Competing together: Assessing the dynamics of team–team and player–team synchrony in professional association football

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This study investigated movement synchronization of players within and between teams during competitive association football performance. Cluster phase analysis was introduced as a method to assess synchronies between whole teams and between individual players with their team as a function of time, ball possession and field direction. Measures of dispersion (SD) and regularity (sample entropy – SampEn – and cross sample entropy – Cross-SampEn) were used to quantify the magnitude and structure of synchrony. Large synergistic relations within each professional team sport collective were observed, particularly in the longitudinal direction of the field (0.89 ± 0.12) compared to the lateral direction (0.73 ± 0.16, p < .01). The coupling between the group measures of the two teams also revealed that changes in the synchrony of each team were intimately related (Cross-SampEn values of 0.02 ± 0.01). Interestingly, ball possession did not influence team synchronization levels. In player–team synchronization, individuals tended to be coordinated under near in-phase modes with team behavior (mean ranges between –7 and 5° of relative phase). The magnitudes of variations were low, but more irregular in time, for the longitudinal (SD: 18 ± 3°; SampEn: 0.07 ± 0.01), compared to the lateral direction (SD: 28 ± 5°; SampEn: 0.06 ± 0.01, p < .05) on-field. Increases in regularity were also observed between the
first (SampEn: 0.07 ± 0.01) and second half (SampEn: 0.06 ± 0.01, \( p < .05 \)) of the observed competitive game. Findings suggest that the method of analysis introduced in the current study may offer a suitable tool for examining team’s synchronization behaviors and the mutual influence of each team’s cohesiveness in competing social collectives.

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1. Introduction

Competing teams in sports like Association Football are composed of different individuals interacting together to achieve common goals. In order to succeed, individual teammates develop cooperative relations to achieve common goals and competitive relations to prevent opposing players from achieving theirs. These relations usually underlie emergent team behaviors that go beyond the sum of individual performances per se (Duarte, Araújo, Correia, & Davids, 2012; Sumpter, 2006). Indeed, many studies in the fields of psychology and biology have demonstrated the superior performance of grouping individuals over singletons in a wide range of human phenomena (Krause, Ruxton, & Krause, 2010). In the field of team sports, the nature of cooperative and competitive interaction tendencies constrains players to perform as a group, displaying intra- and inter-team spatial-temporal couplings between the players (McGarry, Anderson, Wallace, Hughes, & Franks, 2002; Pasos, Araújo, & Davids, 2013; Travassos, Araújo, Correia, & Esteves, 2010). Functional groupings of structural elements in complex systems (e.g., the human body or players in a sport team), that are temporarily constrained to act as a single coherent unit, have been called synergies (Bernstein, 1967; Turvey, 2007). A synergy is a key concept for understanding the process in which individual system components (e.g., the players) interact to create coherent, emergent group behaviors. These processes are important to investigate since they arise from genetic to social levels of organization in neurobiological systems (Kelso, 2009). Here, we propose that the on-field spatial-temporal synchronization between players within a competitive sport team can be regarded as a functional synergy. Despite the possibility that other sub-group interactions may also be conceived of as functional synergies, in this study we defined the team system organization as the selected level of analysis. However, every complex system comprises interdependence between different scales, such as the individual players’ movements and the collective movements of the whole team. This characteristic interdependence between levels of a complex system suggests a compelling need to integrate both scales of analysis in research on team sport performance (Bar-Yam, 2003, 2004). It is especially important to understand how these existing system tendencies may mutually influence each other, creating a collective synergy at the team level.

