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The hegemonic struggle in antagonistic sports:

Conceptualizing cooperation, antagonism, and hegemony within antagonistic sports

Luis Ignacio Gómez-Jordana Martín

Orientador*:* *Professor Doutor Pedro* José Madaleno Passos

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Tese especialmente elaborada para a obtenção de grau de Doutor em Motricidade Humana e na especialidade de Comportamento Motor

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Juri:

Presidente:

Doutor António Prieto Veloso
Presidente do Conselho Científico
Faculdade de Motricidade Humana da Universidade de Lisboa

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Doutor Rui Jorge Lopes
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Doutor Pedro José Madalena Passos
Professor Auxilia com agregação
Faculdade de Motricidade Humana da Universidade de Lisboa

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Abstract

In antagonistic sports, two antagonistic entities coordinate with each other as they *struggle* over the hegemony of the game. Such hegemonical struggle can be divided into two different dimensions: a dimension of cooperative coordination (within a team or an individual) and a dimension of antagonistic coordination with an opposing rival. The cooperative dimension is characterized by common goals which leads to synergetic behavior. On the other hand, the antagonistic dimension is characterized by the principle of opposition, and therefore by antagonistic goals (goals that negate each other). Hegemony on this thesis will depict the on-going relation of forces in between two rivals that are struggling with each other to win a sport contest. Such hegemony will emerge of the dynamic interaction in between these two dimensions, and could possibly be the level were the actual result of the sport is decided. Therefore, in Chapter 2 of this thesis we studied the synergetic behavior of a defensive unit during successful plays and unsuccessful plays. The results showed that successful behavior is related to the successful management of variability rather than the reduction of such variability, as the plays with more stable behavior correspond to plays were the unit did not succeed. In chapter 3, we showed the uniqueness of antagonistic coupled behavior using a simple rhythmical task. The results showed the appearance of intermediate steady states (away from 0º and 180º), increase fluctuations as well as metastable switchy behavior. All these reinforces the uniqueness of such situations calling for the use of specific models and terminology for such situations. Finally, in Chapter 4 we show a hegemonic approach to study football games in the form of landscapes of passing opportunities. The model, despite its early stages of development, already showed the capability to react to specific constrains emerging in the football game as well as its capability to depict weak areas that are underused. We suggest that the hegemonical macroscopic level (the relation of forces between two rivals) will be the level of interest for antagonistic sports, as it will show which rival is imposing itself over the other.

Keywords: Hegemony, Antagony, Synergy, Team analysis, Landscape of affordances.

Resumo

Nos desportos antagónicos, duas entidades antagónicas coordenam-se entre si enquanto lutam pela hegemonia do jogo. Tal luta hegemónica pode ser dividida em duas dimensões diferentes: uma dimensão de coordenação cooperativa (dentro de uma equipa ou de um indivíduo) e uma dimensão de coordenação antagónica com um adversário. A dimensão cooperativa é caracterizada por objectivos comuns que conduzem a um comportamento sinergético. Por outro lado, a dimensão antagónica é caracterizada pelo princípio da oposição, e portanto por objectivos antagónicos (objectivos que se negam mutuamente). Hegemonia nesta tese irá retratar a relação contínua de forças entre dois rivais que lutam um com o outro para ganhar um concurso desportivo. Tal hegemonia emergirá da interacção dinâmica entre estas duas dimensões, e poderá eventualmente ser o nível em que o resultado real do desporto for decidido. Assim, no Capítulo 2 desta tese estudamos o comportamento sinergético de uma unidade defensiva durante jogadas bem sucedidas e jogadas mal sucedidas. Os resultados mostraram que o comportamento bem sucedido está mais relacionado com a gestão bem sucedida da variabilidade do que com a redução dessa variabilidade, uma vez que as jogadas com comportamento mais estável correspondem a jogadas em que a unidade não teve sucesso. No capítulo 3, mostrámos a singularidade de um comportamento antagónico associado utilizando uma simple tarefa rítmica. Os resultados mostraram o aparecimento de estados estáveis intermédios (longe de 0º e 180º), aumento das flutuações, bem como comportamento 'switchy' e metastable. Tudo isto reforça a singularidade de tais situações, exigindo a utilização de modelos e terminologia específicos para tais situações. Finalmente, no Capítulo 4 mostramos uma abordagem hegemónico ao estudo de jogos de futebol sob a forma de paisagens de oportunidades de passe. O modelo, apesar das suas fases iniciais de desenvolvimento, já mostrou a capacidade de reagir a constrangimentos específicos emergentes no jogo de futebol, bem como a sua capacidade de retratar áreas fracas que são subutilizadas. Sugerimos que o nível hegemónico macroscópico (a relação de forças entre dois rivais) será o nível de interesse para os desportos antagónicos, pois mostrará qual o rival que se impõe sobre o outro.

Palavras-chave: Hegemonia, Antagonia, Sinergia, Análise da equipa, Paisagem das possibilidades.

Chapter 1: *Introduction: The hegemonic struggle in antagonistic sports*

Abstract

In antagonistic sports, two antagonistic entities coordinate with each other as they *struggle* over the hegemony of the game. Such hegemonical struggle can be divided into two different dimensions: a dimension of cooperative coordination (within a team or an individual) and a dimension of antagonistic coordination with an opposing rival. The cooperative dimension is characterized by common goals, which leads to synergetic behavior. Thus, this should lead to the stabilization of some performance variable due to adaptations in the microscopic behavior. Basically, the elements cooperating should be behaving like a unit. On the other hand, the antagonistic dimension is characterized by the principle of opposition, and therefore by antagonistic goals (goals that negate each other). This should lead to specific behavior that is not found in cooperative behavior, which raises questions on how to categorize such behavior in the macroscopic level. Hegemony will emerge of the dynamic interaction in between these two dimensions. Hegemony on this thesis will depict the on-going relation of forces in between two rivals that are struggling with each other to win a sport contest. In the second chapter of this thesis we will study a multilevel synergy (involving the four players of the defensive unit) using the UCM method. On the third chapter of the thesis we will study a simple antagonistic rhythmical task to show the difference of such behavior with synergetic behavior. Finally, the fourth chapter will use a landscape of passing opportunities to display the hegemonical struggle through five competitive football matches.

Keywords: *Team Sport; Performance; Motor Control; Coordination; Methodology*

1. The hegemonical struggle of antagonistic sports

In antagonistic sports, two antagonistic entities coordinate with each other as they *struggle* over the hegemony of the game[1,2](also called dominance[3]). Therefore in the core of this relation is the principle of two opposites[4] (*principle of opposition*), and the relation of forces in between these two[5] (*rapport de forces*). In essence hegemony is such relation of forces, which team is exhorting a higher dominance[3] (over the game and specific plays), shaping in each moment different actions that can be perform, as well as their value for the overall result of the game. Therefore, players' movement are defined by opposing short term goals highly influenced by prospective information that emerges in the course of the players' interactive behavior, i.e. a temporary open gap in the opponent defense[6]. Thus, this information continuously suggests not only *what* to do, but also *when*, *where*, and *how* to do it, highlighting ongoing possibilities of action[7,8,9].

This hegemonic *struggle* unveils in a certain space. Such space is define by constrains that emerge due to 1) the *rules* of the sport, 2) the *architecture* of the sport and 3) in the *physiology of athletes.* For example, martial arts are differentiated in between which strikes or techniques are allowed and how points are scored. Meaning that *rules* constrain the techniques a martial art performer can use, as well as which ones generate a better ratio of threat/safeness. Furthermore, different martial arts are practice with different rings. It is not the same to fight in a 5.5 to 6.7 meter kickboxing ring, a ring delimited by ropes, than fighting on a MMA (mixed martial arts) octagon of 9.1 meters of diameter with a fence as a delimiter. As we see the geography available is different, which in turns is going to affect how a martial art performer control the space and manages distance. Furthermore, different characteristics of the delimiters of the area to fight (ropes against a fence) afford different actions that can be performed in turn shaping the *struggle* to win the fight. Lastly, the techniques and the energy needed to perform are affected by the capabilities of the athletes, all under constrains of gravity and laws of motion. Therefore, the fight emerges from the spatiotemporal movement of the athletes constrain by three interacting dimensions (a set of *rules*, an *architecture*, and the *physiology* of athletes) and is in the interaction of these dimensions in which the hegemony of the game exhorts its influence.

Hegemony in this thesis stemmed from two complementary and similar approaches, the principle of opposition[4,5], and hegemonical *struggle*[2] in Gramsci theory. For Gréhaigne team sports were open systems in which two group of opposite players *struggle* to achieve victory[5]. Thus, this opposition principle shapes players' into two different groups, with players within teams sharing common goals (*team level*[4]). Such common goals should shape collective behavior making the players behave as a unit (as synergies). On the other hand, the opposition principle also defines a set of possible interactions with rivals in order to generate superiorities (such as placing the ball in good position to shot the ball to the goal in football). This set of goals are not any more common, but rather antagonistic, and should define a relation of forces (rapport de forces[5]).

Similarly, in Gramsci's theory, hegemony was defined as the ongoing relation of forces in between two antagonistic entities as they *struggle* over the control of geographical, economical and sociological spaces within a society. As we see antagonistic goals (i.e., that negate each other), shape the *struggle* in between competing entities. Moreover, this relation of forces was shaped by what Gramsci defined as the two moments of hegemony, 1) *Organization* of people into coherent political groups[10], and 2) *Struggle* to capture political power from groups that hold it in the present time[11]. Similarly, in any antagonistic sport we could define two separate moments the internal *organization* in between elements of a moving group and/or individual, and the *struggle* with a competing entity to increase the dominance or hegemony in a certain moment of the match.

