

Synchronization Assessment for Collective Behavior

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Abstract

Team cognition can be defined as the ability that humans have 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 of 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 team cognition.

Keywords: Team Cognition; Synchronization; Ecological Dynamics;

Introduction

Central to the definition of a team are the interactions amongst its components (McNeese, Cooke, Fedel & Gray, 2016). When players cooperate together as a team, the resulting collective behaviors rarely are expressed in terms of the simple summation of the individuals' activities. That is, the team's activity emerges from the coordination of actions and often nonlinear interactions of its players. For example, to be successful in European football (soccer), players must coordinate their actions with others across many different spatial and temporal scales. While recent research has focused on elucidating the mechanisms that facilitate such large-scale coordination, the identification of the fundamental, self-organizing principles that underlie team dynamics remains an unresolved matter (see e.g., Memmert, Lemmink & Sampaio, 2016; Folgado, Duarte, Fernandes & Sampaio, 2014). Indeed, techniques to measure collective

emergent behavior are still in an early stage of development (Araujo, Silva & Ramos, 2014), while many attempts to measure team work have typically focused on measuring outcome performance rather than team dynamics. However, recent attempts to study the dynamics of multi-agent activity have benefitted from concepts and tools from Dynamical Systems Theory (DST) (e.g., Duarte, Araújo, Correia, Davids, Marques, & Richardson, 2013). 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. Amongst the broad range of DST tools, one of the most common approaches used by students of perception, action and cognition is the study of synchronization.

Measuring Synchronization

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 natural sciences, engineering or even social life (Pikovsky, Rosenblum & Kurths, 2001).

Whereas in physical, nonliving systems synchrony is often mediated via mechanical coupling (e.g., Huygens famous observations regarding the synchronization of two clock pendulums, (1673/1986), psychological and social systems often synchronize via *informational* (e.g., visual) *coupling* (Schmidt, Carello & Turvey, 1990). Although most research on the synchrony and coupling between actors has focused on dyads, a recently developed method, *cluster phase analysis* (CPA, Frank & Richardson, 2010), has been used to extend synchrony measures to groups larger than two people. CPA has been used, for example, to assess the degree to which a group of people successfully synchronized their intentional, oscillatory rhythmic movements with rocking chairs; with synchrony measured using an adaptation of the Kuramoto

order parameter (*aka* cluster amplitude, \hat{r} where high synchronization = 1). Similar methods have been used to characterize teams' phase synchrony in football (see e.g., Duarte et al., 2013; Duarte, Travassos, Araujo & Richardson, 2014). Here, separate measures of team synchrony are derived using players' displacements along either the latitudinal or longitudinal axis, where a common result is that synchrony is higher in longitudinal displacements than in lateral displacements (Duarte, et al., 2013). Using this method, researchers have also noted that the observed degree of synchrony was not subject to possession of the ball (see e.g., Pinto, 2014; Duarte, et al. 2013), presumably one of the key factors of team organization during the match. However, it may be argued that the technical aspects of this methodological approach do not consider relevant contextual features of the game that are key to self-organizing principles in team sports. This lack of situational context is a consequence of 1) the behavioral variable submitted to the model and 2) the constraints that presents the mathematical model. Behavior is measured in a time-series of displacements along one dimension; however, the Kuramoto model requires phase angles as its input. To overcome this incompatibility, the displacement time-series are transformed to instantaneous phase angles by using the Hilbert Transform (see Pikovsky, et al. 2001 for details). However, this method is limited in that high synchrony can be a consequence of the players simply being very close to each other within that one-dimensional space (e.g., x -dimension), whereas, conversely if players are far apart within that dimension, synchrony would be low.

Considering these issues (technical and contextual) we aimed to further extend the use of CPA by using insights from a recently developed framework that applies the ecological-dynamics approach to perception and action in football (López-Felip, 2014). Our model parameters were defined by two situational variables of the game: such as players' *orientation-to* and *distance-from* the goal of interest (i.e. the goal being actively attacked by the offense and defended by the defense). Our main hypothesis was that when accounting for these two contextual variables, team synchrony would be dependent on ball possession. This result would suggest the need for further exploring context dependent analyses for evidence-based measures of team cognition.

Method

Participants

Twenty-two male elite football players from two European clubs played a friendly game during the pre-season 2016-2017. Participants ranged in age from 17 years to 34 years (average 26.5 ± 0.4 years). At the time of data collection, neither of the teams had initiated their regular competitions, however, the away team was a member of what is typically considered to be a superior league. The entire first half of the match was registered with no injuries or substitutions.

Instruments

Player position data were collected via GPS (sampling rate of 15 Hz) for an entire half of forty-five minutes plus extra time. These GPS monitors could reliably capture positional raw data (2D) based on the latitude and longitude positions of all players throughout the match.

