

## A multilevel hypernetworks approach to capture meso-level synchronisation processes in football

RIBEIRO, Joao, LOPES, Rui, SILVA, Pedro, ARAUJO, Duarte, BARREIRA, Daniel, DAVIDS, Keith <<http://orcid.org/0000-0003-1398-6123>>, RAMOS, Joao, MAIA, Jose and GARGANTA, Julio

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### Published version

RIBEIRO, Joao, LOPES, Rui, SILVA, Pedro, ARAUJO, Duarte, BARREIRA, Daniel, DAVIDS, Keith, RAMOS, Joao, MAIA, Jose and GARGANTA, Julio (2019). A multilevel hypernetworks approach to capture meso-level synchronisation processes in football. *Journal of Sports Sciences*, 1-9.

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5 [Ribeiro J.](#), [Lopes R.](#), [Silva P.](#), [Araújo D.](#), [Barreira D.](#), [Davids K.](#), [Ramos J.](#), Maia J., &

6 [Garganta J.](#)

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## 1 **Abstract**

2 Understanding team behaviours in competitive sports performance requires a  
3 robust understanding of the interdependencies established between their levels  
4 of complexity in organisation (micro-meso-macro). Previously, most studies  
5 have tended to examine interactions emerging at micro- and macro-levels, thus  
6 neglecting those emerging at a meso-level (a level which reveals connections  
7 between the micro and macro levels, depicted by the emergence of  
8 coordination in specific sub-groups of players during performance). We  
9 addressed this issue using the multilevel hypernetworks approach, adopting a  
10 cluster phase method, to record player-simplice local synchronies in two  
11 performance conditions where the number, size and location of goal scoring  
12 targets were manipulated (1st-condition: 6x6+4 mini-goals; 2nd-condition:  
13 Gk+6x6+Gk). We investigated meso-level coordination tendencies as a function  
14 of ball-possession (attacking/defending), field-direction (longitudinal/lateral) and  
15 teams (Team A/Team B). Univariate Anova was used to assess the cluster  
16 amplitude mean values that emerged between game conditions, as a function of  
17 ball-possession, field-direction and team composition. Generally, large  
18 synergistic relations and more stable patterns of coordination were observed in  
19 the longitudinal direction of the field than the lateral direction for both teams,  
20 and for both game phases in the first condition. The second condition displayed  
21 higher synchronies and more stable patterns in the lateral direction than the  
22 longitudinal plane for both teams, and for both game phases. Results suggest:  
23 (i) usefulness of hypernetworks in assessing synchronisation of teams at a  
24 meso-level; (ii) coaches may consider manipulating the number, location and

1 size of goals to develop levels of local tendencies for emergent synchronies  
2 within teams.

3 **Keywords:** Multilevel hypernetworks, Meso-level, Emergent Synchronisation  
4 tendencies, Team sports, Association football.

## 5 **Introduction**

6 Sports teams consist of social entities composed of individual agents who  
7 correlate and coordinate actions to establish effective team communication  
8 networks (Gonçalves et al., 2017; Ribeiro et al., 2017).

9       The synergetic behaviours (i.e., players combine actions to produce goal-  
10 oriented behaviours) that underlie the formation and development of such  
11 communication networks can be expressed at different levels of complexity.  
12 Typically, there are three general levels of complexity into which networks may  
13 typically fall: the micro-, meso- and macro-levels. The micro-level focuses  
14 essentially on the relationships that each player has with other players in a  
15 team, while the meso-level sheds light on the interpersonal synergies emerging  
16 between small groups of players coordinating actions together during  
17 performance. Finally, the macro-level tends to consider the whole structure of  
18 social interactions emerging within a team and how it relates to team  
19 performance outcomes.

20       The interdependence of team players' behaviours and actions suggests  
21 that all three levels are interconnected. For example, players at a micro-level  
22 might interact with their nearest team members (at a meso-level), under n-ary  
23 interpersonal relations to produce more complex sets of behaviours or patterns  
24 emerging at a macro-level. Typically, the majority of previous studies has  
25 tended to focus on the relations established at a micro-level (dyads, i.e.,

1 relations established between pairs of individuals), or at a macro level of team  
2 organisation (whole team behaviours organised together). Other research (e.g.,  
3 Duarte et al., 2013) has focused on the link between micro and macro relations,  
4 by measuring the synchronisation processes between such levels. Indeed, the  
5 study by Duarte et al. (2013) sought to analyse the movement synchronies  
6 evidenced at *player-team* and *team-team* levels. These investigators tried to  
7 understand how such synchronisation tendencies varied as a function of key  
8 events and characteristics such as transitions in ball possession  
9 (attacking/defending), halves of the match (first/second), team status  
10 (home/visiting) and field direction (longitudinal/lateral), by means of a cluster  
11 phase method (see Frank and Richardson, 2010, for detailed descriptions on  
12 this method).

13 Despite these meaningful theoretical and empirical insights regarding  
14 team game performance, research has not yet captured the synchronisation  
15 tendencies emerging at a meso-level scale. These processes should not be  
16 neglected as they fall between the micro- and macro- levels and can provide  
17 relevant information regarding the interconnections established between such  
18 levels (e.g., how players interact locally with their nearest teammates to  
19 produce regular patterns of behavior during performance). Given the  
20 interdependency between levels in a complex system, there is a need to  
21 integrate all scales of analysis (micro-to-meso-to-macro) in research on team  
22 sports performance (Bar-Yam, 2003; Bar-Yam, 2004).