Typically, most previous studies have tended to focus either on coordination between pairs of individuals (i.e., dyads) or at the team level of organization, and not on the relations established between the two levels. Some previous research has analyzed whole team behaviors (e.g., 11-a-side in association football) using compound positional variables to capture specific cooperative and competitive interaction tendencies between teams. For example, Lames, Ertmer, and Walter (2010) demonstrated that the geometrical centers (i.e., the players) interact to create coherent, emergent group behaviors. These processes are important to investigate since they arise from genetic to social levels of organization in neurobiological systems (Kelso, 2009). Here, we propose that the on-field spatial-temporal synchronization between players within a competitive sport team can be regarded as a functional synergy. Despite the possibility that other sub-group interactions may also be conceived of as functional synergies, in this study we defined the team system organization as the selected level of analysis. However, every complex system comprises interdependence between different scales, such as the individual players’ movements and the collective movements of the whole team. This characteristic interdependence between levels of a complex system suggests a compelling need to integrate both scales of analysis in research on team sport performance (Bar-Yam, 2003, 2004). It is especially important to understand how these existing system tendencies may mutually influence each other, creating a collective synergy at the team level.

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emergence of the collective behaviors of sports teams, which may be a somewhat erroneous proposition (McGarry, 2009). The weighting of each player contribution may change as a function of the evolving game context, the action capabilities of each individual and the social influence of each individual within the team (Duarte, Araújo, Correia et al., 2012).

However, determining a contribution weighting of an individual player can be a very difficult, if not speculative, task. In order to enhance understanding of collective behaviors in team sports, other potentially valuable research approach is to analyze sub-unit relations such as the coordination tendencies between pairs of players (dyads from the same or opponent team). Bourbousson, Sève, and McGarry (2010a) and Travassos, Araújo, Vilar, and McGarry (2011) measured the phase differences between all the possible dyadic system relations in competitive team games in order to assess the predominant coordination modes underlying team behaviors. Together, their data have shown how differences in intra- and inter-team dyadic coordination tendencies can be explained by numerical advantage or equality in the number of players of each team. This methodological strategy regards collective behaviors in teams, not as arising from the sum of individual behaviors, but as displaying coordination tendencies between pairs of players.

Although these studies have provided some useful theoretical and empirical insights into team game performance, the measures reported have typically failed to explain how the actions of different players can become synchronized within the collective behaviors of the team. For a deeper understanding of how repeated interactions between teammates can scale to emergent collective team behaviors, one needs to capture the synchronization process of individuals shaping the competitive behaviors of the whole team. Such analyzes of synchronization processes are significant and necessary because they may reveal a fundamental property of sport teams that might be related to the status and level of collective performance (Duarte, Araújo, Correia et al., 2012; Marsh, Richardson, Baron, & Schmidt, 2006).

Recently, Frank and Richardson (2010) proposed a quantitative approach to detect phase synchronization in noisy experimental multivariate data – a cluster phase method – by deriving a test statistic based on the Kuramoto order parameter. This method was initially proposed to investigate phase synchronization in systems with a large number of oscillating components (Kuramoto, 1984). The investigators (Frank & Richardson, 2010) adapted and successfully showed the applicability of this method using a multiple-rocking chair experiment in which six individuals tried to synchronize their rocking movements. Specific measures of individual and whole group synchrony obtained with this method were able to distinguish intentional from chance level coordination tendencies (Richardson, Garcia, Frank, Gregor, & Marsh, 2012). Clearly, the diversity of on-field movement displacements of football players can be more complex to study than simple rocking chair oscillatory movements and there have been no investigations of the collective synchronization of football players during competitive performance.

In this study we extend the previous analysis of Richardson et al. (2012) to investigate the utility of the cluster phase method for assessing synchronization processes during competitive team sports performance. Using a professional association football match, team–team and player–team synchronization processes were investigated as a function of transitions in ball possession (attacking/defending), halves of the game (first/second), team status (home/visiting), and field direction (longitudinal/lateral).

