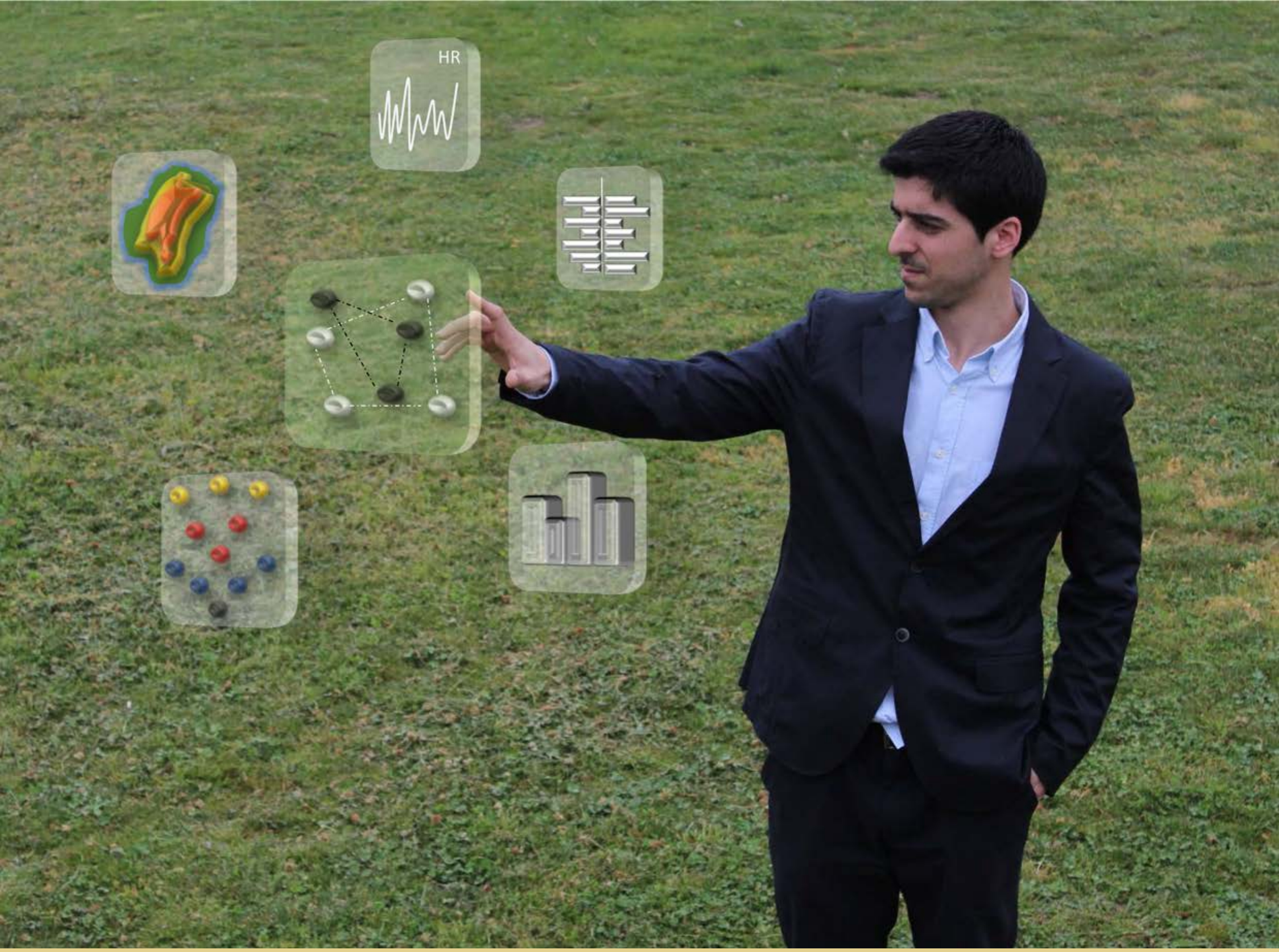

Filipe Manuel Batista Clemente

Towards a New Approach to Match Analysis: Understanding football players' synchronization using tactical metrics

Tese de doutoramento em Ciências do Desporto, Ramo de Treino Desportivo, orientada pelo Senhor Professor Doutor António José Figueiredo e Senhor Professor Doutor Rui Sousa Mendes e apresentada à Faculdade de Ciências do Desporto e Educação Física da Universidade de Coimbra.

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Universidade de Coimbra

FILIPE MANUEL BATISTA CLEMENTE

TOWARDS A NEW APPROACH TO MATCH ANALYSIS

Understanding football players' synchronization using tactical metrics

Tese de doutoramento apresentada à Faculdade de Ciências do Desporto e Educação Física da Universidade de Coimbra com vista à obtenção do grau de doutor em Ciências do Desporto – Ramo Treino Desportivo.

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“Not everything that counts can be counted, and not everything that can be counted counts.”

Albert Einstein

ABSTRACT

The aim of this dissertation was to research the collective organisation of football players during official matches. It was also the aim of this dissertation to update and to propose new computational match analysis methodologies that use the Cartesian information of players' location on the field throughout the time. Based on the existing literature it was found that the computational metrics has the potential to assess players' tactical performance during the matches. Thus, the first study of this dissertation was to optimize the tracking of football players by using an estimation approach involving the Fractional Calculus. In this context, based on the information of players' location over the time it was possible to update the spatio-temporal metrics previously proposed by the literature. In the second study of this dissertation, not only the update versions of spatio-temporal metrics were proposed, but also new metrics were designed based on the specificity of the football game. Thus, the Centroid and Stretch Index metrics were updated by introducing a weighted based on the proximity of each player to the ball, thus designating the new versions of *w*Centroid Index and *w*Stretch Index. Moreover, a new metric was proposed to replace the usual Surface Area, that is, by inserting an efficacy criterion to define the moments where the triangulations of both teams are overlapped. This metric was called *Effective Area of Play*. These spatio-temporal metrics were analysed throughout the official matches in the moments with and without the possession of the ball and between the 1st and 2nd half of the match. It was found that the highest levels of *w*Centroid Index, *w*Stretch Index and Effective Area of Play was in the moment with the possession of the ball during 1st half. In the third study, the spatial occupation of players on football field was assessed using the Territorial Domain that split the field into 12 regions and the numerical relationship between opponents within each region was analysed. It was observed that the highest variability of such numerical relationship was found in the midfield regions. In order to convert the manual observation into automated method a set of criteria were defined based on the offensive principles of play in the fourth and fifth studies. No differences were found between different matches, nevertheless using such metrics it was possible to observe that the studied team opted to a direct style of attacking play and not by a circulation style. Once again, by using the Cartesian

information about the players' position it was possible to propose two new metrics in the sixth study: Defensive Play Area and Sectorial Lines. By using these metrics it was observed that the highest area of defensive pressing was in the midfield region, and a small correlation between the three sectorial lines within the team, thus being partially independent from each other. In conclusion, it was possible throughout this dissertation to propose a set of new computational and automated metrics that can allow characterizing user-friendly team's properties, opening the gates for a new era of match analysis and sports training optimization.

Keywords: Collective Organization. Match Analysis. Football. Metrics. Tactics.

RESUMO

O objetivo da presente dissertação foi investigar a organização coletiva de jogadores de futebol em jogos oficiais. Foi ainda objetivo da presente dissertação atualizar e propor novas metodologias de análise de jogo auxiliadas computacionalmente considerando a localização cartesiana dos jogadores no campo ao longo do tempo. Para o efeito, e a partir da literatura existente, procurou-se enquadrar e sintetizar as potencialidades das métricas computacionais de avaliação tática no contexto da análise de jogo. Propôs-se, nesta dissertação, um método de otimização do processo de estimação do posicionamento dos jogadores utilizando o Cálculo Fracionário. Tendo como referência a estimação dos jogadores ao longo do tempo procurou-se, numa primeira fase, adaptar e modernizar as métricas espácio-temporais existentes. Posteriormente, propôs-se novas métricas tendo por base o estado da arte sobre a análise de jogo em futebol. Desta forma, às métricas de *Centroid* e *Stretch Index* foi proposta uma ponderação que determina a organização coletiva em função do posicionamento da bola designando as novas métricas de *wCentroid* e *wStretch Index*. Adicionalmente, em substituição da métrica existente de *Surface Area* foi proposta a *Effective Area of Play* que acrescenta um critério de eficácia defensiva no momento de interceção entre as áreas ocupadas pelas equipas adversárias. Estas métricas espácio-temporais foram analisadas ao longo de jogos oficias nos instantes com e sem posse de bola e entre as partes do jogo tendo-se a existência de diferenças estatisticamente significativas no desempenho coletivo, com valores mais elevados do *wCentroid*, *wStretch Index* e *Effective Area* of play nos instantes com posse de bola durante a primeira parte. A ocupação espacial dos jogadores em regiões do terreno foi averiguada utilizando a métrica designada de *Territorial Domain* que determina 12 setores de jogo e verifica a relação numérica entre adversários. Através de métodos estatísticos não-lineares, verificou-se que a maior variabilidade na relação numérica ocorreu nos setores centrais do meio-campo. Tendo-se como objetivo converter métodos observacionais manuais em métodos observacionais auxiliados computacionalmente, estabeleceram-se critérios de eficácia no cumprimento dos princípios de jogo ofensivos. Verificou-se que não existiram diferenças estatisticamente significativas ao longo dos jogos observados, no entanto, foi possível

identificar que a equipa observada privilegiou o estilo de jogo direto em detrimento do estilo de jogo em apoio. Ainda tendo como base a informação sobre o posicionamento cartesiano dos jogadores propuseram-se as métricas de determinação das áreas de pressing defensivo e de determinação das linhas sectoriais. Através da análise efetuada foi possível verificar que as áreas mais amplas de pressing ocorreram no meio-campo e que as três linhas da equipa possuem uma correlação baixa. Em suma, foi possível através da presente dissertação propor um conjunto de novas métricas computacionais que permitirão caracterizar de forma rápida e intuitiva as características específicas de cada equipa, abrindo espaço para um novo futuro da análise de jogo e otimização do processo de treino.
Palavras-chave: Organização Coletiva. Análise de jogo. Futebol. Métricas. Tática.

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LIST OF ABBREVIATIONS

ADZ – Attacking Definition Zone

ApEn – Approximate Entropy

AR – Augmented Reality

CV – Coefficient of Variation

D1HMR – Defensive 1st half of the middle region

D2HMR – Defensive 2nd half of the middle region

DBR – Defensive Backward Region

DFR – Defensive Forward Region

DLT – Direct Linear Transformation

DM_r – Depth Mobility Ratio

DPL – Defensive Play Area

EAP – Effective Area of Play

EC_r – Ratio of Effective Cover

ECS_r – Ratio of Effective Cover in Support

ECV_r – Ratio of Effective Cover in Vigilance

FC – Fractional Calculus

FIFA – Fédération Internationale de Football Association

GPS – Global Positioning System

ODZ – Offensive Definition Zone

OU_r – Offensive Unit

POS – Previous Position

P_r – Penetration ratio

RFID – Radio-Frequency Identification

RMSE – Root Mean Square Error

SA – Surface Area

SL – Sectorial Lines

VEL – Velocity Vector

*w*C – Weighted Centroid

WL_r – With and Length ratio

*w*SI – Weighted Stretch Index

Chapter I

Introduction

Chapter based on the following publication:

Martins, F. M. L., Clemente, F. M., & Couceiro, M. S. (2013). From the individual to the collective analysis at the football game. In *Proceedings Mathematical Methods in Engineering International Conference* (pp. 217-231). Porto: Instituto Superior de Engenharia do Porto.

1. INTRODUCTION

1.1. Football as a Dynamic System ruled by principles of cooperation

This section will present the concepts of collective organization that contribute to explaining the game of football. The systemic nature of team sports, their internal logic and the strategic and tactics underlying the game will be discussed here in some detail.

1.1.1. Team Sports: Systemic Nature

Animals such as elephants, bison and quail form defensives circles, and predators often adopt complex attacking patterns to cope with these defensive formations (Deneubourg & Goss, 1989). Additionally, many collective activities performed by social insects result in complex spatio-temporal patterns (Bonabeau, Theraulaz, Deneubourg, Aron, & Camazine, 1997). Thus, individual agents in complex systems have a tendency to spontaneously organize themselves into rich coordinated patterns by modifying their movements on the basis of local social interactions (Couzin, Krause, Franks, & Levin, 2005). Jarman and Jarman (1979) propose that the tendency to take the same speed and direction is the major force that allows ungulate herds to be a stable and structured organization. The behaviour of agents – either natural or artificial – was perceived as similar, and it was reported that collective behaviours in both systems emerged from non-linear responses over time supported by local interaction rules (Halloy et al., 2007).

A system is said to be quasi-decomposable if it can be decomposed into isolated subsystems, with some interaction between them and the environment (Gréhaigne, Bouthier, & David, 1997). Therefore, they may be considered either: *i*) microsystems, obtained by retaining only a few subsystems with all of their interactions (e.g. confrontation between two force lines at a given instant); and *ii*) infrasystems, obtained by retaining only a few subsystems with some of their interactions (1 vs. 1 or 2 vs. 2 at a given point in the match).

As with the general characteristics of systems, interactions among subsystems are either energy-based or information-based. These subsystems may organize themselves into various types of networks, which are either superimposed upon or merged inside the system (Gréhaigne et al., 1997). One example of this fact occurs when some players act during an offensive moment, thereby generating specific forms of cooperation, i.e. generating a subsystem.

System analysis has been developed as a result of the interaction between various scientific areas, including biology, information theory, cybernetics and the theory of systems (Gréhaigne et al., 1997). Complex systems manifest a number of fundamental characteristics, including many different levels in the system; a capacity for stable and unstable patterned relationships among parts of the system, and which emerge through system self-organization; and the ability of subsystem components to constrain the behaviour of other subsystems (Kauffmann, 1993; Kelso, 1995). The way in which order emerges in the complex behaviour of dynamical systems is a fundamental problem for scientists studying natural phenomena within this framework of analysis (Handford, Davids, Bennett, & Button, 1997).

In trying to describe dynamical systems' etymological sense, it is possible to report that the system is an agglomeration of related parts that can be perceived as a single entity. "Dynamical" means that the system changes over time. Therefore, a dynamical system is a system where the state changes over time (Araújo, 2006). Dynamical system theory may offer a greater scope and potential for scientific endeavour in performance analysis (Glazier, 2010). Therefore, dynamical systems can be interpreted either via a mathematical and physics-based conception. From the mathematical viewpoint, dynamical systems theory is the branch concerned with studying the evolution of numerical systems in the form of equations of motion (Araújo & Davids, 2009). From the physics-based viewpoint, on the other hand, it is possible to analyse spontaneous patterns formations, phase transitions, symmetry breaks, self-organization, and micro or macro complexity. Summarily, a dynamical system is a set of quantitative variables that change continually, simultaneously and interdependently throughout time, and according to mathematical equations (Araújo, 2006).

Structurally speaking, the elements of the system are represented by the two opposing teams, while the communication network between the two is defined by the rules of the sport (Gréhaigne et al., 1997). A more dynamic aspect of interpersonal coordination involves synchrony or entrainment, in which the movements of interacting individuals become organized in time and space (Richardson, Marsh, & Schmidt, 2005). To this end, collective systems are dependent on information available in specific contexts, particularly the information that is created by each individual's tactical actions (Passos et al., 2008).

A player has to act in order to perceive a teammate's behaviours, as well as those of a defender and the opposition (Passos et al., 2011). Interactions among players originate in coadaptive behaviours, where players adjust their behaviours relative to the perceived actions of neighbouring players in order to achieve performance goals (Fajen, Riley, & Turvey, 2009). Effectively, aggregations often behave as a unit, with properties that are not merely a sum of individual behaviours, but which also sometimes result in new functions (Parrish & Edelstein-Keshet, 1999). Thus, the idea is to characterize the opposition's rapport from a space standpoint. In doing so, we can analyse the relationship and dynamic between the strengths of the attack system, on the one hand, and those of the defensive system on the other, and thereby ascertain how collective behaviours emerge. The notions at stake here include 'in block', 'in pursuit', centre of gravity and ball circulation (Gréhaigne et al., 1997).

1.1.2. Team Sports: Classification and Analysis

Logic, tactics and practice each constitute the notions that involve two central and associated ideas: *i*) the reality of the game is intelligible; and *ii*) any intervention in this reality can be the subject of objective, and thus rational, inquiry (Gréhaigne, Richard, & Griffin, 2005). Therefore, some authors advocate that the essence of game style is inherent in their players (Deleplace, 1995; Wade, 1970). The statement emphasizes that players have the greatest influence in the evolution of the playing style, as the game actions are performed by them (Gréhaigne et al., 2005). However, coaches, referees and rules constitute the complementary factors that influence the game.

The properties of the sport constitute a fundamental constraint to the potential improvement of players (Almond, 1986). Therefore, match analyses need to consider relevant factors that determine the quality of collective performance in the relationship of strengths between opposite teams, as well as the competency network between teammates (Gréhaigne et al., 2005). Knowledge about relationships within the opposite team and their style of play represents essential information for the efficacy of match analysis.

So does the intrinsic dynamic of the game constrain and determine the quality of a team's performance? This intrinsic dynamic of each sport is related with specific components and their rules, and thus players' type of action and performance depends directly on the sport's characteristics (Gréhaigne et al., 2005). Indeed, the rules determine the sport's essence, as do the type and principles of play, as well as the relations between teammates and opponents. These rules can be defined as: *i*) the modalities of scoring (i.e. the characteristics of the game's target); *ii*) the players' rights (based upon the modalities of scoring); *iii*) the liberty of action (that players have with the ball); and *iv*) the modalities of physical engagement (that ensure the respect of the three previous rules). These characteristics allow us to group sports in the following four categories according to their specificities: *a*) target games; *b*) net/wall games; *c*) striking/fielding games; and *d*) invasion games (Webb, Pearson, & Forrest, 2006).

The aim of target games is to place a projectile in a target in order to achieve the best possible score (Webb et al., 2006). Target games can be classified according to whether they are unopposed or opposed. In the case of unopposed target games (e.g. golf, archery, bowling), the accuracy of the player in relation to the target determines their own success. In opposed target games (e.g. bocce), players have the opportunity to constrain the opponent, interfering with their ball position in order to take advantage for themselves (Webb & Pearson, 2008).

In net/wall games, the player or team aims to send an object into their opponent's field so that it cannot be played our returned. Examples of the net games are tennis, badminton or volleyball. Racquetball or squash are examples of wall games (Webb & Pearson, 2008).

The main goal of striking/fielding games (e.g. baseball, softball, cricket) is to score more runs than the other team using the number of innings and time allowed. This is usually achieved through the efficacy of the strike in relation to a ball when it is projected by the opposing team.

The purpose of invasion games is to invade your opponent's field, aiming to score more points within the time limit than the opposing team (Webb et al., 2006). Invasion games can be grouped into subcategories (Webb & Pearson, 2008) including: *i*) where the ball can be carried or caught across the line (e.g. rugby, American football); *ii*) can be thrown or shot into a target (e.g. basketball, netball); or *iii*) can be struck with a stick or foot into a target area (e.g. hockey, football).

It is important emphasize that the target's positioning, as well as the type and dimension of the field, can define the type of technical and tactical skills inherent to the game (Gréhaigne et al., 2005). The space to run, as well as the format and position of the target, are strong constraints to the technical action and the tactical behaviour of the teams' attempts to achieve their main goals. As such, it is fundamental analyse the systemic model of sports games in order to understand how players act collectively when trying achieve collective goals.

1.1.3. Internal Logic of Team Sports

The opposition and coordination between two teams is the essence of invasion sports, where each team tries to recover, maintain and move the ball to the score zone in order to score a goal (Gréhaigne & Godbout, 1995). Metzler (1987) describes the essence of the team sports as a possibility to actively solve an unpredictable set of problems with the highest efficacy possible. This problem-solving occurs simultaneously in the offensive and defensive phases, depending on the ball possession state. Therefore, invasion team sports constitute a complex and dynamical system that persist throughout the match, constantly adapting to the contextual constraints (Gréhaigne et al., 1997; McGarry, 2005).

1.1.3.1. Rapport of Strength

The fundamental notion of opposition leads us to consider two opposing teams interacting as organized systems within a match (Gréhaigne, Godbout, & Zerai, 2011). Usually, the relationship between teams is antagonistic, as each are trying to achieve their own goals while hampering their opponent's actions. These antagonistic links between several groups of players, who are each confronted by virtue of certain game rules, may in fact determine interaction patterns (Gréhaigne et al., 1997). Thus, the opposition concept helps in highlighting the pressure notion at a particular point in the game so as to break the balance of forces during momentary configurations of play (Gréhaigne et al., 2011). Therefore, ball possession may change at any instance, inverting the direction of play, and thus making team sports a dynamic, variable and at certain points an unpredictable game (Gréhaigne et al., 2005). This proves that their complexity is composed of many interactive components (McGarry, Anderson, Wallace, Hughes, & Franks, 2002).

Despite these complex characteristics, different organizational levels can be identified in many team sports. During the match, the global opposition relationship breaks down into partial oppositional relationships, i.e. sub-phases. These opposition settings momentarily involve a few players, generating specific shapes of play (Gréhaigne et al., 2005). Thus, this strength rapport is a permanent characteristic of the game in terms of ball possession and the organizational quality of the teams in their attempt to achieve their main goals and annul their opponent's strong points.

1.1.3.2. Network

At the organizational level, the numerous interrelations between players within the team make up what one might call a competency network (Gréhaigne, 1992). The competency network is based on each player's recognized strengths and weaknesses with reference to the practice of the sport, and also in relation to the group's dynamism (Gréhaigne et al., 2005). Therefore, team function performance in sports is assured by a complex network of interpersonal relationships among players (Passos et al., 2011); as such, the competency network is more of a dynamic concept than a static one (Gréhaigne, Godbout, & Bouthier, 1999). Any network analysis needs to consider the regular and variable interactions between players. In the study of competency networks, some works have been undertaken in order to improve knowledge about the teams' collective behaviour (Grunz, Memmert, & Perl, 2012; Memmert & Perl, 2009).

Different computer-based approaches have attempted to extract and analyse tactical patterns in team sports (Grunz et al., 2012). Considering Memmert and Perl (2009), there are three ways of using a dynamically controlled network: *i*) as a static tool (if the application context does not change); *ii*) as an adaptive tool (if the application context is changing); and *iii*) as an object of analysis (if the learning dynamics of the network is of interest).

Recently, a water polo team was seen to apply the networking method to analyse intra-team behaviour. Through a networking method – among other analyses – it may be possible to identify the player who most frequently interacts with their neighbour (i.e. teammates), as well as their own contribution to successful and unsuccessful collective performance (Bourbousson, Poizat, Saury, & Seve, 2010a). In their study, Passos et al. (2011) built an adjacency matrix for each unit attack, and found that two linkage levels were established: *i*) identification when a player passed the ball to a teammate; or *ii*) identification when players changed their position in the performance area due to a teammate's displacement. In terms of the usefulness of this method, the results suggest that the networking method provides an interesting tool to qualitatively describe the interactions that occur between team players in water polo games (Passos et al., 2011). Furthermore, it is possible identify the preferential attachments between players and their efficiency.

1.1.4. Strategy and Tactics in Team Sports

Tactics and strategy are two different terms that need to be understood individually when considering the sport context. Strategy relates to the principles of play or action orientations which enable a team's organization and preparation for a given match (Bouthier, 1988). On the other hand, tactics relate to the players' orientation during the game in order to adapt their initial requirements to the dynamical constraints performed by the opposite team. Thus, strategy constitutes the elements previously discussed by the organization (i.e. a team) to prepare for a match (Gréhaigne & Godbout, 1995). Indeed, strategy relates to the general order, i.e. the players' positioning and their distribution in the field, as well as the specific missions of each player (Gréhaigne et al., 1999). Tactics, however, relate to the punctual adaptation to new play configurations, to the state of ball possession and to an opponent's position (Gréhaigne & Godbout, 1995). The tactic concept relates to the behavioural adaptation in response to the opponent and the play status (Gréhaigne et al., 2005).

Therefore, there are substantial differences between strategy and tactic at the time and space levels. Strategy relates to the more elaborate cognitive processes due to the larger amount of time needed to prepare and lower constraints (Gréhaigne et al., 1999). In comparison, the tactic concept requires higher levels of decision-making and behaviour adaptations in functions related to contextual constraints, i.e. action decisions. Thus, tactical behaviour prevails during the game (Gréhaigne et al., 1999).

Considering the above-mentioned points, some principles underlying the team's strategies and tactical behaviour provide a higher organization and structure to collective behaviour. Without principles of play, teammates' relationships may lose some organization, decreasing the opportunity to play as a team or unit. Thus, the team sports theory has developed some principles over the years that potentiate collective behaviour and the quality of play.

The principles behind strategy and tactics are predominantly related to players' actions. All of these principles are linked to the main goal of the game, i.e. surpass the opponent's actions and achieve victory. The general principles are fundamentally related to a relationship with strength or the establishment of a competency network. As such, these principles could be related with the majority of collective invasion sports games. Following will be presented nine principles underlying strategy and tactics, as suggested by Gréhaigne et al. (2005).

1.1.4.1. Deception Principle

This principle is related to the ability to force the opponent to make mistakes. Through the deception principle, players (collectively or individually) use fakes to outwit their opponents. Deception has an essentially collective basis, requiring higher levels of the involvement among teammates. One example of the deception principle is collective organization against the opposing team in order to force it into making mistakes in the final phases. Another example is to force the opponent team to play on their weak side by covering their strong side with more players.

1.1.4.2. Surprise Principle

This principle is closely related to the offensive phase. The objective is to show more unpredictability levels in collective actions in order to destabilize the opponent team in the defensive phase. It is possible to surprise them so as to increase the opportunities to complete offensive actions with success. Thus, this principle relates with the mobility and opportunity principles mentioned below.

1.1.4.3. Mobility Principle

Unbalancing a defensive organization is one of the chief objectives in an offensive phase. Through fast shifting and good ball circulation, attackers may intrude into a given area of the score zone, disrupting the equilibrium of the defensive organization. Disrupting the opponent's defensive organization is the easiest way to explore the score zone and finalize an offensive action. Therefore, in the offensive phase, the permanent oscillation of the ball around the field is fundamental to moving defenders within the central zone.

1.1.4.4. Opportunity Principle

This principle relates to the opportunity to take advantage of an opponent's mistakes. Thus, any mistakes committed by the opponents need to be duly taken advantage of in order to increase the opportunity to win. This is a fundamental principle, applicable to all sports that involve competition with others.

1.1.4.5. Cohesion Principle

All individual actions need to correspond to collective principles so as to ensure that all players are tuned into the specific objective. In other words, all players must play in harmony. The ability to maintain collective structure and act according to the state of the team can help to achieve the key goals, particularly in defensive and offensive phases. By maintaining cohesion, players will have more support to act both in the defensive and offensive phase.

1.1.4.6. Competency Principle

Cohesion is obtained through the competency network, which involves different roles and functions among teammates. Thus, the whole system acquires a certain homogeneity that makes it possible to lower maintenance energy costs (Gréhaigne et al., 2005). In other words, the competency principle relates to the efficiency of collective action when trying to reduce individual energy costs and act more closely and more organized, i.e. not depending directly on individuals or isolated actions within the collective action.

1.1.4.7. Reserve Principle

A support player acts as an alternative to immediately restarting a sequence of play, such as when certain manoeuvres have failed. In football, for example, having the forwards take possession of the ball makes it possible to distribute other players and deploy a reserve along the longitudinal axis of play (Gréhaigne et al., 2005).

1.1.4.8. Economy Principle

This principle is closely related to players' cognitive processes when deciding their actions during functions of efficiency, i.e. achieving better results at the lowest possible cost. Thus, this process depends on to the capacity to organize the team to achieve their goals while maintaining personal principles. The economy principle relates to the competency to understand the whole game and solve problems efficiently.

1.1.4.9. Improvement Principle

A team's preparation for a match is made by considering their own characteristics and principles, as well as those of their opponents. These knowledge and competences are an initial stage of the team, and thus enable an individual approach to a specific match. Nevertheless, the complex and dynamic processes that occur in a match may require adjustments in order to outperform the opposing team. As such, this ability to understand the dynamic reality of the game, as well as solutions to these problems, may improve collective efficacy, increasing the opportunity to win the match and develop as a team.

1.1.5. Football's Tactical Principles

Tactical principles are defined as a set of play shapes that allows players to quickly achieve tactical solutions to solve any problems originated by the opponent team (Garganta & Pinto, 1994). Collectively, the tactical principles' application helps a team to control the match, maintaining efficacy in offensive and defensive phases. Over the years, many tactical principles have been developed and characterized (Castelo, 1996; Duprat, 2007; Garganta & Pinto, 1994; Zerhouni, 1980). From such authors it is possible organize three theoretical constructs: *i*) general principles; *ii*) operational principles; and *iii*) fundamental principles.

General principles are common to all phases of the game, and are characterized by their spatial and numerical relations to team players and opponents. There are three general principles of the game: *i*) to not allow a numerical disadvantage; *ii*) to avoid numerical equality; and *iii*) to attempt numerical superiority (Costa, Garganta, Greco, & Mesquita, 2009).

The operational principles are the procedures required to solve a set of problems in the game by considering defensive and offensive phases. In the defensive phase, the operational principles are: *i*) to avoid opponent finalization; *ii*) to recover the ball; *iii*) to prevent the opponent's progression; *iv*) to protect the goal; and *v*) to reduce the opponent's playspace. Considering the offensive phase, the operational principles are: *i*) to maintain ball possession; *ii*) to create offensive actions; *iii*) to advance on the opponent's field; *iv*) to create finalization situations; and *v*) to try to score.

These fundamental principles represent a set of basic rules that guide the action of players and teams in the two phases of the game (i.e. defensive and offensive). These maintain balance in one's own team and unbalance the opponent by trying to take advantage of their weaknesses. These principles are grouped into offensive and defensive categories, wherein each opposes the other. Its importance is essential to improve the tactical quality of the teams, as it organizes collective behaviour in the game status.

1.1.5.1. Fundamental Defensive Tactical Principles

The defensive principles of play enable better coordination between team players, improving their collective intervention. All defensive principles aim for quick and effective action in order to protect the goal and recover ball possession (Worthington, 1974). The accomplishment of these principles guides the players' positioning on the field in relation to the ball, teammates, opponents, as well as to the main objectives of the team. Thus, the defensive tactical principles aim to constrain the space and time of the opponents so as to achieve their goal, avoiding the effectiveness of the opponent's offensive phase (Bangsbo & Peitersen, 2002).The five fundamental defensive tactical principles are: *i*) delay; *ii*) defensive coverage; *iii*) balance; *iv*) concentration; and *v*) defensive unity (Costa et al., 2009).

1.1.5.1.1. Delay Principle

The delay principle is characterized by the action of the opposition defender over the attacker, with ball possession aimed at reducing the offensive space, and constraining the opportunities to pass or conclude an offensive action successfully. The guidelines of this principle is the individual and rigorous marking of the attacker with ball possession so as to delay offensive progression, as well as the constraint of passing lines or shooting attempts. During this process, defenders should maintain their position between their own goal and the ball's position.

1.1.5.1.2. Defensive Coverage Principle

Defensive coverage refers to the protective action of the first defender, i.e. the second defender protects the defender that makes the delay principle over the attacker with ball possession. Thus, if the attacker with ball possession overtakes the first defender, the second will try to slow the offensive progress. Furthermore, the protective action of the second player can allow an improvement of their defensive action, because they feel safer in cases of failure to attack the ball (Worthington, 1974).

1.1.5.1.3. Balance Principle

The first theoretical assumption to accomplish the balance principle is ensuring numerical superiority (or at least numerical equality) in the defensive phase over the opponent. The second theoretical assumption is the frequent adjustments in reaction to the opponent's positioning. The guidelines of the balance principle are to cover the space and mark the attackers without ball possession, avoiding passing lines, and thus reducing success opportunities.

1.1.5.1.4. Concentration Principle

The concentration principle aims to reduce the effective play area of the opposing team; as such, the higher proximity between teammates in the defensive phase increases the effectiveness of the defensive coverage, as well as the protection of the score zone. Therefore, for an effective defensive pressing process, the highest priority is to ensure the concentration principle, as this will make it easier to recover ball possession (Bangsbo & Peitersen, 2002). The guidelines of this principle are to orientate the opponent to play in less dangerous areas, and decrease the length and width of the players' distribution so as to reduce the free spaces between teammates. The concentration principle can be accomplished in any field zone, but depends on the strategies and orientation of the team, as well as the match status.

1.1.5.1.5. Defensive Unit Principle

The defensive unit principle is the positioning of off-ball defenders so to decrease the effective playspace of the opponents (Costa, Garganta, Greco, Mesquita, & Seabra, 2010). To accomplish this principle, a deeper knowledge and understanding of the game is indispensable, as is knowledge of the strategic orientations of one's own team. A defensive unit conception depends on the ability to position oneself in the right place according to one's teammates, the ball's position, opponents' position and the status of one's own team. This unit should be ensured throughout the game and in any field zone. By reducing the dispersion of teammates within the ball possession zone, it will make it more difficult for opponents to penetrate between defensive lines. Theoretically, the dispersion level of the team is smaller during an offensive phase and triangulations, and within the area between team defenders.

1.1.5.2. Attacking Fundamental Tactical Principles

Offensive tactical principles aim to give players fundamental information that allows them to improve collective behaviour. Through tactical principles, it is possible for all players to act in an organized manner, attuning their behaviour with the main goal of the team, i.e. to create successful finalization opportunities and score. Thus, tactical principles are essential guidelines, allowing an improvement of the collective behaviour in order to overtake the defensive organization of the opposing team. The five offensive fundamental principles of play in football are: *i*) penetration; *ii*) offensive coverage; *iii*) depth mobility; *iv*) width and length; and *v*) the offensive unit (Costa et al., 2009).

1.1.5.2.1. Penetration Principle

The penetration principle is characterized by the progress of the attacker with ball possession in the direction of the score zone. Their main objective is to reach the zone closest to the goal by aiming to finalize the offensive attempt. The guidelines of this tactical principle are to overtake the direct opponent and unbalance the defensive organization in order take advantage of this situation, thereby bringing the ball to a favourable position in the score zone. Actions that identify the penetration principle include progress with ball when trying to approximate the attacker's position to the goal, or when the direct opponent tries to take advantage by overtaking in order to create space to play or finalize.

1.1.5.2.2. Offensive Coverage Principle

The coverage principle is characterized by the backing action provided by a teammate to the player with possession. The support provided by the teammates is fundamental to the offensive phase, providing him with many options to conclude the process with efficacy. To benefit from this principle, the attacker with ball possession needs to simplify their actions, usually by opting for safe passes or actions. Furthermore, it is fundamental that teammates take actions towards or away from the player with ball possession, depending on the position of opponents and the ball.

1.1.5.2.3. Depth Mobility Principle

Depth mobility is characterized by teammates' optimal movements to receive the ball from the player with ball possession. These movements can be completed away from the player with ball possession (i.e. break movements) or close to them (i.e. support movements). The guidelines for this principle are the variability of the actions of the ball and opponents' positions, as well as the velocity of the movements when trying to unbalance the defensive organization. All of the mobility processes should be made with intent, i.e. giving valid solutions to successfully conclude the offensive phase (Worthington, 1974). Thus, it is fundamental that teammates understand the dynamic processes that allow them to improve their quality during the offensive phase.

1.1.5.2.4. Width and Length Principle

The movements of players should extend and utilise the effective playspace. Increasing the dispersion of players during an offensive phase will make it easier to attract defensive players to non-vital zones (e.g. lateral lines), thereby removing them from the vital ones (i.e. the middle side). Thus, the width and length principle is in opposition to the defensive concentration principle of the opposite team described previously. Resituating some opponent defenders to non-vital areas will make it possible to explore the central area of the score zone. Furthermore, it will be possible for the player with ball possession in the central area to try and overtake the direct opponent, allowing them to benefit from the additional space and successfully conclude the offensive process.

1.1.5.2.5. Offensive Unit Principle

The positioning of off-ball defenders decreases the effective playspace of their opponents. Maintaining collective cohesion and the balance between team sectors is as important as an effective and functional distribution of players in relation to ball position, the phase and match status of the game, as well as the opponents' positioning. Thus, a team needs to function as a whole, positioning itself functionally on the field. The fundamental guideline of this principle is their efficient positioning on the field, considering not only their individual missions, but also the collective objective and functionality of the team (Castelo, 1996). This unit principle assumes a balance between the team’s sectors (i.e. defenders, midfielders and forwards) as a determinant factor to success when a team loses ball possession. Keeping proximity between team sectors and their balanced organization is easier during defensive organization (Teodorescu, 1984), and increases the opportunities to improve high-quality defensive action. The ultimate goal is to avoid imbalance in the team at any stage of the game.

All those principles are regulated by the inter-players’ relationships in a given space and time. This spatio-temporal relationship is truly important and one of the most important variables to be optimized by sports training, i.e. the synchronization of multiple players to achieve a common goal. Therefore, coaches and sports analysts have a specific mission: to observe and collect relevant information about the collective behaviour of players. Using such information the football training and the tactical behaviour of football teams can be improved. Thus, specific metrics that inspect the collective synchronization of football players has emerged in the most recent literature of match analysis. Despite this important opportunity in literature, few studies have inspected inter-player relationships using specific technological metrics, even though this would provide coaches and analysts with an easy and quick method to help them obtain information and provide support to plan football training sessions. Thus, the following section will present a survey about the technological metrics to assess the collective behaviour at football teams.

1.2. Technological metrics applied to the match analysis: A survey

Team sports are complex systems (McGarry et al., 2002) that require specifics strategies of observation to improve the intervention's quality of coaches and sports analysts (Franks & McGarry, 1996). Such observations are commonly designated as match analysis (Carling, Williams, & Reilly, 2005), thus including a set of analysis procedures (e.g., notational, kinematical and tactical analysis). Nevertheless, to analyse the collective team's performance, it is essential to further understand and determine the relevant parameters to achieve the main goals of the observation (Clemente, Couceiro, & Martins, 2012b). Therefore, the use of specific parameters or performance' indicators may give an important information to sports analysts, thus improving the interventions quality (Carling, Reilly, & Williams, 2009).

These performance indicators are a selection or combination of action variables that aim in defining some aspects of the performance in a given sport, considering its properties and specificities (Clemente, Couceiro, Martins, & Mendes, 2013b). Performance indicators allow a better understanding about sports behaviour enabling an improvement of coaches' intervention (Hughes & Bartlett, 2002). Therefore, the effective evaluation of these indicators requires knowledge about the contextual factors that can potentially affect performance (Taylor, Mellalieu, James, & Shearer, 2008). Hence, the reality of sports performance may be a strongly constraint to correctly understand a specific team. Variables such as match status (i.e., winning, losing or drawing), venue (i.e., playing at home or away) and specifics tactical and strategic principles of the team (Lago & Martín, 2007) may influence the collective behaviour, thus resulting in changes that may be identified by the performance indicators. Therefore, is strongly important improve observation systems that allow new measures to provide fundamental information to coaches during and after match.

1.2.1. Micro Analysis on Football Game: 1vs1 Sub-phase

From 1*vs*1 to many-*vs*-many, the interactions in sports context may be analysed based on the attacker-defender symmetry (Clemente, Couceiro, Martins, Dias, & Mendes, 2013a). Therefore, 1*vs*1 interactions have been profusely analysed on collective sports, mainly in order to understand how players behave and to inspect the self-organization of this specific sub-system. Therefore, to research interpersonal coordination in team games, the ecological dynamic studies of performance have undertaken analyses of the emergent patterns of coordination in attacker-defender systems (Vilar, Araújo, Davids, & Button, 2012a). The attacker-defender dyad is one of the main fundaments from collective sports because inside of it there are opposite behaviours representing the main content of team sports. In football, the attacker aims to disrupt the symmetry of the dyad and introduce some instability to the original state so as to destroy the regular order, thus aiming to overcome the defender (Davids, Araújo, & Shuttleworth, 2005). On the other hand, the defender produces an opposite action that aims to counteract the attacker movements and retain the dyad stability, thus preventing any clear attacking opportunities (Headrick, 2011). On such inter-player interaction, one may observe several changes in some human process parameters, such as the distance between the dyad members, the relative velocity, the acceleration, the angular oscillation between players or the space covered by each player (Clemente et al., 2013a; Correia, Araújo, Davids, Fernandes, & Fonseca, 2011; Vilar et al., 2012a). Therefore, some works that bring to us evidences about these process variables will be discussed.

Some studies identified interpersonal distance as a physical variable useful to explain the interpersonal interactions of players (Araújo, Davids, Bennett, Button, & Chapman, 2004; Passos et al., 2009). For instance, in the case of the rugby game, Passos et al. (2009) suggested that an interpersonal distance inferior to 4 meters combined with a relative velocity of, at least, 1 $m.s^{-1}$ was essential to predict the attacker movement against the defender (Headrick, Davids, Renshaw, Araújo, & Passos, 2012; Passos et al., 2009). It was also identified in the examples provided by Clemente *et al* (2013a) that a higher variability on the velocity and angular position happens when the inter-player distances are smaller. A similar evidence was described by Vilar et al. (2012b) when they suggested that decreasing interpersonal distances between opposing players can trigger a “criticality” state on the dyadic system. Let us show a methodological example about the procedures used by Clemente *et al* (2013a) to analyse the distance between players.

The authors calibrated the half-field with 27 points in the field margin. The physical space was afterwards calibrated using direct linear transformation (*DLT*) which relates the object’s position in the metric space with the corresponding image

(Duarte et al., 2010). After this calibration, the manual tracking of players at regular intervals was carried out, resulting in the Cartesian positioning of each player over time (Clemente, Couceiro, Martins, Dias, & Mendes, 2012a). After obtaining each player's trajectory in the *x, y* plane (*i.e.*, plane defined by the field), the inter-player distance and the distance of each player to the goal were obtained using the following equation:

$$d = \sqrt{x^2 + y^2}. \tag{1.1}$$

It is possible to assess some interesting analysis by using the attacker-defender distance. For instance, in the case of the futsal game, the relationship between the attacker and the defender has been studied to understand how task constraints (*i.e.*, locations of the goal and the ball) enable the creation or prevention of opportunities to score (Vilar, Araújo, Davids, Travassos, Duarte, & Parreira, 2012b). The results suggested that the attacker scored more goals when it could maintain a larger distance from its direct defender. This evidence was confirmed for the moments with or without ball possession (*i.e.*, player movements to receive the ball), suggesting that a larger space increase the successful opportunities to score or perform a pass to goal (Vilar et al., 2012b). This evidences can also be observed in some other sports such as football (Duarte et al., 2012) or rugby (Passos et al., 2009).

Nevertheless, not only the distance contributes to the successful action from the attacker or the defender. Higher values of velocities were identified as critical to the success of the attacker or the rebalancing of the dyad by the defender opponent (Clemente et al., 2013b). Players' velocity can be computed using the following equation:

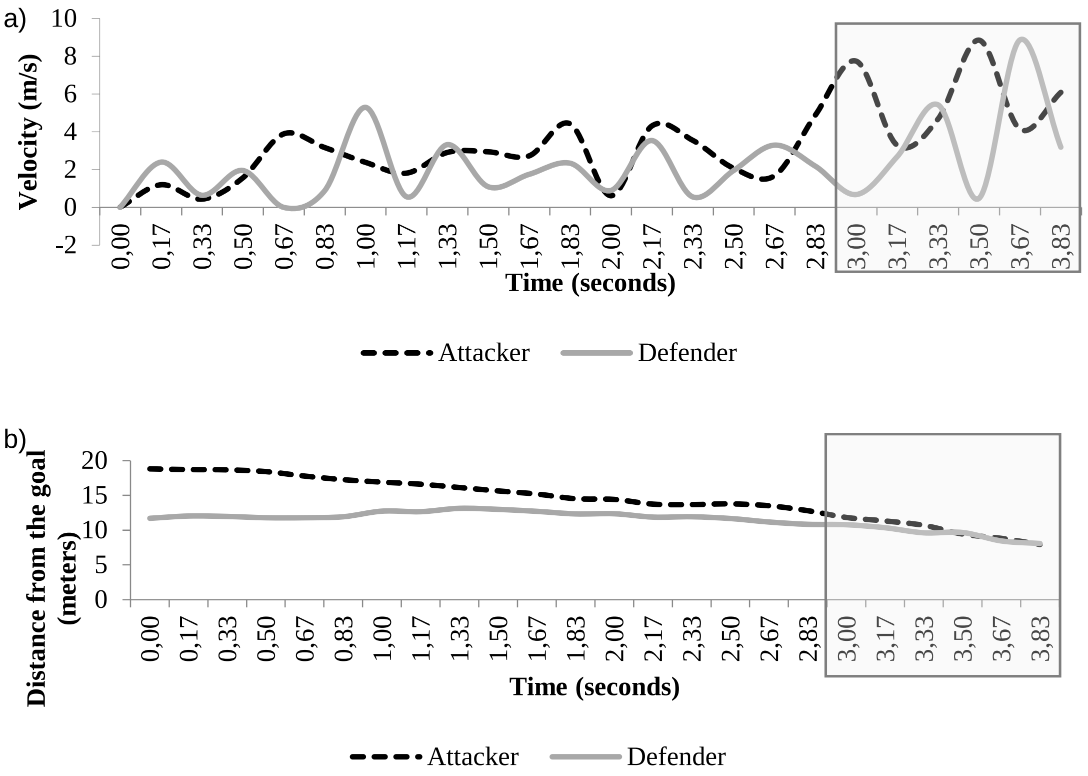
$$v = \sqrt{{v_x}^2 + {v_y}^2}, \tag{1.2}$$

wherein v_x and v_y respectively corresponds to the discrete derivative of the position in the x-axis and the y-axis over time, calculated as:

$$\begin{cases} v_x = \frac{x(t)-x(t-1)}{\Delta t} \\ v_y = \frac{y(t)-y(t-1)}{\Delta t}, \end{cases} \quad (1.3)$$

where Δt represents the discrete time interval. In some studies the interval of 0.12 seconds was found as the maximum sample period that assures the manual tracking' efficiently to accurately identify players' trajectories and reduce the size of the raw data (Clemente et al., 2012a).

In football, the analysis of phase transitions show that this instant is related to lower values of interpersonal distance and higher values of relative velocity (Duarte et al., 2010). When these control parameters were expressed as a single variable, the maximum peaks were related to the exact moment in which the phase transition occurred. Clemente et al. (2013a) concluded that when the interpersonal distance decreases, there is an increase in players' speed and angular positioning, especially by the attacker.