23 Despite this gap in the field, there is a clear paucity of studies seeking to  
24 propose methods for measuring and providing insights on the processes  
25 underlying the establishment of synchronisation processes of players, within

1 and between teams, at a meso-level scale. An exception is the study of López-  
2 Felip et al. (2018) which used the cluster phase method (CPM) to capture team  
3 coordination by analysing players' behavioral variables (players' orientation-to  
4 and distance-to goal). Most previous studies (e.g., Folgado et al., 2018;  
5 Gonçalves et al., 2018) have used phase synchronisation (players viewed as  
6 "oscillators") to assess coordination between players. Nonetheless, it is worth  
7 mentioning that phase synchronisation is just one of the many metrics and/or  
8 methods that can be used to assess coordination between cooperating and  
9 competing players (see, for example, generalised synchronisation (e.g., Rulkov  
10 et al., 1995), or granger causality (e.g., Kirchgässner & Wolters, 2007)). Recent  
11 developments in network analyses applied to team sports performance have led  
12 to the introduction of a novel methodology: multilevel hypernetworks (Ramos et  
13 al., 2017; Ribeiro et al., 2019). This approach shows signs of helping  
14 researchers ascertain the complexity rooted at such levels of team coordination  
15 processes.

16 Therefore, in this study, we sought to extend the previous analysis of  
17 Duarte et al. (2013) by proposing a multilevel hypernetworks approach for  
18 capturing the movement synchronies of players at a meso-level scale.  
19 Moreover, we aimed to analyse whether such synchronisation tendencies  
20 changed between game conditions (1st condition – 6x6 (6 vs. 6 players) +4  
21 mini-goals; 2nd condition – Gk+6x6+Gk (goalkeeper plus 6 players vs.  
22 goalkeeper plus 6 players)). These manipulations involved the location, number  
23 and size of goal scoring targets. We also investigated these tendencies a  
24 function of ball-possession (attacking/defending), field direction  
25 (longitudinal/lateral) and different teams (Team A/Team B). Our hypotheses are

1 as follows: (i) the first condition will result in the emergence of greater  
2 synchronisation and more stable patterns of coordination in the longitudinal  
3 direction, compared to the lateral direction of the field. This effect may be due  
4 to the absence of goalkeepers, as well as the lack of an offside rule and the  
5 increased number of goals/targets; (ii) The second condition will result in the  
6 emergence of greater, and more stable, coordination tendencies in the lateral  
7 direction of the field, compared to the longitudinal direction, due to a) the  
8 location of the goal/scoring target (located in the centre of the field), and b), the  
9 presence of the goalkeeper.

10

## 11 **Methods**

### 12 *Participants*

13 Fourteen male youth football (soccer) players registered with an U19 yrs squad  
14 (mean age  $17,9 \pm 0,7$  years, mean height  $175,6 \pm 5,7$  cm, mean weight  $69,7 \pm$   
15  $9,9$  Kg, and training experience:  $9,2 \pm 2,9$  years), competing at a regional level,  
16 were recruited to participate in this study. All participants gave prior informed  
17 consent before initiating the experiment. All procedures followed the guidelines  
18 of the Declaration of Helsinki and were in accordance with the ethical standards  
19 of the lead institution.

20

### 21 *Task and procedures*

22 This study was conducted over a two-week period during the 2017/2018  
23 competitive season. Participants performed in two game conditions in which the  
24 number, location and size of goals were manipulated. Each game was  
25 preceded by a 10-minute standardised warm-up composed of low-intensity

1 running, ball-passing actions and dynamic stretches. All these activities were  
2 part of the regular training sessions that players were involved with. The first  
3 game condition (conducted in the first week) consisted of two 6-a-side (6vs.6)  
4 games without Goalkeepers (Gk), where players from opposing teams were  
5 solicited to attack/defend two mini-goals sized 0,90 x 0,90 m (height x width)  
6 located in both right- and left-hand sides of the pitch (Figure 1a). The second  
7 game condition (conducted in the second week) comprised two 6-a-side plus  
8 Gk (Gk+6vs.6+Gk) games with two football goals sized 6 x 2 m (height x width)  
9 centered on the end line of the pitch (Figure 1b). The players were split by the  
10 team coaches into two technically-balanced teams. In the first condition, players  
11 were organised on field according to a 2-3-1 tactical disposition, with 1 right  
12 central defender (RCD), 1 left central defender (LCD), 1 left midfielder (LM), 1  
13 right midfielder (RM), 1 central midfielder (CM), and 1 forward (FW). In the  
14 second condition, the organisation of players on field was similar to the first  
15 condition, but now with the inclusion of a goalkeeper (Gk) (1-2-3-1). The  
16 objective of teams in both game conditions was to score as many goals as  
17 possible while preventing the opposing team from scoring. The respective field  
18 dimensions of the playing area in both conditions (63, 6 x 40,7 m, height x  
19 width) were obtained based on the minimum dimensions permitted by the  
20 *International Football Association Board* (100x64 m, height x width), and the  
21 number of players involved in each game (Hughes, 1994).

22

23 **\*Please insert Figure 1 near here\***

24 Figure 1. Experimental task schematic representation: a) 6x6+4 mini-goals  
25 condition; b) Gk+6x6+GK condition.

26



1 Each match had a duration of 15 minutes interspersed by a recovery interval of  
2 7 minutes to minimise the influence of fatigue on participants. During recovery  
3 periods, players could recovery at will and rehydrate. Additionally, during this  
4 period, players were asked to respond to the Borg Rating of Perceived Exertion  
5 (RPE) Scale (Borg, 1982). The RPE was utilised with verbal anchors, which  
6 comprehended a 15-grade scale ranging from 6 (minimum effort) to 20  
7 (maximum effort) (Borg, 1982), with players being asked the following: “how do  
8 you classify the physical effort in the task from 6 (minimum effort) to 20  
9 (maximum effort)?” Moreover, all matches were undertaken at the same hour of  
10 the day (19:00 pm) in order to prevent possible circadian effects on  
11 performance (Cappaert, 1999). Several balls were placed around the pitch to  
12 prevent trial stoppages. Additionally, coaches were instructed to not provide any  
13 sort of encouragement and/or feedback to the players, before and during  
14 practice, since it can influence levels of practice intensity in individual  
15 participants, thus affecting performance (Rampinini et al., 2007).

