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Time scales for exploratory tactical behaviour in football small-sided games

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Time scales for exploratory tactical behaviour in football small-sided games

Original Research

Abstract

The aim of this study was to identify the dynamics of tactical behaviour emerging on different time scales in football small-sided games and to quantify short- and long-term exploratory behaviour according to the number of opponents. Two teams of four professional male footballers played small-sided games against two different teams with a variable number of opponents (3, 5 and 7). Data were collected using a combination of systematic observation and a non-differential global positioning system (15 Hz). The temporal diversity and structural flexibility of the players were determined by calculating the dynamic overlap order parameter q , entropy and trapping strength. Analysis of the exploratory dynamics revealed two different timescales, forming a different metastable landscape of action for each constraint. Fast dynamics lasted on average a few seconds and consisted of changes in tactical patterns. The long timescale corresponded to the shared tasks of offence and defence lasting tens of seconds. The players' tactical diversity decreased with an increasing number of opponents, especially in defence. Manipulating numerical imbalance is likely to promote changes in the diversity, unpredictability and flexibility of tactical solutions. The fact that the temporally nested structure of constraints shaped the emergence of tactical behaviour provides a new rationale for practice task design.

Key words: *Metastability, emergence, task constraints, dynamic overlap, entropy, game dynamics*

Introduction

Football can be understood in terms of self-organized dynamics (Gréhaigne, Zerai, & Godbout, 2011; McGarry, Anderson, Wallace, Hughes, & Franks, 2002; Araújo et al., 2015; Bourbousson et al., 2014). Self-organized dynamics means that the flow of the game is not imposed or prescribed by an external agency. It emerges from the interactions of players with specific environmental contexts (Vilar, Araújo, Davids, & Button, 2012; Davids, Araújo, Correia, & Vilar, 2013), i.e. the information created by each individual's tactical action (Passos et al., 2008). In this sense, tactical behaviour can be understood as the players' individual or collective functional adaptations to the task demands presented in a dynamic environment (Araújo et al., 2015, Sampaio, Lago, Gonçalves, Maças, & Leite, 2014; Vilar et al., 2012). This spontaneous social ordering emerges from the rich interactions between agents and is characterized by adaptability, stability and flexibility (Seifert, Button, & Davids, 2013; Hearn, Rodriguez & Bridgstock, 2014). Adaptability means ability to fit functionally one's actions to immediate environmental constraints. Stability means the capacity of the system to quickly recover from external (opponent team) perturbations and maintain the general shared goals, for example maintaining the possession of the ball. This is achieved by flexible reconfiguration of the task solutions to the external perturbation by the opponent team. Importantly, the agents involved are not permanently strongly coupled and/or their couplings are more temporally and spatially heterogeneous (couplings and tasks vary in time and space), and this makes it difficult to form highly coherent self-organized behaviours, especially over long timescales (Challet, Marsili, & Zecchina, 2000). In fact, such behaviour seems to be short term and to emerge as a consequence of the use of ecological information available in the local environment (Araújo, Davids, & Hristovski, 2006; Araújo et al., 2015; Pinder, Davids, Renshaw, 2012). Due to task heterogeneity (different players have different immediate tasks to solve) and personal constraints, therefore, a more global and long-term coherent behaviour involving all players fine-tuned with local information would seem to be an unlikely state. The most likely states are short term and locally coherent, but globally incoherent. A direct effect of the heterogeneity of social interactions is therefore a division of labour. In this way, short-term and locally coherent

