2002), and (iii), quality control operators verifying (and re-identifying when necessary) that the displacement trajectories identified for each player remained constant to that specific player (see Di Salvo et al., 2006, for further details).

Raw positional data for each player were provided through individual spreadsheet files at a sampling rate of 10Hz. The 2D positional raw data of 11 on-field players of each team divided by half and by direction of the field originated eight different input files. Moreover, 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. However, the individual synchrony of the substituted players with the team was assessed only for the time they were effectively playing on-field. After a preliminary examination of the game events, all the periods corresponding to stoppages in play (i.e., injury assistance, free kicks, corners, substitutions, goal celebrations) longer than 25 s were excluded in order to avoid a biased assessment of synchrony. Thus, the final database for the first half had 23214 data points (i.e., 38 mins and 41 s), while in the second half it had 24967 data points (i.e., 41 mins and 37 s).

### 7.3.2. Cluster phase method

The cluster phase method used to assess whole team and player-team synchrony was recently proposed by Frank and Richardson (2010). This method was adapted from the Kuramoto order parameter (e.g., Kuramoto & Nishikawa, 1987), a model which is usually defined in the thermodynamic limit (i.e., for systems where the number of oscillatory units tends to infinite, Strogatz, 2000). Frank and Richardson (2010) adapted the model in order to analyze systems with a small number of oscillatory units and successfully tested its applicability using a multiple-rocking chair experiment with only six oscillating components. This method allows for the calculation of the mean and continuous group synchrony, $\rho_{group}$ and $\rho_{group}(t_i)$ as well as the individual's relative phase with the group measure. These dependent measures are ideally suited for assessing changes in team and player synchrony and can be calculated as follows.

Given the phase time-series obtained with Hilbert transform, $\theta_k$, for $n$ player movements measured in radians [-π π], where $k = 1,\ldots,n$ and $i = 1,\ldots, T$ time steps, the group or *cluster* phase time-series can be calculated as:

$$\acute{r}(t_i) = \frac{1}{n}\sum_{k=1}^{n} \exp(\mathrm{i}\theta_k(t_i))$$

and:

$$r(t_i) = \mathrm{atan2}(\acute{r}(t_i))$$

where $i$ $\sqrt{-1}$ = (when not used as a time step index), $\acute{r}(t_i)$ and and $r(t_i)$ are the resulting cluster phase in complex and radian form, respectively. The relative phase time-series, $\phi_k$, between each player and the group cluster phase is then equal to:

$$\phi_k(t_i) = \theta_k(t_i) - r(t_i)$$

with the mean relative $\bar{\phi}_k$ phase for every player $k$ with respect to the team calculated from:

$$\bar{\acute{\phi}}_k = \frac{1}{N}\sum_{i=1}^{N} \exp\left(i\phi_k(t_i)\right)$$

$$\bar{\phi}_k = \operatorname{atan2}(\bar{\acute{\phi}}_k),$$

where $N$ is the number of time steps $t_i$, $\bar{\acute{\phi}}_k$ and $\bar{\phi}_k$ is the mean cluster phase in complex and radian [-π π] form. Note that $\bar{\phi}_k$ captures the phase shift of a movement with respect to the team behaviors $r(t_i)$. For stable synchrony (i.e., low SD of relative phase) it can be used to compare whether movements of an individual have the same mean phase with the team and, thus, determine the between-movement relative phase relations. For instance, if $\bar{\phi}_n = \bar{\phi}_m$ then the mean relative phase between player $m$ and $n$ is zero and they are perfectly in phase with one another.

Finally the continuous degree of synchronization of the team as a whole (i.e., the cluster amplitude) $\rho_{group,i}$ at every time step $t_i$ can be calculated as:

$$\rho_{group}(t_i) = \left|\frac{1}{n}\sum_{k=1}^{n} \exp\{i(\phi_k(t_i) - \bar{\phi}_k)\}\right|$$

where $\rho_{group,i} \in [0,1]$ and the mean degree to group synchronization is computed as

$$\rho_{group} = \frac{1}{N}\sum_{i=1}^{N} \rho_{group,i}$$

The cluster amplitude corresponds to the inverse of the circular variance of $\phi_k(t_i)$. Thus, if $\rho_{group,i}$ or $\rho_{group}$ = 1 the whole group is in complete intrinsic synchronization. If $\rho_{group,i}$ or $\rho_{group}$ = 0, the whole group is completely unsynchronized. So, the larger the value of $\rho_{group,i}$ and $\rho_{group}$ (i.e., close to 1), the larger the degree of team synchronization.

All the computations were undertaken using dedicated routines implemented in Matlab® software (The MathWorks Inc, Natick, MA, USA) and are available online (http://homepages.uc.edu/~richamo/index.html).

### 7.3.3. Data analysis

Sample entropy (SampEn) and cross sample entropy (Cross-SampEn) were used to assess the regularity of cluster amplitude in each team and each player's relative phase with the group/cluster measure, as well as the degree of team-team synchrony, respectively. These nonlinear statistical tools were introduced by Richman and Moorman (2000) because they were considered to be: (i) more consistent over different choices of input parameters, (ii) less sensitive to data series length, and (iii), unbiased statistics by avoiding self-matches, than the better known approximate entropy (ApEn, Pincus, 1991) and cross approximate entropy (Cross-ApEn, Pincus & Singer, 1995). SampEn measures the presence of similar patterns in a time-series revealing the nature of their intrinsic structure of variability. Given a series, *Y(t)*, of *T* points (*t* = 1, ..., *T*), SampEn measures the logarithmic probability that two similar sequences of *m* points extracted from *Y(t)* remain similar (i.e., within tolerance limits given by *r*) in the next incremental comparison (i.e., for *m*+1 sequences). Values close to zero were indicative of regular/near-periodic evolving behavior for the cluster amplitude of teams and relative phase with group of each player, whilst the higher the SampEn, the more unpredictable the patterns (Preatoni, Ferrario, Donà, Hamill, & Rodano, 2010).