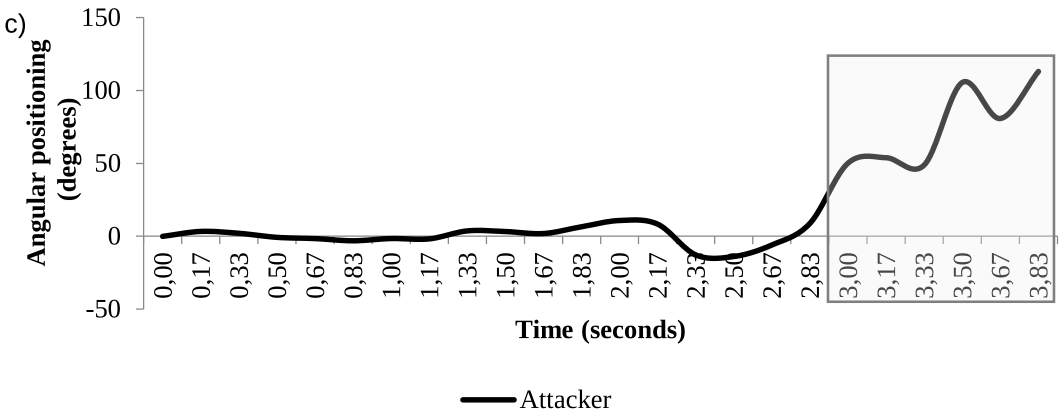


Figure 1.1. Example of a dyad at 1-*vs*-1 football sub-phase.

The authors suggested that a significant increase in the velocity is used to break the stability and balance of the opponent (Figure 1.1a), while a significant increase of the angular positioning in relation to the defender means that the attacker tries to overtake the defender on one side (Figure 1.1c), in order to avoid the proximity of the ball with the defenders' feet (Clemente et al., 2013a). These evidences can be observed on the example of 1-*vs*-1 sub-phase on football represented by the Figure 1.1, mainly in the last second. It is possible to observe that the attacker highly increases its velocity generating an instability on the defender (Figure 1.1a), allowing to overcome him. This sentence can be confirmed by the distance to the goal (Figure 1.1b), as well as by the attacker's angular oscillation.

Moreover, in a different way, some studies showed that to score a goal the attacker tries to maintain a high velocity before and after the moment it receive the ball (Vilar et al., 2012b). Vilar et al. (2012b) suggest that this strategy allows to overcome the defender or prevent from getting close enough to intercept the ball. Furthermore, Vilar et al. (2012b) showed that defenders that cannot increase their velocity decreases the possibilities to intercept the passes or shots from the attacker.

A complementary analysis on the 1-*vs*-1 sub-phase can be performed trying understand the angular oscillation of the attacker over the defender. To that end, Clemente *et al* (2013a) considered an angle of 0° as the angle between the defender and the attacker when forming a line perpendicular to the goal, being the defender closer to it. The way the angle increases or decreases follows the basic principles of the unit circle where the origin of the referential is the defender. Therefore, when the attacker overcome the defender, the angle would be situated on the 2nd or 3rd quadrant, *i.e.*, 90º<|θ|≤180º. An example can be observed on the Figure 1c. When the attacker overtakes the defender by its right side the angular positioning increases considerably (*see* Figure 1c).

Some other studies have been discussing the relevance of the angular positioning to analyse the 1-*vs*-1 sub-phase. For instance, Vilar et al. (2012b) analysed the defender's angle in relation to the attacker and the goal. This relationship between the defender and the goal and the defender and the opponent is crucial to ensure the best position to recover the ball or intercept it. One of the evidences provided by Vilar et al. (2012b) was that, only a slight misalignment of the defender could greatly benefit the ball's interception since there was enough time for the defender to intercept the ball's trajectory.

Until now we have been describing the most prominent process variables analysed on the 1-*vs*-1 sub-phase. Nevertheless, the individual player's trajectory may also provide an interesting feature of its play style: the variability. To that end, histograms or heat maps have been used to complement the others process variables by benefiting from variability measures such as the entropy. Clemente et al. (2012a) introduced the heat maps approach to inspect the space covered by each attacker player against the defender. On their work, the aim was to research the influence of different kind of coaches' instruction on the space covered by the attacker. Their results suggested that the attacker decreased the space covered when it needed to score in a faster way (*e.g.*, by direct instruction of the coach). Nevertheless, the histograms *per se* cannot provide an output about the variability how players covered the space. Thus, an alternative solution may be resorting to the entropy. Let us show two examples of heat maps (Figure 1.2).

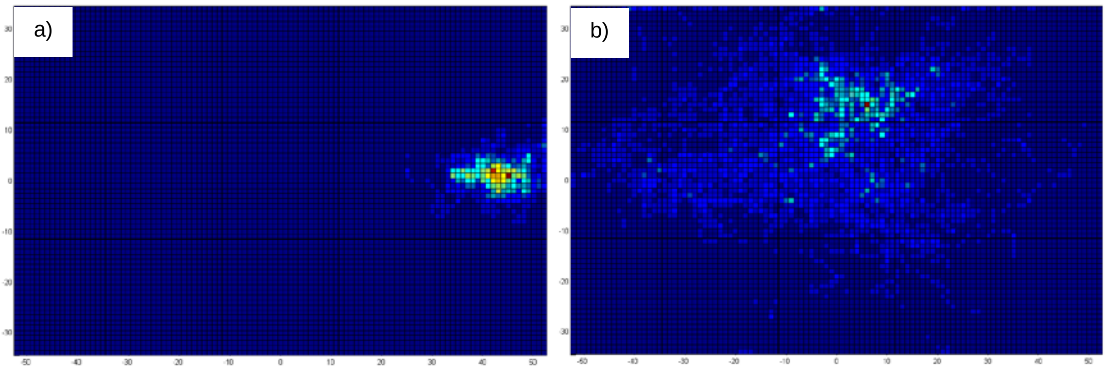


Figure 1.2. Heat maps of the goalkeeper (a) and midfielder (b).

For a high dimensional discrete random variable $X = (X_1, \dots, X_d) \in \mathbb{R}^d$ that has a probability mass function of $p(x_1, \dots, x_d)$, the entropy formula can be extended (Sabuncu, 2006):

$$H(X) = \sum_{x_1,\dots,x_d} p(x_1, \dots, x_d) log \frac{1}{p(x_1, \dots, x_d)} \tag{1.4}$$

The normalized histogram can be an estimate of the underlying probability of pixels intensities, *i.e.*, $p(i) = h_U(i)/N$, where $h_U(i)$ denotes the histogram entry of intensity value i in image U and N is the total number of pixels of U. Using this model, one may compute the entropy of the image represented by the heat maps as (Sabuncu, 2006):

$$H(U) = \sum_i \frac{h_U(i) logN}{h_U(i)} \tag{1.5}$$

Hence, following the data shown on the Figure 1.2 the heat map entropy would be 0.804 on goalkeeper (a) and 2.449 on the midfielder (b). These results suggest a high variability on the midfielder, thus meaning a lower regularity on the space covered. On the other hand, the results also suggest a lower distribution and variability of the goalkeeper that can be easily understood by their own specific missions.

So far, a set of process variables usually applied on the individual performance analysis on football was presented. Now comes the time to understand how a given player contributes to its own team. Thus, next section presents a set of network metrics that allows to understand how a player can interact with its teammates and what is its own weight for the team's behaviour.

1.2.2. Meso-analysis on Football Game: Network Metrics

In team sports, the individual acts in function to the collective principles of play. Therefore, their individual contribution is always attached to the connectivity with their teammates. The way how teammates interacts is essential to determine the quality of play, as well as may constrain the collective performance. These interactions between teammates can be called by competency network (Gréhaigne, 1992; Gréhaigne et al., 2005). In sports, the relationship between teammates is ensured by complex and dynamic processes (Passos et al., 2011), thus the competency network can be considered as a dynamic concept instead of a static one (Gréhaigne et al., 1999).

Some works have been using graph theory to study networks in team sports (Bourbousson et al., 2010a; Lusher, Robins, & Kremer, 2010). However, only some few works went a step further on using complementary quantitative metrics based on the weights of each nodes (*i.e.*, player) (Bourbousson et al., 2010a). Actually, these metrics allow to measure the individual contribute of each player for the team's network. Therefore, based on the weighted network metrics proposed for the systems biology, some metrics that measure the individual influence of each player for the team's network will be presented (Horvath, 2011).

1.2.2.1. Player's Connectivity Scale

The player's connectivity scale is an approach based on the scaled connectivity (Horvath, 2011). For the football approach the connectivity k_i is equal to the sum of connections weights between player i with their teammates. Therefore, the most cooperative players can be identified using the individual index of the maximum connectivity by each player:

$$k_{max} = max(x). \tag{1.6}$$

For the case of player i the player's connectivity scale of k_i can be defined as (Horvath, 2011):

$$Player'sConnectivity_i = \frac{k_i}{k_{max}} = k_i, \tag{1.7}$$

such that $s = [s_1 \quad \cdots \quad s_n] \in \mathbb{R}^{1\times n}$ is the vector of the relative connectivity of players.

By definition the player's connectivity (as equal to scaled connectivity) ranges between 0 and 1, *i.e.*, $0 \leq k_i \leq 1$ (Couceiro, Clemente, & Martins, 2013). For the football context this scale can be useful to measure the cooperation level of a given player. High values of $s_{i=1,\ldots,n}$ suggest that the player had a great cooperation with all teammates. Lowest values suggest a tendency to cooperate with certain teammates, thus not equally distributed by all teammates.

Now let us show an 11-a-side example of one professional football match. For the matrices building was considered the number of participations of each player by each offensive play (attack unit).

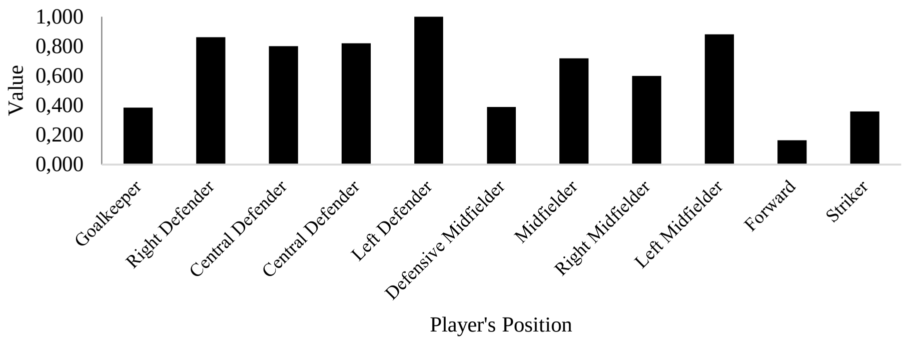


Figure 1.3. Player's connectivity scale.

It is possible to identify in Figure 1.3 that the less cooperative players are the goalkeeper and the forward players (forward and striker). This seems understandable because they are the players that act at the longitudinal edges of the field. Therefore, it is hardest to cooperate with all players at the same distribution level. In other words, it is more predictable that the forwards and the goalkeeper have a higher tendency to cooperate with specific players, even considering different tactical and strategic team's behaviours.

In this particular case, the most cooperative players were the lateral defenders and the left midfielder. These results should be expected as the participation of each player by each offensive play was considered, thus trying to identify the overall participation of players at the offensive moment. The number of passes performed by each player was not considered. For instances, two players participating in the same offensive play will be evaluated equally, even if one of them executed 4 passes while the other only 1. These results suggest that the majority of offensive plays are performed by the wings, maybe using these players to explore the width of the field trying avoiding the areas with higher number of opponent players.

1.2.2.2. Player's Clustering Coefficient

The player's clustering coefficient is a weighted network metric based on the Clustering Coefficient (Horvath, 2011). The clustering coefficient of player i is the density measure of local connections. In a non-weighted network, the *i*th clustering coefficient can be defined as the proportion of observed triangles between all possible triangles involving node i (Horvath, 2011):

$$Player'sClusterCoef_i = \frac{number\ of\ triangles\ involving\ node\ i}{number\ of\ triples\ (i.e., possible\ triangles)}. \qquad (1.8)$$

At an algebraic viewpoint, the clustering coefficient can be computed as (Horvath, 2011):

$$\begin{aligned} Player'sClusterCoef_i &= \frac{\sum_{j\neq i}\sum_{k\neq i,j} A_{ij}A_{jk}A_{ki}}{\left(\sum_{j\neq i} A_{ij}\right)^2 - \sum_{j\neq i}\left(A_{ij}\right)^2} \\ &= \frac{\sum_{j\neq i}\sum_{k\neq i} A_{ij}A_{jk}A_{ki} - \sum_{j\neq i} A_{ij}^2 A_{ij}}{\left(\sum_{j\neq i} A_{ij}\right)^2 - \sum_{j\neq i}\left(A_{ij}\right)^2}. \end{aligned} \qquad (1.9)$$

The clustering coefficient for a weighted network can be defined by simply evaluating on a weighted adjacency matrix (Zhang & Horvath, 2005). Thus, was proved that $0 \leq A_{ij} \leq 1$ implies that $0 \leq Player'sClusterCoef_i \leq 1$ (Horvath, 2011).

A Player's Clustering Coefficients closer to 1 suggests a great cooperation between their teammates, *i.e.*, beyond cooperate with player i they also cooperate each other. Nevertheless, values closer to 0 suggest that the teammates around player

i do not cooperate each other. This is actually very interesting because some players can generate a higher cooperation between their teammates and other players can generate some kind of non-related clusters into the team. Therefore, this metric contribute toward an understanding on how players cooperatively contribute to their own team.

Following the same kind of network analysis, the player's participation in the offensive plays (attack units) of one professional football match were analysed. The player's clustering coefficient was computed for each player and can be observed on Figure 1.4.

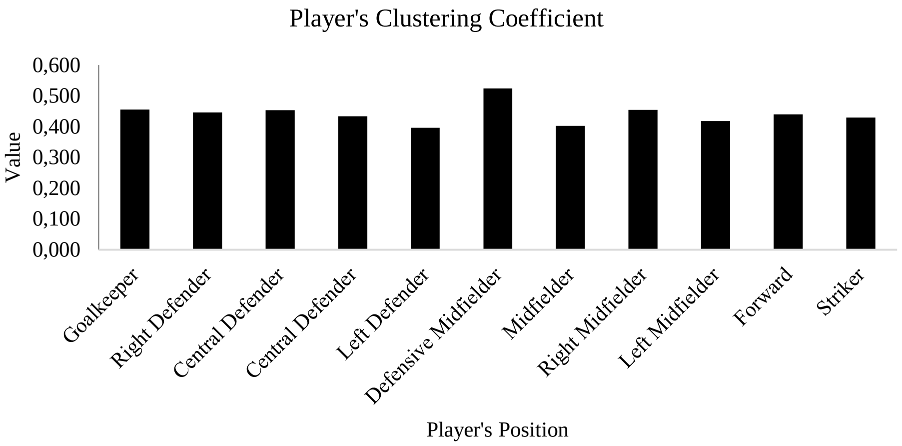


Figure 1.4. Player's Clustering Coefficient.

It is possible to observe that the defensive midfield player has the higher clustering coefficient value. Furthermore, forward players and wing midfielders have also high values. These results suggest that these players generated a great cooperation between their teammates. It is important to remind that in this case was just considered the participation per each offensive play. With some regularity, the forwards players are the last to receive the ball when the attack unit begins from behind (at defensive area). Usually the ball runs by the remaining players (defenders and midfielders) before to achieve the most forward players. Therefore, when the forward players participates at offensive units the ball ran for many other players before, thus increasing their clustering coefficient.

It is also important discuss the higher value on defensive midfielder. Usually, the offensive play (attack unit) can be performed in two main ways: *i*) direct play, with some long passes from the defenders for the forward players; and *ii*) indirect play, building the offensive play from behind and crossing the midfield area until the forward. The indirect play involves more players, thus it is normal that when the ball crosses the midfield area these players increases their clustering coefficient. Moreover, the defensive midfielder is the main link between defenders and the midfielder and forward players. Therefore, it is understandable the higher clustering coefficient on the defensive midfielder.

Until now, both network metrics allowed a set of possibilities to increase the understanding about the individual contribute of each player for the team’s behaviour. Before to this individual contribute analysis for the team was explored the individual performance. Now it is time to explore how teams behave as a whole. This is actually one of the main fundaments of the match analysis. Understanding how a set of individuals may generates a self-organized system acting as a whole. Therefore, let us introduce some collective metrics used until now in the football context.

1.2.3. Macro-analysis on football game: acting as one

The football game as a collective one seeks to improve the interactions between teammates in order to achieve the best performance. Therefore, the 11 players of a team generates a system bigger than only a sum of the parts. Actually, the team’s system can be understood as a one specific and self-organized system that emerge at each constraint of the game. Thus, it is important to develop some collective match analysis metrics, not looking for the individual but seeking to understand how these 11 players act as a whole.

Following for a better understanding about the collective behaviour some metrics have been proposed, based on the player’s bidimensional position in the Cartesian plan at each instant. These coordinates information are truly important to indirectly understand how players act. Thus, let us introduce some collective metrics that has been used in the last few years at the football game.

1.2.3.1. The team's centre and players' dispersion

One of the most applied collective metrics on football is the centroid. The centroid is the geometric centre calculation of the team players. One of the first centroid's applications was performed as follows (Frencken & Lemmink, 2008):

$$\begin{bmatrix}\bar{x}\\ \bar{y}\end{bmatrix}=\frac{1}{\sum_{i=1}^{N} w_i}\begin{bmatrix}\sum_{i=1}^{11} w_i x_i\\ \sum_{i=1}^{11} w_i y_i\end{bmatrix} \tag{1.10}$$

wherein the position of the i^{th} player is defined as (x_i, y_i).

Thus, the centroid is based on the calculus of average position $(\bar{x}, \bar{y})$ of all players (x_n, y_n) of each team (excluding the goalkeeper). Further works were followed, applying the same approach (Bartlett, Button, Robins, Dutt-Mazumder, & Kennedy, 2012; Bourbousson, Sève, & McGarry, 2010b). Despite of their intrinsic importance this algorithm do not considered the ball position and the goalkeeper. Thus, every player has the same weight for the final centroid position.

Therefore, a new approach was proposed for the centroid's calculation (Clemente et al., 2013b). Using the ball location were assigned weights to all players (including the goalkeeper). Considering the ball location was allowed providing weights for each player's influence, in which the higher weight is assigned to the player closer to the ball and the lower weight was assigned to the player farther from it. In other words, the relevance of each player to the team's centroid, *i.e.*, w_i weight, was based on the Euclidean distance from each player to the ball as (Clemente, Couceiro, Martins, Mendes, & Figueiredo, 2013c):

$$w_i=1-\frac{\sqrt{(x_i-x_b)^2+\left(y_i-y_b\right)^2}}{d_{max}} \tag{1.11}$$

where (x_b, y_b) corresponds to the position of the ball and d_{max} is the Euclidean distance of the farthest player to the ball at each iteration (Clemente et al., 2013c).

Using the centroid's approach as a spatial reference of the team's location can be also possible to measure the dispersion of all players to this centroid. Thus, two main metrics have been used to this: *i*) stretch index; and *ii*) team's spread.

The first used approach was the stretch index. The stretch index measures the space expansion or contraction of the team on the longitudinal and lateral directions (Bourbousson et al., 2010b). One of the first studies using the stretch index was performed by Bourbousson et al. (2010b) as follows:

$$SI = \frac{1}{n} \times \sum_{i=1}^{n} |x_i - x_c|, \qquad (1.12)$$

where (x_c) summarizes the distances of all players from the team centroid and (x_i) the team's centroid based on the players' positions (Bartlett et al., 2012). Nevertheless, this stretch index approach used the non-weighted centroid. Thus, Clemente *et al* (2013b) suggested a weighted stretch index based on the weighted centroid:

$$s_{ind} = \frac{\sum_{i=1}^{N} w_i d_i}{\sum_{i=1}^{N} w_i}, \qquad (1.13)$$

where d_i is the Euclidean distance between player i and the team's centroid (Clemente et al., 2013b), *i.e.*,

$$d_i = \sqrt{(x_i - \bar{x})^2 + (y_i - \bar{y})^2}. \qquad (1.14)$$

The higher stretch index values represents a largest players' dispersion in relation to team's centroid in both cases (non-weighted and weighted stretch indexes).

Another dispersion measure have been used by Moura et al. (2012). The team's spread concept is based on Frobenius norm (Moura et al., 2013), *i.e.*, the square root of sums of the squares of the distances between all pairs of players not considering the goalkeeper. For each instant of time (t) is computed the Euclidian distance between the 11 players (Moura, Martins, Anido, Barros, & Cunha, 2012). Thus, the distances between players are organized in a symmetric matrix $D_{(t)}$ of all players of the team (Bartlett et al., 2012). Then, it is process the lower triangular matrix $L_{(t)}$ and calculate the Frobenius norm ($\|L\|_F$), representing the team's spread as follows (Moura et al., 2013):

$$\left\|L_{(t)}\right\|_F = \sqrt{\sum_{i=1}^{n}\sum_{j=1}^{n}\left|l_{ij}\right|^2}. \qquad (1.15)$$

Large values of the Frobenius norm of the matrix L characterize players spread across the football field, whereas low values characterize players close to each other (Bartlett et al., 2012).

Despite of their importance any of these metrics just provide a relative information about the players' locations. It is possible to detect the centre of the team and detect how teams oscillates on the match. It is also possible to analyse the dispersion of the players, being important to identify some patterns in the defensive and offensive phases. Nevertheless, still remain some options to identify the area covered by team at each instant. Therefore, let us introduce the coverage areas proposed in the last few years.

1.2.3.2. Coverage Areas

The coverage area or surface area represents the overall team position (Frencken & Lemmink, 2008). Let us adopted the term surface area to simplify. The surface area can be defined as the total space covered by a team, referred to as the area within the convex hull (Frencken, Lemmink, Delleman, & Visscher, 2011).

The first similar concept was proposed in 2004 with the name coverage area (Okihara et al., 2004). The same concept was suggested by Moura et al. (2012), using the convex hull area to analyse the team covers. The convex hull of a set of points S

(i.e., each player's position on the same team in each t instant) on a plane is the smallest convex set containing S; if S is finite, the convex hull is always a polygon whose vertices are a subset of S (Preparata & Shamos, 1985). The convex hull was computed by Moura et al. (2012) using the Quickhull technique (Barber, Dobkin, & Huhdanpaa, 1996). Thus, at each t instant the convex hull of the team was divided in triangles to aid the calculation of the convex hull area (i.e., summing the areas of all triangles within the convex hull). Similar concept using the term 'surface area' was performed by Frencken et al. (2011) and Duarte et al. (2012).

The convex hull is calculated determining firstly a pivot point, in this case, the lowest y-value player. If there were multiple, then the player with the highest x-value was the pivot point. Then, the angle from the pivot to each player was calculated. Players were sorted by angle and removed if not part of the convex hull (Frencken et al., 2011). An arbitrary point within the convex hull, here the centroid, was taken to create a triangle with the player that was designated as pivot and one of the remaining players. Therefore, the area was calculated by adding the triangles of consecutive points of the convex hull and the centroid (Frencken et al., 2011). Let us exemplify the surface area of two teams (see Figure 1.5).

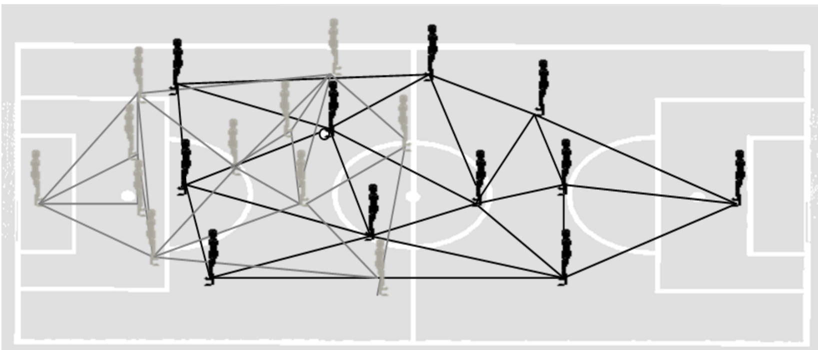


Figure 1.5. Example of the Teams' Surface Area.

The surface area consider all the area covered by players. Nevertheless, in football a great area may not be effective, mainly in defensive phase. The principle of defensive concentration advocates that the players should be closer without the ball possession to reduce the penetration possibilities for the opponent. Nevertheless, the surface area not considers the ball possession and computes all the area covered by the team players. Thus, Clemente et al. (2012b) introduced the effective area of play approach, trying to add a qualitative indicator to the regular surface area. Let us firstly show the Figure 1.6 collected from one 7-a-side football match.

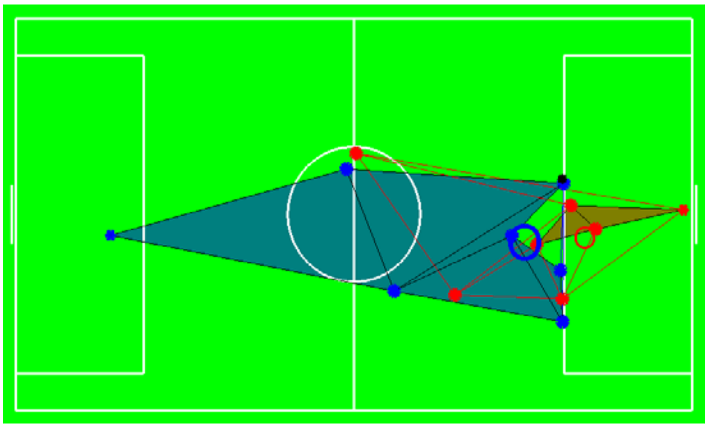


Figure 1.6. Example of the Effective Area of Play.

The effective area of play firstly considers the ball possession. After, as a qualitative parameter only considers an effective defensive triangulation, all triangles not intercepted by the opponent with ball possession or the triangles with a perimeter lower than 36 meters (this parameter can be changed based on the coach's perspective) (Clemente et al., 2012b). Only after are computed the offensive triangulations. Thus, all the offensive triangulations overlapped by effective defensive triangulations are not considered (Clemente et al., 2013b).

Following the example of Figure 1.6, it is possible to observe that the defenders (red team) are too far allowing a great space for the offensive team (blue team) attack. It is also important explain that the order of triangulations and the perimeter for an effective area of play are adjustable, thus allowing to the coach adapt the metric with your own principles or ideas for the match analysis.

1.2.3.3. Territorial Domain

A study on elite teams of 11-a-side football game was recently presented wherein the numerical advantage and disadvantage on specific football spaces was analysed, thus showing a team’s pattern to focus on defensive stability, *i.e.*, teams allocates more players than their opponents in sub-areas closer to their own goal to ensure a higher security (Vilar, Araújo, Davids, & Bar-Yam, 2013). The field was segmented into 7 channels. For each field was analysed at each instant the numerical vantage or disadvantage, thus identifying the tendency to be more or less offensive or defensive.

The territorial domain can be a useful tool to understand the regions with numerical advantage or disadvantage. Let us provide one example (Figure 1.7).

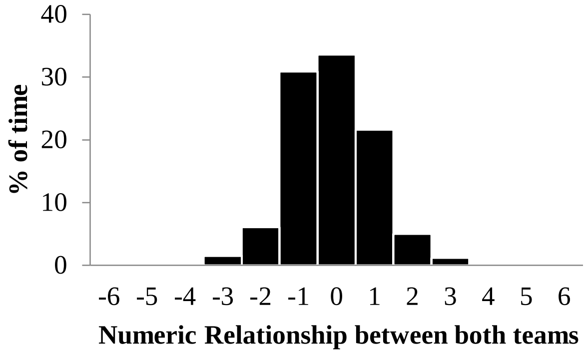


Figure 1.7. Example of the territorial domain in the sector 1 (offensive midfield) applied on 7-a-side football match.

In the sector 1 (Figure 1.7), almost on 35% of time the teams have the same number of players. Nevertheless, there is a more time on numerical disadvantage.

The territorial domain can help coaches to analyse the critical areas and support some strategy adjustments to optimize the team's process. Sometimes, the midfield 'fighting' is one of the most important processes to recover the ball and begin the offensive process. Therefore, using the territorial domain can be possible analyse if the teams are in numerical vantage or disadvantage in a specific region of the field during the match.

A high percentage of numerical disadvantage can be a 'warning information' for the coach and staff. Using this information can be possible analyse if this situation are in line with the team's strategy or if is a non-functional process, increasing the danger to suffer the goal.

1.2.3.4. Summary

The practice of match analysis has undergone much development over the last few years. By taking advantage of the latest technological advances, namely tracking systems, it is now possible to gain a better understanding of how players behave, both as individuals and within the context of a team. In this survey it was possible to identify some individual ways of measuring a player as an individual in a match, by exploring process variables such as velocity, trajectories and interpersonal distance in relation to specific opponents. A player’s individual contribution to the team was examined by using connectivity and clustering weighted network metrics. The individual metrics were used for micro and meso analysis, and the collective metrics for providing macro information about the team’s behaviour. Therefore, all the phases of match analysis contributed to a survey of the most recent mathematical methods used in football analysis. Despite the recent evolution of such methodologies, the use of these tactical metrics is still very new, which means that it is still hard to use them effectively to obtain specific results. Until the way that such information is provided to coaches is clearer, many doubts will remain. An in depth study of these metrics needs to be performed to enhance the coaches’ perception of the collective organization of football teams. Having more information about players’ and teams’ behaviour may increase the opportunities to achieve better sporting performance and help the game evolve. Thus, the main contribution of the present thesis will hopefully be to enhance coaches’ perception of the tactical performance of football teams, using these new technological metrics to assess the collective organization of football players.

1.3. Aim of the Thesis

The aim of the thesis is to contribute to match analysis by providing new methodological approaches to inspecting the collective behaviour of football players throughout matches. It aims to propose a set of new technological metrics that assess teammates' spatio-temporal synchronization by using Cartesian information about players and ball location in each second of the match. This bidimensional information on football players will be used in the various sections of this study. This data provides the common core of the thesis.

All the metrics proposed in this thesis are totally new or constitute an updated version of previous studies. The main goal was to make this thesis a launch pad for a new vision of football match analysis, providing new solutions to traditional methods based on notational analysis or manual and observational methods. It is expected that these tactical metrics could be used as a complement to the existing methods.

With regard to the state-of-the-art collective metrics that had been proposed up till now, their potential for use by football coaches and sports analysts is considerable. Moreover, throughout this thesis the practical applications of these metrics for daily football training will be highlighted, in order to generate a new approach and new concepts of match analysis.

With reference to the different possibilities of establishing forms of match analysis using technological tactical metrics, a set of specific goals were defined:

- The first objective was to propose a new strategy to estimate the current position of football players benefiting from fractional calculus concepts. This will make it possible to overcome the automatic and manual tracking problems that are the basis of computational tactical metrics;
- The second objective was to update the spatio-temporal metrics which had developed until now, providing them a more structured information for football coaches. Moreover, it was also an objective to propose a new tactical metric to replace the regular surface area. The results of both updated and new metrics were compared between moments with and without possession of the ball;

- The third objective was to propose a computational solution to identify the degree of strength being displayed in different sectors of the field. Therefore, a new metric was proposed to inspect the numerical relationship between both teams during football matches in specific regions of the field. In using such information, it was also an objective to assess the variability of this numerical relationship between teams;
- The fourth objective was to propose a computational solution to inspect the coverage principles of play that until now it were only assessed using manual observation protocols. use of a set of coefficients that measured the accomplishment of those principles throughout the match was also proposed;
- The fifth objective was to assess the penetration, width and length and unit principles of play using a computational metric based on the spatio-temporal relationship between players. The use of a set of coefficients that measured the accomplishment of those principles throughout the match was also proposed;
- The sixth objective was to propose a new method to determine the momentary tactical mission of each player during a match, taking in account the position and the status of the possession of the ball. Using such information one metric was also proposed to assess the defensive pressing regions of football teams and another to inspect the players' coordination lines within the team sectors.

1.4. Structure of the Thesis

A collection of seven original research articles, which were submitted, accepted or published in peer-review journals indexed on Journal Citation Reports® Thomson Reuters and Scopus, constituted the core of this thesis. Each article was presented as an individual chapter following a specific structure.

The current chapter (Chapter 1) introduces the principles that assess the football players' coordination. Through these concepts it was possible to highlight the pertinence of match analysis to football games. Finally, a survey of the technological metrics used to assess the individual and collective behaviour of football players was performed, as well establishing the main goals of the thesis.

Chapter 2 (A methodological approach to optimize the manual tracking of football players) presents a methodological proposal to enhance the manual and automatic tracking systems of a football game. The Fractional Calculus approach was used to predict the next position of football players over time and to solve some issues that may occur during tracking procedures.

Chapter 3 (Using collective metrics to analyse spatio-temporal relationships between football players: Inspecting the impact of each half of the match on ball possession) proposes an updated version of centroid and stretch index metrics, and generates a new metric called Effective Area of Play. Moreover, in this chapter the influence of being in or out of possession of the ball will be also inspected with reference to the collective parameters being assessed by spatio-temporal metrics.

Chapter 4 (Measuring the territorial domain of football teams) proposes a metric to assess the numerical relationship between opposing players in specific regions of a field during a match. Moreover, using such information can measure the variability of this relationship using non-linear techniques.

Chapter 5 (Inspecting teammates' coverage during attacking play in a Football Game) introduces a technological approach to turn the manual observation protocols into automatic ones. The coverage principles of play will be computationally assessed using the Cartesian position of players and the ball. Also, coefficients to measure the accomplishment of principles of play during a match will be proposed.

Chapter 6 (Evaluating the offensive definition zone in football) proposes the use of a set of computational metrics that assess the accomplishment of penetration, width and length and unit principles of play. Coefficients to measure the accomplishment of those principles during football matches will also be generated.

Chapter 7 (Developing metrics to inspect the defensive tactical principles of football teams) introduces a new method to determine the momentary tactical mission of each player during a match, based on their location and that of their teammates. Two metrics that measure the defensive behaviour of football teams will also be proposed. The defensive play area will estimate the pressing area of teams. The sectorial lines of play will assess the teammates' coordination within their specific tactical region.

Finally, Chapter 8 (General discussion and conclusion) synthesizes the main findings of the studies. The practical implications of the use of tactical metrics on match analysis and on sports training are also discussed A technological approach that integrates these metrics will be used, focusing on data retrieval, processing and visualization. Therefore, concepts such as augmented reality, cloud computing and human-computer interaction are considered to be first steps towards the future application of a football game analysis system.

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Chapter II

A methodological approach to optimize the manual tracking of football players

Chapter based on the following publication:

Couceiro, M. S., Clemente, F. M., & Martins, F. M. L. (2013). Analysis of Football Player's Motion in View of Fractional Calculus. *Central European Journal of Physics*, 11(6), 714-723.

2. A METHODOLOGICAL APPROACH TO OPTIMIZE THE MANUAL TRACKING OF FOOTBALL PLAYERS

Abstract

Accurately retrieving the position of football players over time may lay the foundations for a whole series of possible new performance metrics for coaches and assistants. Despite the recent developments of automatic tracking systems, the misclassification problem (*i.e.*, misleading a given player by another) still exists and requires human operators as final evaluators. This paper proposes an adaptive fractional calculus (*FC*) approach to improve the accuracy of tracking methods by estimating the position of players based on their trajectory so far. One half-time of an official football match was used to evaluate the accuracy of the proposed approach under different sampling periods of 250, 500 and $1000\ ms$. Moreover, the performance of the *FC* approach was compared with position-based and velocity-based methods. The experimental evaluation shows that the *FC* method presents a high classification accuracy for small sampling periods. Such results suggest that fractional dynamics may fit the trajectory of football players, thus being useful to increase the autonomy of tracking systems.

Keywords: Football; Prediction Methods; Fractional Calculus; Fractional Dynamics.

2.1. Introduction

Football is one of the most popular sports in the world being of great interest for many scientific areas (Figueroa, Leite, & Barros, 2006). The main interest for sport sciences is to improve the teams' performance increasing the opportunities to win (Hughes & Bartlett, 2002). Therefore, many mathematical and technological approaches have been proposed and developed over the last few years (Franks & Goodman, 1986). One of them is the on-the-fly, *i.e.*, online, match analysis (Carling, Williams, & Reilly, 2005). Through tracking techniques, either manual or automatic, it has been possible to collect each player's positioning on the field at every instant (Gudmundsson & Wolle, 2012). Such information is considered one of the most relevant that may contribute to improve the performance understanding (Allen, Butterfly, Welsh, & Wood, 1998). This spatio-temporal information allows many kind of analysis such as kinematical (Di Salvo, Collins, McNeill, & Cardinale, 2006), technical and tactical (Clemente, Couceiro, & Martins, 2012). Bearing such idea in mind, some systems have been developed to collect the players' positional data (Baca, Dabnichki, Heller, & Kornfeind, 2009). Despite of other technological approaches such as Global Positioning System (GPS) or Radio-Frequency Identification (RFID), the video analysis is, by far, the most adopted one in official football, as it does not allow the use of devices on players during the matches (Barros et al., 2007). Therefore, for now only two main video analyses can be performed to collect the positional data from official matches: *i*) automatic tracking; and *ii*) manual tracking.

The automatic tracking of only one player was originally presented by Ohashi *et al* (1988). The method considered the calculation of player's position and speed through trigonometric techniques. Over the years, many other automatic tracking techniques were proposed, in which some few systems such as *AMISCO Pro* and *ProZone* already have the ability to track all players and the ball at each iteration (Carling, Bloomfield, Nelsen, & Reilly, 2008). These kind of video-based multi-player tracking systems generally require the permanent installation of several fixed cameras in optimally calculated positions to cover the whole field (Carling et al., 2008). Systems such as *AMISCO Pro* or *ProZone* provide online information to coaches and their staff about players' movements (*e.g.*, energy spent by a player). Despite of their efficiency and autonomous properties, many problems still remain. For instance, player-to-player occlusion, similar player appearance, number of players changing over time, variability of players' motion and noises or video blur present themselves as open problems (Liu, Tong, Li, Wang, & Zhang, 2009). Therefore, despite being generally autonomous, these tracking systems still require some human input as well as continual online verification by an operator to make sure that players are correctly tracked by the computer program (Carling et al., 2008). Hence, beyond their expensive devices (*e.g.*, many high-definition video cameras), the automatic tracking of multiple player still requires human operators to fix some mistakes. In order to overcome this situation, some studies have been proposed using monocular solutions. For instance, in the approach presented in (Kataoka & Aoki, 2011), the authors use a particle filter to track each player. Preliminary results suggest that to overcome occlusions, the classifier detects players and resample the centre of gravity (Kataoka & Aoki, 2011). Despite their promising results, some questions about the applicability of this technique still remain due to its computational complexity (D'Orazio & Leo, 2010). Moreover, this tracking strategy only allows to identify the players without any memory properties. Nevertheless, it is those memory properties that may provide further information about the variability, predictability and stability level of each player. Moreover, these systems are based uniquely on colour segmentation eve despite soccer matches can occur at different moments of the day with or without artificial light (D'Orazio & Leo, 2010). It is due to those reasons that many scientific studies have been using the manual tracking as a low-cost solution to overcome the expensive automatic multi-player tracking.

Many manual tracking methods only use a single high-definition video camera to collect the positional data from the players (Duarte et al., 2010). In this context, the image treatment is performed after the match, *i.e.*, in an offline fashion. The *TACTO* software is one of the many manual tracking systems with accuracy levels reported as superior to 95% (Fernandes, Folgado, Duarte, & Malta, 2010). Similarly, many other software's designed for specific applications have been used in the literature (Clemente et al., 2012). Most of those software's use the Direct Linear Transformation (*DLT*) technique to relate an object point located in the object space/plane and the corresponding image point on the image plane of the camera (Duarte et al., 2012). Despite of its user-friendly technology, the manual tracking to analyse official football matches can be a massive and exhaustive work since it requires the manual tracking of 22 players and the ball at each iteration. Furthermore, as most of those use only one camera it reduces the possibility to concretely define the players' identification and position.

In sum, both manual and automatic tracking systems present advantages and disadvantages. Nevertheless, they still require human operators to ensure the accuracy of players' identification. Next section formalizes our problem and presents a couple of classical initial strategies to estimate the current position of a given player.

2.2.1. Problem Formulation

In both manual and automatic multi-player tracking systems, a matrix containing the planar position of each player n of team δ over time is generated. Let us call this as the *positioning matrix* $X_\delta[t]$ wherein row n represents the planar position $\mathbb{R}^2$ of player n of team δ at time t, *i.e.*,

$$X_\delta[t] = \begin{bmatrix} x_1[t] \\ \vdots \\ x_{N_\delta}[t] \end{bmatrix}, \ x_n[t] \ \in \ \mathbb{R}^2, \tag{2.1}$$

wherein N_δ represents the current number of players in team δ at iteration/time t. For the 11-football match, teams will start with an initial number of 11 players, *i.e.*, $N_\delta = 11$, thus resulting in a 11×2 positioning matrix $X_\delta[t]$.

Nevertheless, the row-order of the matrix may be incorrectly retrieved due to all the problems previously mentioned. Therefore, many techniques may be proposed to overcome this issue.

For instance, the most easiest way to correctly sort the positioning matrix at iteration $t+1$, *i.e.*, $X_\delta[t+1]$, may be carried out as a minimization problem of the distance between its rows, *i.e.*, $x_n[t+1]$, and the rows from the positioning matrix at iteration t, *i.e.*, $x_n[t]$. Nevertheless, the accuracy of estimating the current position based on the previous one may significantly decrease as the time between iterations, *i.e.*, *sampling period* T, increases. For instance, as the average velocity of football players may reach $3.06\, m.s^{-1}$ (Di Salvo, et al., 2007), and considering a sampling period of 1 second, *i.e.*, $T = 1$, results in an average difference between two consecutive positions of 3.06 meters. This may easily lead to the misidentification of players. Moreover, players' velocity may vary between 0 and $6.39\, m.s^{-1}$ (Di Salvo et al., 2007), with some outstanding cases such as Cristiano Ronaldo (second FIFA world player of the 2012) that is able to achieve an average maximum velocity of $9.33\, m.s^{-1}$, which would result in difference between two consecutive positions of $9.33\, m$. Although limited, the estimation of the current position based on the previous one only requires a memory complexity of $\mathcal{O}[N_\delta]$ as it only requires memorizing the previous position of all players in team δ.

Alternatively, and considering players' dynamics, one may contemplate the velocity vector of players. Note that, as we consider discrete systems with a constant sampling period, the velocity vector of a given player may be obtained based on its consecutive planar positions, thus returning both magnitude and direction (McGinnis, 1999). To do this, let us consider the discrete case in which the motion of player n may be defined as:

$$x_n[t+1] = x_n[t] + v_n[t+1], \tag{2.2}$$

in such a way that the position of player n from team δ at iteration $t+1$ will be its previous position incremented of its current velocity vector $v_n[t+1]$. Nevertheless, as the current velocity vector is unknown, the following approximation may be carried out:

$$x_n^s[t+1] = x_n[t] + v_n[t], \tag{2.3}$$

in which $x_n^s[t+1]$ is the estimated position of player n and $v_n[t]$ is the velocity vector retrieved from the previous iteration which may be calculated as:

$$v_n[t] = x_n[t] - x_n[t-1]. \tag{2.4}$$

This may only be accomplished for small sampling periods (*e.g.*, $T \leq 1$), as players may not be able to drastically change their velocity between two consecutive iterations. The estimation of the current position based on the previous velocity vector may overcome the non-dynamical characteristics of the previous method. Such higher accuracy is achieved by slightly increasing the memory complexity of the algorithm to $\mathcal{O}[2N_\delta]$ as the two previous positions of all players in team δ are necessary to compute the velocity vector of each player (*cf.* equation (2.4)).

Nevertheless, considering the unpredictable movements of football players, the previously presented strategies may be inefficient as they do not consider the whole trajectory performed by players so far. A possibility to overcome such limitations is by taking advantage of Fractional Calculus (*FC*) properties.

2.2.2. Statement of Contribution

Only a few number of applications based on *FC* has been reported so far within sport sciences literature. One of them was the development of a correction metric for golf putting to prevent the inaccurate performance of golfers when facing the golf *lipout* phenomenon (Couceiro, Dias, Martins, & Luz, 2012a). The authors extended a performance metric using the *Grünwald–Letnikov* approximate discrete equation to integrate a memory of the ball's trajectory.

Although *FC* was not fully explored in sport sciences, many other areas have been taking full use of its properties. For instance, *FC* has been used to describe the dynamical characteristics of robots' motion since it is well suited to describe irreversibility and chaos due to its inherent memory property (Couceiro, Martins, Rocha, & Ferreira, 2012b; Sabatier, Agrawal, & Machado, 2007). In this line of thought, the dynamic phenomena of a robot's trajectory configure a case where fractional calculus tools fit adequately (Couceiro et al., 2012b).

Football has been regularly identified as a complex dynamic system wherein the motion of each player is usually chaotic and difficult to predict (Gréhaigne, Bouthier, & David, 1997). Under those assumptions, this article proposes a new strategy to estimate the current position of football players benefiting from fractional calculus concepts. This will allow overcoming the automatic and manual tracking problems described above.

2.2. Fractional Order Estimation

2.2.1. Preliminaries

This section summarizes some preliminaries regarding fractional calculus. For a more detailed description please refer to Machado et al. (2010) or Couceiro et al. (2012a).

Briefly, *Fractional Calculus* (*FC*) can be considered as a generalization of integer-order calculus, thus accomplishing what integer-order calculus cannot. As a natural extension of the integer (*i.e.*, classical) derivatives, fractional derivatives provide an excellent instrument for the description of memory and hereditary properties of processes. The concept of *Grünwald–Letnikov* fractional differential is presented by the following definition.

Definition 1. (Machado et al., 2010) *Let* Γ *be the gamma function defined as*:

$$\Gamma(k) = (k-1)! \tag{2.5}$$

The signal $D^{\alpha}[x(t)]$ *given by*

$$D^{\alpha}[x(t)] = \lim_{h\to 0}\left[\frac{1}{h^{\alpha}}\sum_{k=0}^{+\infty}\frac{(-1)^{k}\Gamma(\alpha+1)x(t-kh)}{\Gamma(k+1)\Gamma(\alpha-k+1)}\right], \tag{2.6}$$

is said to be the ***Grünwald–Letnikov fractional derivative of order*** $\boldsymbol{\alpha}$*,* $\alpha \in \mathbb{C}$*, of the signal* $x(t)$*.*

An important property revealed by (2.6) is that while an integer-order derivative just implies a finite series, the fractional-order derivative requires an infinite number of terms. Therefore, integer derivatives are “local” operators while fractional derivatives have, implicitly, a “memory” of all past events. However, the influence of past events decreases over time.

The formulation in (2.6) inspires a discrete time calculation presented by the following definition.

