Shared affordances guide interpersonal synergies in sport teams

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1. Introduction

Team sports performance has been described by means of notational techniques with the purpose of inspecting the behaviours of performers during different sub-phases of play in team games. The aim of such analysis is to provide accurate, augmented information to practitioners to improve future performance (Vilar et al., 2012). The recorded variables include scoring indicators such as goals, baskets, winners, errors, the ratios of winners to errors and goals to shots; or performance indicators such as turnovers, tackles, and passes (see Passos et al, 2016/in press for a recent review). An important criticism of notational analysis research is that it has been somewhat reductionist (Glazier, 2010), typically omitting reference to the *why* and *how* of performance that underlie the structure of recorded behaviours, which would define their functional utility (McGarry, 2009). This points towards the need for a sound theoretical rationale of performance behaviours. In fact, there are some theoretical approaches that go beyond analytics, which are relevant *per se*, and present viable hypotheses to test (see Chapter ??? in this book, by Araújo & Bourbousson). Ecological dynamics is such a framework for studying behaviours in team games. It has the advantage of recognising the 'degeneracy' of collective biological systems (i.e. teams). Its principles can explain how the same performance outcomes can emerge from different movement or tactical patterns.

2. Ecological dynamics approach to team's behavior

Ecological dynamics proposes performer-environment relations as the relevant scale of analysis for understanding sport performance (see also Chapter ?? of this book, by Araújo & Bourbousson; Davids & Araújo, 2010). The functional patterns of coordinated behaviour emerge through a process of self-organisation from performers' interactions with each other under specific task and environmental constraints (Araújo, Davids, & Hristovski, 2006). Ecological dynamics analyses of team sports have attempted to explain how the interaction between players and information from the performance environment constrains the emergence of patterns of stability, variability and the transitions in organisational states of such systems. The emergent coordination patterns in team sports are channelled by the surrounding constraints, as they structure the state space of all possible configurations available to the team game as a complex system (Davids, Button, Araújo, Renshaw, & Hristovski, 2006). Constraints are boundaries or features, which interact to shape the emergence of the states of system organization. For example, the surrounding patterned energy distributions that performers can perceive act as important sources of information to support their decisions and actions (e.g., reflected light from the ball) (Araújo & Davids, 2009).

The interaction between constraints of the performance environment and each individual's characteristics allows opportunities for action to emerge (Araújo, et al., 2006). For example, an opportunity to score a goal in football may emerge between the performer's ability to shoot the ball (individual constraints) and the distance to the goal or to the goalkeeper (task constraints). Moreover, performers are also able to identify relations between other performers and key environmental objects (e.g., the ball and target zone in team games) that can constrain their behaviours (Richardson, Marsh, & Baron, 2007). By perceiving opportunities for others to act, performers make use of environmental information to coordinate their actions with others.

Due to the complex spatial-temporal relations among performers that characterize team sports, performance constraints change on a momentary basis. Opportunities to act (or affordances, Gibson, 1979) may appear and disappear over time (Araújo & Davids, 2009). The concept of affordances presupposes that the environment is perceived directly in terms of what an organism can do with and in the environment (i.e., it is not dependent on a perceiver's expectations, nor mental representations linked to specific performance solutions) (Richardson et al., 2008). It has been suggested in team sports (Davids, Araújo & Shuttleworth, 2005) that individuals base their movement decisions on locally acquired information sources such as the relative positioning, motion direction, or changing motion direction, of significant others operating in a system, making a collective response all the more remarkable. This hypothesis implies that the actions of individuals functioning in a team need to be intimately coordinated. The interactions of agents in sports teams reveal common underlying principles while exhibiting simultaneously their own 'signatures' or idiosyncratic behaviours.