Cross-SampEn is a statistical tool to compare two correlated time-series in order to evaluate their degree of synchrony or similarity (Pincus & Singer, 1995; Richman & Moorman, 2000). For two related time series *u(i)* and *v(i)*, Cross-SampEn measures, within tolerance *r*, the conditional regularity or frequency of *v*-patterns similar to a given *u*-pattern of window length *m* (Richman & Moorman, 2000; Pincus, Mulligan, Iranmanesh, Gheorghiu, Godschalk, & Veldhuis, 1996). In the same line of reasoning, greater synchrony between teams can be indicated by high instances of (sub) pattern matches, quantified by Cross-SampEn values tending to zero (Pincus, 2000). Before the use of Cross-SampEn, Pearson correlations were also used to measure the bivariate linear association between group synchrony time-series data. Input parameters were set as $m$=1 and $r$=0.2 standard deviations for both entropy estimations as suggested in other investigations on neurobiological systems (Pincus et al., 1996; Preatoni et al., 2010; Richman & Moorman, 2000).

Univariate 2x2x2 mixed-model ANOVAs were used to analyze the variations of the SD and SampEn values within-halves (first and second) and between- teams (home and visiting) and field direction (longitudinal and lateral). Violations of the sphericity assumption for the within-participant factors were checked using Mauchly's test of sphericity. When a violation of this assumption was apparent, the Greenhouse-Geisser correction procedure was used to adjust the degrees of freedom. Effect sizes were measured as partial eta squared ($\eta^2$) (Levine & Hullett, 2002). All the inferential statistical analyses were performed using IBM SPSS® 19.0 software (IBM, Inc., Chicago, IL). Alpha levels were maintained at $p$ < .05 for all statistical procedures.

## 7.4. Results

### 7.4.1. Whole group synchrony

The time-series of group synchrony, $\rho_{group,i}(t_i)$, of the two teams as a function of game half and field direction are depicted in Figure 7.1. Vertical grey bands highlight the game stoppages longer than 25 s that were excluded from further analyses.

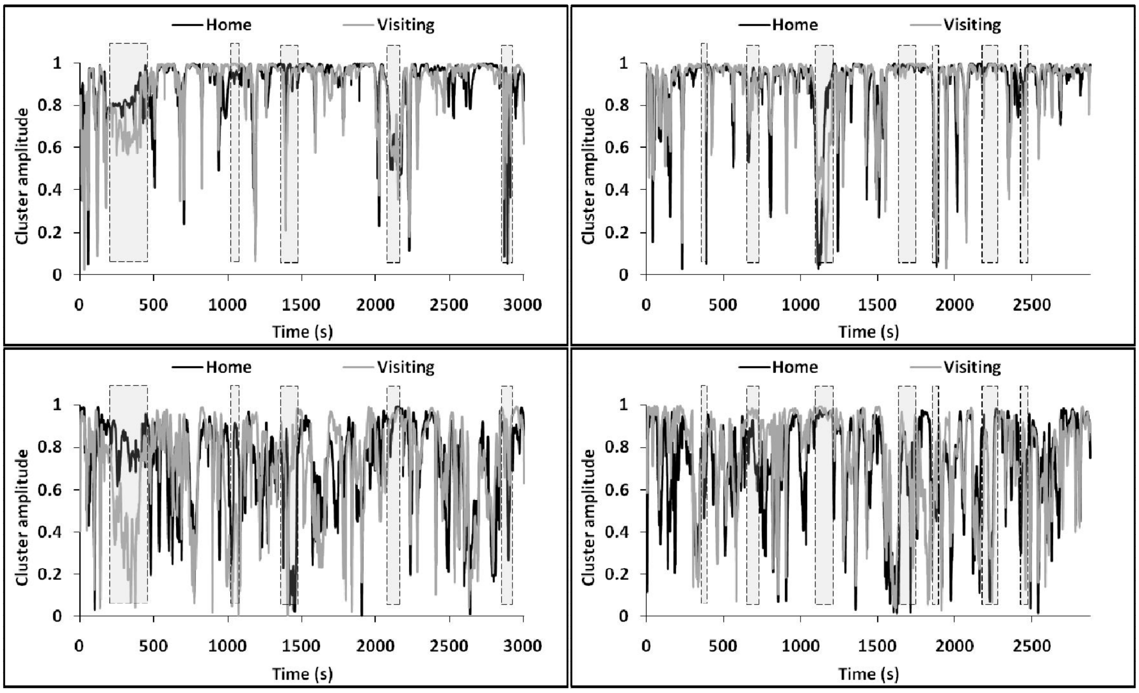


Figure 7.1. Time-series of group synchrony of the two teams using cluster amplitude measures, $\rho_{group}$ ($t_i$), as a function of each game half and field direction. Cluster amplitude ranges from 0 (no synchrony) to 1 (complete synchrony). Left and right panels display values for the first and second halves of the game, respectively. Upper and bottom panels display values for longitudinal and lateral directions, respectively. Vertical grey bands highlight the stoppages in play longer than 25 s.

Descriptive data (mean and SD), as well as nonlinear measurements using SampEn, are presented in Table 7.1. Data showed superior mean values of within-group synchrony, less magnitude of variation (SD) and more regularity (SampEn) in the longitudinal than in the lateral dimension of the field.

Table 7.1. Mean, SD and SampEn values of the within-group synchrony time-series.

| | First half | | | | Second half | | | |
|---|---|---|---|---|---|---|---|---|
| | **Home team** | | **Visiting team** | | **Home team** | | **Visiting team** | |
| | Longitud | Lateral | Longitud | Lateral | Longitud | Lateral | Longitud | Lateral |
| *Mean* | 0.89 | 0.72 | 0.88 | 0.70 | 0.89 | 0.72 | 0.89 | 0.76 |
| *SD* | 0.14 | 0.21 | 0.15 | 0.23 | 0.16 | 0.22 | 0.16 | 0.22 |
| *SampEn* | 0.02 | 0.04 | 0.02 | 0.04 | 0.01 | 0.04 | 0.01 | 0.03 |

Longitud = Longitudinal direction of the field; Lateral = Lateral direction of the field.