Definition 2. (Machado et al., 2010)*The signal* $D^{\alpha}\left[x[t]\right]$ *given by*

$$D^{\alpha}\left[x[t]\right] = \frac{1}{T^{\alpha}} \sum_{k=0}^{r} \frac{(-1)^{k}\Gamma[\alpha+1]x[t-kT]}{\Gamma[k+1]\Gamma[\alpha-k+1]}, \tag{2.7}$$

where T *is the sampling period and* r *is the truncation order, is the* ***approximate discrete time Grünwald–Letnikov fractional difference of order α****,* $\alpha \in \mathbb{C}$*, of the discrete signal* $x[t]$*.*

The series presented in (2.7) can be implemented by a rational fraction expansion which leads to a superior compromise in what concerns the number of terms versus the quality of the approximation. That being said, it is possible to extend an integer discrete difference, *i.e.*, classical discrete difference, to a fractional-order one, using the following definition.

Definition 3 (Ostalczyk, 2009) *The classical integer "direct" discrete difference of signal* $x[t]$ *is defined as follows:*

$$\Delta^{d}x[t] = \begin{cases} x[t] & , d = 0 \\ x[t] - x[t-1] & , d = 1, \\ \Delta^{d-1}x[t] - \Delta^{d-1}x[t-1], & d > 1 \end{cases} \tag{2.8}$$

where $d \in \mathbb{N}_0$ *is the order of the integer discrete difference. Hence, one can extend the integer-order* $\Delta^{d}x[t]$ *assuming that the fractional discrete difference satisfies the following inequalities:*

$$d - 1 < \alpha < d. \tag{2.9}$$

The features inherent to fractional calculus make this mathematical tool well suited to describe many phenomena, such as irreversibility and chaos, because of its inherent memory property. In this line of thought, the dynamic phenomena of a player's trajectory configure a case where fractional calculus tools may fit adequately.

2.2.2. Fractional Calculus Approach

FC will be addressed in our study based on problem formulation presented in Section 2.2.1. At first, let us rewrite equation (2.3) as:

$$x_n^s[t+1] - x_n[t] = v_n[t], \tag{2.10}$$

Hence, $x_n^s[t+1] - x_n[t]$ corresponds to the discrete version of the fractional difference of order $\alpha = 1$, *i.e.*, the first order integer difference. By Definition 2 it is possible to consider:

$$D^\alpha\left[x_n^s[t+1]\right] = v_n[t]. \tag{2.11}$$

Based on the *FC* concept and Definition 3, the order of the position derivative can be generalized to a real number $0 < \alpha < 1$, thus leading to a smoother variation and a longer memory effect. Equation (2.11) can then be written as:

$$x_n^s[t+1] = v_n[t] - \frac{1}{T^\alpha}\sum_{k=1}^{r}\frac{(-1)^k\Gamma[\alpha+1]x[t+1-kT]}{\Gamma[k+1]\Gamma[\alpha-k+1]}. \tag{2.12}$$

Replacing $v_n[t]$ in function of the position as presented in equation (2.4) results in:

$$x_n^s[t+1] = x_n[t] - x_n[t-1] - \frac{1}{T^\alpha}\sum_{k=1}^{r}\frac{(-1)^k\Gamma[\alpha+1]x[t+1-kT]}{\Gamma[k+1]\Gamma[\alpha-k+1]}. \tag{2.13}$$

It should be noted that such strategy increases the memory complexity as it requires memorizing the last r positions of each player, *i.e.*, $\mathcal{O}[rN_\delta]$. Nonetheless, the truncation order r does not need to be too large and will always be inferior to the current iteration/time t, *i.e.*, $r \leq t$. For instance, considering a truncation order $r = 10$, $\alpha = \frac{2}{3}$ and $T = 1$ second, *i.e.*, considering the last 10 previous seconds, results in an attenuation of players' position at time $t-9$, *i.e.*, the $x[t+1-10]$, of approximately 99.5%, *i.e.*, $\frac{(-1)^{10}\Gamma\left[\frac{2}{3}+1\right]}{\Gamma[10+1]\Gamma\left[\frac{2}{3}-10+1\right]}$.

Correctly choosing the possible next position of player n may be achieved by minimizing the distance between the estimated position $x_n^s[t+1]$and the positions on the football match matrix $X_\delta[t+1]$:

$$\left[d_n^{min}, i_n^{min}\right] = \min_{i \in N_\delta}(x_n^s[t+1] - x_i[t+1]). \qquad (2.14)$$

where d_n^{min} is the minimal distance between the last known position at time t of player n and all new positions stored on an estimated positioning matrix $X_\delta^s[t+1]$, with $X_\delta^s[t+1] = \left[x_1^s[t+1] \ldots x_n^s[t+1]\right]^T$, retrieved by the method at time $t+1$, in such a way that the position represented by player i_n^{min} has a strong possibility of being player n.

Considering α as the fractional order derivative, then by using α values near 0, past events are not that relevant to the final result. On the opposite, using α values near 1, it means that past events have a major influence in the final result (Couceiro et al., 2012a). In football context, analysing the fractional coefficient α of each player may imply the predictability of players' motion. Therefore, the α value can be useful information to analyze the level of unpredictability of each player.

Yet, a problem arises regarding the tuning of the fractional coefficient α that may vary from player to player and from iteration to iteration. Hence, one should find out the most fitted α for player n at time t, *i.e.*, $\alpha_n[t]$, based on its last known positions so far, *i.e.*, the $\alpha_n[t]$ that would result in a smaller d_n^{min}. This $\alpha_n[t]$ will be used to assess the next possible position and, once again, be systematically updated at each t. This may be formulated by the following minimization problem:

$$\min_{\alpha_n[t]} d_n^{min}(\alpha_n[t]) = \left| -x_n[t+1] + x_n[t] - x_n[t-1] - \frac{1}{T^\alpha}\sum_{k=1}^{r}\frac{(-1)^k\Gamma[\alpha_n[t]+1]x[t+1-kT]}{\Gamma[k+1]\Gamma[\alpha_n[t]-k+1]}\right|. \quad (2.15)$$

$s.t\ \ \alpha_n[t] \in [0,1].$

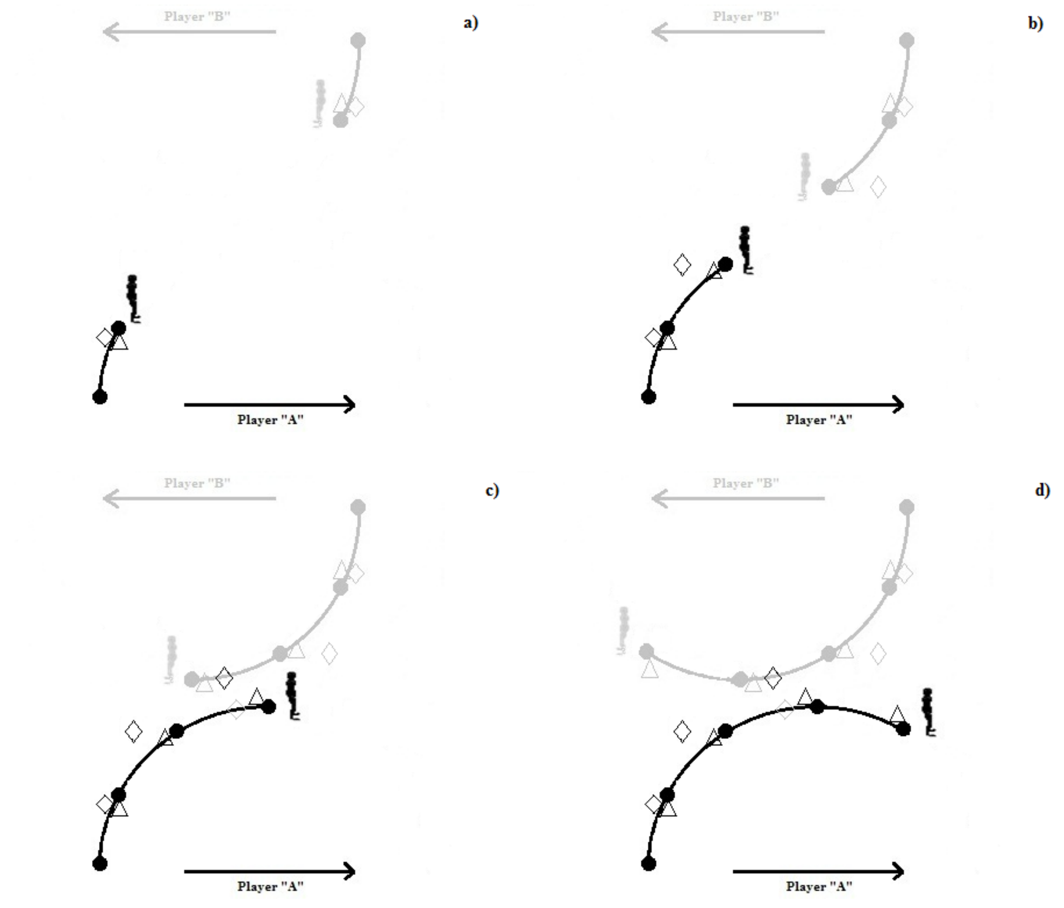
We will not focus on the most adequate type of optimization method in this paper. In this paper, the solution of equation (2.15) was based on golden section search and parabolic interpolation. Successive parabolic interpolation allows finding the minimum distance by successively fitting parabolas to the optimization function at three unique points and, at each iteration, replacing the "oldest" point with the minimum value of the fitted parabola. This method is alternated with the golden section search hence increasing the probability of convergence without hampering the convergence rate. For a more detailed description about this optimization methods please refer to (Forsythe, Malcolm, & Moler, 1977; Brent, 1973).

A particular case occurs for an iteration/time inferior to 2. Considering that the game starts at the 1 second and $T=1$, it is noteworthy that for an iteration/time inferior to 2, *i.e.*, $t<2$, it is impossible to compute $x_n^s[2]$ due to $x_n[0]$. In other words, it is necessary to have the first two consecutives positions of a given player. A way to overcome this problem is to consider the pregame start position equal to the first ingame position, *i.e.*, $x_n[0]=x_n[1]$. This assumption holds for a small periodic time t between iterations. Due to the human movement dynamics, and since football players are still in the first iteration/time, *i.e.*, $v_n[1]=0$, the difference between the first two steps (immediately pre and after game start) is usually minor, *i.e.*, $v_n[0]\approx v_n[1]$. As the average velocity of football players is $4\,m/s$, one may considered a maximum iteration time of 1 second, *i.e.*, $T=1$, thus representing an average difference of 4 meters between two consecutive positions. In other words, for the second iteration and considering the main equation, one may approximate $x_n^s[2]$ as:

$$x_n^s[2] = \frac{3}{2}\alpha[1]x_n[1]. \tag{2.16}$$

Considering that a player is considerably near the same position for the first 2 seconds after the game starts, which may be assumed due to players' dynamics, then $\alpha_n[t]$ may be initially defined as $\frac{2}{3}$ for all players, $\alpha_n[1] = \frac{2}{3}$, $\forall\, n \in [1, N_\delta]$.

Figure 2.1 depicts the predicted position of two players using the methods presented in this paper. It is noteworthy that although the position-based method is not explicitly presented, it corresponds to the exact point of the previous position of each player.



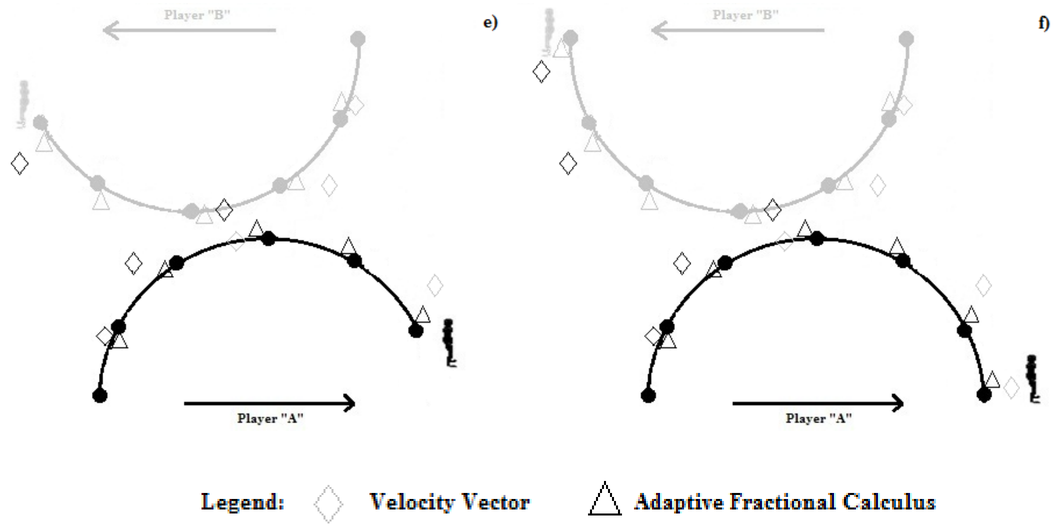


Figure 2.1. Estimation position of two players.

As one may observe, the crossing events between two players from the same team can be one of the most challenging and deceiving aspects for estimation methods. For instance, from Figure 2.1b to Figure 2.1c, the velocity vector method turns out to provide erroneous information since the position estimation of each player gets closer to the real position of the opposing player. This would induce the tracking system into the misclassification of players. This misinformation can be critical to analyze the behavior of a specific player over time. On the other hand, the fractional calculus method starts following a certain tendency since it takes into account the whole trajectory so far. In other words, the fractional calculus and its inherent memory property provide a better alternative for multi-player tracking systems.

Next section evaluates and compares the herein proposed approach on a real example of football match.

2.3. Results

To evaluate the accuracy of the proposed method, one half-time of an official football match was analysed (1833 seconds of useful match). All players' position in the field was acquired using a single camera (*GoPro Hero* with 1280 × 960 resolution), with capacity to process images at 30 Hz (*i.e.*, 30 frames per second) and recording with a wide angle of 180º. The camera was placed on an elevated position on the stadium to capture the whole field without any changes from the beginning to the end of the match. The movements of the 22 players (goalkeepers included) from the two competing teams were recorded during the entire game. After capturing the football match, the physical space was calibrated using Direct Linear Transformation (*DLT*) (Abdel-Aziz & Karara, 1971), thus obtaining the Cartesian planar positioning of all players and the ball over time. The whole process inherent to this approach, such as the detection and identification of players' trajectories, the space transformation and the computation of metrics, was handled using the high-level calculation tool *MatLab*.

For a matter of efficiency, only play moments were used, hence excluding all the pause moments in which the ball was not in the field (*i.e.*, ball out-of-bounds). This resulted in 1833 seconds of useful match, *i.e.*, approximately 31 minutes. To evaluate the methods under different configurations, sampling periods of $T = \{250{,}500{,}1000\}\ [ms]$ were used. Moreover, the players were afterward identified by a human operator at each iteration so as to compare the accuracy of the methods, *i.e.*, the number of times they correctly predict the right player, *i.e.*, number of true positives. The human operator performed the manual tracking at each iteration, depending on the sampling period T, following the players in such a way to correctly sort the positional matrix $X_\delta[t]$ over time. Afterwards, the human operator manual tracking was compared with the sorting performed by the estimation methods.

As the fractional methodology herein proposed have higher memory complexity than the other methods, a truncation order of $r = 10$ was settled (*cf.* Section 2.2.2.), thus resulting in a memory complexity of $\mathcal{O}[10N_\delta]$. The first experiment was used to compare the method using adaptive fractional coefficients $\alpha_n[t]$ with predefined α_n values (Figure 2.2). As a performance metric, the overall accuracy of the fractional method was defined as the fraction of correctly classified players over the whole process, *i.e.*, ratio between the number of samples and the number of true positives.

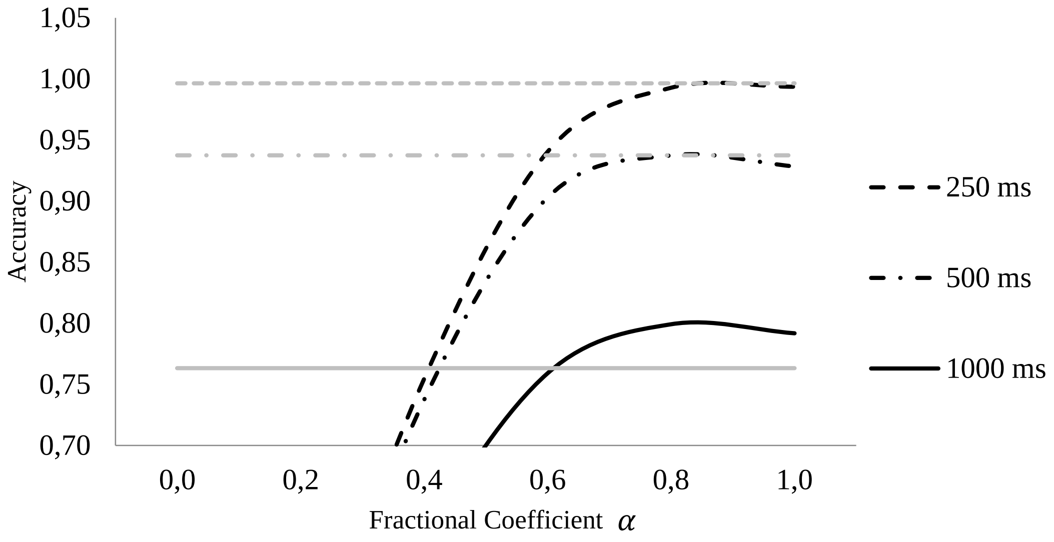


Figure 2.2. Comparing adaptive fractional coefficients $\boldsymbol{\alpha_n}[\boldsymbol{t}]$ with predefined values $\boldsymbol{\alpha_n}$.

The horizontal lines on Figure 2.2 (*i.e.*, constant values) correspond to the accuracy of the algorithm under the adaptive mechanism (adaptive $\alpha_n[t]$ for each player). The corresponding curves (*i.e.*, with the same line style) represents the accuracy of the algorithm for each α_n between 0 and 1. Therefore, as one may observe, the adaptive $\alpha_n[t]$ generally results in a higher performance than when using a fixed α_n. For sampling periods of 250 and $500\ ms$, such performance may be almost attained by using a fixed α_n between 0.8 and 0.9. The only case in which this tendency is broken may be observed for a larger sampling period of 1 second. Under such sampling period, a fixed α_n between 0 and 1 results in a better accuracy when compared to the adaptive one. This may be explained by the fact that a large sampling period may not be ideal to represent the dynamic behaviour of players.

Despite this specific situation, it may be observed that the adaptive mechanism turns out to partially overcome the unpredictability of players, thus presenting an overall accuracy above 90% for smaller sampling periods. Hence, the fractional method with adaptive $\alpha_n[t]$ (**FC**) was compared with the traditional methods presented in the preliminaries, namely the estimation based on the velocity vector (**VEL**) and the estimation based on the previous position (**POS**).

Once again, the classification accuracy was used to evaluate the performance of the methods. Due to the number of classes (*i.e.*, players) and to allow a straightforward comparison between the three methods under different configurations (*i.e.*, sampling period T), the traditional confusion matrices were used. The confusion matrix will be represented by a N_δ-by-N_δ matrix, where each (i, j) entry will be the number of samples whose target is the *i*th player that was classified as the *j*th player. For instance, Table 2.1 presents the confusion matrix for a sampling period of $T = 250\ ms$ wherein the 3rd player was misclassified as the 2nd player 5 times, as the 4th player 3 times, as the 5th player and 7th players only once and as the 6th player 4 times using the proposed fractional method. Even so, the overall classification accuracy of the fractional method (**FC**) greatly outperforms the other methods with a success percentage of 99.65% against the 99.36% and the 97.18% from velocity vector method (**VEL**) and the previous position method (**POS**), respectively. The same conclusions may be withdrawn from a sampling period of $T = 500\ ms$ (Table 2.2). Nevertheless, one may observe that for a higher sampling period of $T = 1000\ ms$ (Table 2.3), the fractional method (**FC**) presents a higher misclassification ratio, thus failing to correctly identify the team at each second 23.67% of the time, against a misclassification percentage of 20.79% and 14.31% from the velocity vector method (**VEL**) and the previous position method (**POS**).

This is an interesting phenomenon and may be explained by the common strategy of football teams. At each match, players have a playing position wherein they spend most of their time (*e.g.*, goalkeeper, defender, midfielder, forward). With a large sampling rate, the position method (**POS**) turns out to present a better accuracy since players keep around their playing position. Although this was verified in this match, some football strategies include switching playing positions which would greatly jeopardize the position method.

Table 2.1. Confusion matrix for the sampling periods of $T = 250\ ms$.

		Predicted Player											
Actual Player	Method	1	2	3	4	5	6	7	8	9	10	11	Accuracy
1	FC	**7330**	0	0	0	0	0	0	0	0	0	0	1.0000
	VEL	**7330**	0	0	0	0	0	0	0	0	0	0	1.0000
	POS	**7330**	0	0	0	0	0	0	0	0	0	0	1.0000
2	FC	0	**7310**	5	0	0	4	3	2	4	1	1	0.9973
	VEL	0	**7304**	8	0	0	7	4	0	5	1	1	0.9965
	POS	0	**7195**	38	0	2	39	7	2	37	1	9	0.9816
3	FC	0	5	**7316**	3	1	4	1	0	0	0	0	0.9981
	VEL	0	8	**7308**	3	2	9	0	0	0	0	0	0.9970
	POS	0	27	**7214**	26	5	31	7	7	9	1	3	0.9842
4	FC	0	0	4	**7310**	9	4	1	1	0	1	0	0.9973
	VEL	0	1	5	**7304**	12	5	1	2	0	0	0	0.9965
	POS	0	1	20	**7182**	54	14	12	21	5	10	11	0.9798
5	FC	0	0	1	8	**7297**	0	3	12	1	8	0	0.9955
	VEL	0	0	1	12	**7271**	0	4	28	1	13	0	0.9920
	POS	0	3	4	58	**7118**	9	8	92	5	29	4	0.9711

	Method	1	2	3	4	5	6	7	8	9	10	11	Accuracy
6	FC	0	4	3	5	0	**7300**	9	3	6	0	0	0.9959
	VEL	0	7	4	8	0	**7269**	19	7	13	2	1	0.9917
	POS	0	35	37	12	8	**7068**	88	27	38	7	10	0.9643
7	FC	0	4	1	1	3	9	**7282**	14	2	5	9	0.9935
	VEL	0	4	3	1	5	20	**7229**	18	11	9	30	0.9862
	POS	0	10	4	7	16	95	**6901**	137	40	24	96	0.9415
8	FC	0	1	0	3	11	3	13	**7288**	4	6	1	0.9943
	VEL	0	0	0	2	26	8	16	**7258**	5	12	3	0.9902
	POS	0	2	6	34	85	33	120	**6967**	24	41	18	0.9505
9	FC	0	4	0	0	1	6	3	4	**7306**	1	5	0.9967
	VEL	0	4	1	0	0	11	15	4	**7280**	3	12	0.9932
	POS	0	53	5	4	3	33	38	22	**7128**	10	34	0.9724
10	FC	0	1	0	0	8	0	5	6	1	**7303**	6	0.9963
	VEL	0	1	0	0	14	1	10	10	4	**7284**	6	0.9937
	POS	0	2	2	4	38	2	31	38	10	**7157**	46	0.9764
11	FC	0	1	0	0	0	0	10	0	6	5	**7308**	0.9970
	VEL	0	1	0	0	0	0	32	3	11	6	**7277**	0.9928
	POS	0	2	0	3	1	6	118	17	34	50	**7099**	0.9685
								Overall Accuracy FC					**0.9965**
								Overall Accuracy VEL					**0.9936**
								Overall Accuracy POS					**0.9718**

Table 2.2. Confusion matrix for the sampling periods of $T = 500\,ms$.

Actual Player	Method	Predicted Player 1	2	3	4	5	6	7	8	9	10	11	Accuracy
1	FC	**3664**	0	0	0	0	0	0	0	0	0	0	1.0000
	VEL	**3664**	0	0	0	0	0	0	0	0	0	0	1.0000
	POS	**3664**	0	0	0	0	0	0	0	0	0	0	1.0000
2	FC	0	**3457**	52	5	3	51	26	12	40	3	15	0.9435
	VEL	0	**3428**	48	6	7	60	26	12	61	5	11	0.9356
	POS	0	**3427**	55	7	3	63	21	8	65	2	13	0.9353
3	FC	0	43	**3520**	45	5	23	7	8	10	1	2	0.9607
	VEL	0	44	**3462**	66	6	46	9	13	11	2	5	0.9449
	POS	0	49	**3439**	55	12	44	21	11	15	4	14	0.9386
4	FC	0	4	42	**3449**	59	21	23	49	3	9	5	0.9413
	VEL	0	6	56	**3421**	64	29	28	39	7	5	9	0.9337
	POS	0	1	56	**3411**	62	36	15	44	9	13	17	0.9309
5	FC	0	6	3	61	**3421**	11	26	88	9	32	7	0.9337
	VEL	0	9	5	62	**3407**	13	19	100	9	33	7	0.9299
	POS	0	6	7	66	**3369**	15	16	103	9	63	10	0.9195
6	FC	0	72	26	27	7	**3341**	79	55	42	2	13	0.9118
	VEL	0	59	44	20	18	**3299**	80	62	55	10	17	0.9004
	POS	0	57	58	34	15	**3260**	112	55	49	10	14	0.8897
7	FC	0	16	8	19	16	99	**3263**	87	42	33	81	0.8906
	VEL	0	23	16	24	20	90	**3210**	99	55	38	89	0.8761
	POS	0	21	11	17	22	111	**3103**	154	60	49	116	0.8469
8	FC	0	4	3	52	103	55	72	**3288**	28	41	18	0.8974
	VEL	0	13	10	43	87	63	105	**3247**	28	42	26	0.8862
	POS	0	6	11	47	111	59	145	**3185**	30	45	25	0.8693
9	FC	0	53	5	3	3	41	38	20	**3440**	15	46	0.9389
	VEL	0	67	15	6	4	39	58	22	**3385**	13	55	0.9239
	POS	0	77	14	8	6	42	57	23	**3359**	9	69	0.9168
10	FC	0	4	2	1	42	5	32	39	10	**3497**	32	0.9544
	VEL	0	5	4	7	38	5	35	42	13	**3484**	31	0.9509
	POS	0	6	7	5	54	7	43	52	15	**3414**	61	0.9318
11	FC	0	5	3	2	5	17	98	18	40	31	**3445**	0.9402
	VEL	0	10	4	9	13	20	94	28	40	32	**3414**	0.9318
	POS	0	14	6	14	10	27	131	29	53	55	**3325**	0.9075
								Overall Accuracy FC					**0.9375**
								Overall Accuracy VEL					**0.9285**
								Overall Accuracy POS					**0.9169**

Table 2.3. Confusion matrix for the sampling periods of $T = 1000\ ms$.

Actual Player	Method	Predicted Player 1	2	3	4	5	6	7	8	9	10	11	Accuracy
1	FC	**1833**	0	0	0	0	0	0	0	0	0	0	1.0000
	VEL	**1833**	0	0	0	0	0	0	0	0	0	0	1.0000
	POS	**1833**	0	0	0	0	0	0	0	0	0	0	1.0000
2	FC	0	**1405**	78	20	10	105	59	27	91	12	26	0.7665
	VEL	0	**1457**	61	28	7	101	45	27	81	8	18	0.7949
	POS	0	**1457**	61	28	7	101	45	27	81	8	18	0.8762
3	FC	0	73	**1442**	114	20	50	31	30	34	14	25	0.7867
	VEL	0	77	**1492**	90	24	33	24	24	31	15	23	0.8140
	POS	0	77	**1492**	90	24	33	24	24	31	15	23	0.8893
4	FC	0	20	102	**1438**	74	50	39	63	14	14	19	0.7845
	VEL	0	16	97	**1483**	71	43	30	51	21	9	12	0.8091
	POS	0	16	97	**1483**	71	43	30	51	21	9	12	0.8816
5	FC	0	16	20	71	**1436**	32	35	105	21	76	21	0.7834
	VEL	0	9	23	77	**1479**	26	32	79	10	74	24	0.8069
	POS	0	9	23	77	**1479**	26	32	79	10	74	24	0.8707
6	FC	0	120	72	41	25	**1273**	101	88	61	14	38	0.6945
	VEL	0	82	54	35	31	**1356**	89	85	62	15	24	0.7398
	POS	0	82	54	35	31	**1356**	89	85	62	15	24	0.8112
7	FC	0	44	33	33	33	106	**1160**	146	90	66	122	0.6328
	VEL	0	45	28	23	22	91	**1253**	139	75	49	108	0.6836
	POS	0	45	28	23	22	91	**1253**	139	75	49	108	0.7561
8	FC	0	18	39	69	125	90	129	**1209**	33	66	55	0.6596
	VEL	0	21	31	61	105	98	113	**1280**	30	52	42	0.6983
	POS	0	21	31	61	105	98	113	**1280**	30	52	42	0.7812
9	FC	0	97	21	20	22	63	84	35	**1370**	24	97	0.7474
	VEL	0	93	26	8	13	48	79	39	**1408**	18	101	0.7681
	POS	0	93	26	8	13	48	79	39	**1408**	18	101	0.8554
10	FC	0	9	10	12	68	29	69	65	25	**1470**	76	0.8020
	VEL	0	11	10	12	53	17	54	61	21	**1522**	72	0.8303
	POS	0	11	10	12	53	17	54	61	21	**1522**	72	0.8773
11	FC	0	31	16	15	20	35	126	65	94	77	**1354**	0.7387
	VEL	0	22	11	16	28	20	114	48	94	71	**1409**	0.7687
	POS	0	22	11	16	28	20	114	48	94	71	**1409**	0.8265
									Overall Accuracy FC				**0,7633**
									Overall Accuracy VEL				**0,7921**
									Overall Accuracy POS				**0,8569**

It is noteworthy, however, that such misclassification is related with the distance between the estimated position $x_n^s[t+1]$ and the real one $x_n[t+1]$, *i.e.*, d_n^{min}. Therefore, and to further compare the three methods, the average accumulated error distance over time was analysed. Once again it is possible to observe that the fractional method (**FC**) presents a higher performance for sampling periods of $250\ ms$ and $500\ ms$ (Tables 2.1 and 2.2).

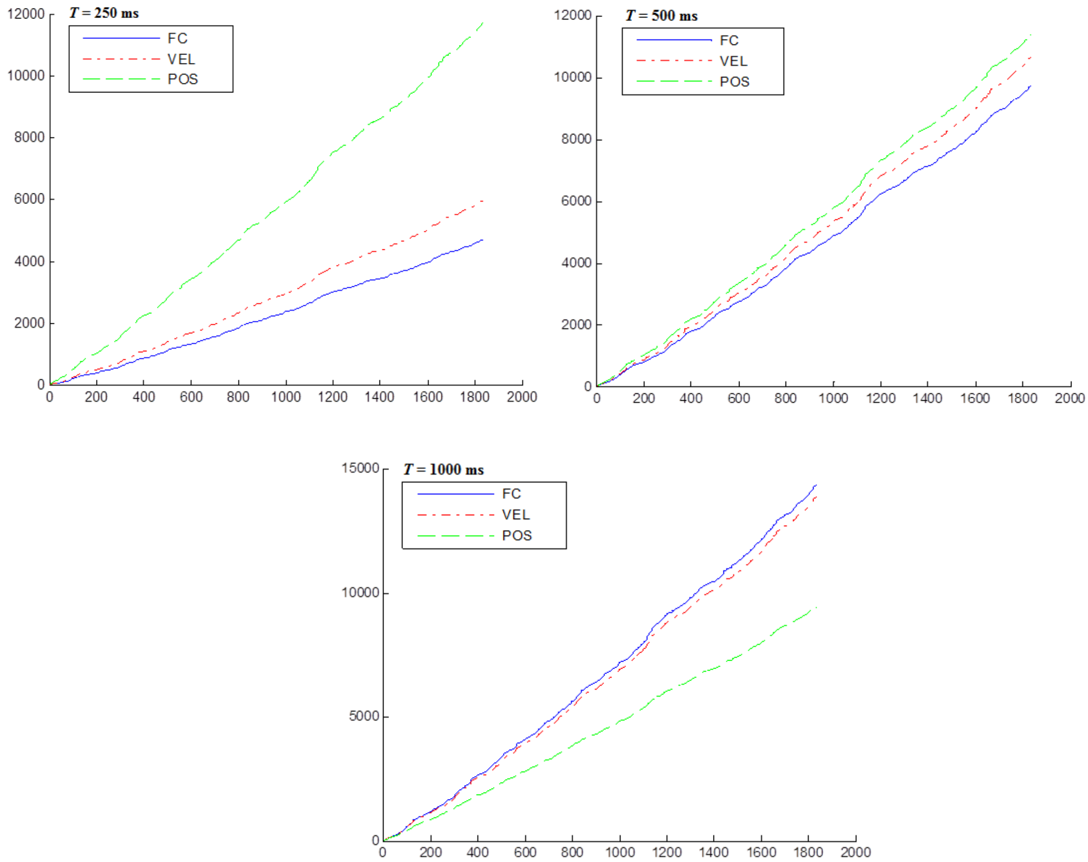


Figure 2.3. Comparing FC, VEL and POS methods for the sampling periods of $\boldsymbol{T = 250\,ms}$, $\boldsymbol{T = 500\,ms}$ and $\boldsymbol{T = 1000\,ms}$.

Also, the previous position method (**POS**) is considerably worse than the other methods for a small sampling period, presenting an error almost 3 times higher than the fractional method (**FC**) for $T = 250\,ms$. This means that the dynamical characteristics of players may be more accurately represented as the sampling period decreases, thus being able to predict their position with a higher performance using the fractional (**FC**) and velocity vector (**VEL**) methods. However, for a larger sampling period of $T = 1000\,ms$, the previous position method (**POS**) once again presents a better classification accuracy. The explanation about this phenomenon still remains the same and allows concluding that a large sampling rate of 1 second turns out to be too high to correctly represent players' dynamics. Therefore, and as players usually play around a specific region, the previous position method (**POS**) present a better performance, and yet with a high accumulated error of almost $10\,km$.

2.4. Discussion and Conclusion

Increase the autonomy and accuracy of multiplayer football tracking systems is one of the main goals to improve the performance analysis of football players and teams. Nevertheless, problems such as players' occlusion can produce erroneous information that may deceive the automatic tracking system, requiring the intervention of human operators to solve such situations.

This paper proposed a fractional calculus method to predict the position of players over time in the field. The first step was to analyze the influence of the fractional coefficient in the performance of the method. This analysis showed that an adaptive $\alpha_n[t]$ generally results in a higher performance than when using a fixed α_n. Afterwards, the adaptive fractional calculus approach was compared with two other classical methods based on the previous position and the previous velocity of players. It was possible to observe a superior accuracy using the proposed strategy for sampling rates of $T = 250\,ms$ and $T = 500\,ms$. These results suggest that the motion of football players may be explained using fractional dynamics for small sampling periods, especially for long periods of time. Using the fractional order intrinsic memory property, one can predict the location of occluded players based on their trajectory so far. Also, a simple exclusion mechanism may be used to reinforce the robustness of the approach, *i.e.*, the fractional method can predict the position of all visible players with high accuracy in such a way that the remaining players will be the lasts to be considered. Note that if it turns out to be impossible to detect a player due to a high level of occlusions, as the fractional algorithm still returns an estimated position based on its trajectory so far, one may consider it as the correct one and posteriorly correct it based on new acquired positional data. This is an assumption that holds as the positional error obtained on the results is still considerably inferior to other methods.

Regardless on that, the experiments fulfilled so far showed that it was possible to overcome most of occlusions occurring during the game combining the herein proposed fractional approach with a single monocular camera. Nevertheless, the fractional coefficient still has a major influence on such accuracy. Therefore, we propose to further analyze this parameter and, at some extent, evaluate the stability of players.

In sum, this study fostered the use of fractional calculus to improve the accuracy of tracking systems, thus overcoming some of the misclassification problems that still occur in most traditional methods. Moreover, using this information one may benefit from online tactical metrics, thus helping coaches to understand how players behave in a collective way.

2.5. References

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Chapter III

Using collective metrics to analyse spatio-temporal relationships between football players:

Inspecting the impact of each half of the match on ball possession

Chapter based on the following publications:

Clemente, F. M., Couceiro, M. S., Martins, F. M. L., Mendes, R., & Figueiredo, A. J. (2013). Measuring collective behaviour in football teams: Inspecting the impact of each half of the match on ball possession. *International Journal of Performance Analysis in Sport*, 13(3), 678-689.

Clemente, F. M., Couceiro, M. S., Martins, F. M. L., Mendes, R., & Figueiredo, A. J. (2013). Measuring the tactical behaviour using technological metrics: Case study of a football game. *International Journal of Sports Science & Coaching*, 8(4), 723-740.

3. Using collective metrics to analyse spatio-temporal relationships between football players: Inspecting the impact of each half of the match on ball possession

Abstract

The aim of this study was to inspect the influence of each half of match and the ball possession status on the players' spatio-temporal relationships. Three official matches of a professional football team were analysed. From the players' locations were collected the team's *w*centroid, *w*stretch index, surface area and effective area of play at 9218 play instants. The results suggested that the values of teams' dispersion and average position on the field decreases during the 2nd half of the match. In sum, this study showed that the half of match and the ball possession status influenced players' spatio-temporal relationships, in a way that significantly contributes to the collective understanding of football teams.

Key-words: Football, collective behaviour, metrics, match analysis.

3.1. Introduction

Match analysis on football teams has been well studied based on the notational and kinematical analysis in the past years (Vilar, Araújo, Davids, & Bar-Yam, 2012a). Recently many findings were published highlighting the relevance of several performance indicators contributing to the improvement of individual and collective behaviour during playtime (Hughes & Franks, 2004; Carling, Williams, & Reilly, 2005). For instance, the difference in ball possession in the 1st and 2nd half of the football game is considered to be one of the main bases for performance improvement (Lago & Martín, 2007; Bangsbo, Mohr, & Krustrup, 2006). The fatigue component is generally associated with the two halves of a game (Mohr, Krustrup, & Bangsbo, 2005). Ball possession can be associated with both defensive and offensive moments, and it also determines the number of individual and collective actions (Lago & Martín, 2007). Nevertheless, notational and kinematic analysis are not the only solutions to identifying the properties of a football team (Duarte, Araújo, Correia, & Davids, 2012). In the past few years it became possible to identify a spatio-temporal dimension of football teams

(Vilar et al., 2012a) based on the bidimensional positions of the players. In this paper the spatio-temporal analyses are depicted as collective metrics.

Some basic collective metrics have been proposed in order to inspect the intra- and inter-team relationships (Bourbousson et al., 2010; Frencken et al., 2011; Moura et al., 2013). These metrics use a player's Cartesian coordinates on the field to compute a set of relationship parameters (Clemente, Couceiro, Martins, & Mendes, 2013). One of the metrics used the most is the team's centroid (Bartlett et al., 2012). This metric is very similar to the concept of centre of gravity, *i.e.*, the centroid position is calculated by examining the x and y coordinates of all players (Clemente et al., 2013). Several studies suggest that due to the instability between the centroid of both teams it is possible to analyse some goals scored in open play (Frencken et al., 2011). Another collective metric concept is the stretch index (Bourbousson et al., 2010). This metric is based on the standard deviation concept, where the centroid is the "average" value. Based on regular expansion-contraction relationship between the football teams, the higher dispersion values are naturally associated with the offensive moments (Bartlett et al., 2012). Furthermore, an inverse relationship is expected between both teams' stretch indexes (Clemente et al., 2013).

The metric proposed in order to inspect the team's configurations of play is the surface area (Frencken et al., 2011; Moura et al., 2013). This metric detects all possible triangulations performed by the team players (Moura et al., 2013). The combined area of all triangles is then computed based on these triangulations, thus providing the entire area covered by the team (Frencken & Lemmink, 2008). This metric enables the identification of the possible actions for each team by inspecting the geometric configuration performed by all players (Gréhaigne et al., 2011). A similar concept is exhibited in the effective area of play metric (Clemente et al., 2013). It detects all possible triangulations but considers only some of them. The effective area of play metric is based on the effective defensive triangulations and only considers those that are not overlapped by the opposite team or the defensive triangulations with a small and balanced perimeter (Clemente et al., 2013). This concept enables the detection of regions with higher and lower effectiveness of teammates' spatial coordination.

Despite the introduction of many technological advances in the past few years, a team's analysis based on tactical inspection or collective metrics (*e.g.*, spatio-temporal dimension) is still underdeveloped in comparison to the notational analysis (Vilar et al., 2012). Due to the increase in efforts needed to develop collective metrics, some parameters (*e.g.*, half of the match, ball possession) have not been included in the collective changes analysis so far. Therefore, the aim of this study is to analyse the influence of the two halves of match and ball possession status on collective behaviour. Thus, several dependent variables would be analysed during three games of one team: centroid value, stretch index, surface area and effective area of play. It is expected that higher values of the centroid, stretch index, surface area and effective area of play will occur during the moments with ball possession, *i.e.*, offensive moments. It is also expected that the lower values of the centroid, stretch index, surface area and effective area of play will occur during the 2^{nd} half of the match.

3.2. Methods

3.2.1. Sample

Three home matches of a professional team were analysed. At each match the final score was different, *i.e.*, winning, losing or drawing. Thus, every match was considered by each final score. From those 3 matches were collected 9218 instants. All of the collected data complies to the APA ethical standards for the treatment of human or animal subjects.

3.2.2. Data Collecting

The teams' actions were captured using a digital camera (*GoPro Hero* with 1280 $\times$ 960 resolution), with the capacity to process images at 30 Hz (*i.e.*, 30 frames per second). The camera was placed on an elevated position above the ground (from 10 meters to the field lateral line and in an elevation of $15\ m$) in order to capture the whole field. The field dimensions were in $104 \times 68\ m$. The field was calibrated using special markers allowing us to recognise them on the images.

The first step to collect the data was to record the players' behaviour using the digital camera as previous described. The camera was placed after the half line of field. Considering that this digital camera can record with 180º, it was possible not to move the digital camera, thus ensuring the same markers positions on the digital image. The field was calibrated using 19 markers positioned on the referential field lines. Those markers were metrically identified from point zero, which was the inferior vertex of field (see Figure 3.1).

Figure 3.1. Initial calibration to extract the DLT coefficients based on real references of table 1.

After capturing the football match, the physical space was calibrated using Direct Linear Transformation (*DLT*), which transforms elements' position (*i.e.*, players and ball) in pixels to the metric space (Abdel-Aziz & Karara, 1971). This method consists of a proportional equivalence of virtual space on real physical space. This calibration is based on identification of field markers (real coordinates) on virtual images (virtual coordinates) (Fernandes et al., 2010). This procedure was performed using the software MATLAB.

First, a calibration based on the first frame of each half of each match was performed. The initial calibration aimed to extract the DLT coefficients provided from 19 bi-dimensional markers on virtual space (pixels) for the real physical space (meters), following the correspondence between Figure 3.1 and Table 3.1.

Table 3.1. Correspondence between virtual space (pixels) represented by Figure 1 and the physical space (meters) for the initial calibration.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
x	0	52	104	104	104	104	104	104	52	0	0	0	0	0	87,7	87,7	16,3	16,3	52
y	0	0	0	13,9	30,4	37,9	54,4	68	68	68	54,4	37,9	30,4	13,9	13,9	54,4	54,4	13,9	34

After, a graphical interface allowing for the visualisation of one frame of the match per second, was developed. During each frame to the operator was requested identify the locations of all players and the ball following the typical approach point and click.

That identification corresponded to one point in the centre of players' feet. Each point on the virtual space (pixels) of image was converted using an algorithm[1] based on the relationship between virtual coordinates and real coordinates defined by Figure 3.1 and Table 3.1.

In order to ensure that the reliability of such conversion were defined experimental tests with random points on the field previously collected were mapped with real coordinates and measured metrically on space. Then, on the toolbox developed through MATLAB were identified those points and the results were identified to allow for the identification of the higher standard deviation was 5 centimetres in relation to the real coordinates. This border was considered viable to perform the study because it did not compromise the main goal of study, i.e., to identify the spatio-temporal relationship between players. For a deeper description of this tracking process (DLT) please see Woltring and Huiskes (1990).

For matters of efficiency, only play moments were used; all moments in which the ball was not in the field (*i.e.*, ball out of play) were excluded from the analysis. The methodology herein proposed has a computational complexity inherent to it, meaning each second will correspond to each analysed instant.

3.2.3. Computing the collective behaviour

Four collective metrics were computed for the match analysis: *i*) weighted centroid; *ii*) weighted stretch index; *iii*) surface area; and *iv*) effective area of play. The following section presents a descriptive summary of each metric.

3.2.3.1. Weighted Centroid (*w*C)

The centroid value is a computation of the geometric centre of a team. This metric is considered for its usefulness in computing the in-phase relations between two opposing teams in longitudinal and lateral directions (Bourbousson et al., 2010). Moreover, it is also used to analyse the equilibrium point of a team, considering the

[1] The script that allow the remapping of virtual coordinates in real coordinates having as input the DLT coefficients can be seen at http://isbweb.org/software/movanal/reconfu2.m

distribution among its players. The centroid calculation has been introduced without considering the position of the ball and the player's proximity to it. Nevertheless, the proximity to the ball is an important factor that should be considered. Therefore, the Clemente et al. (2013) approach was used, considering that the proximity of the players to the ball would assign different weights to the centroid position. The relevance of each player to the team's centroid, *i.e.*, w_i weight, was based on the Euclidean distance between each player and the ball as follows:

$$w_i = 1 - \frac{\sqrt{(x_i - x_b)^2 + (y_i - y_b)^2}}{d_{max}}, \tag{3.1}$$

wherein (x_b, y_b) corresponds to the position of the ball and d_{max} is the Euclidean distance of the farthest player to the ball at each iteration (Clemente et al., 2013).

In order to improve the statistical analysis, inverted players displacement was introduced so as to overcome the changes after each half of the match. Thus, team A would always attack towards positive coordinate values and the opponent team would always attack toward negative coordinate values.

3.2.3.2. Weighted Stretch Index (*w*SI)

The stretch index value represents the expansion or contraction of area covered by the team in longitudinal and lateral directions (Bourbousson et al., 2010). The stretch index is measured based on the centroid position, thus it is the sum of each player's dispersion on both axes. Similarly to the team's centroid, a weighted team's stretch index metric may then be calculated as (Clemente et al., 2013):

$$wSI = \frac{\sum_{i=1}^{N} w_i d_i}{\sum_{i=1}^{N} w_i}, \tag{3.2}$$

wherein d_i is the Euclidean distance between player i and the team's centroid, *i.e.*,

$$d_i=\sqrt{(x_i-\bar{x})^2+(y_i-\bar{y})^2}. \tag{3.3}$$

Within this context, the stretch index can be obtained by computing the mean of the distance between each player and the centroid of the team.