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3 states are continuously formed, yielding a permanent flow of team reconfigurations in the state
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5 space. These states of temporary stability, but long-term instability, are called metastable states
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7 (Hristovski, Venskaityte, Vainoras, Balagué & Vazquez, 2010) and are directly linked to the
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9 adaptability, stability and flexibility as defined above.
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12 It has been shown that under constraints complex neurobiological systems form nested dynamic
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14 coherent states, with the highest level containing the longer-term weakly coherent (correlated)
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16 configurations (patterns) and the lowest level containing the strongly coherent patterns that exist
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18 over shorter timescales. These findings lead to a qualitative prediction of dynamics involving
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20 many ordered metastable states (Hristovski, Davids, Araujo, & Passos, 2011). Recently, the
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22 existence of these states in complex heterogeneous social systems was independently supported
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24 by the wide probability distribution functions of dyad and team correlations found in rugby
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26 union dyads (Correia et al., 2014), futsal (Corrêa, Alegre, Freudenheim, Santos, & Tani, 2012),
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28 football (Duarte et al., 2012) and, more recently, in contact improvisation dance dyads (
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30 Torrents, Ric, & Hristovski, 2015). The wide probability distribution of correlated states is
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32 strongly suggestive of a hierarchy of states with different degrees of action coherence between
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34 players.
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39 In team sports, small-sided games (SSG) are often used to simulate sub-phases of full-sided
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41 games, representing their unstable, dynamic and unpredictable nature (Davids et al., 2013).
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43 Therefore, they likely share the properties described above. Furthermore, in such settings
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45 players are permanently exposed to a large set of action possibilities fostered by the competitive
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47 environment. In SSG, one of the most important issue is the manipulation of task constraints to
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49 facilitate the emergence of several individual and collective behaviours. Vilar, Araújo, Davids,
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51 and Bar-Yam (2013) demonstrated the importance of numerical advantage as a key element in
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53 maintaining defensive stability and creating scoring opportunities in attack. Applied to SSG,
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55 Sampaio and colleagues (2014) suggested that playing with a numerical disadvantage decreases
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57 the randomness of players' distances to the team centroid, promoting less unpredictable
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59 behaviours. Similarly, Travassos, Vilar, Araújo, and McGarry (2014a) studied situations in
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3 which the futsal goalkeeper for the attacking team is substituted with an extra outfield player
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5 and identified different coordination dynamics for defending and attacking dyads.
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9 Although these findings contribute to a better understanding of SSG situations, the knowledge
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11 about the timescales of game dynamics remain unexplored. In fact, previous studies have
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13 highlighted the need to analyse team sports at different levels or time scales (Duarte, Araújo,
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15 Correia, & Davids, 2012a; Travassos, Davids, Araújo & Esteves, 2013; Bourbouson,
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17 Deschamps & Travassos, 2014). A clearer understanding of this concept would enable coaches
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19 to develop stimuli that are properly adapted to the nature of interpersonal coordination (Lemke,
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21 2000), thereby improving the efficiency of the training process, which in turn would have
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23 consequences for the exploratory behaviour of players, i.e. the process of adaptation to find
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25 effective and efficient tactical solutions in ever-changing game contexts. Therefore, the aim of
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27 this study was to identify the timescales of dynamics in SSG settings, and to quantify
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29 exploratory behaviour under different practice task constraints by identifying the influence of
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31 the number of opponents on short- and long-term exploratory behaviour.
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38 **Methods**

39 *Participants*

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42 Power analysis was first performed to determine the required sample size. Similar studies of
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44 exploratory dynamics have identified large effect sizes (mean value of $d = 1.4$) (Duarte et al.,
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46 2012b). Using a more conservative effect size of $d = 1.0$, $\alpha < 0.05$, power $(1 - \beta) = 0.80$, for
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48 within-participants comparisons, we estimated a required sample size of eight (Faul, Erdfelder,
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50 Lang, & Buchner, 2007). Consequently, eight male professional footballers from the same team
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52 were recruited for this study (age: 26 ± 4.96 years, playing experience: 19.6 ± 4.9 years; training
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54 schedule of five sessions per week). All participants were informed about the research
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56 procedures and they provided prior informed consent. The local institutional Research Ethics
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58 Committee approved the study, which also conformed to the recommendations of the
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60 Declaration of Helsinki.

Procedure

Three different SSG were designed involving different numerical imbalances: small numerical advantage (4 vs. 3), small numerical disadvantage (4 vs. 5) and large numerical disadvantage (4 vs. 7). Twenty-two players from a professional football team were distributed in two different balanced teams of four players, taking into account their playing positions, and physical, technical and tactical level, according to a coach's subjective criteria, to ensure that the teams' performances were comparable (Aguiar, Botelho, Gonçalves, & Sampaio, 2013). Similarly the opponents were distributed in two different teams of up to seven players. Goalkeepers participated in the protocol but were excluded from the data analysis. All SSG were played on an artificial pitch measuring 40×30 metres, and in accordance with the official rules of soccer. In order to maintain the rhythm of play and avoid the influence of fatigue, and given the lack of consensus regarding the duration of SSG (Aguiar et al., 2013), each game involved two 3-minute periods of play separated by 4 minutes of passive rest (360 seconds playing in each condition). The three different conditions were presented in a randomized order, yielding a total of six situations for each team. In order to increase the effective playing time, several balls were placed in the goals, with goalkeepers being responsible for supplying a ball whenever play was interrupted.