Procedures

The positional raw data were subsequently matched to corresponding events throughout the competition (captured via video). This allowed us to assess when during each time-series a team was in possession of the ball (i.e. attacking role), as well as identify any prolonged periods of stoppage (e.g., from injury assistance, goals, etc.) to remove from analysis. The criteria for determining ball possession was based on Reis, Duarte, Araújo, Folgado, & Frias (2013).

Data Analysis

Starting with the positional raw data, exocentric coordinates were used to define the state space in which trajectories of players were captured. Then, the goals were represented as specific variables of this state space to create a new variable, angle of the direction to the goal (θ_g):

(Eq. 1)

$$\theta_g = \tan^{-1} \left(\frac{x_{goal} - x_{player i}}{y_{goal} - y_{player i}} \right)$$

This measure provided a metric of each player's orientation with respect to the goal. Relative angles were submitted to CPA, creating a time-series of Kuramoto parameter values describing each team's synchrony at every time step.

(Eq. 2)

$$\hat{r}(t_i) = \left| \frac{1}{n} \sum_{k=1}^n \exp(i\theta_k(t_i)) \right|$$

To account for the distance of a team to the goal of interest, each team's center of mass was assessed at each time step. Distance of the center of mass (d_{COM}) was measured as the mean longitudinal position of all team members over time.

(Eq. 3)

$$COM = \frac{1}{N} \sum_{player=1}^n x_{player}$$

To simplify our analysis, d_{COM} values were categorized into four quadrants each spanning 25 m; where Q1 contained distances closest to the goal of interest and Q4 contained distances furthest away (see Figure 1).

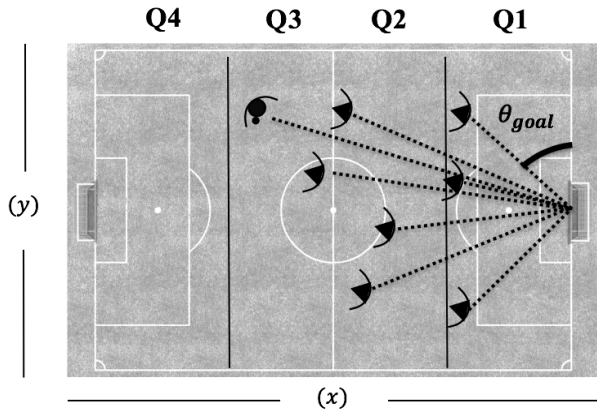


Figure 1: Black disc represents the attacking team and black triangles represent the defending team. Dashed lines represent each player's goal angle. Vertical black lines divide the field in 4 equidistant quadrants. Q1 is the quadrant closest to the active goal and Q4 the furthest. Then, x - y axes represent the longitude and latitude coordinates from where positional raw data were collected.

Then, provided our research question, we assessed changes in each team's synchrony as 1) a function of ball possession (whether teams were attacking or defending) and 2) the distance between the team's center of mass to the goal of interest, d_{COM} . To do so, each point in the time series of Kuramoto parameter values was independently evaluated as a function of the corresponding d_{COM} quadrant. The resulting mean values for each quadrant were submitted to further analysis, resulting in values reported in Figure 2.

Results

As determined using the cluster amplitude analysis the overall degree of synchronization of teams were between 0.55 and 0.99. When phase synchrony was assessed for each team as a function of the playing role in the game (i.e., attacking or defending) and the d_{COM} to the goal of interest, synchronization differed. Figure 2 shows how the mean tendency of synchrony varies as a context of where and when a team is attacking or defending. That is, mean synchrony decays as teams' d_{COM} approaches Q1.

Table 1: Mean synchrony of each team as a function of playing role and d_{COM} .

Team	Quadrants	\hat{r} = Attacking	\hat{r} = Defending
Home	Q1	NA	0.86
Away	Q1	0.84	0.89
Home	Q2	0.92	0.95
Away	Q2	0.93	0.97
Home	Q3	0.97	0.98
Away	Q3	0.97	0.98
Home	Q4	0.99	NA
Away	Q4	0.99	0.99

Overall, synchrony increased as the teams moved farther from the goal of interest. At the same time differences in synchrony depending on the team's role became more pronounced as the teams moved closer to the goal of interest. A similar pattern of effects [role: $F(1, 15488) = 31, p < .001$; quadrant: $F(3, 15488) = 6484, p < .001$; role \times quadrant: $F(3, 15488) = 622, p < .001$] was observed for the home team (note that the d_{COM} of the home team never entered Q1 when attacking or Q4 when defending; likely due to the away teams dominance of the match).

