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Modeling intra- and inter-team spatial interaction patterns in invasive team sports

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Abstract

Team sports games are recognized as dynamic systems of interaction, where individual and collective patterns of behavior emerge from a confluence of multiple organismic, environmental and task-related constraints on the players. Researchers have been interested in studying the dynamic interaction of these many degrees of freedom for at least two decades considering various methods, approaches and techniques. In this thesis we aimed to provide a fruitful contribution in this area of research presenting innovative methods of analysis that overcome some identified methodological limitations in measures that are often considered to (1) assess the complexity of behavioral dynamic systems (ApEn) and (2) to describe the spatial interaction behavior of a team.

Regarding the first issue, we have defined normalized measures of the original ApEn to measure, and compare, the regularity of signals generated from any behavioral system. These were tested and validated using two well-known data series of regular (sine) and irregular (random) behavior. As for the second issue, we developed two new models, Voronoi diagram (VD) and Superimposed Voronoi Diagram (SVD), from which strong candidates to collective variables were derived: from the VD model we defined the size of the dominant region (DR) and, from the SVD model, the percentage of free area (%FA) and the maximum percentage of overlapped area (Max%OA). Given that %FA that is largely dependent on the distance between each pair of exclusive opponents, we have conjectured SVD patterns for two specific rules of dyadic interaction: (1) exclusive pairing and (2) random interaction. While the former rule was thought to be associated with a specific defensive method, the man-to-man defense, the second rule is associated with a reference spatial pattern used for analysis purposes. Patterns simulated under each of these two rules, and according to the settings in the

observed tasks (5 vs 4+GK in a limited play area of 20×20m^2), were considered to generate reference values of %FA. As for the Max%OA, data from simulated SVD patters have shown that this variable is inversely associated with the number of opponent neighbors, i.e., the more the opponents the smaller the Max%OA.

Results from formal applications of the described methods have suggested the following: (1) having considered data signals from the collective variable that describes the dyadic sub-system in rugby union, we found that the physical contact between the players (tackle) increases the complexity of the emergent behavior, making this more predictable in try situations; (2) in Futsal (5 vs 4+GK in a limited play area of 20×20m^2), the size of the DR was measured to assess how teams manage space – the attacking team has presented greater DR than the defending team throughout the task, also, the attackers presented a more regular spatial behavior, which means spatial behavior of the team defending is more unpredictable; (3) the %FA has captured the presence of low levels of exclusive dyadic interaction when the defense team has numerical disadvantage; (4) the Max%OA was able to identify the attacker under more pressure.

Key words: ApEn, Voronoi diagrams, Superimposed Voronoi diagrams, team interaction behavior, collective variables

Resumo

Jogos desportivos colectivos podem ser considerados como sistemas dinâmicos de interação, onde padrões de comportamento individual e coletivo emergem de uma confluência de vários constrangimentos (indivíduo, ambiente e tarefa) na acção dos joagadores. Há pelo menos 20 anos, os investigadores têm-se interessado pelo estudo da interação dinâmica desta multiplicidade de graus de liberdade, considerando para tal vários métodos de análise, abordagens e técnicas. Pretende-se que o trabalho apresentado nesta tese constitua uma contribuição frutífera para esta área de investigação, sendo aqui apresentados métodos inovadores de análise que pretendem superar algumas limitações metodológicas identificadas nas medidas que são muitas vezes consideradas (1) para avaliar a complexidade de sistemas dinâmicos (ApEn) e (2) para descrever o comportamento de interação espacial entre equipas.

Quanto à primeira questão, foram aqui propostas medidas normalizadas de entropia aproximada (ApEn) para medir e comparar a regularidade de sinais gerados por qualquer sistema comportamental. Estas medidas foram testadas e validadas considerando séries de referência para comportamento regular (função seno) e irregular (função geradora de números aleatório). Quanto à segunda questão, foram considerados dois novos modelos de análise, os diagramas de Voronoi (DV) e os Diagramas de Voronoi Sobrepostos (DVS), dos quais foram derivadas medidas candidatas a variáveis coletivas: a partir do modelo DV definimos a área da região dominante (RD) e, a partir do modelo DVS, a percentagem de área livre (AL%) e máxima percentagem de área sobreposta (Max%AS). Dado que a AL% dependente da distância interpessoal de diades exclusivas, conjecturamos padrões DVS de acordo com duas regras de interacção diádica: (1) emparelhamento exclusivo e (2) interacção aleatória. A primeira regra está teoricamente associada ao método de defesa homem-a-homem e a segunda regra está associado a um padrão de referência espacial utilizado para análise. Foram simulados padrões de distribuição espacial sob estas duas regras, e de acordo com as características da tarefa em estudo (5 vs 4 + GR numa área de $20{\times}20m^2$), para gerar valores de referência da AL% para as duas situações. Quanto à Max%AS, os dados simulados evidenciaram uma relação inversa com o número de adversário vizinhos, ou seja, quanto maior o número de vizinhos adversários, menor a Max%AS.

Os resultados de aplicações formais dos métodos descritos sugeriram o seguinte: (1) considerando a variável colectiva que descreve o sub-sistema diádico de no Rugby, verificou-se que o contacto físico entre os jogadores (placagem) aumenta a complexidade do comportamento emergente, tornando-o mais previsível em situações em que o Ensaio é marcado, (2) no Futsal (5 vs 4 + GK numa área de 20×20m^2), o tamanho da RD foi medida para avaliar como as equipas gerem o espaço – a equipa que ataca apresenta uma RD maior do que a equipa que defende, e os atacantes apresentam um comportamento espacial mais regular, o que significa que o comportamento espacial da equipa que defende é mais imprevisível; (3) a %AL permitiu detectar baixos níveis de interação diádica exclusiva quando a equipa que está a defender se encontra em desvantagem numérica; e (4) a Max%AS permite identificar o atacante que se encontra sob mais pressão.

Palavras-chave: ApEn, diagramas de Voronoi, diagramas de Voronoi sobrepostos, comportamento de interação entre as equipas, variáveis colectivas

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Chapter 1: General introduction

Framework

Team sports of an invasive nature are those sports where each of the two competing teams tries, simultaneously, to gain possession of an object, e.g. the ball, in order to move it across a field toward the goal of the other team, and to prevent the opposing team from doing the same thing (Bayer, 1994). Thus, during a game, the two teams act concurrently and their behavior alternates between attempting to score, if they are in possession of the ball, and preventing the other team to score, if they are not in possession of the ball.

During a game, players from both teams act continuously according to game rules and principles, but fundamentally according to their perception of, and interaction with, the information available in the environment (Araújo, Davids & Hristovskic, 2006). According to the same author, behavior in team sports ecologically emerges from a confluence of multiple organismic (e.g. fatigue), environmental (e.g. size of the field) and task-related (e.g. defend) constraints on the players (Newell, 1986; Handford, Bennet & Button, 1997). Given these many degrees of freedom, behavior in team sports can then be seen as a dynamic system (Gréhaigne, Bouthier & David, 1997; McGarry et al., 2002).

In general, dynamical systems have nonlinear properties, and therefore they cannot be studied using linear methods of analysis. Hence, dynamical system has been approached by means of synergetic and nonlinear equations (Haken, 1987; Davids et al., 2003), which are defined based on order and control parameters, the 'yin and yang' of the synergetic approach (Kelso, 1995). An order parameter, or collective variable, is a low-dimensional variable that capture the dynamic behavior of the system, and a control parameter are properties that constrain the behavior of the dynamical system. At some critical values of the control parameter, the order parameter can change from one state to another, with fluctuations during transition between states (Kelso, 1995; Stergiou, 2004). Thus, the choice of a collective variable is a critical step for characterizing a dynamic system, and depending on the level of analysis to be undertaken, this could be quite difficult to accomplish (Thelen & Smith, 2006).

Studying behavior in sports games by mean of collective variables was first considered in a dyadic level of interaction, specifically, in individual sports, such as squash (McGarry & Franks, 1996; McGarry, Khan & Franks, 1999; McGarry, 2005) and tennis (Palut & Zanone, 2005; Lames, 2006) and in dyads from team sports, such basketball (Araújo et al., 2004; Cordovil et al., 2009) and rugby (Passos et al., 2006; Passos et al., 2008). The collective variables suggested to describe the behavioral dyadic system were mainly distance related measures, as suggested by Schmidt, O'Brien & Sysko (1999). Results from these innovative studies have contributed greatly for a better understanding of the dynamical interaction behavior in sports. Nevertheless, a comprehension of interaction behavior at a higher level, i.e., team level, could not be inferred from the former, neither those collective variables could be effectively applied in systems with multi-players (McGarry, 2009).

Following this, some ideas were developed regarding holistic measures that could be considered for describing team behavior, at a collective level, as a dynamical system (Schöllhorn, 2003). It is commonly accepted among researchers and coaches that teams' positioning and distribution in the field is often associated to strategic decisions, principles and prescriptions (Garganta, 2009), which are likely to be printed in the behavioral patterns observed during a game. Hence, some quantitative measures extracted from the positioning of all teammates have, in theory, potential to be considered collective variables. The covered area, the geometric shape formed by team members and the common centre of gravity were putted forward by Schöllhorn (2003) and somehow adapted in posterior studies, as those described next.

Some of the variables currently considered as capable of capturing the dynamics of team behavior during a game are the convex hull (Frencken et al., 2011), the stretch index (Bourbousson, Sève, & McGarry, 2010a) and simple measurements derived from the average position (centroid) of the whole team (Frencken & Lemmink, 2008; Bourbousson, Sève, & McGarry, 2010b; Frencken et al., 2011; Sampaio & Maças, 2012). Despite the ability of these variables of describing some characteristics of the underlying dynamical system, they are calculated neglecting one of the major characteristics of the structural dimension, this being the boundaries which establish the frontiers of the system (McGarry, 2009). This is illustrated using a simple example in Figure 1.

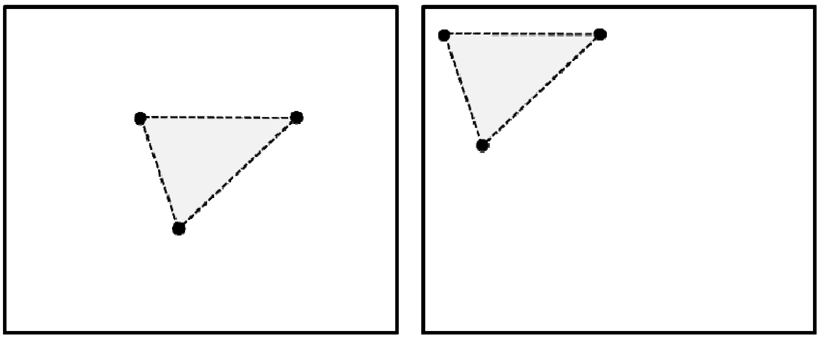

Figure 1: Three players of a team at the same interpersonal distances but placed in different locations form the same geometric shape as it does not account for the boundaries of the field (the black dots are the 2D spatial representation of the players).

Another drawback is that those measures are often calculated for each team separately, not considering information regarding the distribution characteristics of the other. This limits the analysis of intra- and inter- team interaction behaviors as, conceptually, interaction between and among groups assumes a global interaction, where all players play a role.

There are, however, spatial construction, named Voronoi diagram (Dirichlet, 1850, Voronoi, 1908), that partition the area of interest, the field, into as many cells as the existing points, players, taking into account the position of all players and the limits of the field. These diagrams have already been successfully applied in a variety of game settings, namely, real soccer games (Taki, Hasegawa & Fukumura, 1996), electronic soccer games (Kim, 2004), robotic soccer (Law, 2005) and real hockey games (Fujimura & Sugihara, 2005), in which the authors suggested some variables to characterize players individual and collective behavior. However, this was not approached under the theory of the dynamical systems.