Data collection

Data were gathered through a combination of systematic observation and the use of a 15 Hz non-differential global positioning system (SPI-ProX, GPSports, Canberra, ACT, Australia). All SSG were recorded using a digital video camera. The video recording was processed and analysed using the Lince software (Gabin, Camerino, Anguera, & Castañer, 2012), with an *ad hoc* instrument being used to notate tactical actions (Costa, Garganta, Greco, Mesquita, & Maia, 2011) based on shared task goal from which players act in the two phases of the game (offence and defense). The context of each player was defined using the 'inter-player context' variables (see Table I), providing information about the positional changes of analysed players with respect to all other players, i.e. the relative position with respect to teammates and opponents. In

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3 order to provide a satisfactory guarantee of data quality (Altman, 1990), intra- and inter-
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5 observer agreement were assessed and yielded very good kappa coefficients of 0.84 and 0.78,
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7 respectively. The pitch zones and movement speeds (Coutts, & Duffield, 2010) (see Table I)
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9 were determined using latitude and longitude coordinates exported from the GPS units and
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11 computed using dedicated routines in Matlab R2014a software (MathWorks, Inc.,
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13 Massachusetts, USA) (for complete guidelines, see Folgado, Duarte, Fernandes, & Sampaio,
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15 2014).
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22 **** Table I near here ***
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28 The data collected for each player yielded data vectors derived from 37 variables, which
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30 belonged to four categories (tactical actions, inter-player context, pitch zones and movement
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32 speeds) (see Table I). Using Boolean logic, the number 1 was ascribed to the variables that were
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34 active and 0 to the non-active ones, representing the full action configuration during the same
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36 unit time interval of 1 second. Because players changed their states during the game (lasting
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38 360 seconds), the active and non-active variables from the full set of 37 variables changed as
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40 well. In this way, multivariate binary (Boolean) time series matrices of size 37 x 360 seconds
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42 were created for each player. In total, there were 2880 data vectors representing the
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44 configurations for the eight participants.
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48 *Data analysis*

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51 To understand the dynamic properties of the game there is a clear need to use concepts that are
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53 able to capture these properties with validity. The dynamic overlap was used to provide
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55 information about the timescale on which the exploratory behaviour sufficiently saturates and
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57 opens up the possibility of defining the scale of short- vs long-term game dynamics. In addition,
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59 as a relational variable, it contributes information about the average similarity of game patterns
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taking place at increasing lengths of time apart, or in other words, about the exploratory breadth

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3 of the game at different timescales. The dynamic overlap $\langle q_d(t) \rangle$ was calculated as an average
4 cosine auto-similarity of the overlap between configurations with increasing time lag
5 (Hristovski, Davids, Araújo, Passos, Torrents, Aceski, & Tufekcievski, 2013). The trapping
6 strength of configurations gives the probability of remaining inside the same attractor. This
7 measure contributes to detecting the overall flexibility of tactical behaviour of the game under
8 different imbalance conditions. The larger (lower) the trapping strength the smaller (larger) is
9 the overall behavioural flexibility respectively. This means that the probability that the extant
10 configuration will be reorganized, i.e. change to another configuration', is lower (higher).
11 Trapping strength was calculated as conditional probabilities of a configuration being
12 subsequently repeated (Saxton, 1996). The unpredictability of emergence of players' action
13 configurations was assessed using the Boltzmann-Gibbs-Shannon entropy measure (Balescu,
14 1975) and this helped to understand the variability of game contexts in which the player was
15 immersed. The probabilities of configurations were calculated as limit (large N) relative
16 frequencies for stationary distributions: $p_i = n_i/N$, where n_i is the frequency of the configuration
17 and N is the total number of configurations.

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The long-term behaviour of the dynamic overlap, i.e., its stationary part, the entropy and the trapping strength of the configurations reveal similar information about the exploratory behaviour of players. The reduced number of available states for the system determined by the large trapping strength means larger overlap of the configurations, i.e. their larger auto-similarity. However, whereas the trapping strength and entropy reveal only information about the long-term behaviour of the system (they are *numbers*), the dynamic overlap is a *function* of the time lag and hence it is able to inform about the dynamics on different timescales. In fact, the dynamic overlap provides information about the timescale on which the exploratory behaviour sufficiently saturates and opens up the possibility of defining the scale of short- vs long-term tasks and task solutions. Short-term tactical patterns are associated with the sharply decreasing part of dynamic overlap behaviour and the long-term tactical patterns are associated with the stationary part of the function.