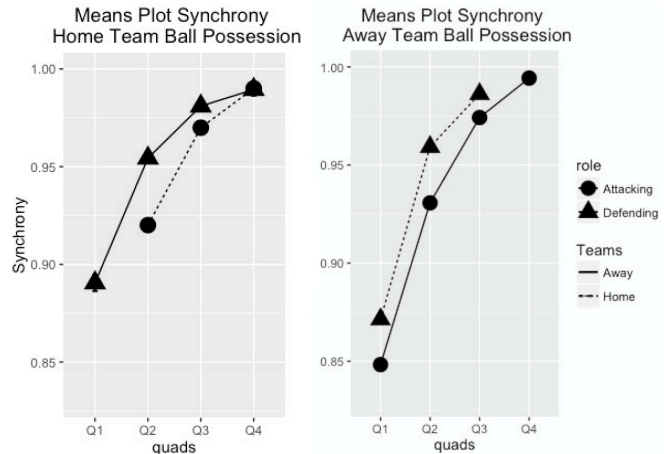


Figure 2: Mean synchrony of each team based on field location and role.

Discussion

The purpose of this study was to develop a method of analyzing team coordination that is sensitive to the context in which team actions unfold over the course of a game. It was hypothesized that by using a measure of phase synchrony sensitive to the contextual circumstances of ball possession, synchrony of a team would change. To test this, two variables that were relevant to the context of the game such as footballer's angle relative to the direction of the active goal and COM of each team on the field were used.

With respect to the experimental hypothesis, a linear effects mixed model showed that team synchrony is dependent on team role and distance from the active goal. Significant effects were found for role and quadrant, qualified by a role \times quadrant interaction in both teams.

Measures of team synchrony showed higher mean values when a team was in defense. These data suggest that individuals tend to coordinate their movements together relative to the goal more in those instances in which they are defending, than the ones in which they are attacking. At the same time, lower synchrony values were found in those instances in which a team was closer to the opponent's goal. This is not surprising for the attacking team, because behavior of a football team when attacking is to spread out and create as many open spaces as possible to the opponent team. Interestingly, the team in defense showed also low values of synchronization in Q1. One possibility is that this

may be due to the driving-driver effect (Step & Turvey, 2010). According to this, the team in defense would try to anticipate the actions of the team in possession of the ball, reflected in the drop of mean synchrony of the defense team in Q1. This conjecture remains an open question.

Although these data showed differences of synchrony in terms of ball possession, the levels of whole team synchrony were, overall, high. All the mean values of cluster amplitude for the angle to the direction of the active goal ranged between 0.84 and 0.99. These values are similar to those found in football (Duarte et al., 2013) or in intentional oscillatory rhythmic movements of rocking chairs (Frank & Richardson, 2010).

Implications for Measuring Synchronization

Based on the approach of previous studies, the present work assessed synchrony by means of an adaptation of the Kuramoto Order Parameter. As explained in the introduction section, when using time-series of displacements in the x , y or z axes to assess synchronization, there is the need to calculate the instantaneous phase angle of the time-series (usually done by the Hilbert Transform). By following these steps, synchrony may remain high and unchanged due to the limitations of the methodology as explained earlier in the introduction.

Hence, the present work, approaches the assessment of synchrony via an alternative methodology. First, we considered that we could explore the possibility of using an angle that was not limited to a one-dimensional plane. Simply because representing dynamics of collective behavior at one dimension did not seem to lead us to our purposes (i.e., provide contextual meaning to assessments of collective behavior). Second, based on previous research, displacements from a time-series have not been able to discriminate between synchrony levels and ball possession during the game. Thus, our approach attempted to link a behavioral variable to the final target that a team aims (i.e., scoring a goal). For example, in models of steering and obstacle avoidance (see e.g., Fajen & Warren, 2003; Warren, 2006), one of the variables taken in their assessments is the relative angle of the performer's position relative to the goal or obstacle. Here, using a similar variable and clustering the angle of each player relative to the active goal, allowed us to model team dynamics at a 2-dimensional plane and do it relative to the final purpose of the game.

Taking this approach to using the Kuramoto, is not a final model. This is just a preliminary step towards developing a more robust model of synchronization in collective behavior that aims to be sensitive to the context in which team activity occurs.

Conclusions

This study investigated the degree to which ball possession impacts team synchrony as a function of the team's d_{COM} . López-Felip and Porter (2015) argued that both variables were proposed as proper parameters to include when

modeling football team behavior as a dynamical system. Our findings suggest that appropriately modeling team behavior must take into account variables that capture the meaningful current state of affairs of the game—such as players' orientation and location relative to key points of interest. Future research in this domain should seek to identify and incorporate additional, meaningful aspects (e.g., tactics) to addressing team coordination.

More broadly, these findings may be understood in the claim that efforts to model living systems and their actions should account for context. Understanding the functional, context dependent relationship that exists between organism-environment and situation could serve to guide and constrain future dynamical analyses and mathematical modeling of team systems (Turvey, 1992; Turvey & Shaw, 1995).

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