2. Methods

2.1. Sample and data acquisition

Twenty-eight male professional football players (22 starting players and 6 substitutes) participated in a competitive match in the English Premier League season 2010–2011. Participants ranged in age from 22 years to 34 years (average 26 years) and included 19 international-level performers from 8 different countries. At the time of data collection, the home team was ranked 4th, and the visiting team was the 10th in league standings. The entire game was played by the two teams with a balanced scoreline and score advantages were no higher than 1 goal. The final score was 2-1 in favor of the home team. Positional raw data (2D) on player performance was obtained using the ProZone tracking system (Prozone®, ProZone Holdings Ltd., UK), validated by Di Salvo, Collins, McNeill, and Cardinale.
This video-based, multi-player tracking system uses 8 color cameras (Vicon surveyor 23x cameras dome/SVFT-W23) installed in the stadium to ensure that every area of the pitch is covered by at least two cameras to provide image data. This coverage prevents possible losses of signal during moments of high aggregation of the players during performance. After automatic tracking, quality control procedures consisted in the use of: (i) Kalman filters to predict possible direction of an object, given its current speed (Kalman, 1960), (ii) computer vision homography to convert image coordinates into real world pitch coordinates (Hartley & Zisserman, 2002), and (iii) quality control operators verifying (and re-identifying when necessary) that the displacement trajectories identified for each player remained constant to that specific player (see Di Salvo et al. (2006) for further details).

Raw positional data for each player were provided through individual spreadsheet files at a sampling rate of 10 Hz. The 2D positional raw data of 11 on-field players of each team divided by half and by direction of the field originated eight different input files. Moreover, when a player was substituted by a teammate, the 2D positional data of his colleague was added to his data columns with a timestamp corresponding to the moment of substitution. However, the individual synchrony of the substituted players with the team was assessed only for the time they were effectively playing on-field. After a preliminary examination of the game events, all the periods corresponding to stoppages in play (i.e., injury assistance, free kicks, corners, substitutions, goal celebrations) longer than 25 s were excluded in order to avoid a biased assessment of synchrony. Thus, the final database for the first half had 23,214 data points (i.e., 38 min and 41 s), while in the second half it had 24,967 data points (i.e., 41 min and 37 s).

2.2. Cluster phase method

The cluster phase method used to assess whole team and player–team synchrony was recently proposed by Frank and Richardson (2010). This method was adapted from the Kuramoto order parameter (e.g., Kuramoto & Nishikawa, 1987), a model that is usually defined in the thermodynamic limit (i.e., for systems where the number of oscillatory units tends to infinite (Strogatz, 2000)). Frank and Richardson (2010) adapted the model in order to analyze systems with a small number of oscillatory units and successfully tested its applicability using a multiple-rocking chair experiment with only six oscillating components. This method allows for the calculation of the mean and continuous group synchrony, $\rho_{\text{group}}$ and $\rho_{\text{group}}(t)$, as well as the individual’s relative phase with the group measure (Richardson et al., 2012). We therefore consider that these dependent measures may be ideally suited for assessing changes in team and player synchrony and can be calculated as follows.

Given the phase time-series obtained with Hilbert transform, $\theta_k$, for $n$ player movements measured in radians $[-\pi, \pi]$, where $k = 1, \ldots, n$ and $t = 1, \ldots, T$ time steps, the group or cluster phase time-series can be calculated as:

$\dot{r}(t_i) = \frac{1}{n} \sum_{k=1}^{n} \exp(i\theta_k(t_i))$

and:

$r(t_i) = a \tan 2(\dot{r}(t_i))$

where $i = \sqrt{-1}$ (when not used as a time step index), $\dot{r}(t_i)$ and $r(t_i)$ are the resulting cluster phase in complex and radian form, respectively. The relative phase time-series, $\phi_k$, between each player and the group cluster phase is then equal to:

$\phi_k(t_i) = \theta_k(t_i) - r(t_i)$

with the mean relative phase $\bar{\phi}_k$ for every player $k$ with respect to the team calculated from:

$\bar{\phi}_k = \frac{1}{N} \sum_{i=1}^{N} \exp(i\phi_k(t_i))$

and:

$\bar{\phi}_k = a \tan 2(\bar{\phi}_k)$,
where \( N \) is the number of time steps \( t_i \), \( \bar{\phi}_k \), and \( \bar{\phi}_k \) is the mean cluster phase in complex and radian \([-\pi, \pi] \) form. Note that \( \bar{\phi}_k \) captures the phase shift of a movement with respect to the team behaviors \( r(t_i) \). For stable synchrony (i.e., low SD of relative phase) it can be used to compare whether movements of an individual have the same mean phase with the team and, thus, determine the between-movement relative phase relations.