3.2.3.3. Surface Area (SA)

The surface area is based on the calculation of the entire area covered and the sum of triangulations emerging from the match (Frencken et al., 2011). Therefore, the sum of emerging triangulations is the value of all possible triangular combinations of N players, in which N is the total number of players within a team (Clemente et al., 2013). In the particular case of football, a maximum of eleven players (for each team) could be on the field at the same time. Hence, all possible combinations of three out of eleven players, is a total of 165 cumulatively formed triangles (Clemente et al., 2013) as can be observed in the following algorithm 3.1. Consequently, the sum and area of the triangulations are computed at every instant.

Algorithm 3.1. Calculate the surface area of the team.

```
l = 0 // counter of the combinations of N players taken three at a time
For i = 1:N − 2
    For j = i + 1:N − 1
        For k = j + 1:N
            l = l + 1
            Δ_l = [x_i x_j x_k; y_i y_j y_k]^T // each triangle is defined by the position of three different players
P = Δ_1   // initialize the polygon as the first triangle defined by players 1, 2 and 3
For i = 2:l
    P = P ∪ Δ_i , where P = (p_1, ..., p_α) and α ≤ N // build the polygon by accumulatively uniting itself to the remaining triangles
A_Pol = 1/2 Σ_{i=1}^{α−1} (p_{1,i} p_{2,i+1} − p_{1,i+1} p_{2,i}) , with α ≤ N  // calculate the area of the polygon
```

In order to understand how teams behave in the field, it is important to analyse the effective free-space to play. The concept of effective play area comes from Gréhaigne (1992), defining it as the instant peripheral position of players. In other words, one could define the limitation of the surface area as the effective available space a team can play. Figures 3.2 and 3.3 show how Algorithm 3.1 improves the feasibility of the team's surface area.

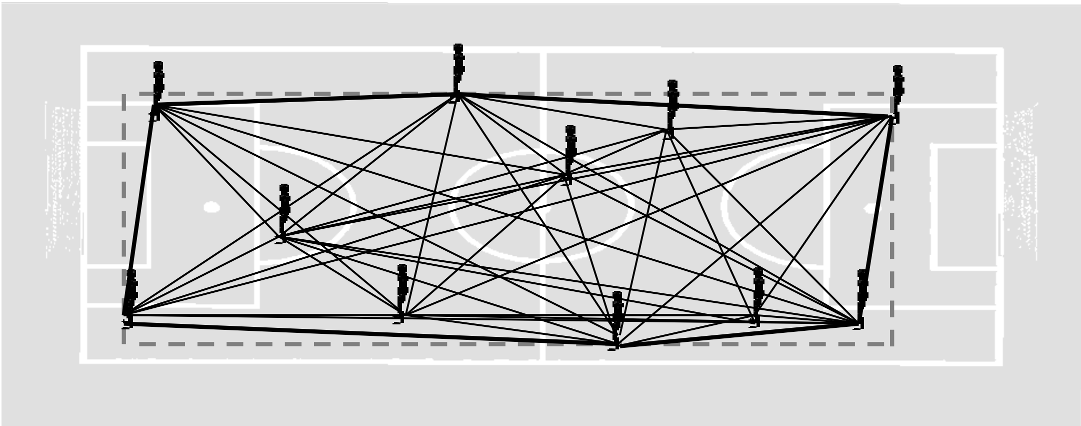

Figure 3.2. Example of the application of Algorithm 3.1 in the Surface Area.

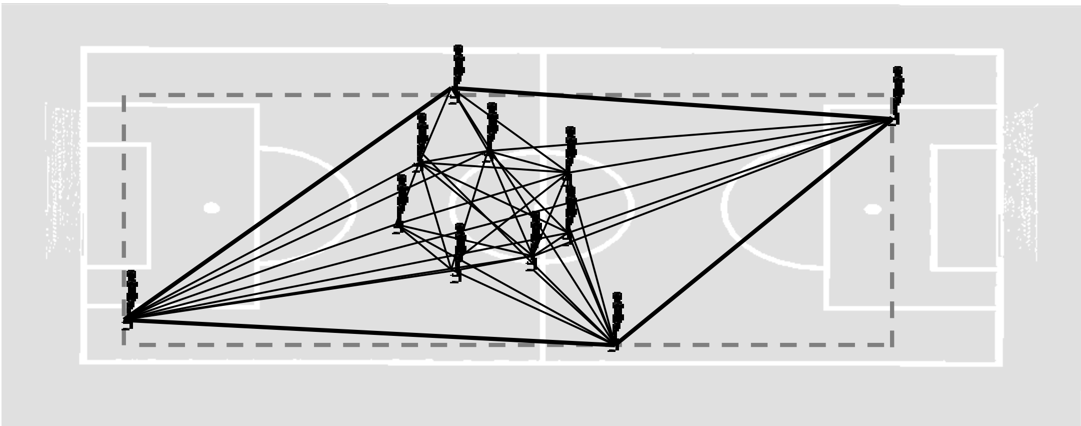

Figure 3.3. Example of the application of Algorithm 3.1 in the Surface Area.

However, it is important to further understand how teams behave and find the real effective area of each team over time. Hence, it may be important to contemplate the effective area of a team, *i.e.*, the real area that a team covers without intercepting the effective area of the opposing team (Clemente et al., 2013). In fact, the effective area needs to consider the space that a team can efficiently cover. Therefore, tactical football can be geometrically analysed to further understand how team behaves.

3.2.3.4. Effective Area of Play (EAP)

Lucchesi (2001) refers that the geometric figures that allow the most successful play along the field are triangles. The author enhances that the ability of the team to “draw up” such triangles on the field allows developing a good offensive play. In the defensive organization, triangles towards the ball, known as defensive triangles, are always being formed in an attempt to create a "defensive shadow", *i.e.*, the space through which the opponent cannot pass or dibble owing to the triangular-shaped positioning of players (Dooley & Titz, 2011). Therefore, the main objective of Algorithm 3.2 is to calculate all the non-overlapping triangles formed by the players of the same team. The main condition to this is to generate, at first, the triangles with smaller perimeters (*cf.* Figure 3.4).

Algorithm 3.2. Calculate the surface area of team δ with non-overlapping triangles.

$l^{\delta} = 0$ // counter of the combinations of N players of team δ taken three at a time
For $i = 1{:}N^{\delta} - 2$
  For $j = i + 1{:}N^{\delta} - 1$
    For $k = j + 1{:}N^{\delta}$
      $l^{\delta} = l^{\delta} + 1$
      $\Delta_l^{\delta} = \begin{bmatrix} x_i & x_j & x_k \\ y_i & y_j & y_k \end{bmatrix}^T$ // each triangle is defined by the position of three different players
      $\rho_l = \sum_{i=1}^{3} \left\| \left(x_i - x_j \, , \, y_i - y_j \right) \right\|$, $with\ i \neq j\ and\ i < j$
$\vec{s} = sort\_ascending\ (\vec{\rho}) \in \mathbb{R}^{1\times\beta}$, $where\ \vec{\rho} = (\rho_1, \ \ldots, \ \rho_\alpha)\ and\ \beta = \binom{N^{\delta}}{3}$
$P^{\delta} = \Delta_{s_1}^{\delta}$ // initialize the polygon as the triangle with the smallest perimeter
$\Delta_1^{\delta} = \Delta_{s_1}^{\delta}$ // initialize the non-overlapping triangles of team δ
$\tau^{\delta} = 1$ // counter of the non-overlapping triangles of team δ
For $i = 2{:}l^{\delta}$
  $\Gamma = P^{\delta} \cap \Delta_i^{\delta}$, $where\ \Gamma = (\gamma_1, \ \ldots, \ \gamma_\alpha)\ and\ \alpha \leq N^{\delta}$ // analyze intersections between triangles
  $A_{Pol} = \frac{1}{2} \sum_{i=1}^{\alpha-1} \left(\gamma_{1,i}\gamma_{2,i+1} - \gamma_{1,i+1}\gamma_{2,i} \right)$ $with\ \alpha \leq N^{\delta}$ // calculate the area of the intersection
  If $A_{Pol} = 0$ // condition is verified when there is no intersection between triangles
    $\tau^{\delta} = \tau^{\delta} + 1$
    $P^{\delta} = P^{\delta} \cup \Delta_i^{\delta}$ // build the polygon by accumulatively uniting the non-overlapping triangles
    $\Delta_{\tau^{\delta}}^{\delta} = \Delta_i^{\delta}$ // non-overlapping τ^{δ} triangle of team δ

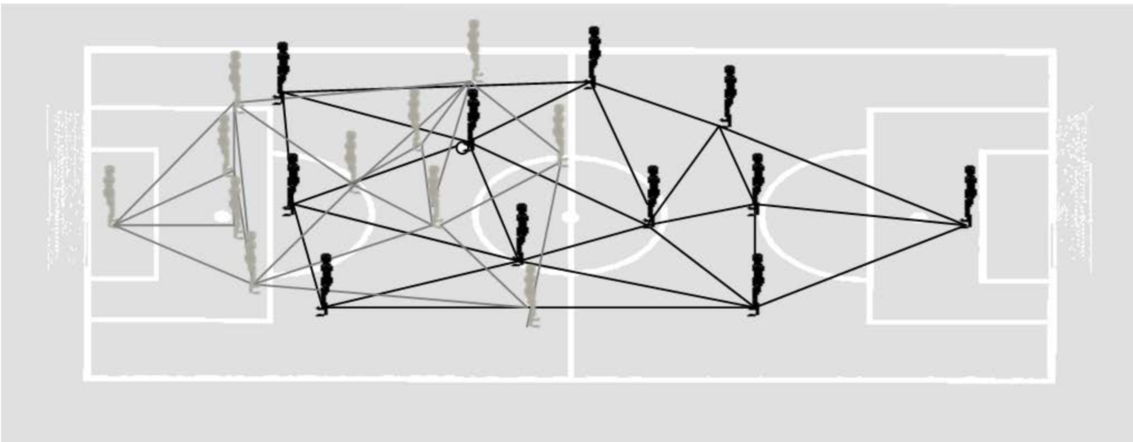

Figure 3.4. Example of the triangles constitution in the strategic disposition.

Therefore, as the number of formed triangles within a team increase, the less effective space is left for the opposing team. For instance, Trapattoni (1999) affirms that when players are pressured and cannot turn around and dribble, the ball must travel along triangles until a solution for forward play is found, *i.e.*, the offensive triangles are annulled by the defensive triangles.

After generating all triangles of each team, the next step is to consider all triangles of each team without interception. Through this condition it is possible to calculate the area of each team without interception (*cf.* Figure 3.5). Hence, Algorithm 3.3 computes the triangles of each team that do not suffer from the intersection of the opposing team.

Algorithm 3.3. Effective Area - Triangles of team δ that do not intersect the surface area of the opposing team ζ.

$\varepsilon^{\delta} = 0$ // counter of the effective triangles of team δ
$A^{\delta} = 0$ // effective area of team δ
$E^{\delta} = [\,]$ // polygon of the effective area of team δ is initialized as an empty array
For $i = 1{:}\tau^{\delta}$
    $\Gamma = \Delta_i^{\delta} \cap P^{\zeta}$, $where\ \Gamma = (\gamma_1, \ \cdots, \ \gamma_\alpha)\ and\ \alpha \leq 6$ // analyse intersections between triangles
    $A_{Pol} = \frac{1}{2}\sum_{i=1}^{\alpha-1}(\gamma_{1,i}\gamma_{2,i+1} - \gamma_{1,i+1}\gamma_{2,i})\ with\ \alpha \leq 6$ // calculate the area of the intersection
    If $A_{Pol} = 0$ // condition is verified when there is no intersection between the triangle from team δ and the surface area of team ζ
        $A_{Pol} = \frac{1}{2}\sum_{i=1}^{3}(x_i y_{i+1} - x_{i+1} y_i)$ // calculate the area of the triangle
        $A^{\delta} = A^{\delta} + A_{Pol}$ // cumulative effective area of team δ
        $\varepsilon^{\delta} = \varepsilon^{\delta} + 1$ // counter of the effective triangles of team δ
        $E^{\delta} = E^{\delta} \cup \Delta_i^{\delta}$ // build the polygon of the effective area of team δ by accumulatively uniting its effective triangles

In algorithm 3.3, both teams are simultaneously considered in which δ and ζ are the team *ID* such that $\delta = 1{,}2$ and $\zeta = 1{,}2$ with $\delta \neq \zeta$.

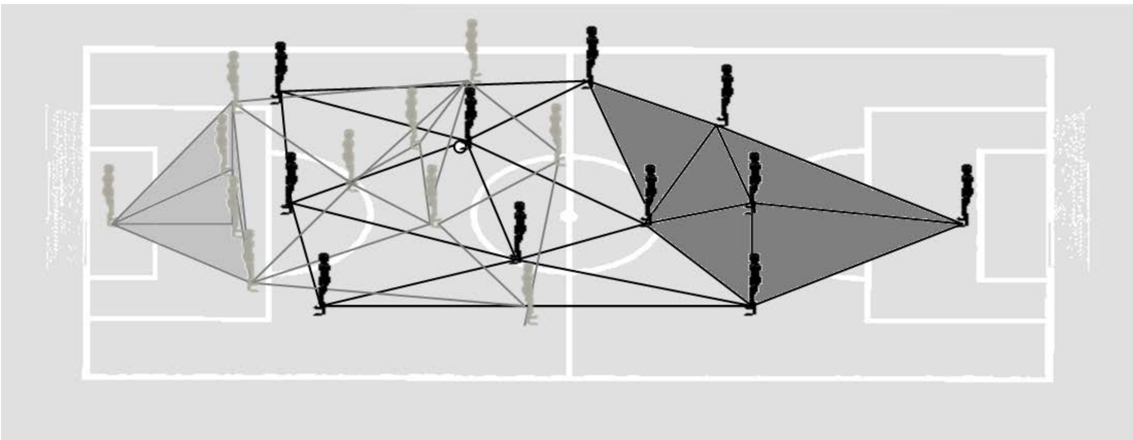

Figure 3.5. Number of effective triangles without overlapping.

However, in the presence of interceptions between opposing triangles, and based on the supposition that effective defensive triangles can annul the offensive triangles (Trapattoni, 1999), the effective area to be considered is the one of the defensive triangles (Figure 3.6a), thus reducing the effective area of the offensive team.

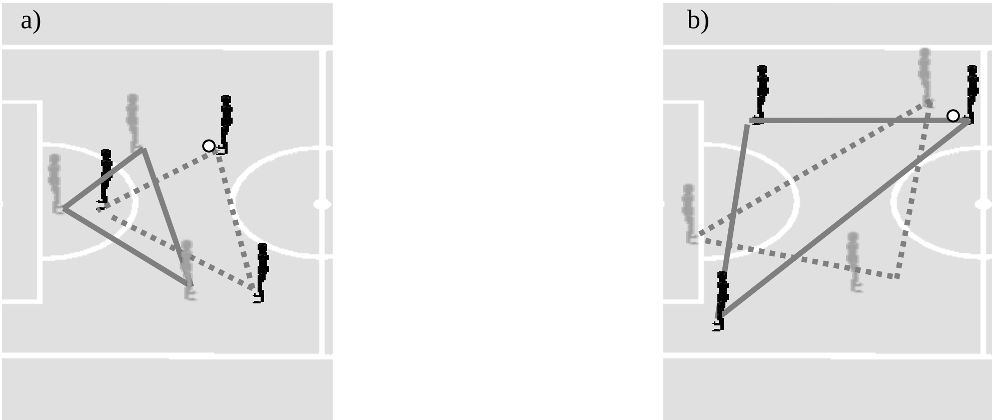

Figure 3.6. Example of triangles interception.

However, Dooley and Titz (2011) proves that in order to form effective defensive triangles, it is necessary to have an approximate distance of 12 meters between each vertex (*i.e.*, defensive players), *i.e.*, a defensive triangle with a maximum perimeter of 36 meters. Hence, if a defensive triangle have a perimeter superior to 36 meters (figure 3.6b), it will be nullified by the offensive triangles since there are no guarantees that the defensive players will be able to intercept the ball.

After considering the triangles without interception, it is necessary to consider all triangles of the team that does not have the ball possession (*i.e.*, defensive team) with perimeters inferior to 36 meters (*cf.* Figure 3.7). Therefore, the algorithm considers all the defensive triangles that have this condition, overlapping the interceptive offensive triangles (Algorithm 3.4).

Algorithm 3.4. Effective Area - Defensive triangles of team δ that intersect the surface area of the opposing team ζ.

If $ball\_possession(\zeta) = 1$ // condition is verified when team ζ has the possession of the ball
For $i = 1{:}\tau^{\delta}$
$\Gamma = \Delta_i^{\delta} \cap P^{\zeta}$, $where\ \Gamma = (\gamma_1, \ \cdots, \ \gamma_\alpha)\ and\ \alpha \leq 6$ // analyse intersections between triangles
$A_{Pol} = \frac{1}{2}\sum_{i=1}^{\alpha-1}(\gamma_{1,i}\gamma_{2,i+1} - \gamma_{1,i+1}\gamma_{2,i})\ with\ \alpha \leq 6$ // calculate the area of the intersection
$\rho_{Pol} = \sum_{i=1}^{3}\|(x_i - x_j\ ,\ y_i - y_j)\|$, $with\ i \neq j\ and\ i < j$

If $A_{Pol} > 0$ and $\rho_{Pol} \leq \rho_{\varepsilon}$ // condition is verified when there is intersection between the defensive triangle from team δ and the surface area of team ζ and the perimeter of the defensive triangle is smaller than ρ_{ε}

$A_{Pol} = \frac{1}{2}\sum_{i=1}^{3}(x_i y_{i+1} - x_{i+1} y_i)$ // calculate the area of the triangle
$A^{\delta} = A^{\delta} + A_{Pol}$ // cumulative effective area of team δ
$\varepsilon^{\delta} = \varepsilon^{\delta} + 1$ // counter of the effective triangles of team δ
$P^{\delta} = P^{\delta} \cup \Delta_i^{\delta}$ // build the polygon of the effective area of team δ by accumulatively uniting its effective triangles

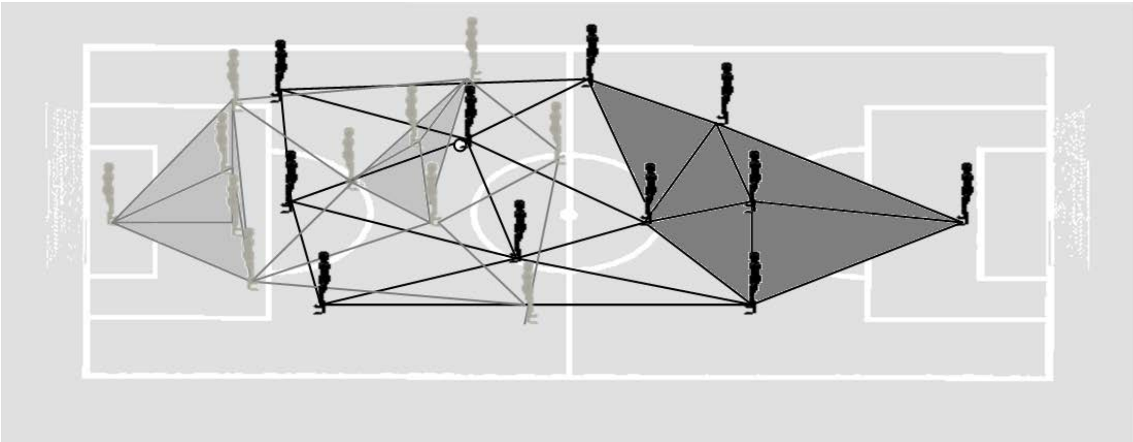

Figure 3.7. Example of effective area and effective defensive triangles.

At last, all offensive triangles that are not intercepted by the defensive triangles with perimeter inferior to $36\,m$ are considered (*cf.* Figure 3.8). Consequently, the algorithm calculates all triangles, thus calculating the respective effective areas of both teams at every instant (Algorithm 3.5).

Algorithm 3.5. Effective Area - Offensive triangles of team δ that are not intersected by the defensive triangles of the opposing team ζ.

If $ball\_possession(\delta) = 1$ // condition is verified when team δ has the possession of the ball
For $i = 1{:}\tau^{\delta}$

$\Gamma = \Delta_i^{\delta} \cap (P^{\delta} \cup P^{\zeta})$, $where\ \Gamma = (\gamma_1, \ \ldots, \ \gamma_{\alpha})\ and\ \alpha \leq 6$ // analyze intersections between offensive triangles and the effective area of both teams
$A_{Pol} = \frac{1}{2}\sum_{i=1}^{\alpha-1}(\gamma_{1,i}\gamma_{2,i+1} - \gamma_{1,i+1}\gamma_{2,i})$ $with\ \alpha \leq 6$ // calculate the area of the intersection
If $A_{Pol} = 0$ // condition is verified when there is intersection between the defensive triangle from team δ and the surface area of team ζ and the perimeter of the defensive triangle is smaller than ρ_{ε}

$A_{Pol} = \frac{1}{2}\sum_{i=1}^{3}(x_i y_{i+1} - x_{i+1} y_i)$ // calculate the area of the triangle
$A^{\delta} = A^{\delta} + A_{Pol}$ // cumulative effective area of team δ
$\varepsilon^{\delta} = \varepsilon^{\delta} + 1$ // counter of the effective triangles of team δ
$P^{\delta} = P^{\delta} \cup \Delta_i^{\delta}$ // build the polygon of the effective area of team δ by accumulatively uniting its effective triangles

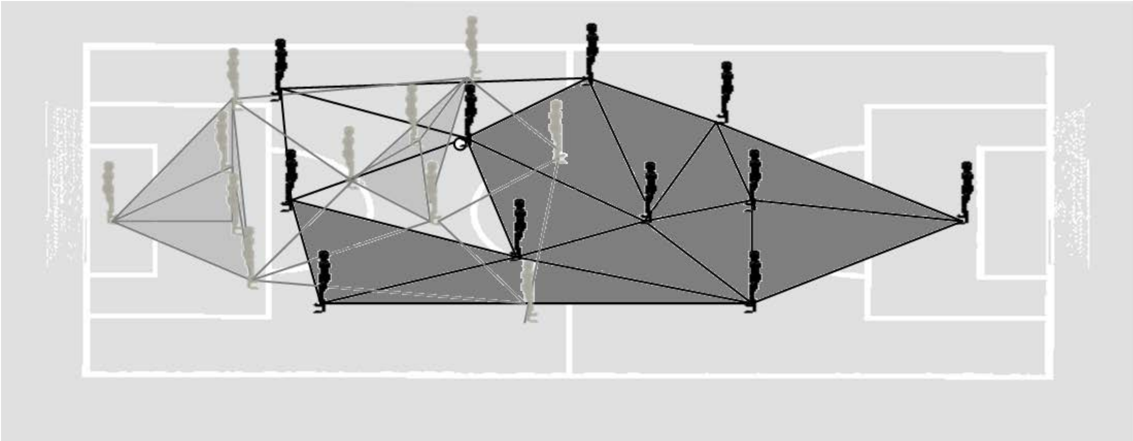

Figure 3.8. Example of effective area with defensive and offensive effective triangles.

Through this tactical metric, *i.e.*, the effective area of play, a coach may analyse if the team, in the defensive phase, acts as a defensive “block”, *i.e.*, the union of the defensive triangles form a defensive polygon that constrains the opponents to loss the ball (Clemente et al., 2013). Also, over time, the coach or the assistant may analyse if, the midfielders’ triangles are large enough to allow that offensive triangle moves forward without effective opposition. Therefore, the effective area can give to the coach important information about how teams behave and where mistakes or weakness in relation to the opponent may emerge from a specific tactical definition.

3.3. Results

The applied descriptive statistics during the moments without ball possession (Table 3.2) shows that the x-*w*centroid presents higher values on the first half. This phenomenon may suggest that the defensive phase is performed closer to their penalty area. Although during the first half the team’s y-*w*centroid is closer to the central midfield than in the second half, during the whole game the team depicts a tendency to ensure that its y-*w*centroid remains on the left side of the field.

Table 3.2. Descriptive statistics of dependent variables in the moments without ball possession.

Ball Possession			Mean	Std. Deviation	Minimum	Maximum
Without Ball Possession	x-*w*centroid [m]	1st Half	-8.247	13.349	-46.233	32.364
		2nd Half	-7.462	13.922	-50.888	31.810
		Total	-7.851	13.645	-50.888	32.364
	y-*w*centroid [m]	1st Half	0.420	9.470	-24.123	24.486
		2nd Half	0.674	10.634	-28.939	24.755
		Total	0.548	10.074	-28.939	24.755
	*w*Stretch Index [m]	1st Half	15.339	2.867	3.227	25.529
		2nd Half	14.953	3.565	4.771	31.128
		Total	15.144	3.243	3.227	31.128
	Surface Area [m^2]	1st Half	1369.689	349.381	142.705	2659.604
		2nd Half	1277.547	468.929	92.451	3432.162
		Total	1323.247	416.484	92.451	3432.162
	Effective Area of Play [m^2]	1st Half	349.327	210.364	0.000	1166.673
		2nd Half	369.614	284.472	0.000	2812.880
		Total	359.552	250.650	0.000	2812.880

The dispersion metrics (*i.e.*, stretch index and surface area) applied on the team exhibited a decreasing tendency during the second half of the match. Nevertheless, it was possible to identify an increasing evidence by benefiting from the effective area of play, with a total effective area of $369.614\ m^2$ in the second half and $349.327\ m^2$ in the first half.

In Table 3.3, it is possible to observe the results of all dependent variables during the ball possession moments. Similar to the moments in which the team does not possess the ball, the x-*w*centroid presents higher values during the first half, thus suggesting that the team remains closer to their own goal. Nevertheless, the y-*w*centroid reveals a change of flank between the first and second halves. During the first half, the team remains closer to right side of the field (average value of $-2.132\ m$) while in the second half, the team tends to left side of the field (average value of $2.006\ m$).

Table 3.3. Descriptive statistics of dependent variables in the moments with ball possession.

Ball Possession			Mean	Std. Deviation	Minimum	Maximum
With Ball Possession	x-*w*centroid [m]	1st Half	-2.888	13.748	-45.305	41.079
		2nd Half	-0.225	13.583	-50.913	40.411
		Total	-1.560	13.729	-50.913	41.079
	y-*w*centroid [m]	1st Half	-2.132	9.563	-25.611	22.967
		2nd Half	2.006	10.675	-29.871	23.661
		Total	-0.068	10.341	-29.871	23.661
	*w*Stretch Index [m]	1st Half	18.018	3.057	6.438	25.878
		2nd Half	17.064	4.168	5.854	35.193
		Total	17.542	3.684	5.854	35.193
	Surface Area [m^2]	1st Half	1831.319	452.003	260.162	3082.400
		2nd Half	1638.088	644.066	151.683	3789.971
		Total	1734.948	564.419	151.683	3789.971
	Effective Area of Play [m^2]	1st Half	1334.243	485.381	0.000	3048.152
		2nd Half	1140.255	641.618	0.000	3275.304
		Total	1237.494	576.848	0.000	3275.304

Both *w*stretch index and surface area shows a higher tendency to spread the team during the offensive moments occurred in the first half. This may be observed considering the results of the first half *w*stretch index ($18.018\ m$) and surface area ($1831.319\ m^2$) when compared with the results from the second half, namely $17.064\ m$ for the *w*stretch index and $1638.088\ m^2$ for the surface area.

The overall results (*i.e.*, considering all possession moments) are presented on Table 3.4. As previously addressed, the team has a tendency to approximate the x-*w*centroid to its own goal during the first half. Moreover, during the first half, the team tends to remain in right side of the field ($-0.900\ m$ of y-*w*centroid) while during the second half it remains in the left side ($1.356\ m$ of y-*w*centroid).

Table 3.4. Descriptive statistics of dependent variables in all moments.

Total			Mean	Std. Deviation	Minimum	Maximum
Total	x-*w*centroid [m]	1st Half	-5.476	13.817	-46.233	41.079
		2nd Half	-3.758	14.216	-50.913	40.411
		Total	-4.615	14.044	-50.913	41.079
	y-*w*centroid [m]	1st Half	-0.900	9.602	-25.611	24.486
		2nd Half	1.356	10.675	-29.871	24.755
		Total	0.231	10.216	-29.871	24.755
	*w*Stretch Index [m]	1st Half	16.724	3.255	3.227	25.878
		2nd Half	16.033	4.026	4.771	35.193
		Total	16.378	3.678	3.227	35.193
	Surface Area [m^2]	1st Half	1608.387	466.670	142.705	3082.400
		2nd Half	1462.070	593.359	92.451	3789.971
		Total	1535.038	538.911	92.451	3789.971
	Effective Area of Play [m^2]	1st Half	858.604	620.843	0.000	3048.152
		2nd Half	764.023	631.323	0.000	3275.304
		Total	811.191	627.868	0.000	3275.304

Both *w*stretch index and surface area reveal a decreasing tendency on the second half. Similar results can be observed for the effective area of play, where the team presents a mean result of $858.604\ m$ during the first half and $764.023\ m$ during the second half.

3.4. Discussion

The spatio-temporal relationship in football teams is one of the main bases to explain the relationship between football players (Duarte et al., 2012). From the individual perspective to the collective organization, most works emphasize on players' synchronization (Bourbousson et al., 2010; Moura et al., 2013). As part of the spatio-temporal relationship, collective metrics can provide some more insights toward an improved understanding of players and teams' dynamics (Clemente et al., 2013). As this specific information cannot be retrieved using regular notational information, collective metrics recently started to play a major role in sports' analysis (Vilar et al., 2012b). Despite these developments, explaining some changes in the collective performance over time still remains a challenge. Therefore, the aim of this study was to inspect how the ball possession status and the half of match can influence the collective organization by benefiting from collective metrics.

The different performance during the halves of the match has been mainly associated with the fatigue (Carling et al., 2005). Usually, studies have demonstrated that a set of indicators, such as sprinting, running and distance covered, are lower in the 2nd half of match (Bangsbo, 1994). Therefore, this may suggest a performance inhibition (Mohr et al., 2005). Nevertheless, the question on how the spatio-temporal relationships between players can be affected by this fatigue was still uncovered. This study presented statistical differences between the 1st half and 2nd half of matches. In all dependent analysed variables, a decreasing tendency was found in the 2nd half. The *w*centroid position in the longitudinal axis decreased for all 2nd half matches. This can be associated with a specific adjustment of the team on trying to reduce their general exposure to offensive moments. In fact, the team may still present a similar amount of offensive situations but with fewer players or with more balance. This can be associated with the more active recovery periods in the 2nd match by each player on trying to manage their own fatigue. Nevertheless, it is unanimous that players in all team, regardless of their position in the field, experienced a significant decline in high-intensity running closer to the end of match (Bangsbo et al., 2006). Therefore, the number of players per each attack unit can be lower, thus reducing the *w*centroid position in the longitudinal axis.

Furthermore, it was possible to observe a decreasing tendency in the stretch index, surface area and effective area of play during the 2nd half of match. Once again, the fatigue can explain the willingness to take some offensive and defensive collective behaviour (Mohr et al., 2005). With higher physical capacity, it is possible to explore the whole width and length of the field, while trying to unbalance the opponent team. Moreover, the intensity and frequency of exploring actions can be higher in the 1st half because the fatigue is not as evident (Bangsbo et al., 2006). As a consequence, if the offensive actions are more intense and frequent, then the defensive actions will be higher in number too (Dooley & Titz, 2011). A higher offensive expansion will attract a higher expansion of the defensive team, despite their contraction playing principle (Gréhaigne et al., 2011). Moreover, the higher physical capability during the 1st half allows players to coordinate their actions with higher proximity. This proximity promotes a higher effectiveness in the triangulations, subsequently increasing the team's effective area of play (Dooley & Titz, 2011). In spite of this, the fatigue cannot be the only phenomenon yielding to these collective oscillations over match (Duarte et al., 2012). Indicators such as the score, team's strategy or ball possession can also determine the predisposition to perform some collective behaviours (Lago & Martín, 2007; Taylor et al., 2005). For that particular reason, the influence over the ball possession was also studied.

Regarding the ball possession, it was possible to observe an increasing tendency to expand players' displacement on the field along offensive moments. This finding can be associated with the stretch index, surface area and effective area of play. In point of fact, in the offensive phase (*i.e.*, with ball possession) the team explores the width and length of the field and tries to unbalance the focus and unit of the opponent team (Clemente et al., 2013). In other words, the outcome is in line with the width and length offensive playing principle (Costa et al., 2010). Conversely, without ball possession one can observe a decreasing tendency on the total area covered and the dispersion. This behaviour is associated with one of the main goals during the defensive phase, *i.e.*, to ensure the team's balance and reduce the inter-sectorial spaces (Moura et al., 2013). A certain proximity between teammates is necessary to reduce the inter-sectorial spaces (Vilar et al., 2012b). This proximity helps to ensure an inter-coverage between each other, *i.e.*, each player tries to maintain an optimal distance with his teammates to be covered by him and, at the same time, to cover himself (Dooley & Titz, 2011). By reducing the inter-sectorial spaces, the opponent team will need to struggle so as to penetrate and unbalance the defensive formation. Therefore, these findings are in line with the expansion-contraction relationship (Moura et al., 2013). Beside the team's dispersion, the collective behaviour on defensive and offensive states can also be observed in the longitudinal *w*centroid. In fact, the team's *w*centroid gets closer to its own goal. This is a normal behaviour in defensive phase. Nevertheless, the *w*centroid is weighted based on how closer players are to the ball, thus suggesting a high level of participation of all players in the defensive phase.

About the effective area of play between both moments (*i.e.*, with and without ball possession) it can be discussed based on the optimal inter-relationship between teammates in both moments. Even reducing the space during the defensive moments, their proximity ensures the effective triangulations, thus reducing the opportunity to build the offensive triangulations. Hence, there is a kind of equilibrium between offensive and defensive moments, wherein the defensive triangulations try to reduce the offensive triangulations. Nevertheless, it is normal to obtain a higher effective area of play while with ball possession since the offensive triangulations can be generated with larger inter-player distances (Figure 3.9.).

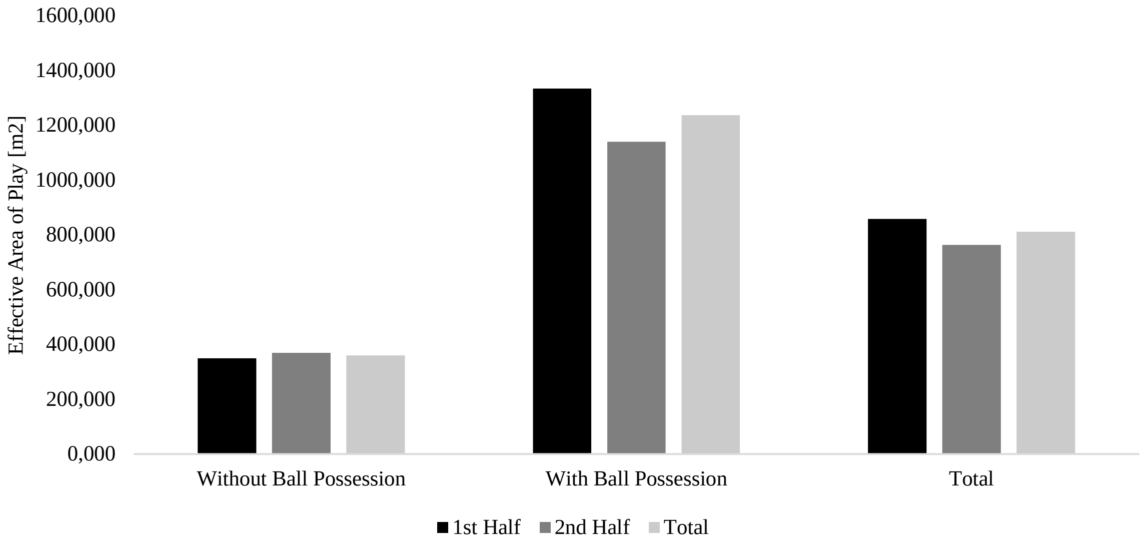

Figure 3.9. Effective area of play during the match.

The interaction between both factors (*i.e.*, half of match and ball possession) was also analysed. By crossing these variables it was possible to observe a higher average of longitudinal *w*centroid on the 2nd half with ball possession. On the other hand, the lower average of longitudinal *w*centroid was found in the 1st half without ball possession. These findings can be associated with each team's strategy. In fact, there is a tendency to explore the counter-attack on the 2nd half in order to explore the opponent defenders fatigue, thus resulting in an increase in the *w*centroid position. The reduced position in the 1st half without ball possession may suggest a conservative approach on protecting their own goal, reducing the *w*centroid position.

It was also found that the higher dispersions measured using the *w*stretch index and surface area are associated with offensive moments in the 1st half. On the other hand, a smaller dispersion value was found in the 2nd half without ball possession. In fact, this makes sense since players' physical capability is higher during the first half of the game it is easier to unbalance the opponent's defensive equilibrium (Bartlett et al., 2012). Thus, the dispersion from the width to the length is bigger. This expansion behaviour also attracts the defenders, thus increasing at the same time the defensive dispersion while trying to maintain an optimal concentration and proximity (Costa et al., 2010). Thus, if the offensive expansion is higher in the 1st half, it is possible that its reduction during the 2nd half can increase the defensive contraction, thus reducing the defensive dispersion. It was also discovered that the effective area of play value is higher in the 1st half with ball possession and lower in the 2nd half without ball possession. The higher expansion observed using the dispersion metrics can justify the higher area of play in offensive instants (Clemente et al., 2013). On the other hand, the higher effective area of play without ball possession in the 1st half can be associated with the higher physical capability to ensure an optimal proximity between teammates.

However, a lot of research remains to be done on the factors that influence collective behaviour. This study was influenced by some limitations since it is not possible to measure the fatigue levels precisely. Nevertheless, similarly to other studies performed on official matches, fatigue levels were inferred by the reduced individual kinematic performance from the 1st to the 2nd half of the game (Carling et al., 2005). Thus, a decreasing tendency in the values measured by collective metrics was observed in this study. Other examples of the aforementioned limitations include the score of the match and each team’s strategies (Lago & Martín, 2007). Nevertheless, the aim of this study was to analyse the collective behaviour as a spatio-temporal relationship, trying to justify some changes over the course of the match in relation to several parameters. Naturally, it is impossible to consider all variables justifying collective behaviour, thus this study only focuses on two main factors used in notational analysis.

In summary, this study performed an analysis on the collective behaviour during a game of football, based on several match variables in order to explain the inter-relationship oscillation. The novelty presented in this study is the analysis performance based on collective metrics, thus bringing forth new possible future approaches. For instance, the notational, kinematic and collective metrics could be integrated at the same time in order to explain a given reality. Furthermore, new independent variables could be introduced such as the classification, season's moment or even the specific playing strategies. Nevertheless, the practical contribution of this study is to present a new match analysis approach based on collective metrics, as well as to analyse the influence of match variables in order to explain existing changes in players' inter-relationships. Using this information makes it possible to improve the understanding of the teams' play style and to possibly detect specific properties. Utilizing this knowledge in the daily trainings makes it possible to overcome some non-desired collective behaviour changes.

3.5. Conclusion

The specific spatio-temporal relationships between football players are some of the main factors for the understanding of the football game as a whole. Nevertheless, few studies have been performed in order to analyse the factors influencing those relationships so far. Therefore, the aim of this study was to inspect how the half of match and ball possession status can influence the collective organization. The results suggested that the values of teams' dispersion and average position on the field decreases during the 2^{nd} half of the match. The possible cause of this is the increase of fatigue which in turns leads to a decrease in players' ability to secure an optimal spatio-temporal relationship between their teammates at any moment of the match. Furthermore, an expansion-contraction relationship between the offensive and defensive moments was detected. Thus, the results suggested a higher team's dispersion during the 1st half and the instants with ball possession. This higher dispersion value can be associated with the width and length offensive principles of play, as well as with the higher physical capability of the players to displace in the field. The lower dispersion values are associated with the concentration of defensive principles of play, as well as with the active recovery management.

3.6. References

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Chapter IV

Measuring the Territorial Domain of Football Teams

Chapter based on the following publication:

Clemente, F. M., Couceiro, M. S., Martins, F. M. L., Mendes, R. S., & Figueiredo, A. J. (ahead-of-print). Soccer team's tactical behaviour: Measuring territorial domain. *Proceedings of the Institution of Mechanical Engineers, Part P: Journal of Sports Engineering and Technology*, doi: 10.1177/1754337114547064

4. Measuring the Territorial Domain of Football Teams

Abstract

New tactical metrics have been introduced in the last years to allow an understanding on the collective behaviour behind the results provided by notational analysis. This paper proposes a new application developed on MatLab to understand the territorial domain of teams during the game based on players' position. Furthermore, this study aims to analyse the territorial domain on 7-a-side football game, so as to understand the sectors with more variability considering the advantage or disadvantage of team players. A total of 1508 instants of a 7-a-side football game were analysed. The herein proposed MatLab application allows obtaining the differences between players from Team A and Team B. Moreover, the approximate entropy is used to assess the variability of each of the twelve field sectors. The results show that the sector with higher variability is the central offensive midfield (1.114), closely followed by the central defensive midfield (1.033). A more dynamic rapport of strength within the central sectors may be the explanation for such a higher variability. Furthermore, this study presented an easy and effective application to analyze the territorial domain that can be matched with automatic tracking systems to improve their online potential.

Key-words: Match analysis; football; tactics; collective behaviour; technology.

4.1. Introduction

Match analysis has been developed over the years in order to improve the knowledge about team's behaviour (Carling, Williams, & Reilly, 2005). This analysis mainly began through a notational way (Nevill, Atkinson, Hughes, & Cooper, 2002). Nevertheless, some studies suggested that only notational analysis may not provide a deep understanding about team's collective processes (*e.g.*, Lees, 2002; Folgado, Lemmink, Frencken, & Sampaio, 2012), thus not allowing to understand how one may change the play processes to improve the collective efficacy.

More recently, some works studied the relation between the collective behaviour and teams' outcomes (*e.g.*, Frencken, Lemmink, Delleman, & Visscher, 2011; Bartlett, Button, Robins, Dutt-Mazumder, & Kennedy, 2012), trying to avoid reductionist approaches that emphasise the analysis in an individual way (Schöllhorn, 2003). Nevertheless, recent research mainly focused in a systemic viewpoint to explain the complexity of the game (*e.g.*, Bourbousson, Sève, & McGarry, 2010; Folgado et al., 2012). Despite their fundamental importance, it is important to improve the practical applications of these new tactical metrics, thus improving the technological contribution for coaches and staff (Pfeiffer & Hohmann, 2012).

Some recent works have found some characteristics of teams' behaviour through new methodological techniques by using automatic tracking systems (*e.g.*, ProZone®, Amisco Pro®) to detect, at each instant, the exact position of each player (Di Salvo, Gregson, Atkinson, Tordoff, & Drust, 2009; Weston, Castagna, Impellizzeri, Rampinini, & Abt, 2007). Therefore, it is possible develop some metrics that characterize the tactical behaviour based on players' position. Generally, the most common metrics in football may be designed to: *i*) inspect the team's geometric centre, centroid (*e.g.*, Lames, Ertmer & Walter, 2010; Frencken et al., 2011); *ii*) inspect the team's dispersion, as stretch index (*e.g.*, Bourbousson et al., 2010; Bartlett et al., 2012), team's spread (*e.g.*, Moura et al., 2012), coverage area (*e.g.*, Okihara et al., 2004), surface area (*e.g.*, Frencken et al., 2011; Duarte et al., 2012) or ipwratio (Folgado et al., 2012); *iii*) inspect the effective triangulations (*e.g.*, Clemente, Couceiro, Martins & Mendes, 2013); and *iv*) inspect the variation of players in a given space (*e.g.*, Vilar et al., 2012).

Nevertheless, only a few papers have dedicated their analyses to the spaces occupied by football players (Vilar et al., 2012). Players' distribution on specific areas should be a permanent concern of coaches and their staff (Costa, Garganta, Greco, Mesquita, & Seabra, 2010). However, only this information may be too naïve, since heat maps are computed using players' position but is time invariant (Clemente, Couceiro, Martins, Dias, & Mendes, 2012). Therefore, an instant visualization of team's advantage or disadvantage considering the number of players in each area could be an important information to understand the most prominent sectors and how team's behave in order to achieve their advantages in specifics situations. This will overcome the limitations inherent to the cumulative (*i.e.*, offline or post match) analysis (Vilar et al., 2012).

This paper aims to develop an easy-to-use application to analyze, in an online fashion, the team's advantage or disadvantage (territorial domain). Moreover, through the cumulative results, the proposed application will allow to understand which sectors the teams' are trying to maintain the most players in relation to the opponents and how this behaviour is variable during the game.

A recent study on elite teams of 11-a-side football game was recently presented by Vilar et al. (2012), wherein the numerical advantage and disadvantage on specific football spaces was analyzed, thus showing a team's pattern to focus on defensive stability, *i.e.*, teams allocates more players than their opponents in sub-areas closer to their own goal to ensure a higher security. This conservative behaviour can be explained by the nature of low scoring on football game constraining teams to keep an important focus on defensive behaviour and avoiding conceding a single goal.

Nevertheless, the literature lacks on the analysis of the numerical advantage or disadvantage on small-sided football games and youth players. This paper proposes two key contributions. First, analyze the football team's collective behaviour at 7-a-side game through a systemic viewpoint. Secondly, provide an easy-to-use application to implement this technique in an online fashion. In other words, the numerical advantage and disadvantage of teams during each instant of time over an experimental match will be analyzed, thus allowing informing the coach about its team's numerical status at each field sector. The cumulative results at the end of the game will be evaluated using the variability of team's advantage and disadvantage in each field sector based on the approximate entropy (Pincus, Gladstone, & Ehrenkranz, 1991). In brief, this paper will try to explain which field sectors present a higher or lower variability in function of the team's numerical advantage or disadvantage, by systematically comparing it with the opposing team at each instant of time.

4.2. Methods

4.2.1. Data Collection

Fourteen (14) male players participated in a 7-a-side football game at the under-13 Final of the Portuguese Regional League. All data collected complies the APA ethical standards for the treatment of human or animal subjects. The total duration of the match was 60 minutes and 21 seconds. The performance of all participants was monitored using a single camera (*GoPro Hero* with 1280 × 960 resolution), with capacity to process images at 30 Hz (*i.e.*, 30 frames per second). The movements of the 14 players (goalkeepers included) from the two competing teams were recorded during the entire game. After capturing the football match, the physical space was calibrated using Direct Linear Transformation (DLT) (Abdel-Aziz & Karara, 1971), which transforms elements' position (*i.e.*, players and ball) to the metric space. After calibration, the tracking of players was accomplished, thus resulting in the Cartesian positioning of players and the ball over time. The whole process inherent to this approach, such as the detection and identification of players' trajectories, the space transformation and the computation of metrics, was handled using the high-level calculation tool *MatLab*. For a matter of efficiency, only play moments were used, excluding all moments in which the ball was not in the field (*i.e.*, ball out of bounds), thus resulting on 1508 seconds of useful match. As the methodology herein proposed have a computational complexity inherent to it, each second will correspond to each analyzed instants, *i.e.*, 1508 positions tracked from each player and the ball.