16

### 17 *Data collection*

18 Positional data (x, y) were acquired through utilisation of global positioning  
19 tracking devices (Qstarz, Model: BT – Q1000Ex) at 10Hz, placed on the upper  
20 back of each player. Previous studies have confirmed the usefulness and  
21 reliability of such GPS devices (e.g., Silva et al., 2016). All pitches were  
22 calibrated using the coordinates of four GPS devices stationed at each corner of  
23 the pitch for about 4 min. The absolute coordinates of each corner were  
24 calculated as the median of the recorded time series, yielding measurements  
25 that were robust to the typical fluctuations of the GPS signals. These absolute

1 positions were used to set the Cartesian coordinate systems for each pitch, with  
2 the origin placed at the pitch center. Longitudinal and latitudinal (spherical)  
3 coordinates were converted to Euclidean (planar) coordinates using the  
4 Haversine formula (Sinnott, 1984). A GoPro Rollei Ac415 actioncam (Rollei  
5 GmbH & Co. KG, Norderstedt, Germany) was utilised to record and capture  
6 players' interactions on field, which encompassed the following characteristics:  
7 (i) resolution: FullHD; (ii) processing capacity of 30Hz; (iii) maximum lens  
8 aperture:  $F=2.4$ ; (iv) sensor type: CMOS; (v) capture angle:  $140^\circ$ . The Gopro  
9 was stationed on a higher level above the pitch (approximately 4 m high) to  
10 ensure an optimal viewing angle (allowing views of the entire field) during the  
11 games.

12

### 13 *Hypernetworks approach*

14 Hypernetworks extend the concept of hypergraphs to model interactions of a set  
15 of elements (e.g., the players) that make up a given system (e.g., a football  
16 team). In mathematics, a hypergraph consists of a generalisation of a graph (a  
17 structure composed by a set of elements that may share some type of relation)  
18 in which an edge can connect any number of nodes. Therefore, a hypergraph  $H$   
19 corresponds to a pair  $H=(X, E)$  where  $X$  encompasses a set of elements called  
20 nodes/vertices, while  $E$  comprises a set of non-empty subsets of  $X$  named  
21 hyperedges (Johnson, 2009). Hyperedges can connect more than two nodes  
22 (i.e., the players), thus they support representation of simultaneous  $n$ -ary  
23 relations ( $n>2$ ), be it cooperative and/or competitive, established between a  
24 given set of players (called simplex, plural—simplices) (Johnson & Iravani, 2007;  
25 Johnson, 2016; Ramos et al., 2017). A hypersimplex is effectively a hypergraph

1 edge where the relation between the elements is explicit. This is necessary  
2 because, for example, three players may collaborate in one 3-ary relational  
3 configuration when scoring a goal, but in a completely different 3-ary relational  
4 configuration when trying to win back the ball from opposition. A hypernetwork  
5 is defined as a set of hypersimplices (for more details, please see Johnson,  
6 2016). Thus, by adopting the hypernetworks approach we were able to assess  
7 how players synchronise their movements in relation to the simplices (intra and  
8 inter relationships) that they interacted with during competition (see Figure 2).  
9 This is a major advantage compared with simply measuring the synchronisation  
10 of players' phases, since it is now possible to assess the synchronisation  
11 emerging within and between simplices. These simplices can capture the  
12 interactions between sets of players that may include an arbitrary number of  
13 teammates and opponents. The criteria chosen for selecting the set of nodes  
14 was based on the geographical proximity (non-parametric) between players  
15 (i.e., a player does interact with his nearest player and/or goal for goalkeepers  
16 (2nd condition) and mini-goals for players (1st condition)) and directional speed  
17 of players that enable them to interact (through disaggregation and/or  
18 aggregation) with other simplices (Ramos et al., 2017). In short, the  
19 hypernetworks approach allowed us to assess the synchronies evidenced in  
20 intra- and inter-team relationships between players during competition.

21

22 **\*Please insert Figure 2 near here\***

23 Figure 2. Example of an illustration of hypernetworks representing simplices'  
24 interactions in an association football pitch, retrieved from performance in the  
25 first game condition (6x6+4 mini-goals). The 4 mini-goals (1 and 2 for Team A;  
26 15 and 16 for Team B) are represented by black dots. Team A (represented in

1 blue) is attacking from left to right and Team B (represented in red) is attacking  
2 from right to left. Each simplex is represented by the polygon (or a line when  
3 only two players are involved, e.g., players 7 and 14) defining the convex hull  
4 that connects the players (identified by numbers, or goals – identified by black  
5 points). Players can also be linked to the goals due to the proximity-based  
6 criteria (e.g., player 6 and 3 from the blue team and player 10 from the red team  
7 are connected to the mini-goal number 2). A velocity vector for each player is  
8 also represented.

9

### 10 *Cluster phase method*

11 Frank and Richardson (2010) proposed the CPM by adapting the model from  
12 the Kuramoto order parameter (Kuramoto & Nishikawa, 1987). Such a model  
13 was originally developed for analysing systems whose oscillatory unit's number  
14 tended to infinity (Strogatz, 2000). Frank and Richardson (2010) decided to test  
15 the applicability of the same model in analysing systems composed by a small  
16 number of oscillatory units (a multiple-rocking chair experiment with only six  
17 oscillatory units).