For example, in field-invasion sports, such as football, players *organize* into two teams that *struggle* in order to recover the ball or advance it into areas of the field that pose a higher threat for the defense[12]. In these type of sports the hegemony is mainly define by the spatio-temporal movement of the ball as well as with which player is in possession of the ball. In this case, player need to organize with the teammates in their vicinity, all this taking into account which team (and player) has ball possession and its position on the field. On the other hand, players/units of a team *struggle* with the closest opponents in order to generate superiorities (e.g., player in an area of the field, which consequently outnumber the opposition players). This should help them further the position of the ball for the attack (team in possession of the ball) or to recover the ball for the defense (team that is not in possession of the ball).

To resume, hegemony is the expression of the dominance a team or athlete is imposing over the other. Such hegemony is constrain by three levels, the rules of the sport, the space available in the field where the game is played and the physical limitations to the movements that athletes need to perform. This hegemony is the result of two interacting moments, a moment of internal *organization* and a moment where two *antagonistic* groups *struggle* against each other. Therefore, hegemony is affected by the *organization* of internal groups that *struggle* against each other. Hegemony is not the result of any of these two moments, or the sum of those two moments, but rather emerges over the interaction in between these two.

In this thesis, we tried to define elements that are important for the two moments of hegemony, the moment of *cooperative coordination* (the moment of organization in Gramsci's theory) in within coherent entities, and the moment of *antagonistic* *coordination* in between two opposites (the moment of struggle in Gramsci's theory). More concretely, we studied relevant elements for *cooperative coordination* in between teammates, which is essential to understand the hegemony of team sports. Furthermore, in the case of the *antagonistic coordination* between two opposites, this has been largely under conceptualized, either not been studied, or studied using models that correspond to cooperative behavior. Therefore, in the case of the *antagonistic coordination* we use a simple rhythmical task to be able to show the uniqueness that opposition imposes in human coordination. Finally, we did a football game analysis that shows a hegemonic measure, with its limitations and advantages.

2. Cooperative coordination in within teammates

The moment of *cooperative coordination* is characterized by the aggrupation of muscles and individuals into units due to short-term goals, thus into synergies[13]. Synergies is a concept coined by the physicist Hermann Haken, which was interested in the emergence of macroscopic behavior due to the cooperation of the microscopic elements of a unit[14]. The idea was that organization in a microscopic level lead to the stabilization of some global (performance) variable. Therefore, cooperative aggregation in the microscopic level led to coherent behavior in a macroscopic level. Such concept was employed effectively to study rhythmical coupled behavior, (movement of dyadic entities that are coupled, i.e. HKB model[15]) predicting effectively the possible states the unit can achieve, as well as the relative stability of each state. In essence the members of a unit could move in-phase (been in the same moment of the cycle), or in anti-phase (been in opposite moments of the cycle), been the in-phase steady state more stable than the anti-phase steady state.

In team sports, athletes need to *coordinate cooperatively* with players of their own team[16] as they *antagonistically coordinate* with players of the opposing team. Such synergetic behavior have been shown mainly in football, where players stayed mainly in-phase during games[17,18,19,20,21,22,23]. It is important to note that these studies used the relative phase as a measure of coordination without reporting normalization methods of any type. Studies have shown that phases calculated without any normalization lead to unreliable results, which raises doubts about these studies[24,25]. Furthermore, relative phases can only be calculated in between couples of players not for groups of players. Moreover, the relative phase only provides evidence of stabilization in a macroscopic level, with no linkage with the microscopic behavior of the unit. This raises doubts on the reasons of such stabilization in the macroscopic level, as the only way of confidently capturing synergetic behavior, is proving that stabilization of the macroscopic variable is due to adjustments in the microscopic elements. On the other hand, in team sports groupings can happen in between groups of more than two players[26]. All these raises questions about the use of the relative phase to study coordination in team sports and the validity of past results.

A more suited way of capturing synergetic behavior is the Uncontrolled Manifold hypothesis (UCM[27]). The Uncontrolled Manifold (UCM) hypothesis[27] assumes that when a synergy emerges a performance variable is stabilized around a reference value by the adaptive change of a set of task elements (e.g., the position or velocity of individual players). When this happens, a subspace is created. This subspace, called UCM, is a geometrical representation of which variance of the task elements, due to compensatory adjustments, is leading to the stabilization of the performance variable. If the variance that is leading to the stabilization of the performance variable is greater than the one that is not stabilizing it, a synergy can be assumed to exist.

The UCM method has been successfully employed to study the emergence of synergies in the individual level for example, in gait analysis[28], dart shooting[29,30] or pointing task[31]. However, although developed to study intrapersonal behavior, in recent years, the method has been used to study interpersonal behavior. Such examples entail a Rugby Union task[32], Badminton doubles in the course of a match[33], and a cooperative slackline task[34]. In those studies, the UCM was used to study just dyadic behavior, although there is no limitation in the method in this regard (see Furmanek and collegues[35] for an example of a multilevel muscle synergy).

In that regard, team sports present a perfect opportunity to study the presence of such multilevel interpersonal synergies. Within a team, interpersonal synergies can potentially form from the interactive behavior of more than two players[26] (e.g., a defensive football line with four players), thus, it seems relevant to study these multilevel synergies in within a team during a sports event. In this regard, the UCM presents a unique opportunity to study the assemblage of such interpersonal synergies. First, because is perfectly equipped to study situations with a multitude of degrees of freedom. On the Second because the UCM method can be used for a myriad of situations, as long as a performance variable that can be stabilized and certain reference configurations can be defined.

To recall this first level of hegemony, in the case of teams' sports, deals with intra-team coordination. Such *cooperative coordination* happens through compensatory movements at the level of the individual variables, which leads to certain steady state at the team level; in essence, this coordination must be leading to some sort of stabilization of a performance goal at the team level. However, it is important to note that such stabilization does not necessarily means a reduction of variability but rather the management of such a variability (Kelso et al.,). Moreover, this *cooperative coordination* it is not the only element that defines how antagonistic sports are played. As important as the coordination in between players of a team is, in antagonistic sports players also need to modulate their behavior while they struggle against players in the opposing team.

3. Antagonistic coordination in between opponent athletes

There is another dimension (largely understudy) of how the hegemonic process may happen in antagonistic sports. This entails the coordination that occur in between two entities that have *antagonistic* intentions and goals that are therefore, *competing* against each other (note that players within a team also compete, but together not against each other). Although coordinated behavior can also be formed at this level, it is difficult to argue that such a process can be defined as a synergy. Synergies are formed because of a common shared objective in between the elements of a unit. Such cooperation at the microscopic level leads to certain type of organization at the macroscopic level. In the case of interpersonal coordination in team sports, this macroscopic level was assume as the team, a group or a dyad, whereas the athlete is situated at the microscopic level[36]. However, in *antagonistic coordination* the elements involve in it do not share common goals but rather have antagonistic goals, which probably leads to radically different forms of organization in the macroscopic level.

Kelso and colleagues[37] define such an interaction as emerging from a conflict of intentions. Such conflict of intentions was model in a rhythmical task by introducing opposing forces on the HKB model. This can be defined as the introduction of a repulsive force[38] (the one that wants to break away; modeled by a negative symbol in the coupling term) into a model that if not had two attractive forces (modeled by a positive symbol in the coupling term)[1]. Such a way of modelling led to the appearance of novel states (90º and 270º) as stable solutions, which, until then, were not seen as stable. The other expected result is that these situations should be less stable than the classic cooperative ones. This happens due to asymmetric opposing forces that lead to attractors been less stable. Furthermore, this should also be affected by antagonistic intentions (opposite negating intentions), meaning that if one of the two opponents achieve their objective, the other cannot achieve it. Therefore, in any given moment at least one member of such an antagonistic interaction must be in a state undesirable for itself. Thus, opponents *may* disturb the system more commonly leading to increase fluctuation and instability.

Support for this way of modelling antagonistic behavior has been mainly extracted from previous research in racket sports. For example, de Poel and Noorbergen[38] found that in 31 competitive ATP (Association of Tennis Professionals) rallies the two-tennis players' exhibit intermediate coordination states, which remain stable around 90º and 270º, with the in-phase steady state also been stable. Furthermore, McGarry[39] (see McGarry and de Poel[40] for the reanalysis of the data) in experimental squash rallies also found steady states around 90º and 270º, with the difference that the steady states were in the anti-phase coordination steady state in contrast with the in-phase steady state found in tennis rallies. Finally, Palut, and Zanone[41] found similar results to McGrarry[39] in a study with tennis rallies, which displayed stable steady states concentrated around 90º or 270º, with a peak also around 0º (here we suggest that the authors incorrectly interpret their results when they reported stable interpersonal steady states around 0º or 180º).

As displayed by the previous examples with racket sports, intermediate states, which are not typically present in cooperative situations, become stable in antagonistic (competitive) situations. In addition, it is important to note that one of the stable states identified in cooperative situations (e.g., in-phase for tennis, and anti-phase for squash) remain as stable even in an antagonistic situation. Although these promising results and the predictions from the model, there is still a lack of experimental evidence that support this model for antagonistic behavior.

To our knowledge, the only experimental task that try to show evidence of antagonistic coupling in a rhythmical task was the one by Kelso et. al.[37] In this experiment, the researchers design and programmed a Virtual Partner (VP) to move on the opposite direction that the human participant was moving to, trying to generate an anti-phase steady state. On the other hand, the human participant was instructed to perform an in-phase steady state, generating therefore a conflict of intentions. Unfortunately, the way the VPI was programmed allow human participants to achieve novel strategies that prevented the program to work as intended. This led to stabilization only around in-phase or to the dead of the oscillations of the VPI. Thus, there is still a need to explore such antagonistic coupling in experimental situations, but regarding this lack of evidence it seems as if antagonistic coupling leads to unique dynamics that do not emerge under the typical synergetic situations (e.g. intermediate states, near 90º or 270º and increase fluctuations).