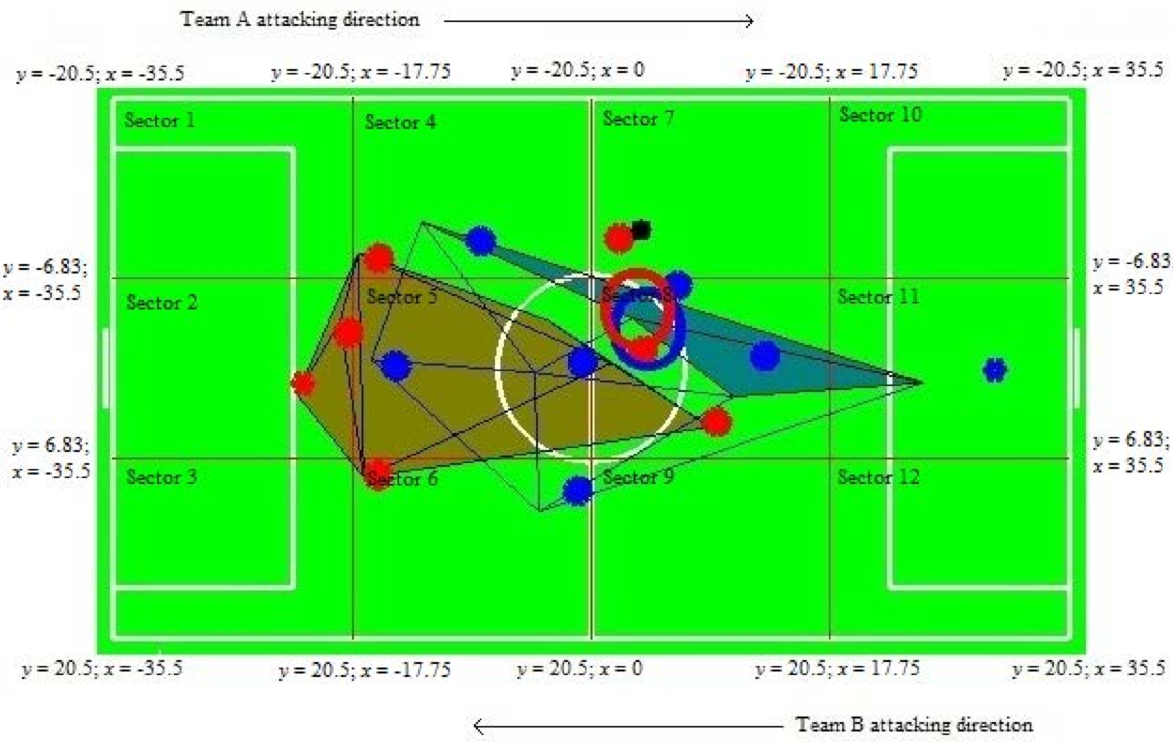

Figure 4.1. The football field and the locations of the fourteen players, area of play and sub-areas of play in one exemplar instant.

Excluding the out-of-bound locations to which players went during play, the playing space was $41\ m$ wide (from $y = -20.5\ m$ to $y = 20.5\ m$) and $71\ m$ long (from $x = -35.5\ m$ to $x = 35.5\ m$). Teams switch sides of the field halfway the game. To facilitate the visualization and understanding of results, the players displacements was inverted for the second half of the game in such a way that team A would always attack toward the positive coordinate values and team B would always attack toward the negative coordinate values (*see* Figure 4.1).

4.2.2. Data Processing: Computing the territorial status

The balls out of bounds were all excluded, such as for injuries (5 minutes and 48 seconds), goal celebrations (3 minutes and 12 seconds) or others. From the location of the 14 players at each instant, the triangulations were computed based on Clemente et al. (2013) approach. The analysis considered the distribution of players in such triangulations as a dynamically adaptive region changing from iteration to iteration during the match.

To segmentation, the field was equitably divided into a matrix of 4 columns and 3 lines (*see* Figure 4.1). To that end, the following divisions were carried out: three lateral (side line to side line) vectors that divided the field into three areas - left side (from $y = -20.5\ m$ to $y = -6.82\ m$), central side (from $y = -6.83\ m$ to $y = 6.82\ m$) and right side (from $y = 6.83\ m$ to $y = 20.5\ m$); and four longitudinal (goal to goal) vectors that divided the field into three areas - defensive area (from $x = -35.5\ m$ to x = - 17.76 m), pre defensive area (from $x = -17.75\ m$ to $x = -0.1\ m$), pre offensive area (from $x = 0\ m$ to $x = 17.74\ m$), and offensive area (from $x = 17.75\ m$ to $x = 35.5\ m$).

Figure 4.2 depicts the graphical user interface with the information regarding the territorial domain at each second and the cumulative one representing team A domain over team B so far.

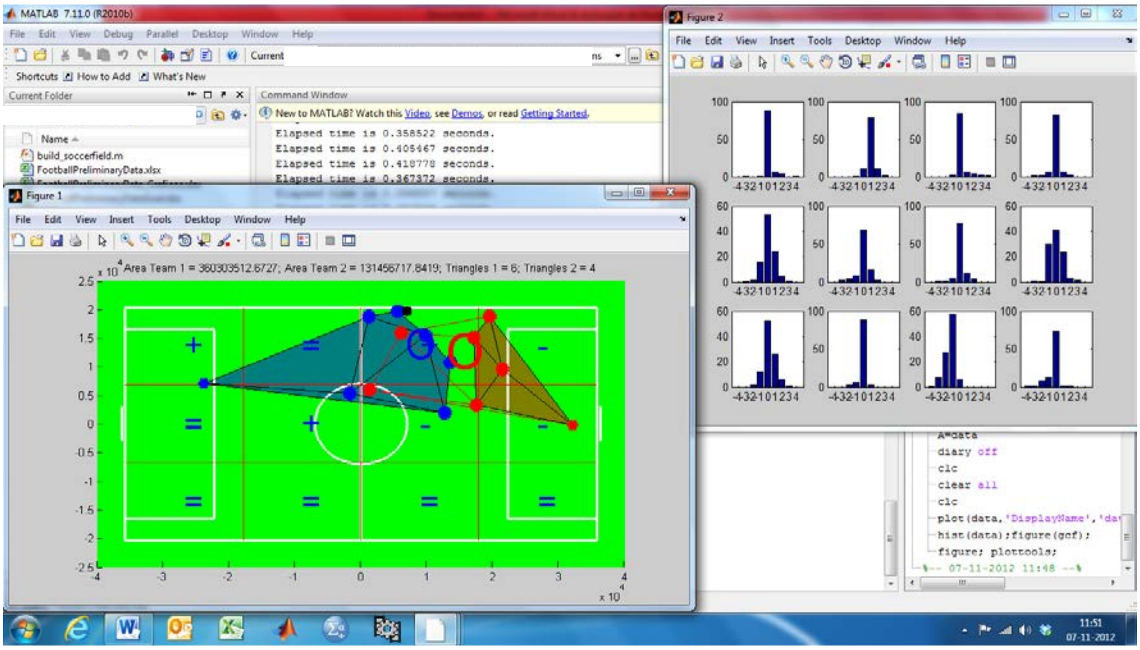

Figure 4.2. Graphical user interface depicting the territorial domain computed: a) at each instant; and b) cumulatively.

The herein proposed methodology is summarized in Algorithm 4.1. It is noteworthy that the algorithm run at each iteration, *i.e.*, in this case at each second. Moreover, the cumulated territorial domain S_{acum} is defined globally before this procedure as an array of zeros with 15 elements that represents the maximum range of the difference between the number of players in 7-a-side match, *i.e.*, -7, …, 0, …, 7.

Algorithm 4.1. Territorial Domain - Team δ versus Team ζ.

$S^{\delta} = [0 \quad \dots \quad 0]$ // counter of players from team δ in each sector
For $i = 1{:}\tau^{\delta}$ // τ^{δ} represents the number of players within team δ
  $n = sector(x_i, y_i)$ // returns the sector n based on the position of the i^{th} player, $n = 1, \dots, 12$
    $S^{\delta}(n) = S^{\delta}(n) + 1$
$S^{\zeta} = [0 \quad \dots \quad 0]$ // counter of players from team ζ in each sector
For $i = 1{:}\tau^{\zeta}$ // τ^{ζ} represents the number of players within team ζ
  $n = sector(x_i, y_i)$ // returns the sector n based on the position of the i^{th} player, $n = 1, \dots, 12$
    $S^{\zeta}(n) = S^{\zeta}(n) + 1$
$S = S^{\delta} - S^{\zeta}$ // difference between the number of players in team δ and team ζ
For $i = 1{:}12$ // count S in each sector of the field cumulatively
  For $j = -N_T{:}N_T$ // N_T represents the maximum number of players in one team (*e.g.*, $N_T = 7$)
    If $S(i) = j$ // check if team δ have j more players than team ζ in section i
      $S_{acum}(j + 8) = S_{acum}(j + 8) + 1$ // calculate the cumulative territorial domain
If $ball\_possession = \zeta$ // team ζ has the ball possession
  $S = S^{\zeta} - S^{\delta}$ // difference between the number of players in team ζ and team δ
For $i = 1{:}12$ // check numerical advantage/disadvantage in each sector of the field for the offensive team

If $S = 0$ // the number of defensive players is the same than the number of offensive ones in sector i
  $print(i, '=')$ // represents equilibrium of players in sector i
If $S > 0$ // the number of defensive players is smaller than the number of offensive ones in sector i
  $print(i, '+')$ // represents advantage over sector i
If $S < 0$ // the number of defensive players is smaller than the number of offensive ones in sector i
  $print(i, '-')$ // represents disadvantage over sector i

4.2.3. Data analysis

At each instant, the number of players inside the different sectors was computed as well as the relation between the number of players of Team A and Team B, thus resulting on the analysis of the numerical status (N_s) following the rule: $N_s = N_s^A - N_s^B$. Frequency histograms were plotted as example for Team A (*see* Figure 4.2). Based on the results provided during the game, the variability of the numerical advantage or disadvantage of the team across sectors was computed using the approximate entropy.

Pincus et al. (1991) described the techniques for estimating the Kolmogorov entropy of a process represented by a time series and the related statistics approximate entropy. Let us consider that the whole data of the T iterations (*i.e.*, seconds) is represented by a time-series as $u(1), u(2), \ldots, u(\mathrm{N}) \in \mathbb{R}$, from measurements equally spaced in time, which form a sequence of vectors $x(1), x(2), \ldots, x(N-m+1) \in \mathbb{R}^{1\times m}$, each one defined by the array of data $x(i) = [u(i) \quad u(i+1) \quad \cdots \quad u(i+m-1)] \in \mathbb{R}^{1\times m}$. The parameters N, m, and r must be fixed for each calculation. N is the length of the time series (*i.e.*, number of data points of the whole series), m is the length of sequences to be compared and r is the tolerance for accepting matches. Thus, one can define:

$$C_i^m(r) = (number\ of\ j\ such\ that\ \leq r)/(N-m+1), \tag{4.1}$$

for $1 \leq i \leq N-m+1$. Defining $d\big(x(i), x(j)\big)$ for vectors $x(i)$ and $x(j)$, and based on Takens' work (1983), results in:

$$d\big(x(i), x(j)\big) \;= \max_{k=1,2,\ldots,m} (|u(i+k-1) - u(j+k-1)|). \tag{4.2}$$

From the $C_i^m(r)$, it is possible to define:

$$C_i^m(r) = (N-m+1)^{-1} \sum_{i=1}^{N-m+1} C_i^m(r), \tag{4.3}$$

and

$$\beta_m = \lim_{n \to 0 \; N \to \infty} \frac{\ln(\,C^m(\mathrm{r}))}{\ln \mathrm{r}}. \tag{4.4}$$

in such a way that for sufficiently large m, β_m is the correlation dimension. Such a limiting slope has been shown to exist for the commonly studied chaotic attractors. This procedure has frequently been applied to experimental data; researchers seek a "scaling range" of r values for which $\frac{\ln(\,C^m(\mathrm{r}))}{\ln \mathrm{r}}$ is nearly constant for large m, and they infer that this ratio is the correlation dimension (Grassberger & Procaccia, 1983). In some instances, researchers have concluded that this procedure establishes deterministic chaos. Let us define the following relation:

$$\Phi^m(r) = (N-m+1)^{-1} \sum_{i=1}^{N-m+1} ln\, C_i^m\,(r). \tag{4.5}$$

One can define the approximate entropy as:

$$ApEn(m, r, N) = \Phi^m(r) - \Phi^{m+1}(r). \tag{4.6}$$

On the basis of calculations that included the theoretical analysis performed by Pincus et al. (1991), the authors drew a preliminary conclusion that choices of *r* ranging from 0.1 to 0.2 of the standard deviation of the data would produce reasonable statistical validity of $ApEn(m, r, N)$.

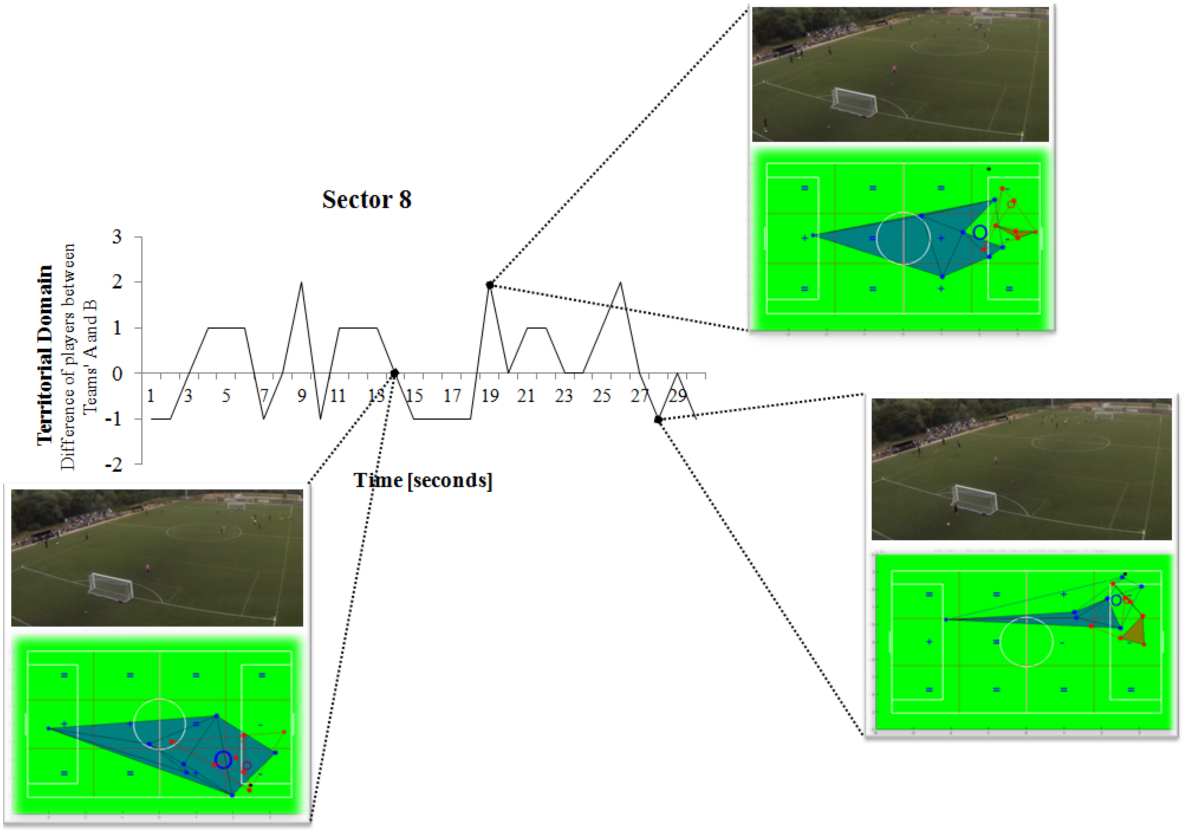

Figure 4.3. Example of concatenation of 30 seconds.

Approximate entropy values may vary between 0 and 2, with values closer to 2 identifying data series with less regular and predictable patterns (*i.e.*, chaotic signals/systems of high variability and complexity), and low values closer to 0 is associated with regularity data series, *i.e.*, data are more regular and predictable (Harbourne & Stergiou, 2009; Fonseca et al., 2012). Figure 4.3 depicts the territorial domain on sector 8 (*see* Figure 4.1) of the first 30 seconds of the match. As one may observe, this sector shows a high variability and, consequently, a reduced regularity, being complex to predict the frequency and stability of the wave. Only in the first 30 seconds of the match, sector 8 shows a territorial domain ranging between –1 to +2 players of Team A.

4.3. Results

Table 4.1 presents the descriptive statistic for Team A territorial domain by sectors (*see* Figure 4.1 for an easier understanding). It is important to explain that, as an individual example, the algorithm performed the subtraction of Team A by Team B in such a way that positive values means that team A have more players than team B at an specific sector, and vice-versa. The descriptive statistics present the median and mode, as well as the standard deviation since the results have both negative and positive numbers, thus invalidating the use of the coefficient of variation (Pallant, 2011).

Table 4.1. Descriptive statistics of the Teams A territorial domain by sectors (S).

	Sectors											
	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12
Median	.00	1.00	.00	.00	.00	.00	.00	.00	.00	.00	-1.00	.00
Mode	.00	1.00	.00	.00	.00	.00	.00	.00	.00	.00	-1.00	.00
Std. Deviation	.57	1.21	.68	.68	1.10	.80	.72	1.10	.87	.50	1.19	.57
Minimum	-3.00	-4.00	-3.00	-3.00	-4.00	-5.00	-4.00	-4.00	-4.00	-3.00	-6.00	-4.00
Maximum	4.00	5.00	5.00	4.00	4.00	4.00	4.00	3.00	3.00	2.00	3.00	4.00

It is possible to observe that sector 2 present a numerical superiority, *i.e.*, positive mode, and, inversely, sector 11 reveals a numerical inferiority, *i.e.*, negative mode. Furthermore, the results shows that sectors 2 and 11 have a higher minimum and maximum values, corresponding to the most higher standard deviations (1.21 and 1.19 correspondingly).

Table 4.2. Frequency (%) of team A numerical advantage (disadvantage for negative values) in each sub-area of play, over the entire match.

	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6
Sector 1	0	0	0	0.5	0.8	2.7	84.1	9.6	1.9	0.2	0.3	0	0
Sector 2	0	0	0.1	1.4	4.4	11.2	13.7	57	7.4	3.3	1.1	0.4	0
Sector 3	0	0	0	0.1	0.1	6.3	80	8.2	3.4	1.5	0.3	0.1	0
Sector 4	0	0	0	0.1	0.9	7	71.8	16.2	3.2	0.7	0.1	0	0
Sector 5	0	0	0.1	2	7	13.7	42.2	28.8	5.4	0.7	0.1	0	0
Sector 6	0	0.1	0.1	0.4	2.1	9.8	67.6	14.7	4.3	0.7	0.2	0	0
Sector 7	0	0	0.1	0.3	2	11.7	70.8	12	2.5	0.7	0.1	0	0
Sector 8	0	0	0.1	1.5	6.1	30.9	33.6	21.6	5	1.2	0	0	0
Sector 9	0	0	0.2	0.9	5.5	16.6	60.8	12.7	2.9	0.3	0	0	0
Sector 10	0	0	0	0.5	1.9	6.2	85.5	5.5	0.5	0	0	0	0
Sector 11	0.1	0.3	1.6	4.7	15.1	55.6	7.4	12.3	2.2	0.8	0	0	0
Sector 12	0	0	0.1	0.4	2.6	6.1	84.3	5.6	0.8	0.1	0.1	0	0

The time's percentage of numerical advantage or disadvantage at each sector allows concluding that, generally, the difference on the number of players of each team is equitably distributed through the sectors during most of the time. Sectors that vary this tendency are 2, 5, 8 and 11, *i.e.*, the central zones of the field (*see* Figure 4.4).

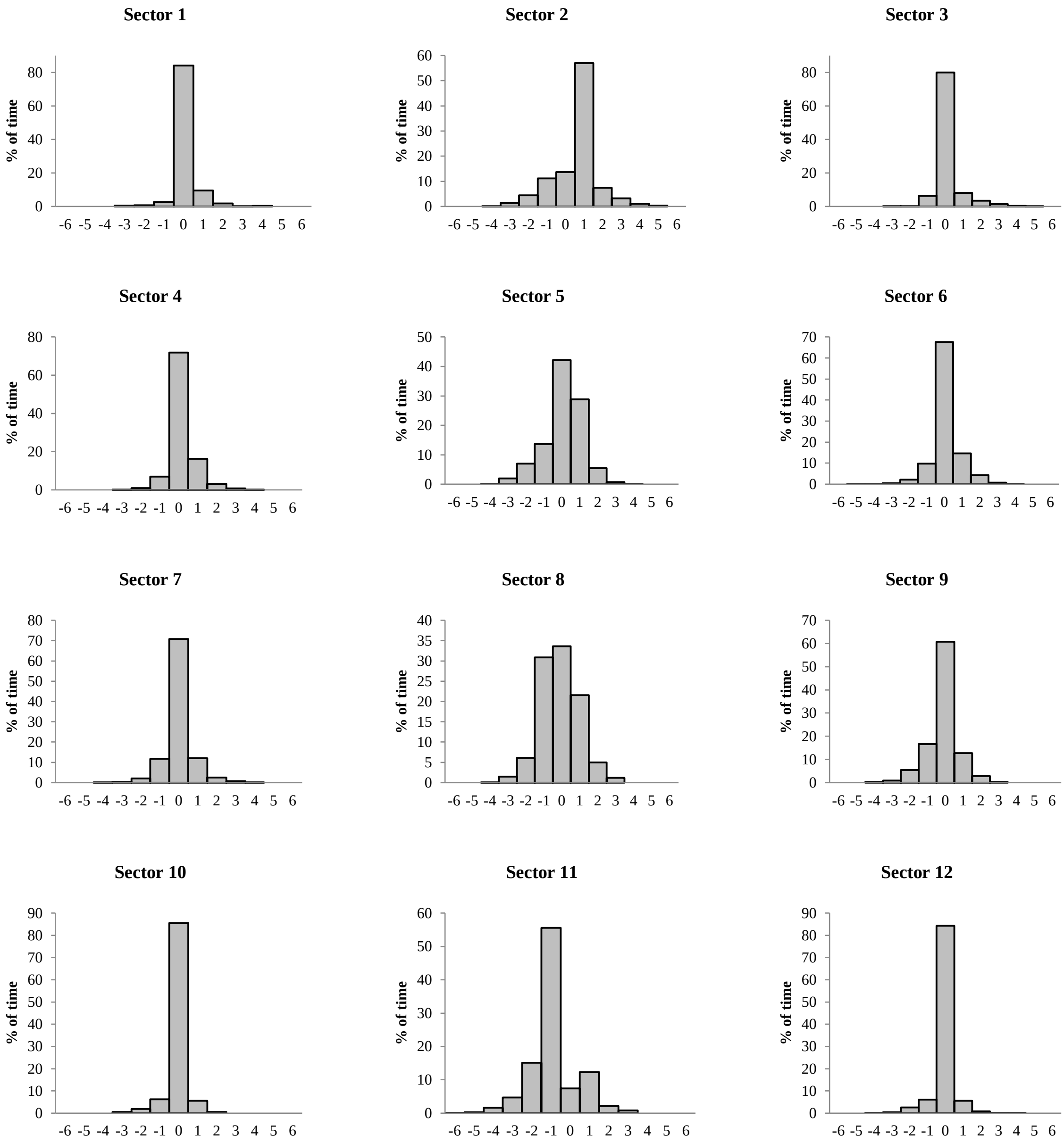

Figure 4.4. Frequency histograms of team A numerical advantage (disadvantage for negative values) in each sub-area of play, over the entire match.

Nevertheless, linear statistics do not allow understand the variability of the number of players during all match because it does not consider the regularity of the distribution but only the dispersion around the average or median values. Hence, the approximate entropy was carried out so as to analyse the sectors with higher variability (*see* Figure 4.5).

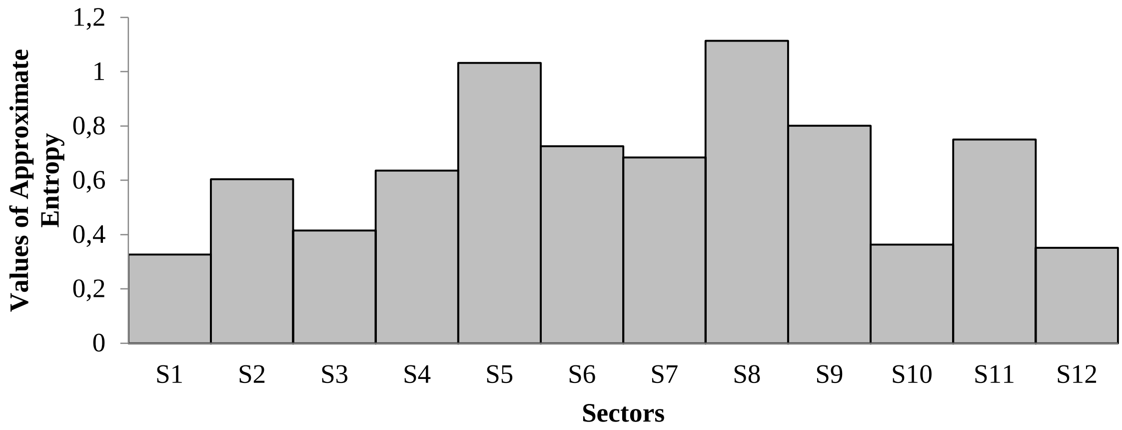

Figure 4.5. Approximate entropy of Team A territorial domain by each sector.

The approximate entropy shows that the sector with higher variability (1.114) is the 8, *i.e.*, the offensive midfield of Team A, followed by the sector 5 (1.033) and 9 (0.801). In the defensive sectors (1 to 3), it is possible to observe that sector 2 presents the higher variability (0.604), *i.e.*, the central sector. The same kind of evidence is revealed on the offensive sector where sector 11 shows a higher variability (0.751). Similar results were found for the defensive midfield in sector 5 and the offensive midfield at sector 8. The less variability is shown on defensive and offensive wings. The defensive left wing shows the lowest value of entropy (0.326), followed by the right (0.351) and left (0.363) offensive wings.

4.4. Discussion

Despite the complex characteristics of collective sports, different organizational levels can be identified (Gréhaigne et al., 1997). During the match, the global opposition relationship breaks down into partial opposition relationships, *i.e.*, sub-phases. These opposition relationships momentarily involve a small amount of players, generating specific playing shapes that represent the organizational levels of the partial forefront (Gréhaigne et al., 2005). Furthermore, these sub-phases can be characterized by the team's territorial advantage in a specific field sector. This study aimed to analyse the territorial occupation of the players during the football game, thus trying to identify the sectors in which a team has more players in relation to the opposing team, as well as the variability of this advantage or disadvantage during the match. This study also aimed to propose to the football match analysts an easy application for a real-time analysis of the territorial status.

The application developed and presented during the methodology section presented two main references to coaches or analysts. First, it presents a graphical user interface that allows observing the instantaneous territorial domain of the team with ball possession, *i.e.*, the numerical advantage or disadvantage at each sector for the team possessing the ball is shown. This visualization allows further understanding the sectors with more possibilities for exploration at the offensive phase. Nevertheless, the instantaneous analysis does not allow representing the entire match. Therefore, the application also offers the global information by means of a cumulative bar graph of territorial domain so as to increase the understanding about possibilities to explore a specific sector. This information can be used online to inform the coach at any instant. It is important to consider that the cumulative results are achieved through the subtraction of the number of players within Team A and the number of players within Team B. This kind of functionality can be easily interconnected to automatic tracking systems (*e.g.*, ProZone®, Amisco Pro®), so as to allow the computation of such metrics in an online fashion.

This technique provides results that can be used to explain a team's rapport of strength (Gréhaigne et al., 2011). Hence, it is possible to analyse the team's behaviour through a systemic viewpoint and compare it with similar studies. For instance, the study on the 11-a-side football game (Vilar et al., 2012) shows that the central zone of the defensive area presents a numerical advantage for both teams in the defensive phase (57% of time on team A and 55.6% of time on team B). Consequently, these results may suggest that the defensive phase team should try to secure those regions by keeping more players in the score zone than the opponent in order to avoid the opponent's opportunities to score. Furthermore, these results and the variable number of players in each sector reinforces that specific patterns of coordination may emerge from the interactions between opponent players under the influence of some constraints (Bourbousson et al., 2010; Travassos et al., 2011), *e.g.*, the principles of play, ball possession, ball position, opponents' position or match status. Therefore, as these constraints are presented at any instant of the game, it is necessary to analyze the variability related to a team's behaviour, mainly in functional sectors, while considering the real dynamical complexity of the game (Gréhaigne et al., 1997).

The behaviour of players has a high degree of variability depending on the interactions between teammates or opponents and the ball possession (Davids et al., 2005). Therefore, the approximate entropy was calculated in order to analyse the sectors with higher variability in numerical advantage or disadvantage. Previous studies on the 11-a-side football game suggested higher variability values on the central sectors (Vilar et al., 2012). Through the entropy analysis, the authors identified the centre-middle area as the region with most transitions between stable and unstable modes of coordination. The following sections with higher variability were the centre-front and centre-back ones. Similarly to the study on the 11-a-side game (Vilar et al., 2012), the present study shows that the central sector of the offensive midfield, *i.e.*, sector 8, is the sector with the highest variability. This factor can be explained by the highest interaction in order to achieve the score zone through the opponent midfield, *i.e.*, at any instant the offensive team varies its position to break the opponent's defensive organization. Respectively, to maintain the defensive stability, the team without ball possession tries to avoid the numerical advantage of the offensive team. This permanent rapport of strength may justify the higher levels of variability.

Besides the central offensive sector, the remaining central sectors, *i.e.*, sector 2, 5 and 11, also present high values of approximate entropy when comparing to the remaining sectors. The higher variability on central areas can be explained by two main factors: the experience of performers and the offensive process. Generally, in order to destabilize the defensive organization, the offensive team displace their players in an irregular way to promote local instabilities on the opponent's organization (Vilar et al., 2012). Furthermore, younger players tend to quickly approach the goal using the depth of the field, reducing the exploration of the width (Ouellette, 2004). Thus, this central areas exploration increases the variability, representing an exploratory behaviour seeking for more functional coordinated solutions (Davids et al., 2003). Indeed, variability is essential to adapt to complex dynamics such as sport environments (Chow et al., 2006).

Through this study it was possible to analyse that the proposed application may be a useful and easy way to improve the match analysis techniques. The numerical advantage or disadvantage can be a useful information to coaches in order to control the superiority or inferiority zones, reorganizing a team's strategies according to its weaknesses or strengths. Thus, further studies should evaluate this technique on automatic tracking systems as this would improve its online application. Furthermore, a greater amount of data should be collected in order to further validate the results herein presented. This study on 7-a-side game is in line with previous results on 11-a-side game, by showing that central midfield sectors present the highest variability values of players' occupation. Nevertheless, further studies should analyse more small sided games with young players (*e.g.*, 11-a-side game), to better understand if a greater number of players would improve the variability on lateral sides of the field, which would help reorganizing teams' strategies exploring the width (Ouellette, 2004).

4.5. Conclusion

This study aimed at providing a useful application to analyse the numerical superiority or inferiority during a football match. Using a *MatLab* collection of scripts, it was possible to generate a graphical user interface based on the players' position to provide information about it at each instant of the game. Combined with automatic tracking systems, this routine may provide a useful online tool for football match analysts and coaches. Furthermore, by using this device it was possible to undertake a study about the numerical advantage or disadvantage variability on each sector of the game. For this, an experimental 7-a-side football game of youth players was analysed. The cumulative results showed the highest variability of the advantage/disadvantage trade-off on the central sectors of the field which, in turn, confirmed the findings of previous studies on 11-a-side professional football game.

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Chapter V

Inspecting teammates' coverage during attacking plays in a football game

Chapter based on the following publication:

Clemente, F. M., Martins, F. M. L., Couceiro, M. S., Mendes, R. S., & Figueiredo, A. J. (2014). Inspecting teammates' coverage during attacking plays in a football game: A case study. *International Journal of Performance Analysis in Sport*, 14(2), 384-400.

5. Inspecting teammates' coverage during attacking plays in a football game

Abstract

The tactical behaviour of football players is fundamental in sport teams. Despite this importance, the methods to measure such behaviour are very time-consuming for human operators. Therefore, the aim of this case study was to propose a set of collective technological metrics to evaluate the attacking coverage provided by teammates to the player in possession of the ball. For this case study data was collected from three official matches of the same professional team. Using the information about the Cartesian position of players in the field provided from a tracking method, it was possible to propose four different technological metrics and ratios: i) cover in support; ii) cover in vigilance; iii) attacking cover; and iv) depth mobility. Using those metrics it was possible to observe that on average the team observed use with higher regularity support in vigilance as well as depth mobility, thus suggesting a specific tactical behaviour. In summary, it was possible to apply all metrics to real data from three official matches, thus allowing a new technological method to improve the match analysis systems that use multiplayer tracking.

Keywords: Match analysis, tactics, metrics, football.

5.1. Introduction

The football game is a complex team sport that depends from coordination processes within and between players during match (Davids, Araújo, & Shuttleworth, 2005). As such, it is important to propose and develop match analysis methods that may allow to inspect the interpersonal coordination dynamics within playing patterns emerging from each different sub-phase (e.g., 1vs1, 2vs2). When developing such methods one should keep in mind the synchronization of all collective behaviours (Gréhaigne, Bouthier, & David, 1997; McGarry, Anderson, Wallace, Hughes, & Franks, 2002). This synchronization and dynamic behaviour depend from a spatiotemporal relationship that emerges during the match (Bourbousson, Sève, & McGarry, 2010).

In the last few years, the scientific community have paid an increased attention to such synchronization and dynamic behaviour, with the main purpose of providing useful methods to analyse the coordination patterns between players in team sports (Bourbousson et al., 2010; Clemente, Couceiro, Martins, Dias, & Mendes, 2013a). The first studies around this topic, such as Passos et al. (2009) and Clemente et al. (2013a), were carried out by considering each sub-phase of the game separately (1v1), thus inspecting the dynamics behind the attacker-defender dyad in a spatiotemporal way. Nevertheless, the study of interpersonal distances, speed or acceleration synchronization was only considered as the starting point of the necessary match analysis metrics. From the 1v1 perspective, Bourbousson et al. (2010) and Frencken, Lemmink, Delleman, and Visscher (2011) developed a set of collective metrics (e.g., *centroid*, *stretch index* and *surface area*) to inspect the synchronization dynamics between teammates using the space and time as reference. Later, Clemente, Couceiro, Martins, Mendes, and Figueiredo (2013c) developed an updated version of these metrics and introduced a new concept called *effective area of play* that considers a tactical parameter based on the defensive and attacking triangulations.

In sum, the study of teammates' synchronization have been based on the distance between players. Nevertheless, the football game is a team sport that depends from a set of collective rules to increase the coordination possibilities between teammates. These rules are described as tactical principles (Costa, Garganta, Greco, Mesquita, & Seabra, 2010). These tactical principles are rules that deal with the spatiotemporal relationships as well as behaviours. From many and various theoretical considerations of those principles, there is a consensus about their importance for attacking and defensive situations (Costa et al., 2010; Gréhaigne, Richard, & Griffin, 2005). Despite the great importance of defensive situations, the main aim of a football match is to score. Therefore, following is a discussion of the tactical attacking principles.

The tactical attacking principles aim to give fundamental information to players, allowing an improvement of collective behaviour (Clemente, Couceiro, Martins, & Mendes, 2013b). These tactical principles provide some behaviour rules for organizing and attuning players' behaviour to the main goal of the team, thus creating successful opportunities to score. Thus, tactical principles are fundamental guidelines, allowing an improvement of collective behaviour in order to disrupt the defensive organization of the opponents' team. The five fundamental attacking principles in football are (Costa et al., 2010): *i*) penetration; *ii*) attacking cover; *iii*) depth mobility; *iv*) width and length; and *v*) attacking unit. From those principles it is possible to identify that attacking cover and depth mobility are the two that most require an inter-players' perception to support those teammates in possession of the ball.

The coverage principle is characterized by the supporting action provided by a teammate to the player with ball possession. Thus, this support provided by the teammates to the player with ball possession is fundamental to the attacking phase, providing him with many options to conclude the process with efficacy (Costa, Garganta, Greco, & Mesquita, 2009). To benefit from this principle, the attacker with ball possession needs to simplify his/her action, opting for safe passes or actions. Furthermore, it is fundamental that teammates move towards or away from with possession of the ball depending on the position of opponents and the ball.

Depth mobility is characterized by optimal teammates' movements to receive the ball from the player in possession (Costa et al., 2009). These movements can be done away from the player with the ball (i.e. break movements) or near to them (i.e. support movements). The guidelines for this principle are the variability of actions depending on the position of the ball and the opponents, as well as movements' speed trying to unbalance the defensive organization. All of the mobility processes should be made with meaning, i.e., giving valid solutions for a successful conclusion to the attacking phase (Worthington, 1974). Thus, it is fundamental that teammates understand the dynamic processes, allowing the quality of their play to improve during the attacking phase.

Despite them being of great importance for football coaches, the analysis of these principles are so far based on a manual observational process. As a result, this process takes a lot of time and human resources. Nevertheless, using the new technologies of computational tracking of players it is now possible to develop an automatic system (automatic data processing) to identify tactical principles. Therefore, the aim of this study is to propose a set of computational tactical metrics based on Cartesian information provided from tracking systems. These tactical metrics will be developed based on manual observation indicators in order to continue the research performed until now and to give new opportunities for football match analysis.

5.2. Methods

5.2.1. Sample

Three official home matches of a professional team from the *Portuguese Professional Premier League* were analysed. The team used the same strategic distribution in the field (1-4-3-3) throughout all games. At each match the final score was different, i.e. a win, lose, or draw. Thus, the final score of each match was considered. From those three matches were collected 9218 moments. All of the collected data complies to the APA ethical standards for the treatment of human or animal subjects.

5.2.2. Data Collecting

Teams' actions were captured using a digital camera (*GoPro Hero* with 1280× 960 resolution), with the capacity to process images at 30 Hz (i.e. 30 frames per second). The camera was placed on an elevated surface above the ground in a way that would capture the whole field. The field dimensions were 104×68 metres. After recording the football match, the physical space was calibrated using Direct Linear Transformation (DLT), which amends the position of the elements (i.e. players and ball) in pixels to the metric space (Abdel-Aziz & Karara, 1971). In order to ensure the reliability of such conversion, experimental trials were carried out by considering random points on the field were initially collected, metrically assessed and then mapped into real coordinates.

The manual tracking of players was accomplished after calibration, thus returning the position of the players and the ball over time in Cartesian coordinates (see Figure 5.1). A graphical user interface was developed so as to visualize the match by controlling the framerate with a sampling time of one second. During each frame, the operator was requested to identify the location of all players and the ball, following the typical point-and-click approach. That identification corresponded to one point in the centre of each players' feet and the centre of the ball. The whole process associated with this approach (i.e. detection and identification of players' trajectories, space transformation and metrics computation), was performed using the high-level calculation tool *MatLab* (Couceiro, Clemente, & Martins, 2013).

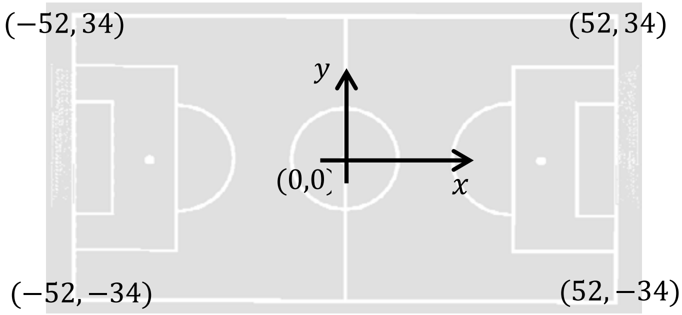


Figure 5.1. Football referential field.

As a matter of efficiency, only played time was considered, excluding all moments in which the ball was not in the field (i.e. ball out of bounds). Since the methodology proposed herein involves some computational complexity, each second will correspond to an analysed instant of each player and the ball.

5.2.3. Computing the Tactical Attacking Principles

The first concept that must be developed is the attacking definition zone (ADZ). This concept comes from Costa et al. (2009) and consists of the development of a circumference of 5-metre radius around the ball (Figure 5.2). Using this circumference (centre-of-game) a set of tactical metrics will be developed that will identify the effectiveness of the tactical principles performed by the team.

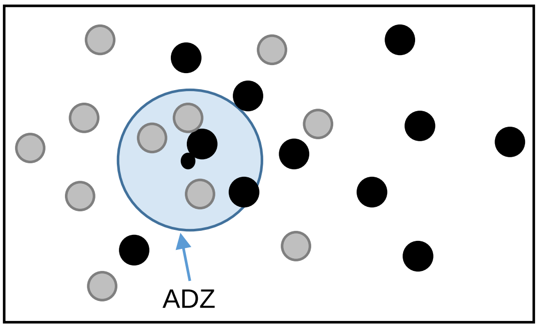


Figure 5.2. Attacking Definition Zone (ADZ): Centre-of-game representation.

From the Cartesian position of all players and the ball the circumference (centre-of-game) around the ball at each second of match is developed.

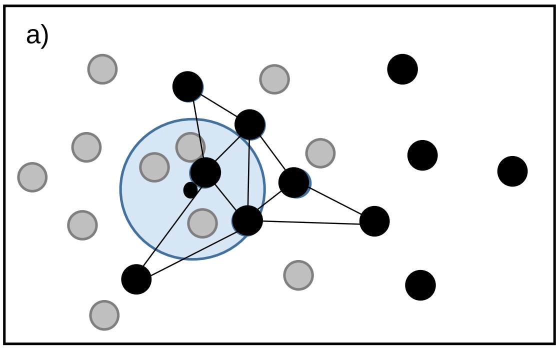
Using the centre-of-game it is possible to identify the players closest to and farthest from the ball and zone of definition. From all this information can be computed a set of metrics based on the indicators that characterize the effectiveness of the attacking principles of play. All metrics herein described were computed, at each second, whenever the team had the possession of the ball. Considering those instants, the average of each attacking play was considered, *i.e.*, starting at the beginning of attacking play (instant 1) until the moment that ball was lost (last instant). Each metric varies over time throughout the play efficacy.

5.2.3.1. Attacking Cover

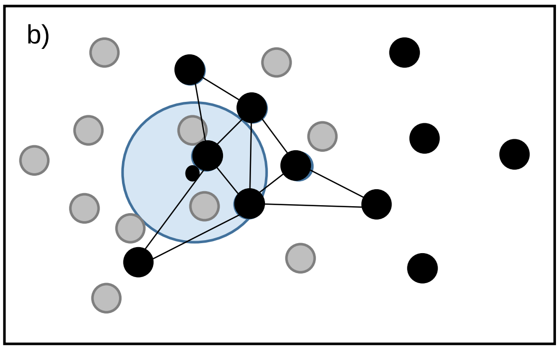
The attacking cover can be classified as: *i*) in support (teammates who support the player in possession of the ball in the centre-of-game); and *ii*) in vigilance (teammates who support the player in possession outside of the centre-of-game). Therefore, each kind of cover must have a specific criteria to be classified as effective:

1. Cover in support: inside the ADZ there must be at least two players of the team in possession of the ball and a numeric equality or superiority against the opposite team must be observed (Figure 5.3);
2. Cover in vigilance: outside the ADZ there must be teammates making up an effective triangulation with one of the players inside the ADZ (Figure 5.3).

The effective triangulation comes from Clemente, Couceiro, Martins, Mendes, and Figueiredo (2013c). Such classification depends from metric interaction between attacking and defensive triangulations. In the moments in which the team possesses the ball (attacking), the effective triangulation will only be considered if the overlapping defensive triangulation has a perimeter higher than 36 meters, or if no defensive triangulation at all overlaps the attacking triangulation. On the other hand, the non-effective attacking triangulation will be considered if the attacking and defensive triangulations are overlapped and if the defensive have a perimeters lower than 36 meters.



There is no coverage in support (due to a numeric disadvantage of the black team with ball possession) but there is cover in vigilance (effective triangulation performed by 5 teammates outside the ADZ).



There is cover in support (due to numeric equality) and there is coverage in vigilance (effective triangulation performed by 5 teammates outside the ADZ).

Figure 5.3. Examples of coverage in support and in vigilance.

By identifying the effective cover in support and in vigilance three main ratios can be analysed: *i*) ratio of effective cover in support; *ii*) ratio of effective cover in vigilance; and *iii*) ratio of effective attacking cover.

The ratio of effective cover in support (ECS) counts the number of times that the support complied with the requirements previously explained over the total number of ADZ. For this metric (ECS), the effectiveness of one kind of coverage (in support or in vigilance) is required, at least, per each second of play. Such metric it is a relative metric and is obtained from:

$$ECS_r = \frac{Number\ of\ ECS}{Number\ of\ ADZ}. \tag{5.1}$$

A similar ratio defined using the effective cover in vigilance (ECV) performed by teammates outside of the centre-of-game is a relative metric and is obtained from:

$$ECV_r = \frac{Number\ of\ ECV}{Number\ of\ ADZ}. \tag{5.2}$$

From the accomplishment of at least one kind of cover (support or vigilance) in each ADZ can be computed the ratio of attacking cover is a relative metric and is obtained from:

$$EC_r = \frac{Number\ of\ effective\ covers}{Number\ of\ ADZ}. \tag{5.3}$$

All these ratios allow the analysis of how teammates interact in order to provide a useful opportunity to the player in possession of the ball. This is also very important for identifying whether this cover is performed more in proximity (i.e. in support) or in further way (i.e. in vigilance). These three metrics can be computed second-by-second, varying the cumulative results throughout an attacking play (starting at the moment the team possesses the ball until the moment that the ball is lost). When the attacking play is interrupted, the average of the ratio throughout the play is computed and then attributed to this specific attacking play. When another attacking play starts, the process of computing begins again as previously described.

5.2.3.2. Attacking Depth Mobility

The attacking depth mobility will be considered based on a simple indicator: Always when one teammate offers a line of pass in proximity to the last opposition defender this will be considered as effective attacking depth mobility (Figure 5.4). This proximity will be considered as the 5 metres behind the line of last opposition defender (considering the x-axis).