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Friedman ANOVA was used to compare the average stationary overlaps $\langle q_{stat} \rangle$, total entropy and total trapping strength of configurations, defence and offence entropy, and defence and offence trapping strength under the three different conditions. The effect sizes were measured as eta-squared and interpreted according to the following criteria: significant but weak ($ES \leq 0.04$), moderate ($0.04 < ES \leq 0.36$) and strong ($ES > 0.36$) (Tabachnick & Fidell, 2007). The follow-up tests were conducted using the Wilcoxon matched-pairs test. Effect sizes here were calculated as Cohen's d . To control for possible effects of small sample size, Cliff's delta was used as a non-parametric analogue. The level of statistical significance was set as $p < 0.05$.

Results

Dynamics of players' patterns overlap on different timescales

The average dynamic overlap $q_d(t)$ showed a characteristic behaviour involving relaxation to an average stationary value $\langle q_{stat} \rangle$. Figure 1(a) shows that for different task conditions a different stationary value was attained in the lag interval from around 15–30 s. The differences between stationary values are analysed in the next sub-section. In general, the first quickly relaxing part of the curve shows that exploration of different game patterns by individual players exists on a timescale of seconds. Over a scale of a few tens of seconds, however, the exploratory dynamics slows down and attains stationary values. On even larger timescales (hundreds of seconds), the degree of exploration is stationary, partly repeating the already created tactical patterns.

This is consistent with the calculated pooled averages of the short-term characteristic timescale of changing patterns consisting of tactical actions, inter-player contexts, pitch zones and movement speeds for all conditions, $\tau_1 = 3.09 \pm 3.01$ s, and the longer-term change of defensive and offensive patterns, $\tau_2 = 12.71 \pm 9.32$ s (Mendes, Malacarne, & Anteneodo, 2007). These two timescales reflect the characteristic dwell times of patterns at each level: 1) the level of short-lived tactical patterns, belonging to either defensive or offensive phases; and 2) the global level of defensive or offensive task constraint phases. They roughly satisfy the condition $\tau_1 \ll \tau_2$ and define the existence of two separate timescales ($d = 1.39$). In this respect, the exploratory

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3 dynamics of players attains its stationary value, that is, the slope of the short-term characteristic
4 timescale vanishes, as soon as players switch several times between offensive and defensive
5 patterns of play. The rest of the game produces more detailed changes within this core
6 offensive-defensive switching dynamics, but does not change the average exploration breadth.
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10 11 12 *Short-term and long-term shifts in tactical patterns*

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15 The interplay between the two timescales of SSG under different conditions is depicted in
16 Figure 1 (b, c and d). The bold lines connecting *two large regions* of offensive and defensive
17 actions represent the shifts that emerge over longer timescales (tens of seconds, i.e. $\tau_2 = 12.71 \pm$
18 9.32 s) between offensive and defensive patterns (long-term reconfigurations), while darker
19 shaded areas *within* each of these regions represent attractive tactical action–pitch zone regions
20 that are subject to short-term changes ($\tau_1 = 3.09 \pm 3.01$ s) in tactical patterns over a scale of a
21 few seconds (short-term reconfigurations).. The valleys between phases of offensive and
22 defensive actions are separated by higher barriers than are those belonging to tactical action–
23 pitch zone classes within defensive or offensive phases. Due to the Arrhenius law (Balescu,
24 1975), the height of the barriers is directly proportional to the average time needed for the
25 system to pass over them. The hierarchy of the barriers translates into the timescale hierarchy of
26 SSG dynamics.
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46 ***** Figure 1 near here *****
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52 *Attractiveness of tactical patterns*