As this particular partition of space captures some essential details of players' distribution, which are neglected in other more popular methods (Figure 2 in opposition to Figure 1), it is possible to recognize the potential of the Voronoi diagrams for studying the spatial characteristics of the team behavior and for deriving from these diagrams some strong candidates to collective variables.

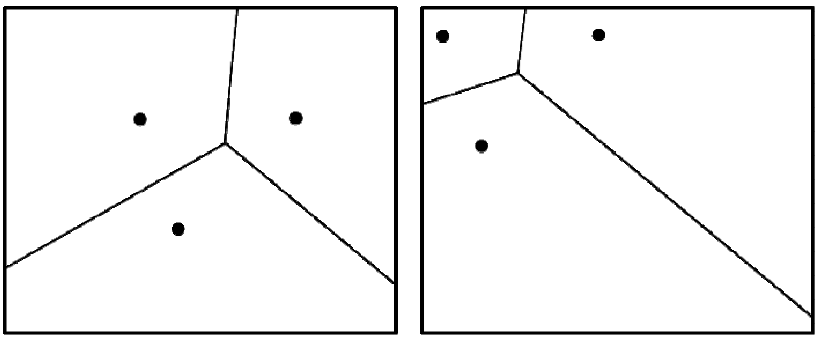

Figure 2: Three players of a team at the same interpersonal distances but placed in different locations form a very different spatial pattern as assessed by a Voronoi diagram, which partitions the field taking into account its boundaries (the black dots are the 2D spatial representation of the players).

When the collective variable(s) of a dynamical system is defined, it is possible to capture its behavior by measuring that variable across time. The characteristics of the observed dynamical system, such as self-organization, perturbations, critical fluctuations, etc., will be printed in that signal. In addition to these, the level of complexity of the system can also be assessed by studying the characteristics of the generated data series. The regularity of a signal relates to the complexity of the system generating it (Pincus, 1995), thus, by quantifying regularity it is possible to measure complexity.

The Approximate Entropy (ApEn) is a nonlinear measure of regularity in behaviors of complex systems (Pincus, 1991) and it was much applied in the analysis of physiological time series such as heart rate variability, electrocardiogram measures, respiration, anesthesia, gene sequences, pulse waveform and electroencephalography (Xu, Wang & Wang, 2005). Such systems can be observed in a fixed time window, often rather long, so that each of their realizations produces a signal of a pre-determined fixed length, which is a requirement for applying the ApEn measure. Unlike these, team sports' dynamical systems cannot be framed temporally as they evolve across time towards a certain goal and finish whenever that goal is achieved by one of the two parties involved, being possible to vary between very short and very long series. Clearly, this is a limitation that needed to be addressed as dynamical system has become a dominant approach to the analysis of team sports' behavior in different levels and dimensions.

Some authors have already suggested modified measures of the original ApEn, such as the sample entropy (Richman, & Moorman, 2000), which are less dependent on record length and more stable for short series, however, these do not allow, for example, revisiting studies where the old ApEn was applied and compare their complexity with the complexity of other systems.

Aims

In aim of the present research work was, firstly, to address the identified limitations on applying the ApEn measure to quantify the regularity of time series data from collective variables measured in team sports dynamical systems. Secondly, to develop models for formally describing behavioral patterns of spatial interaction in team sports using Voronoi diagrams. From these models, we aimed to derive reliable collective variables for assessing inter- and intra-team interaction behavior at different levels, and to establish reference values for specific patterns of interaction in order to distinguish modes of spatial interaction behavior during a game.

Outline

The thesis is constituted by four chapters, the first two (Chapter 2 and Chapter 3) are articles that were submitted, revised and accepted for publication in the course of this process.

Chapter 2 presents normalized measures of approximate entropy (ApEn) which allow quantifying the complexity of a system responsible for a given time series signal. This work emerged from an identified limitation on using the original ApEn measure in team sports' data given that, in the majority of situations, the signals under study are of varying lengths and are likely to be small (less than 50 data points). Thus, in order to measure and compare the regularity of team and players' behavior across a game, plays or trials, we suggest these normalized measures. In this study we have consider an application of the new ApEn measures in rugby union attacker-defender system.

Chapter 3 describes the results from an application of Voronoi diagrams (VD) to Futsal data under a dynamical systems approach. This work is based on the assumption that the spatial distribution of players in the field relates with the spatial interaction behavior established at player and team levels, and hence, this will vary according to the modes of interaction assumed. We suggest collective spatial variables, derived from the mentioned spatial tessellation, for describing intra-team interaction behavior in invasive team sports.

Chapter 4 presents a paper recently submitted for publication to the journal of Behavior Research Methods and it is, to date, waiting a revision. Here is presented a novel conceptual spatial model for assessing spatial configuration patterns in invasive team sports based on the previously introduced VD. This Superimposed Voronoi diagram (SVD) model, as it was named, was applied to Futsal data and the collective variables suggested for measuring spatial interaction at team and player levels were then tested. Additionally, for this particular data, reference values for two modes of spatial interaction modes were calculated using data from simulated spatial patterns and used for identifying patterns of spatial behavior in Futsal.

Finally, in Chapter 5, a general discussion of the main results from the three articles is presented, along with some final considerations about the contribution of this work to both sport and scientific communities.

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Chapter 2: Approximate entropy normalized measures for analyzing social neurobiological systems

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Abstract

When considering time series data of variables describing agent interactions in social neurobiological systems, measures of regularity can provide a global understanding of such system behaviors. Approximate entropy (ApEn) was introduced as a nonlinear measure to assess the complexity of a system behavior by quantifying the regularity of the generated time series. However, ApEn is not reliable when assessing and comparing the regularity of data series with short or inconsistent lengths, which often occur in studies of social neurobiological systems, particularly in dyadic human movement systems. Here, we present two normalized, non-modified, measures of regularity derived from the original ApEn which are less dependent on time series length. The validity of the suggested measures is tested in well-established series (*random* and *sine*) prior to their empirical application, describing the dyadic behavior of athletes in team games. We consider one of the ApEn normalized measures to generate the 95th percentile envelopes that can be used to test whether a particular social neurobiological system is highly complex, i.e., generates highly unpredictable time series. Results demonstrated that suggested measures may be considered as valid instruments for measuring and comparing complexity in systems that produce time series with inconsistent lengths.

Keywords: analysis of regularity, entropy measures, social neurobiological systems, time series

Introduction

Approximate Entropy (ApEn) was first introduced in 1991 by Pincus as a nonlinear measure to quantify regularity in the behaviors of complex systems (Pincus, 1991). The regularity of a signal relates to the complexity of the system generating it (Pincus, 1995), thus, the greater the value of ApEn, the lower the regularity of the time series, and the greater the complexity of the system under study. ApEn values vary between 0 and 2, with high values identifying data series with less regular and predictable patterns, and low values associated with data series containing many repetitive patterns, i.e., data which are more regular and more predictable. Since its introduction, ApEn has been established as a measure of regularity in a time series, with numerous applications in analysis of physiological time series such as heart rate variability, electrocardiogram measures, respiration, anesthesia, gene sequences, pulse waveform and electroencephalography (Xu, Wang & Wang, 2005).

A major interest when analyzing the complexity of physiological systems is to compare the regularity of a given time series between different groups, for instance, compare the ApEn of pulse data records in healthy persons, inpatients with cardiovascular disease and inpatients without any cardiovascular disorder (Wang, Xu, Li, Zhang, Li & Wang, 2003). However, given that ApEn values are highly dependent on times series length, and are particularly unstable for short time series (e.g. Pincus & Golberger, 1994; Xu et al., 2005; Richman, 2007), the application of such a regularity measure is only recommended when considering signals of the same length, preferably with at least 50 data points (Stergiou, Buzzi, Kurz, & Heidel, 2004). To ensure such conditions, when considering physiological time series (e.g. heart rate variability, pulse), individuals are monitored during a fixed amount of time and data are collected at the same rate (Pincus, & Viscarello, 1992; Ryan, Goldberger, Pincus, Mietus, & Lipsitz, 1994; Pincus, Padmanabhan, Lemon, Randolph, & Midgley, 1998; Wang et. al, 2003).

When the conditions above cannot be guaranteed, modified measures of the original ApEn can be applied, e.g. sample entropy (Richman, & Moorman, 2000), Gaussian Kernel approximate entropy (Xu et al., 2005), modified sample entropy (Xie, He, & Lui, 2008) and Fuzzy approximate entropy (Chen, Zhuang, Yu, & Wang, 2008). These measures have been shown to be less dependent on record length and more stable for short series.

In the study of social neurobiological systems, such as flocking birds, schooling fish, herding animals, human societies and sports teams (Couzin, 2007; Sumpter, 2006), unlike physiological systems, it may not be possible to ensure that all system output samples are of the same length. This is particularly difficult in studying social neurobiological systems because of the continuous interactions of system agents in tasks where a specific performance goal has to be achieved. Since the length of the captured time series is dependent on the time required by the agents to conclude a particular performance task (as exemplified by an attacking or defending performance sub-phase in a team game), the use of ApEn for assessing regularity is not advisable. Modified measures of regularity, such as those mentioned above, could be applied here however, we suggest in this paper two normalized measures of the original ApEn. By applying these new measures one can compute a straightforward normalization of any ApEn value where the original ApEn was used, which allows a reliable comparison of time series regularity in different complex systems.

Material and Methods

Given a data series with N points, say $\{x_1, x_2, \ldots, x_N\}$, ApEn (*m*, *r*, N) can be used to measure the logarithmic likelihood that runs of patterns with *m* points that are close, remain close within a tolerance factor *r* in ensuing incremental comparisons (Pincus, 1991), i.e., to measure the predictability of the data series. In order to compute ApEn (*m*, *r*, N), the parameters *m*, the length of compared runs, and *r*, the tolerance factor, need to be fixed for all calculations to ensure reliable analysis (Pincus, & Goldberger, 1994). In our analysis, as suggested in studies of other neurobiological systems, we considered $m = 2$ and $r = 0.2$. All calculations were performed in Matlab (7.6.0) using routines written for this purpose (Kaplan, & Saffin, 2009).

The techniques for normalization considered here are based on the ratio between an observed ApEn value and a threshold reference ApEn value, for a specific data series length. This normalization allows the regularity of data series of different lengths to be compared.

Our first normalized measure, designated $\text{ApEn}_{\text{RatioRandom}}$, is given by

$$\text{ApEn}_{\text{RatioRandom}} = \frac{\text{ApEn}(2, 0.2, N)_X}{\sum_{i=1}^{100} \text{ApEn}(2, 0.2, N)_{U_i} / 100}$$

Here, the regularity of the data series $X=\{x_1, x_2, \ldots, x_N\}$ is quantified by means of the ratio between its original ApEn value, $\text{ApEn}(2, 0.2, N)_X$, and the mean ApEn calculated in 100 *random* series U_i with the same length N. Note that for each generated *random* series, U_i, the corresponding approximate entropy, $\text{ApEn}(2, 0.2, N)_{U_i}$, represents a maximum value of approximate entropy for that particular length. Hence, $\text{ApEn}(2, 0.2, N)_X$ is normalized with respect to a maximum value of ApEn of a series of length N.

Our second normalized measure, designated $\mathrm{ApEn}_{\mathrm{RatioShuffle}}$, is given by

$$\mathrm{ApEn}_{\mathrm{RatioShuffle}} = \frac{\mathrm{ApEn}(2,0.2,N)_X}{\sum_{i=1}^{100} \mathrm{ApEn}(2,0.2,N)_{S_i} / 100}$$

Here, the regularity of the data series X={x1, x2, …, xN} is given by the ratio between its original ApEn value, ApEn (2, 0.2, N)$_X$, and the mean ApEn calculated in 100 shuffled replicas S_i of the original data. Note that for each shuffled replica of X, S_i, the corresponding approximate entropy, $\mathrm{ApEn}(2,0.2,N)_{S_i}$, represents a maximum value of approximate entropy for that particular set of points. Hence, ApEn (2, 0.2, N)$_X$ is normalized with respect to a maximum value of ApEn of that particular set of points. In both methods described here, low values of the corresponding measures will indicate that the time series under study is generated by a social neurobiological system that is less predictable than *random* time series of the same length.

