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A cluster phase analysis for collective behavior in team sports

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ABSTRACT

Collective behavior can be defined as the ability of humans to coordinate with others through a complex environment. Sports offer exquisite examples of this dynamic interplay, requiring decision making and other perceptual-cognitive skills to adjust individual decisions to the team self-organization and vice versa. Considering players of a team as periodic phase oscillators, synchrony analyses can be used to model the coordination of a team. Nonetheless, a main limitation of current models is that collective behavior is context independent. In other words, players on a team can be highly synchronized without this corresponding to a meaningful coordination dynamics relevant to the context of the game. Considering these issues, the aim of this study was to develop a method of analysis sensitive to the context for evidence-based measures of collective behavior.

1. Introduction

Multi-agent coordination and large-scale group dynamics have become especially hot topics of research in the biological and cognitive sciences. Today, researchers in both domains study a wide range of complex multi-agent phenomena—from small-scale interactions involving the signaling and collective response of bacteria (e.g., Conrad, 2012), to dyadic-level interactions as when two people rhythmically coordinate their limb movements (e.g., Schmidt, Carello, & Turvey, 1990), to the types of large-scale coordination dynamics that are present in sports (e.g., Duarte et al., 2013). A general framework for addressing these sorts of phenomena borrows from the tools and principles of complex systems and self-organization. These tools have proven to be especially useful in describing large-scale, collective behavior in animal (e.g., Cavagna et al., 2010; Ouellette, 2015; Sumpter, Mann, & Perna, 2012) and more recently, human ensembles (Kiefer, Rio, Bonneaud, Walton, & Warren, 2017; Rio, Rhea, & Warren, 2014).

However, human behaviors involve rule-based contexts and time-constraints that not only shape the specific procedures of the performed activity, but also involve regulating behavior to satisfy goals on longer time-scales. Thus, as researchers continue to apply dynamical systems approaches for collective human behavior, key considerations must be given to the proper characterization and parameterization of dynamical models that faithfully account for the additional context and constraints of the focal behavior. In this spirit, our present efforts are centered in European football (soccer), where players must coordinate their actions with others across many different spatial and temporal scales. Recent research has focused on elucidating the mechanisms that facilitate such large-scale coordination, but the identification of the fundamental, self-organizing principles that underlie team dynamics remains an unresolved matter (see e.g., Folgado, Duarte, Fernandes, & Sampaio, 2014; Memmert, Lemmink, & Sampaio, 2016). Indeed, techniques to measure collective emergent behavior are still in the early stages of development (Araujo, Silva, & Ramos, 2014), while many

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attempts to measure team work have typically focused on measuring outcome performance rather than team dynamics (Hughes & Franks, 2004; McGarry, 2009).

Although attempts to study the dynamics of multi-agent activity have benefitted from concepts and tools from Dynamical Systems Theory (DST) (e.g., Davids, Araujo, & Shuttleworth, 2005; Duarte et al., 2013), two important issues remain. First, while DST provides suitable techniques for modeling living systems, it makes no direct claims about their status nor provides a theoretical basis for understanding goal-directed behavior. In other words, one still needs to make critical decisions about *what* aspects of a given system one needs to model and *how* in order to understand its behavior. As a consequence, most of the DST models in team sports lack task-specific context (Ramos-Villagrasa, Marques-Quinteiro, Navarro, & Rico, 2017). The lack of a contextual anchor in these models leaves them open to the criticism that they are not appropriately constrained. Simply put, we can in principle choose to use any *degrees of freedom* (DoFs) to describe a team's behavior, but only a subset of all the possible sets of DoFs will properly correspond to those variables that allow us to make faithful predictions. For example, recent findings demonstrate that global patterns can arise from different behavioral rules at the local scale (Sumpter et al., 2012; Vicsek & Zafeiris, 2012). Local interactions of starlings seem to be independent of the flock density as opposed to those in shoals of fish (Hemelrijk, Hildenbrandt, Reinders, & Stamhuis, 2010). Nevertheless, the global pattern is akin to the ones in animal collective behavior exhibiting cohesive flocks (Ballerini et al., 2008; Bode, Franks, & Wood, 2010). Therefore, it has been suggested that exploration of individual interactions must be gained to further understand collective dynamics.

With this in mind, our purposes are 1) to review the use of tools of DST, with a particular emphasis on Cluster Phase Analysis (*CPA*) and 2) extend the use of this method to characterize team coordination dynamics according to the context of the game. To achieve Goal 1, after a review of previous models assessing synchrony in team sports, we address a few issues that have been reported in the literature. Based on those, we then approach Goal 2 by including different behavioral variables at the local level characterizing players' displacements on the field and subsequently submitting them to *CPA*.