An important understanding of affordances is that, they can be perceived by a group of individuals trained to become perceptually attuned to them (Silva et al., 2013). In collective sports, both teams in opposition have the same objective (i.e., to overcome the opposition and win). Hence, the perception of collective affordances acts as a selection pressure (Reed, 1996) for overcoming opponents, and achieving successful performance. In this sense, collective affordances are sustained by common goals between players of the same team who act to achieve success for the group. From this perspective, team coordination depends on being collectively attuned to shared affordances founded on joint practice to become attuned to specific environmental circumstances (Silva et al., 2013). Through practice, players become perceptually attuned to affordances *of* others and affordances *for* others during competitive performance and undertake more efficient actions (Fajen et al., 2009) by adjusting their behaviours to functionally adapt to those of other teammates and opponents. This process enables them to act synergistically with respect to specific team task goals (Folgado et al., 2012; Travassos et al., 2012). By means of tracked positional data, recent studies have started to reveal how players and teams *continuously* interact during competition. For example, teams tend to be tightly synchronised in their lateral and longitudinal movements (Vilar et al., 2013) with a counterphase relation regarding their expansion and contraction movement patterns (Yue et al., 2008), commonly caused by changes in ball possession (Bourbousson et al., 2010).

Following these types of compound measures, specific training effects found by Sampaio and Maçãs (2012) indicate that players adjust constantly their positions on the pitch, according to the game ebb-and-flow, a that more effective team coordination was expressed by the fact that the most powerful variable in distinguishing pre and post-test conditions was the distance of players from the team geometric centre (obtained by computing the mean lateral and longitudinal positional coordinates of each performer in a team). As it was expected, inter-player coordination in pre-test seems to reflect individual affordances, and not shared affordances among team players. However, post-test values showed that players became more coordinated with increased expertise. The coordination patterns found, showed compensatory behavior within the team, an essential characteristic of a synergy (Riley et al., 2011). Thus, the decisions and actions of the players forming a synergy should not be viewed as independent. Therefore, the coupling of players' degrees of freedom into interpersonal synergies is based upon a social perception-action system that is supported by the perception of shared affordances.

Specific constraints like the players' individual characteristics, a nation's traditions in a sport, strategy, coaches' instructions, etc., may impact on the functional and goal-directed synergies formed by the players to shape a particular performance behaviour. These informational constraints shape shared affordances available for players, viewed as crucial for the assembly of synergies, that support the reduction of the number of independent degrees of freedom (Riley et al., 2011). Under this theoretical rationale, the properties of synergies guide the information that could be obtained from the diverse behavioural team measures.

3. Synergies organize the meaning of measures of team behaviour in performance environments

A synergy is a task-specific organization of elements, such that the degrees of freedom of each component are coupled, enabling the degrees of freedom to regulate each other (Bernstein, 1967, Gelfand & Tsetlin, 1966). Latash (2008) identifies the characteristics that should be met for a group of components to be considered a synergy: sharing, error compensation, and task-dependence. Sharing means that the components should all contribute to a particular task. A way to quantify the amount of sharing is the matching of the sum of the individual contributions to the task, and the overall measurement of the performance on the task. Error compensation is captured when some components show changes in their contributions to a task, compensating one component that is not doing its contribution. Finally, task-dependence is the ability of a synergy to change its functioning in a task-specific way or, in other words, to form a different synergy for a different purpose based on the same set of components. Therefore, synergies are "task specific devices" (Bingham, 1988).

On the other hand, Riley and colleagues (Riley, Richardson, Shockley, & Ramenzoni, 2011) identify two characteristics of a synergy. One is dimensional compression, which means that degrees of freedom that potentially are independent are coupled so that the synergy has fewer degrees of freedom (possesses a lower dimensionality) than the set of components from which it arises. The behavior of the synergy has even fewer degrees of freedom, a second level of dimensional compression as one moves from structural components to the behavior that emerged from the interactions among the degrees of freedom. Dimensional compression at both stages results from imposing constraints (environmental, task and individual constraints), which couple components so they change together, rather than independently. The other property of a synergy for Riley et al (2011) is reciprocal compensation and it is similar to error compensation, as described by Latash (2008).

Here we address three properties of a synergy 1) dimensional compression (Bingham, 1988; Riley et al., 2011), 2) reciprocal compensation (Latash, 2008; Riley et al, 2011); and 3) degeneracy (Davids et al., 2006; Latash, 2008), and how these properties organize the existing measures of group behavior in sport teams.