Thus, the use of predictions extracted from cooperative models is not suited for antagonistic coupling. Such predictions extracted of cooperative models for antagonistic situations has led to interpreting intermediate states as if they were near to in-phase or anti-phase[39,41], or directly ignored[42]. In all these studies, centered on antagonistic interactions, such interactions are dismissed or ignored because they are not consistent with models that were develop for stable synergetic interactions, rather than for the instable struggles, that characterize antagonistic interactions. Thus, there is a need to study antagonistic coordination to see if the expectations of the models are met, reinforcing the uniqueness of such situations. Therefore, to recap, the *antagonistic* *coordination* in between two opponents should lead to a decrease in the system stability and the appearance of novel states, which are not present in cooperative coordination.

4. An attempt to measure match hegemony: Landscape of action opportunities

Hegemony seems to entail two interacting levels, a level of *cooperative coordination*, in which an athlete or a team internally organizes to generate a coherent movement that helps it achieve its goals, and a moment of *antagonistic coordination*, in which two antagonistic entities *struggle* against each other to generate superiorities. Therefore, hegemony (which should be the relevant level to study the ongoing dynamics of an antagonistic sport), emerges through the dynamic interaction of these two moments along a game.

An example of how to measure hegemony in a football match is the procedures used to capture the term 'dominance' coined by Link and collegues[3]. This measure used four mathematical concepts that in essence take into account ball position, how many defenders are in between the ball and the goal, the position of the teammates of the ball carrier and finally the 'control' the ball carrier has over the ball. It is important to note, that when measuring the dominance the authors did not take into consideration the technical, physical and tactical capabilities of individual players as well as the physics of the ball (e.g. what is the arc the ball can follow, its weight and the effects of spin), limiting is usability. Despite the limitations, it is a suitable procedure that can be apply to measure hegemony, as it takes into consideration the *cooperative coordination* of the team in possession of the ball, in relation with the defenders to whom they are antagonistically coordinated to; all of this taking into account the geography of the field (e.g. the size, the limiters and the position of the goals), rules of football and some physiological limitations.

Another good candidate to capture the match hegemony in football are the landscapes of action opportunities[43,12]. Such landscapes are the depiction of the ongoing possibilities for action of the team that possesses the ball, taking into account than in a football match the complex interactive set of individual and task constraints suggests the existence of a rich set of potential actions. Therefore for the sake of clarity these maps are reduced to a single potential action (passes in the case of [43,12]). Such a map is dependent on the positions and displacements of the ball carrier, the off ball teammates, and the defenders which try to neutralize such opportunities.

A limitation of such methods in football is that opportunities for action are multiple in any given moment, which calls for some sort of classification. In any team sport, some actions taken by attacking players are more threatening than others. Thus, defenders are more willing to neutralize certain offensive actions while allowing others to happen easier. For instance, to increase the chances to shot at goal, the ball carrier must perform passes that outplay as many opponents as possible[44]. The number of 'outplay' players are the defending players that after a pass are further away from their own goal than the ball[45,46]. Therefore, this *outplayed principle* can be proposed as a way to categorize different types of passes that can be used to create a landscape model of passing opportunities in football. Passes that outplay more opponents have been shown to be correlated with the number of goals scored[47,48], are therefore, more threatening but are also generally more risky to make[3,49].

Even with the limitations or improvements needed, landscapes of opportunities of action allow to identify the most vulnerable defending areas, providing information where the attacking squad is creating more threatening situations. Thus, it seems to be a suitable tool to capture match hegemony. These landscapes may, provide information regarding the ongoing *hegemonic struggle,* offering a promising route to study match dynamics in team sports.

5. Objectives

The main goal of this thesis was to tackle important research issues regarding how to measure match hegemony and its two dimensions: i) the *cooperative coordination* which characterized intrateam behavior, and ii) the *antagonistic coordination* between two opponents.

On the *cooperative coordination* dimension, most studies have centered on dyadic behavior (even when studying groups of more than two players) and used the relative phase. As we already reinforce when talking about *cooperative coordination*, these studies did not report any normalization when calculating the relative phase, raising doubts about such results as the synchronization around in-phase could be more related to distortions in such calculation than the actual dynamics happening in the game. Furthermore, limiting to just dyads in a sport such as football were groupings can happen in between multiple players seem quite inadequate. Finally, the relative phase only shows evidence of synchronization, Thus, there is a need to study multilevel synergies within team sports using alternative measures to the relative phase that capture the existence of synergies. Thus, the aim of the first research study of this thesis was to study the soft assembly of multi-level interpersonal synergies (the *cooperative coordination* dimension) within a defensive set of players of a football team (4 defenders of a team) during competitive football matches. To do so we used the UCM hypothesis as a multilevel alternative to the relative phase.

Second, most of the research studies in *antagonistic coordination* suffer from a lack of formal models and experimental data that support an accurate description of such a type of interaction. As stressed in the section about the antagonistic coordination, this may lead to incorrect interpretations of the data[39,41], or to the mask of results[42] that antagonistic models predict will appear. This is especially apparent in articles that used concepts such as synergies to define antagonistic situations (see Krabben and Van der Kamp[50]). Therefore, the aim of the second research study of this thesis was to test the predictions of the HKB model under antagonistic coupling. To do so participants were invited to perform a rocking chairs task under antagonistic instructions, which creates a 'competitive' setting. We hypothesized the uniqueness of coordination states under antagonistic coupling, which may be useful to characterize the *antagonistic coordination* dimension of the match hegemony, with increase variability and the appearance of intermediate states (90º and 270º).

Finally, the interaction of both dimensions the *cooperative coordination* (e.g., stabilize a performance goal which neutralizes any attacking action) and the *antagonistic coordination* (e.g., that should lead to temporary asymmetries, which create passing opportunities) should shape match hegemony, leading to different opportunities of action been available shortly. These opportunities left a footprint from which a landscape was created. Taking into account that team sports involved several players, a huge set of opportunities of action should be available in the course of a match. The interactive behavior between off-ball players, defenders, and the ball carrier create a wide range of short-term opportunities for actions (even when referring to one single type of action, such as passing) which can be define as a landscape of passing opportunities, which we suggest that may be used as a tool to characterized match hegemony.

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Chapter 2: *Cooperative coordination within a team.*

Keeping the goal safe! Measuring synergistic behavior in a defensive unit of a football team

Currently under review in the European journal of sport science.

Abstract

In team sports, teammates formed functional synergies as they struggle to impose their dominance over the opposing team. There is evidence of synchronization changing when the defense succeeded compared to when the defense did not. Therefore, we aimed to unravel what mediates the formation of synergies in a defensive football unit when they succeed and fail. Thus in the current study the Uncontrolled Manifold (UCM) hypothesis was used to measure the behavior of a defensive line during a set of 60 successful and 34 unsuccessful defensive outcomes plays selected over five competitive football matches. The performance variables were related with the average position (*Centroid*) and the structure (*Stretch Index*) of the set of defending players. Successful defensive sub phases were associated with lower values of UCM, meaning the performance variables were under less changes due to task elements reciprocal compensation than in unsuccessful defensive situations. Thus, successful movement of the unit may be related to an effective management of its variability rather than the limitation of this variability. Furthermore, the defensive unit stabilizes its structure (*Stretch Index*) more than its average geographical position (*Centroid*), meaning that synergies are formed stronger and more commonly in order to keep a certain structure than its actual position. Finally, there was no difference in between the *Lateral* and *Longitudinal* directions. In conclusion, when the defensive football unit under study succeeded the degree of stabilization of the unit was lower than when the unit failed.

Keywords: *Team Sport; Performance; Motor Control; Coordination; Methodology*

1. Introduction

In a football match, players within a team need to coordinate their behavior as they struggle to impose their dominance over the opposing team[1]. Thus players coordinate with the teammates in their neighborhood in order to recover the ball possession or pass the ball to other teammates on the field that pose a higher threat to the opposing team[1,2]. A potential consequence of this coordination is the soft-assembling of functional synergies[3] (temporary cooperative coordination due to short term goals). For instance, evidence of studies in synchronization in football have shown that the velocity of players[4] mediate the time players spend near in-phase, suggesting a mediation of velocity in the formation of synergies. A synergy can be defined as the covariation in between individual members of a unit leading to the stabilization of a performance variable[5] (i.e., a performance goal common to two or more players[6,7]). Therefore a synergy emerges, when two or more players spontaneously behave as a single unit in order to stabilize one (or more) performance goal(s) (e.g., stabilize a position on the pitch and/or the structure of the defensive sector). Stabilizing each performance variable can be a key issue to generate favorable situations for a team, such as surpassing a defensive line, maintaining a defensive structure to avoid threatening situations, recovering ball possession, achieving a shot to the goal or scoring a point.

Previous research studies on interpersonal coordination in competitive team sports displayed extended evidence of coordinated dyadic behavior in sports such as Rugby Union[8,9]; Football[10,11]; Futsal[12,13]; and Basketball[14]. Moreover, some studies have shown synchronization between two teams[15,16], as well as between subunits within such teams[17]. However, this synchronization patterns could emerge by chance or because of coupling with the ball displacement[18], as none show a formal evidence that links the stabilization of one (or more) performance goal (e.g., an interpersonal distance; an interpersonal angle) as a consequence of player's reciprocal adjustments (e.g., by mutual changings on running line velocities), a linkage that is crucial to identify the existence of interpersonal synergies. However, the method used on the current research study may fill this gap.

1.1. Interpersonal synergies and the uncontrolled manifold hypothesis

The Uncontrolled Manifold (UCM) hypothesis[7] assumes that when a synergy emerges a performance variable is stabilized around a reference value by the adaptive change of a set of task elements (e.g., the position or velocity of individual players). When this happens a subspace[1] is created. This subspace, called UCM, is a geometrical representation of which variance of the task elements due to compensatory adjustments is leading to the stabilization of the performance variable. From this subspace two types of variances can be calculated[7,19]: i) the variance parallel to the UCM, which is the variance of the task elements that stabilize the performance variable around specific reference values, and ii) the variance perpendicular to the UCM, which is the variance of the task elements that does not stabilize the performance variable. By calculating the ratio in between these two types of variances, a UCM value can be calculated which can be used to identify the presence of a synergy.