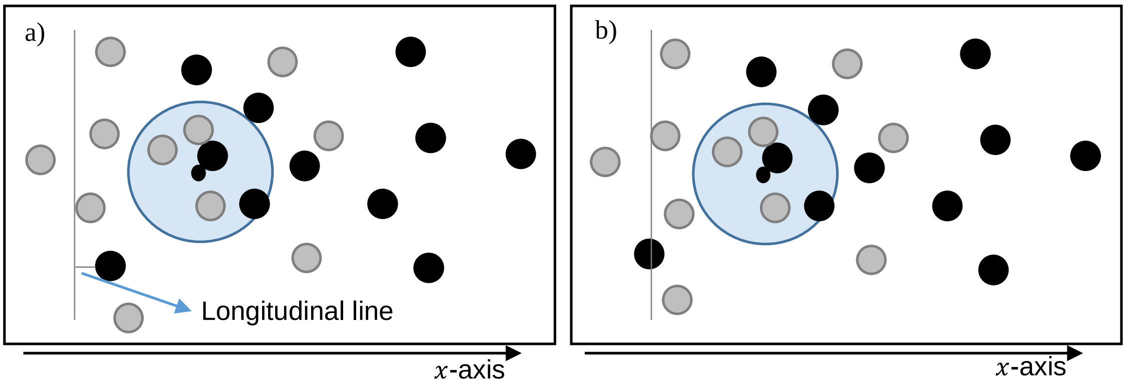


Figure 5.4. Depth mobility examples: a) effective depth mobility (inside the proximity of 5 metres to the last defender line); b) non-effective due to being offside.

Using this relative metric it is possible to define the depth mobility ratio (DM) as follows:

$$DM_r = \frac{Number\ of\ DM}{Number\ of\ ADZ}. \tag{5.4}$$

The depth mobility metric allows the identification of whether the longitudinal line (distance between the last opponent defender and the forward player in the x-axis) is being explored by the forward players in order to provide a possible different way to play and to press the opponents' defenders.

Once again, this metric can be computed second-by-second, varying the cumulative results throughout an attacking play. When the attacking play is interrupted, the average of the ratio throughout the play is computed and then attributed to this specific attacking play. When another attacking play starts, the process of computing begins again as previously described.

5.2.4. Statistical Procedures

Descriptive statistics was used to inspect the results from the four tactical principles. The three case study matches were organized by each half of the game, thus resulting in six variables: M1H1 (match 1 and half 1), M1H2, M2H1, M2H2, M3H1, M3H2. Moreover, for each tactical principle, a boxplot was computed to support the graphical representation of the results.

For the descriptive analysis the mean value, the standard deviation, the minimum and maximum value and the coefficient of variation were determined. The classification of dispersion using the coefficient of variation was performed using the following scale (Pestana & Gageiro, 2008): *i*) low dispersion [0; 15% of CV[; *ii*) moderate dispersion [15; 30% of CV[; and *iii*) great dispersion ≥ 30% of CV.

All statistical procedures were computed using the SPSS statistics software (version 21).

5.3. Results

From the obtained results, it was possible to retrieve the descriptive tables of attacking coverage ratio (Table 5.1 and Figure 5.5), coverage in support (Table 5.2 and Figure 5.6), coverage in vigilance (Table 5.3 and Figure 5.7) and depth mobility (Table 5.4 and Figure 5.8).

Table 5.1. Descriptive statistics of attacking coverage ratio.

	Mean	Std. Deviation	%Coefficient of variation	Minimum	Maximum
M1H1	0.78	0.22	27.49	0.28	1
M1H2	0.81	0.22	27.04	0.29	1
M2H1	0.81	0.22	27.06	0.3	1
M2H2	0.71	0.22	30.91	0.17	1
M3H1	0.81	0.20	25.18	0.35	1
M3H2	0.78	0.25	31.36	0.14	1
Total	0.78	0.22	28.49	0.14	1

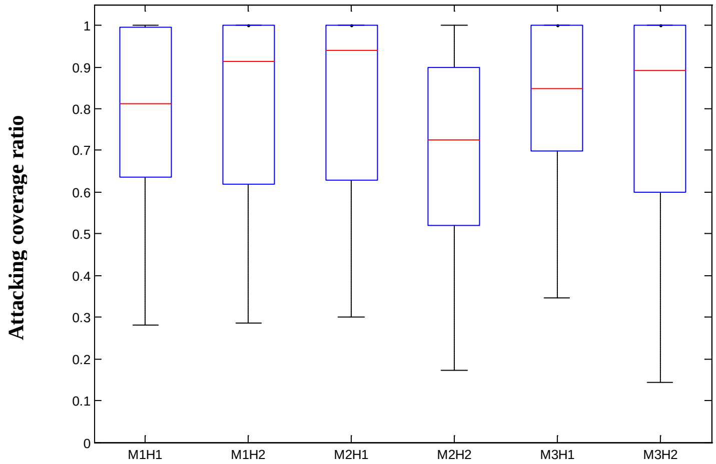


Figure 5.5. Box plots of attacking coverage ratio.

It is possible to observe that the attacking coverage was accomplished with great regularity. The mean value of 0.78 suggests that at least one in-support or in-vigilance cover are performed during attacking play, thus improving the lines of pass. The lowest value was 0.14 and the maximal value was 1. The coefficient of variation for all matches was around 28%, thus suggesting a moderate dispersion from play to play.

The first quartiles of box plots (Figure 5.5) are bigger in the majority of cases. This can result from the higher value of the second quartile (median), thus reducing the possibility of increasing. The highest value of the cover ratio is 1, thus the tendency is for the third quartile to be smaller.

Table 5.2. Descriptive statistics of coverage in support ratio.

	Mean	Std. Deviation	%Coefficient of variation	Minimum	Maximum
M1H1	0.22	0.12	54.97	0.04	1
M1H2	0.34	0.27	79.24	0.05	1
M2H1	0.34	0.27	79.24	0.05	1
M2H2	0.31	0.16	52.82	0.08	1
M3H1	0.45	0.35	76.45	0.05	1
M3H2	0.40	0.16	40.74	0.05	1
Total	0.35	0.24	69.83	0.04	1

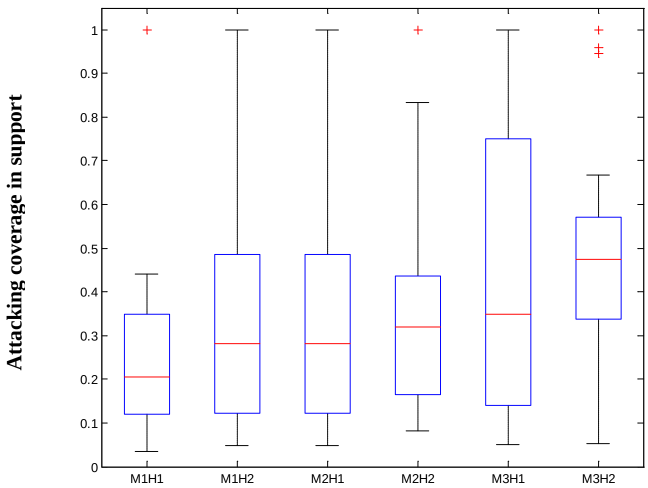


Figure 5.6. Box plots of coverage in support.

The mean of cover in support is 0.38. This lower value can be explained by the team's own characteristics of increasing the lines of passes far away from the ball position. It is also possible to analyse that the coefficient of variation is great, achieving values of 79%. In the mean, the coefficient of variation is around 70%, suggesting a great variability of this principle from move to move.

In this case, the bigger quartiles are the thirds (Figure 5.6). This can be explained by the proximity of the second quartile (median) to the lower ratio value. In all matches it is possible to observe that the median is higher in the second half, thus suggesting a greater proximity to building the attack.

Table 5.3. Descriptive statistics of cover in vigilance ratio.

	Mean	Std. Deviation	%Coefficient of variation	Minimum	Maximum
M1H1	0.77	0.21	27.61	0.28	1
M1H2	0.82	0.22	27.29	0.29	1
M2H1	0.79	0.23	28.91	0.22	1
M2H2	0.70	0.24	33.63	0.17	1
M3H1	0.79	0.20	25.06	0.35	1
M3H2	0.76	0.25	32.64	0.14	1
Total	0.77	0.23	29.51	0.14	1

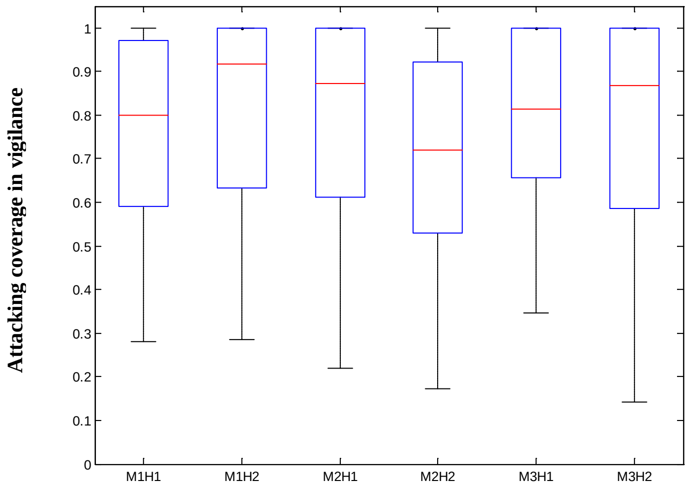


Figure 5.7. Box plots of coverage in vigilance.

The cover in vigilance is performed more than cover in support. It is possible to observe that the mean of the ratio for all matches is 0.77. This result suggests that teams have more options for the player with ball possession in spaces outside of the centre-of-game. The mean coefficient of variation is 29.5%, thus the variability is lower than in the case of cover in support but still has a moderate dispersion.

From the box plots (Figure 5.7) it is possible to observe that the first quartiles are bigger than the third. This can be explained by the higher proximity to the maximal value of ratio. In two of the three matches it was possible to observe that the median of ratio was higher.

Table 5.4. Descriptive statistics of depth mobility ratio.

	Mean	Std. Deviation	%Coefficient of variation	Minimum	Maximum
M1H1	0.89	0.15	17.13	0.42	1
M1H2	0.82	0.24	29.85	0.2	1
M2H1	0.91	0.12	13.18	0.57	1
M2H2	0.96	0.06	6.27	0.75	1
M3H1	0.94	0.1	10.81	0.61	1
M3H2	0.89	0.19	21.01	0.35	1
Total	0.90	0.16	18.06	0.2	1

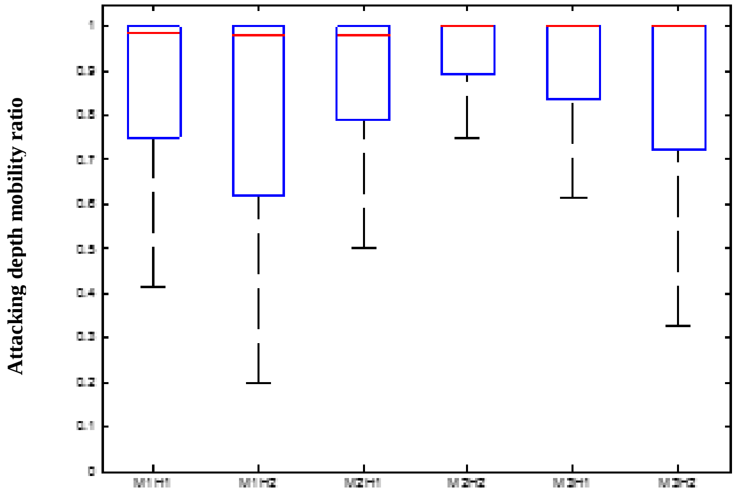


Figure 5.8. Box plots of depth mobility.

The mean value of depth mobility is around 0.90. This greater value suggests that there is regularly one striker closer to the opponents' defenders. The coefficient of variation is around 18%, thus suggesting a low dispersion from play to play.

The box plots (Figure 5.8) allow a higher median closer to maximal value (1) to be observed. All first quartiles are bigger than the third. These results can be explained by the greater value of the median.

5.3.1. Variation of tactical metrics coefficients throughout matches

The mean per each attacking play coefficient was computed and then used in a temporal series throughout a match. Hence, the temporal analysis is not the real time but the sequence of all attacking plays. A fitting smoothing spline was considered in order to ensure at least a coefficient of determination (R^2) of 0.70. The values of the

R^2 and the Root Mean Squared error per each match and tactical metric can be observed in table 5.5.

Table 5.5. Data of *R*-square and root mean squared error per each tactical metric.

Data set	Fitting method	R^2	Root Mean Squared Error
M1 coverage	Smoothing spline	0.6986	0.1851
M1 coverage in support	Smoothing spline	0.7505	0.2323
M1 coverage in vigilance	Smoothing spline	0.7184	0.1803
M1 depth mobility	Smoothing spline	0.7503	0.1946
M2 coverage	Smoothing spline	0.7047	0.1927
M2 coverage in support	Smoothing spline	0.7480	0.1848
M2 coverage in vigilance	Smoothing spline	0.7536	0.1987
M2 depth mobility	Smoothing spline	0.7295	0.1581
M3 coverage	Smoothing spline	0.7694	0.1850
M3 coverage in support	Smoothing spline	0.8988	0.2135
M3 coverage in vigilance	Smoothing spline	0.7137	0.1876
M3 depth mobility	Smoothing spline	0.7521	0.1779

It is possible to observe in Figure 5.9 a variation of coefficient throughout the attacking plays. Nevertheless, such variability seems to be regular mainly in the attacking coverage and the coverage in vigilance, with values greater than 0.4. The coverage in support tends to be reduced during attacking instants.

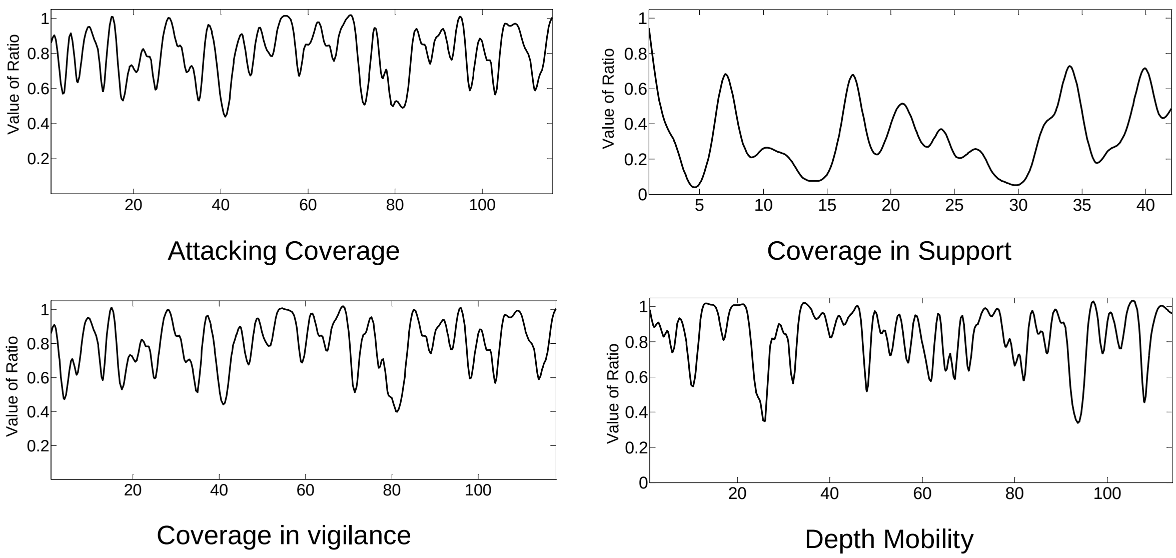


Figure 5.9. Temporal-series of tactical metrics coefficient [range between 0 and 1] throughout first match.

In the second match (Figure 5.10), it was possible to observe similar patterns of variability throughout the match when compared to the first match. The coverage in support still presents lower value but, in this case, the wave seems to be more regular that in match 1.

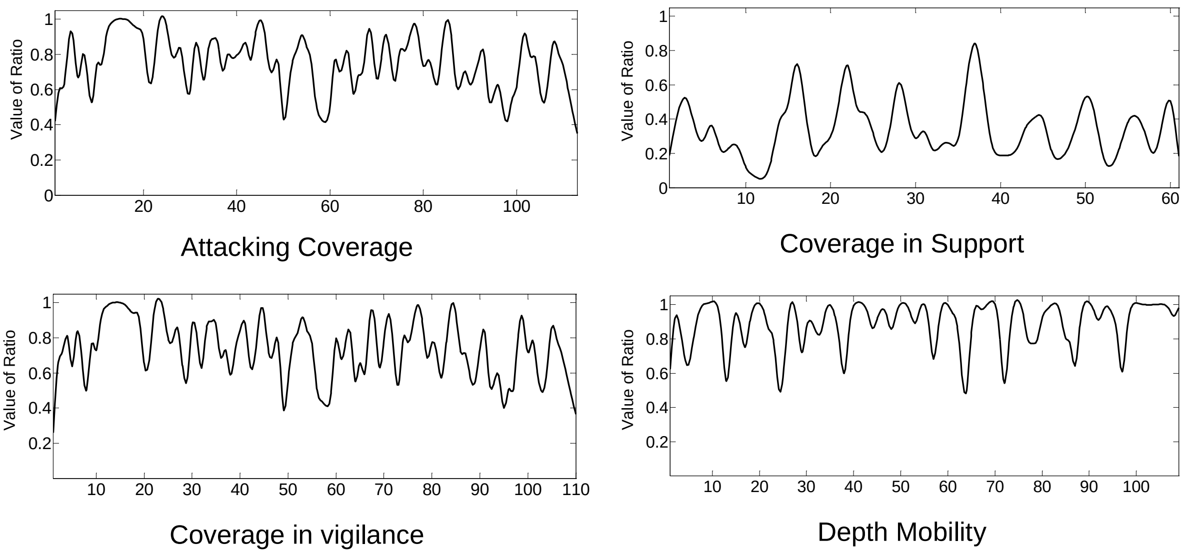


Figure 5.10. Temporal-series of tactical metrics coefficient [range between 0 and 1] throughout second match.

In the third match (Figure 5.11), it is possible to observe the highest values of coverage in support coefficients throughout the temporal series. The waves of attacking in coverage and coverage in vigilance are very similar and this can be justified by the fact that the team opts to play using long passes, thus reducing the possibilities of short passes.

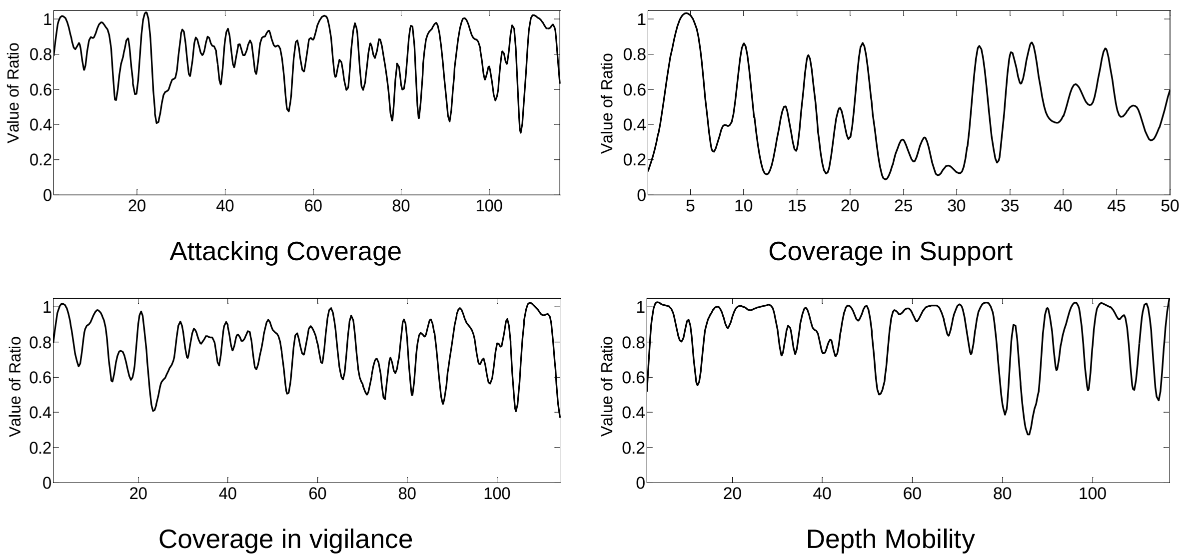


Figure 5.11. Temporal-series of tactical metrics coefficient [range between 0 and 1] throughout third match.

From these temporal-series, it was possible to observe values of Root Mean Squared Error between 0.2323 and 0.1581.

5.4. Discussion

The new possibilities that come from new technological advances allow the development of new metrics to evaluate human performance (Clemente et al., 2013c). In the particular case of team sports it is important to understand how players cooperate and synchronize their spatiotemporal relationships in organizing themselves to achieve the main goal (Duarte, Araújo, Correia, & Davids, 2012). Therefore, the study of teammates' synchronization represents an important step forward to improve sports training, organizing sessions using the information collected from the matches or even the collective performance during training sessions.

Therefore, the aim of this study was to propose a set of automatic collective metrics (automatic data processing) to estimate how teammates cooperate and synchronize their spatiotemporal relationship during the attacking process to support each other. In such behaviour designated as cover it is very important to provide the player in possession of the ball some different solutions to ensure success in the building of the attack (Trapattoni, 1999; Dooley & Titz, 2011). Taking this into consideration four different metrics (attacking coverage; attacking coverage in support; attacking coverage in vigilance; depth mobility) with an individual ratio were developed in order to provide information about how a team provides such coverage.

The principle of cover can be performed in two main ways: *i*) in vigilance; and *ii*) in support. In support mean the great proximity of teammates to the player with ball possession, providing him with a short line of passes. In the case of cover in vigilance, this mean teammates perform some movements to create a line of passes in a peripheral position from the ball's location (Castelo, 1996).

Using both ratios of cover in support and vigilance it was possible to observe that in this case study the teammates ensured a higher level of cover in vigilance (0.7 in mean) than in support (0.3 in mean). Such results can be explained by the way the measure was developed. To ensure coverage in support it is necessary to have at least two players in the attacking definition zone and a numerical equality or superiority with opponents as well. Therefore, both conditions decrease the possibilities of ensuring such a principle in every move. Moreover, the closer to the opponents' defensive area, the greater the number of opponents' players inside the centre-of-game. In that sense, in order to overcome this problem, the cover in vigilance is very important for providing the player in possession with some possibilities to take off the ball from the zone with pressing. Consequently, the higher value ratio in the case of cover in vigilance is understandable given the previous discussion.

The option to provide a greater level of coverage in vigilance can be associated with the space covered by the team. In fact, the attacking process is characterized by all the team covering a large space (Clemente et al., 2013c). Consequently, inter-players' distances increase, thus reducing the proximity to the player in possession of the ball and increasing the possibilities to generate long lines of passes. Such hypothesis must be inspected in further studies in order to better understand how both facts are connected.

From both types of cover, measuring the attacking cover was also proposed in this study. To accomplish such a principle at each play, one in support or in vigilance cover must be performed. The mean ratio of 0.78 suggested a higher regularity of performing such a principle at each offensive play. Moreover, the level of dispersion was moderate, thus reinforcing the accomplishment of this principle throughout the match. In fact, the cover action is one of the main actions to be performed during the match. In 'invasion' sports, such as football, the player with the ball must have the greatest possible number of options to ensure the success of their action. Even in the defensive phase cover is important to support the first teammate that tries to recover the ball. In that sense, these cover principles should be one of the main indicators to measure tactical behaviour in sports teams. It would be interesting in further studies to combine some spatiotemporal metrics such as the stretch index or the effective area of play with these principles of cover. With such an analysis it will be possible to understand whether the distance between teammates contributes to a better accomplishment of cover principles.

The last ratio proposed in this study was the depth mobility. This principle allows the analysis of how forward players provide solutions closer to the opponents' defenders. Depth mobility is very important for many teams who opt to play in a counter-attack style or that use many long and deep passes. In this case study it was possible to observe a ratio closer to maximal value (0.90). This value can be explained by the option to ensure that at least one player stays closer to the last opponents' defender, providing a forward option for the teammate with the ball.

In this case study it was possible to analyse that the team opted to perform attacking coverage using the farthest players from the ball. The greater values of success ratio were in the cover in vigilance and depth mobility, thus suggesting that this specific team play a specific type of game. As a case study, there still remain many issues to be solved in the future. One of them is to explore such tactical principles in a bigger sample with different teams that have different styles. It would also be interesting, as discussed above, to combine the information from the principles of play with other spatiotemporal metrics (e.g., Bourbousson et al., 2010; Clemente et al., 2013c) to identify some specific properties and how those relationships improve the quality of tactical behaviour measured using these ratios.

In another perspective, it would be interesting to use these tactical metrics to inspect the variability of teammates' synchronization throughout the football game. Moreover, it may be possible to inspect possible variations of playing patterns between different periods of the match. It can also be possible to use those metrics to compare the performance of the collective behaviour between top-level and amateurs teams or between novice and expert players.

5.5. Conclusion

The aim of this case study was to propose four different tactical metrics to inspect the behaviour of football teams. The results showed that the team opted to use, with higher regularity and success, cover in vigilance and the depth mobility, suggesting a tendency to play in a larger space. From the results, it is expected that these metrics will help coaches to analyse the regularity of how their players provide cover throughout the matches, even during the training sessions. Using this information, it is possible to organize the training sessions and tasks to improve such playing principles. Moreover, these ratios can complement by a match analysis software that considers multiplayer tracking in a real or post-match way. Such metrics are only dependent from the Cartesian information of players' positions in the field, thus reducing the time expended by operators to perform such manual analysis.

5.6. References

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Chapter VI

Evaluating the Offensive Definition Zone in Football

Chapter based on the following publication:

Clemente, F. M., Martins, F. M. L., Couceiro, M. S., Mendes, R. S., & Figueiredo, A. J. (in press). Evaluating the offensive zone definition in football: A case study. *South African Journal for Research in Sport, Physical Education and Recreation*, 37(1), pp.

6. Evaluating the Offensive Definition Zone in Football

Abstract

New technological solutions have been improving match analysis systems for inspecting players' performance. Nevertheless, there still remains a large space in the collective analysis where improvements can be made, mainly in the use of automatic information gathering. Therefore, the aim of this case study was to propose a set of three computational tactical metrics and their respective ratios for use in inspecting and estimating the tactical performance of football teams. Three official football matches from the same professional team were analysed and Cartesian information about the position of players and the ball in the field was collected. Using such information, tactical metrics for penetration, offensive space and offensive unity were developed. The results showed that the unity principle was the tactical principle most often accomplished at the mean (ratio of 0.83) and the penetration principle was the principle fewer performed with success (ratio of 0.42). This case study proposes some automatic indicators to evaluate the collective performance of football teams, providing football coaches with some additional information to be used to characterize their teams.

Key words: Match Analysis, Metrics, Tactics, Offensive process, Football.

6.1. Introduction

Match dynamics need to be supported by strategic and tactical processes that try to improve collective behaviour potentiality (Clemente, Couceiro, Martins, Mendes, & Figueiredo, 2013). Tactics and strategy have always had a strong relevance to opposing actions between humans. Nevertheless, tactics and strategy are two different terms that need to be understood differently, considering their different meanings in a sporting context. 'Strategic' relates to the principles of play or the orientation of actions that allow the organization and preparation of the team in readiness for the match (Bouthier, 1988). On the other hand, 'tactics' relates to operations performed during the game by players in order to adapt the initial requirements to the dynamic constraints imposed by the opposite team.

Thus, strategy is constituted of the elements previously discussed by the organization (i.e. the team) to prepare for the match (Gréhaigne & Godbout, 1995). Indeed, strategy relates to the general order; namely, to the players' positioning and their distribution on the field, as well as the specific missions of each player (Gréhaigne et al., 1999). Tactics, on the other hand, relates to the punctual adaptation to new playing configurations as a function of the state of ball possession and the opponent's positions (Gréhaigne & Godbout, 1995). The concept of tactics relates to behavioural adaptation in response to the opponent and the play status. Therefore, there are substantial differences between strategy and tactics at the levels of time and space. Strategy relates to more elaborate cognitive processes, due to the greater amount of time to prepare it and the lower level of constraints (Gréhaigne et al., 1999). Compared to strategy, the tactical concept involves higher levels of decision making and behavioural adaptations as a function of the contextual constraints; thus, it is the decision in action. During the game, tactical behaviour prevails (Gréhaigne et al., 1999).

Considering the above, there are some principles underlying the team's strategies and tactical behaviour that provide a higher level of organization and structure to collective behaviour (Costa et al., 2009). Without principles of play the teammates relationships may become less organized, which reduces the opportunity to play as a team and as a unit. Thus, football theory over the years has developed some offensive principles that potentiate collective behaviour and quality of play (Metzler, 1987; Gréhaigne et al., 2005; Costa et al., 2010).

The offensive tactical principles aim to give fundamental information to players, allowing an improvement in their collective behaviour (Costa et al., 2009). These tactical principles provide some behavioural rules for organizing and attuning players' behaviour in accordance with the main goal of the team; namely, to successfully create finalization opportunities and to score. Thus, the tactical principles are essential guidelines for allowing an improvement in the team's collective behaviour in order to overtake the defensive organization of the opposing team. According to Costa et al. (2010) the five offensive fundamental principles of play in football are: (i) penetration, (ii) offensive coverage, (iii) depth mobility, (iv) width and length (space), and (v) offensive unit. From these principles penetration, width and length, and offensive unit are the principles that require a better synchronization of movement, when considering the teammates, the ball and the opponents. Hence, these are the principles chosen to be the subject of this study.

The penetration principle is characterized by the progress of the attacker with ball possession in the direction of the score zone (Costa et al., 2009). The attacker’s main objective is to reach the zone closest to the goal with the aim of finalizing the offensive attempt. The guidelines of this tactical principle are to overtake the direct opponents and unbalance their defensive organization in order take advantage of this situation by bringing the ball to a favourable position in the score zone. Progress with the ball by trying to approximate the attacker's position to the goal or overtaking the direct opponent and trying to take advantage from this by creating space to play or finalize are actions that are characteristic of the penetration principle.

The width and length (space) principle aims to extend and use a larger effective play space (Costa et al., 2010). By increasing the dispersion of the players during the offensive phase it will be easier to attract defensive players into non-vital zones (e.g. lateral lines), removing them from the vital zone (i.e. the middle side). Thus, the width and length principle opposes the defensive concentration principle of the opposite team described previously. By removing some opponent defenders to non-vital areas it will be possible explore the central area of the score zone. Furthermore, it will be possible for the player with ball possession in the central area to try to overtake the direct opponent, benefiting from more space to successfully conclude the offensive process.

The offensive unit principle involves the positioning of off-ball defenders so as to decrease the effective play-space of the opponents. To keep the collective cohesion and balance between team sectors it is important to have an effective and functional distribution of the players in relation to the ball position, the phase and match status of the game, and the opponents’ positioning. Thus, the team needs to function as a whole, positioning itself functionally on the field. The fundamental guideline for this principle is the efficient positioning of players on the field, which not only takes account of players’ individual missions but also considers the collective objective and functionality of the team as a whole (Castelo, 1996). The offensive unit principle assumes a balance between the team’s sectors (i.e. defenders, midfielders, forwards) as a determining factor for success when the team loses possession of the ball. By maintaining the proximity between the team sectors and a balanced organization it will be easier to move to the defensive organization (Teodorescu, 1984), thus increasing the opportunities to improve the quality of the defensive action. The ultimate goal is not to unbalance the team at any stage of the game.

The tactical principles have been observed using manual methods. Nevertheless, this kind of analysis requires a lot of time to be spent, which can be minimized if it is conducted in an online way. Therefore, the aim of this study was to propose a group of offensive metrics based on the analysis of tactical principles. These metrics will be automatically computed using kinematic information about the players' positioning on a Cartesian field. This automated analysis will allow a step forward in increasing the speed at which analysis can be undertaken and thus its usefulness for coaches during and after matches.

6.2. Methods

6.2.1. Sample

Three official home matches of a professional team were analysed. At each match the final score was different: winning, losing and drawing. Thus, each of these matches was considered according to its final score. All of the collected data complied with the APA's ethical standards for the treatment of human or animal subjects.

6.2.2. Data Collection

The teams' actions were captured using a digital camera (*GoPro Hero* with 1280 $\times$ 960 resolution) with capacity to process images at 30 Hz (i.e. 30 frames per second). The camera was placed on an elevated surface above the ground in a way that would capture the whole field. The field dimensions were $104 \times 68\, m$. After recording the football match, the physical space was calibrated using Direct Linear Transformation (DLT), which measures the position of the elements (i.e. players and ball) in pixels to the metric space (Abdel-Aziz & Karara, 1971).

The tracking of the players was accomplished after calibration which returned the position of the players and the ball over time according to their Cartesian coordinates (see Figure 6.1). The whole process associated with this approach (i.e. detection and identification of players' trajectories, space transformation, computation of metrics) was performed using the high-level calculation tool *MatLab*.

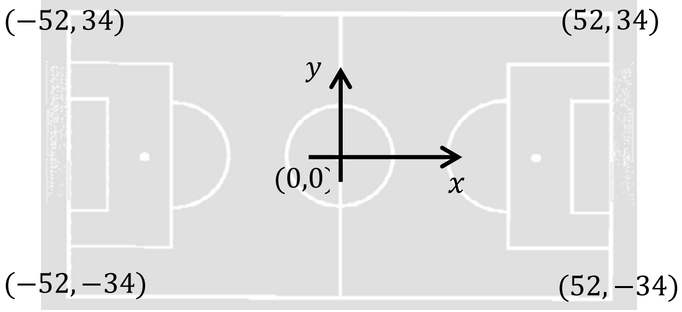

Figure 6.1. Football referential field.

For the sake of efficiency, only time when the ball was in play was considered and all moments when the ball was not in the field (i.e. out of bounds) were excluded from the analysis. Since the methodology proposed here has some computational complexity, each second corresponded to an analysed instant for each player and the ball. From the three matches 9218 instants were collected.

6.2.3. Computing the Offensive Tactical Principles

The first concept that must be developed is the offensive definition zone (ODZ). This concept comes from Costa et al. (2009) and consists of the development of a circumference of 5 metres radius around the ball. Using this circumference (centre-of-game) a set of tactical metrics was developed that identified the effectiveness of the tactical principles performed by the team (Figure 6.2).

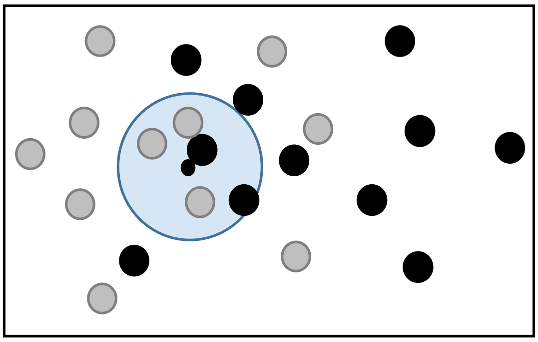

Figure 6.2. Centre-of-game representation in an 11-a-side game.

From the Cartesian position of all players and the ball, the circumference (centre-of-game) around the ball at each second of the match was developed.

Using the centre-of-game, it is possible to identify the closest and farthest players from the ball and zone of definition. From all this information a set of metrics can be computed based on the indicators that characterize the effectiveness of the offensive principles of play.

6.2.3.1. Penetration Metric

Two main indicators were used to evaluate the effectiveness of the tactical principle of the penetration metric:

1. The centre-of-game must maintain forward movement at each second; thus the centre-of-game should move to a forward position compared to the immediately previous position.
2. The numeric relationship between the teammates and opponents should not be an inferior one; thus if the position is 2 against 2 (equality) in the centre-of-game, the next movement cannot pass to a numeric disadvantage (Figure 6.3).

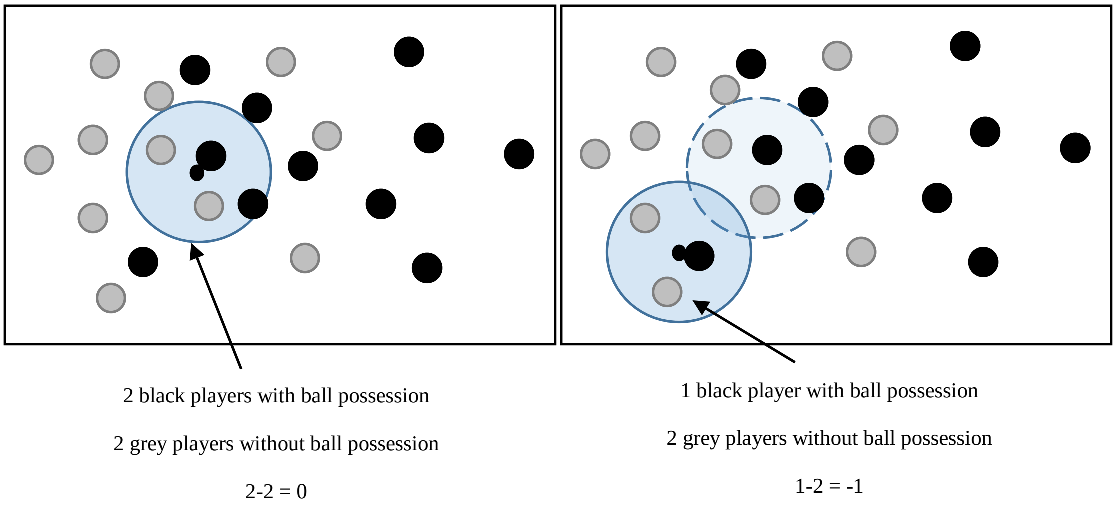

Figure 6.3. The centre-of-game movement: example of non-penetration effectiveness.

From the effectiveness calculation, the numeric relationship during the match can be analysed, identifying the evolution of better, equal or worse numeric situations. Moreover, from the relative metric the effective penetration ratio (EP) can be computed:

$$P_r = \frac{Number\ of\ EP}{Number\ of\ ODZ}. \tag{6.1}$$

This ratio is developed at each iteration, thus it is cumulative.

6.2.3.2. Width and Length Offensive Principle

The width and length principle depends on the exploitation of all the spaces in the field in order to expand the playing space and create new opportunities to perform the attack (Figure 6.4). Therefore, two criteria were defined for considering the effectiveness of this tactical principle:

1. At least one forward player performs the mobility principle (see the criteria for this achievement in the depth mobility principle).
2. At least one player who does not perform the mobility principle moves to the position out of the opponent's surface area on the lateral axis (width).

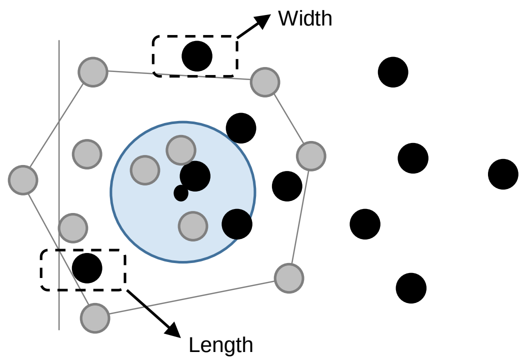

Figure 6.4. Example of width and length effective movements.

By using this metric, the ratio of the effective width and length (WL) principle of play can be computed:

$$WL_r = \frac{Number\ of\ WL}{Number\ of\ ODZ}. \tag{6.2}$$

The width and length is an extremely important principle in play that brings about the expansion of offensive moments by ensuring opportunities to avoid the penetration of the midfield where there are more opponent players. Therefore, the ratio of width and length allows the identification of how the team performs this principle during offensive play.

6.2.3.3. Offensive Unit

The offensive unit was measured using two main criteria:

1. Only the players behind the ball's longitudinal line will be considered in this metric.
2. At least half of the players behind the line of the ball always move in synchrony with the ball's trajectory on at least one axis (Figure 6.5).

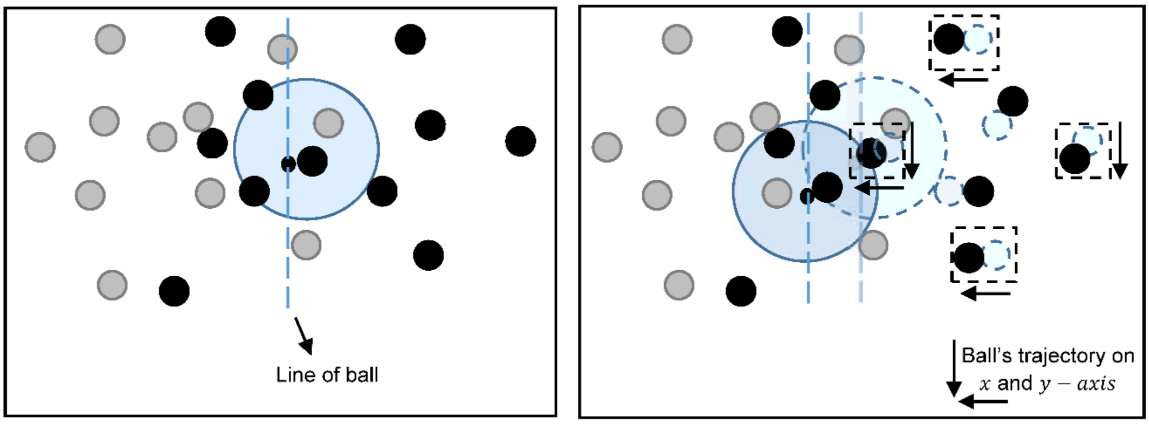

Figure 6.5. Example of effective offensive unit following the ball's trajectory.

By using this metric it was possible to count for each offensive play the number of players moving in synchrony with the ball's trajectory and the relative frequency. Moreover, it was possible to develop the offensive unit (OU) ratio:

$$OU_r = \frac{Number\ of\ OU}{Number\ of\ ODZ}. \quad (6.3)$$

This ratio allows it to be understood if the players behind the line of the ball move in synchrony with the ball's trajectories and the centre-of-game. This is very important in preventing the eventual loss of the ball, as well as in giving a closer line of pass to teammates with ball possession.

6.2.4. Statistical Procedures

For the descriptive analysis the mean value, standard deviation, minimum and maximum value, and the coefficient of variation were determined. The classification of dispersion using the coefficient of variation was performed using the following scale (Pestana & Gageiro, 2008): *i*) low dispersion [0; 15%[of CV; *ii*) moderate dispersion [15; 30%[of CV; and *iii*) great dispersion ≥ 30% of CV.

The box plots for each principle of play were also presented. All statistical procedures were computed in the SPSS statistics software (version 21).

6.3. Results

Descriptive statistics were used to inspect the results for the three tactical principles. The data on the three case study matches were organized by each half, thus resulting in six variables: M1H1 (Match 1 and Half 1), M1H2, M2H1, M2H2, M3H1, M3H2. Moreover, for each of the tactical principles a box plot was computed to provide a graphical representation of the results.

It is possible to observe that the mean values of the penetration principle are around 0.41 (Table 6.1). Such results allow us to discuss why teams are unable to penetrate the opponent's area at each offensive play. Actually, the penetration principle has a set of requirements that are not only in line with having ball possession. In this case, teams can have ball possession but do not play in a penetrating way, only passing the ball to comfort zones. Another explanation can be that by penetrating the teams reduce their potential for ensuring a favourable numeric relationship, thus as they advance on the field the possibility of being disarmed is increased. In the majority of cases the coefficient of variation is higher than 30%, which suggests a great degree of dispersion from play to play.

Table 6.1. Descriptive Statistics of the Penetration Ratio.

	Mean	Std. Deviation	Coefficient of variation%	Minimum	Maximum
M1H1	0.46	0.15	31.35	0.24	0.81
M1H2	0.39	0.12	29.84	0.16	0.65
M2H1	0.41	0.07	17.43	0.24	0.59
M2H2	0.41	0.15	36.82	0.12	0.75
M3H1	0.41	0.15	35.41	0.10	0.77
M3H2	0.42	0.13	32.31	0.11	0.71
Total	0.42	0.13	32.03	0.10	0.81

In considering the box plots (Figure 6.6) it is possible to observe that in the first and third matches the first quartiles are bigger than the third, thus suggesting a tendency to be lower than the median. Only in the second match is this tendency reversed, thus the bigger quartile is the third.

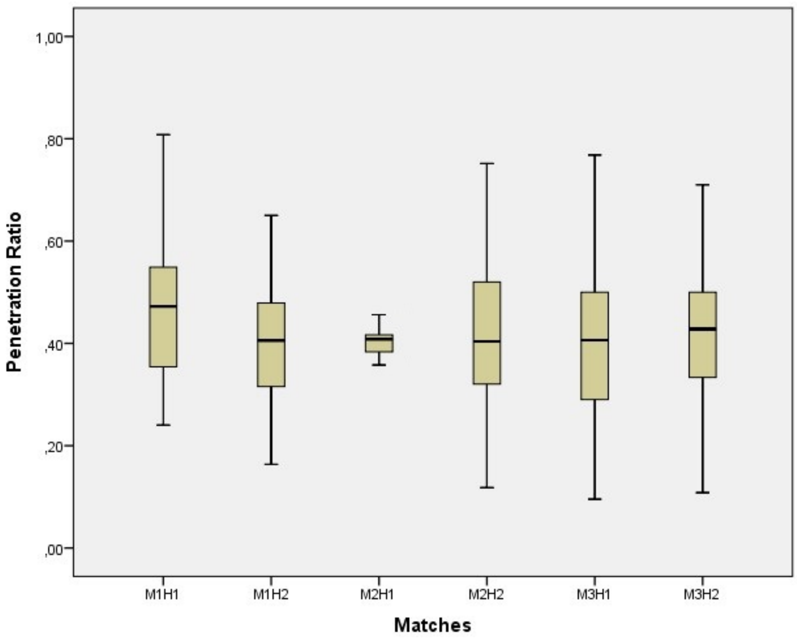

Figure 6.6. Box plots for the penetration principle.

From the descriptive statistics for the offensive space principle (Table 6.2) it is possible to observe that the mean ratio of the three matches is 0.79. Such a result suggests that this is a fundamental tactical principle that does not only depend on the location of the ball, and that it is easier to ensure this tactical behaviour during the majority of offensive plays. It is observed that the mean for each play ranges from 0.1 to 1 (the maximum). The coefficient of variation is higher than 30% for the majority of matches, thus suggesting a high level of dispersion.

Table 6.2. Descriptive Statistics of the Offensive Space Ratio.

	Mean	Std. Deviation	Coefficient of variation%	Minimum	Maximum
M1H1	0.79	0.26	32.82	0.10	1
M1H2	0.72	0.26	35.90	0.18	1
M2H1	0.79	0.26	32.69	0.24	1
M2H2	0.88	0.15	17.27	0.45	1
M3H1	0.84	0.20	23.76	0.36	1
M3H2	0.76	0.29	38.75	0.12	1
Total	0.80	0.24	30.58	0.10	1

It is also possible to observe from the box plots that the bigger quartiles in the majority of cases are the first (Figure 6.7). This result is due to the high median for this tactical principle in all the analysed matches. In all the box plots the third quartile achieved the maximum value, thus suggesting that this tactical principle had a strong tendency to be carried out in the match.