Bivariate correlations analyses showed significant values of association between the group synchrony of the two teams in the first half, for the longitudinal field directions, $r(23211) = .77$, $p \leq .001$, and the lateral field directions, $r(23211) = .62$, $p \leq .001$. Similar results were observed in the second half, for the longitudinal field directions, $r(24964) = .75$, $p \leq .001$, and for the lateral directions, $r(24964) = .68$, $p \leq .001$. Thus, Pearson correlation and Cross-SampEn analyses were combined in order to evaluate the coupling dynamics of team-team synchronies. Figure 7.2 showed three identified modes of team-team synchrony.

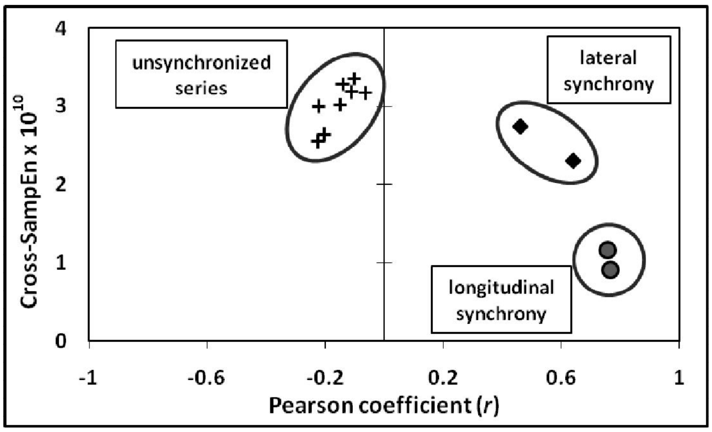


Figure 7.2. Coupling dynamics of team-team synchrony pairs combining the discrete values of Cross-SampEn with Pearson correlation coefficients.

Unsynchronized time-series corresponded to within- and between-teams pairs of data in different directions of the field (i.e., testing lateral with longitudinal synchrony). Team-team synchrony for the lateral direction displayed slightly lower Cross-SampEn values and significantly higher Pearson correlation values. For the longitudinal field direction, team-team synchrony showed Cross-SampEn values that were even lower and with the highest correlations, suggesting the highest levels of similarity in the structure of variability of the two teams.

### 7.4.2. Player-team synchrony

Mean, SD and SampEn of relative phase between each player and team behavior (i.e., the cluster phase) are presented in Table 7.2.

Table 7.2. Mean, SD and SampEn values of player-team synchrony as a function of the game half, team and field direction.

| | | First half | | | | Second half | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Home team | | Visiting team | | Home team | | Visiting team | |
| | | Long. | Lat. | Long. | Lat. | Long. | Lat. | Long. | Lat. |
| *Mean* | *Max* | 4 | 4 | 5 | 3 | 3 | 4 | 3 | 5 |
| | *Min* | -4 | -7 | -4 | -3 | -3 | -3 | -4 | -3 |
| | *Range* | 8 | 11 | 9 | 6 | 6 | 7 | 7 | 8 |
| *SD* | *Max* | 25 | 38 | 22 | 32 | 25 | 36 | 26 | 34 |
| | *Min* | 14 | 18 | 15 | 19 | 13 | 20 | 15 | 22 |
| | *Range* | 12 | 20 | 7 | 13 | 11 | 16 | 11 | 12 |
| *SampEn* | *Mean* | 0.07 | 0.06 | 0.08 | 0.06 | 0.07 | 0.06 | 0.07 | 0.06 |
| | *SD* | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 |

Mean and SD values are presented in degrees. Long. = longitudinal direction; Lat. = lateral direction.

Data showed a high narrow range of mean relative phase values around an in-phase mode of coordination between individual players and whole team behaviors (i.e., cluster phase). Regarding the magnitude of stability around the mean trend indicated by SD, a univariate 2(Game Halves) x 2(Team) x 2(Field Direction) mixed-model ANOVA revealed a significant main effect for Direction, $F(1, 44) = 83.123$, $p \leq .001$, $\eta^2 = .675$, with higher SD values for lateral (28±5 degrees) compared to longitudinal (18±3 degrees) field movements. No significant main effects were observed for Team, $F(1, 44) = .578$, $p = .451$, $\eta^2 = .014$, nor Game Halves, $F(1,44) = .010$, $p = .921$, $\eta^2 = .001$. Also, no significant interaction effects were observed.

Concerning the regularity of the player-team synchronization process, a univariate 2(Game Halves) x 2(Team) x 2(Field Direction) mixed-model ANOVA revealed higher SampEn values for the longitudinal (.07±.01) compared to the lateral (.06±.01) Direction in the field of play, $F(1, 44) = 16.907$, $p \leq .001$, $\eta^2 = .297$. Also, a significant main effect was found for Game Halves, $F(1,44) = 4.194$, $p = .047$, $\eta^2 = .095$, with superior values of SampEn in the first (.07±.01) compared to the second half of the match (.06±.01). No significant main effect was observed for Team, $F(1, 44) = 2.771$, $p = .104$, $\eta^2 = .065$, nor were there interaction effects.

## 7.5. Discussion

### 7.5.1. Teams as synergistic collectives

The main goal of this study was to capture synchronization processes between- and within-teams during competitive football performance by means of a *cluster phase* method. Measures of whole team synchrony showed superior mean values and high levels of stability (low SD and SampEn) for the longitudinal field direction compared to the lateral direction. These data suggest that individuals are more likely to coordinate their movements together in the longitudinal (goal-to-goal) direction, than in the lateral (side-to-side) direction. However, all the mean values of cluster amplitude were observed between .70 and .89. Frank and Richardson (2010) found a value of .70 for oscillatory rhythmic movements of rocking chairs, which suggests that team players in the present study are intimately and thoroughly coordinated during performance.