Although originally develop to study intrapersonal joint synergies[20], the UCM hypothesis has been recently used to study interpersonal coordination such as a cooperative slackline task[21], rugby dyadic behavior[22], and badminton doubles[23]. In these studies, participants were coupled in dyads, although there is no theoretical or

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[1] *A subspace is a vector space contained in within another vector. Therefore, in the UCM hypothesis such sub-space is a representation of those combinations of the task elements that lead to the stabilization of the performance variable around a specific reference value.*

methodological limitation that constrain the UCM computation to only pairs of players (see [24] for an example of a multilevel muscle synergy). Taking into account that interpersonal synergies can potentially emerge from the interactive behavior of more than two players[25] (e.g., a defensive football line with four players) it seems relevant to study these multilevel synergies in cooperative/competitive settings.

Thus, the first aim of this research was to identify the soft assembly of multi-level interpersonal synergies, for that purpose a defensive set of four defensive players of a football team during competitive football matches was used. Specifically our research question was: What drives the soft-assembly of defensive synergies within a football match? As such, we decided to use the four players in the defensive line based on the evidence that when defending, coordination in within a team is dominated by highly coordinated movement among defenders, which may have lead them to behave as a unit (see [26] for further information). However, studying this unit in isolation is more due to a methodological limitation (the need to select certain performance variables and elemental variables), and we acknowledge that along a game synergies could potentially emerge because of coordination between other players, not limited to the defensive line.

To test the presence of synergies, a set of performance variables that are related with the whole unit behavior need to be defined. The performance variables candidates use in this study were the mean position of all the players of the defensive unit (captured by the centroid), and the spatial expansion/contraction of the unit on the longitudinal and lateral directions (captured by the stretch index)[27]. Several studies have shown that the stretch index[15] and centroids[15,17,28] show signs of synchronization in between teams or subunits of the team[29]. This evidence suggests that these variables could be potential candidates to be stabilize when a synergy is forming. Furthermore, they represent different processes (the stabilization of a certain structure, or the position in the field) through which a synergy may be formed. Thus, the stabilization of the structure of the defensive set (captured by the stretch index) or its geographical (local) position (captured by the centroid) within the pitch were used to test the presence of synergies. Additionally, four candidates to task elements, were defined as the four defensive players running line velocities, as studies in synchronization shows that the velocity of players mediates the time they spent in a synchronize state[4].

Moreover, a recent study[17] has found differences in tactical synchronization measures in successful and unsuccessful attacking football plays from competitive matches, suggesting that the synergetic behavior of a team mediates its capability to succeed or fail during a game. Therefore, a second aim of the study was: did the formation of synergies differ in between successful and unsuccessful situations for the defense? This design allows going further than previous studies on interpersonal coordination that were focus on studying dyadic behavior (see[30], for a review including synchronization studies in football) as well as providing insights into how synergies emerge within a defensive set in a football team.

2. Methods

2.1 Data acquisition

The data used for the analysis corresponds to five competitive matches of one team of the Spanish second league on to the 2017/18 season. The players under analysis were the four players of the defensive line. Only plays that included the four starting defenders where used, which were the same over the five matches. The data corresponds to bi-dimensional (*Longitudinal* and *Lateral*, captured by Footvision, Paris, France) coordinates for each player, that were captured from video recorded games at 25 fps using an opto-tracking system. From these five games, 94 plays were selected, corresponding to 34 plays where the attacking team made a goal, a shot to the goal, or force a penalty (Unsuccessful defensive plays) and 60 plays where a player of the defensive set recover the ball possession (Successful defensive plays). To avoid undesirable effects from having trials with very different lengths only plays that lasted more than 10 seconds and less than 40 seconds were selected. This study received institutional ethics approval from the university where the research took place.

2.2 The Uncontrolled Manifold beyond a two player's dyad

On this study, we focus on the multi-player behavioral level of analysis, considering four defensive players. Two possible outcomes of the plays were analyzed: i) Unsuccessful Defensive outcome (UDO), in which the offensive team scored a goal, a shot to the goal or forced a penalty, and ii) Successful Defensive outcome (SDO), in which one of the four players of the defensive set recover the ball possession within the field. The positional data of each of the 94 plays was analyzed at a frequency of 5 Hz. The duration of each play and the corresponding total number of time points N, is defined from moment in time when the attacking team starts the play (i.e. with a throw in, a foul, or a recovery), until the moment in time N, for which any player of the defensive set recover ball possession (for SDO), or when a goal, a shot to the goal or a penalty happens (for UDO). Therefore, the time discretization for each play, is defined by a dataset of time points t varying between frame 1 and frame N, i.e., $t=1 \ldots N$).

The running line velocities of the four players within a defensive set were used as the task elements. The four defensive players are designated by their field positional role as Left Back [LB], Left Center Back [LCB], Right Center Back [RCB], and Right Back [RB] players. Video plots of the plays were checked ensuring that the players selected were within the defensive line and did not switch positions with any midfielders or forwards of their own team. Therefore, four running line velocities (v_{LB}, v_{LCB}, v_{RCB} and v_{RB}), respectively for the LB, LCB, RCB and RB, define the matrix of task elements over the duration of each play. Running line velocities were computed using the finite difference method from the *x* and *y* coordinates of the players' trajectories. Before deriving the positional data, a Savitzky-Golay filter[31] with an order of 4 and a window of a second was used. The corresponding vector **T** with dimension n=4 for the task elements, is given at each time point *t* by:

$$\mathbf{T}^t = \begin{bmatrix} v_{LB}^t \\ v_{LCB}^t \\ v_{RCB}^t \\ v_{RB}^t \end{bmatrix} \qquad [1]$$

For performance variables the defensive set *Centroid* and *Stretch Index* in the lateral and longitudinal directions were chosen.. The use of four different performance variables allows to analyze if there is a stronger stabilization[32] of the performance variable on any of the two dimensions (i.e., on the *Lateral* or on the *Longitudinal* displacement) and on the structure (by *Stretch Index*) or the position of the defensive set (by the *Centroid*).

These four performance variables were labeled as x_{cen} and y_{cen} for the *Longitudinal* and *Lateral Centroid* and by x_{str} and y_{str} for the *Longitudinal* and *Lateral Stretch Index* of the defensive set (see Figure 1). The *Centroid* was calculated as the geometrical center of the set of defenders at each point in time, while the *Stretch Index* was obtained by computing the mean of the distances between each player and the spatial center in the *Longitudinal* and *Lateral* directions[27].

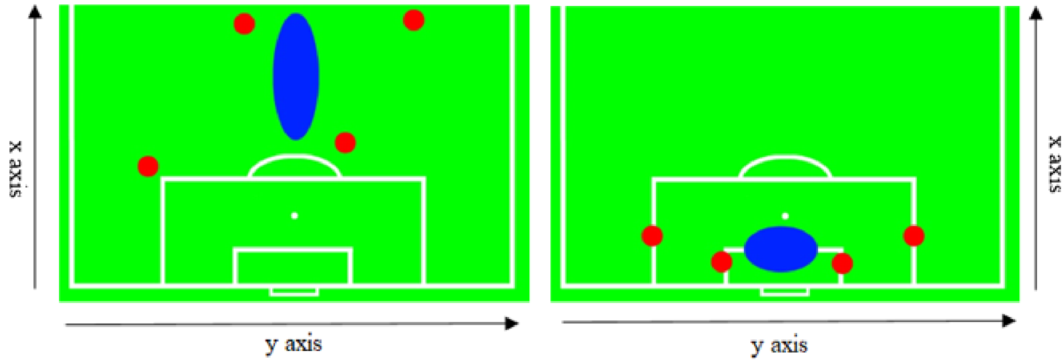

Figure 1: The red dots in the figures represent the positions of the four players of the defensive set in a moment in time. The position of the blue dot represents the x and y coordinates of the *Centroid*, while the size of the blue dot represents the *Stretch Index* in the y and x directions. As depicted, the left figure has a *Centroid* further up in the field with a higher *Stretch Index* in the *Longitudinal* direction (x axis) while the right figure has a higher *Stretch Index* in the *Lateral* direction (y axis) with the *Centroid* very near to its own goal.

Each of the four performance variables (x_{cen}, y_{cen}, x_{str}, and y_{str}) was evaluated independently creating a vector **p** of dimension *d*=1, given at each time point t by:

$$\mathbf{p}^t = [P_{var}^t] \quad [2]$$

The component P_{var}^t represents each of the four performance variables under study at each moment in time (x_{cen}^t, y_{cen}^t, x_{str}^t and y_{str}^t). The reference values correspond to the state of the task elements designated as $\mathbf{T^0}$ and the performance variable designated as $\mathbf{p^0}$ given by:

$$\mathbf{T}^0 = \begin{bmatrix} v_{LB}^0 \\ v_{LCB}^0 \\ v_{RCB}^0 \\ v_{RB}^0 \end{bmatrix} \quad [3]$$

$$\mathbf{p}^0 = [P_{var}^0] \quad [4]$$

The reference configuration corresponds to the mean of the task elements and of the performance variable values retrieved during the last second of all plays of each type (i.e. SDO and UDO). This mean-based reference configuration is established under the assumption that the defensive set behavior converges towards values found when the set recover the ball possession (SDO), or when the attacking team achieves a positive result (UDO). As these values vary greatly in between matches, reference values were calculated specifically for each match. A Jacobian matrix $\mathbf{J}(\mathbf{T}^0)$ of the system, evaluated at the reference configuration, was used to described how small changes in the output of the task elements are reflected in the performance variable, given at each point in time by:

$$\mathrm{p}^t - \mathrm{p}^0 = \mathrm{J}(\mathrm{T}^0).(\mathrm{T}^t - \mathrm{T}^0) \qquad [5]$$