18 Basically, the CPM allows the calculation of the mean and continuous  
19 group synchrony,  $\rho_{group}$  and  $\rho_{group}(t_i)$ , as well as the individual's relative  
20 phase,  $\theta_k$ , in regard to the group measure (Richardson et al., 2012). This  
21 method has been used in a study by Duarte et al. (2013) to assess whole team  
22 synchrony (at a macro-scale level) and player-team synchrony (at a micro-scale  
23 level) in a professional football match. Implementation of this method allowed  
24 them to calculate a global measure, the cluster amplitude  $\rho_{group}(t_i)$ , depicting  
25 the team synchronisation at every instant time of the match. It also supported

1 use of a relative phase measure reporting the level of individual player's  
2 synchronisation with respect to the team,  $\phi_k(t_i)$ .

3 A major advance proposed in the present study, compared to that of  
4 Duarte et al. (2013), is that we introduced a multilevel hypernetworks approach  
5 to assess the synchronisation processes emerging at a micro-to-meso level  
6 depicted through measurement of player-simplices (P-S) synchronisation. To  
7 achieve that aim, we assessed how each player synchronises his movements  
8 with the corresponding simplices into which he is inserted.

9 The extension to other groups, i.e. player sets, beyond teams is  
10 supported by the following generalisations to the definitions and equations  
11 presented by Duarte et al. (2013).

12 These procedures starts with the phase time-series acquired through  
13 Hilbert transformation,  $\theta_k(t_i)$ , for the  $k^{th}$  player movements measured in  
14 radians  $[-\pi \pi]$ , where  $k = 1, \dots, N$  and  $i = 1, \dots, T$  time steps. In the  
15 generalisation proposed in the current study we use the definition of group,  $\Gamma_j$ .  
16 These groups correspond to the different hypernetworks' player sets. For each  
17 group,  $\Gamma_j$  its size,  $n_j$ , is defined by the number of players that compose that  
18 group (i.e., simplex).

19 Using this generalisation, the group cluster phase time-series,  $\bar{\phi}_j(t_i)$ , can  
20 be calculated as:

21

$$22 \quad \hat{r}_j(t_i) = \frac{1}{n_j} \sum_{k \in \Gamma_j} \exp(i\theta_k(t_i)) \dots \dots \dots (1)$$

23 and:

$$24 \quad \bar{\phi}_j(t_i) = \text{atan2}(\hat{r}_j(t_i)) \dots \dots \dots (2)$$

1 where  $i = \sqrt{-1}$  (when not used as a time step index),  $r_j(t_i)$  and  $\bar{\vartheta}_j(t_i)$  comprise  
 2 the resulting cluster phase in complex and radian form, respectively.

3 Finally, the continuous degree of synchronisation of the group  $\rho_{\Gamma_j}(t_i) \in$   
 4  $[0, 1]$ , i.e., the cluster amplitude  $\rho_{\Gamma_j}(t_i)$  at each time step  $t_i$  can be calculated  
 5 as:

$$7 \quad \rho_{\Gamma_j}(t_i) = \left| \frac{1}{n_j} \sum_{k \in \Gamma_j} \exp(i(\theta_k(t_i) - \bar{\vartheta}_j(t_i))) \right| \dots \dots \dots (3)$$

8  
 9 and the temporal mean degree of group synchronisation,  $\rho_{\Gamma_j} \in [0, 1]$ , is  
 10 computed as:

$$11 \quad \rho_{\Gamma_j} = \frac{1}{T} \sum_{i=1}^T \rho_{\Gamma_j}(t_i) \dots \dots \dots (4)$$

12 The cluster amplitude corresponds to the inverse of the circular variance of  
 13  $\vartheta_k(t_i)$ . Therefore, on the one hand, if  $\rho_{\Gamma_j} = 1$ , the group is in complete intrinsic  
 14 synchronisation. On the other hand, if  $\rho_{\Gamma_j} = 0$ , the group is completely  
 15 unsynchronised. Therefore, the larger the value of  $\rho_{\Gamma_j}$  (i.e., close to 1), the  
 16 larger the degree of group synchronisation. The same expressions can be  
 17 applied to teams by replacing the simplice sets  $\Gamma_j$  by the set of players of each  
 18 team  $\Gamma_A$  and  $\Gamma_B$ , respectively.

19 All the computations were conducted by using dedicated routines  
 20 implemented in GNU Octave software v4.4.1.

21

22 *Data analysis*

1 Sample entropy (SampEn) was used to evaluate the regularity of cluster  
2 amplitude for each group (P-S) during performance in the two conditioned  
3 matches. This nonlinear statistical tool was introduced by Richman and  
4 Moorman (2000) and presents the following characteristics: (i) greater  
5 consistency with regards to different choices of input parameters; (ii) lower  
6 sensitivity to data series length (data length independence), and; (iii) less  
7 propensity to statistical bias by eschewing self-matches when compared with  
8 traditional approximate entropy (ApEn – Pincus, 1991).

9 SampEn comprises a modification of ApEn and evaluates the existence  
10 of similar patterns in a time-series, thus unveiling the nature of their intrinsic  
11 structure of variability (Duarte et al., 2013). Thus, given a series  $Y(t)$  of  $T$  points  
12 ( $t = 1, \dots, T$ ), SampEn calculates the logarithmic probability that two similar  
13 sequences of  $m$  points retrieved from  $Y(t)$  remain similar. Or, in other words, it  
14 evaluates whether the sequences are kept within tolerance bounds given by  $r$ ,  
15 in the next incremental comparison (i.e., for  $m+1$  sequences) (Duarte et al.,  
16 2013).

17 In the current study, input parameters were established as  $m=1$   $r=0.2$   
18 standard deviations for entropy estimations, as suggested in other  
19 investigations of neurobiological system behaviour (e.g., Preatoni et al., 2010;  
20 Richman & Moorman, 2000). Values close to zero indicated the presence of  
21 regular/near-periodic evolving behaviours for the cluster amplitude regarding  
22 the P-S interactions. Higher values of SampEn indicated more unpredictable  
23 patterns of synchronisation (Preatoni et al., 2010).