Finally, the continuous degree of synchronization of the team as a whole (i.e., the cluster amplitude) \( \rho_{\text{group},i} \) at every time step \( t_i \) can be calculated as:

\[
\rho_{\text{group}}(t_i) = \left| \frac{1}{n} \sum_{k=1}^{n} \exp \left( i(\bar{\phi}_k(t_i) - \bar{\phi}_k) \right) \right|
\]

where \( \rho_{\text{group},i} \in [0,1] \) and the mean degree to group synchronization is computed as

\[
\rho_{\text{group}} = \frac{1}{N} \sum_{i=1}^{N} \rho_{\text{group},i}
\]

The cluster amplitude corresponds to the inverse of the circular variance of \( \phi_k(t_i) \). Thus, if \( \rho_{\text{group},i} \) or \( \rho_{\text{group}} = 1 \) the whole group is in complete intrinsic synchronization. If \( \rho_{\text{group},i} \) or \( \rho_{\text{group}} = 0 \), the whole group is completely unsynchronized. So, the larger the value of \( \rho_{\text{group},i} \) and \( \rho_{\text{group}} \) (i.e., close to 1), the larger the degree of team synchronization (see Fig. 1).

All the computations were undertaken using dedicated routines implemented in Matlab® software (The MathWorks Inc, Natick, MA, USA).

2.3. Data analysis

Sample entropy (SampEn) and cross sample entropy (Cross-SampEn) were used to assess the regularity of cluster amplitude in each team and each player’s relative phase with the group/cluster
measure, as well as the degree of team–team synchrony, respectively. These nonlinear statistical tools were introduced by Richman and Moorman (2000) because they were considered to be: (i) more consistent over different choices of input parameters, (ii) less sensitive to data series length, and (iii) unbiased statistics by avoiding self-matches than the better known approximate entropy (ApEn; Pincus, 1991) and cross approximate entropy (Cross-ApEn; Pincus & Singer, 1995). SampEn measures the presence of similar patterns in a time-series revealing the nature of their intrinsic structure of variability. Given a series, \( Y(t) \), of \( T \) points (\( t = 1, \ldots, T \)), SampEn measures the logarithmic probability that two similar sequences of \( m \) points extracted from \( Y(t) \) remain similar (i.e., within tolerance limits given by \( r \)) in the next incremental comparison (i.e., for \( m+1 \) sequences). Values close to zero were indicative of regular/near-periodic evolving behavior for the cluster amplitude of teams and relative phase with group of each player, while the higher the SampEn, the more unpredictable the patterns (Preatoni, Ferrario, Donà, Hamill, & Rodano, 2010).

Cross-SampEn is a statistical tool to compare two correlated time-series in order to evaluate their degree of synchrony or similarity (Pincus & Singer, 1995; Richman & Moorman, 2000). For two hypothetical related time series \( u(i) \) and \( v(i) \), Cross-SampEn measures, within tolerance \( r \), the conditional regularity or frequency of \( v \)-patterns similar to a given \( u \)-pattern of window length \( m \) (Pincus et al., 1996; Richman & Moorman, 2000). In the same line of reasoning, greater synchrony between teams can be indicated by high instances of (sub) pattern matches, quantified by Cross-SampEn values tending to zero (Pincus, 2000). Before the use of Cross-SampEn, Pearson correlations were also used to measure the bivariate linear association between group synchrony time-series data. Input parameters were set as \( m = 1 \) and \( r = 0.2 \) standard deviations (with \( SD \) ranging from 0.14 to 0.23 in the original data sets) for both entropy estimations as suggested in other investigations on neurobiological systems (Pincus et al., 1996; Preatoni et al., 2010; Richman & Moorman, 2000).