The Jacobian matrix $\mathbf{J}(\mathbf{T}^0)$ is a matrix of partial derivatives of the performance variable with respect to relevant task elements. As no analytical kinematic model is available, the Jacobian matrix cannot be obtained by differentiation. These Jacobian matrix was calculated using a linear multiple regression method based on the methodology presented by[33]. Considering the dimensionality d=1 (p_{var}), n=4 (T), and t=N, this method assumes the form given by:

$$(P_{var}^t - P_{var}^0) = K_1.(v_{LB}^t - v_{LB}^0) + K_2.(v_{LCB}^t - v_{LCB}^0) + K_3.(v_{RCB}^t - v_{RCB}^0) + K_4.(v_{RB}^t - v_{RB}^0) \qquad [6]$$

The required dataset for the multiple regression computation is defined by $t=1,\dots,N$, corresponding to all the time points for each play. The coefficients of the regression K_1, K_2, K_3, and K_4 obtained for each play are arranged in a matrix that corresponds to the Jacobian matrix such that:

$$\mathbf{J}(\mathbf{T}^0) = [K_1\ K_2\ K_3\ K_4] \qquad [7]$$

When working with a linear regression, multicollinearity of the predictor regression vectors (e.g., each player running line velocities) may produce unreliable regression coefficients, low robustness of the model and unreliable out-of-sample predictions, making the model non-generalizable. To assess multicollinearity, we used the variance inflation factor (VIF) which is calculated as the diagonal elements of the inverse of the correlation matrix[34]. The VIF estimates how much the variance of a coefficient is magnified because of linear dependence with other predictors, ranging from a lower bound of 1 (no magnification) to an upper bound with no limit. For each play four VIF values were calculated, one for each task relevant element (the running velocities of each defensive player). On this study, plays with at least one VIF with value over 10 or two VIF with values over 5, were remove from the sample, leading to 8 UDO and 10 SDO plays being remove, leaving for further analysis 28 UDO and 50 SDO plays.

The UCM subspace was calculated using the null space of the Jacobian matrix that represents the combinations of task elements that leave the performance variable unaffected. The null-space was measured by *i*=*n* (number of elemental variables)-*d* (degrees of freedom) basis vectors ε_i, solving the equation:

$$0 = \mathrm{J}(\mathrm{T}^0).\,\varepsilon_i \qquad [8]$$

For the present study *i* =4-1=3, meaning we had three basis vector $\boldsymbol{\varepsilon_i}$. This null-space was computed numerically for each play using the MATLAB Null function. The vector $(\mathbf{T^t} - \mathbf{T^0})$ of the deviations of the task elements vector from the reference configuration was projected into f∥ (the UCM subspace) and the component perpendicular f⊥ to the UCM subspace, as:

$$f_{\parallel} = \sum_{i=3}^{N} \left(\varepsilon_i^T.(T^t - T^0)\right).\,\varepsilon_i \qquad [9]$$

$$f_{\perp} = (T^t - T^0) - f_{\parallel} \qquad [10]$$

When compensation of the task elements is stabilizing the performance variables the variability of the players will lay along the UCM (var_{comp}). On the other hand, when the compensation of task elements is not stabilizing the performance variable the variability of the players will lay orthogonal to the UCM (var_{uncomp}). The variance in each of the subspaces var_{comp} and var_{uncomp}, normalized by the number of degrees of freedoms (d) of the respective subspaces, were calculated as:

$$var_{comp} = \sigma_{\parallel}^{2} = \frac{1}{(n-d).N}\sum_{i=4}^{N} f_{\parallel}^{2} \qquad [11]$$

$$var_{uncomp} = \sigma_{\perp}^{2} = \frac{1}{d.N}\sum_{i=4}^{N} f_{\perp}^{2} \qquad [12]$$

In order to quantify functional synergies the UCM method compares which of these variances is higher, testing if the projections parallel and perpendicular to the UCM (i.e. $f_{\parallel}$ and $f_{\perp}$) statistically differ. If the two variances cannot be confidently assumed to differ, the ratio between them may produce misleading interpretations on the presence of synergies. Thus, a one-way ANOVA was conducted ($p=0.05$) comparing the distributions of $f\parallel$ and $f\perp$ for each play. For ANOVA results revealing non-significant statistically differences, the plays were excluded from the analysis.

For ANOVA results with statistical differences between the two variances, the ratio between them was calculated. This ratio was transformed logarithmically in a scale of 10, such that values of UCM > 0 signify the presence of synergies (i.e., $var_{comp} > var_{uncomp}$) and UCM<0 signify that no synergies were formed (i.e., $var_{comp} < var_{uncomp}$):

$$UCM = \log_{10}\left(\frac{var_{comp}}{var_{uncomp}}\right) \qquad [13]$$

Using a logarithmic transformation means that the same ratio in between the two variances will keep the same values with opposite symbols, and consequently with different meanings. Hence, UCM>0 identified the presence of synergies, as the compensation of the task elements will be leading to the stabilization of the performance variable, whereas UCM<0 means there were no synergies. Furthermore, higher values will mean that the variability of the task elements is used to a larger extent to stabilize the performance variable than lower values. Furthermore, for the interpretation of the UCM, the usage of a scale of order 10 ensures that values of ±1,2,3…quantifies one variance being higher than the other in the order of 10^1, 10^2, 10^3…, and the ratio positive or negative sign indicating which of these variance is higher, var_{comp} for positive results and the var_{uncomp} for negative results.

In order to categorize the strength of the synergies we developed an ordinal scale for the UCM with three levels (weak, medium and strong synergy levels). We used the median and the interquartile range (*iqr; Median*= 0.397 & *Iqr*= 0.308) for the distribution of the UCM values higher than zero (which represents the presence of a synergy). The rational of using the median and interquartile range was that the data distribution was not normal, as shown by Saphiro-Wilk normality test[35] (W=0.939 & $p<0.001$). Thus values below the median minus half the iqr (*0.243*) were categorized as weak level synergies, values in between the median minus half the iqr (*0.243*) and the median plus half the iqr (*0.551*) are categorized as medium level synergies, and values above the median plus half the iqr (*0.551*) were categorized as strong synergies.

2.3 Data analysis

A three-way ANOVA with factors (Type of Defensive Outcome x Direction x Performance variable) was run. The Defensive Outcome factor had levels *Successful* and

Unsuccessful defensive outcomes, the factor Direction had levels *Lateral* and *Longitudinal* direction, and the Performance variable had levels *Centroid* and *Stretch Index*. To run the ANOVA the UCM values were transformed exponentially. This exponential transformation ensure that the data kept a normal distribution (shown by a Saphiro-Wilkins no significant test[35]), and therefore an ANOVA could be calculated with confidence. The power of the effect was quantified using the eta squared ($\eta 2$) statistic, with values near 0.01 meaning the effect was small, 0.06 medium, and 0.14 high[36]. Mean results for each level of each factor were presented with the correspondent standard deviation.

3. Results

3.1 Trials excluded from the analysis

UDO ($x_{cen}= 6; y_{cen}= 4; x_{str} = 8; y_{str}= 8$), and SDO ($x_{cen}=7; y_{cen}= 13; x_{str} = 9; y_{str}= 15$) plays were remove from the analysis because the two variances were not statistically different.

3.2 Unsuccessful defensive outcomes

Table 1 shows the percentage of the UCM values for UDO trials for each of the four performance variables. The *Longitudinal Centroid* displayed a high presence of strong synergies with over 40% of the trials, with weak synergies been the less common below 4% of the trials. The *Lateral Centroid* also exhibits a low presence of weak synergies (4.2%) with medium synergies been more common than strong synergies. Concerning the structure of the defensive set, weak synergies were the less common in the two directions of the *Stretch Index* with medium synergies been the most prevalent in the *Longitudinal Stretch Index* (accounting slightly above 60% of the trials), and strong synergies been more common in the *Lateral Stretch Index*.

Table 1. Percentage of the UCM values for the Udo (N=28) for each one of the performance variables divided by: i) category strength - weak synergies (0<UCM<0.243), medium (0.243<UCM<0.551) and strong synergies (UCM> 0.551). ii) defensive outcomes without synergies formation (UCM < 0);

	Weak	Medium	Strong	No synergy
Longitudinal Centroid	3.8%	30.7%	42.3%	23.0%
Lateral Centroid	4.2%	37.5%	29.1%	29.1%
Longitudinal Stretch Index	13.0%	60.9%	21.7%	4.3%
Lateral Stretch Index	15.0%	27.2%	40.0%	15.0%

3.3 Successful defensive outcomes

Table 2 shows the percentage of the UCM values for SDO trials, for each of the four performance variables. Concerning the *Centroid* and the *Stretch Index* of the defensive set, results display a prevalence of medium strength synergies. Furthermore, for the *Longitudinal Centroid* 32.6% of the trials did not exhibit the presence of synergies while the *Lateral Centroid* did not exhibit the presence of synergies in 32.4% of the trials.

Table 2. Percentage of the UCM values for the Sdo (N=50) for each one of the performance variables divided by: i) category strength - weak synergies (0<UCM<0.243), medium (0.243<UCM<0.551) and strong synergies (UCM> 0.551). ii) defensive outcomes without synergies formation (UCM < 0);

	Weak	Medium	Strong	No synergy
Longitudinal Centroid	18.6%	30.2%	18.6%	32.6%
Lateral Centroid	16.2%	35.1%	16.2%	32.4%
Longitudinal Stretch Index	21.9%	39.0%	17.1%	21.9%
Lateral Stretch Index	17.1%	48.6%	20.0%	14.3%

3.3 Statistical analysis of the defensive outcomes

A significant effect of factor type of play ($F_{(1,235)}$= 12.616, p<0.01) was found with *UDO* having higher UCM index than *SDO* (*UDO*= 0.369± 0.365 & SDO = 0.206 ± 0.379; see figure 2), with a medium power of the effect (η^2 = 0.07). A significant effect of the factor performance variable ($F_{(1,235)}$= 6.32, p=0.04) was also found, with the *Stretch Index* having higher UCM index than the *Centroid* (*Centroid*= 0.221± 0.416 & *Stretch Index*= 0.314 ± 0.336, see figure 2), and a weak power of the effect (η^2 = 0.04). Finally, there was not a significant effect of factor direction.