For testing the methods presented in this paper, we considered data from a dyadic human movement system; more precisely, a rugby union attacker-defender system where the attacker aims to score and the defender tries to prevent it. Results should be in accordance with findings in the literature that suggest that physical contact between an attacker and defender increases the complexity of this system (Passos et al., 2009), making the dyadic sub-system behaviors that emerge in try situations (success for the attacker) more predictable than in tackle situations (success for the defender) where players do experience physical contact.

In this regard, the interactive behaviors that emerges in each trial of this social neurobiological system is accurately measured, across its duration, by a one-dimensional variable X defined in previous work by Passos et al. (2009) and designated as collective variable. This variable represents the vector connecting the agents in the dyad, and is formally given by the value of the angle between the defender–attacker vector and a horizontal line parallel to the try line with the origin in the defender. The values of X range from -90º to 90º, which occur when an attacker and defender are in the same vertical position, being 90º when the defender is closer to the try line and -90º when the attacker is closer to the try line. X is zero when attacker and defender are in the same horizontal position.

To assess the regularity of this collective variable, we considered 47 experimental dyadic trials in which participants were male rugby players aged 11–12 years, with an average of 4.0 ± 0.5 years of rugby practice. Treatment of participants was in accordance with the ethical standards of American Psychological Association (APA). Trials were performed on a field of 5 m width × 10 m depth and two fixed digital video cameras at 25 Hz were used to capture players' movements. The angle given by the variable X was calculated from players' trajectory motion data extracted from the videos using the methodology described in detail in Passos et al. (2009). Figure 3 displays two examples of these data, one from a successful situation (try scored) and the other from an unsuccessful situation (try not scored).

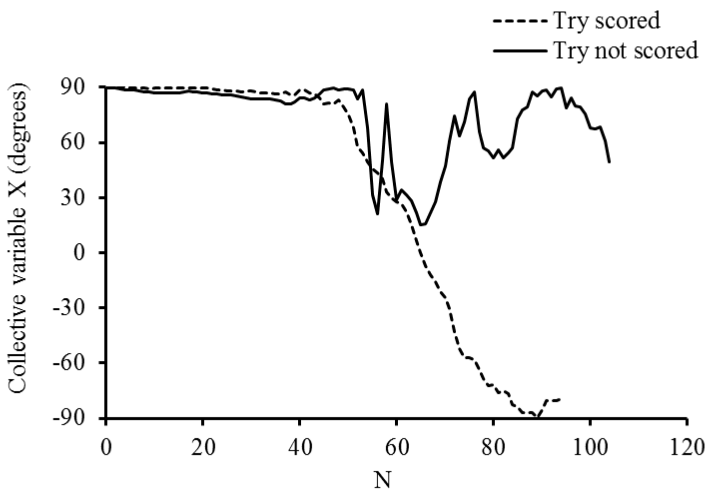
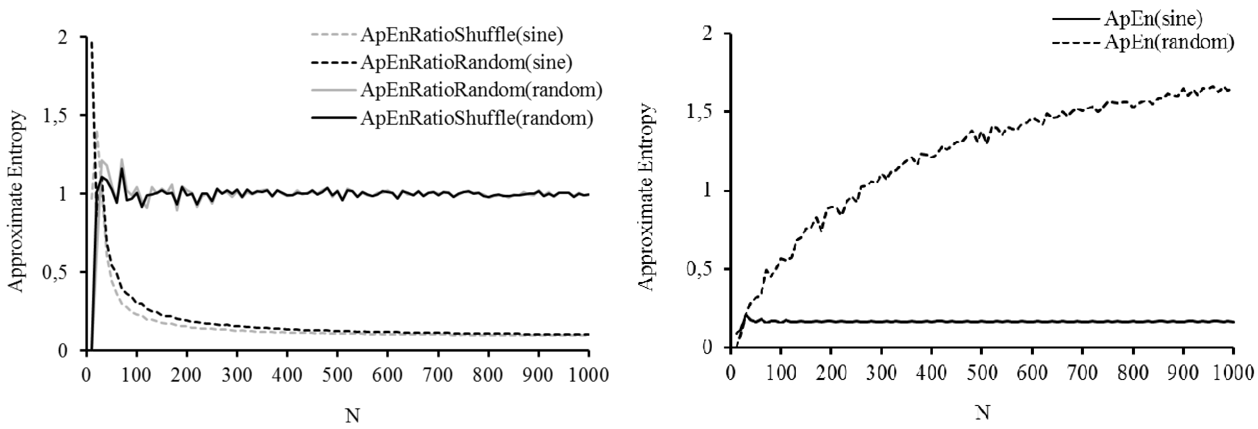


Figure 3: Example data for the collective variable X measured in a successful trial (Try scored) and in a unsuccessful trial (Try not scored)

The 47 data series analyzed, try scored (n=20) and try not scored (n=27), had a record length ranging from 69 to 230 data points (112 ± 36.3). Both normalized measures of ApEn were calculated and comparative statistical analyses were performed using non-parametric tests (Mann-Whitney test) due to lack of normality in the data and the small sample size. The level of statistical significance was fixed at 5%.

Results

The normalized measures of ApEn suggested in this paper, $ApEn_{RatioRandom}$ and $ApEn_{RatioShuffle}$ were tested in regard to the series length effect. An application of these two well-known data series (*sine* and *random*) with different lengths, has shown the advantages of these (Figure 4a) in comparison to the original ApEn measure (Figure 4b).



(a) (b)

Figure 4: (a) Normalized entropy measures and (b) original entropy measure calculated for *sine* and *random* series data of different lengths (N)

Both normalized measures appeared to be less dependent on record length for both data series, reaching stability for small lengths. This observation reinforces the need of considering more reliable measures for analyzing complexity in systems that produce time series with inconsistent lengths, a typical occurrence when studying social neurobiological systems. Nevertheless, a minimum of 50 data points is also advised to allow reliable approximate entropy comparisons (Stergiou et al., 2004). In a specific application of these measures to a dyadic sub-system (1v1) interaction in the team sport of rugby union, where physical contact is associated with less regular interaction behaviors, both ApEn normalized measures indicated, accordingly, greater unpredictability in situations with effective contact between the players, i.e. an attacker was tackled by an opposing defender (try not scored) (see Figure 5).

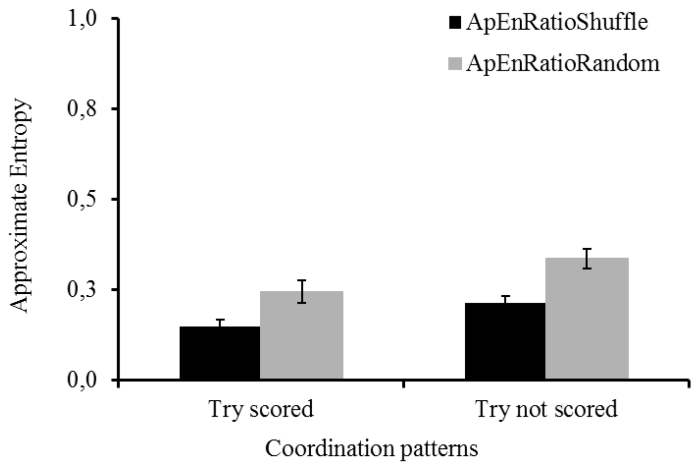


Figure 5: Mean approximate entropy for each of the two task outcomes using Apen$_{RatioRandom}$ and ApEn$_{RatioShuffle}$

Using the non-parametric Mann-Whitney test, significant differences were found between the two task outcomes for ApEn$_{RatioRandom}$($p=0.0196$) and ApEn$_{RatioShuffle}$ ($p=0.0185$), confirming that behavioral outcomes in try situations are more regular than tackle situations.

Given the similarity of both measures, we considered the ApEn$_{RatioRandom}$ to determine the 95th percentile envelope of this normalized measure, calculated from 100 simulations of *random* data series of length from 50 to 1000 (Figure 6).

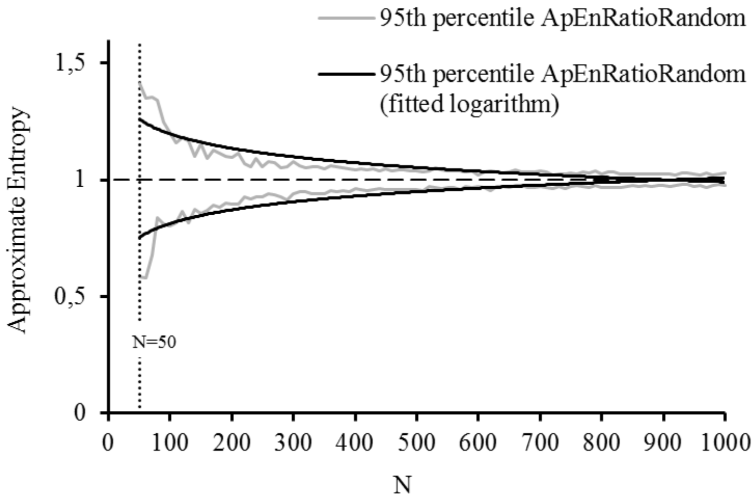


Figure 6: 95th percentile envelopes of $ApEn_{RatioRandom}$ for random series of different lengths (N) and the fitted logarithm curves for the upper and lower bounds

The logarithm curves fitted to the upper (U) and lower (L) bounds of the 95th percentile of the $Apen_{RatioRandom}$ for *random* time series with length greater than 50 are given by

$$\mathrm{ApEn}_{\mathrm{RatioRandom}}\Big|_{U}^{95th} = -0.09\ln(N) + 1.6089$$

$$\mathrm{ApEn}_{\mathrm{RatioRandom}}\Big|_{L}^{95th} = 0.0845\ln(N) + 0.4233$$

with a corresponding R^2 for the logarithm fitting of 0.752 and 0.742, respectively.

Given these, deviations from complete behavioral randomness, i.e., high unpredictability, observed in a specific social neurobiological system could be tested by computing the median $ApEn_{RatioRandom}$ for a sample of time series of that system to verify whether the obtained value is within the envelopes estimated for N equal to the median of dimension of the time series considered. For the social neurobiological system considered in this study, the median of the time series dimension is 98 and 105 for try and no-try situations and therefore the respective envelopes are [0.81, 1.2] and [0.82,1.19], respectively. The median $ApEn_{RatioRandom}$ in try and no-try situations were 0.23 and 0.33, being both below the respective lower reference value. This finding suggests that, regardless of the outcome, the dyadic system behavior under study is more predictable than would be expected in the case of complete randomness. Nevertheless, results suggested that the level of system output regularity was significantly different between the try and no-try performance situations, being more predictable for try situations.

Conclusion and Discussion

In this paper we presented two normalized measures based on the original Approximate Entropy (ApEn) for quantifying and comparing regularity in the interactions of agents in social neurobiological systems, particularly in those that produce time series with inconsistent lengths. The limitations associated with the application of the original ApEn to time series of varying lengths, have been previously addressed by other authors (Richman & Moorman, 2000; Xu et al., 2003; Xie, He & Lui, 2008; Chen et al., 2008) introducing modified measures of the original ApEn. Alternatively, the measures here presented consider the same limitations but are based on the use of the original ApEn.