A \( 2 \times 2 \times 2 \times 2 \) univariate ANOVA was used to analyze the cluster amplitude mean values as a function of synchrony or similarity (Pincus & Singer, 1995; Richman & Moorman, 2000). For two hypothetical related time series \( u(i) \) and \( v(i) \), Cross-SampEn measures, within tolerance \( r \), the conditional regularity or frequency of \( v \)-patterns similar to a given \( u \)-pattern of window length \( m \) (Pincus et al., 1996; Richman & Moorman, 2000). In the same line of reasoning, greater synchrony between teams can be indicated by high instances of (sub) pattern matches, quantified by Cross-SampEn values tending to zero (Pincus, 2000). Before the use of Cross-SampEn, Pearson correlations were also used to measure the bivariate linear association between group synchrony time-series data. Input parameters were set as \( m = 1 \) and \( r = 0.2 \) standard deviations (with \( SD \) ranging from 0.14 to 0.23 in the original data sets) for both entropy estimations as suggested in other investigations on neurobiological systems (Pincus et al., 1996; Preatoni et al., 2010; Richman & Moorman, 2000).

A \( 2 \times 2 \times 2 \times 2 \) mixed-model ANOVAs were used to analyze the variations of the mean, \( SD \) and SampEn of relative phase values within game halves (first and second) and between-teams (home and visiting) and field direction (longitudinal and lateral). Violations of the sphericity assumption for the within-participant factors were checked using Mauchly’s test of sphericity. When a violation of this assumption was apparent, the Greenhouse–Geisser correction procedure was used to adjust the degrees of freedom. Effect sizes were measured as partial eta squared (\( \eta^2 \)) (Levine & Hullett, 2002). All the inferential statistical analyses were performed using IBM SPSS® 19.0 software (IBM, Inc., Chicago, IL). Alpha levels were maintained at \( p < .05 \) for all statistical procedures.

3. Results

3.1. Whole team synchrony

The time-series of each whole team synchrony, \( \rho_{\text{group},i}(t_i) \), as a function of game half and field direction are depicted in Fig. 2. Vertical grey bands highlight the game stoppages longer than 25 s that were excluded from further analyses.

Univariate ANOVA analyses showed that interaction or main effects of ball possession and team did not influence mean values of within-team synchrony. However, there were significant differences in game halves, \( F(1,65) = 4.225, p < .040, \eta^2 = .007 \), with higher values in the second half \((0.82 \pm 0.16)\) compared to the first half \((0.79 \pm 0.17)\). There were also significant main effects for direction, \( F(1,65) = 198.656, p < .001, \eta^2 = .254 \), with larger synchrony mean values for longitudinal \((0.89 \pm 0.12)\) compared to lateral \((0.73 \pm 0.16)\) field movements. Data showed also less magnitude of variation \((SD)\) and more regularity \((\text{SampEn})\) in the longitudinal than in the lateral dimension of the field (see Table 1).

Bivariate correlations analyses showed significant values of association between the group synchrony of the two teams in the first half, for the longitudinal field directions, \( r(23211) = 0.77, p < .001 \), and the lateral field directions, \( r(23211) = 0.62, p < .001 \). Similar results were observed in
the second half, for the longitudinal field directions, \(r(24964) = 0.75, p < .001\), and for the lateral directions, \(r(24964) = 0.68, p < .001\). Thus, Pearson correlation and Cross-SampEn analyses were combined in order to evaluate the coupling dynamics of team–team synchronies. Fig. 3 showed three identified modes of team–team synchrony.

Unsynchronized time-series corresponded to between-teams pairs of data in different directions of the field (i.e., testing lateral with longitudinal synchronies). Team–team synchrony for the lateral direction displayed slightly lower Cross-SampEn values and significantly higher Pearson correlation values. For the longitudinal field direction, team–team synchrony showed Cross-SampEn values that were even lower and with the highest correlations, suggesting the highest levels of similarity in the structure of variability of the two teams’ collective movement synchronization tendencies.