Additionally, the combination of Cross-SampEn and Pearson correlations revealed a tightly coupling between teams in both field directions, especially in the longitudinal plane. Once fluctuations are observed in the continuous cluster amplitude measure (i.e., the whole group synchrony measure), it seems that teams increase and decrease their synchronies in a highly related fashion. In other words, a team performing in a synergistic manner attracts the other team to behave in a synchronized way too. A near-perfect matching between the time-evolving structures of cluster amplitudes was observed for the longitudinal collective movements of the two teams. These findings reinforced the importance of the co-adaptation processes that emerge between teams during competitive performance. These processes represent a specific property of team sport collectives as demonstrated in a study of rugby union by Passos and colleagues (2011), addressing evidence on the mutual influence of each team's cohesiveness. Previous work has suggested that, under certain environmental conditions, individuals are able to continuously adjust their behaviors, based on informational properties such as positions, movements and changes in movement of other individuals (Fajen, Riley, & Turvey, 2009). The data from this study have challenged the common notion about the importance of the physical boundaries of each individual by showing how mutual ongoing adjustments in synchronization processes are achieved by collectives functioning as a single entity (i.e., at the team level as a whole system). This finding also highlighted how the mechanical and informational components of sports teams as collective systems cooperated in an integrated manner to achieve functional and purposeful patterns of coordination (Turvey, 1990; Araújo, Davids, & Hristovski, 2006).

### 7.5.2. How player synchronizes itself with the team

Regarding player-team synchrony, mean relative phase of each individual with team (i.e., with cluster phase) showed a narrow range of values around zero degrees, indicating a general tendency for a near in-phase mode of coordination. The magnitude of variability indicated by *SD* of relative phase, with values ranging from 13 to 38, revealed the relative stability of this preferred near in-phase mode level of coordination. Interestingly, Frank and Richardson (2010) observed *SD* values slightly higher for their analysis of oscillatory rhythmic movements in individuals in rocking chairs. However, *SD* values observed in the present study were significantly higher in the lateral direction than in the longitudinal plane, revealing that players tended to be more stable in their coordination with whole team movement in the longitudinal direction. Bourbousson and colleagues (2010a) also reported a trend for preferred relative coordination modes within dyads to be higher in the longitudinal than in lateral direction.

In contrast, the differential effect of field direction on SampEn values showed that players generally displayed a more regular structure of coordination with team behavior in the lateral compared to longitudinal field direction. The apparent contradiction between SD and SampEn measures has been discussed recently (see for example Harbourne & Stergiou, 2009). Although both statistics are measures of variability, SD values provide information on the magnitude of deviations in the distribution around a mean value, while SampEn reveals the underlying structure of such variations (Glazier & Davids, 2009). A significant decrease in SampEn values was also observed between the first and second half of the game. This decrease in variability of structure could be attributed to changes in specific performance constraints such as fatigue (Mohr, Krustrup, & Bangsbo, 2005) due to the increased physical work rates observed in balanced games (O'Donoghue & Tenga, 2001). However, it is not clear how an increase in the quantities of movement (i.e., the physical work rates) may have influenced the synchronization processes within a team. Further research on this topic is needed to reveal how synchronization of players is affected by accumulated levels of fatigue.

### 7.5.3 How micro-variability contributes to stabilization of team(macro) performance

Finally, the low values of SampEn observed for cluster amplitude (ranging from .01 to .04), compared with the values calculated for each individual's relative phase with the group (ranging from .06 to .07) are worth noting. It has been suggested that local variability is responsible for increased stability at a higher level of temporal and spatial organization (Davids, Glazier, Araújo, & Bartlett, 2003; Torre & Balasubramaniam, 2010). Data from the present study are consistent with this proposition, showing low levels of irregularity for group measures, compared with individual synchronies with the team. Bardy and Laurent (1998) have also suggested that expert performers are more sensitive to visual information in order to exploit and use local variability to increase stability in behavior at a higher-level of organization. A similar process of visual exploitation might have occurred in this investigation, with expert team players having more irregular patterns of coordination with team behaviors, which contributed to the higher regular variation (i.e., more periodicity) of the cluster amplitude measure.

## 7.6. Conclusion

This study investigated synchronization processes within and between teams captured with the use of a cluster phase method. Large synergistic relations within each professional team sport collective were observed, particularly in the longitudinal direction of the field. The coupling between the group measures of the two high level teams also revealed that synchronization increases in one team were concomitantly accompanied by synchronization increments in the opposing team, indicating the mutual influence of synchronization processes in social competing collectives. Moreover, team players exhibited evidence of *relative coordination*, with a tendency towards an in-phase mode of behavior with the group (Von Holst, 1973; Turvey, 1990, 2007). Stability of these tendencies was higher in the longitudinal than in lateral direction of the field, whilst the structure of variability was more irregular.

The data from this study revealed that the main advantages in the use of a *cluster phase* method are: (i) the capacity to calculate an unbiased measure of group coordination due the weighted contribution of each individual, (ii) the use of this measure to assess player-team synchrony, evidencing the continuous individual contribution of each player to the team performance as the game unfolds, and (iii), the potential to assess the coupling dynamics of two competing teams as synergistic collectives. When grouping individuals produced more or less constant phase lags with respect to the group, the continuous group measure (i.e., the cluster amplitude) revealed these behaviors as exhibiting relative phase synchronization even if phase lags were different from zero (Frank & Richardson, 2010). This observation implies that the cluster amplitude can capture the functional and idiosyncratic mode of relations of each individual as contributing to the synchrony of the whole group. Future research in a wide range of social phenomena may benefit from this methodological approach.

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# 8. General Discussion and Conclusion

*"The 'particle' conception of matter has contributed to this incorrect conception of self, founding the illusion that we exist as discrete bodies without relations to all other matter. Recent discoveries on the wave structure of matter show that human beings do not exist in isolation, but are in fact structures of the Universe. Thus they do not have dominion over the earth and all living things by divine decree, on the contrary, Humans are intimately interconnected both to all other matter in the cosmos, and to all other life on Earth."*

(James Lovelock, 1996, p. 24)

## 8.1. Synthesising main findings

The present thesis was composed by 6 original research articles. Four of them presented experimental designs that allowed the study of interpersonal coordination at different levels of analysis of association football. The major findings of each experimental study will be discussed here in order to achieve an integrated and global perspective of the overall thesis.