We considered two well-known data series (*sine* and *random*) with different lengths, for testing the advantages of these normalized measures in comparison to the original ApEn measure. For the normalized measures we calculate the 95th percentile envelopes which can be interpreted as reference values for testing deviations from complete randomness, i.e. low predictability, in social neurobiological time series of any length greater than 50. An application of these measures to empirical data from a dyadic system behavior in rugby union suggested that the emergent behavior of this particular social neurobiological system is more regular than expected in the case of complete randomness, given that the agents in this system have a specific performance goal. Additionally, the analysis of regularity indicates that the complexity of this system was significantly lower when physical contact between the two players occurred, as suggested by Passos et al. (2009). Overall, the application of the normalized ApEn measures to both theoretical (*sine* and *random*) and empirical data suggest that they can be regarded as reliable measures for quantifying and comparing regularity of time series with different lengths. These findings could be used to re-interpret previous work on behaviors of social neurobiological systems (e.g., Araújo, Davids, Bennett, Button, & Chapman, 2004) with criteria to compare the regularity of time series of different lengths, something that was not possible previously beyond simple visual inspection. Moreover, an exciting possibility for future research is to study complex daily social interaction behaviors to identify different patterns, without concerns over the possible loss of explanatory power.

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Chapter 3: Spatial dynamics of team sports exposed by Voronoi diagrams

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Abstract

Team sports are complex systems, where the players interact continuously during a game, forming patterns of interaction that, once identified, can describe their behavior in both individual and collective levels. In order to identify these interaction patterns, we considered Voronoi diagrams to describe the spatial dynamics of players' behavior in Futsal plays.

We considered 19 plays of a sub-phase of a Futsal game played in a reduced area ($20\times20m^2$) from which the trajectories of all players were extracted. Results from a comparative analysis of player's Voronoi area (dominant region) and nearest teammate distance, show that there are different patterns of interaction between attackers and defenders, at both player and team levels. Namely, we found that, in comparison with the defender team, attacker players have larger dominant regions. In addition, these regions are more variable in size among players from the same team but, at a player level, the attackers' dominant regions are more regular during performance than those associated to each of defender players. These findings support a formal description of the dynamic spatial interaction of the players, in this sub-phase of the game.

This approach may be extended to other team behaviors where the actions taken at any instant by each of the involved agents are associated with the space they occupy at that very time.

Keywords: Interaction patterns, Team sports, Voronoi diagrams

Introduction

Team sports can be seen as complex systems where players, the agents of the system, interact continuously during a game (Davids, Araújo & Shuttleworth, 2005, McGarry, Anderson, Wallace, Hughes, & Franks, 2002) and it is their interaction behavior what determines the occurrence of specific events during a game (Passos et al., 2008). Therefore, having a good understanding of this dynamic behavior would allow not only a better characterization of these systems but also could help coaches to anticipate some outcomes or events.

Players' interaction behavior can be assessed in a spatial perspective. For instance, players change their location continuously during a game as they adjust their relative position according to the information that they can perceive (Passos et al., 2008; Travassos, Araújo, Vilar, & McGarry, 2011), acting collectively as a result of phenomena such as cooperation and competition. Thus, players collective behavior cannot be explained by the simple addition of behaviors from each player (Gréhaigne, Bouthier, & David, 1997), instead, players' behaviors could be considered within the whole dynamic system that they form (Glazier, 2010; McGarry, 2009; Passos et al., 2009), where both time (Araújo et al., 2006) and space (Davids, Handford and Williams, 1994; Schöllhorn, 2003) need to be brought into the equation. Considering both space and time, it is possible to evaluate the spatial configuration that players present during a game.

To illustrate, spatial configurations can be classified as random, regular or clustered. A random classification can be defined when players are at random distances from each other in the field, regular, when players are equally distant from each other in the field, or clustered, when we can identify different groups of players aggregated in different parts of the field (Figure 7). These spatial distribution patterns can be easily identified by measuring interpersonal distances, in particular the minimum interpersonal distance, or nearest neighbor distance (Clark, & Evans, 1954).

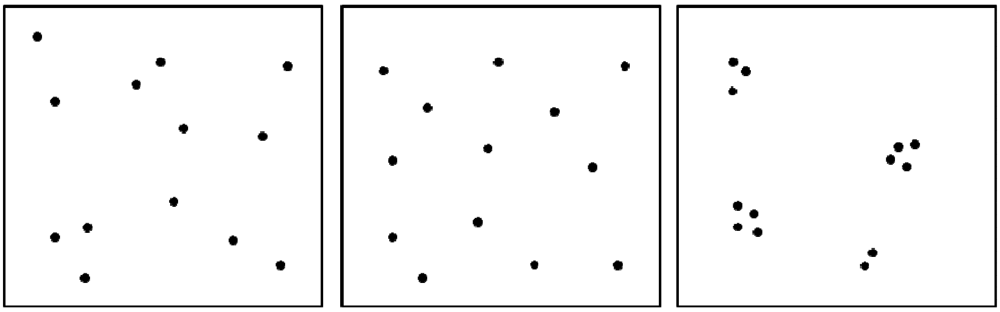
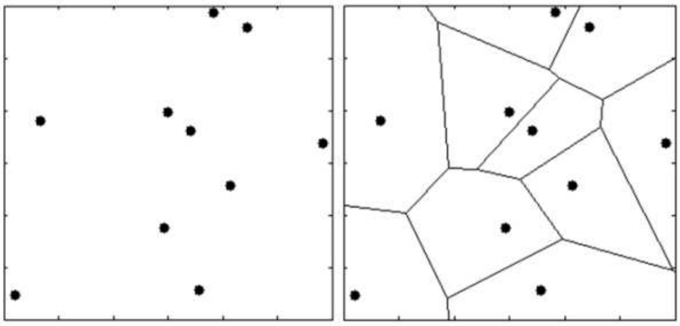


Figure 7: Example of spatial distribution patterns (a) random, (b) regular and (c) clustered.

The spatial distribution of the players in a field, and hence the space that a players has to act, is dependent on a large number of constraints that change continuously throughout a game, being ball possession an obvious one. In principle, the attacker team normally tries to free-up space while the defender team tries to tie-up space (McGarry et al., 2002, Gréhaigne, Bouthier, & David, 1997). Therefore, in terms of nearness, it is expected that the interpersonal distance between players is kept greater for the attacker team and smaller for the defender team, which results in more space for the attack. This relationship was already observed using surface area (Frencken, Lemmink, Delleman, & Visscher, 2011) and stretch index variables (Bourbousson, Sève, & McGarry, 2010).

An alternative method to study the spatial relation established between players at each instant of a game is the Voronoi diagram (Dirichlet, 1850, Voronoi, 1908), which is a spatial construction that allows a spatial partition of the field area into cells, each associated to each of the players, according to their positions (Figure 8). These cells result from applying a very simple nearest-neighbor rule: each player, represented by the coordinates of his/her location in the field, is associated to all parts of the field that are nearer to that player than it is to any other player (see Okabe et al., 2000).



(a) (b)

Figure 8: Example of a Voronoi diagram generated for the set of points represented in the figure.

Voronoi diagrams have already been suggested by other authors in the study of players' spatial distribution in team sports and to define players' and teams' dominant regions, having been applied in a variety of game settings, namely, real soccer games (Taki, Hasegawa & Fukumura, 1996), electronic soccer games (Kim, 2004), robotic soccer (Law, 2005) and real hockey games (Fujimura & Sugihara, 2005). When real games were considered, dominant regions were calculated considering more than just players' location, in particular, Taki, Hasegawa & Fukumura (1996) has considered players' direction and speed, whereas Fujimura & Sugihara (2005) has taken into account players' distance from ball and distance to goal. In all these studies it was shown that the position of the ball influences the location of the players and hence the size of their respective dominant regions.

Besides the advances of the work mentioned above towards the analysis of spatial patterns of behavior in team sports, an important dimension has not been considered. In fact, when analyzing systems of interacting agents, it is necessary to measure its degree of complexity (Stergiou, Buzzi, Kurz, & Heidel, 2004, Harbourne, & Stergiou, 2009), as this is a key issue to understand the emergence of successful performances in dynamical movement systems (Bartlett, Wheat & Robins, 2007, Davids, Glazier, Araújo, & Bartlett, 2003). To assess the complexity of a system, one can consider a nonlinear measure suggested by Pincus in 1991, the Approximate Entropy (ApEn), which quantifies the regularity (predictability) of signal from a variable measured in the system under study. When this variable expresses the state of the system (Harbourne, & Stergiou, 2009), its regularity is directly proportional to the system's complexity, i.e., lower values of ApEn indicate more regularity and hence low complexity.

Thus, the main goal of the present paper was to characterize the spatial interaction dynamics of players in team sports, by understanding how players from two opposite teams coordinate their location in the field during a game and how they define and adjust their dominant regions throughout the game. We expect that players from the attacker team present greater interpersonal distances, greater dominant regions, and greater regularity overtime in terms of space area as they are with the ball.

Material and Methods

In this study were considered 19 experimental plays of Futsal, in which participants were 15 male senior players (23.25 ± 1.96 years old), treated in agreement with the ethical standards of American Psychological Association (APA). Plays represent the sub-phase of Futsal of 5 vs 4+GK performed in half field (20 m width × 20 m depth) where all players occupied fixed initial positions. This is a common scenario in Futsal when the team losing the game has ball possession and aims to score where, due to numerical disadvantage, the defender team retract their positions to their half field. Accordingly, in each play, the aim of the attacker team is to score while the defender team tries to avoid it, and each play ends whenever the attack loses ball possession.

Two fixed digital video cameras at 25 Hz were used to capture players' movements during each play. The trajectory of each player was extracted from the recorded videos using TACTO software (see more in Duarte et al., 2010; Fernandes, & Malta, 2007) and transformed into real coordinates *(x,y)* using a direct linear transformation method (2D-DLT) (Abdel-Aziz, & Karara, 1971). The 19 plays had, on average, 848 (± 374) frames (corresponding to approximately 34.2 (± 14.94) seconds), minimum of 315 and maximum of 1558 frames (approximately 12.6 and 62.4 seconds, respectively).

In the present work two variables were considered to describe this system, players' dominant region, as defined by the respective Voronoi cell, and the minimum interpersonal distance between teammates. The minimum interpersonal distance between all teammates (N), here designated nearest teammate distance ($\mathrm{Dist}_{\mathrm{NT}}$), was calculated at each frame (*f*), considering the Euclidean distances between all pairs of players of a team (A), as described below.

$$\mathrm{Dist}_{\mathrm{NT}}(\mathrm{A})^{f} = \min_{\substack{i,j \\ i \neq j}} \left\{ \sqrt{(x_i^f - x_j^f)^2 + (y_i^f - y_j^f)^2} \right\}, \; i, j = 1, \ldots, N$$

As for players' individual dominant region, we considered the respective Voronoi cells and calculated their area ($\mathrm{Area}_{\mathrm{DR}}$) as described next.

The field was mapped with a grid of 20×20 positions. At each frame (*f*), the area of the DR of player k (k∈[1,M]) is the sum of all grid positions (i,j) (where i=1,..,20 and j=1,…,20) that are closer to that player than it is to any other player. This can be mathematically defined as presented below,

$$\mathrm{Area}_{\mathrm{DR}}(\mathrm{k})^{f} = \sum_{i=1}^{20} \sum_{j=1}^{20} I_{(i,j)} \qquad k = 1, .., M$$

where I(i,j) is a Boolean function that takes value 1 if player k is the closest player to the grid position (i,j) and 0 otherwise:

$$I_{(i,j)} = \begin{cases} 1 & \text{if} \quad \sqrt{(i - x_k^f)^2 + (j - y_k^f)^2} < \sqrt{(i - x_m^f)^2 + (j - y_m^f)^2}, \forall m \neq k, m = 1,.., M \\ 0 & \text{otherwise} \end{cases}$$

Grid points that are equidistant to two or more players constitute the boundaries of their respective regions and therefore are not added to the corresponding areas.

For each player and team we investigated how the size of their dominant regions changes over time and how the size of such regions relates to each other. MATLAB routines were written to generate, at each frame, the Voronoi diagram associated to the spatial distribution of the players, and to calculate the size of the dominant region ($Area_{DR}$) according to descriptions above.