3.1 Dimensional compression

For dealing with the problem of dimensional reduction, there are some useful approaches to data analysis aimed at system identification. For this, experiential knowledge from expert coaches may be a good starting point, by capitalizing on educated guesses about which collective variables are most relevant.

3.1.1. Grouping measurements in sports teams

The joint work of expert coaches and sport scientists arrived at team measures such as team centre and team dispersion. Coaches often mention the importance of the "centre of gravity" of a team (Grehaigne et al., 2011). An operational approach to this tactical concept is team's centre (also denominated centroid, or geometrical centre). This variable can be obtained by computing the mean lateral and longitudinal positional coordinates of each player in a team. It has been used in various ways to evaluate intra- and inter-team coordination in team sports like association football (Frencken, Lemmink, Delleman, & Visscher, 2011, and see Clemente, Couceiro, Martins, Mendes, & Figueiredo, 201 for a "weighted" centroid), futsal (Travassos, Araújo, Duarte, & McGarry, 2012) and basketball (Bourbousson, Sève, & McGarry, 2010). The teams' centres alone can represent the relative positioning of both teams in the forward-backward and side-to-side movement displacements, but when analysed in respect to other measures, may provide important descriptions of team tactics.

According to the basic principles of attacking and defending in invasion team sports, the team in possession must create space by stretching and expanding in the field while the defending team must close down space by contracting and reducing distances between players. Such collective movements may be captured by specific measures of team coordination that quantify the overall spatial dispersion of players. The stretch index (or radius), the team spread and the effective playing space (or surface area) are quantities that have been used to assess such spatial distributions. The stretch index is calculated by computing the average radial distance of all players to their team's centroid. It also can be calculated according to axis expansion, providing distinct measures of dispersion for the longitudinal and lateral directions (e.g., Yue, Broich, Seifriz, & Mester 2008; and see Moura, Martins, Anido, Barros, & Cunha, 2012 for team spread - the square root of the sums of the squares of the distances between all pairs of players, excluding the goalkeeper). The effective playing space (or surface area) is defined by the smallest polygonal area delimited by the peripheral players containing all players in the game and can also provide information about the surface that is being effectively covered by the two teams. It informs how the occupation of space unfolds throughout the game and how stretched both teams are in the field. This effective playing space may also be computed as a function of attacking and defending, discriminating the surface areas of both teams in confrontation while representing the overall team positioning (Frencken & Lemmink, 2008). Similarly to the stretch index and team spread, the relationship between the offensive and defensive surface areas can highlight the balance of the opposition relationship during matches (Gréhaigne & Godbout, 2013). Moreover, Folgado and colleagues (2012) calculated the team's length and width in small-sided games performed by youth football players of different ages. The team's length and width were calculated by measuring the distance between the players furthest forward and backward, and furthest to the left and to the right, respectively. Through these quantities, the authors computed the ratio between length and width, based on the assumption that teams with different tactical approaches would display different length per width ratios. Recently, Silva and colleagues (2014a) developed "team separateness" metric. It is defined as a measure of the degree of free movement each team has available. In football, it was computed based on sum of distances (in meters) between each team player and the closest opponent, excluding goalkeepers, and can be interpreted as the overall radius of action free of opponents. It is different from previous metrics because it accounts for the teams' dispersion differences which may impact on the players' radius of free movement. A value of TS close to 0 indicates that all players are closely marked, while a high value indicates more freedom of movement. Interestingly, team separateness increased independently of skill level with the increase in pitch size.

A key idea of invasion team sports assumed to promote effective performance is to outnumber the opposition (creation of numerical overloads) during different performance phases (attack and defense) in spatial regions adjacent to the ball, as expresses by inter-team coordination. Inter-team coordination was recently examined through analysis of the distances separating the teams' horizontal and vertical opposing line-forces in football (Silva et al., 2014b). This measure captures the existence of possible differences in the players' interactive behaviors at specific team locations (e.g., wings and sectors). Each team's horizontal lines are calculated by averaging the longitudinal coordinate values of the two players furthest from, and nearest to their own goal line, which corresponded to the forward and back lines, respectively. Similarly, the vertical line-forces of each team are computed by averaging the mean lateral coordinates of the players furthest to the left and to the right on the pitch, corresponding to the left and right lines, respectively.