Interpersonal coordination tendencies of two competing football players were investigated in Chapter 4. Findings revealed that different modes of interpersonal coordination emerging from attacker-defender dyads influenced the 1vs1 performance outcomes. Attacking player's success was associated to more irregular and unpredictable space-time synchronisation with the defender. That is, players frequently approach and move away from the target area in a synchronised mode, but in an irregular manner. On the other hand, the success of a defending player was attributed to a more predictable coordination mode developed with the attacker, displaying a frequent lead-lag relation (i.e., the to-and-fro movement displacements of the defender preceded the moves of the attacking player). Therefore, these findings demonstrate that specific features associated to the mutual influence of each player on dyadic behaviours tend to shape different performance outcomes.

Emergent coordination processes, displayed by two competing groups composed of 3 football players each, were investigated in Chapter 5. Centred on a different level of analysis, this study demonstrated how the creation of goal-scoring opportunities in small-group confrontations was influenced by within- and between-groups space-time relations. The collective movement of the two sub-groups captured by the geometrical centre demonstrated a strong symmetrical relation describing the coordinated actions in the approach to the scoring zones. Conversely, changes in the spatial areas covered by the sub-groups did not reveal a predominant nor stable pattern of coordination between them. However, attacking and defending sub-groups tended to increase the difference in their covered areas, particularly just before an assisted pass was made for the scoring zones.

The study presented in Chapter 6 investigated emergent collective behaviours at another level of analysis: the team level. Positional data obtained with a sophisticated multi-player video-based tracking system allowed studying an entire competitive match between two professional football teams. Five compound positional variables were used to capture changes in the coordinated behaviours of the teams as wholes. Those collective measures showed complementarity in capturing the global idiosyncratic behaviours of the opposing football teams, with high variations observed when a team scored a goal. Also, teams tended to became significantly more regular and predictable in their organisational shape over the natural course of a match, which can be attributed to the mutual co-adaptation between teams.

A different research strategy was followed in the study presented in Chapter 7. Instead of defining a single level of analysis, this study investigated how the individual behaviour of each player influenced the synchronisation of the whole team. By means of the cluster phase method, the relation between two levels of biological organisation – individual and team levels – was assessed. Large synergistic relations within each football team were observed, particularly in the longitudinal direction of the field. Moreover, increases in each team synchrony were intimately related, addressing evidence on the mutual influence of each team's cohesiveness. Concerning player-team synchronisation, footballers tended to be coordinated under near in-phase modes with the team behaviour. Their magnitudes of variations were low, but more irregular in time, for the longitudinal than in lateral direction of the field. Decreases of these synchronies were also observed from the first to the second half time.

The next section provides an in-depth discussion into the theoretical implications and methodological value of the main findings just reported.

## 8.2. Theoretical and methodological considerations

Findings from all the four experimental studies consistently revealed how opposing players mutually interact in different levels of social biological organisation. Mutuality had been suggested in literature as a central tenet of a social synergistic approach to the study of interpersonal coordination (Marsh, Richardson, Baron, & Schmidt, 2006; Richardson, Marsh, & Schmidt, 2010; Schmidt, Fitzpatrick, Caron, & Mergeche, 2010). However, beyond the dyadic level, few examples of such phenomena are available in research literature. For an exception see Néda and colleagues (2000) who described how tumultuous audience applause can transform itself into waves of synchronised clapping. The present thesis showed experimental evidence that mutuality is a ubiquitous property found at various levels of organisation of football teams, ranging from dyads to collectives. Worthy of note is the mutual relation found between two competing teams captured by measures of whole team synchrony (Chapter 7). The fact that teams intimately co-adjust their internal synchronies in a high related manner challenges the common notion about the relevance of the physical boundaries of individual organisms when they perform in group. It seems that, more than their individual physical properties, the emphasis was given to team cohesiveness or *entitativity* (i.e., to behave as an entity, a term coined by Campbell, 1958). These findings were also consistent with the proposal made in Chapter 2, in which the superorganism concept was suggested as profitable to capture the functional integrated behaviour of sport teams.

Another important notion related to the emergence of social coordinated behaviours is the concept of functional social (interpersonal) synergies (Kelso, 2009; Marsh, Richardson, & Schmidt, 2009). Data from Chapters 5, 6 and 7 also demonstrated how functional-related grouping individuals soft-assemble into synergistic collectives. Findings support the thought that individuals sharing common goals, purposes or intentions (as in the experimental settings of the referred chapters) typically display non-random behaviours in relation to their counterparts (Passos, Araújo, Davids, Milho, & Gouveia, 2009; Schmidt, O'Brien, & Sysko, 1999). Besides, the shaping of a functional synergy within a group of football players does not imply a rigid and stereotyped sequence of movement assembles. If players are regarded as a team's degrees of freedom, patterns of interpersonal coordination shaping a synergy are likely to show intrinsic functional variability (Davids, Glazier, Araújo, & Bartlett, 2003). Functional variability during coordination processes has been theoretically sustained in a ubiquitous property of biological systems – degeneracy (Edelman, & Gally, 2001). Therefore, functional equivalent or degenerative patterns of interpersonal coordination are likely to stabilise team effectiveness and to offer the advantage of promoting team adaptation under changing performance constraints such as the evolving scoreline and halftime breaks suggested in Chapter 6. Also, findings from Chapter 7 revealed that the individual synchronisation of each player with the team was more irregular and variable than the global behaviour of the team as a whole. As suggested in the literature (e.g., Bardy, & Laurent, 1998), this data proves how degeneracy expressed by the increased variability at low levels of organisation contributes to stabilise collective behaviours at higher levels.