The regularity of time series data from $Area_{DR}$ and $Dist_{NT}$ was measured using the $ApEn_{RatioRandom}$ (Fonseca et al., 2012), which is a normalized measure of Pincus (1991) approximate entropy (ApEn), obtained by dividing the ApEn of the original series, Y, by the average ApEn of 100 random series of the same size of Y. This measure allows the comparison of entropy values calculated in series of varying lengths. A value of $ApEn_{RatioRandom}$ of approximately 0.2 indicates regularity (high predictability), whereas 1 indicates low regularity (high unpredictability) (Fonseca et al., 2012).

We used descriptive statistics (Mean (M) ± Standard Deviation (SD)) and inferential statistics (ANOVA, t-test and paired t-test) to compare the spatial behavioral complexity between players, teams, and teams by play, respectively.

Reliability

From all the plays, one of them was randomly selected and the data trajectories of the players re-digitized by the same researcher. Data were then assessed for accuracy and reliability using technical error of measurement (TEM) and coefficient of reliability (R), respectively (Goto & Mascie-Taylor, 2007). The TEM yielded values of 0.137 meters (0.23%) and the coefficient of reliability was equal to 0.984.

Results

When looking at changes on the minimum interpersonal distance between teammate players ($Dist_{NT}$) and area of the dominant region ($Area_{DR}$) across each play, we found that, on average, players from the attacker team tend to be further from each other in comparison with players from the defender team, as expected (Figure 9: exemplar single play). Consequently, the space occupied by each player is, on average, greater for the team with the ball (attacker team) in comparison with the defender team (Figure 10: exemplar single play).

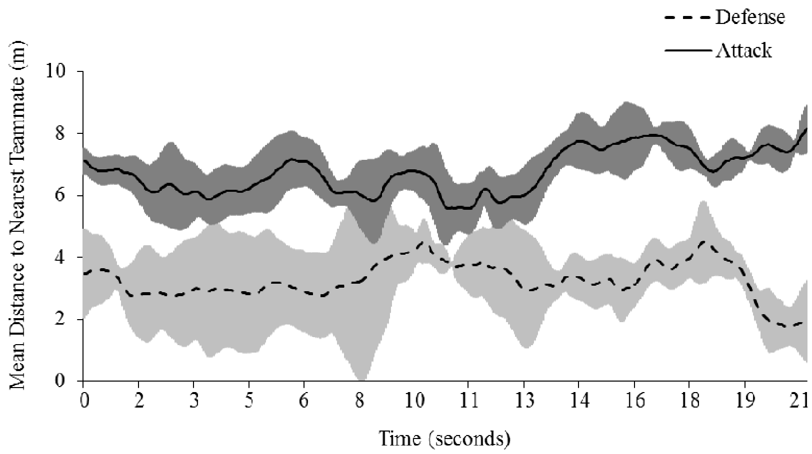


Figure 9: Mean distance to nearest teammate distance, across time, for the attacker and defender teams in a randomly selected play (error bars represent the standard deviation).

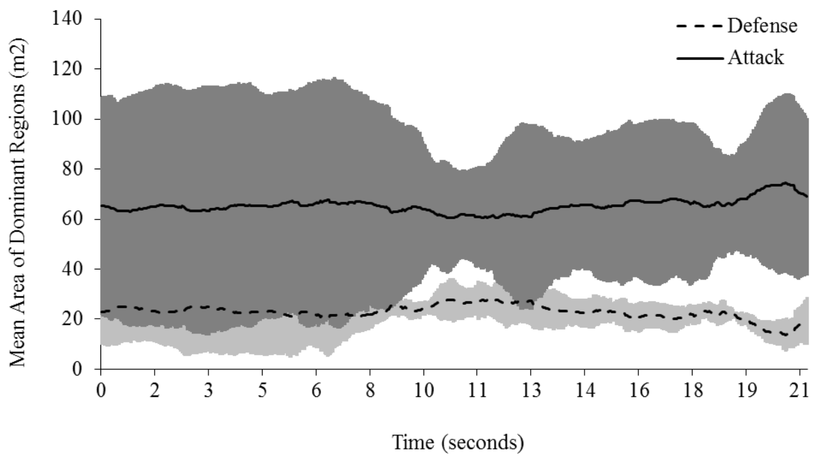


Figure 10: Mean area of the dominant region, across time, for the attacker and defender teams in a randomly selected play (error bars represent the standard deviation).

When comparing the amount of variability within each team for both variables, it is clear that the attacker team shows less variability than the defender team in the $Dist_{NT}$ and more variability than the defender team in the $Area_{DR}$, as shown by the error bars in Figure 9 and Figure 10, respectively, This tendency was observed in all plays, suggesting that, in comparison to what was found in the defender team, the area occupied by the attacker team is much more variable within each frame, whereas the minimum interpersonal distance is less variable. In Figures 9 and 10, the moment captured at time 10 s. corresponds to the exact moment (observed by visual inspection) when the ball is received by an attacker inside the defensive structure, which is, according to Futsal's literature, a critical occurrence for the defender team (Lucena, 2007). As a consequence, all defenders were trying to close the space around the ball carrier and avoid the attacker team to score, and both $Dist_{NT}$ and $Area_{DR}$, presented particularly low variability.

To better understand and characterize the system under study, we measured the regularity of $Dist_{NT}$ and $Area_{DR}$, at both player and team levels and within each play, using a normalized measure of the ApEn due to presence of signals with varying lengths (for more detail see Fonseca et. al, 2012). At a player level, the regularity of the $Dist_{NT}$ and $Area_{DR}$ was calculated separately for each player in all plays. We found that the regularity of both variables is significantly different between at least two players ($Dist_{NT}$: $F(9,180)=9.5$, $p<0.001$; $Area_{DR}$: $F(9,180)=12.5$, $p<0.001$), being this difference only found between opponent players. This means that players within a team have similar behavioral patterns regarding proximity to their teammates and management of their dominant regions. At a team level, the regularity of the same two variables was compared between the teams (Defender vs Attacker) and significant differences were found in both variables ($Dist_{NT}$: 0.165 ± 0.048 vs 0.106 ± 0.043, $p<0.001$; $Area_{DR}$: 0.264 ± 0.135 vs 0.114 ± 0.061, $p<0.001$). In addition, and having shown a team effect, we tested the effect of the play in the spatial interacting behavior between teams. Hence, for the same two variables, we considered, for each play and for each team, the median entropy. Our results were consistent with what was shown above, suggesting that, within a play, $Dist_{NT}$ and $Area_{DR}$ were significantly more regular for the attacker team in comparison with the defender team ($t(18)=8.26$, $p<0.001$; $t(18)=8.86$, $p<0.001$, respectively) (Figure 11).

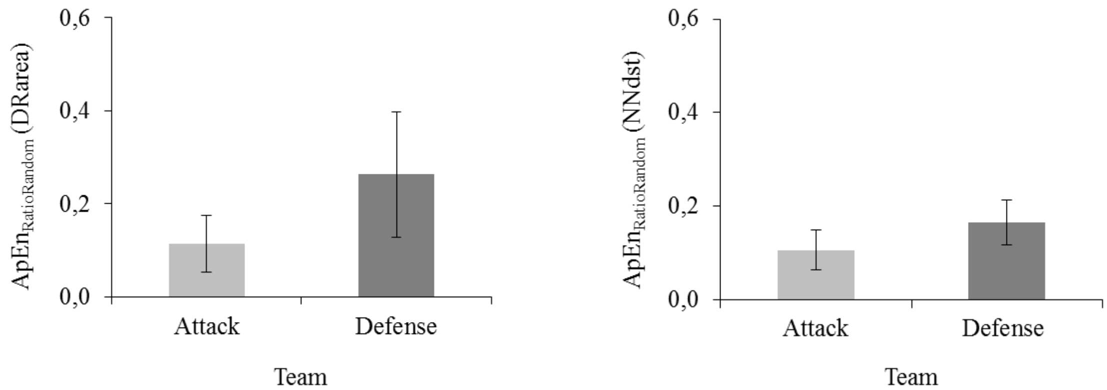


Figure 11: Comparison of the mean entropy of the distance to nearest teammate (DistNT) and area of the dominant region (AreaDR) between teams in the same play. Error bars represent the standard deviation (* p<0.001).**

Discussion

The aim of this study was to characterize the spatial dynamics of players and teams in Futsal using Voronoi diagrams. We considered the minimum interpersonal distance between teammates ($Dist_{NT}$) and the area of the dominant region of each player ($Area_{DR}$) as variables that can be considered to characterize the individual and collective behavior of the players. Both variables mentioned above appear to capture some interesting characteristics of this system of interactions, namely, players from the team with the ball, are further apart from each other whereas defenders are closer from each other. This spatial organization has direct influence on the dominant region defined by each player. These individual dominant regions were defined using Voronoi diagrams and they appear to be greater for the attacker team and smaller for the defender team. These results are in agreement with what was theoretically expected (McGarry et al., 2002). The spatial behavior assessed by these two variables did not present significant differences between players of the same team as their actions are, to some extent, regulated by their goal as a team, which is scoring and avoiding a score for the attacker and defender teams respectively.

Moreover, we found that the $Area_{DR}$ and $Dist_{NT}$ present, across time, lower regularity in the defender team being their behavior more unpredictable that the interaction behavior observed in the attacker team. This greater unpredictability associated to the defender team may be justified by the fact that the players on this team are constantly adjusting their spatial organization to protect the goal in function of what the attacker team does (Frencken, Lemmink, Delleman, & Visscher, 2011). On the other hand, the attacker team explores the free space in a more regular way, possibly acting according to the trained coordination patterns that are assumed to increase chances of scoring.

Voronoi diagrams can then be considered to measure individual and team dominant regions. The observed signals of this variable appear to capture particular phases of the game, such as when the ball is received by an attacker inside the defensive structure, presenting behavioral patterns that may be used to describe and explain the performance outcome

(Glazier, 2010; McGarry, 2009). Unlike other authors, in this paper, we did not consider any factor to weight players' Voronoi regions, so their areas were simply based on the position of the players which, according to our results, are naturally influenced by ball possession. However, there are other factors, such as players' individual characteristics (Cordovil et al., 2009), distance from ball (Fujimura & Sugihara, 2005), motion direction, speed and acceleration (Taki, Hasegawa & Fukumura, 1996; Fujimura & Sugihara, 2005), that are likely to determine players' actions and hence their spatial distribution in the field. In future work, some of the mentioned constraints could be considered to weight the distances used in the calculation of the dominant regions.

In addition, future research in this topic could consider other sub-phases of the game (e.g. 5 vs 5, counter-attack, corners) and study players' spatial configurations (e.g. attacker team vs defender team) in order to formally describe their spatial behavior and compare these with the principles that regulate them. With the same reasoning, the definition of players' spatial profiles for different game scenarios could be of much interest to the training processes (Travassos et al., 2010).

Conclusion

In conclusion, we showed that Voronoi diagrams can be used to characterize players' spatial interaction behavior in Futsal. The interpersonal relationship between players and teams is well described by the variables considered and the quantification of their predictability was able to capture the interaction behavior between and within teams during performance.

This analysis can be further applied to other team sports to describe individual and collective behavior, identify patterns of coordination in different sub-phases of a game, and compare spatial patterns of coordination between teams of different levels of expertise.

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Chapter 4: Measuring spatial interaction behavior in team sports using superimposed Voronoi diagrams

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Abstract

In team sports, the spatial distribution of players in the field is determined by the interaction behavior established at both player and team levels. The distribution patterns observed during a game emerge from specific technical and tactical methods adopted by the teams, and from individual, environmental and task constraints that influence players' behavior. By understanding how specific patterns of spatial interaction are formed, one can characterize the behavior of the respective teams and players. Thus, in the present work we suggest a novel spatial method for describing teams' spatial interaction behavior, which results from superimposing the Voronoi diagrams of two competing teams.