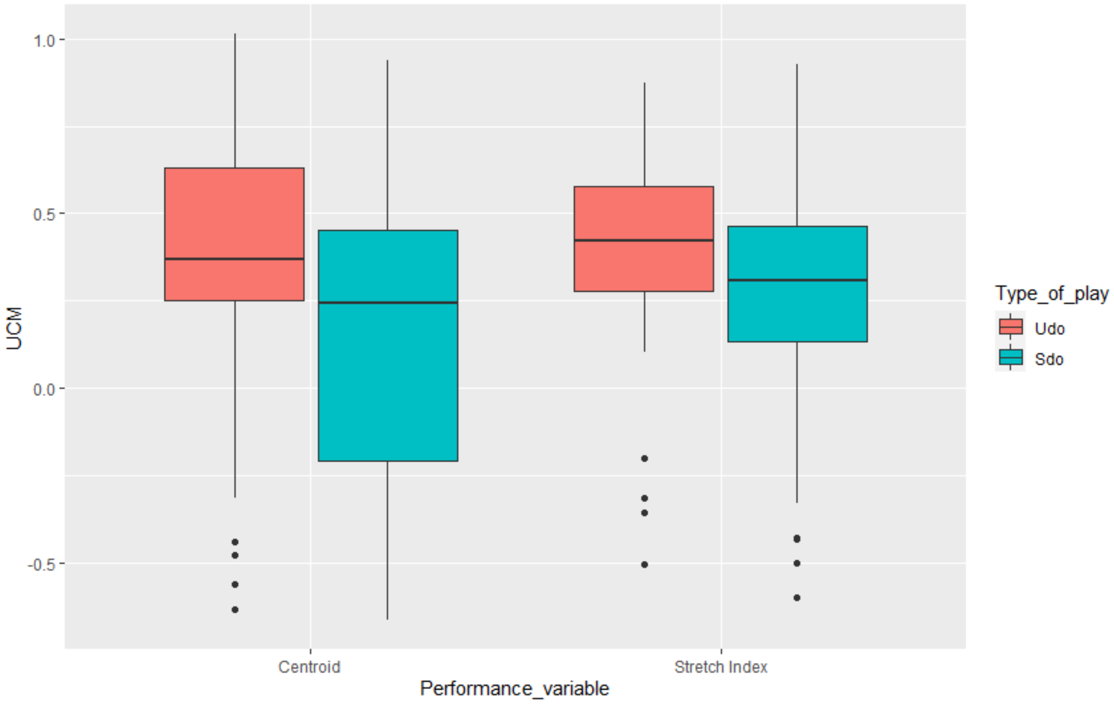

Figure 2. The figure shows median values and distribution of the UCM values (y axis) for the two performance variables (i.e., *Centroid, Stretch Index*) over the two levels of factor type of play (red and blue box).

4. Discussion

The synergetic behavior, of the four players that formed a defensive football unit was captured using the UCM approach from match situations selected from five competitive football matches. Higher UCM values were found for UDO than for SDO with the *Stretch Index* having higher values than the *Centroid*. This is supported by the UDO having more percentage of rigid synergies as well as SDO having more trials with no synergies. Our results displayed that the relative occurrence of flexible synergies for the four performance variables is higher in the SDO compared to UDO. Furthermore, trials without evidence of synergies were higher for SDO than UDO. Thus, it seems that in SDO the unit weakly stabilizes the performance variables. This means that when a successful behavior was achieved the defensive unit loosely stabilized the performance variable allowing some degree of perturbation of the task elements. On the other hand, when they did not succeed the defensive unit stabilized the performance variables to a greater degree. This is in line with findings on previous research[17] that found a marginal increase in synchronization during successful attacks when compared to attacks where the defense succeeded.

Moreover, in line with growing evidence, this suggests that a successful movement is not achieved by reducing variability but rather by successfully managing such variability[37]. Thus, our results reinforce the notion that variability is both a source and a consequence of team success[38]; the management of player's variability is a key issue to the soft-assembly of collective synergies and consequently for the performance of the defensive unit.

Within a defensive unit the management of player's variability can be done by constraining their position relative to the others, contributing to the internal structure of the defensive unit, and/or by the position of the defensive unit in the pitch. Our results displayed evidence that the *Stretch Index* lead to the presence of stronger synergies than the *Centroid*. Therefore, the defensive unit stabilized to a greater degree its internal structure rather than its position. This suggests that player's adjustments within a defensive unit are constrained to stabilize its structure while leaving the geographical position of the defensive unit freer to vary as the play evolves.

Several studies have centered on the synchronization of the centroids of different units of the teams[15] or the whole teams[15,16,28], with one study[15] analyzing the synchronization of the stretch index of subunits of a team. Results displayed that the centroid of different units and teams had high levels of synchronization, been higher the percentage of synchronized time for the centroid than for the stretch index[15]. On the contrary, our results may suggest that the structure of the defense line (capture with the stretch index) may be more relevant for the formation of synergies than the centroid of these defensive units. It is important to note that previous results that found synchronization patterns between centroids did not explicitly measures synergetic behavior. Thus this synchronization may not be related to synergetic behavior, but rather to a coupling of all players with the position of the ball[18].

Moreover, studies have shown differences in synchronization depending on the directions of player's displacements on the pitch (lateral or longitudinal[15,4]). In contrast, in this study there was no difference in the strength of synergies between these two axes of displacements. This may seem like conflicting results at first but it is important to note that these studies used the relative phase to measure synchronization. Such a measure, although it may be of interest does not tackle the formation of synergies, which accordingly with the definition provided in the introduction, is supported on the reciprocal compensation of individual task elements in order to stabilize a performance variable. On contrast, the UCM method tackles directly this issue which may have led to the differences in the results.

Finally, there is some limitations of the UCM and our approach that are important to address. The first is the dependence on specific reference values[39]. As UCM relies in the orthogonality of the variance along an axis, which is built using specific reference values, the selection of this reference values is central to the results that are found. If the reference values are not selected appropriately it is possible that there is a low amount of variance along the UCM axis, and consequently abnormal UCM results can be found. This happens because the axis built is not well directed for the variability of the data (see[40], for a more detailed explanation of this limitation). In this study, reference values were chosen with the assumption that the end of each play represents a state to which the behavior of the defensive unit is converging. Nevertheless, the question of the optimization of these reference values remains open. A possible future path of research could be the optimization of the selection process to choose the reference value in order to optimize the orthogonality of the UCM to the data.

Furthermore, in this study we measure the formation of synergetic behavior of a defensive unit within a football team. Such a unit was always the four players of the defensive line. Nevertheless, studies with hypernetworks in football[25] suggested that players dynamically form groupings (called simplex) based on players proximity, which led to changes in the composition of such groupings during the course of the plays. Thus, it is possible that the specific players that formed synergies are not limited to the four defensive players under analysis, and that such defensive groupings may change over the match. This may have affect the results, as synergies in SDO may not be related with weaker synchronization but rather with different synergetic groupings than in UDO. Thus future research should tackle such a limitation by including the dynamic composition of units that may led to collective synergies along a match.

In conclusion this article adds new insights to the growing body of research that uses the UCM to measure interpersonal synergies in sports[21,22,23], studying the synergy that emerges in a defensive football line. Furthermore, the synergetic behavior formation of such line is driven to a larger extent on the need to maintain the structure of the defensive line rather than its average position on the field, which suggests that the defensive unit is more willing to stabilize its structure than its position in the field. Finally, successful outcomes for the defensive unit had weaker synergies than unsuccessful outcomes, reinforcing the idea that successful movements are characterized by the correct management of the variability inherit to these degrees of freedom rather than the limitation of this variability.

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Chapter 3: Antagonistic coordination in between rivals

Rocking against each other: Antagonistic coupling in a rhythmical task yields unique coordinative patterns/behaviors/dynamics.

Abstract

When a dyad performs a (rhythmical) task together, the between-agent interaction is often of collaborative nature. Interaction can also entail conflict or opposition, such as in racket sports or combat sports, implying antagonistic coupling in such tasks. In contrast to classic synergetic behavior, which is characterized by common attractive coupling, antagonistic interactions are defined by repulsive-attractive coupling (cf. 'attacker-defender'). Modeling using the HKB model under such antagonistic coupling yields the emergence of unique intermediate states towards 90º and/or -90º relative phase, with the oscillator leading in time being the one that exerts the repulsive force. Here we present experimental results regarding between-agent antagonistic situations. Inspired by previous dyadic studies, in the experiment 20 couples were asked to rock chairs in cooperative and antagonistic settings. To generate interactional conflict, incongruent intentions were delivered: one participant was instructed to generate an in-phase pattern (reflecting attractive coupling) while the other was instructed to generate an antiphase pattern (reflecting repulsive coupling). Results demonstrated increased variability in antagonistic trials compared to classic synergetic behavior, with the relative phase accumulating somewhere between 0º and 90º (or -90º). Surprisingly, antagonistic patterns tended towards a phase lead of the attractively coupled agent (instructed to generate in-phase), which was not in line with the models predictions. Nonetheless, we also found that the attractively coupled agent produced smaller rocking amplitude than the repulsively coupled agent, which could explain the observed lead-lag results in terms of amplitude difference. Moreover, compared to the cooperative trials, the antagonistic condition appeared to boost amplitude and frequency of the rocking movement altogether. Finally, the antagonistic trials comprised a variety of different behaviors, dominated by 'switchy' behavior that showed changes between different coordinative patterns. All this shows the unique behavior that dyads express when coupled antagonistically, highlighting the necessity to study and conceptualize such situations distinctively from cooperative scenarios.