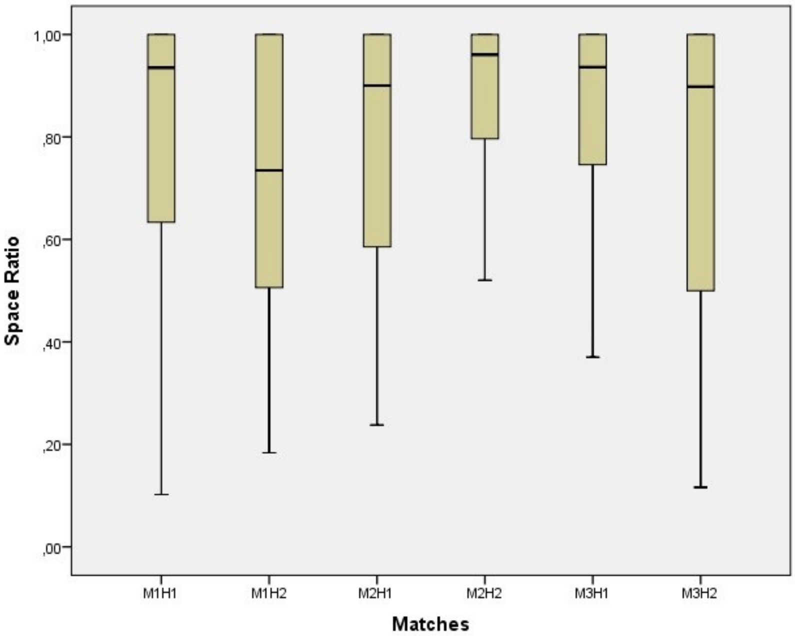

Figure 6.7. Box plots for the space principle.

Again, the result for the unity principle suggests that this was accomplished to a high level during the matches (Table 6.3). The mean value is 0.82 and the coefficient of variation is around 24%. This more moderate dispersion than the other principles could suggest that a higher regularity in performing this principle is essential to ensure a homogeneity in the offensive process. The unity principle allows the player with ball possession to be covered and it also prevents the loss of the ball.

Table 6.3. Descriptive statistics of the Unity Ratio.

	Mean	Std. Deviation	Coefficient of variation%	Minimum	Maximum
M1H1	0.78	0.19	24.77	0.33	1
M1H2	0.83	0.20	24.13	0.33	1
M2H1	0.87	0.15	17.11	0.50	1
M2H2	0.77	0.22	27.91	0.18	1
M3H1	0.84	0.18	21.41	0.40	1
M3H2	0.87	0.19	21.21	0.41	1
Total	0.83	0.19	23.22	0.18	1

The box plots show that the first quartile is bigger in the majority of cases due to the higher median (Figure 6.8). The third quartile achieved the maximum value in five of the six considered cases.

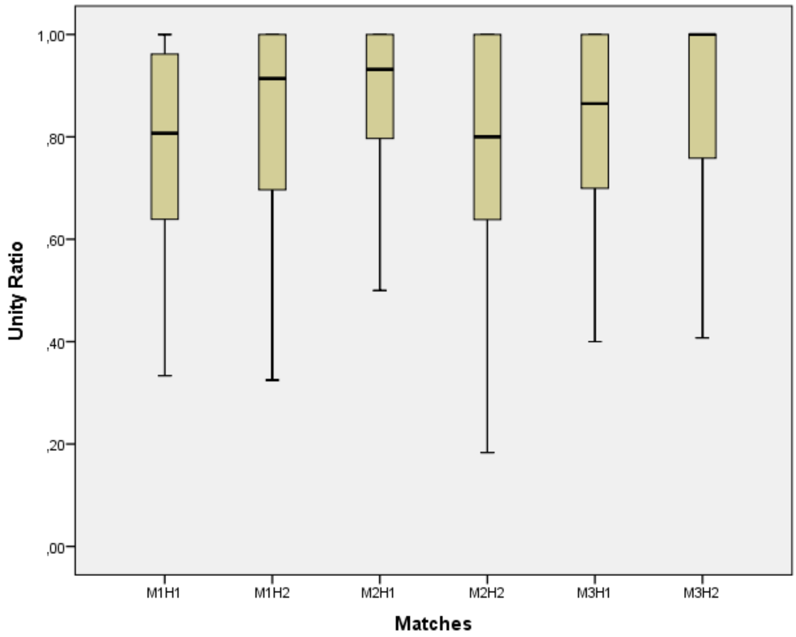

Figure 6.8. Box plots for the unity principle.

Only in the first half of the first match did the third quartile not achieve the value of 1. It is also important to consider that the ratio was never lower than a mean of 0.18. Such a result suggests the higher importance of this principle for the team.

6.4. Discussion

The study of collective sports such as football has been developing due to new technological advances in other scientific areas (Vilar et al., 2013). Using these new resources and concepts it is now possible to improve some systems of analysis to measure how teammates cooperate and to characterize the style of game performed by each team (Clemente et al., 2013). For sure, such an analysis can be performed using manual methods; however, the new technologies allow the development of computational systems to provide easier and quicker information for coaches.

Therefore, the main goal of this study was to propose a set of metrics to convert the manual systems of performance evaluation into automatic ones. For this purpose data were collected from three official matches by the same professional football team as a proof of concept. The aim of this study was to identify whether the three metrics developed were able to measure the tactical principles.

The first tactical principle that was inspected was the penetration. The main aim of this principle is to ensure that the ball progresses in a forward movement in the attempt to disrupt the opponent’s defensive organization (Costa et al., 2009). This process must be performed ensuring the minimum requirements for maintaining possession of the ball and it must create real opportunities to score. Although it appears to be a more individual process that depends on the player with the ball, penetration is actually a collective process that depends on all teammates. To identify the success of this principle, the algorithm proposed considered the forward movement of the ball as well as the non-deterioration of the numerical relationship with opponents inside the centre-of-game.

It was observed that the mean at the three analysed matches was 0.42, thus suggesting a low level of success. Such a result can be justified by the requirements imposed by this algorithm. In fact, the requirement to ensure the non-deterioration of the numerical relationship inside the centre-of-game reduces the possibilities for accomplishment. In truth, the highest defensive pressure is performed closer to the defensive area. Therefore, if the team with the ball moves forward more opponent players will appear in the centre-of-game, thereby reducing the possible numerical advantage of the team with ball possession. In that sense, the possible higher values of this ratio can mean that the strategy of the team is to move the ball forward to areas without a great concentration of opponents such as to the lateral sides (Dooley & Titz, 2011).

The other principle of play inspected in this case study was the offensive space (width and length). This principle offers to the player with possession of the ball some options to take the ball from the middle zone, where there is more opponent pressure, to try to open the space to play at the lateral sides or closer to the last defensive line of opponents (Castelo, 1996). The aim of this principle is to reduce the concentration of opponents in their central zone, thus attempting to open up some spaces to penetrate between the opponent players (Trapattoni, 1999).

A high mean value could be observed for the accomplishment of this principle. The ratio of 0.80 for the three matches suggests that teammates tried to ensure this principle during the offensive process. Nevertheless, this principle can differ from team to team. In fact, in this case study the team used two forward wings. Thus, it is easier to accomplish this principle because of the strategic position of the two players that have the opportunity to play in the wings. In other cases, such as the diamond 1–4–4–2, there are not two fixed players in the forward wings; thus, it is possible that the space ratio may be smaller than in this specific case. In that sense, it would be interesting in further studies to perform a comparison between different teams that used different player strategic distributions in the field.

The last principle of play inspected in this case study was that of offensive unity. This principle aims to ensure that there is a reduced space between the different lines of the team (defensive, midfield, forward), thus providing a higher and closer support to the player with ball possession. Furthermore, offensive unity ensures that in the case of loss of the ball, the reduced spaces between the lines will immediately put pressure on the opponent’s team (Costa et al., 2009). Both objectives are very important for increasing the possibilities of success in collective action.

In this case study it was possible to observe a mean of 0.83 in the ratio for offensive unity. Such a result suggests a high degree of synchronization between teammates following the ball location during the offensive process. In fact, the accomplishment of this tactical principle is very important for any strategy adopted by a team. The capability to move players in a synchronized way is essential for improving the collective behaviour and for playing as a team. Therefore, it is very important that further studies should be performed on a large sample and on different teams to help us understand how teammates synchronize their movements to achieve the unity principle during the offensive process.

In this case study a set of three tactical metrics were proposed, and their respective relative ratios measured the tactical behaviour in the offensive processes. By using the Cartesian information about the positions of players and the ball it was possible to develop computational metrics that provided information about tactical behaviour. Such metrics mean a step forward to an easier and quicker match analysis process, reducing the time spent by human operators. It was not possible to generalize the results of this case study. Nevertheless, future work should compare a larger sample of teams and matches to inspect differences from team for team. Future studies could be expected to identify some of the specific characteristics of each team using these tactical metrics. Furthermore, it will be very important to crossmatch the information about these tactical metrics with other indicators of match analysis such as notational analysis and spatio-temporal analysis.

6.5. Conclusion

In this case study three metrics and ratios were proposed to inspect and estimate the tactical behaviour of football teams. Three computational metrics were developed that were derived from the Cartesian players' position in the field: (i) penetration, (ii) space and (iii) unity. From the results it was possible to identify that the highest ratio was achieved for the unity principle in play and the lowest ratio was observed in the penetration ratio. Using current technologies it could be possible to provide some computational solutions for the inspection of a team's performance, thus providing new opportunities to develop match analysis systems.

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Chapter VII

Developing metrics to inspect the defensive tactical principles of football teams

Chapter based on the following publication:

Clemente, F. M., Martins, F. M. L., Couceiro, M. S., Mendes, R. S., & Figueiredo, A. J. (2014). Developing a football tactical metric to estimate the sectorial lines: A case study. In Murgante, B., Misra, S., Rocha, A. M. A. C., Torre, C., Rocha, J. G., Falcão, M. I., Taniar, D., Apduhan, B. O., & Gervasi, O. (Eds.), *Computational Science and Its Applications – ICCSA 2014* (pp. 743-753). London, UK: Springer.

7. Developing metrics to inspect the defensive tactical principles of football teams

Abstract

This study proposes three technological metrics to inspect the tactical mission of football players throughout matches and to characterise the defensive play area, defensive triangulations and the sectorial lines. These metrics only require Cartesian information about the players' positions on the field. As a proof of concept three case study matches played by the same professional football team were used. The data was collected second-to-second, and from this process 9218 moments of useful time were collected. The results about the defensive area of play and defensive triangulation revealed that the final score had significant main effects and a small effect (Pillai's Trace = 0.157; $F_{(20,8924)}$ = 37.910; *p-value* = 0.001; η_p^2 = 0.078; *Power* = 1.000) on tactical performance. The half of match had a significant main effect and a small effect size (Pillai's Trace = 0.040; $F_{(10,4461)}$ = 18.383; *p-value* = 0.001; η_p^2= 0.040; *Power* = 1.000) on tactical performance. About the sectorial lines significant differences were found between the two statuses of the possession of the ball for the defensive line ($F_{(1, 9216)}$ = 44.520; *p-value* = 0.001; η^2 = 0.005; Power = 1.000; very small effect size) and forward line ($F_{(1, 9216)}$ = 26.175; *p-value* = 0.001; η^2 = 0.000; Power = 0.108; very small effect size). From the specific results of this case study, it was possible to propose a new concept to help coaches observe a match with some tactical parameters that can allow an easier and quicker identification of team properties.

Keywords: Match analysis, tactical metrics, defensive play area, tactics, football.

7.1. Introduction

In the last few years match analysts have introduced a new approach to the analysis of collective behaviour. Beyond traditional notational analysis and manual observational procedures (Hughes & Franks, 2004) it is now possible to use technological advances to inspect the performance of football players (Duarte, Araújo, Correia, & Davids, 2012). Such technological advances have been called metrics (Clemente, Couceiro, Martins, Mendes, & Figueiredo, 2013a) that use the spatio-temporal relationship between players throughout the match to estimate collective synchronisation (Bourbousson, Sève, & McGarry, 2010). Usually, such metrics used Cartesian data about a football player's position during the match to compute a set of metrics that characterised the collective organisation of a given team (Bartlett, Button, Robins, Dutt-Mazumder, & Kennedy, 2012).

One of the first metrics was proposed by Yue et al. (2008) and developed the concept of the centroid in a football game. This metric is a kind of geometric mean of different points (players). Later Frencken et al. (2011) used the same concept to produce new metrics for small-sided football games and Bourbousson et al. (2010) for basketball games. An adaptation of the centroid was also proposed by Clemente et al (2013b) for football games that used the ball position to attribute weight to the players' positions, calling such metrics "weighted centroids". Starting from the centroid, Bourbousson et al. (2010) developed the concept of a stretch index that measures the dispersion of players from the team's centroid. A similar method was proposed by Clemente et al. (2013b) but using the weighted method. Both metrics use the position of players to inspect the centre-of-team and the players' dispersion.

Other metrics were developed to estimate the area coverage of a given team. The first methods were the coverage area (Okihara et al., 2004) and the surface area (Frencken et al., 2011) both developed for football games. These metrics allow an estimate of the area coverage of one team, using this information about the minimum number of triangulations performed by all players. The polygon made up of all players is used to determine the coverage area. Another concept was developed by Clemente et al. (2013b) called the 'effective area of play'. This metric determines the defensive triangulations and attacking triangulations and uses information about both teams to estimate the triangulations with higher or lower effectiveness.

These metrics were only the beginning of a new era of match analysis. It is important to base the methods on the conditions of a given sport. In a football game it is very important to determine the strategic positions of all players, but this strategic definition is not a static one. Throughout a game the tactical mission of a player changes from time-to-time. One of these cases of tactical mission changes is the lateral defender that contributes to the attacking process. Thus a lateral midfielder or even a lateral forward is beyond the lateral defender during attacking moments. Thus, their tactical mission varies based on the moments with or without possession of the ball by their team. Until now no method had been developed to determine the tactical mission of each player throughout a match. Another important issue in a football game is to determine the specific areas of pressing during the defensive process. In fact, during defensive instants all players acts in synchronisation to reduce the possibilities of success for the opposing team. The synchronisation is different based on the regions being pressed. Usually, closer to the goal and in the central area of the field pressing is higher. No metric has been proposed to measure the different kinds of pressing within the team.

Another of the specific indicators used in football are the lines performed by defenders, midfielders and forwards (sectors of play). These lines are important for understanding the space between players and for understanding the synchronisation between the team's sectors. The notion of lines of play is not a novel approach. In fact, the development of such an idea comes from Gréhaigne (1992) who refers to the lines as the axes of inertia. In this study some photographs of attacking phases were used. Using this technique, the orientation of defensive and attacking axes of both teams was studied based on the players' positions. Later, a similar approach was used by Lenoine et al. (2005) by inspecting the players' positions before the shot on goal.

In both studies only the axes of inertia was used to characterise the attacking moments that precede the shot attempts. Nevertheless, their potential is greater than that. In fact, the lines of play can be very useful for understanding the dynamics between sectors (defensive, midfield and forward) throughout the match. Thus, this study aims to propose one technological tactical metric that computes one line per sector, thus developing a sectorial line metric. To compute such sectorial lines a method to estimate the players' tactical mission (defender, midfielder and forward) in a given instant will be developed.

Based on the previous paragraphs this study have two main goals. Besides to propose three tactical metrics will be performed two different analysis. The sectorial lines will be organised in defensive line, midfield line and forward line. Using such information an analysis will be performed of the variance between defensive and attacking moments, in an attempt to establish whether the angles of such lines in relation to the field are different. In the case of defensive play areas metrics will be only used for moments without possession of the ball. The variance between the 1^{st} and 2^{nd} half of the matches and the final scores will be inspected in order to understand whether different halves and scores induce changes in the tactical performance of football teams.

7.2. Methods

7.2.1. Sample

Three official home matches of the same professional football team from the *Portuguese Professional Premier League* were used as the sample. There were three different final scores in these three matches: win, lose and draw. The initial home team distribution was 1-4-3-3 for all analysed matches. From these three matches all useful times were recorded and then processed in a computational system that recorded the players' Cartesian positional data in the field. The data was collected second-to-second, and from this process 9218 instants of useful time were collected. The entire process complies with the APA ethical standards for the treatment of human or animal subjects.

7.2.2. Data Collecting

To collect the data three official matches were recorded using a digital camera (*GoPro Hero* with 1280× 960 resolution) with the capacity to process images at 30 Hz (i.e. 30 frames per second). To capture the whole field the camera was placed on an elevated surface above the ground. The dimensions of the football field were $104 \times 68\ m$.

Before processing the images, the football field was calibrated using 19 markers throughout the official lines of field. Such markers allowed identification in virtual space of the points of calibration in order to match the virtual space (pixels) with real physical space (meters). Using this information the Direct Linear Transformation (DLT) method was used, which amends the position of the elements (i.e. players and ball) in pixels according to the metric space (Abdel-Aziz & Karara, 1971). The reliability of such a conversion was assessed through experimental trials.

The football players and ball were tracked using a manual tracking method. Such procedures was done after calibration, thus returning the position of the players and the ball over time in Cartesian coordinates. A graphical user interface was developed to visualise the match by controlling the frame rate with a sampling time of one second. In each frame the location of all players and the ball were recorded, following a typical point-and-click approach. Such identification corresponded to one point at the centre of the feet of each player and the centre of the ball. The whole process associated with this approach (i.e., detection and identification of player trajectories, space transformation and metric computation), was performed using the high-level calculation tool *MatLab* (Couceiro, Clemente, & Martins, 2013).

For efficiency, only played time was considered, excluding all moments in which the ball was not in the field (e.g., ball out of bounds). Since the methodology proposed herein involves some computational complexity, each second will correspond to an analysed instant for each player and the ball.

7.2.3. Developing the Defensive Play Area

The defensive play area developed in this project emerges from the observational analysis performed by Seabra (2010) which developed the concept of effective play space. Using the main concept of such a method, a new technological and automatic metric was developed that uses the spatio-temporal information about players and computes the tactical mission of each player throughout the match. In fact, the strategic mission of one player is relatively permanent during the match (e.g., for a lateral defender), but throughout the match the lateral defender moves forward until the attacking phase. At this moment, their tactical mission is different than that of the defensive phase. Starting from such an idea, a metric will be developed that computes the tactical mission of each player second-to-second.

7.2.3.1. Computing the Momentary Tactical Mission

To develop the Defensive Play Area, the first task is to develop the surface area of players constituted by the sum of triangulations between teammates. This surface area can be computed as proposed by Clemente et al. (2013b) and as illustrated in the following Figure 7.1.

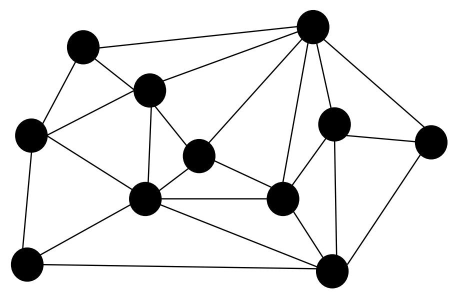


Figure 7.1. Surface area of one team in a given moment.

After to developing the surface area the second step is to define the criteria to classify the tactical mission of football players.

To that end, one can define a positional relationship, at each instant, between the most backward player (typically the goalkeeper) and the most advanced player. The most adequate way to represent this relationship is by considering the distance between both players from a given team δ, herein denoted as d_δ^{max}. Variable d_δ^{max} can also be described as the longitudinal range of the team from end to end, being computed as:

$$d_\delta^{max}[t] = \max_{N_\delta} \left\| X_\delta^1[t] \right\|, \tag{7.1}$$

wherein $X_\delta[t]$ is the positioning matrix in which row n represents the planar position $\mathbb{R}^2$ of player n of team δ at time t as:

$$X_\delta[t] = \begin{bmatrix} x_1[t] & y_1[t] \\ \vdots & \vdots \\ x_{N_\delta}[t] & y_{N_\delta}[t] \end{bmatrix}, \ x_n[t], y_1[t] \in \mathbb{R}^1, i = 1, \dots, N. \tag{7.2}$$

Note that equation (7.1) only considers the first dimension, *i.e.*, longitudinal x-axis, of players position, identifiable as $X_\delta^1[t]$.

This amplitude is then used to normalize the longitudinal (x-axis) coordinates of each player in regards to the most backward player (the Goalkeeper), thus resulting in a normalized positioning x-vector:

$$\hat{x}_\delta[t] = \begin{bmatrix} \frac{x_1[t]}{d_\delta^{max}[t]} \\ \vdots \\ \frac{x_{N_\delta}[t]}{d_\delta^{max}[t]} \end{bmatrix}, \hat{x}_\delta[t] \in [0,1], i = 1, \dots, N. \tag{7.3}$$

After computing the normalized longitudinal position of players, a simple set of thresholds was used to classify them as Goalkeeper, Defenders, Midfielders and Forwards, according to Figure 7.2.

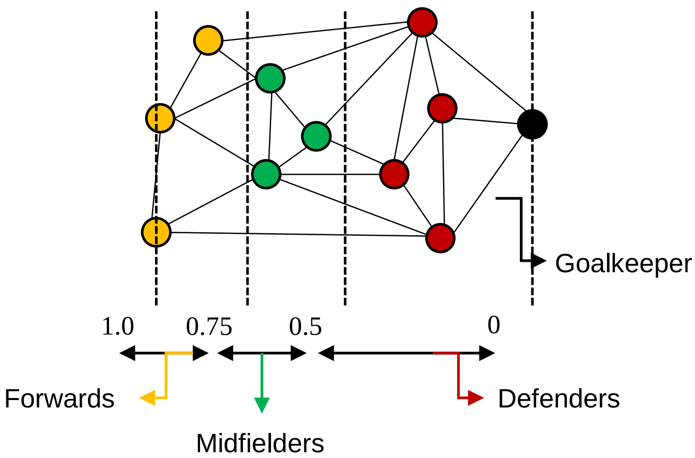


Figure 7.2. Momentary tactical position in a given moment.

From this method it was possible to analyse second-to-second the number of defenders, midfielders and forwards. For the statistical analysis each variable was codified as follows: *i*) TM_Defenders; *ii*) TM_Midfielders; and *iii*) TM_Forwards.

7.2.3.2. Computing the Relative Defensive Play Area

After computing the momentary tactical mission of each player it is possible to develop the concept of the relative defensive play area. The region between each tactical mission (Goalkeeper, Defender, Midfielder and Forward) can be classified during the defensive phase (in this case during moments without possession of the ball by a given team). From the different tactical missions that constitute a triangulation it is possible to define a set of defensive regions. Four different regions were defined: *i*) defensive backward region – DBR (that it is the space between the Defenders and the Goalkeeper); *ii*) defensive 1st half of the middle region – D1HMR (that it is the region between the Defenders and the Midfielders); *iii*) defensive 2nd half of the middle region – D2HMR (that is the region within Midfielders and between Midfielders and Forward players); and *iv*) defensive forward region – DFR (the region within forward players and between the Forwards and Midfielders). Such a classification is generic but it was defined from the multiple combinations that can occur throughout a match, and all the possibilities and the respective relative defensive area, as can be seen in Table 7.1.

Table 7.1. Possible combinations between the tactical positions on a field and the corresponding defensive area.

	G	D	D+D	D+M	D+F	M	M+M	M+F	F	F+F
G			1	2	2		2	3		3
D			2	2	3		3	3		3
D+D						2			3	
D+M						3			3	
D+F						3			3	
M							3	3		4
M+M									3	
M+F									4	
F										4
F+F										

1	Defensive Backward Region (DBR)	4	Defensive Forward Region (DFR)
2	Defensive 1st half of the middle Region (D1HMR)	3	Defensive 2nd half of the middle Region (D2HMR)
	Not possible to compute		The same process as in the example

Under these conditions (Table 7.1) it is possible to compute the relative area (m^2) of each defensive play area and to compute the number of triangulations within a given defensive play area. Such information can be computed throughout all defensive plays, thus the information varies from second to second. Using a frame as an example it is possible to define the defensive play area as presented in Figure 7.3.

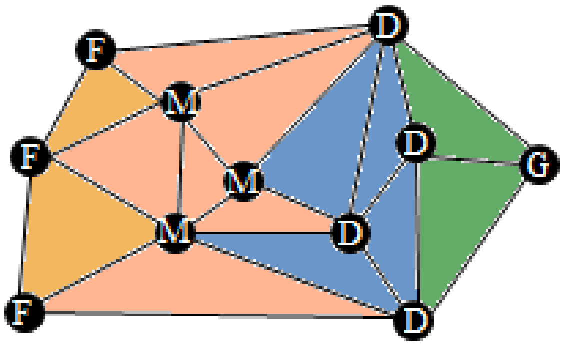


Figure 7.3. Example of one frame and the respective relative defensive play area.

From this example (Figure 7.2) it is possible to see 2 triangulations in DBR, 4 triangulations in D1HMR, 6 triangulations in D2HMR and 2 triangulations in DFR. The area of each triangle (m^2) is estimated and computed based on the distance between the players that constitutes such a triangle. Once again, such variables (the number of triangulations at each defensive play area and the area of such a defensive play area) are computed second-to-second, varying based on the conditions previously defined. From this output it is possible to obtain the following variables: *i*) DPA_DBR (partial area in m^2); *ii*) DPA_D1HMR (partial area in m^2); *iii*) DPA_D2HMR (partial area in m^2); *iv*) DPA_DFR (partial area in m^2); *v*) Triang_DBR (number of triangulations in that region); *vi*) Triang_D1HMR (number of triangulations in that region); *vii*) Triang_D2HMR (number of triangulations in that region); and *viii*) Triang_DFR (number of triangulations in that region).

7.2.3.3. Computing the Sectorial Lines

By considering the information about the tactical mission of each player, it is possible to define the active region of the defenders, the midfielders and the forwards. To define such regions, one can compute sectorial lines, i.e., frontier divisions between regions, by benefitting from linear regressions applied to the positional co-ordinates of players that were previously classified in the data collecting section. In other words, the sectorial lines will be represented by a first degree polynomial equation of the type $y = mx + b$ that minimises the root mean squared error (*RMSE*) between the linear equation and the real positional data of each set of players, applying a simple nearest-neighbour interpolation (Surhone, Tennow, & Henssonow, 2010). This requires computing the fitting line for each class of player, namely, defenders, midfielders and forwards, as classified in the tactical mission section.

Afterwards, one can compute the angular displacement of each line in relation to the y-axis of the field, wherein an angle of zero (0) means that the line is completely perpendicular to the x-axis and, as such, players with a given tactical mission are roughly in line with each other (see Figure 7.4).

Note that each fitting line requires at least two players on a given tactical mission. For the specific case of having a single player, i.e., one point, the corresponding line will be drawn parallel to the y-axis and pass through that point

This process is illustrated in Figure 7.4. As one may observe, applying the linear regression for a given number of Cartesian points (i.e., players), it is possible to have three sectorial lines: *i*) defensive line; *ii*) midfield line; and *iii*) forward line. Each line has a specific gradient and tendency.

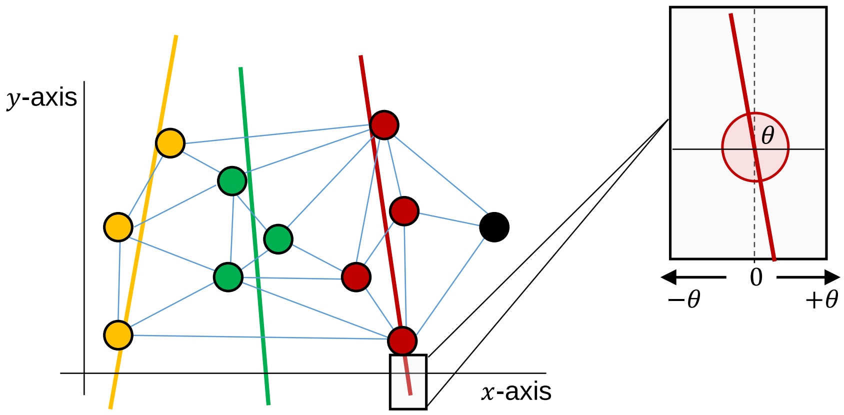


Figure 7.4. Example of sectorial lines for a given moment.

The computation of the sectorial lines was performed at each second, in both defensive and attacking moments. Those allowed the retrieval of the following variables: *i*) angle of the defensive line; *ii*) angle of the midfield line; and *iii*) angle of the forward line.

7.2.4. Statistical Procedures

Two analyses were carried out in this study: *i*) study of the defensive play area and defensive triangulations; and *ii*) study of the sectorial lines.

All the statistical analyses were performed using *IBM SPSS Statistics* (Version 21) for a significance level of 5%.

7.2.4.1. Study of the defensive play area and defensive triangulations

Descriptive statistics (mean and standard deviation) were used to inspect the results from the tactical missions, defensive area of play and the number of triangulations in a given region of a defensive area of play. The three case study matches were organised into both halves of each game, thus resulting in six variables: M1H1 (match 1 and half 1), M1H2, M2H1, M2H2, M3H1, M3H2.

The influence of "*final score*" and "*half of the match*" factors on the dependent variables of "*TM_Defenders*", "*TM_Midfielders*", "*TM_Forwards*", "*DPA_DBR*", "*DPA_D1stHMR*", "*DPA_D2ndHMR*", "*DPA_DFR*", "*Triang_DBR*", "*Triang_D1stHMR*", "*Triang_D2ndHMR*" and "*Triang_DFR*" was analysed using two-way *MANOVA* after validation of normality and homogeneity assumptions.

The assumption of normality for each of the univariate dependent variables was examined using the univariate tests of Kolmogorov-Smirnov (*p-value* < 0.05). The univariate normality of each dependent variable was not verified, however, since $n \geq 30$, this statement was assumed (Maroco, 2010) by using the Central Limit Theorem (CLT). Consequently, the assumption of multivariate normality was validated (Pallant, 2011). The assumption of the homogeneity of variance/covariance matrix in each group was examined with the Box's M Test. Such tests showed no homogeneity. However, the *MANOVA* technique is robust to this violation due to its execution of the Pillai's Trace, even for non-balanced samples (Maroco, 2010).

When *MANOVA* detected significant statistical differences between the two factors, we proceeded to the commonly-used two-way *ANOVA* for each dependent variable (5) followed by Tukey's HSD Post Hoc. When the factor interactions were verified using the two-way MANOVA, a new variable was developed by crossing the two independent variables (half of match and ball possession status) for each dependent variable. The one-way ANOVA was then performed for each new factor (crossing both initial independent variables) (Maroco, 2010). Next, Tukey's HSD Post Hoc test was performed to analyse the multiple comparisons.

The classification of the effect size (*i.e.*, the measure of the proportion of total variation in the dependent variable explained by the independent variable) and the power of the test was made according to Hopkins et al. (1996).

7.2.4.2. Study of the Sectorial Lines

Descriptive statistics (mean and standard deviation) was used to inspect the outcomes from the sectorial lines. The influence of "*status of possession of the ball*" factor on the dependent variables of "*angle of defensive line*", "*angle of midfield line*" and "*angle of forward line*" was analysed using a one-way ANOVA test after validation of normality and homogeneity assumptions.

The classification of the effect size (i.e., the measure of the proportion of the total variation in the dependent variable explained by the independent variable) and the power of the test were determined according to Hopkins et al. (1996): very small: 0-0.01; small: [0.01; 0.09[; moderate: [0.09;0.25[; large: [0.25;0.49[; very large: [0.49;0.81[; and nearly perfect: [0.81;1.0].

A correlation analysis was also performed between the sectorial lines to characterise how such lines act from sector to sector. Thus, an *r*-pearson correlation between sectorial lines was carried out.

7.3. Results

7.3.1. Results of Defensive Play Area and Defensive Triangulations

Two-way MANOVA results revealed that the final score had significant main effects and a small effect size (*Pillai's Trace* = 0.157; $F_{(20,8924)}$ = 37.910; *p-value* = 0.001; η_p^2 = 0.078; *Power* = 1.000) on tactical performance. The match half had a significant main effect and a small effect size (*Pillai's Trace* = 0.040; $F_{(10,4461)}$ = 18.383;

p-value = 0.001; η_p^2= 0.040; *Power* = 1.000) on tactical performance. Finally, significant interaction effects between the two factors of tactical performance were observed (*Pillai's Trace* = 0.083; $F_{(20,8924)}$ = 19,429; *p-value* = 0.001; η_p^2= 0.042; *Power* = 1.000; small effect size).

After observing the significance of the final score and the match half in MANOVA, an univariate ANOVA analysis and relevant post hoc comparisons were performed for each dependent variable. The descriptive statistics and the corresponding post-hoc results in the final score variable can be found in Table 7.2. A similar procedure can be seen in Table 7.3 for the match half variable.

Table 7.2. Comparison of tactical metrics between final scores. Values are the average of the 1st and 2nd half.

	Loss		Draw		Win	
	Mean	SD	Mean	SD	Mean	SD
TM_Defenders	$3.05^{b,c}$	1.97	3.51^{a}	1.59	3.44^{a}	1.93
TM_Midfielders	$3.39^{b,c}$	1.42	$2.94^{a,c}$	1.17	$3.27^{a,b}$	1.35
TM_Forwards	3.56^{c}	1.43	3.55^{c}	1.42	$3.30^{a,b}$	1.43
DPA_DBR	$1744.17^{b,c}$	1331.82	$2590.69^{a,c}$	1499.05	$2038.50^{a,b}$	1410.14
DPA_D1stHMR	2668.71^{b}	1478.38	$2891.67^{a,c}$	1668.17	2523.63^{b}	1336.69
DPA_D2ndHMR	3000.96^{b}	1582.18	$3787.28^{a,c}$	2236.88	2930.95^{b}	1576.47
DPA_DFR	$1333.18^{b,c}$	1238.43	$1635.94^{a,c}$	1649.42	$1084.61^{a,b}$	1127.18
Triang_DBR	$1.42^{b,c}$	1.05	$1.81^{a,c}$	0.98	$1.64^{a,b}$	1.06
Triang_D1stHMR	3.81^{c}	1.95	3.77^{c}	1.77	$4.12^{a,b}$	1.96
Triang_D2ndHMR	5.49^{b}	1.84	$5.22^{a,c}$	1.70	5.58^{b}	1.78
Triang_DFR	3.39^{c}	2.29	3.24^{c}	2.26	$2.96^{a,b}$	2.22

Significantly different compared to Loss^{a}; Draw^{b}; and Win^{c} at *p-value*<0.05

Significant statistical differences were found between the three final scores for TM_defenders ($F_{(2, 4470)}$ = 28.199; *p-value* = 0.001; η^2 = 0.012; *Power* = 1.000; small effect size); TM_Midfielders ($F_{(2, 4470)}$ = 39.998; *p-value* = 0.001; η^2 = 0.018; *Power* = 1.000; small effect size); TM_Forwards ($F_{(2, 4470)}$ = 16.310; *p-value* = 0.001; η^2 = 0.007; *Power* = 1.000; very small effect size); DPA_DBR ($F_{(2, 4470)}$ = 138.692; *p-value* = 0.001; η^2 = 0.058; *Power* = 1.000; small effect size); DPA_D1stHMR ($F_{(2, 4470)}$ = 21.383; *p-value* = 0.001; η^2 = 0.009; *Power* = 1.000; very small effect size); DPA_D2ndHMR ($F_{(2, 4470)}$ = 94.884; *p-value* = 0.001; η^2 = 0.041; *Power* = 1.000; small effect size); DPA_DFR ($F_{(2, 4470)}$ = 56.810; *p-value* = 0.001; η^2 = 0.025; *Power* = 1.000; small effect size); Triang_DBR ($F_{(2, 4470)}$ = 54.004; *p-value* = 0.001; η^2 = 0.024; *Power* = 1.000; small effect size); Triang_D1stHMR ($F_{(2, 4470)}$ = 13.213; *p-value* = 0.001; η^2 = 0.006; *Power* = 0.998; very small effect size); Triang_D2ndHMR ($F_{(2, 4470)}$ = 13.011; *p-value* =

0.001; η^2 = 0.006; *Power* = 0.997; very small effect size); and Triang_DFR ($F_{(2, 4470)}$ = 16.869; *p-value* = 0.001; η^2 = 0.007; *Power* = 1.000; very small effect size).

Table 7.3. Comparison of tactical metrics between 1st and 2nd halves. Values are the average of the three final scores.

	1st Half			2nd Half		
	Mean	SD	CV(%)	Mean	SD	CV(%)
TM_Defenders	3.33	1.94	58.26	3.29	1.79	54.41
TM_Midfielders	3.22	1.34	41.61	3.23	1.34	41.49
TM_Forwards	3.46	1.40	40.46	3.48	1.47	42.24
DPA_DBR	2213.45[b]	1491.21	67.37	1946.19[a]	1389.38	71.39
DPA_D1stHMR	2816.53[b]	1492.61	52.99	2548.80[a]	1486.65	58.33
DPA_D2ndHMR	3334.99[b]	1720.57	51.59	3058.56[a]	1910.08	62.45
DPA_DFR	1399.72[b]	1311.02	93.66	1267.80[a]	1382.58	109.05
Triang_DBR	1.62	1.06	65.43	1.59	1.03	64.78
Triang_D1stHMR	3.89	1.96	50.39	3.92	1.87	47.70
Triang_D2ndHMR	5.38[b]	1.76	32.71	5.51[a]	1.82	33.03
Triang_DFR	3.15[b]	2.20	69.84	3.26[a]	2.33	71.47

Significantly different compared to 1stHalf[a]; and 2ndHalf[b] at *p-value*<0.05

Significant differences were found between the three final scores for TM_defenders ($F_{(2, 4470)}$ = 1,737; *p-value* = 0.188; η^2 = 0.000; *Power* = 0.261; very small effect size); TM_Midfielders ($F_{(2, 4470)}$ = 0.466; *p-value* = 0.495; η^2 = 0.000; *Power* = 0.105; very small effect size); TM_Forwards ($F_{(2, 4470)}$ = 1.161; *p-value* = 0.281; η^2 = 0.000; *Power* = 0.190; very small effect size); DPA_DBR ($F_{(2, 4470)}$ = 44.980; *p-value* = 0.001; η^2 = 0.010; *Power* = 1.000; small effect size); DPA_D1stHMR ($F_{(2, 4470)}$ = 19.471; *p-value* = 0.001; η^2 = 0.004; *Power* = 0.993; very small effect size); DPA_D2ndHMR ($F_{(2, 4470)}$ = 17.476; *p-value* = 0.001; η^2 = 0.004; *Power* = 0.987; very small effect size); DPA_DFR ($F_{(2, 4470)}$ = 4.735; *p-value* = 0.030; η^2 = 0.001; *Power* = 0.585; very small effect size); Triang_DBR ($F_{(2, 4470)}$ = 2.925; *p-value* = 0.087; η^2 = 0.001; *Power* = 0.401; very small effect size); Triang_D1stHMR ($F_{(2, 4470)}$ = 0.019; *p-value* = 0.891; η^2 = 0.000; *Power* = 0.052; very small effect size); Triang_D2ndHMR ($F_{(2, 4470)}$ = 5.559; *p-value* = 0.018; η^2 = 0.001; *Power* = 0.654; very small effect size); and Triang_DFR ($F_{(2, 4470)}$ = 4.328; *p-value* = 0.038; η^2 = 0.001; *Power* = 0.548; very small effect size).

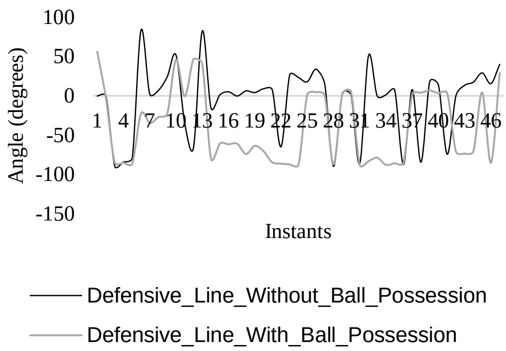
7.3.2. Results of the Sectorial Lines

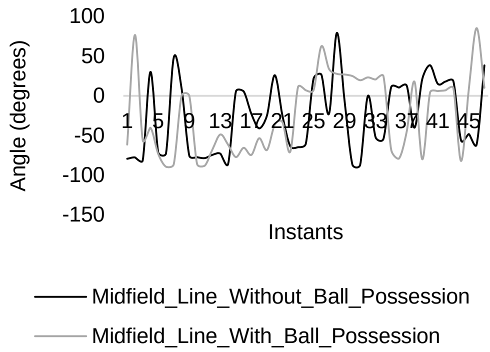
The descriptive statistics of sectorial lines can be observed in the following Table 7.4. The one-way ANOVA was performed to analyse the variance between the status with and without possession of the ball.

Table 7.4. Comparison of sectorial lines between with and without possession of the ball.

Sectorial Line	Possession of the Ball	Mean	Standard Deviation
Defensive Line	Without PB	40,79[b]	33,33
	With PB	36,21[a]	32,60
Midfield Line	Without PB	40,91	27,55
	With PB	40,50	29,07
Forward Line	Without PB	40,83[b]	25,27
	With PB	43,50[a]	24,77

Significant statistical differences were found between the two statuses of the possession of the ball for defensive line ($F_{(1,\ 9216)}$ = 44.520; *p-value* = 0.001; η^2 = 0.005; *Power* = 1.000; very small effect size) and forward line ($F_{(1,\ 9216)}$ = 26.175; *p-value* = 0.001; η^2 = 0.000; *Power* = 0.108; very small effect size). No significant differences were found between the two statuses of the possession of the ball for midfield line ($F_{(1,\ 9216)}$ = 0.483; *p-value* = 0.487; η^2 = 0.003; *Power* = 0.999; very small effect size).

a)


b)


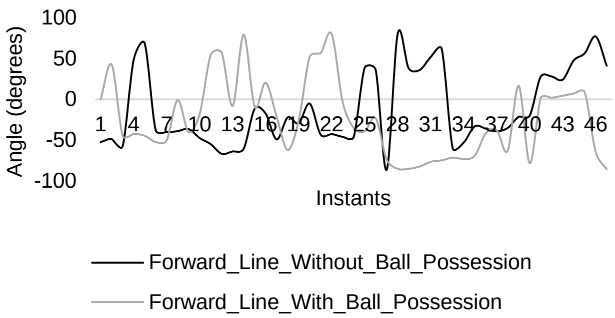
c)


Figure 7.5. A sample-period example of variation of sectorial lines in the instants with and without the possession of the ball.

It is possible to observe (Figure 7.5) that usually the defensive and forward lines had the highest angles (range) in instants with the possession of the ball. In the midfield line there is no a clear tendency between the status of possession of the ball. The values vary in both statuses between 0° and ~89°.

Table 7.5. Correlation values between sectorial lines.

	Angle of Defensive Line	Angle of Midfield Line	Angle of Forward Line
Angle of Defensive Line	1	0.008	-0.034*
Angle of Midfield Line	0.008	1	0.011
Angle of Forward Line	-0.034*	0.011	1

*. Correlation is significant at the *p-value*<0.05.

A very small correlation was found between all sectorial lines (Table 7.5). Nevertheless, it was possible to observe a very small inverse correlation between the defensive and forward line. Moreover, it was possible to observe that the midfield line had a positive correlation with both defensive and forward lines. A statistical significance of correlation was also found between the defensive and forward line (*p-value* = 0.001).

7.4. Discussion

This study proposed to develop a method to identify tactical missions using only the Cartesian positional data of football players. Moreover, it were also introduced new concepts called by defensive play area and the sectorial lines. To a better organization the discussion will be splitted in two sections.

7.4.1. Defensive Play Area and Defensive Triangulations

The first method developed in this study defined the tactical mission of all players in a given moment. Such a method was performed based on the Cartesian positional data of all players throughout the match. From such information it was possible to estimate the number of defenders, midfielders and forwards at a second-to-second rate. It is important to highlight that one player can be lateral Defender (as a strategic position) but in a given moment of match can have a tactical mission as a Midfielder (Couceiro, Clemente, Martins, & Tenreiro Machado, 2014). This method therefore only considers the tactical mission and not the strategic position (Gréhaigne, Bouthier, & David, 1997). The outcomes suggested that on average the highest number of Defenders (3.51) are in the final score of a draw. The smallest average was identified on loss score (3.05). On the other hand, the highest average of Midfielders (3.39) and Forwards (3.56) in a tactical mission occurs in the loss score. The lowest value of Midfielders (2.94) was found in a score draw and the smallest average of forwards (3.30) was found in a winning score. In fact, this is a very interesting outcome. In the win score the defensive organisation may be more structured, rather than decreasing the number of forwards. Moreover the highest average of midfielders and forwards in a tactical mission during loss score means specific behaviour to increase the pressing closest to the opponent defenders.

The influence of match halves in the variation of tactical missions was also inspected. No statistical differences were found between the 1st and 2nd halves. Nevertheless, it was possible to identify a small increasing tendency to decrease the number of defenders and increase the number of midfielders and forwards from the first to the second half. Such a result can be justified by the attempt to explore opponent fatigue in second half, and trying to develop counter-attacks, thus increasing the defensive pressing by the highest average of forwards (Clemente et al., 2013a).

To inspect the area covered by teammates during defensive moments in football the defensive play area metric was developed. Such a method was proposed based on the interactions between tactical missions. The defensive play area was organised in four relative regions. The results showed that the defensive pressing in the 2nd half of the midfield had the highest area coverage in all scores in comparison with the other defensive regions. The second highest area was the 1st half of midfield, thus suggesting that a great amount of defensive pressing occurs on the whole midfield. The forward and backward regions of pressing correspond to the smallest regions of pressing. In the four defensive regions the greatest amount of area was performed in final score of draw, being statistically different from the remaining results (win and loss). This can be justified by the team's strategy in gaining disadvantage or advantage. In fact, if a team needs to reverse their losing status it will increase the pressing in block, thus reducing the area of action and increasing the intensity of tactical actions to quickly recover the ball (Trapattoni, 1999). Winning status will also reduce the area of coverage acting in block closest to their defensive region. Only in the case of a draw is an equilibrium point achieved, acting in order so as not to suffer but at the same time with the opportunity to score. Such behaviour increases the coverage area of defensive pressing to exploit the counter-attacks.

The comparison between 1st and 2nd halves showed that the greatest area in all regions of defensive pressing was higher in the 1st half. This is in line with a previous study that measured the weighted stretch index and effective area of play in football matches (Clemente et al., 2013a). In this study a large amount of effective area of play and weighted stretch index in 1st half was found. Such results suggest that the fatigue effect may determine the collective organisation of football teams.