3.1.2. Sharing patterns within teams

Sharing pattern, also known as labour division (Duarte et al., 2012; Araújo et al., 2015), is the specific contribution of each element to a group task (Latash, 2008). The behaviour of each individual in a team is constrained by several factors like his/her position on the field (in relation to the other teammates and opponents), strategic and tactical missions, playing phases (i.e., attacking and defending), game rules, etc. Collective behaviour is thus, composed of many individual labours (Eccles, 2010) performed by two or more players looking to cooperate together towards common intended goals and linked together by a communication system (Silva, Garganta, Araújo, Davids, & Aguiar, 2013). The joint analysis of all these individual behaviours can translate group behaviour as all players constrain and are constrained by the entire dynamic system that they compose (Glazier, 2010). This property could be captured by measures of heat maps, major ranges, player-to-locus distance, and Voronoi cells.

Heat maps provide a clear picture of the distribution of each player on the field. Heat maps highlight with warmer colours the zones where each player has lingered for larger periods of time during the match (Araújo et al., 2015). Another approach to assess the division of labour in team sports is by measuring the area covered by each player. Major ranges imply the calculation of an ellipse centred at each player's locus and with semi-axes being the standard deviations in the x- and y-directions, respectively (Yue et al., 2008). Through the simple visualization of major ranges it is possible to identify preferred spatial positions, major roles for each player and playing styles (Araújo et al., 2015).

Contrary to the former two measurements, the distance of each player to a private locus on field, over time, capture the time-evolving nature of their movements' trajectories. The locus represents the player's spatial positional reference around which he/she oscillates (McGarry, Perl, & Lames, 2014). Individual playing areas attributed to each player on a team, delimited the Voronoi cells of players in team ball sports, and offer a time-evolving analysis of the trajectories of these areas (Fonseca, Diniz & Araújo, 2013). A Voronoi cell contains all spatial points that are nearer to the player to whom that cell is allocated than to the other players. By measuring the total area of all Voronoi cells from each team, it is possible to obtain a dominant ratio of one team over the other (Fonseca, Milho, Travassos, & Araújo, 2012).

3.1.3. Order parameters

Dimensional reduction is particularly important because advances in data acquisition have allowed for simultaneous recordings of multiple signals for considerable time spans, resulting in huge data sets. Therefore techniques for *a priori* data reduction, such as principal component analysis (PCA) are very useful (Daffertshofer et al., 2004). Based on the covariance matrix between signals, eigenvectors rank the degree to which a principal component contributes to the entire variance (see Button et al., 2014 for applications in sports). However a even more principled approach to pursue dimensional reduction is to focus on phase transitions because theory dictates that very near the critical point the dynamics of the complex system under study is reduced to a small set of collective variables or order parameters. Phase transitions are accompanied by a huge separation of time scales between different system components. In dynamics terms, the transition of a pattern to another implies that the first becomes unstable and the second becomes stable. From the view point of the order parameters, all the subsystems become arbitrarily quick so that they can adapt instantaneously to changes in the order parameters. The system dynamics thus amount to that of the order parameters, implying the ordered states can always be described by a very few variables if in the neighbourhood of behavioral transitions. In other words, the state of the originally high-dimensional system can be summarized by a few variables or even a single collective variable, the order parameter (Beek & Daffertshofer, 2014).

However, before that it is important to identify the system (Daffertshofer & Beek, 2014). The identification of the system is nothing more than the characterization of a system's dynamics, in terms of regularity and stability. For this, measures of regularity like sample entropy (see Kuznetsov et al., 2014, for a review) are needed in combination with conventional statistics. Sample entropy quantifies the regularity or repeatability of a signal (i.e., empirical time series). Similarly, Lyapunov exponents are used for estimating the stability properties of dynamical systems involving the emergence and disappearance of behavioral patterns (Stergiou et al., 2004).