We considered theoretical patterns of spatial distribution in a well-defined scenario (5 vs 4+ GK played in a field of $20\times20m^2$) in order to generate reference values of the variables derived from the superimposed Voronoi diagrams (SVD). These variables were tested in a formal application to empirical data collected in 19 Futsal trials with identical playing settings.

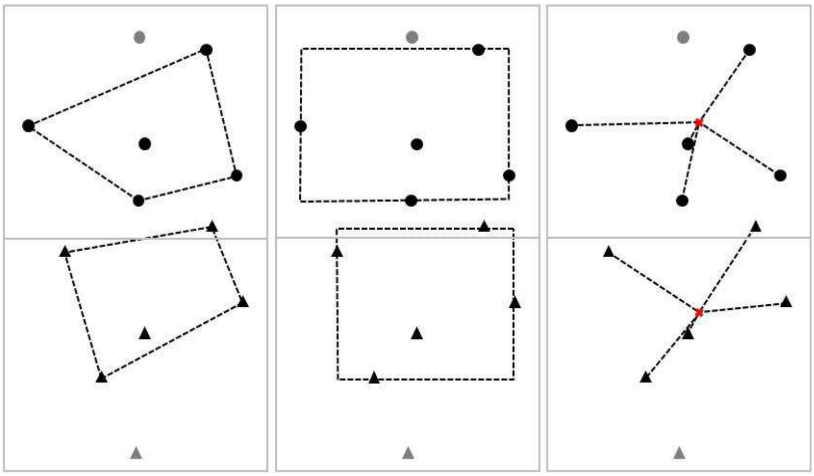
Results suggest that it is possible to identify a number of characteristics that can be used to describe players' spatial behavior at different levels, namely the defensive methods adopted by the players.

Introduction

Team sports are considered dynamic systems of interaction, where players from both teams continuously change, adapt, adjust and coordinate their position and actions in order to win the game (Davids, Araújo & Shuttleworth, 2005; Passos et al., 2009). Pre-determined tactical and technical methods, along with individual, environmental and task constraints (Newel, 1986), regulate players' spatial behavior and are responsible for a continuous emergence of patterns of intra-and inter-team interaction. Research on this subject should therefore assume a holistic character considering a time and space continuous approach, which is accomplished when defining variables capable of describing the collective behavior of a team (Davids et al., 2005; Schölhorn, 2003, McGarry, 2009).

When considering the space dimension, players' trajectories during a game are a relevant source of information but they only provide a measure of team behavior when considered simultaneously. Following this reasoning, spatial team variables, such as the convex hull (Frencken et al., 2011), the stretch index (Bourbousson, Sève, & McGarry, 2010a) and simple measurements derived from the average position (centroid) of the whole team (Frencken & Lemmink, 2008; Bourbousson, Sève, & McGarry, 2010b; Frencken et al., 2011), have been considered to describe the behavior of a team. These variables are illustrated in Figure 12 a), b) and c), respectively.

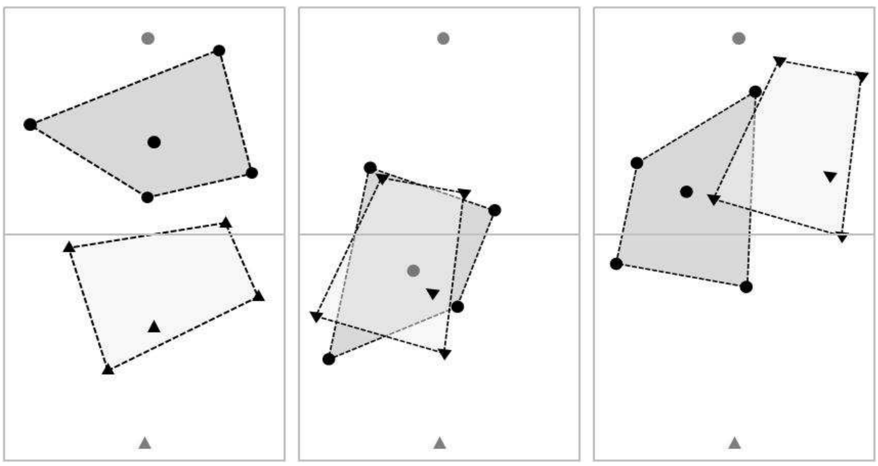
The mentioned variables became popular for describing the spatial behavior of each team across the duration of a game (or task). Typically, the area of the geometric shape (Figure 12 a) and b)) is calculated for each team or, in case of using the centroid (Figure 12c)), its distance or angle to the aimed target (e.g. goal) is considered as a measure of individual team behavior.



(a) (b) (c)

Figure 12: Variables for describing team spatial organization of two opponent teams (players of each team are represented by black dots and triangles, respectively, grey players on the top and bottom of the field are the goalkeepers) – (a) convex hull, (b) horizontal and vertical stretch and (c) centroid position (red dots).

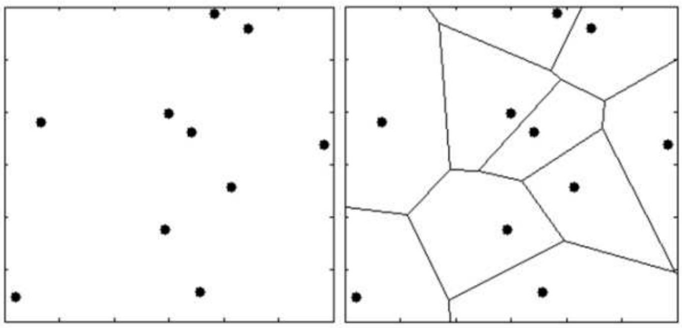
For the analysis of these data series, researchers consider the use of entropy measures to quantify and compare the complexity of the spatial behavior of the teams (Passos et al., 2009; Fonseca et al., 2012a, Sampaio & Maças, 2012) and, for assessing teams' coordination, a relative phase analysis is considered (Bourbousson, Sève, & McGarry, 2010a; Travassos et al., 2011). While these approaches are a step forward towards the understanding of players' behavior in team sports, some limitations can be identified, as illustrated in Figure 13.



(a) (b) (c)

Figure 13: The same spatial configuration of two teams 5+ GK vs 5+GK (players of each team are represented by black dots and triangles, respectively, grey players on the top and bottom of the field are the goalkeepers) measured using the area of the respective convex hull (shaded areas) in three very different scenarios (a, b and c).

Figure 13 shows the same spatial configuration of two teams in three very different scenarios of team interaction, which would present no differences if, for example, the area of the convex hull of each team is considered. This limitation can be found in some variables currently used to describe spatial behavior in invasive team sports as they are calculated for each team ignoring the spatial distribution of the opponent team and the dimension of the field. Given that the spatial organization of one team is much influenced by the spatial organization of its opponent, it seems reasonable to consider the position of all players in the field, as well as its dimension, to define variables that describe teams' spatial arrangement. Thus, some authors have suggested measures of spatial organization based on a geometric partition of space called Voronoi diagram (see Okabe et al., 2000), in which parts of the field, the Voronoi cells, are associated to each of the players. Figure 14 shows an example of a Voronoi diagram generated for a set of 10 points in a limited square area.



(a) (b)

Figure 14: Example of a set of points in a plane (a) and respective Voronoi diagram (b).

The application of this spatial tessellation in team sports has been welcomed as the points can represent the position of the players and the associated Voronoi cells can be interpreted as the dominant region of each player within the limits of the playing area (field). Not surprisingly, such approach has been considered in a variety of settings, namely, electronic soccer games (Kim, 2004), robotic soccer (Law, 2005), on-field hockey games (Fujimura & Sugihara, 2005), on-field soccer games (Taki, Hasegawa, & Fukumura, 1996) and on-field futsal (Fonseca et al., 2012b). Although some principles of the game are fully capture in these studies (e.g., the idea that the attack team has to free-up space and the defense team has to tie-up space), it is still unknown how relationships established at a player level relate to this.

Hence, we suggest a novel spatial method for describing inter-teams spatial interaction patterns of behavior in invasive team sports, which also allows characterizing the type of play of defending teams. Results from an application of this approach in futsal task situations are presented.

Method

The spatial method suggested here, illustrated in Figure 15, results from superimposing the Voronoi diagrams (VD) of the two teams competing (VD of team A - black, over VD of team B - white), hereafter named Superimposed Voronoi Diagram (SVD).

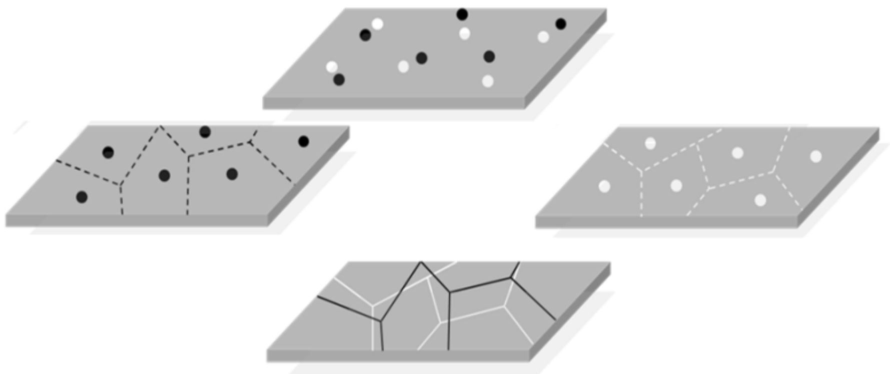
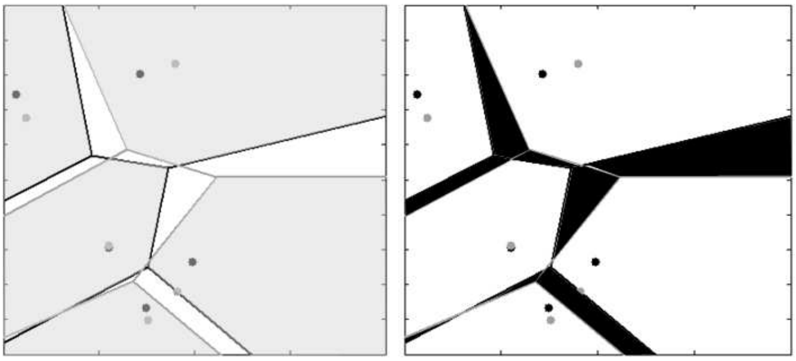


Figure 15: Construction of the superimposed Voronoi diagram (at bottom) from considering, separately the Voronoi diagrams for team A (black dots) and team B (white dots).

Given this graphical construction, we defined two measures of spatial interaction: the maximum percentage of overlapped area (Max%OA) and percentage of free area (%FA). The former (Max%OA) is calculated for each player and it represents the maximum percentage of the player's Voronoi cell that is covered by the cell of an opponent; as for the latter (%FA), it is a measure that summarizes the degree of similarity between the overlapped diagrams, and is calculated by extracting from the play area the sum of the Max%OA calculated for players of a team. A representation of these measures is presented in Figure 16.



(a) (b)

Figure 16: Measures from the superimposed Voronoi diagram (SVD): (a) shaded grey areas are the maximum Overlapped Area for each player of the team represented with black dots; (b) the sum of the shaded black area is the Free Area.

The fitting of the two diagrams, VD of team A and VD of team B, is clearly dependent on the spatial distribution of the players from both teams, and a perfect fit would only occur if players of a team could be in the exact same position of the players from the other team, which in a sports context would make no sense (note that in this case the Max%OA would be equal to 100% to all players and hence the %FA would be null).

A more likely scenario in invasive team sports is having players exclusively paired, i.e., matched one-to-one as in a man-to-man defensive method, in which case the two VD would be similar, but not identical. Alternatively, in case players are not so tightly coupled, one would expect a weaker match of the two diagrams. Having described these two possibilities, we recognize the importance of understanding how these two measures of interaction (%FA and Max%OA) differ in these two scenarios. Thus, simulated spatial patterns of exclusive pairing and random interaction were performed to derive the properties of the SVD. Note that random interaction was considered as a reference model for spatial patterns assessment. The simulation settings matched those in the empirical data considered for application purposes (5 vs 4+ GK players in a limited region of 20×20m^2), nevertheless, it is supported that this can be adjusted to other scenarios.