24 A 2 (game condition) x 2 (ball-possession) x 2 (field direction) x 2 (teams)  
25 univariate ANOVA was used to ascertain the cluster amplitude mean values

1 between game conditions, and as a function of ball possession  
2 (attacking/defending), field direction (longitudinal/lateral) and teams (Team  
3 A/Team B). The repeated measures ANOVA's possible violation of sphericity  
4 assumption for the within-participant factors was checked using the Mauchly's  
5 test of sphericity. Effect size values were calculated as partial eta square ( $\eta^2$ )  
6 (Levine & Hullett, 2002). All statistical comparisons were conducted by using  
7 the IBM SPSS 24.0 software (IBM, Inc., Chicago, IL); Significance level was set  
8 at 5%.

9

## 10 **Results**

### 11 *Player-simplice synchronisation*

12 Mean, SD, and SampEn values of P-S cluster amplitude are presented in Table  
13 1. Results revealed significant main effects for teams, ball-possession, and field  
14 direction between game conditions.

15

16 Table 1. Mean, SD, and SampEn values of P-S cluster amplitude as a function  
17 of teams (Team A/Team B), ball-possession (Attacking/Defending), and field  
18 direction (Longitudinal/Lateral) for each game condition

19

20 **\*Insert Table 1 near here\***

21

### 22 *Between game conditions*

23 Higher mean values of cluster amplitude were found for the longitudinal  
24 direction of the field in the attacking phase of the first condition for both Team A  
25 ( $F(1,48224) = 1055,960$ ;  $p < 0,001$ ,  $\eta^2 = 0,021$ ) and Team B ( $F(1,48224) =$   
26  $387,406$ ,  $p < 0,001$ ,  $\eta^2 = 0,008$ ), compared to the second condition. Moreover, we



1 observed higher mean values in the lateral direction when attacking in the  
2 second condition, for Team A ( $F(1,48224) = 1271,121, p < 0,001, \eta^2 = 0,026$ ) and  
3 Team B ( $F(1,48224) = 1352,441, p < 0,001, \eta^2 = 0,027$ ), compared to the first  
4 condition.

5 Significant differences for the longitudinal direction of the field when  
6 defending were verified in the first condition, for both Team A ( $F(1,48224) =$   
7  $418,547, p < 0,001, \eta^2 = 0,009$ ) and Team B ( $F(1,48224) = 226,151, p < 0,001$   
8  $\eta^2 = 0,005$ ), when compared to the second condition. Furthermore, we observed  
9 higher mean values for the lateral direction for both Team A ( $F(1,48224) =$   
10  $295,393, p < 0,001, \eta^2 = 0,006$ ) and Team B ( $F(1,48224) = 2087,341, p < 0,001,$   
11  $\eta^2 = 0,041$ ) when defending in the second condition compared to the first  
12 condition.

13

#### 14 *Magnitude and structure of synchrony*

15 Our data also revealed that in the first condition, Team A displayed a lower  
16 magnitude of variation (SD) value in the lateral direction of the field compared to  
17 the longitudinal direction. However, they exhibited greater regularity (SampEn)  
18 in the longitudinal direction in both attacking and defending game phases. Team  
19 B displayed a lower magnitude of variation and greater regularity in the  
20 longitudinal direction, compared to the lateral direction of the field, in both  
21 attacking and defending phases. In the second condition, we verified a lower  
22 magnitude of variation and greater regularity in the lateral direction of the field  
23 compared to the longitudinal plane for both teams, in attacking and defending  
24 phases.

1           Thus, when comparing values of the magnitude of variation and  
2 regularity between game conditions we observed greater stability in the  
3 longitudinal direction of the field in the first condition (although Team A  
4 presented lower SD values in the lateral direction). The second condition  
5 presented more stability in the lateral direction of the field for both teams, and in  
6 both attacking and defending game phases.

7

8   **\*Please insert Figure 3 near here\***

9     Figure 3. Example of the time-series representing the P-S synchronisation for  
10 both teams using the cluster amplitude, as a function of field direction and game  
11 condition. Cluster amplitude values range from 0 (no synchrony) to 1 (complete  
12 synchrony). Left and right panels display values for the first and second  
13 condition, respectively. Upper and bottom panels display values for the lateral  
14 and longitudinal direction, respectively.

15

## 16     **Discussion**

17     To the best of our knowledge, this is the first study that sought to investigate  
18 synchronisation processes emerging at a micro-to-meso (P-S) level of analysis.

19     To fulfil this purpose, the multilevel hypernetworks approach along with the  
20 cluster phase method, previously used in the study of Duarte et al. (2013), was  
21 applied to capture the P-S synchronies formed within and between competing  
22 players. The results obtained in this study support our hypotheses. Indeed, we  
23 observed that local synchronisation tendencies changed when the number,  
24 location and size of goals were altered between game conditions, and as a  
25 function of ball-possession, field direction and teams. This is particularly  
26 interesting, as previous studies (e.g., Duarte et al., 2013; Pinto, 2014) have  
27 reported that synchrony does not change as a function of ball possession.

1 However, a study by López-Felip et al. (2018) identified changes in team  
2 synchrony according to ball possession. The results of that study reported  
3 higher mean values of team synchrony in defensive sub-phases of play.