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54 On the 2D projection of the 3D potential landscape, the strengths of attractiveness of different
55 tactical action–pitch zone patterns are depicted in darker or lighter shades corresponding to the
56 probability of their occurrence. A change in the number of opposing players changed the most
57 probable tactical action–pitch zone patterns. For example, as shown in Table I, each variable
58 corresponds to a number. Tactical action number 0 corresponds to penetration. On Figure 1b,
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3 the depth of attraction basins is represented as a dark shaded surface, and reflects the probability
4 of detecting that pattern. The darker the shade, the deeper the attractor basin, and consequently
5 the higher is the probability of that pattern. Tactical action 0 possesses the darkest shade and
6 hence is the most probable pattern in 4 vs. 3 SSG, defined by penetration of a player with the
7 ball into the mid-defensive zone centre (5). Offensive coverage and width and length in the mid-
8 offensive zone centre was highly probable as well. The most attractive defensive pattern was
9 balance in the mid-offensive zone. Following the same explanatory scheme, it can be seen that
10 under 4 vs. 5 (Figure 1c) the landscape shows larger stable states (patterns). The dominant
11 offensive patterns were offensive coverage in the mid-defensive zone and the deep-defensive
12 zone centre. In defence the most probable pattern was balance in the centre of the mid-defensive
13 zone and the mid-offensive zone, and it seems that players delayed the action of the opponent
14 with the ball in the centre of the mid-offensive zone. Under 4 vs. 7 the most attractive patterns
15 in offence were offensive coverage in the deep- and mid-defensive zones, and balance in the
16 defensive phase in the same zones (Figure 1d).

17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 *Effects of player imbalance on stationary overlap of game*

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37 The Friedman ANOVA performed on $\langle q_{stat} \rangle$ profiles showed a significant effect of practice task
38 constraints on the auto-similarity of game patterns: $[\chi^2 (8,2) = 7.00; p = 0.03; \eta^2 = 0.71]$. The
39 follow-up results are presented in Table II and show a consistent increase in the stationary
40 overlap of the tactical patterns with an increasing number of opposing players.
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47 48 49 50 51 52 53 54 55 56 57 58 59 60 *Effects of player imbalance on game entropy*

50 The same procedure applied to the total game entropy and the entropy of defensive play showed
51 a significant strong effect of practice task constraints on the unpredictability of tactical patterns:
52 $[\chi^2 (8,2) = 8.87, p = 0.012; \eta^2 = 0.69]$ and $[\chi^2 (8,2) = 12.25, p = 0.002; \eta^2 = 0.69]$, respectively.
53 However, the Friedman ANOVA failed to show a significant effect of task constraints on the
54 offensive play entropy $[\chi^2 (8,2) = 1.75, p = 0.417; \eta^2 = 0.32]$. The result of the follow-up
55 comparison given in Table II shows that players' total tactical entropy decreased with an
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3 increasing number of opponents, mostly on the basis of the decrease in the entropy of defensive
4 tactical patterns.
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9 *Effects of player imbalance on trapping strength of the game*

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11 Similar results were obtained when analysing the pattern trapping strength. Here the Friedman
12 ANOVA showed a significant strong effect of task constraints on the values of total pattern
13 trapping strength [$\chi^2(8,2) = 16.00$; $p = 0.0003$; $\eta^2 = 0.89$] and trapping strength in defensive
14 play [$\chi^2(8,2) = 13.00$; $p = 0.0015$; $\eta^2 = 0.74$], but not on the values for offensive game play [χ^2
15 (8,2) = .77; $p = 0.687$; $\eta^2 = 0.16$]. These strong effects were supported by the results of a follow-
16 up comparison (see Table II), which predominantly showed an increase in the trapping strength
17 of game patterns under an increasing number of opponents, the effect being based on the
18 increase in the trapping strength of defensive patterns.
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33 **** Table II near here ****
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39 **Discussion**