Keywords: Antagonistic coupling, HKB model, coupled oscillators, coordination dynamics, relative phase

1. Introduction

When performing a rhythmical task together, humans coordinate their behaviors with each other, either intentionally or unintentionally[1]. To do so, the performers stabilize a common goal by the co-adaptation of their individual behavior[2]. In such situations, the coordinative behavior can be reduced to the level of a collective variable, which converges towards certain stable coordinative patterns, or 'steady states'[3]. Such cooperative rhythmic behavior has been commonly conceptualized as a synergy, meaning that a group of coupled components/agents performs as a unit[4,5]. Common examples are walking side-by-side and/or hand-in-hand [6], rocking chairs together[1], and crew rowing[7,8].

Coordinative behavior has been formalized using coupled oscillator models. An influential and often used model in the present context is the HKB model[9], which couples two self-sustaining oscillators in such a way that cooperative behavior can be formally reduced to the level of the relative phase (RP: the difference in the phase of the movement between them). The model predicts the presence of two stable steady states, namely in-phase (being in the same point of a cycle movement, RP= 0º) and antiphase (being in opposite points of a cycle, RP= 180º), as well as a wide range of dynamics that arise in such situations (see [10], for a recent review of the HKB model and relevant extensions). It is important to note that, although originally designed to capture interlimb coordination within an individual, the model has been since successfully employed to the study of between-person coordination[11,12].

The novelty of the present study will be to study antagonistic interaction, which in contrast with the cooperative situations introduced above (where the intentions of the participants are congruent), entails situations where the two participants have antagonistic (conflictive) intentions, such as defensive-attacking dyads, or two players in racket sports. Before getting to the experiment, antagonistic interaction will be conceptualizaed, and a possible adaption of the HKB, that can serve to model such situations, will be presented. In the next section, examples of antagonistic situations extracted from racket sports will be shown. Finally, the actual study will be presented which consisted of a simple rocking chair experiment under incongruent instructions (meaning that each participants was instructed to perform a different pattern).

1.1. Cooperative vs. antagonistic interaction

Human coordination also entails situations where two or more entities have *conflictive* rather than cooperative intentions. Especially in competitive sports, athletes are constrained to coordinate with their opponent(s) in an antagonistic way, as they struggle to get a favorable situation over them. This stems from the ultimate goal of these sports context that is generating advantages over the opponents, by scoring more points, being faster, or literally beating them in the case of combat sports. Hence, in the core of these sports contexts lays the principle of opposition. This means that the two performers do not share a common, collaborative goal, but rather have antagonistic ones (or 'conflict of intention'[13]): if one achieves the desired outcome, the other one fails, and vice versa. This paradoxical situation constraints performers to not behave like a unit, but rather as two opposites[14], which may question the usability of classic cooperative model settings to study such situations.

Although coupled oscillator models like HKB[9] were initially adopted to capture the dynamics of mutually attracting (i.e., cooperative/collaborative) coupled oscillators, it has recently been advanced that antagonistic inter-agent dynamics (cf., 'attacker-defender') may substantially differ from the canonical in-phase and antiphase states[15]. This entails modifying the way that the two oscillators are coupled[13,15], more specifically by introducing a repulsive (rather than attracting) coupling force. Whereas in the typical cooperative scenarios the HKB model supports a mutual attraction (modeled by two positive coupling terms), antagonistic scenarios involve a repulsive coupling force (modeled by introducing a negative coupling term) so that one component attracts (positive coupling) while the other repels (negative coupling). When the oscillators are antagonistically coupled, intermediate states in between in-phase and antiphase , such as 90º or -90º RP), cease to be unstable solutions and start appearing as possibly stable novel solutions[13,15] (see figure 1a). In the appendix, we briefly illustrate this with numerical simulations.

1.2 Empirical study of antagonistic dyads

While in general theoretical modeling studies have recently gained interest in combining attractive with repulsive coupling forces[16,17,18,19,20], empirical evidence from the dynamics of conflicting human interaction are limited. Initial support for antagonistic dyadic dynamics is mainly extracted from previous research in racket sports. For example, Palut & Zanone[21] in an experiment with tennis rallies, found that coordination patterns between the two opponent players concentrated close to 90º and -90 = 270º (here we note that at the time Palut & Zanone somewhat improperly interpreted their results as concentrating around 0º and 180º). Similarly, De Poel & Noorbergen[22] found in 31 competitive ATP (Association of Tennis Professionals) rallies that the lateral displacements of the two opponent tennis players frequently showed patterns around 90º and -90º RP, with in-phase occurring less often. These results found support on a previous research with experimental squash rallies[23] (see McGarry & De Poel[24] for re-inspection of those results), which also yielded dominant occurrence of patterns around 90º and -90º for lateral displacements. In sum, as displayed by these examples from racket sport situations, intermediate coordination patterns which are unstable patterns in interpersonal cooperative situations seem to emerge as stable patterns in antagonistic situations.

To our knowledge, the only experimental lab study that tried to head-on test antagonistic coupling in a rhythmical task was the one by Kelso et al.[13]. In this experiment, the researchers designed a Virtual Partner (VP) that was programmed to move to the opposite direction than the human participant was moving to, hence trying to generate an antiphase pattern. On the other hand, the human participant was instructed to move in-phase with the VP, thereby generating a *conflict of intentions* between the human and the VP. However, the way the VP was programmed allowed human participants to achieve novel strategies that prevented the setup to work as intended. These strategies included participants modulating the amplitude of their movements, yielding stabilization only around in-phase, or even the complete cease of the oscillations of the VP (cf. 'oscillation death'[17,25]).

The antagonistic goals illustrated by the VP-human interactive behavior could be considered similar to attacker-defender interactions in field invasion sports[26,27,28]. This similarity comes from the defender continuously trying to neutralize the attacker's movements, while the attacker wants to 'break free' (aiming to move *opposite* to the defender). Therefore, similarly to the VP-human interaction, defender-attacker interactions could entail a conflict of intentions (or antagonistic interaction) that may lead to unique dynamics.

1.3 Current experiment: rationale and expectations

Inspired by the above, the main aim of the present experiment was to test predictions of the HKB model in antagonistic coupling. To do so, pairs of participants were invited to perform a rocking chairs task following both cooperative[1] and antagonistic instructions. Similar to Kelso et al. [13], the antagonistic instructions were aimed at generating a conflict of intentions: one participant was instructed to achieve an in-phase pattern, while the other was instructed to achieve an antiphase pattern. In this operationalization, it is assumed that the participant instructed to do an in-phase pattern is subjected to attractive coupling force, and that the participant instructed to do an antiphase pattern is subjected to repulsive coupling force[13] (see also appendix 1).

Thus, in the antagonistic condition we expected the appearance of intermediate patterns around 90º and -90º RP, depending on which participant received which instruction. Given the simulations results (see Appendix 1) and the according logic, the participant instructed to perform antiphase is repulsively coupled and thus should be the one who is leading the other participant in time (see figure 1B, i.e. 90º for participant 1 and -90º for participant 2). As seen in figure 1B the participant leading is the one whose cycle starts first, hence leads the other one in time. In that regard, it is important to note that probably the attractive influence may be larger than the repulsive influence, which means that the instructed antagonism may not be perfectly balanced. Consequently, intermediate RP-values *below* 90º may be expected as this will mean that the attractive force is stronger than the repulsive force. Furthermore, while cooperative situations can be maintained stable, antagonistic intermediate patterns (which could be conceptualized as patterns of continuous symmetry breaking[15]), are less stable and would be much more difficult to maintain. Therefore, rather trivially, we hypothesized an increased instability in antagonistic trials, when compared to cooperative trials.

2. Methods

2.1. Participants

Forty healthy volunteer undergrad students (ages 18-30) were selected for the experiment and assigned to twenty dyads with the criteria of having similar weights. This yielded five female dyads, fourteen male dyads and one mixed dyad. The participants gave their informed consent prior to the experiment and if applicable were rewarded with university credits for their participation. The study received ethical approval from the local ethical board.

2.2. Apparatus

Participants sat in identical rocking chairs positioned on raised platforms 30 cm laterally away from each other. The platforms were assembled to prevent the chairs from sliding or rotating in lateral directions. The motion of each rocking chair was recorded at 100 Hz using an active motion tracking system (Optotrak Certus, Northern Digital). A marker was attached unobtrusively to the back of each chair in such a way that the camera could capture its movement during all the trial.

A curtain between the chairs ensured that no direct visual cue or communication from the other participant of the dyad was available. Each rocking chair had a laser pointer attached to the side, pointing to the wall that was 90 cm in front of the platforms. Both participants could see each other's laser points moving. Stereo headphones were used to deliver the instructions, together with some low volume noise to mask sound coming from the environment or the other participant. Together, this ensured that the only information available to perform this interpersonal coordination task was the visual information regarding the laser point movement on the wall (see figure 1A).

2.3. Protocol and design

Upon arrival, the participants of each dyad randomly chose one of the two rocking chairs. To familiarize with the characteristics of the rocking chair and its movement, each participant first rocked the chair individually. Next, participants were informed regarding the two different instructions they could receive: *Same* (in-phase coordination) or *Opposite* (antiphase coordination). Then participants put on the headphones and performed some practice trials. This practice consisted of at least two antiphase and two in-phase trials. If after these four trials participants could not generate the adequate patterns, the dyad did some more practice trials until they were capable of performing the in-phase and antiphase patterns. As such, two couples ended performing eight and ten practice trials respectively, as they were not capable of producing the needed patterns within the first four practice trials.

Each experimental trial started with participants hearing an instruction, delivered individually, either *Same* or *Opposite*. Then the two participants heard an instruction that asked them to rock the chair with the eyes closed. At this point, the noise started playing at a low volume for the remainder of the trial. Participants rocked the chairs for ten seconds before hearing a new instruction that asked them to open their eyes. At this moment participants had to coordinate with the other participant to produce the pattern they were instructed to produce. This part of the trial lasted for another 50 seconds, until participants were instructed to stop moving.