4         However, it is worth mentioning that our study analysed differences in  
5 ball-possession according to game conditions, and not between attacking and  
6 defending phases. Moreover, a common finding reported in the current literature  
7 (e.g., Bourbousson et al., 2010; Duarte et al., 2012a; Duarte et al., 2012b) is  
8 that longitudinal displacements present higher levels of synchrony than lateral  
9 displacements. Indeed, typical displacements of players on field tend to unfold  
10 more frequently in the longitudinal direction of the field, as the attacking team  
11 advances upfield seeking to create goal-scoring opportunities. Simultaneously  
12 the defending team moves backward trying to prevent the opposing team from  
13 creating goal-scoring opportunities in the critical scoring region of the field  
14 (Frencken et al., 2011). Both the location of goals and the offside rule has been  
15 proposed as two plausible reasons for explaining such results (e.g., Duarte et  
16 al., 2012b; Travassos et al., 2012).

17         It is worth noting that, unlike analyses reported in previous studies of  
18 performance in 11-a-side football matches, in the current study the two game  
19 conditions consisted of conditioned matches with manipulations of the number,  
20 location and size of goals, which did not consider the effects of the offside rule.  
21 By not considering the offside rule players were given the opportunity to freely  
22 explore the space left behind the opponent's defensive line whenever they  
23 wanted. This task constraint led teams to explore more in-depth attacking  
24 movements with- and without ball-possession, in the longitudinal direction of the  
25 field when performing in the first condition. Travassos et al. (2014) observed

1 that teams reduced their distances to each other (evaluated through  
2 measurement of teams' centroids) when the number of goal targets were  
3 manipulated (from two official goals to six mini-goals). The absence of a  
4 goalkeeper, in combination with an increased number of possibilities for scoring  
5 (due to increased number of goals/targets), possibly led teams to utilise  
6 affordances for more forward-backward movements on field (Araújo & Davids,  
7 2016, after Gibson, 1979). The attacking team tried to perform more long  
8 passes to get behind the opposition's defence, thus exploiting the absence of  
9 the offside law. The defending team tried to prevent this behaviour by reducing  
10 distances (approaching defending lines) to the attacking team in the longitudinal  
11 direction of the field, seeking to pressurise opponents, while not conceding  
12 suitable passing and/or shooting opportunities.

13 In the second condition, the location of goals at the centre of the field  
14 might have constrained players without ball-possession to tightly defend the  
15 centre corridor of the field. This tactical approach offered behavioural invitations  
16 for the attacking team to circulate the ball to both left and right-hand sides of the  
17 pitch (outside riskier zones), thus increasing chances for the defensive team to  
18 recover ball-possession. By passing the ball from one side of the field to the  
19 other, the movements of the attacking players were designed to pull the  
20 defenders away from the central corridor of the field. In fact, maintaining ball-  
21 possession, when the team is on the attack, is key to creating goal-scoring  
22 opportunities (Garganta, 1997; Guilherme, 2004). Moreover, these actions are  
23 grounded on a set of tactical principles of play and/or strategical rules that guide  
24 players' actions during competitive performance (Garganta, 1997; Guilherme,  
25 2004). This approach caused the opposing team to stretch on field and created

1 possible empty spaces left between defenders to exploit. Such synergetic,  
2 collective movements, manifested by both attacking and defending teams might  
3 have increased the synchronisation tendencies in the lateral direction of the  
4 field.

5         However, like the study of Duarte et al. (2013), the differences reported  
6 in the current investigation revealed small effect sizes, suggesting the need for  
7 further empirical clarification. Nonetheless, these results suggested how players  
8 needed to continually reorganise and adjust their functional behavioural  
9 patterns (re-organisation of team synergies) to surrounding informational  
10 constraints (number, location and size of goals). These constant adaptations  
11 produced goal-oriented behaviours coherent with the fulfilment of performance  
12 goals (Bernstein, 1967; Davids, 2015). These results imply the sensitivity of  
13 inherent synergy formation tendencies to changing performance constraints  
14 (Riley et al., 2012), with players temporarily (re)assembling into collective  
15 synergies to achieve specific task goals (Silva et al., 2013).

16         By participating in two conditioned competitive matches with different  
17 performance objectives, the participants needed to engage in exploratory  
18 behaviours to search for functional movement solutions aiming to satisfy the  
19 changing task demands (Davids et al., 2012). They needed to co-adapt their  
20 behaviours to changing performance constraints to attain competitive goals  
21 (Passos et al., 2016; Passos et al., 2009). The emergence of different  
22 behavioural solutions, as evidenced in both game conditions, may signify, for  
23 example, that previous preferred coordination tendencies, i.e., higher  
24 synchronisation levels verified in the longitudinal direction of the field in the first

1 condition, may no longer have been functional under the constraints of the  
2 second condition.

3 In the first condition, Team B exhibited lower values of SD and SampEn  
4 in the longitudinal direction of the field compared to the lateral direction in both  
5 game phases. This finding suggested that players displayed greater stability in  
6 their coordination tendencies in the simplices with which they interacted in the  
7 longitudinal direction of the field. However, Team A showed slightly higher  
8 values of SD and lower values of SampEn in the longitudinal, rather than lateral  
9 direction of the field in both game phases. In the second condition, we observed  
10 lower values of SD and SampEn for both teams in the lateral field direction than  
11 longitudinally in both attacking and defending phases. This finding signified that  
12 players coordinated their actions in a more regular and stable phase with  
13 reference to the simplices they were involved with in the lateral direction of the  
14 field.

15

## 16 **Conclusions and practical applications**

17 The multilevel hypernetworks approach, along with a CPM, successfully  
18 captured the synchronisation processes emerging at a meso-level scale through  
19 measurement of P-S synchronies. Nevertheless, this study has some  
20 limitations. First, this analysis was typically focused on the "phase" of  
21 synchronisation tendencies, when the trajectory of a dynamical system (for  
22 example describing coordination in team sports) is a combination of "phase and  
23 amplitude". In this way, a movement in a different direction with a different  
24 velocity, produced as a consequence of a movement of another player, cannot  
25 be quantified as a synchronized behaviour just using the 'phase' characteristic,

1 when it is indeed a "coordinated" motion. Thus, in future studies, there is a need  
2 to ascertain whether it is more adequate to consider players as "oscillators"  
3 (whose phase is adjusted) instead of vectors (whose direction is adjusted).  
4 Furthermore, the results are constrained by the specific rules of the game  
5 designed by coaches, which could lead to the emergence of diverse results  
6 regarding the levels of synchronization in the longitudinal and lateral directions.