### 3.2. Player–team synchrony

Mean, SD and SampEn of relative phase between each player and team behavior (i.e., the cluster phase) are presented in Table 2.
A univariate 2 (Game Halves) × 2 (Team) × 2 (Field Direction) mixed-model ANOVA revealed an absence of significant interaction or main effects for relative phase mean values. Mean data showed a high narrow range of mean relative phase values around an in-phase mode of coordination between individual players and whole team behaviors (i.e., cluster phase). Regarding the magnitude of stability around the mean trend indicated by SD, a univariate 2 (Game Halves) × 2 (Team) × 2 (Field Direction) mixed-model ANOVA revealed a significant main effect for direction, \( F(1,44) = 83.123, p < .001, \eta^2 = .675 \), with higher SD values for lateral (28 ± 5°) compared to longitudinal (18 ± 3°) field movements. No significant main effects were observed for team, \( F(1,44) = 0.578, p = .451, \eta^2 = .014 \), nor game halves, \( F(1,44) = 0.010, p = .921, \eta^2 = .001 \). Also, no significant interaction effects were observed.

Concerning the regularity of the player–team synchronization process, a univariate 2 (Game Halves) × 2 (Team) × 2 (Field Direction) mixed-model ANOVA revealed higher SampEn values for the longitudinal (0.07 ± 0.01) compared to the lateral (0.06 ± 0.01) direction in the field of play, \( F(1,44) = 16.907, p < .001, \eta^2 = .297 \). Also, a significant main effect was found for game halves, \( F(1,44) = 4.194, p = .047, \eta^2 = .095 \), with superior values of SampEn in the first (0.07 ± 0.01) compared to the second half of the match (0.06 ± 0.01). No significant main effect was observed for team, \( F(1,44) = 2.771, p = .104, \eta^2 = .065 \), nor were there interaction effects.

**Fig. 3.** Coupling dynamics of team–team synchrony pairs combining the discrete values of Cross-SampEn with Pearson correlation coefficients. Each sample corresponds to a pair of cluster amplitude measures during each half of the match. Unsynchronized series are pairs of cluster amplitude measures from different directions, but also from a different team.

**Table 2**
Mean, SD and SampEn values of player–team synchrony as a function of the game half, team and field direction.

<table>
<thead>
<tr>
<th></th>
<th>First half</th>
<th></th>
<th></th>
<th>Second half</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Home team</td>
<td>Visiting team</td>
<td>Home team</td>
<td>Visiting team</td>
<td>Home team</td>
<td>Visiting team</td>
</tr>
<tr>
<td>Mean Max</td>
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<td>4</td>
<td>3</td>
<td>3</td>
<td>3</td>
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<td>Mean Range</td>
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<td>9</td>
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<td>7</td>
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<tr>
<td>SD Max</td>
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<td>32</td>
<td>25</td>
<td>36</td>
</tr>
<tr>
<td>SD Min</td>
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<td>15</td>
<td>19</td>
<td>13</td>
<td>20</td>
</tr>
<tr>
<td>SD Range</td>
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<td>20</td>
<td>7</td>
<td>13</td>
<td>11</td>
<td>16</td>
</tr>
<tr>
<td>SampEn Mean</td>
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<td>0.08</td>
<td>0.06</td>
<td>0.07</td>
<td>0.06</td>
</tr>
<tr>
<td>SampEn SD</td>
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<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
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</tr>
</tbody>
</table>

Mean and SD values are presented in degrees. Long. = longitudinal direction; Lat. = lateral direction.
4. Discussion

4.1. Teams as synergistic collectives

The main goal of this study was to capture synchronization processes between- and within-teams during competitive football performance by means of a cluster phase method. Measures of whole team synchrony showed superior mean values and high levels of stability (low SD and SampEn) for the longitudinal field direction compared to the lateral direction. These data suggest that individuals are more likely to coordinate their movements together in the longitudinal (goal-to-goal) direction, than in the lateral (side-to-side) direction. This is an important issue for further research, but is likely due to the constraining influence of goal location (Travassos, Araújo, Duarte, & McGarry, 2012; Travassos et al., 2011) as well as the off-side rule (Duarte, Araújo, Freire et al., 2012). These two factors can constrain performers to achieve high levels of spatial–temporal synchrony for creating and avoiding attacking/defending instabilities. Further investigations can verify this issue using simulated matches without an off-side rule and, for instance, laterally stretching the field and setting up the goals opposite each other on the pitch side lines. Interestingly, our data showed that ball possession did not influence the collective synchronization of teams. So, independently of each teams’ on-field stretching tendencies (Bourbousson et al., 2010b; Yue et al., 2008), both attacking and defending teams tended to display high levels of whole team synchronization. Indeed, all the mean values of cluster amplitude (both longitudinal and lateral directions) were observed between 0.70 and 0.89. Richardson et al. (2012) found values ranging from 0.70 to 0.90 for intentional oscillatory rhythmic movements of rocking chairs, which suggests that team players in the present study are also intimately and thoroughly coordinated during performance. Moreover, as highlighted in Fig. 2, the absence of common movement goals during prolonged stoppages in play decreased the internal synchronization of the teams.