The advantages of group behaviour are well documented in systems biology literature (Couzin, 2009). Living systems such as animal societies typically display emergent collective patterns as an evolutionary strategy to find food sources, avoid predators, organise migrations and survive in extreme environmental conditions (Sumpter, 2006). An interesting example of the last referred case was recently introduced in the literature, as evidencing the superorganismic properties of animal societies as suggested by many authors (e.g., Hölldobler, & Wilson, 2009). In this investigation Mlot, Tovey and Hu (2011) demonstrated how fire ants living in rainforests self-assemble into waterproof rafts to survive floods. Individual organisms cooperate performing complementary tasks such as supporting and trapping their conspecifics to create a higher-order emergent structure. The position statement presented in Chapter 2 argues for the advantages of regarding sport teams as functionally integrated superorganismic entities. This proposal was strengthened by suggesting some innovative measurement tools such as the use of major ranges, small-world networks, various compound positional variables, cluster phase and dominant regions.

Grounded on recent theoretical background that joins ecological psychology, complex non-linear dynamical systems and evolutionary biology (e.g., Araújo, Davids,

& Hristovski, 2006), the present thesis used a wide range of measurement tools and up-to-date data analysis methods. Chapter 3 presented a tutorial methodological article focused in the description of a straightforward motion analysis method suitable to capture movement displacement trajectories of team players in the field. This method opens the possibility to investigate interpersonal coordination processes in representative sports tasks (Davids, Button, Araújo, Renshaw, & Hristovski, 2006) and to test the effect of manipulating relevant constraints imposed in on-field performance. Another technological appointment is the use of positional data obtained with a sophisticated multi-player video-based tracking system (Prozone®). These data were gathered from an entire match of two competing professional football teams and allowed the development of new measurement tools able to capture their collective behaviours. Worth of note is also the cluster phase method developed by Frank and Richardson (2010) and used in the last experimental study. This innovative method is very promising for future research in the sense that it provides measures of whole group synchrony weighting the individual contribute of each player to the team. Also, it allows the measurement of player-team synchrony which can be used as a relevant index of individual players' performance.

Regarding the theoretical framework underlying this research programme and the necessary agreement with data analysis methods, all the experimental studies employed non-linear statistical tools to assess the time-evolving dynamics underlying the behaviours under analysis. Complemented with more conventional linear statistical measures, the former include relative phase analysis, running correlations, approximate and sample entropy, as well as cross-sample entropy. The last years have assisted to an increase in the use of these non-linear measures in the scientific research community (see for instance Harbourne, & Stergiou, 2009, and Richman, & Moorman, 2000), with some authors advocating their advantages to assess the time-evolving structure underlying the behavioural dynamics (Riley, & Turvey, 2002; Glazier, & Davids, 2009). In line with these claims, we used these tools in order to gain understanding on the stability, regularity and predictability of such behaviours.

All the conceptual and methodological advances presented in this thesis will certainly serve as a basis for the future reinforcement of this programme of work (presented in point 8.4.), as well as a basis to potential practical applications discussed in the next section.

## 8.3. Practical applications

This section discusses the potential practical applications of the present thesis, regarding learning and training design as well as sports performance analysis.

### 8.3.1. Learning and training design

Chapter 3 and 4 presented data on 1vs1 sub-phases of association football. Analyses showed that the initial stability of attacking-defending dyads was broken when players simultaneously achieved low interpersonal distances and high relative velocity values. Observations of individual velocity profiles were not consistent with some technical literature that typically suggests the success of the attacking player as associated to an unexpected and explosive change of motion/pace, with some independence from the behaviour of the defending player (e.g., Castelo, 1996). Therefore, it seems that more than an individual action, breaking the initial stability of the dyad implies a highly coupled relational process. Only when players achieve low critical distances, and the difference between the velocities of the players is high, the loss of stability of the dyad occurs. Tuning players to some features such as the reached interpersonal distances, the approaching movements and angles or decreases in velocities could be potentially useful informational sources to improve learning in 1vs1 sub-phases of football. Coaches might be able to manipulate task constraints in order to promote the use of the referred relevant information and encourage players to explore the more effective action modes according to their actual action capabilities (Davids, Button, & Bennett, 2008).

Moreover, Chapter 4 showed that the success of the defending player was associated to a lead-lag relation with the attacker. These data suggest that when the movement displacements of defenders precede the moves of the attacking player, the former has high probability to succeed. Thus, coaches should constrain defenders to move before their opponents, influencing their movements at specific areas of the field where the risk might be potentially low and they might press the opponent to recover the ball. Conversely, the success of the attacker was related with a predominance of synchronised movements between players in space and time, with more unpredictable modes of interpersonal coordination. That finding suggests the importance of promoting creative and unpredictable relational behaviours imposed by the attacking player in order to succeed.

Chapter 5 offered some practical information concerning how goal-scoring opportunities emerge from confrontations of sub-groups of players. The creation of shooting opportunities was associated to an approach (even a crossing) of the sub-groups' centre of gravity immediately before the emergence of an assisted pass to a scoring zone. Moreover, the difference in the occupied areas between the attacking and defending sub-groups significantly increased immediately before the assisted pass was made. This means that the success of the attacking sub-group is related with a collective movement of approaching to the other sub-group and an increase in its covered areas compared with the defending players. Manipulations of practice task constraints should promote environmental conditions in which the available information for attacking sub-groups might constrain their exploratory actions in the way mentioned above. An interesting example of a practice task is the experimental task itself (or adaptations from it) used in Chapter 5.

Chapter 6 and 7 used a case study approach with data from an entire competitive match. Despite the diminished power of generalisation, some interesting findings can be highlighted. The first one is the high sensitivity of the teams' collective behaviours to changes in scoreline. Despite the need of further investigations on this topic, this finding reinforces expert coaching knowledge showing that a goal scored can abruptly change the performance of the teams. The design of practice tasks that might simulate changes in these performance constraints could be a useful strategy to improve teams adaptability and prevent them to be surprised (Seirul-lo Vargas, 2003).