Random interaction: 1000 SVDs were generated for random interaction, i.e., all players except GK are randomly allocated in the field, the GK is fixed at location (10,18) – example of one simulated pattern is shown in Figure 17a.

Exclusive pairing: Given the numerical advantage for the attack in the present setting (5 vs 4+GK), each defender, except GK, was paired with one of the 4 attackers closer to the center of the goal. The GK remains fixed at location (10,18). Thus, 1000 SVDs were generated for exclusive pairing at different maximum distances between pairs, from 0.5 to 7 meters with increments of 0.5 meters – example of one simulated pattern is shown in Figure 17b.

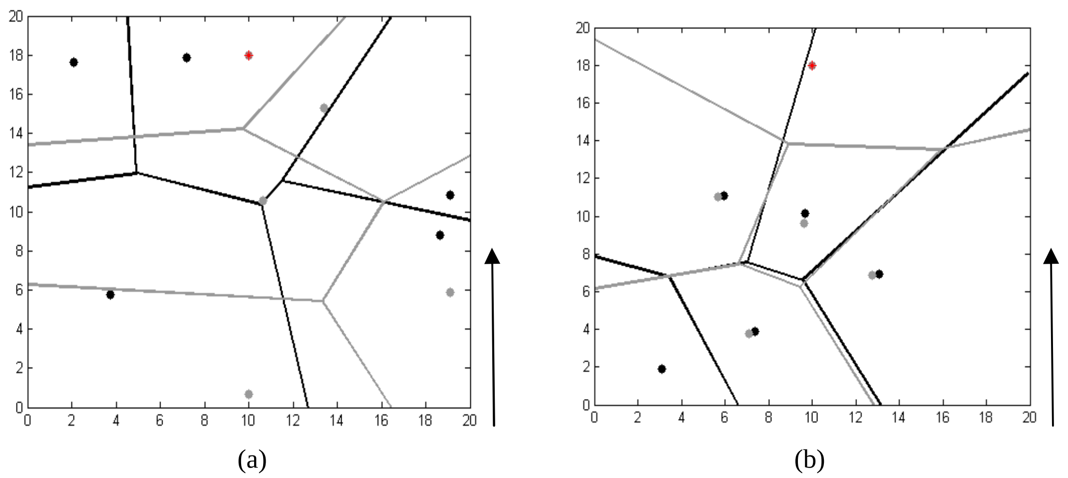


Figure 17: Example of a generated SV in a situation where (a) players from both teams (grey and black dots) are randomly distributed in the field and (b) defender players, grey dots, are exclusively paired with the attacker players, black dots, that are closer to the goal. The GK (red dot) is in both cases fixed at position (10, 18). The arrow indicates the direction of the attack.

Inter-Team interaction assessment

For measuring inter-team interaction the %FA was considered. In case of random interaction, this measure is, on average, equal to 36 ± 7.2% and the corresponding 95% confidence interval is (0.22, 0.50)%. As for the exclusive pairing patterns, given that in this case the %FA calculated for each of the 14 distances was not normally distributed, we have computed the 95% confidence envelopes. These are compared with the values expected in the presence of random interaction in Figure 18.

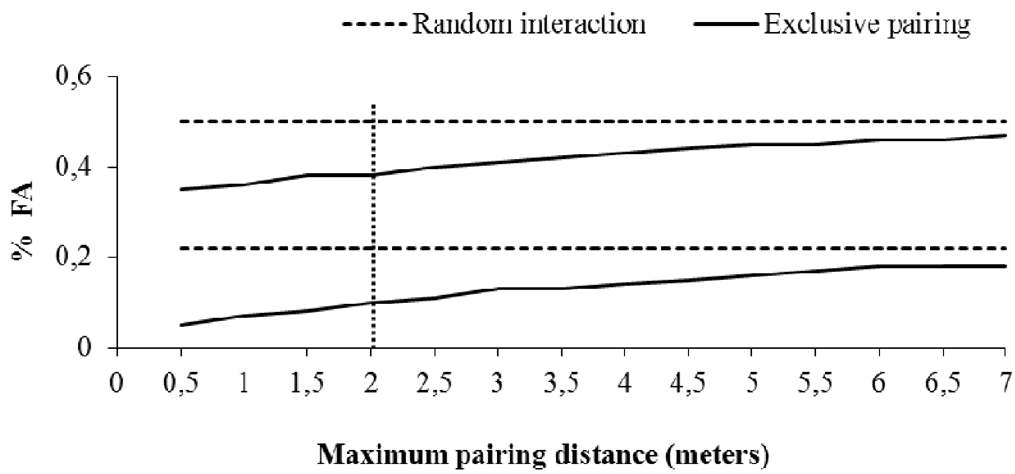


Figure 18: 95% confidence envelopes for simulated patterns of exclusive pairing at different maximum pairing distances (solid lines) and 95% confidence interval for simulated patterns of random interaction (dashed lines).

As expected, when opponent dyads are tightly paired, i.e., for very small pairing distances, the %FA is smaller than what is expected by chance (random interaction). As this distance increases, the pairing becomes weaker and the %FA increases towards the values observed under complete randomness. In fact, results suggest that for the specific settings considered in this study, 5 vs 4+GK played in a field of $20{\times}20m^2$, it is only possible to identify exclusive pairing at a team level when the distance between all pairs is below two meters (dotted vertical line in Figure 18).

Opponent interaction assessment

For assessing spatial interaction at a player level we consider the maximum percentage of overlapped area (Max%OA) for each player. As illustrated in Figure 19, we found that this variable is associated with the number of opponents within the player's Voronoi area – the more the number of opponents the smaller the value of Max%OA of the attacker ($p<0.001$).

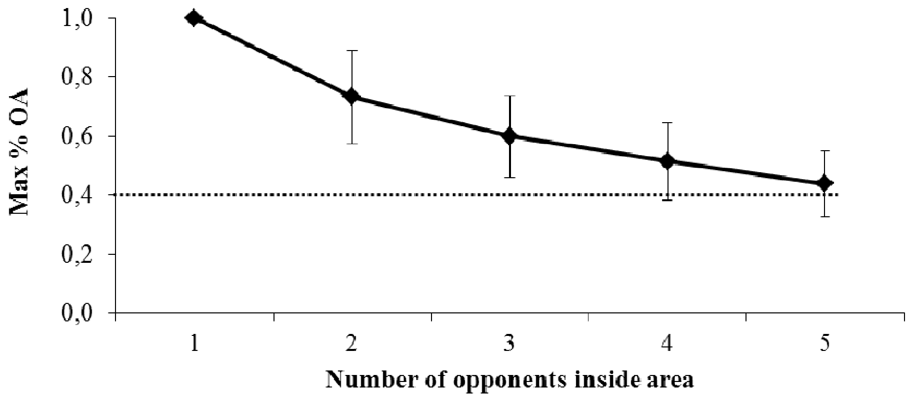


Figure 19: Mean of the maximum percentage of Overlapped Area (Max%OA) calculated for a player in situations where the number of players inside his Voronoi area varies from 1 to 5. The error bars represent the standard deviation.

Hence, this variable can be used to characterize the interaction of one player with the opponents, in particular, the density of opponents in his vicinity. According to the simulated data results presented in Figure 19, values of the maximum percentage of overlapped area (Max%OA) below 0.4 indicate that the attacker is in a situation of clear numerical disadvantage (dotted horizontal line).

Results

The described methodology was applied to empirical data collected from 19 Futsal attack trials, 5 vs 4+GK played in a limited region of $20\times20m^2$. Data results are shown for four randomly selected trials. The observed patterns of behavior, assessed by means of the

%FA (see Figure 20), indicate more towards low levels of exclusive dyadic interaction (%FA values inside the interval (0.22, 0.50)%), which was expected as defense players were playing in a zone defense fashion due to their numerical disadvantage.

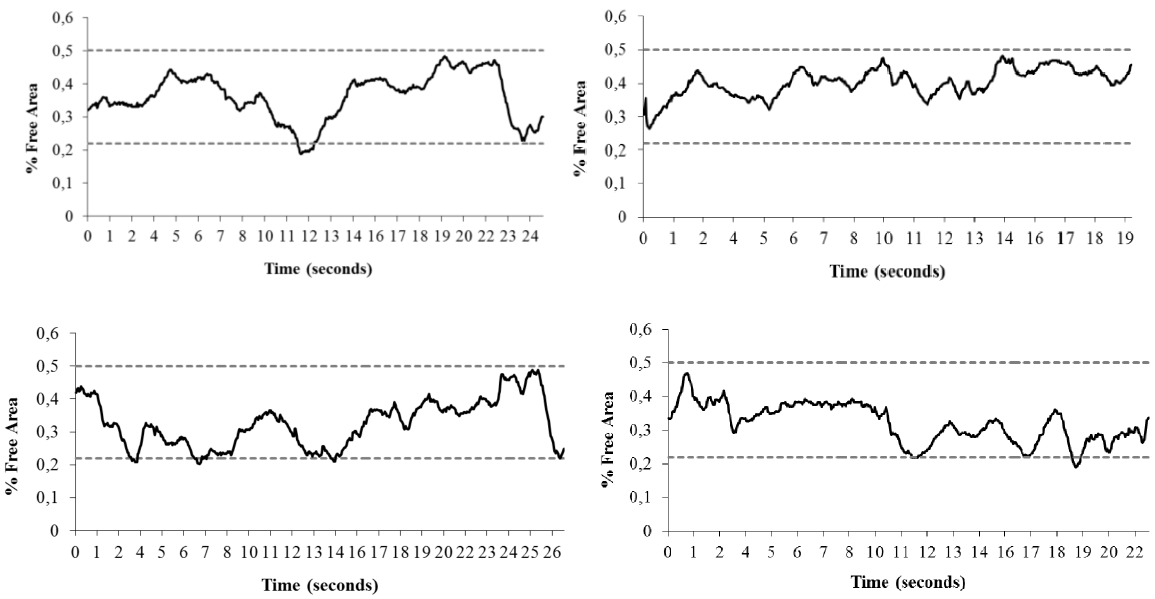


Figure 20: Observed %FA (percentage of Free Area) in a sample of 4 trials (solid black line) and the 95% confidence interval for absence of interaction (dashed grey lines). Values within the dashed lines (0.22, 0.50) indicate low levels of exclusive dyadic interaction.

In addition, for testing for the opponent interaction, and according to what was described above, it was considered the Max%OA for each attacker. Figure 21 (see next page) shows the Max%OA for each of the five attackers across the duration each selected trials. This variable allows identifying the attackers that are under more pressure during the task, i.e., the attackers that have a greater number of opponents in the vicinity (greater density).

In each of the sampled trials, the periods of the task highlighted in Figure 21 are related with two kinds of situations: 1) when the corresponding attacker enters in the defensive structure with the intention of receiving a pass from the ball carrier or 2) when the attacker is the ball carrier and is positioned very close to the goal. In both situations, players from the defense team tend to protect the goal and gain ball possession, which leads to a pressure towards these attackers and hence lower values of their Max%OA.