In addition, the combination of Cross-SampEn and Pearson correlations revealed a tightly coupling between teams in both field directions, especially in the longitudinal plane. Once fluctuations are observed in the continuous cluster amplitude measure (i.e., the whole group synchrony measure), it seems that teams increase and decrease their synchronies in a highly related fashion. Although our measures did not provide information about the directionality of the coupling dynamics between teams’ synchronies, data suggested that a team performing in a synergistic manner may attract the other team to behave in a synchronized way too. This case study neatly highlighted the need for further research, particularly to understand the hypothetical generalizations of these data to analyses of competitive performance in non-professional teams and games with an unbalanced scoreline. Here, a near–perfect matching between the time-evolving structures of cluster amplitudes was observed for the longitudinal collective movements of the two professional teams. These findings can be interpreted in light of co-adaptation processes emerging between teams during competitive performance. Previous studies have suggested that these processes represent a specific property of invasion team sport collectives competing to achieve immediate opposing performance goals in a common, shared field space (Passos, et al., 2013). For example, Passos et al. (2011) showed how sub-units of attacking players of rugby union adjusted their interpersonal distances as a function of approaching successive lines of defenders. This constraining influence of opponent behaviors and the correspondent co-adaptation between teammates provided evidence on the mutual influence of different sub-groups of players. Moreover, previous work has suggested that, under certain performance conditions, individuals are able to continuously adjust their behaviors, based on informational properties such as positioning, movements and changes in positions of other individuals (Duarte, Araújo, Correia et al., 2012). Although limited to a case study approach, the current data challenge the traditional emphasis attributed to individual performers (Krause et al., 2010) showing how mutual ongoing adjustments in synchronization processes are achieved by collectives functioning as a single entity (i.e., at the team level as a whole system). This finding also suggests that the motion and perceptual components of sports teams as collective systems may cooperate in an integrated manner to achieve functional and purposeful patterns of coordination (Araújo, Davids, & Hristovski, 2006; Turvey, 1990), which might open new theoretical and methodological perspectives on game analysis.
4.2. How player synchronizes itself with the team

Regarding player–team synchrony, mean relative phase of each individual with team (i.e., with cluster phase) showed a narrow range of values around 0°, indicating a general tendency for a near in-phase mode of coordination. The magnitude of variability indicated by SD of relative phase, with values ranging from 13° to 38° (in a spectrum of 360°), revealed the relative stability of this preferred near in-phase mode level of coordination. Interestingly, Frank and Richardson (2010) observed SD values slightly higher for their analysis of oscillatory rhythmic movements in individuals in rocking chairs. However, SD values observed in the present study were significantly higher in the lateral direction than in the longitudinal plane, revealing that players tended to be more stable in their coordination with whole team movement in the longitudinal direction. Bourbousson et al. (2010a) also reported a trend for preferred relative intra-team coordination modes to be higher in the longitudinal than in lateral direction. These data suggest that players tended to display more stable spatial–temporal interactions in their goal-to-goal displacement trajectories, probably due to the goals location and the off-side rule constraints (Duarte, Araújo, Freire et al., 2012; Travassos et al., 2012).