7       Regardless, the preliminary findings of this study suggested how task  
8 constraints manipulations during practice, exemplified here by the number,  
9 location and size of target goals, can influence the local synchronisation  
10 processes of competing teams. Therefore, coaches may consider these  
11 manipulations in their training settings to foment the development of specified  
12 local synchronisation tendencies. Here this practical implication was exemplified  
13 by how specific sub-groups of players synchronised their movements,  
14 longitudinally and/or laterally, during specific sub-phases of play (e.g.,  
15 defending phase), to recover ball possession. Multilevel hypernetworks seem to  
16 constitute a set of suitable and promising tools for measuring the meso-local  
17 synchronisation processes emerging in teams during competition.

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## 19 **References**

20 Araújo, D., & Davids, K. (2016). Team synergies in sport: Theory and  
21 measures. *Frontiers in Psychology*, 7, 1449.

22

23 Bar-Yam, I. (2003). Complex systems insights to building effective teams.  
24 *International Journal of Computer Sciences in Sport*, 2, 8-15.

25

- 1 Bar-Yam, I. (2004). *Making things work: Solving complex problems in a*  
2 *complex world*. Cambridge, MA: New England Complex Systems  
3 Institute, Knowledge Press.  
4
- 5 Bernstein, N. (1967). *The coordination and regulation of movement*. New York:  
6 Pergamon.  
7
- 8 Borg, G. (1982). Psychophysical bases of perceived exertion. *Medicine and*  
9 *Science in Sports and Exercise*, 14(5), 377-381.  
10
- 11 Bourbousson, G., Sève, C., & McGarry, T. (2010). Space-time coordination  
12 dynamics in basketball: Part 1. Intra- and inter-couplings among player  
13 dyads. *Journal of Sports Sciences*, 28, 339-347.  
14
- 15 Cappaert, T. (1999). Time of day effect on athletic performance. An update.  
16 *Journal of Strength and Conditioning Research*, 13(4), 412–421.  
17
- 18 Davids, K. (2015). Athletes and sports teams as complex adaptive system: A  
19 review of implications for learning design. *Revista Internacional de*  
20 *Ciências del Deporte*, 39, 48-61.  
21
- 22 Davids, K., Araújo, D., Hristovski, R., Passos, P., & Chow, J. Y. (2012).  
23 “Ecological dynamics and motor learning design in sport,”. In: M. Williams  
24 & N. Hodges (Eds.), *Skill Acquisition in Sport: Research, Theory &*  
25 *Practice* (pp-112-130). (London: Routledge) 112–130.



1

2 Duarte, R., Araújo, D., Correia, V., & Davids, K. (2012b). Sports Teams as  
3 superorganisms: Implications of sociobiological models of behavior for  
4 research and practice in team sports performance analysis. *Sports  
5 Medicine, 42*, 633-642.

6

7 Duarte, R., Araújo, D., Correia, V., Davids, K., Marques, R., & Richardson, M.  
8 (2013). Competing together: Assessing the dynamics of team-team and  
9 player-team synchrony in professional association football. *Human  
10 Movement Science, 32*(4), 555-566.

11

12 Duarte, R., Araújo, D., Freire, L., Folgado, H., Fernandes, O., & Davids, K.  
13 (2012a). Intra- and inter-group coordination patterns reveal collective  
14 behaviors of football players near the scoring zone. *Human Movement  
15 Science. 31*, 1639-1651.

16

17 Folgado, H., Gonçalves, B., & Sampaio, J. (2018). Positional synchronisation  
18 affects physical and physiological responses to preseason in professional  
19 football (soccer). *Research in Sports Medicine, 26*(1), 51-63.

20

21 Frank, T., & Richardson, M. (2010). On a test statistic for the Kuramoto order  
22 parameter of synchronisation: An illustration for group synchronisation  
23 during rocking chairs. *Physica D, 239*, 2084-2092.

24

- 1 Frencken, W., Lemmink, K., Delleman, N., & Visscher, C. (2011). Oscillations of  
2 centroid position and surface area of soccer teams in small-sided games.  
3 *European Journal of Sport Science*, 11(4), 215-223.  
4
- 5 Gibson, J. (1979). *The Ecological Approach to Visual Perception*. Hillsdale, NJ:  
6 Lawrence Erlbaum Associates.  
7
- 8 Goncalves, B., Coutinho, D., Santos, S., Lago-Penas, C., Jimenez, S., &  
9 Sampaio, J. (2017). Exploring team passing networks and player  
10 movement dynamics in youth association football. *Plos One*, 12(1),  
11 e0171156.  
12
- 13 Gonçalves, B., Coutinho, D., Travassos, B., Folgado, H., Caixinha, P., &  
14 Sampaio, J. (2018). Speed synchronisation, physical workload and  
15 match-to-match performance variation of elite football players. *Plos One*,  
16 13(7), e0200019.  
17
- 18 Hughes, C. (1994). *The football association coaching book of soccer tactics and*  
19 *skills*. Harpenden: Queen Anne Press.  
20
- 21 Johnson, J., & Iravani, P. (2007). The multilevel hypernetwork dynamics of  
22 complex systems of robot soccer agents. *ACM Transactions on*  
23 *Autonomous and Adaptive Systems*, 2, 1–23.  
24