Another important application is related with the finding that teams tend to become more regular and predictable in their organisational shape over the natural course of a match. Interestingly, the halftime breaks this trend of teams to become more predictable, which returns to decrease from less to more regular values in the second half of the game. This trend in predictability of teams' behaviours might be due to the complementary relation of the increasing level of fatigue accumulated by players and the co-adaptation of teams, as showed in Chapter 7. In the last years, elite performance has been associated with requirements of high levels of adaptability (Davids et al., 2003). Therefore, coaching staff should conceive practice tasks in which team players need to balance the co-adaptation with the opposing team with some kind of creativity and unpredictable collective movement solutions that can be important to maintain high levels of adaptation during competitive performance.

Another important application could be derived from the data presented in Chapter 7, which demonstrated how superior values of variability at the level of the individual player contributed to the stabilisation of team behaviour. Regarding training methods, it seems that more than prescribing stereotyped individual behaviours, coaches need to offer to players the possibility of exploring and exploiting the available information in order to allow for an ongoing coordination of behaviours toward their common goal (Araújo, Davids, Chow, & Passos, 2010). Also, the fact that teams are intimately related in their intra-synchronisations (i.e., both teams tend to increase and decrease their synchronies in a highly related manner) could be of particular interest for practitioners. For example, it could be expectable that, if a team synchronises its movements sooner, it will have a potential advantage over the opposing team. The common emphasis put on individual performances is somewhat challenged by the data presented in Chapter 6 and 7.

### 8.3.2. Performance analysis

Practical implications of this thesis can be extended to the field of performance analysis. Contemporary technologies such as electronic devices (e.g., GPS) or video-based multi-player tracking systems (e.g., Prozone, Amisco) allow obtaining accurate and reliable positional data (Carling, Bloomfield, Nelsen, & Reilly, 2008; Barris, & Button, 2008). Currently, most professional football clubs use this type of technology as a normal procedure in the analysis of performance (Carling, Reilly, & Williams, 2009). However, analysis is almost always based on the physical work rates demanded to players. The same raw data can be used to compute meaningful information about individual and team behaviours and improve understanding of performance at a new level. Therefore, new measurement tools such as those proposed in Chapter 2, or others used in the experimental studies of this thesis will certainly contribute to a better understanding of group performance. The use of these measurement tools may allow an accurate monitoring of training and competition, in the way that coaches can be informed if teams are expressing the sort of strategies or behaviours that they are pursuing during practice sessions. For example, do the length and the width of a team assume the values that its coach would like for specific game contexts? What is the relation between the covered areas of teams during attacking and defending phases? And how does this influence the movement synchronisation of players? What kind of differences a team displays over two opposing teams with different features and ranking levels? The proposed measurement tools and, more broadly, all the methodology underlying these analyses, may help in answering these types of practical questions.

## 8.4. A conceptual model derived from findings

In order to better integrate all the findings of the current thesis, Figure 8.1 proposes a model showing how the different levels of game organisation can be conceptualised in terms of the functional variability unfolded and the performance constraints imposed to team players.

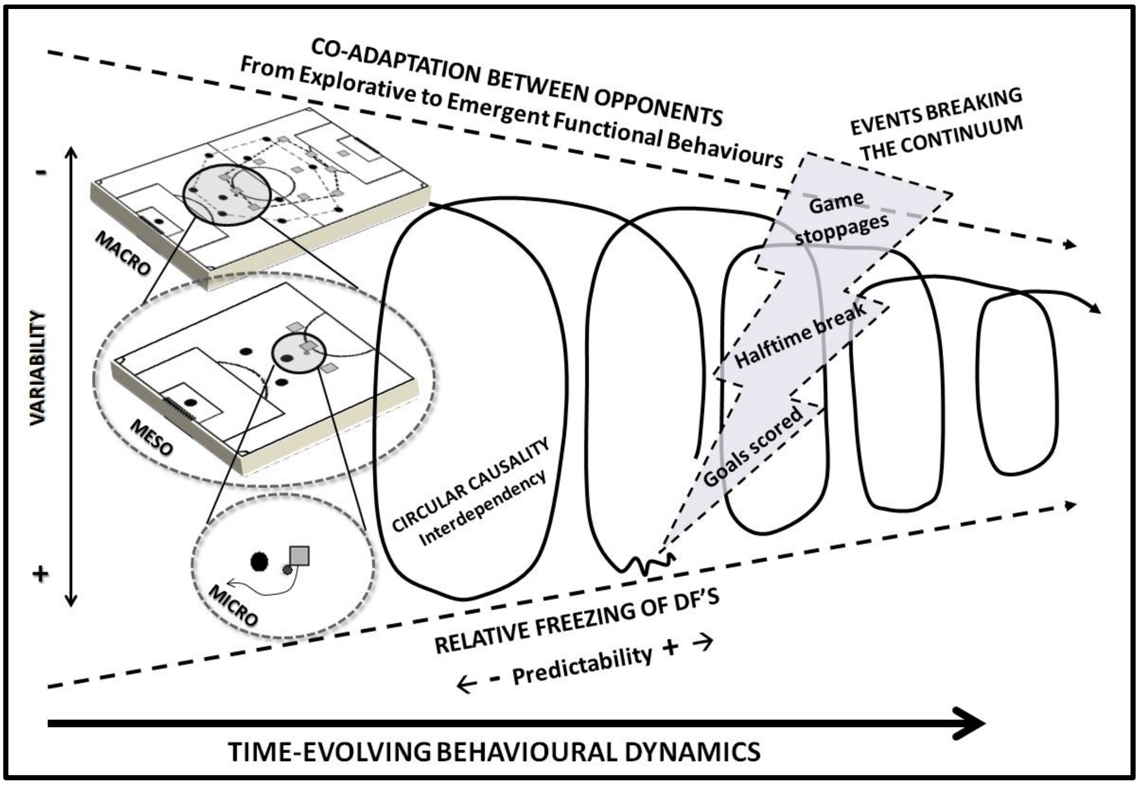


Figure 8.1. A conceptual model of association football performance derived from the experimental findings of the current thesis.