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41 The present study showed how players' exploration of tactical patterns is a temporally nested
42 process in which manipulating the number of opponents produces changes in the exploration,
43 unpredictability and degree of flexibility of tactical patterns.
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49 The exploratory dynamics of SSG lasting 6 minutes generally develops over two timescales.
50 The shortest one lasts, on average, a few seconds and consists of changes in tactical patterns
51 involving the type of tactical action, the inter-player context, the pitch zone and movement
52 speed. This timescale corresponds to short-lived emergent task solutions. The longer timescale
53 corresponds to more slowly changing, global task constraints related to the shared general goals
54 of offensive and defensive phases. The long- and the short-timescale processes are interlinked in
55 a kind of circular causality (Haken, 1983), since the longer timescale task constraints govern the
56 shorter timescale tactical patterns, while the accomplishment of the latter stabilises the former
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3 (Balagué, Torrents, Hristovski, Davids, & Araújo, 2013). The exploratory behaviour
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5 predominantly saturates to the stationary value as the game switches several times between
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7 these two phases.
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11 Importantly, this property of SSG dynamics provides a rationale for using jokers in some SSG
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13 variants (Bourbousson, et al., 2014). Constraining the game by introducing a numerical
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15 advantage or disadvantage using jokers who enter and/or exit the game over the timescales of a
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17 few to several tens of seconds would create a new environment for the players to explore when
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19 the exploratory behaviour saturates. Using jokers effectively relaxes the task constraints of
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21 numerical imbalance by changing the number of opponents on the timescale of tens of seconds
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23 instead of several hundreds of seconds. Exploratory behaviour can also be enhanced by
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25 changing the playing position of players during the same time interval. In this way exploratory
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27 behaviour is necessarily enhanced and becomes more representative of a real match. In general,
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29 changing the numerical superiority and inferiority and the playing positions of players on the
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31 timescale of a few tens of seconds would enable sufficiently larger exploratory breadth and
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33 simultaneously make SSG more representative of real game situations.
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37 In relation to the above, the manipulation of practice task constraints changes the probabilities
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39 of emergent tactical patterns and the dynamics of exploration in different regions of the task
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41 solution space (Pinder et al., 2012;Torrents et al., 2015). The differential attractiveness of
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43 emergent patterns directly reflects the differentiated decision-making abilities that players are
44
45 constrained to develop under varying conditions. For example, under 4 vs. 3 conditions the
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47 offensive and defensive tactical patterns mostly occurred in mid-offensive zones, whereas under
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49 4 vs. 7 conditions they predominantly emerged in deep- and mid-defensive zones. Increasing
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51 the number of opponents promotes an amplification of the information that players need to
52
53 attend to during the game, mostly in the defensive process. This constraint requires an increase
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55 in players' breadth of attention and perceived stimuli to solve an imbalance inferiority situation
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57 (Travassos et al., 2014b).
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3 The total long-term exploratory breadth, unpredictability and flexibility of emergent patterns of
4 individual players all decrease with an increasing number of opposing players. Similar results
5 based on kinematic data were obtained in previous studies (Sampaio et al., 2014). Interestingly,
6 this decrease seems mostly to affect defensive rather than offensive patterns. Thus, an
7 increasing number of opponents imposes stronger constraints on defensive tasks and produces
8 less flexible defensive task solutions among players, whereas the flexibility and exploration of
9 offensive task solutions may decrease only slightly. As shown in the results section, as the
10 numerical disadvantage increases, both the defensive and offensive patterns shift towards
11 defensive zones, since the numerical advantage of opponents constrains the defending team to a
12 smaller number of task solution options for protecting their goal (Travassos et al., 2014b).
13 Conversely, when playing with a numerical advantage, players are less constrained and can
14 decide to recover the ball in the offensive zone by pressing the opponent, because one of the
15 extra players can perform the balance or coverage task.
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32 In relation to the above results, but based on an analysis of kinematic variables, Fonseca, Milho,
33 Travassos, & Araújo, (2012) found that defenders showed greater irregularity than did the
34 attacking team. This finding does not necessarily contradict our results, since it takes into
35 account other variables. For example, it is possible that defenders may, while more spatially
36 active, solve identical or similar tasks. In any case, a caveat is needed when comparing results
37 from the team and individual player levels, since it may be the case that under certain
38 circumstances the smaller degree of diversity at the team level is compensated for by increased
39 diversity in the actions of individual players, and/or vice versa, the effect of which would be a
40 kind of multi-level synergy which has not yet been studied. This possibility warrants more
41 detailed investigation. Besides, further research is needed to analyse full-game football
42 dynamics and its evolution on different timescales using the methods applied herein. On more
43 theoretical grounds, since it is the characteristic timescales of behaviour that unequivocally
44 define the levels of the system dynamics it is possible to define performance collective variables
45 that can serve as parsimonious macroscopic descriptors of what on average happens at the
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3 microscopic level. Such an approach will open the path toward objective definition of the
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5 micro-macro link in football.
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10 11 **Conclusion**