- 1 Johnson, J. (2016). Hypernetworks: Multidimensional relationships in multilevel  
2 systems. *The European Physical Journal Special Topics*, 225, 1037.
- 3 Kirchgässner, G., & Wolters, J. (2007). *Introduction to modern time series*  
4 *analysis*. Berlin: Springer Science & Business Media.
- 5
- 6 Levine, T., & Hullett, C. (2002). Eta square, partial eta square, and misreporting  
7 of effect size in communication research. *Human Communication Research*, 28,  
8 612-625.
- 9
- 10 López-Felip, M., Davis, T., Frank, T., & Dixon, J. (2018). A cluster phase  
11 analysis for collective behavior in team sports. *Human Movement*  
12 *Science*, 59, 96-111.
- 13
- 14 Kuramoto, Y., & Nishikawa, I. (1987). Statistical macrodynamics of large  
15 dynamical systems. Case of a phase transition in oscillator communities.  
16 *Journal of Statistical Physics*, 49, 569-605.
- 17
- 18 Passos, P., Araújo, D., & Davids, K. (2016). Competitiveness and the process  
19 of co-adaptation in team sport performance. *Frontiers in Psychology*, 7,  
20 1562.
- 21
- 22 Passos, P., Araújo, D., Davids, K., Gouveia, L., Serpa, S., Milho, J., & Fonseca,  
23 S. (2009) Interpersonal pattern dynamics and adaptive behavior in  
24 multiagent neurobiological systems: conceptual model and data. *Journal*  
25 *of Motor Behaviour*, 41, 445–459.

1  
2  
3  
4  
5  
6  
7  
8  
9  
10  
11  
12  
13  
14  
15  
16  
17  
18  
19  
20  
21  
22  
23  
24

Pincus, S. (1991). Approximate entropy as a measure of system complexity.

*Proceedings of the National Academy of Sciences of the United States of America*, 88, 2297-2301.

Pinto, C. (2014). The emergence of team synchronisation during the soccer match: understanding the influence of the level of opposition, game phase and field zone. Universidade de Lisboa. Faculdade de Motricidade Humana. Dissertação de Mestrado.

Preatoni, E., Ferrario, M., Donà, G., Hamill, J., & Rodano, R. (2010). Motor variability in sports: A non-linear analysis of race walking. *Journal of Sports Sciences*, 28, 1327-1336.

Ramos, J., Lopes, R., Marques, P., & Araújo, D. (2017). Hypernetworks reveal compound variables that capture cooperative and competitive interactions in a soccer match. *Frontiers in Psychology*, 8, 1379.

Rampinini, E., Impellizzeri, F., Castagna, C., Abt, G., Chamari, K., Sassi, A., & Marcora, S. (2007). Factors influencing physiological responses to small-sided soccer games. *Journal of Sports Sciences*, 25(6), 659-666.

Ribeiro, J., Silva, P., Duarte, R., Davids, K., & Garganta, J. (2017). Team sports performance analysed through the lens of social network theory:

- 1           Implications for research and practice. *Sports Medicine*, 47(9), 1689-  
2           1696.
- 3
- 4   Ribeiro, J., Davids, K., Araújo, D., Silva, P., Ramos, J., Lopes, R., & Garganta,  
5           J. (2019). The role of hypernetworks as a multilevel methodology for  
6           modelling and understanding dynamics of team sports performance.  
7           *Sports Medicine*, 1-8.
- 8
- 9   Richardson, M., Garcia, A., Frank, T., Gergor, M., & Marsh, K. (2012).  
10          Measuring group synchrony: A cluster-phase method for analysing  
11          multivariate movement time-series. *Frontiers in Psychology*, 3.  
12          <http://dx.doi.org/10.3389/fphys.2012.00405>.
- 13
- 14   Richman, J., & Moorman, J. (2000). Physiological time-series analysis using  
15          approximate entropy and sample entropy. *AJP-Heart and Circulatory*  
16          *Physiology*, 278, 2039-2049.
- 17
- 18   Riley, M., Shockley, K., & Van Orden, G. (2012). Learning from the body about  
19          the mind. *Topics in Cognitive Science*, 4, 21-34.
- 20
- 21   Rulkov, N., Sushchik, M., Tsimring, L., & Abarbanel, H. (1995). Generalised  
22          synchronisation of chaos in directionally coupled chaotic systems.  
23          *Physical Review E*, 51, 980.
- 24

- 1 Silva, P., Garganta, J., Araújo, D., Davids, K., & Aguiar, P. (2013). Shared  
2 knowledge or shared affordances? Insights from an ecological dynamics  
3 approach to team coordination in sports. *Sports Medicine*, 43(9), 765-  
4 772.
- 5
- 6 Silva, P., Chung, D., Carvalho, T., Cardoso, T., Davids, K., Araújo, D., &  
7 Garganta, J. (2016). Practice effects on intra-team synergies in football  
8 teams. *Human Movement Science*, 46, 39-51.
- 9
- 10 Sinnott, R. (1984). Virtues of the Haversine. *Sky and Telescope*, 68(2), 159.
- 11
- 12 Strogatz, S. (2000). From Kuramoto to Crawford: Exploring the onset of  
13 synchronisation in populations of coupled oscillators. *Physica D*, 143, 1-  
14 20.
- 15
- 16 Travassos, B., Araújo, D., Duarte, R., & McGarry, T. (2012). Spatiotemporal  
17 coordination behaviors in futsal (indoor football) are guided by  
18 informational game constraints. *Human Movement Science*, 31, 932-945.
- 19
- 20 Travassos, B., Gonçalves, B., Marcelino, R., Monteiro, R., & Sampaio, J.  
21 (2014). How perceiving additional targets modifies teams' tactical  
22 behavior during football small-sided games. *Human Movement Science*,  
23 38, 241-250.
- 24