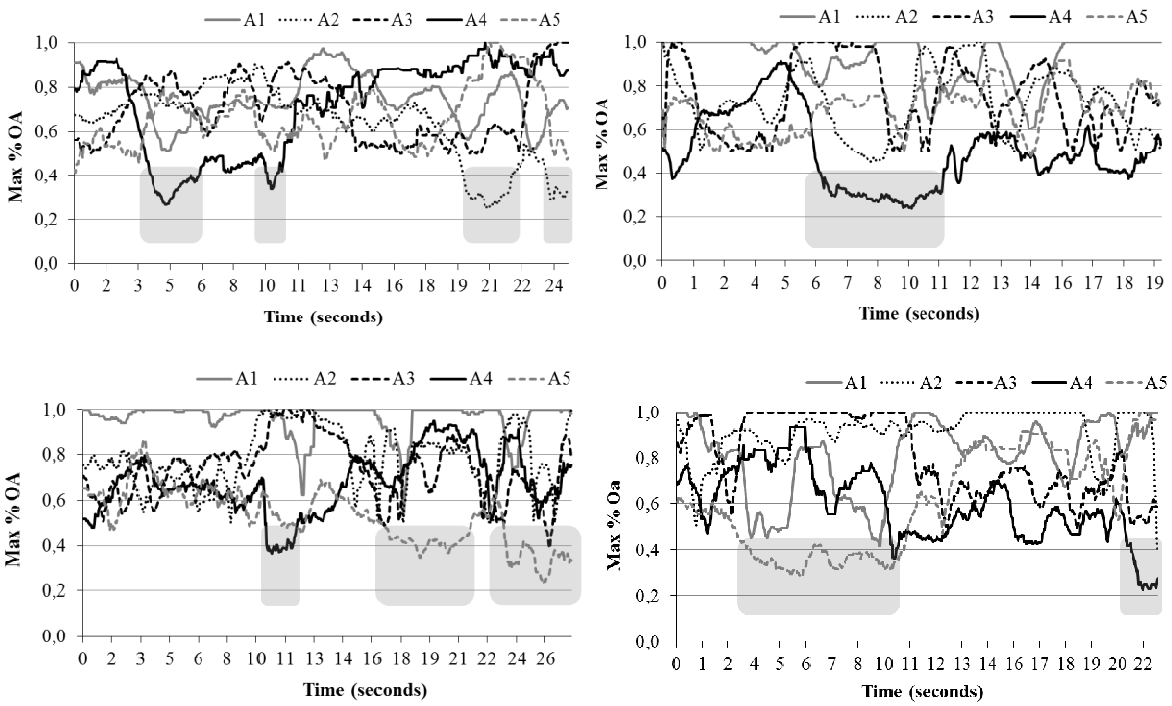


Figure 21: Observed Max%OA (maximum percentage of Overlapped Area) for each of the 5 attackers in each of the 4 sampled trials. The shaded rectangles indicate periods during the task when values of this variable for one of the attackers indicate that the player was surrounded by more than one opponent (see text for details).

Discussion

The Superimposed Voronoi Diagrams method presented in this paper is a novel approach for studying spatial interaction in invasive team sports. Although the reference values considered here were generated for the specific futsal scenario under study, it is possible update them according to other settings of interest.

Results from a formal application of this method to empirical data suggest that it is possible to identify a number of characteristics that can be used to describe players' spatial behavior at different levels. In one hand, it is possible to describe the interaction between the two teams by comparing the spatial pattern formed by the respective players, which is much dependent on the interaction established among pairs of opponents, i.e., if players are exclusively paired, as they would be in a man-to-man defensive method, the % FA will be below the reference values calculated for situations when such interaction is not imposed (random interaction). On the other hand, and by means of a different variable extracted from the same superimposed graphical construction, Max%OA, it is possible to describe, across the duration of the game (or task), the type of interaction established between each attacker and his opponents, in particular to distinguish between different types of numerical relation, for example, situations of more or less pressure, which corresponds to having many or few opponents in his vicinity, respectively.

In this work, the areas defined by the VD for each player of a team are solely based on players' position and limits of the playing area. Other factors likely to influence the size of these areas such as ball position, distance from ball, distance from goal, direction and speed of the displacement as well as players' skills were not considered, but we intend to add these in future work on this area.

Importantly, the fact that the described methodology considers the superimposition of opponent teams' dominant regions adds value to the introduced measures making them more appealing than those that are calculated for each team separately, ignoring the interaction context.

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Chapter 5: General discussion

Under a dynamical system approach to team sports behavior, and with the aim of ascertain the dynamic characteristics of the interaction behavior established at a collective level, researchers have suggested spatial measures to describe inter-team and/or inter-player interaction behavior across the duration of games, plays or trials. Some examples are the convex hull (Frencken et al., 2011), the stretch index (Bourbousson, Sève, & McGarry, 2010a) and simple measurements derived from the average position (centroid) of the whole team (Frencken & Lemmink, 2008; Bourbousson, Sève, & McGarry, 2010b; Frencken et al., 2011; Sampaio & Maças, 2012).

Concerns about the adequacy of the measures mentioned above have arisen after identifying a couple of drawbacks on their conception, namely, the limits of the playing area are neglected and variables are calculated for each team ignoring the spatial information of the other. Accordingly, the models presented in this thesis were specifically designed to address these problems and, consequently, define strong candidates to collective variables for such interacting dynamic behavioral systems.

Pertinence of a Voronoi diagrams' approach

Team sports games are recognized as dynamic systems of interaction, where players from both teams continuously interact, taking measures and countermeasures in order to overcome the opponent (Lames & McGarry, 2007). Deciding where to be (position) and what to do (action), at each moment of the game, emerges from a decision-making process (Araújo et al., 2006), in which players: (a) perceive essential information from the playing environment, e.g. the position of the other players, (b) correctly interpret it and (c) act accordingly (Baker, Côté & Abernethy, 2003). Thus, the spatial organization of a team, assessed throughout a game, play or trial, mirrors what teammates have individually perceived to be the best collective distribution at each moment, according to the present characteristics of the environment, in particular the spatial distribution of the opponent players.

For example, in an offensive play, the attacking team will try to create/find space by avoiding the defenders and positioning themselves in the field according to this intention. More space affords more possibilities of action and by doing so players will be able to have more chances to decide what is best to do at each moment (e.g., pass, run, shoot, etc.) in order to maintain ball possession and progress in the field towards the goal. As expected, the defending team will want to close this space and they will position themselves in the field in order to do so.

Given this, team sports behavior was here approached using Voronoi diagrams as these basic laws of spatial interaction are present in such spatial tessellations: for each point, the size of respective Voronoi cell is related with the closeness to other points, the closer the points the greater the cells' area.

The models

The spatial models here suggested imply that games, plays or trials, of interest are video recorded and that the positional data from all players are available in real world metrics.

Model 1: Voronoi Diagrams (VD)

In the first model was considered a straightforward application of VD to the set of players from both teams. The collective variable here suggested was the size of the dominant regions (area of the Voronoi cells), which allows describing intra- and inter-team spatial behavior. Results from an application to empirical data from Futsal tasks of a 5 vs 4+GK suggested that the area of the dominant region (DR), as well as the distance to nearest teammate, can capture the tactical behavior of both teams. Specifically, the team that is attacking is more spread out, presenting a greater dominant region's area during the whole trial, whereas the team defending is more concentrated, presenting, instead, smaller dominant regions. In addition, as a result of a formal application of a normalized measure of ApEn to these data, we concluded that the size of the DR defined by players is more regular for the attacker team in comparison with the defender team, which means that the spatial interaction behavior of the team defending is more complex.

Model 2: Superimposed Voronoi Diagrams (SVD)

The second model represents a new approach to spatial interaction behavior. This model results from superimposing the VD generated for each of the two competing teams. From this novel spatial construction, were derived two collective variables, %FA and Max%OA. According to how they were defined, %FA is largely dependent on the distance between each pair of exclusive opponents, whereas Max%OA, it is largely dependent on the number of opponent neighbors, and they can be used to identify modes of dyadic interaction and quantify pressure, respectively.

An exploratory application of this model to empirical data from Futsal tasks of a 5 vs 4+GK, allowed to: (a) identify the type of defense method applied, which in this case presented low levels of dyadic interaction due to the numerical advantage of the attack, and (b) to identify the attacker that was under more pressure.

Theoretical contributions

According to our results, these models appear to have potential to study the dynamic characteristics of the spatial interaction behavior established between players and teams in invasive team sports, such as soccer, basketball, handball, etc. The specificity of each team sports is considered in this approach as it allows determining reference values of some collective variables according to the characteristics of the game, play or trial under study, e.g., the number of players and the dimensions of the play area. In this context, reference values can be used as a tool to identifying specific individual and collective characteristics of a dynamic behavioral system of this nature.

Tuned with an ecological approach to decision making in team sports (Araújo et al., 2006), these models can serve constrain-led approaches to team sports behavior (Araújo et al., 2004; Renshaw et al., 2004; Chow et al., 2006; Davids, Button & Bennett, 2008) in order to understand how certain constraints influence the emergent patterns of interaction behavior. Results from a recent study (Celikkaya, Fonseca & Travassos, 2012) have shown that limitation on the number of ball touches has an effect on the spatial interaction behavior established between the attackers. In particular, their minimum interpersonal distance increased significantly in the presence of that specific constraint, which is thought to be a result of players' attempt to increase space. In this context, more space affords more time to decide what to do, when the possibilities of action are limited.

Finally, considering the dynamic nature of these behavioral systems, the collective variables here suggested to describe behavior at different levels of interaction can be considered to evaluate the properties of such systems, for example, visually inspecting the behavior of a specific collective variable, measuring its regularity, identifying eventual qualitative transitions in the system state, perturbations, critical fluctuations, among other properties.

Methodological considerations

Despite the encouraging results from an exploratory application of the two models to Futsal data, they should be applied to data from a variety of different invasive team sports (e.g., basketball, handball, rugby), preferably in situations with transitions in ball possession, in order to test the collective variables here suggested, and assess their true potential to capture the described behavioral characteristics. Having this established, several approaches are worth considering, such as. within and between specific team sports, (a) study how the fitting of the two spatial distributions evolves and changes, (b) compare teams' behavior when they are defending and when they are attacking, (c) identify and compare preferred modes of dyadic interaction and (d) understand how players from both teams reorganize their distribution after transition in ball possession.

Nevertheless, and although VD and SVD models have shown potential towards the understanding of interaction behavior in team sports, we have identified an important limitation on the definition of players' DR. The Voronoi cell of each player is defined based on a non-weighted distance from each player to points in the field, which means that the DR of each player is solely determined by his position. Other factors, such as the anthropometric characteristics of the players (Cordovil et al., 2009), players' performance skills, the kinematic characteristics of their movement (Taki, Hasegawa & Fukumura, 1996; Fujimura & Sugihara, 2005) and the players' distance from ball (Fujimura & Sugihara, 2005), are known to determine players' actions and hence influence their spatial distribution in the field. Future work in this area should consider weighting the DR by some of these factors.

Practical applications in training

As mentioned before, players' space perception is a skill of major importance in the decision-making process during a game, play or task, as players need to correctly perceive the space where they are in order to effectively move on it.

Players acquire and improve their skills during training sessions and so, their performance in a contest is much dependent on what they have learned. The models presented in this thesis, and particularly the measures suggested as collective variables, can be seen as new tools that coaches can consider to effectively assess the characteristics of the spatial interaction behavior of a team, which can be used to quantify performance at team and player levels. Applying these in training sessions can help coaches to understand and anticipate team and players behavior in a game and to evaluate and compare performance under different constrains.

To illustrate, if a soccer coach considers this spatial approach to analyze the interaction behavior of their players in a formal game played in a training session, he would be able to answer the following questions: (1) Do attacking players know how to create space? (2) Do defensive players know how to close space? (3) Do defending players know how to apply a man- man-to-man defense? (4) Can the defense team mark effectively the player with the ball? (5) Which player is more successful in creating/close space? Moreover, if in addition he decides to consider the previously mentioned constrain-led approach, he can further identify how players' and teams' spatial interaction behavior change according to the manipulated constrains and how these can be used to improve performance.

Final remarks

In conclusion, although the pair of models here presented is still in need of some work, they represent a novel and interesting tool for the analysis of players' and teams' behavior in invasive team sports under a dynamic system approach. As described above, the collective variables derived from these models have shown to capture a number of interesting properties that characterize the interacting behavior established at an individual and collective level during a game, play or trial, which can be useful for coaches in a training context.

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