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14 This study attempted to identify the hierarchy of timescales in SSG dynamics and to determine
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16 their role in shaping the exploratory behaviour of players. We showed how manipulating the
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18 numerical relationship between teams engaged in SSG brings about changes in the types of
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20 decision-making skills and the tactical landscape of players, affecting the exploratory breadth,
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22 unpredictability and flexibility of tactical solutions. We also demonstrated that the temporally
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24 nested structure of game constraints shaped the emergence of offensive and defensive tactical
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26 behaviour on different timescales. More specifically, the time interval of a few to several tens of
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28 seconds seems to be the optimal range for manipulating practice task constraints based on the
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30 numerical relationship between teams and playing positions of players engaged in SSG. The use
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32 of jokers could be applied over this timescale, one on which exploratory behaviour sufficiently
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34 saturates. Future research is warranted in order to determine how the simultaneous synergy of
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36 numerical imbalance and the timescales of its manipulation affect the exploratory breadth,
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38 unpredictability and flexibility of tactical task solutions.
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Table I. Data collected to assess the tactical patterns of each player formed by 37 categories.

Each data vector represented a configuration of the player in a 4D category space.

Tactical actions (Costa et al. 2011; Clemente et al. 2014)	Offensive actions	Penetration (0)
		Offensive coverage (1)
		Depth mobility (2)
		Width and length (3)
	Defensive actions	Offensive unity (4)
		Delay (5)
		Defensive coverage (6)
		Balance (7)
		Concentration (8)
Inter-player contexts	Defensive unity (9)	
	Rear teammate between advanced opponent and own goal	
	Intermediate teammate between advanced opponent and own goal	
	Advanced teammate between advanced opponent and own goal	
	Rear teammate between advanced and rear opponent	
	Intermediate teammate between advanced and rear opponent	
	Advanced teammate between advanced and rear opponent	
	Rear teammate between rear opponent and the opposing goal	
	Intermediate teammate between rear opponent and the opposing goal	
Advanced teammate between rear opponent and the opposing goal		
Pitch zones	Deep-defensive right (length <10 m; width <10 m) (1)	
	Deep-defensive centre (length <10 m; width 10 m<20 m) (2)	
	Deep-defensive left (length <10 m; width >20 m) (3)	
	Mid-defensive right (length 10 m<20 m; width <10 m) (4)	
	Mid-defensive centre (length 10 m<20 m; width 10 m<20 m) (5)	
	Mid-defensive left (length 10 m<20 m; width >20 m) (6)	
	Mid-offensive right (length 20 m<30 m; width <10 m) (7)	
	Mid-offensive centre (length 20 m<30 m; width 10 m<20 m) (8)	
	Mid-offensive left (length 20 m<30 m; width >20 m) (9)	
	Deep-offensive right (length >30 m; width <10 m) (10)	
	Deep-offensive centre (length >30 m; width 10 m<20 m) (11)	
	Deep-offensive left (length >30 m; width >20 m) (12)	
Movement Speeds (Folgado et al. 2014)	< 0.7 km/h (stand)	
	0.7 – 3.6 km/h (walk)	
	3.6 – 7.2 km/h (jog)	
	7.2 – 14.4 km/h (medium-intensity running)	
	14.4 – 19.8 km/h (high-intensity running)	
	>19.8 km/h (sprint)	

Table II. Mean values \pm SD for different variables obtained for the three conditions, distinguishing between teams and the offensive and defensive phases of the game