In contrast, the differential effect of field direction on SampEn values showed that players generally displayed a more regular structure of coordination with team behavior in the lateral compared to longitudinal field direction. The apparent contradiction between SD and SampEn measures has been discussed recently (see for example Harbourne & Stergiou, 2009). Although both statistics are measures of variability, SD values provide information on the magnitude of deviations in the distribution around a mean value, while SampEn reveals the underlying structure of such variations (Glazier & Davids, 2009). A significant decrease in SampEn values was also observed between the first and second half of the game. This decrease in variability of structure could be attributed to changes in specific performance constraints such as fatigue (Mohr, Krustrup, & Bangsbo, 2005) due to the increased physical work rates observed in balanced games (O’Donoghue and Tenga, 2001), such as in this case study (i.e., the score remained always with a single goal differentiating the two teams). However, these differences showed small effect size values, suggesting the need for further empirical clarification. Moreover, it is not clear how an increase in the quantities of movement (i.e., the physical work rates) may have influenced the synchronization processes within a team, since the mean values of team synchrony significantly increased from the first to the second half. Further research on this topic is needed to reveal how accumulated levels of fatigue, changes in scoreline line, team strategies and substitutions affect players’ synchronization.

4.3. How micro-variability contributes to stabilization of team(macro) performance

Some evidence has suggested that local variability may be responsible for increased stability at a higher level of temporal and spatial organization (Davids, Glazier, Araújo, & Bartlett, 2003; Torre & Balasubramaniam, 2011). The low values of irregularity observed for cluster amplitude (SampEn ranging from 0.01 to 0.04), compared with the values obtained for each individual’s relative phase with the group (SampEn ranging from 0.06 to 0.07) suggest that such a process might have been occurring in the current study. Bardy and Laurent (1998) have also suggested that expert performers are more sensitive to visual information in order to exploit and use local movement variability to increase stability in behavior at a higher-level of organization. A similar process of visual exploitation might have occurred in this investigation, with expert team players having more irregular patterns of coordination with team behaviors, which contributed to the higher regular variation (i.e., more periodicity) of the whole team synchrony. Cross-comparison between teams of different expertise levels may provide a platform to clarify this issue further.

5. Conclusions and future perspectives

This study investigated the utility of a cluster phase method to capture the synchronization processes within and between sports teams during competitive performance. Large synergistic relations within each professional team sport collective were observed, particularly in the longitudinal
direction of the field. The coupling between the group measures of the two high level teams also revealed that synchronization increases in one team were concomitantly accompanied by synchronization increments in the opposing team, indicating the mutual influence of synchronization processes in social competing collectives. Moreover, team players exhibited evidence of relative coordination, with a tendency towards an in-phase mode of coordination with the group (Turvey, 1990, 2007; Von Holst, 1973). Stability of these tendencies was higher in the longitudinal than in lateral direction of the field, whilst the structure of variability was more irregular. The findings reported in this study can be interpreted with reference to the performance of professional teams competing with a balanced scoreline. Further work, with teams of different skill levels, competing under a range of scorelines, is needed to examine the generality of our initial conclusions.

The data from this study suggest that the cluster phase method possesses many advantages, including: (i) the capacity to calculate an unbiased measure of group coordination due the integration of the natural and idiosyncratic modes of relation of each player with the team, (ii) the use of this measure to assess player–team synchrony, evidencing the continuous coordination of each individual with the team performance behaviors as the game unfolds, and (iii), the potential to assess the coupling dynamics of two competing teams as synergistic collectives. When grouping individuals produced more or less constant phase lags with respect to the group, the continuous group measure (i.e., the cluster amplitude) revealed these behaviors as exhibiting relative phase synchronization even if phase lags were different from zero (Frank & Richardson, 2010). This observation implies that the cluster amplitude can capture the functional and idiosyncratic mode of relations of each individual as contributing to the synchrony of the whole group. Future research should focus on the influence of performance constraints, such as the quality of the opponents, styles of play, players’ positions, roles and substitutions, the long-term stability of collective synchrony and the effects of specific intervention programs in the synchronization processes within football teams. Finally, studies of other emergent social phenomena, at work and in education and training, may also benefit from this methodological approach.

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