Regarding the number of defensive triangulations for each region, it was found that in winning status a team had the highest statistical average of triangulations in the 1st and 2nd midfield regions. This is a truly interesting result because it suggests that higher pressing in the midfield region can be associated with successful results. Nevertheless, such a sentence must be inspected in depth through further studies with a larger number of matches. Another interesting result involves the differences between the 1st and 2nd half. The number of triangulations was higher in the 2nd half of the midfield and forward pressing regions. Such a result in interesting because the greater coverage area was covered in 1st half. Such results may thus suggest that cooperation is higher in the 2nd half (due to the number of triangulations) but it is performed in a closest way (reducing the total of coverage area per region).

In sum, this study showed that greater defensive pressing occurs in the midfield region than in forward or backward regions. Moreover, it was found that the specific team analysed used a balanced distribution between defenders, midfielders and forward tactical missions throughout whole defensive instants. The greatest amount of defensive coverage was found in the 1st half although the greatest number of defensive triangulations were in the 2nd half.

7.4.2. Sectorial Lines

Starting from Gréhaigne's idea (1992) it was possible to develop a concept to use the study of axes throughout all match. This kind of information can be very useful for coaches and analysts particularly in the fundamental phases of a game. One of these phases is the defensive, where players must be synchronised to perform a cycle of compensations (defensive coverage) to avoid instances where a teammate is overcome. In fact, during the matches these lines of protection are truly important to ensure the protection of the team's goal. Therefore, three sectorial lines were developed: *i*) defensive line (incorporating the players in defensive positions); *ii*) midfield line (incorporating the players in midfield positions); and *iii*) forward line (incorporating the players in forward positions).

Using a correlation test it was possible to observe that the synchronisation between the three sectorial lines is very small. Such information leads to a specific behaviour of football players in each sector to achieve the main goal of team. In fact, the oscillations between the sectorial lines may be a specific indicator determined by the specific missions of each tactical position. In that sense, it is important to consider further studies in the future that study how these specific lines interacts throughout match and may be add a another variable such as the ball to determine the rules that are beyond of this specific behaviour. Moreover, it would be interesting to analyse how sectorial lines of different teams reacts to the lines of opponents.

Besides the correlation between sectorial lines, the influence of possession of ball status on the sectorial lines variation was inspected. It was possible to observe that in the moments of possession of the ball, the angle of defensive line was reduced and approach the neutral point (right angle to the field). The inverse occurs in the forward line. In fact, the angle of the forward line increases during the moments of possession of the ball. This would make sense. In the moments of possession of the ball, teams generally opt to exploit one side of the field. Such behaviour is due to one player moving the ball towards the side of the field while the other forward tries to follow such movement. Thus, the wing forward moves the ball and the remaining forwards are behind the line of the ball, thus increasing the gradient of the line. On the other hand, in the case of possession of the ball, the defenders move forward in a right line trying to anticipate the counter-attack. This line is used to put the opponent offside.

Despite these findings, this study had some limitations mainly in the sample size. The main goal of this study was to propose three new methods of match analysis for tactical behaviour, using three case study matches as a proof of concept. Further studies must be done using more analysed matches, as well as simultaneously using other tactical metrics such as effective area of play or weighted stretch index to correlate all metrics and better understand the collective organisation. It would be interesting to identify how teams vary their tactical missions and defensive area of play throughout a match in accordance with different momentary scores.

7.5. Conclusion

Three tactical metrics were proposed in this study, based on players' positions. The methodology to estimate the momentary tactical mission allowed an understanding of the variation of tactical missions and player distribution throughout a match. The defensive play area metric allowed identification of the defensive pressing coverage per region of acting. The triangulations of defensive pressing metric showed how teammates interact to generate the pressing area. The concept of sectorial lines that determines the players' interaction within their tactical region was developed. It was possible to propose a method to estimate the players' tactical mission throughout the match and, based on such information, to compute the sectorial lines. From these metrics was possible to propose a set of new metrics that can help coaches to use information provided by tracking methods such as video-tracking or global positioning systems, to increase the available information about the collective behaviour of football teams. Using these metrics it will be possible to characterise the defensive processes of teams and to optimise sports training in accordance with the information generated from those metrics.

7.6. References

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Chapter VIII

General Discussion

Chapter based on the following publication:

Clemente, F. M., Couceiro, M. S., Martins, F. M. L., Mendes, R. S., & Figueiredo, A. J. (2014). Practical implementation of computational tactical metrics for the football game: Towards an augmenting perception of coaches and sport analysts. In Murgante, B., Misra, S., Rocha, A. M. A. C., Torre, C., Rocha, J. G., Falcão, M. I., Taniar, D., Apduhan, B. O., & Gervasi, O. (Eds.), *Computational Science and Its Applications – ICCSA 2014* (pp. 712-727). London, UK: Springer.

8. General Discussion

In this chapter an overview of the entire study will be given. This will present a global view of the thesis. The main practical applications for match analysis will be discussed, with reference to the main findings. Also, a new integrated vision of the future of match analysis, based on the concepts of data retrieval, processing and visualization, will be proposed. In the end of this discussion there will be a look into the future of new research in this specific field of study.

8.1. Overview: Summarizing the main findings

This thesis is composed of six original research articles exclusively dedicated to the match analysis of a football game using Cartesian information about players' positions on the field. Five of the articles present new metrics to inspect the spatio-temporal relationship between teammates and to analyse the collective performance of football players during official matches. The main conclusions of each part of the study will be discussed in order to achieve an integrated and global perspective.

The first study (Chapter 2) presents a methodological approach to overcome the issues of manual and automatic tracking. In fact, estimation of players' location in each second was conducted. Thus, it was necessary to identify some ways of optimising the manual tracking and to provide some recommendations for the future of automatic tracking. In order to do this, comparisons were made with the position-based and velocity-based methods of the Fractional Calculus (FC) that have a 'memory' property to estimate the future. The experimental evaluation shows that the FC had the highest accuracy for small sampling periods, especially over long periods of time. This information is very important to solve issues such as the occlusions that occur during a match. Moreover, by using this method, it is also possible to estimate the next position of the players, thus ensuring the tracking and recognition of the right player. Using this methodological approach it was possible to optimize the tracking procedure of football games that was necessary for all the experimental studies of this thesis. Using the FC approach, it was possible to develop an in depth study that used the α and β coefficients of FC over time to assess the variability and predictability levels of each player during a match, by determining the tactical region of each player and the frequency with which each player returned to their tactical region (Couceiro, Clemente, Martins, & Tenreiro-Machado, 2014).

By estimating the location of players on a field over time, it was possible to propose and to compute a set of metrics to analyse the teammates' spatio-temporal relationships. The first study that analysed the teammates' synchronization was performed on Chapter 3. In this study an update of the known tactical metrics used until this time was proposed. In order to update the Centroid and Stretch Index metrics it was proposed to assign a weight to each player based on their proximity to the ball. The bigger weights were assigned to the players closest to the ball for each second of useful play. This approach made it possible to introduce the Goalkeeper strategic position into those metrics In Chapter 3 the use of a completely new metric was proposed to replace the Surface Area. Based on the concept of effective triangulation, it was possible to compute the Effective Area of Play (EAP). This approach makes it possible to identify the proximity of teammates during defensive moments, based on the triangulations performed, thus giving the analyst an efficacy indicator.

The four metrics (Centroid, Stretch Index, Surface Area and EAP) were computed during official matches to observe their variation based on some variables. It was found that all metrics increased during moments of possession of the ball. Moreover, it was also possible found that the values of such metrics had decreased from the first to the second half. We believe that it is possible that fatigue could be part of the explanation for such result. Despite the statistical evidence, the metrics proposed in this study suggested that the collective organization can be assessed using metrics based on the positional information about the game. These metrics are based on teammate interaction (with the exception of the EAP). Chapter 4 assesses the occupation of each region of the field and identifies the interaction between opponents.

In Chapter 4 the use of a territorial domain was proposed to identify the numerical relationship between opponents in specific regions of the field. This metric was developed to identify the regions with higher levels of variability and those where the teams could increase their protection or attain a numerical advantage. It was possible to observe that teams generally opted to ensure that they had a numerical advantage in the central defensive region. Moreover, it was also possible to observe that the highest variability of numerical relationships occurred in the central midfield region.

Such results can be justified by the specific properties of each region. In fact, the rapport of strength within the midfield area means that control of the game is a fundamental feature of this sector. Therefore, it is natural that each team makes every effort to ensure a good numerical status in this specific region. Thus, we believe that this metric can be an important indicator, mainly in young players of how they can act as part of a more strategic and organizational plan. In Chapters 3 and 4 was possible to identify interesting solutions to assess the collective organization. Nevertheless, it was also possible to identify that the specificity of the information retrieved was not enough for the specific requirements of a football game. In fact, such metrics (in Chapters 3 and 4) can be used in any invasion team sport. Therefore, Chapters 5 and 6 were developed to assess the specific tactical behaviour of football players.

In Chapters 5 and 6, making an automated version of regular semi-automated systems of football analysis was proposed. Based on the five attacking principles of football game, it was suggested that monitoring tactical behaviour based on the motion profile of each player would be useful. The ratios of efficacy that assess the frequency of accomplishment of each principle of play were taken into account here. Using such an approach, it was possible to conclude that the studied team had high ratios in the majority of principles of play. Nevertheless, between the ratios of coverage in support and coverage in vigilance, it was possible identify a higher tendency to provide coverage of vigilance, thus suggesting a more direct style of play rather than one based on circulation and short passes. These tactical metrics make it possible to estimate the accomplishment of principles of play and can be an interesting solution to post-math analysis. Nevertheless, to use them during games it is necessary to use some visualization solutions that decrease the quantitative analysis and introduce some qualitative indicators. Thus, to enhance the analysts' visualization during games and to provide specific information about the defensive behaviour of football teams, the metrics of Chapter 7 were proposed.

A method to identify the momentary tactical mission of each player and two tactical metrics were proposed in Chapter 7. The momentary tactical mission was proposed in order to identify the specific strategic position (defender, midfielder or forward) in any given moment of play. Such an automatic approach was linked to a proposal for a Defensive Play Area to assess the defensive pressing of teams. This defensive pressing was classified with regard to different regions based on the triangulations performed between the different momentary tactical missions. The defensive pressing was assessed in the global area covered and also in the number of triangulations involved in performing such pressing. Along with the Defensive Play Area, Sectorial Lines were proposed. This metric allows the identification of an angular relationship between three positions (defensive, midfield and forward). It was possible here to identify the area with the highest coverage, while defensive triangulations were performed in the midfield regions. Moreover, it was also possible to see that the sectorial lines were not strongly correlated, suggesting some autonomy of the sectors of play.

These findings results in a solid and consistent contribution to the future of match analyses. In fact, the technological advances lead us towards new visions of the future. In that future, the autonomy of the systems and devices will be extremely important. Thus, all of these metrics are based on the principle of automated systems that depend on tracking information. The use of these systems depends on their practical contribution and the user-friendly processes involved. Therefore, the practical application of each metric needs to be discussed, as well as the new concept of an integrated and automated match analysis system. These important discussions need to be carried out in the following sections 8.2 and 8.3.

8.2. Practical Applications for Match Analysis

Performance analysis seeks quantitative and qualitative methods that help to identify, characterise and estimate human performance during sports activities. In football, match analysis aims to assess the collective performance of players during the games, to identify patterns of play and the weakness and strength of players' synchronisations.

Over the past few years, a great amount of analysis has been traditionally collected using paper-and-pencil notations (Barreira, Garganta, Castellano, & Anguera, 2013). Moreover, until recently the great focus of match analysis was to characterise individual actions, using notational analysis to measure the number of passes, shots or balls lost (Hughes & Bartlett, 2002). Nevertheless, the final outcome comes from a complex and dynamic process of inter-players relationships (Duarte, Araújo, Correia, & Davids, 2012). Therefore, observing the outcomes is insufficient to characterise a complex team's behaviour. Thus, a new vision for the complex process underlying team behaviour is necessary.

In the last few years, new approaches for match analysis have been proposed, mainly supported by new technological advances. Now, it is possible to look for match analysis through different conceptions. It is still possible to use the traditional notational analysis of paper-and-pencil or semi-automatic systems. Nevertheless, the new collective analysis based on computational systems paves the way for new methods of match analysis.

Briefly, it is possible to use semi-automated systems or even totally automated systems. Obviously, the data collected and the data processing are necessarily different from system to system. The present paper makes some contributions to both systems of the match analysis process.

8.2.1. Contribution of semi-automated systems for match analysis

The semi-automated system depends on a human operator who controls and records the necessary data. The semi-automated system helps the human operator to collect, store and treat the data. Nevertheless, the human operator has a preponderant influence during all the process. It is possible to identify analysis that comes from semi-automated systems: *i*) tactical performance of players; *ii*) network analysis of teammates; and *iii*) *t*-patterns of collective interaction.

One example of tactical analysis using the semi-automated system is the *SoccerEye* (Barreira et al., 2013; Barreira, Garganta, Guimarães, Machado, & Anguera, 2014). This system is a software tool for observing, recording and exporting motion data to multiple formats (Barreira et al., 2014). Such a system provides two different recording designs (Barreira et al., 2013): *i*) restricted recording (the observer is able to select the active categories such as the situational variables and the behavioural, spatial and interactional events); and *ii*) open recording (the observed defines the observational categories of interest). In terms of this method, it is interesting to inspect the tactical behaviour of football teams. Nevertheless, each category has specific criteria that must be known by the observer. Besides background requirement about the knowledge of observational methodology, the recording process occurs during all match visualisation consuming much work and time.

The other semi-automated system is the network analysis (Lusher, Robins, & Kremer, 2010). Usually, the network analysis is performed by recording the interaction between teammates throughout the match (Bourbousson, Poizat, Saury, & Seve, 2010). Such interaction can be defined by a linkage variable such as the passes between teammates (Bourbousson et al., 2010), the displacements (Passos et al., 2011) or the defensive coverage (Duarte et al., 2012). There is as yet no specific semi-automated system exclusively dedicated to network analysis. The works which performed network analysis used paper-and-pencil notation or even a general semi-automated system such as Amisco©. Nevertheless, in all cases, it is necessary to build an adjacency matrix where the entries represent the linkage between teammates (Martins, Clemente, & Couceiro, 2013). By using such a matrix and giving to it a weight (Horvath, 2011), it is possible to compute a set of network metrics that characterise the relationship within the team, as well as identify the prominent players in the attacking or defensive strategy. The potential and practical applications of network analysis are too great. It is possible to understand the inter-relationship dynamics in the team, identify the players that highly contribute to the defensive or attacking process or even to characterise some clusters in the team. Such information can be very useful for coaches during the training process or even in matches. Nevertheless, the user's building of the matrix of cooperation requires much time and work, thus the possibilities to use in an online-fashion are too low. Thus, the potential is mainly for post-match analysis.

The last semi-automated system is the *t*-patterns (Magnusson, 1996). Such analysis is used to assess the temporal patterns that occur during the teammates' interaction. These temporal patterns can be detected by using a specific algorithm of the THEME software (Magnusson, 2000). To inspect the *t*-patterns of football teams a dedicated software was built called SOF-CODER (Jonsson et al., 2006). This software consists of manual coding. The coding depends on the user's work, which occurs during the digital match visualisation. Thus, the SOF-CODER is a tool that is used both for observation and recording processes (Jonsson et al., 2006). The *t*-patterns are computed using the THEME software. The outcomes provided by the *t*-patterns recognition are actually interesting, thus giving to the observer an estimation of teammates' patterns of interaction. This information can be useful to detect some patterns of play in a team, to identify its properties of attacking build. Once again, the weakness is the time spent during the data collecting and processing. In fact, the human operator is required to perform the data collection, making it too difficult to carry out such analysis during matches (online).

In sum, in all semi-automated systems previously presented, the recording process still needs the user's selection. It seems obvious that these systems are better than the traditional paper-and-pencil process. Moreover, their practical applications are huge; they can be used in any situation, only requiring the software and the video-recording of a match. Thus, any coach or analyst can use such a system to observe a team's behaviour even an amateur team. Moreover, the information collected is specific to a football game in accordance with the specific principles of play. Nevertheless, the great amount of time spent on observation is an advantage. The online observation (during a game) is also very difficult due to the complexity of data recording and process. Thus, despite the many advantages and practical applications of these semi-automated systems for football, match analysis still awaits quick, automatic and user-friendly systems.

8.2.2. Contribution of automated systems for match analysis

Novel estimation, detection and identification techniques have been recently applied on sports, providing the Cartesian positional information of players over time. This information has been seen as vital within sports science's literature, so as to propose new computational tactical metrics that may allow to inspect the spatio-temporal relationship between teammates. Such technological approaches can improve the understanding of the collective match, providing to coaches and analysts a real-time augmented perception of the game. In that sense, this thesis aimed to identify and propose the most promising tactical metrics that can enhance the match analysis in the next years.

It is possible to observe that all these new technological metrics need to be understandable by a great range of coaches and analysts. In fact, the user-friendly system must be the essence of such metrics. Moreover, the opportunity to collect simple and pertinent information should be taken into account for the system to be generalised by all the football community. There must be a threshold between the complexity of such metrics and the applicability of information for coaches and analysts.

These metrics have a valuable strength in comparison with the semi-automated systems. The use of an integrated system that is totally autonomous from the data retrieval to the data processing allows using such analyses during official matches or even in daily training sessions without a great effort on the part of a human operator. Nevertheless, one main issue can be discussed. In fact, the system depends on an automatic tracking method that is now too expensive for amateur or even some professional teams. Thus, the tracking method must be prioritised in an integrated system. A solution such as a single camera or even a low-cost GPS with heart rate monitor must be considered to reduce the possible costs of such a match analysis system.

Besides the costs of tracking systems, another issue must be discussed in detail: the optimisation of information provided by the spatio-temporal and tactical metrics. In this work, it was possible to identify a set of metrics that have been developed in the last few years. Each of them provides specific information about the collective organisation. Nevertheless, how can such information be used by coaches? This is certainly a priority question.

The first metric proposed in this study is the *w*Centroid. This metric represents the centre-of-mass of the team at a given instant based on the proximity of each player with the ball position. Using such information the coach can identify the strong point of the team at a given moment. This point can be useful to identify the global position of a team during the match. Some studies showed that when the Centroid of a team with possession of the ball overcomes the defensive Centroid, the possibilities to shoot or score increase (Frencken, Lemmink, Delleman, & Visscher, 2011). It was further noted importantly that the *w*Centroid decreases their position from the first to the second half of the match (Clemente, Couceiro, Martins, Mendes, & Figueiredo, 2013b). The authors of this study suggested that fatigue can be one of the causes for such variation (Clemente et al., 2013b). At any rate, the most important information provided by *w*Centroid is identification of the central point of the team, thus representing its global position. In comparison with the opponent's *w*Centroid, it is possible to identify the in-phase or anti-phase pattern with the variation of the opponent's *w*Centroid. Another important pattern that can be detected is the tendency to act on a specific side of the football field.

Using the *w*Centroid, it is possible to extend such an approach to assess the players' dispersion over their centre. Thus, the *w*Stretch Index is proposed to measure the dispersion of players in both attacking and defensive moments. The dispersion of teammates is a very important indicator of collective organisation. In fact, during the defensive moments a concentration behaviour is required where players are closer to each other, trying to reduce the possibilities of penetration. On the other hand, during the attacking moments, the team disperse over the field trying to avoid the opponent's marking and to create opportunities to penetrate and score. Such concentration and dispersion is usually called expansion-contraction behaviour (Moura, Martins, Anido, Barros, & Cunha, 2012). Thus, using the *w*Stretch Index, it is possible to assess the dispersion level of a team and to identify quickly whether it is a regular pattern in attacking or defensive moments. In fact, a development of this metric is to introduce some warning notification for great dispersions during defensive moments or for small dispersions during attacking moments. It is also possible to identify some patterns and characterise the team's dispersion throughout the match.

The concepts of Surface Area and Effective Area of Play were also introduced and discussed during this work. The surface area generates the minimum number of triangulations between all the teammates, thus drawing a polygon that defines the covered area of a team. The original idea comes from Gréhaigne (1992). Using such metric, it is possible to have a similar measure to the *w*Stretch Index. Nevertheless, in this case, the measure is the area covered by all triangulations. However, such information is not enough for coaches mainly to use during matches. In fact, some indicators of efficacy lack surface area. Thus, Clemente, Couceiro, Martins, and Mendes (2013a) proposed a new concept that estimates the triangulations between teammates and also identifies the overlapping triangulations between both teams. To assess the effective triangulations in the overlapping situation, it was proposed a maximal perimeter of defensive triangulations. Thus, the overlapped triangulations with more than 36 *m* of perimeter in defensive moments are considered non-effective because the pressure is too much reduced. Obviously, this one player can recover the ball, but the criteria were generated taking into account the defensive coverage that assumes a greater proximity of teammates to the player in defensive delay process (Costa, Garganta, Greco, & Mesquita, 2009). Using such metric, it is possible to have qualitative criteria mainly during defensive moments. Moreover, the variable of 36 *m* perimeter can be adjusted to the coach's requirement. Such information allows quick identification, using the graphical interface, of the effective triangulations and during a match reorganisation of the collective synchronisation and optimisation of their tactical behaviour (Clemente, Couceiro, Martins, Mendes, & Figueiredo, 2013c).

If the *w*Centroid, *w*Stretch Index, Surface Area and Effective Area of Play can be considered a spatio-temporal metric that evaluates the teammates' synchronisation, the territorial domain was proposed as identifying the numerical relationship between opponent teams within a specific region of the field. This metric was first proposed by Vilar et al. (2013) in a professional football match. The potential of this metric is very interesting as it mainly identifies the strategic distribution of a team and characterises the strength and weakness regions of the field of one team. In this regard, an algorithm was proposed for the seven-a-side game that is used in youth football. In fact, the applications for the coaches of younger teams is fundamental, using this metric to identify whether the players have a rational distribution or whether they play in an agglomerate way. Moreover, such metric can identify how the team acts to reduce the numerical disadvantage in vital regions such as the central defensive area or central midfield.

Besides the previously discussed metrics that can be used in football or even in other invasion team sports (e.g., basketball, futsal, handball), it was proposed a set of metrics that measure the specific football principles of play. A set of criteria using players' location would turn the semi-automated systems into an automatic one. Taking as a reference the Costa et al. (2010) semi-automated system (*FUT-SAT*) to assess the principles of play, it was proposed to develop a full automated attacking metrics inspired in some criteria used by the manual notation. These metrics were also developed based on the information about players' location during the match. Using the criteria to identify the efficacy of the team to accomplish each principle, it was possible to create seven ratios that change during each attacking unit (the instant between the first pass to the loss of the ball).

It was proposed the ratio of penetration, attacking coverage, coverage in support, coverage in vigilance, depth mobility, width and length and attacking unit. All of these metrics assess the efficacy of the team to accomplish during each attacking attempt the fundamental football tactical principles of play. The main findings of these metrics showed that the majority of attacking coverage is performed in vigilance and not in support, thus suggesting that the analysed team opts for a more direct style of play. This suggestion can be enhanced by the great ratio of depth mobility that means a great longitudinal dispersion of the forward players. Another interesting finding was the great ratio of unit principle of play in attacking moments, thus suggesting a notable synchronisation of all teammates with the movement of ball and forward players. These tactical metrics make it possible to define the accomplishment of tactical principles and to identify some specific properties of a team. Obviously, these relative ratios can be complementary information and from a graphical point-a-view are ineffective. In spite of the fragilities during the match, these metrics can provide important information to classify the team's properties after the games.

The last proposed metrics were the defensive play area and the sectorial lines. These metrics were proposed based on the method that estimates the momentary tactical mission of each player in the game. The momentary tactical mission was developed based on the concept that the variability of players' motion determines that their mission is different from the defensive for attacking instants (Couceiro, Clemente, Martins, & Tenreiro Machado, 2014). Such variability implies that their tactical participation can be different from instant-to-instant, i.e., a central defender can act as a striker for a few moments. Thus, it was proposed a method to estimate their momentary tactical mission based on the players' location. This made it possible to define the defensive regions of pressing. These regions were based on manual notation (Seabra, 2010). Thus, different regions of defensive pressing were classified based on the triangulations performed by the teammates and on each momentary tactical mission performed by each player that constitutes the triangulation. It was found that the highest defensive area of pressing was covered in the second half of the midfield region. It was also found that the second highest region of defensive pressing was performed in the first half of the midfield region. Thus, the greatest amount of defensive pressing was performed midfield, a crucial element to be covered in defensive moments. This metric can be an interesting solution to use in an online-fashion, quickly identifying each different region of pressing with different colours. Therefore, their graphical interface with the coach or analyst can be better than the final outcomes.

Besides the defensive play area, it was also proposed the sectorial lines. Such metric uses the information retrieved by the momentary tactical mission to identify the line of play of a given sector. This metric was based on the concept of axes proposed by Gréhaigne (1992) and Lemoine et al. (2005), which was used to define the synchronisation of defensive and attacking axes of a set of players involved in the play in the moments before the shot at goal. In this work, it was proposed to extend the concept of axes to all the team and during all the match using an automatic method. A correlation test was carried out to inspect the synchronisation between the angles of the different sectorial lines (defensive, midfield and forward). It was found a small correlation between the angles of sectorial lines, thus suggesting that each region acts with a relative independence from the other sectors. It was also found that the angle of sectorial lines is more neutral during defensive moments and increases during the attacking moments due to the specific tactical mission performed by the wings' exploitation. Similarly to *w*Centroid, *w*Stretch Index, Surface Area, Effective Area of Play, Territorial Domain and Defensive Play Area, the Sectorial Lines can be graphically used by coaches during a match to enhance the perception about their team behaviour and even about the opposing team.

Obviously, each metric previously discussed has a specific potential in match analysis. Nevertheless, this does not imply that these are better than semi-automated systems. In fact, the information provided by each system (semi- and automated) is particularly relevant to a new era of match analysis. It is now possible to enhance the coaches' information about the tactical behaviour of their team. Moreover, it is possible to provide other information about the physiological (heart rate monitors) and physical responses (time-motion profiles). Thus, a great amount of information is now available for coaches and their staff (Figure 8.1).

Physiological	Physical
Heart rate responses (automated system and online)	Time-motion profiles (automated system and online)

Technical	Tactical
Notational analysis (semi-automated system, available during match with delay)	Spatio-temporal metrics and Tactical metrics (automated system and online) Network and *t*-patterns (semi-automated system, available during match with delay)

Figure 8.1. Possible information to be retrieved during matches or daily training sessions.

Taking into account the above Figure 8.1, it is possible to classify the information available to coaches. Obviously, other information can be automatically measured such as the VO_2max (with portable device). Nevertheless, it was selected in this summary figure the main indicators that can be used during matches and daily training sessions with non-invasive methods and minimal constraint to the players. The indispensable device is the heart rate monitor or even the GPS if no cameras are used for tracking.

The main interest in all of these categories is the automated or semi-automated information that can be of use to a coach, helping him in the decision-making process. Thus, a final question concerns this great amount of information available online: How could all of the information be selected, managed and visualised by a coach during a match or even in daily training sessions in a user-friendly fashion? This issue is considered in the following section.

8.3. Practical Implications: Towards an Augmenting Perception of Coaches and Sport Analysts

The new advances in tracking players can be an effective means of solving the issue of automatic match analysis systems. As mentioned above, there is a set of new automatic solutions that can help to make match analysis a quick and useful process to enhance the perception of coaches and analysts during the match and daily training sessions. All of these automatic metrics only depend on the knowledge of players' location over time. Thus, using the tracking methods available on the market can now overcome the issue of retrieval. The following data processing and visualisation can be the most difficult part of generating a new concept of an integrated match analysis system. Thus this section will present some possibilities and issues which must be taken into account to develop an integrated and automatic match analysis system.

8.3.1. Tracking Methods

In the last few years the computational tactical metrics have been proposed to assess the collective organization and teammates' synchronization (Clemente et al., 2013a). Such metrics are based on the Cartesian information that comes from tracking methods.

Generally, on the football game, tracking methods are based on Global Positioning System (GPS), mainly used during training sessions, and multi-camera systems, mainly used during official matches (Couceiro, Clemente, & Martins, 2013). This is justified by the rules inherent to the *Fédération Internationale de Football Association* (FIFA) does not allow the use of devices during official matches and, therefore, the GPS is not an option (Barros et al., 2007) being mainly confined to training sessions.

Nevertheless, during training sessions the GPS systems are most used due by the low cost and user-friendly devices.

Therefore, to avoid invasive wearable technology, video-based infrastructured solutions have been suggested. These video-based multi-player tracking systems generally require the permanent installation of several cameras strategically located to cover the whole football field (Carling, Bloomfield, Nelsen, & Reilly, 2008). Systems, such as *AMISCO Pro* or *ProZone*, provide online information to coaches and their staff about players' movements (e.g., energy spent by a player). Nevertheless, these systems, and their maintenance, are very expensive as they comprise on more than 8 synchronized cameras. Moreover, the match analysis usually occurs after the game ends due to the amount of information to be cross-processed and analysed.

Some few single-camera alternatives have recently appeared in the context of collective sports. The authors in Santiago, Sousa, Reis, and Estriga (2011) suggested a single IP surveillance camera with a birds-eye perspective. The proposed methodology was only based on colour features by benefiting from several colour image processing techniques, such as background subtraction, blob colour definition and colour blob manipulation, in order to detect the players. As the proposed setup was only evaluated in a small indoor sports scenario (around $600\ m^2$), its applicability to outdoor and larger environments is doubtful. The identification of players under a larger outdoor field (around $8000\ m^2$) only based on colour features is unfeasible, not only due to the distance the camera should be from the field, but also because outdoor environments are commonly associated to variable lighting conditions that considerably affect colours identification. Moreover, due to the difficulty in ensuring a birds-eye (i.e., top-down perspective) in outdoor fields, tracking players is increasingly difficult because of occlusions, i.e., other players or even the referee can obscure the information about a tracked player.

Thus, Dearden, Demiris, and Grau (2006) suggested a way to overcome such issue in outdoor matches by considering multiple state estimates used by a particle filter. This probabilistic approach significantly improve the tracking of players under outdoor conditions. However, the proposed solution is limited to 5 frames per second (fps), thus reducing its applicability in most situations associated within football, such as tracking the ball. Additionally, the authors do not quantify, in terms of accuracy and precision, the estimated measurements over the ground truth.

Regardless on the so far existing tracking methods, data visualization only occurs after the game ends due to the inexistence of an interface that may act as an information medium between teams and coaches (or analysts). Given the recent breakthroughs on augmented reality (AR), this technology presents itself as the most fitted candidate for such interactive interfaces.

8.3.2. Data Visualization: Augmented Reality

Augmented Reality (AR) can be defined as a real-time direct or indirect view of the real and physical world environment that can be enhanced, or augmented, by adding virtual computer-generated information (Carmigniani et al., 2011). AR then supplements the real world with virtual objects that appear to coexist in the same time and space of a given observation (van Krevelen & Poelman, 2010). This is identified as a Reality-Virtuality continuum that comprises both real and virtual environments (Milgram & Kishino, 1994).

AR aims at improving the user's life by bringing virtual information not only to the immediate surroundings, but also to any indirect view of the real-world environment, such as live-video stream (Carmigniani et al., 2011). Therefore, using such information can enhance the user's perception and increase the interaction with real world.

Applications of AR are still growing day after day. The examples can be classified in the following categories (Carmigniani et al., 2011): *i*) advertising and commercial applications; *ii*) entertainment and education; *iii*) medical applications; and *iv*) mobile applications.

However, on sports, there are only a few applications of AR. One of the main applications under this domain was tested on tennis context, using the IBM '*Seer*' to augment the perception of fans during matches. By benefiting from such applications it was possible to observe games occurring in other locations and even to inspect some generic performance indicators (e.g., distance covered by a player). Another similar application dedicated to fans and journalists was developed for the European Championship. In this case, the BBC used the *Viz Trio CGs* software as an AR application to improve the information provided to fans. Nevertheless, both examples were mainly designed for fans.

To enhance the coaches' perception, it is possible to discuss the introduction of such method during daily sessions and games. The possibilities of information provided in real time can actually increases the optimization of training sessions. From the individual data about player's physiological responses, time-motion profiles and individual technique, until the whole real-time picture about the collective organization, the possibilities on applying AR to enhance coaches' perception are massive. It is, however, noteworthy that the available information will always depend on the number of devices and data collected during training sessions and matches.

Let us provide some examples of possible applicability. Nowadays, one of the main interest for performance optimization is to analyse the heart rate variations to measure the training workload during the training sessions. Complementarily, one should be also capable of characterizing the time-motion profile of each player. Both data depends upon two different devices. In the case of the heart rate, it is necessary a heart rate monitor that permanently measure the beats per minute of player during the sessions. This information is of vital importance to regulate the training workload and would inevitably require wearable technology. For the case of time-motion profiles, there are two main devices or techniques that can be used, as previously discussed: *i*) Wearable technology (GPS, RFID, among others); and *ii*) Video-camera tracking. Usually, and as previously addressed, GPS is the most used during training sessions. All the information is collected from different devices with different software. Therefore, the main challenge is to incorporate such informations in the same user-friendly application for coaches. Moreover, the GPS that it is used to characterize the time-motion profiles of football players can also be used to assess the collective organization, thus introducing another whole set of variables in the integrated system.

Despite the difficulties in collecting data, mainly associated to the tracking of players, the major challenge is to select the data and build the system as an intuitive application that can be permanently used by coaches and analysts during the sessions and games. In that sense, another question emerge from this point-a-view: "How information arrives to coaches?"

There are four main devices for required to apply augmented reality concepts (Carmigniani et al., 2011): displays, input devices, tracking and computer. Let us mainly discuss the displays that can be used on football analysis.

In the case of displays there are three major types (Carmigniani & Furht, 2011): *i*) head mounted displays; *ii*) handheld; and *iii*) spatial displays. The head mounted displays is a device worn in the head (AR glasses) that place both images of the real and virtual environment on the user's view (e.g., *Google Glasses*). The handheld displays employ small computing devices (smartphone, PDAs and Tablet PCs) with a display that the user can hold in the hands. Finally, the spatial displays make use of video-projectors, optical elements, radio frequency tags and other technologies.

In terms of real-time match analysis from coaches and staff, the possibilities are limited to head mounted devices or, as an alternative, handheld solutions. Both have some shared weakness and strengths for daily using. The use of handheld displays allows to overlay graphics onto the real environment and easily employ sensors, such as digital compasses or GPS units (Carmigniani & Furht, 2011). Nevertheless, during training sessions or even during matches, the amount of information to be consulted can be considerably high which may reduce the direct coaches' interaction with the environment. Moreover, the use of handheld displays do not offer a practical solution to perform typical actions during training sessions or matches. On the other hand, head mounted displays, such as glasses, can offer a more user-friendly display to coaches. Among the several technologies, glasses display that benefit from an optical-see-through solution can be the best solution for practical applications than video-see-through. The optical-see-through employs a half-silver technology that allows to view the physical world to pass through the lens. New devices, such as *Google Glasses*, are one of the optical-see-through systems. Figure 8.2 depicts a potential applicability of the proposed metrics by benefiting from AR glasses interface with the user's view of a football game. In this example, the user can visualize the teams' effective area of play being generated in real-time.

Figure 8.2. Example of an AR glasses interface with user's view during the interruption of match.

It is important to expect interaction from the user (coach) with the device. Therefore, the selection of variables and information must be consistent with an easy-to-use interface. There are some hypothesis, such as speech recognition or glove-based and vision-based hand gesture (van Krevelen & Poelman, 2010). In the specific case of football application, the speech recognition may be the most adequate solution to avoid taking the eyes from the game or training drills.

Despite all these benefits, the AR system have a considerable amount of information to be exchanged and processed (van Krevelen & Poelman, 2010). In that sense, the data computing and storing must be carefully discussed to optimize an integrated match analysis system that ensures the data retrieval, processing and visualization.

8.3.3. Data Computing and Storing

In the specific cases of mobile and collaborative AR systems, one requires suitable networks to support data retrieval and multi-user interaction. Hence, the overall solution should benefit from the concepts of cloud computing to distribute the computation load between remote servers. With this type of approach one can significantly reduce the computation and communication effort associated with mobile AR systems (Behringer, Tam, MCGee, Sundareswaran, & Vassiliou, 2000).

Some important issues and challenges around cloud computing must be taken into account (Zhang, Cheng, & Boutaba, 2010): *i*) automated service provisioning; *ii*) virtual machine migration; *iii*) server consolidation; *iv*) energy management; *v*) traffic management and analysis; *vi*) data security; *vii*) software frameworks; *viii*) storage technologies and data management; and *ix*) novel cloud architectures.

Although some of these challenges have been considerably mitigated over the past few years, the still non-pervasive internet services make some of those ongoing problems. Regardless on that, the number of works applying concepts inherent to cloud computing in the sports context is low or almost inexistent. For instance, the authors (Hong-jiang, Hai-yan, & Jing, 2013) proposed a sports training auxiliary system design concept based on cloud computing. The authors followed the typical hierarchical service model architecture, in which infrastructure, platform and software are seen as services. Despite the insights provided by the work, the position paper does not presents any details nor discusses the real challenges associated with the technology. Thus, there is a long journey to travel in this specific issue.

8.4. Looking to the Future

The discussion about the implications of tactical metrics for coaches and how information can reach coaches and analysts was based on some suggestions for future research on an integrated match analysis system.

It is possible to highlight in this section two main suggestions: *i*) future research for Sports Sciences; and *ii*) future works on technological advances.

Based on the practical applications, it is possible to cross information on multiple systems of analysis trying to enhance the understanding of collective behaviour in football teams:

- The semi-automated system of network and *t*-patterns can be automated. This can be used to determine the highest proximity of the ball with a given player and to inspect the continuum of play. Thus, the system automatically identifies the player in possession of the ball as well as the trajectory of the ball of the other teammates. Some issues can be found because at the moment that one player tries to overcome the opponent, the ball can be closest to the opponent than the player in possession of the ball. Nevertheless, to avoid this, it is possible to use the Fractional Calculus to predict the continuity of play based on memory. In the case of a player losing the ball, the Fractional Calculus can recalibrate after a few frames.
- By using the information of network and *t*-patterns in real time and crossing with tactical metrics, the team's properties in attacking and defensive moments can be defined. In defensive moments, the information on the effective area of play, defensive play area and sectorial lines can be optimised, giving the coach a new perspective on the triangulations performed in the moments without possession of the ball, as well as being of interest for future research questions. How do the effective area of play, defensive play area and sectorial lines vary based on different score status during the match? In losing status do the team increase their defensive pressing into further areas? Does wining status decrease their defensive pressing and increase the effective area of play? Moreover, the network in defensive moments can be of interest for using the variable of defensive coverage, i.e., the coverage provided by one teammate to another. This can be the variable to define the connection. Such information helps in identifying the relationship system of the team during the defensive moments that explains the effective area of play, defensive play area and sectorial lines.
- In attacking moments the information about the *w*Centroid, *w*Strecth index and Tactical Principles of Play can be crossed with the automated network

and *t*-patterns. It would be interesting to identify the players who most contribute to the collective organisation of the team. Moreover, it would be relevant to identify the connectivity of players and the clusters that contribute to achieving the higher efficacy of principles of play. Such information can provide useful information to characterise the team's properties and the kind of collective organisation that emerges from the football game. Some research questions can be considered using these indicators: How do the clusters within the team influence the *w*Centroid and *w*Stretch Index? How does the collective organisation vary from match-to-match and against different levels of competition? These research questions require a large amount of data collecting as sample such as a full season.

- Trying to aggregate all metrics would be important in order to follow one single team during a full season in all kinds of competition. Some research questions can emerge from this largest data: How do the team vary their tactical performance from competition to competition, and in games home and away? How does the teammates' connectivity change during the whole season? Are the patterns of play area regular from match to match or change based on different constraints? Does the competition level of opponent play influence the tactical performance and players' connectivity? All of these questions and more can be answered using the tactical metrics and the other automated systems that allow in-depth knowledge about the team's properties.
- One final question concerns crossing other kinds of performance variables such as biological, physiological, physical or even social. How does friendship within the team contribute to the network during a match? There are any relations between both indicators. Another interesting aspect can be to cross the physiological responses and physical effort with the tactical performance. How can fatigue influence tactical performance? Or how can the tactical performance influence the players' effort? Can the biological maturation influence the team's network and the highest participation of the more mature players? Can the style of play influence the highest velocity and acceleration or even the kind of effort profile? All of these questions can generate whole research questions based on multiple performance variables that can contribute to a better understanding of the game of football.

Besides the research questions that emerge in sports sciences, a new practical and commercial contribution can emerge from this work. An integrated system of match analysis may allow a new vision to optimise sports training and games preparation. Thus, a set of suggestions can be presented for a new technological concept of match analysis:

- A new integrated system must be user-friendly and contribute to integrating all kinds of performance information. Thus, the main issue to be solved is how to integrate within the same system the physiological responses, physical profile and technical/tactical performance. These indicators can be inspected online, and thus can be used in matches and daily training sessions. To inspect all of these items, it is necessary to have a heart rate monitor to measure the physiological effort and to use a GPS system or digital camera to track the players' motion over time. The GPS system can be more effective in daily training sessions due to the easy-to-use process. Nevertheless, in official matches, the use of devices is not allowed, thus the tracking must be performed using one single camera to reduce the costs of such analysis in comparison with multiple-camera tracking. Ideally, the best technological advance would be an undershirt that incorporates all necessary components without visible devices including a heart rate monitor and GPS system. Another solution would be to use a biochemical marker to identify the players' location, although such an approach needs an infra-red system which does not allow assessment of heart rate responses.
- The visualisation of all the performance variables can be carried out using the Augmented Reality. To do this, we propose a head mounted displays solution based on the optical-see-through system. Thus, the Augmented Reality glasses can be the best solution to provide all information to coaches and analysts. The coach can select the information to visualise during the whole match and daily training session, and with this selection process can be promoted speech recognition.
- The glasses must employ a half-silver technology that allows viewing the physical world through the lens. Such an approach allows a coach to visualise the game or training with his own eyes. However, every time that he wants to

select the information, the performance variables will appear in the right or left superior corner of one lens.

- The variables can be individually selected or connected by the user. The connection of multiple information at the same time implies a simplification of each variable. Moreover, it is possible to define the visualisation in a collective way or player-to-player. Such an option can be defined by the user during the visualisation. Therefore, a complex display must be performed to contemplate all of these possibilities.

In sum, all of the research questions and the technological recommendations can contribute to an optimised system of match analysis. This work is only the beginning of a new era for match and performance analysis in sports sciences and in particular the game of football.

8.5. References

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Appendix A

LIST OF PUBLICATIONS AND COMMUNICATIONS FROM THE PHD STUDIES

APPENDIX A. LIST OF PUBLICATIONS AND COMMUNICATIONS FROM THE PHD STUDIES

Published and Accepted Papers in Journals indexed on Thomson Reuters and Web of Knowledge

Clemente, F. M., Couceiro, M. S., Martins, F. M. L., Mendes, R. S., & Figueiredo, A. J. (ahead-of-print). Soccer team's tactical behaviour: Measuring territorial domain. *Proceedings of the Institution of Mechanical Engineers, Part P: Journal of Sports Engineering and Technology*, doi: 1754337114547064 [Issue: Spatio-temporal relationshiph]

Clemente, F. M., Martins, F. M. L., Couceiro, M. S., Mendes, R. S., & Figueiredo, A. J. (2014). Inspecting teammates' coverage during attacking plays in a football game: A case study. *International Journal of Performance Analysis in Sport*, 14(2), 384-400. [Issue: Tactical Metrics]

Clemente, F. M., Martins, F. M. L., Couceiro, M. S., Mendes, R. S., & Figueiredo, A. J. (ahead-of-print). Evaluating the offensive zone definition in football: A case study. *South African Journal for Research in Sport, Physical Education and Recreation*, 37(1), pp. [Issue: Tactical Metrics]

Clemente, F. M., Couceiro, M. S., Martins, F. M. L., Mendes, R. M., & Figueiredo, A. J. (ahead-of-print). Using collective metrics to inspect spatio-temporal relationships between football players. *South African Journal for Research in Sport, Physical Education and Recreation*, 36(2), pp. [Issue: Spatio-temporal relationshiph]

Clemente, F. M., Couceiro, M. S., Martins, F. M. L., Figueiredo, A. J., & Mendes, R. S. (2014). Análise de jogo no futebol: Métricas de avaliação do comportamento coletivo. *Motricidade*, 10(1), 14-26. [Issue: Spatio-temporal relationshiph]

Couceiro, M. S., Clemente, F. M., Martins, F. M. L., & Tenreiro Machado, J. A. (2014). Dynamical stability and predictability of football players: The study of one match. *Entropy*, 16(2), 645-674. [Issue: tracking optimization]

Clemente, F. M., Couceiro, M. S., Martins, F. M. L., Mendes, R., & Figueiredo, A. (2013). Measuring the tactical behaviour using technological metrics: Case study of a football game. *International Journal of Sports Science & Coaching*, 8(4), 723-740. [Issue: Spatio-temporal relationshiph]

Clemente, F. M., Couceiro, M. S., Martins, F. M. L., Mendes, R., & Figueiredo, A. J. (2013). Measuring collective behaviour in football teams: Inspecting the impact of each half of the match on ball possession. *International Journal of Performance Analysis in Sport*, 13(3), 678-689. [Issue: Spatio-temporal relationshiph]

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Couceiro, M. S., Clemente, F. M., & Martins, F. M. L. (2013). Analysis of Football Player's Motion in View of Fractional Calculus. *Central European Journal of Physics*, 11(6), 714-723. [Issue: Tracking Validation]

Clemente, F. M., Couceiro, M. S., & Martins, F. M. L. (2012). Towards a new method to analyze the Soccer Teams Tactical Behaviour: Measuring the Effective Area of Play. *Indian Journal of Science and Technology*, 5(12), 3792-3801.

Submitted Papers in Journals indexed on Thomson Reuters and Web of Knowledge

Clemente, F. M., Couceiro, M. S., Martins, F. M. L., Mendes, R. S., & Figueiredo, A. J. (submitted). Inspecting the collective behaviours: A survey for football teams. (Issue: Survey)

Clemente, F. M., Couceiro, M. S., Martins, F. M. L., Mendes, R. S., & Figueiredo, A. J. (submitted). Developing a tactical metric to estimate the defensive area of soccer teams: the defensive play area. (Issue: Tactical Metrics)

Published and Accepted Papers in Journals not indexed on Thomson Reuters and Web of Knowledge but with Peer-review

Clemente, F. M., Couceiro, M. S., Martins, F. M. L., & Mendes, R. M. (2013). Novas abordagens da avaliação do comportamento tático no futebol: Análise do centroid e índice de dispersão. *Revista da Educação Física/UEM*, 24(4), 681-694.

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Conference Proceedings

Martins, F. M. L., Clemente, F. M., & Couceiro, M. S. (2013). From the individual to the collective analysis at the football game. In *Proceedings Mathematical Methods in Engineering International Conference* (pp. 217-231). Porto: Instituto Superior de Engenharia do Porto.