2. Tools of dynamical systems theory: the physical nature of synchronization

Synchronization is one of the most common metrics of coordination employed in the study of perception, action and cognition. Measures of synchrony are used for describing phenomena that obey recurrent, dynamical laws; and have been applied for a wide range of phenomena coming from substantially different fields of study as physics, engineering or even social life (Pikovsky, Rosenblum, & Kurths, 2001). In physical, nonliving systems synchrony is often mediated via mechanical coupling. For example, Huygens's famous observations regarding the synchronization of two clock pendulums suggested that the rhythms of two self-sustained oscillators can adjust and start oscillating with a common period due to a *weak interaction* (Huygens, 1673/1986). That is, when two mechanical clocks are coupled via a vibrating physical substrate their movements become synchronized due to the mutual resonance caused by the motions of their pendula and the shared support. In turn, the degree of synchronization of two self-sustained oscillators (e.g., two pendulum clocks), can be described as the phase difference that exists between their relative displacements (i.e., relative phase), where the phase angle is defined by the angular frequency (ω) and its initial phase ϕ_0. The constant change of the angle *phi* ϕ is represented as a time-series of oscillations. Therefore, when comparing two time-series, the degree to which are ϕ_1 *and* $\phi_2 n$: m locked depends on whether the inequality $|n\phi_1 - m\phi_2| < k$ holds. Thus, for values close to $k = 0^\circ$ the synchrony patterns of coordination move in-phase, since $|n\phi_1 - m\phi_2| \approx 0^\circ$, whereas asynchronous patterns of coordination are called anti-phase since they are associated with relative phase values close to 180°, since $|n\phi_1 - m\phi_2| \approx 180^\circ$ (Pikovsky et al., 2001).

In psychological and social systems, synchronization typically occurs via *informational* (e.g., visual) *coupling*. For example, Schmidt et al. (1990) showed how rhythmic movements of interlimb coordination between persons could be modeled with the same coupled-oscillator model as within-person coordination (e.g., Haken, Kelso, & Bunz, 1985). Schmidt et al.'s initial results demonstrated that a variant of the Haken, Kelso, & Bunz model could be used to describe inter-personal (between-persons), interlimb coordination when actors where attending to (i.e., looking at) one another's movements. A large body of subsequent work has supported the influence of visual coupling in inter-personal coordination (e.g., Noy, Dekel, & Alon, 2011; Richardson, Marsh, Isenhower, Goodman, & Schmidt, 2007; Schmidt, Bienvenu, Fitzpatrick, & Amazeen, 1998). The role of informational coupling has been studied in a wide range of sporting contexts, including squash (see e.g., McGarry, 2006; McGarry, Khan, & Franks, 1999; McGarry & Walter, 2007), tennis (see e.g., Lames, 2006; Palut & Zanone, 2005) and team sports such as rugby (Passos, Araújo, Davids, Gouveia, & Serpa, 2006; Passos et al., 2008), basketball (e.g., Bourbousson, Sève, & McGarry, 2010, part 1 & 2) or soccer (e.g., Frencken & Lemmink, 2008; Travassos, Davids, Araújo, & Esteves, 2013) amongst others. In these studies, intra-coupling refers to the coordination between two teammates, whereas inter-couplings of playing dyads refers to coordination between two opponents. Results from the two latter sports (i.e., basketball and soccer), when looking at the coordination dynamics of players moving from basket-to-basket or goal-to-goal, suggest that players are more coupled during longitudinal (i.e., length of the field) displacements, either in intra or inter-coordination, than with lateral (i.e., width of the field) displacements (see e.g., Bourbousson et al., 2010, part 1). However, in these studies, measures of synchronization (relative phase) were limited to two players modeled as self-sustained oscillators. As Duarte et al. (2012) rightfully note, measures of collective behavior at the team-level have failed to fully characterize the global coordination dynamics. Several attempts have focused on the average of players' positions, or information about the geometric shapes and centroids or covered areas of players (see e.g., Clemente, Santos-Couceiro, Lourenço-Martins, Sousa, & Figueiredo, 2014; Frencken, Lemmink, Delleman, & Visscher, 2011; Lames, Erdmann, & Walter, 2010; Schöllhorn, 2003; Yue, Broich, Seifriz, & Mester, 2008). From this perspective, measures of team dynamics may be derived by considering each team as a super-entity, where competing teams' "size", "shape", and "center of mass" are metrics that capture individual team oscillations and thus may be considered as pairs of coupled oscillators.