Dynamical systems approaches to self-organization have emphasized dimensional compression, where the order parameter "relative phase" (e.g., the difference in the segments' oscillation phases, see Kelso 1995) captures the low-dimensional behavior that arises from the high-dimensional neuromuscular system. Relative phase describes the spatiotemporal pattern of rhythmic coordination and the changes in coordination that occur in response to manipulations of the *control parameters* (e.g., movement frequency). The dynamics of relative phase are understood to reflect the behavior of a synergy (Kelso, 1995; Turvey and Carello, 1996).

Several coordination variables have been applied in team sports to assess coordination between two oscillatory units (e.g., the coupling of two centroids, or the phase relations of two players' movements in a dyad). For instance, the phase synchronization of two signals has been previously studied through relative phase analysis (e.g., Travassos, Araújo, Vilar, & McGarry, 2011), and through running correlations (e.g., Duarte, Araújo, Freire, et al., 2012).

In an attempt to capture group synchrony tendencies Duarte and colleagues (Duarte, Araújo, Correia, et al., 2013) shed light on how the players composing a team influence each other to create a collective synergy at the team level. For this, the cluster phase method (Frank & Richardson, 2010), based on the Kuramoto order parameter was applied to the movements of eleven football players from two teams during a football match to assess whole team and player-team synchrony. Synergistic relations from the whole team showed superior mean values and high levels of stability in the longitudinal direction when compared with the lateral direction of the field, whereas the player-team synchrony revealed a tendency for a near in-phase mode of coordination. Also, the coupling of the two teams measures showed that synchronization increased between both teams over time.

Whenever the focus is on phase transitions, mathematical modelling in terms of dynamical systems becomes feasible. Importantly, there were formal demonstrations in sport that did not adhere to the well know relative phase and related measures, as indicated before. For example, Araújo and colleagues (Araújo, Diniz, Passos & Davids, 2014) conceived behavioral phase transitions as the operational definition of decision-making in sport. They modelled how the order parameter "angle between a vector connecting the participants and the try line" expressed the state of a dyadic system composed of attacker and defender in rugby union. Their model, a potential function with two control parameters (interpersonal distance, and relative velocity) and a noise parameter, match empirical evidence that revealed that this kind of system has three stable attractors.

3.2. Reciprocal compensation

Reciprocal compensation indicates that if one element produces more or less than its expected share, other elements should show changes in their contributions such that the task goals are still attained (Latash, 2008).

Contrary to dimensional compression, reciprocal compensation, being intuitively a very important property of a team of players, only recently was operationalized in sport. However, it can be found in motor control with the *uncontrolled manifold (UCM)* approach (Scholz and Schöner, 1999; Latash et al., 2002). This approach assumes that coordinated movement is achieved by stabilizing the value of a performance variable (such as a value of relative phase corresponding to an interlimb coordination pattern). In doing so, a subspace (i.e., manifold) is created within a state space of task-relevant elements (the degrees of freedom that participate in the task), such that within the subspace – called UCM - the value of the performance variable remains constant (Riley et al., 2011).

In sport, Silva and colleagues (Silva et al., in press) created a new metric, called readjustment delay (Rd). The football players' co-positioning delay (Rd) to adjust to teammates' movements (goalkeepers excluded) was computed as a measure of team readiness and synchronization speed during attacking and defending patterns of play. Lower delay values indicate rapid readjustment of movements and faster spatial temporal synchrony between players, whereas a larger readjustment delay might impede spatial-temporal synchrony of player movements. To analyse Rd, the time series of distances to goal of each dyad were lagged in time, reported through the highest correlation coefficient values. A windowed cross-correlation technique was then used for each player with all his nine teammates, producing a moving estimate of association and lag. The max lags were considered to represent the time delay, in seconds, between two players' co-positioning in relation to their own goal. Silva et al. (in press) found that the players Rd decreased over the 15 weeks of the study, evidencing faster readjustments of coupled players, a manifestation of how this property of the synergy evolved in the team.