Variable	Groups	SSG (mean \pm SD)			Mean Differences		
		4vs3	4vs5	4vs7	Cliff's Delta	Cohen's d_{unb} [90% CI]	
$\langle q_{stat} \rangle$	Both teams (n=8)	0.202 \pm 0.015	0.230 \pm 0.025	0.254 \pm 0.029	a)	-0.66	-1.28 [-2.21, -0.36]
					b)	-0.47	-0.84 [-1.71, 0.03]
					c)	-0.89	-2.13 [-3.19, -1.07]
Entropy	Both teams (n=8)	0.909 \pm 0.019	0.886 \pm 0.032	0.868 \pm 0.022	a)	0.46	0.83 [-0.05, 1.70]
					b)	0.36	0.62 [-0.23, 1.47]
					c)	0.84	1.89 [0.87, 2.90]
Trapping Strength	Both teams (n=8)	0.209 \pm 0.025	0.240 \pm 0.022	0.305 \pm 0.020	a)	-0.65	-1.24 [-2.16, -0.33]
					b)	-0.97	-2.92 [-4.16, -1.69]
					c)	-1	-4.01 [-5.51, -2.51]
Entropy	Offence (n=8)	0.859 \pm 0.021	0.848 \pm 0.045	0.836 \pm 0.032	a)	0.18	0.30 [-0.54, 1.13]
					b)	0.17	0.29 [-0.55, 1.13]
					c)	0.45	0.80 [-0.07, 1.67]
Entropy	Defence (n=8)	0.856 \pm 0.021	0.834 \pm 0.021	0.814 \pm 0.019	a)	0.54	0.99 [0.10, 1.88]
					b)	0.52	0.94 [0.06, 1.83]
					c)	0.86	1.98 [0.95, 3.02]
Trapping strength	Offence (n=8)	0.412 \pm 0.045	0.434 \pm 0.078	0.444 \pm 0.062	a)	-0.19	-0.33 [-1.17, 0.51]
					b)	-0.08	-0.13 [-0.97, 0.70]
					c)	-0.32	-0.56 [-1.41, 0.29]
Trapping strength	Defence (n=8)	0.418 \pm 0.036	0.462 \pm 0.044	0.512 \pm 0.034	a)	-0.56	-1.03 [-1.93, -0.14]
					b)	-0.63	-1.2 [-2.12, -0.29]
					c)	-0.94	-2.54 [-3.69, -1.39]

Mean differences are identified as: a) 3 opponents vs. 5 opponents; b) 5 opponents vs. 7

opponents; c) 3 opponents vs. 7 opponents.

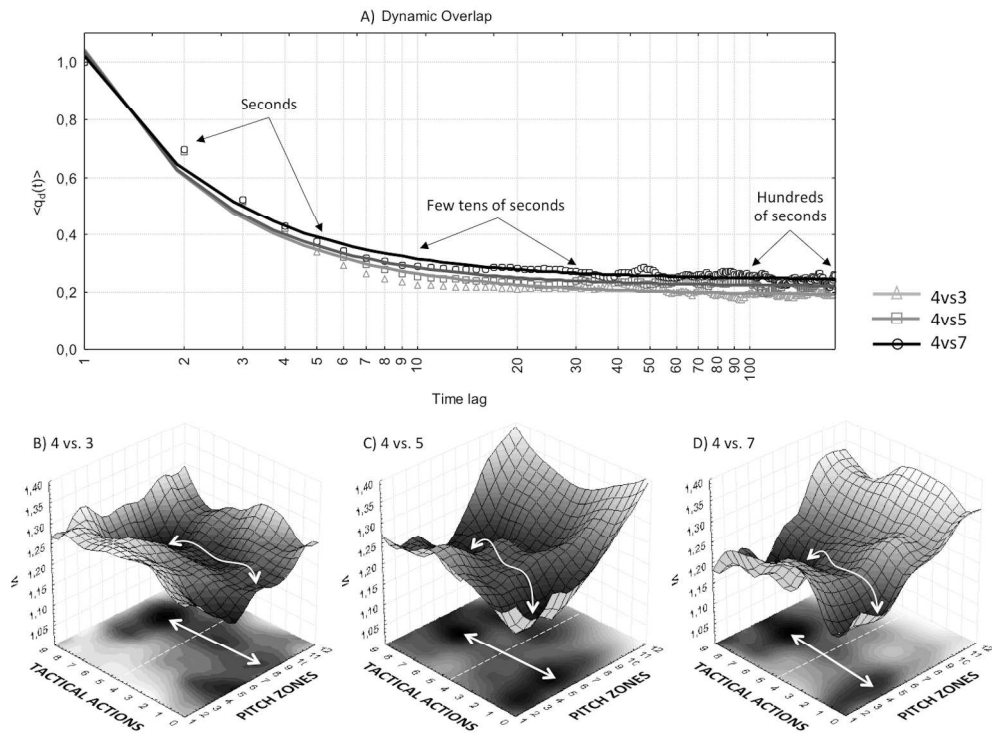


Figure 1. Upper panel: A) profile of the average dynamic overlap $\langle q_d(t) \rangle$ of each condition for different time lags; these dynamics unfold over three time scales (from seconds to several minutes). Lower panel: Attractiveness regions for player action - zone patterns under B) 4 vs. 3, C) 4 vs. 5 and D) 4 vs. 7 task constraints, pooled over all 8 players. The 3D deeper wells correspond to 2D-projected more attractive (i.e. more probable) darker areas.