The conceptual model captures the interdependence between the different levels of organisation investigated in this thesis, ranging from dyads to collectives (i.e., 1vs1, 3vs3 and 11vs11). This interdependence implies a circular causality which means that each individual performer reciprocally influences and are influenced by team's behaviour. The relationship between these two levels of analysis was investigated in Chapter 7. Data revealed higher levels of variability (i.e., more irregularity) in the way individuals synchronised with the team than within team's behaviour (see vertical axis on the left side of the Figure). This finding was interpreted as evidencing how micro-variability functionally contributes to stabilise the behavioural dynamics at the collective (macro) level. Besides the 'vertical' variability associated to the spatial fractal nature of the game, the time-evolving dynamics of the collective behaviours studied in Chapter 6 indicated a trend for an increase in their predictability (i.e., more regularity). These data were likely to have emerged due to the co-adaptation processes between opponent players, which suggest that teams may shift from prevalent explorative and variable collective action modes to more stable and predictable behaviours. This co-adaptation process may be due to a relative freezing of the system degrees of freedom or a decrease in the available functional movement possibilities allowed by the intertwined players' interactions. However, this cyclical and channelling flow is broken by some game events such as goals scored and halftime (as demonstrated in Chapter 6), and also stoppages in play for substitutions and injuries assistances (see Chapter 7). Chapters 3 and 5 also showed how players' behaviours tend to channel when they approach critical events that disrupt the stability of the sub-systems under analysis (i.e., the 1vs1 and 3vs3 sub-phases). Thus, the convergent arrows exemplify both the trend of increasing the predictability of the collective behaviours and the progressive decrease in inter-trial variability found in the 1vs1 and 3vs3 sub-phases previously mentioned.

In view of a multi-scale dynamics approach (Keijzer, 1998, 2001), it could be hypothesised that sequences of channelled goal-directed behaviours at low levels of organisation may be interlinked and then, create a continuum chain integrating specific behaviours associated to the successive sub-goals required by the game. Concomitantly, these apparent discontinuities in the successive behaviours may be regarded as a single continuum flow when viewed at a higher-level of organisation, because larger-scaled events usually exist on a longer time scale than smaller-scaled events (Keijzer, 2001).

## 8.5. 'Extending the picture'... again: Future research perspectives

The end of a stage is the starting of novel challenges. This section tries to frame some future perspectives on this field of research. At the moment, two main complementary paths appear to steer the next research endeavours.

On one hand, some applied research should be undertaken in order to allow knowledge transfer for coaches, performance analysts and football practitioners in general. As a research strategy, the accurate selection of some measurement tools should be combined and integrated in a single software application allowing a quick and quasi-automatic generation of outputs to assist and inform the coaches' decisions, as well as improve the analysis of training and competition. This task is already on the way.

On the other hand, the scientific knowledge commonly advances by successive and cumulative approaches (even in a non-linear sense). Four theoretical-methodological issues derived from the present thesis will be matter of further exploration.

The first one is the examination of individual and team behaviours using the dominant region method proposed by Taki and Hasegawa (1998) and reviewed in Chapter 2. This method is deemed to allocate a high functional and dynamic sphere of influence around each individual by integrating data on position, speed, direction and an acceleration model. These variables can be considered to inform players about the physical properties of their surrounding environment and, in particular, about the optical flow sustaining the individuals' perception and action during performance. This work can represent a theoretical and methodological advancement in compliance with the seminal insights of James Gibson's (1979) ecological approach of perception and action.

The second issue is to continuously pursue the desirable description of the dynamics of competing teams using the methodology of coordination dynamics, namely the search for order (also known as collective or coordinative variable) and control parameters (Kelso, 1995, 2009). The experimental demonstration of these parameters in the study of specific behaviours involves proving their underlying dynamic properties such as qualitative changes, sudden jumps, critical slowing down, hysteresis and critical fluctuations. As an example, the potential influence of the defensive organisation of a team in the transition for the attacking phase can be investigated. A candidate order parameter can be the 'expansion speed' of the team after recovered ball possession (Yue, Broich, Seifriz, & Mester, 2008), while potential control parameter(s) can be the distance of the rearmost player to its own goal, or even the difference in the lengths of the teams (Gréhaigne, Godbout, & Zerai, 2011).

The third issue concerns the use of Recurrence Quantification Analysis (RQA), particularly cross-recurrence methods (Riley, & Van Orden, 2005), to evaluate the dynamics of some relational measures as the ones used in the experimental studies of the present thesis. These methods quantify the degree of temporal coordination of two continuous signals (e.g., two geometrical centres, two surface areas) during interaction (Marsh, Richardson, & Schmidt, 2009). Presumably, the pull to such a coordinated state informs about the connectedness of the two corresponding entities and may reveal their non-linear underlying dynamics.

The fourth and last issue regards the formal description (i.e., mathematical modelling) of a football team as a superorganism. Gardner and Grafen (2009) presented a formal description of group adaptation using 'group as maximizing agent' (GMA) model adapted from economics theory. Conversely, biologists commonly use computer simulations, known as self-propelled particle (SPP) models, that attempt to capture the collective behaviour of animal groups in terms of the local interactions they develop (Sumpter, 2006). For example, Couzin and colleagues (2002) proposed a model in which individual animals follow only three simple rules of thumb: (i) move away from very nearby neighbours; (ii) adopt the same direction as those that are close by and, (iii) avoid becoming isolated. Biological systems such as schools of fish are able to produce very different complex patterns due to small changes in these simple localized rules. SPP models have also been successfully used to formalise some human phenomena by treating people as particles that interact according to a set of 'social forces' (Helbing, & Molnar, 1995; Helbing, Farkas, & Vicsek, 2000). It is likely that adaptations to these models can be successfully applied to capture the time-evolving dynamics of football teams as functionally integrated entities or 'superorganisms'. For example, modelling specific game behaviours such as a team defending its own goal, while the other team uses the passing game for considerable amount of time to destabilise opponents' positioning. This task could potentially reveal how specific attacking teams could explore certain spaces conceded by the opponents or inform defenders about the more effective defensive behaviours to adopt against specific team formations with certain predominant patterns of play. This might be an important advance for sports performance analysis, allowing potentially simulations and accurate predictions about the collective behaviour of teams.

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