3.3. Degeneracy

Bernstein (1967) emphasized that motor system degrees of freedom are temporarily coordinated together according to the performance environment and task requirements (aka task dependence, Latash, 2008). It has been well documented that novices typically freeze their motor system degrees of freedom, while experts release the degrees of freedom not useful in task performance (e.g., Vereijken et al., 1992, and Seifert et al, 2013 for a review). Freezing system degrees of freedom corresponds to rigidly fixing the joints to reduce the control problem for a performer. The varying role of these motor system degrees of freedom in assembling actions is essential, and is exemplified by the degenerate networks existing at different levels of human movement systems (Seifert et al., 2013). Degeneracy, thus, refers to structurally different components perform a similar, but not necessarily identical, function with respect to context (Edelman & Gally, 2001). In this sense, behavioural adaptability reflect the modification of one component of the system and/or a whole modification of coordination realised by 'redundant' elements (i.e. the presence of isomorphic and isofunctional components) or by 'degenerate' elements (i.e. the presence of heteromorphic variants that are isofunctional) (Mason, 2010). A substantial body of literature has highlighted the functional role of movement variability in sport performance environment and exemplifies how degeneracy emerges at an ‘intra-individual’ and ‘inter-individual’ levels in many sports (Davids et al., 2006; Seifert et al., 2013).

A team ball game is sustained by continuous adaptive interactions among players (Araújo et al., 2015). The behaviour of such complex systems emerges from the orchestrated activity of many system components (players) that adaptively interact through pairwise local interactions. A common feature of such complex, social networks is that any two nodes or system agents can become interconnected for action through a path of a few links only (Newman, 2003).

Recently, studies with complex networks revealed that certain forms of network growth produce scale-free networks, that is, the distribution of connections per node in the networks is scale invariant (Baraási & Albert, 1999), as it happens with phase transitions and critical points. This indicates that, degeneracy, as a property of a synergy, might be quantified in the different metrics of social networks

Passos et al., (2011) showed that social networks could be used to analyse the local structure of communication channels among players, during sub-phases of play in team sports. In these networks, nodes represent players and links are weighted according to the number of passes or positional changes completed between players. Players with major competitive roles (importance or centrality) may be easily identified through social network analyses, since they display a higher number and, thus, stronger connections. Additionally, different match networks can be compared to extract the general tactical and strategic features of a team, such as the: i) in-degree that measures the number of players who pass the ball to a focal player; ii) out-degree that measures the number of players to which the focal player passes the ball; and iii) preferential attachments between some team members (Passos et al., 2011; Duch et al, 2010; Grund, 2012) .

It is possible to advance the understanding of team sports performance, by using other existing metrics that consider more than the links between the focal node and its neighbours. For example, for understanding the playing style of a sports team, Gyarmati et al. (2014) did not use any of the metrics that are "focal node" based but other metrics that are founded on the identification and quantification of connection patters. In order to include other relevant aspects of the game, notably technical actions, some authors have extended the definition of the network. For example in the analysis of basketball Fewell et al. (2012) has included rebounds and steals as nodes in the network. But also other metrics such as the flow centrality which gives a quantification of individual and team performance regarding a specific goal like a goal attempt (shot at the goal); or the clustering coefficient that captures the probability of cooperation between players as a function of their mutual interactions do beyond the local structure (e.g, Fewell et al., 2012).

Emergent patterns of interaction have also been studied using different representations of the interactions between the different actors. These include, hypernetworks, where hyperlinks may connect more than a pair of nodes. This latter approach has been applied to robotic soccer (Jonhnson & Iravani, 2007) and has proven particularly powerful.

Networks are a valuable tool to analyse the structure of such communication channels during sub-phases of play in team sports, since it allows the identification of players engaged in more and less frequent interactions within a team and in particular events.

Conclusions

Specific constraints impact on team synergies formed by players during performance. These constraints shape the perception of shared affordances available for players, which underpin the assembly of interpersonal synergies expressed in collective actions. These group processes form synergies, where their key properties – dimentional compression, reciprocal compensation and degeneracy - guide the meaning of operational variables such as team centre, team dispersion, team synchrony, and team communication. Developments in methods of analysis of team coordination and performance can benefit from a theoretical approach that situates and traces relevant team properties as defined by synergies. Here we suggest that shared affordances and synergies embraced by an ecological dynamics perspective present the principles to understand the meaning of existing operational metrics of performance analysis and to guide the search for more meaningful ones.

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