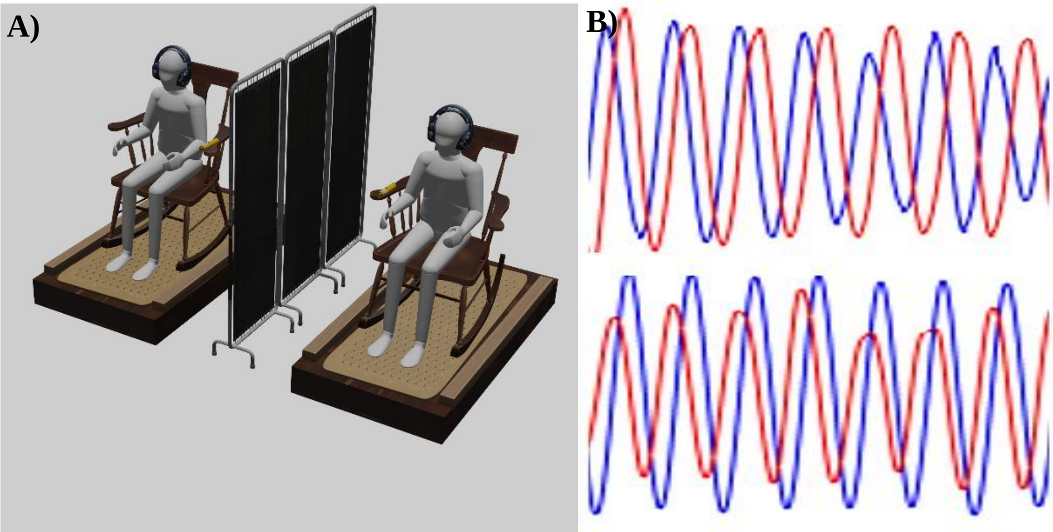

Figure 1. A) Experimental setup representing the rocking chairs with the lasers attach to the arm chair, the curtain separating the two participants and the raising platforms, wearing their corresponding headphones. B) Examples of the oscillatory movement during two trials with a more or less 90º (or -90º) RP. In the top figure the blue oscillator is leading in time while the red oscillator is leading in time in the bottom figure.

The experimental design consisted of two blocks: one *cooperative* block of trials where the two participants received congruent instruction (either *same-same* or *opposite-opposite*) and one *antagonistic* block where the two participants received incongruent instructions (either *same-opposite* or *opposite-same*). The *cooperative* block matched typical studies of cooperative interpersonal coordination. In this block, participants received congruent instructions to ‘move in the same direction as the other performer’ (*Same* instruction; $Coop_{in}$) or to ‘move in the opposite direction as the other performer’ (*Opposite* instruction; $Coop_{anti}$). Dyads performed four trials of each of the two conditions for a total of eight randomized cooperative trials. After that, participants were allowed to rest for five minutes, if they desired to do so.

After this cooperative block, the *antagonistic* block was executed. Here, the two dyad-members received incongruent instructions: one participant received the *Same* instruction whereas her/his partner received the *Opposite* instruction. This yielded two antagonistic conditions: the participant on the left (figure 2A) received instruction *Same*, while the participant on the right received the instruction *Opposite* ($Ant_{in\text{-}anti}$), and vice-versa ($Ant_{anti\text{-}in}$). The antagonistic block consisted of twelve randomized trials, four $Ant_{in\text{-}anti}$ trials, four $Ant_{anti\text{-}in}$ phase trials and four mock trials with congruent instructions (either Same or Opposite). The mock trials were meant to work as distractions from the actual antagonistic trials and were not further used in the analysis.

2.4. Data analysis

For each trial three-dimensional positional data of the movement of the rocking chairs was captured during 60 seconds (10 s with eyes closed; 50 s with eyes open). The movement time series were analyzed using Matlab version R2019b. In the rare occasion that markers were lost, a spline function was used to interpolate the missing points. Subsequently, a low pass filter with a cut-off frequency of 6 HZ was applied. Then the data was differentiated over time to calculate the velocity.

The velocity and position among the sagittal plane of each marker was used to calculate a continuous estimate of the phase angle of the movement of each of the participants. This was based on a procedure in which the movement signals were first normalized each half-cycle for variations regarding the oscillation center and (angular) movement frequency[29] (see also Varlet & Richardson[30]). The purpose of this procedure was to avoid artifacts in the phase calculation derived from the half cycles having different centers and angular velocities.

Peaks and valleys (the highest and lowest points of the movement cycle) were calculated using the findpeaks function from Matlab. Peaks and valleys in the antagonistic trials did not always represent the end or start of a movement cycle and needed to be filtered out a posteriori. In case successive peaks and valleys produced half cycles that were a quarter or less than the median of the amplitude of that trial, these peak and valley indices were excluded in further calculations and analyses. The peaks and valleys were further used to normalize the cycles to then calculate the continuous phase angles of each participant. After this, relative phase (RP) was calculated as the continuous phase angle of the left chair minus the continuous phase angle of the right chair. This implies that RP>0 indicates that the participant in the left is leading in time, while RP <0 indicates that the participant in the right is leading in time (see figure 2B).

Furthermore, if the two individual continuous phases have the same frequency (the time a cycle takes to happen) the RP will be stable around a certain value, which can be described as phase lock. On the opposite, if the two individual continuous phases have different frequencies the PR will drift (the velocity and direction of such drift depending on which participant is moving faster), which can be described as phase wrapping. Finally, the standard deviation of RP was calculated for each experimental trial, for that purpose statistical methods for circular data were applied[31].

2.5. Statistical analysis

The trials that were dominated by phase wrapping in the same direction (phase wrap happened over 75% of the trial) were removed from all the analysis (see figure 2 at the bottom right for an example of such a trial). One $Coop_{in}$ trial, one $Coop_{anti}$ trial, ten $Ant_{in\text{-}anti}$ trials, and ten $Ant_{anti\text{-}in}$ trials were removed from the statistical analysis.

To test whether variability of coordinative performance differed between the two coupling types and between two specific conditions of each coupling type paired t-tests were administered on the standard deviation of the relative phase. Cohen's *d* [32] was used to estimate the strength of the effect with values in between 0.2 and 0.5 being low, in between 0.5 and 0.8 being medium, and above 0.8 being strong.

The distribution of the relative phase per trial was introduced into polar histograms with 12 bins (one for each 30º). This distribution was tested for differences between bins using ANOVAs for repeated measures. Effect size was quantified by the partial eta squared (η_p^2).Where applicable, Holm-Bonferroni[33] post hoc analysis was performed to see which bins differ from each other.

From the obtained valleys and peaks (see previous section) the median of the amplitude and period of the cycles was derived for each trial. ANOVAs for repeated measures were performed on these two outcome measures to test differences in between each instruction (*Same* or *Opposite*) and each coupling type. Estimates of effect sizes were provided by means of the 'partial eta squared' (η_p^2). When needed, main and interaction effects were tested using Holm-Bonferroni post hoc analysis.

When using η_p^2 values in between 0.01 and 0.06 meaning the effect was small, in between 0.06 and 0.14 meaning medium, and higher than 0.14 meaning high[32]. For clarity, the actual statistical analysis that were performed are further specified in the results.

3. Results

3.1. Relative phase analysis

The paired-samples *t*-test performed on the standard deviation of the relative phase indicated that for the $Coop_{in}$ trials (18.91º ± 10.89º) standard deviation was significantly lower than for the $Coop_{anti}$ trials (28.65º ± 17.19º), $t(79) = 4.67$, $p<0.001$, with a medium effect $d= 0.52$). On the other hand, the standard deviation of the relative phase did not differ between $Ant_{in\text{-}anti}$, and $Anti_{anti\text{-}in}$ trials.

A paired-samples *t*-test with factor Type of coupling (*Cooperative* or *Antagonistic*) was performed to study if the type of coupling affected the stability of relative phase. The t-test was significant ($t_{(159)} = -17.34$, $p<0.001$, with a strong effect $d= 1.65$), with the *Cooperative* trials (23.49º ± 14.90º) having lower standard deviation than the *Antagonistic* trials (54.43º ± 15.47º).

In contrast with the Cooperative trials, the distribution of the antagonistic trials was less concentrated around certain phases (see figure 2). in $Ant_{in\text{-}anti}$ trials, the polar histograms seem to have a higher concentration in the bins in between 0º to 90º, meaning the participant in the left, the one with the instruction *Same,* was leading as the RP was positive. On the other hand, in $Ant_{anti\text{-}in}$ the trials the data seems to be concentrating in between -90 and 0º (note there is a slight peak in between 180º and -150 noticeable), which can be concluded as the participant in the right, again the one with the instruction *Same,* is the one leading. Thus, in contrast to classical cooperative studies, where the RP concentrated around in-phase or antiphase, in the antagonistic trials the data concentrated in the span of 0º to 90º, with the one leading being in both cases the participant with the instruction *Same*. Therefore, to test if the distribution of the bins differ from one another, two one-way ANOVAs for the distribution of antagonistic trials were performed. The two of them were significant ($Ant_{in\text{-}anti}$: $F_{(11, 187)} = 10.09$, $p<0.001$, with a strong effect $\eta_p^2= 0.35$; $Ant_{anti\text{-}in}$: $F_{(11, 187)} = 2.53$, $p=0.005$, with a medium effect $\eta_p^2= 0.12$). Post hoc analysis revealed that for $Ant_{in\text{-}anti}$ trials the four bins (-30º:0º, 0º:30º, 30º:60º and 60º:90º) from 330º to 90º differed from all the other bins. While for the $Ant_{anti\text{-}in}$ phase trials, the two bins, -60º: -30º and -30º:0º, had a higher concentration than all other. Bins 0:30º, -90:-60º and 180º:-150º, also had a higher concentration than all other bins excluding bins -60º:-30º and -30º:0º (see figure 2).

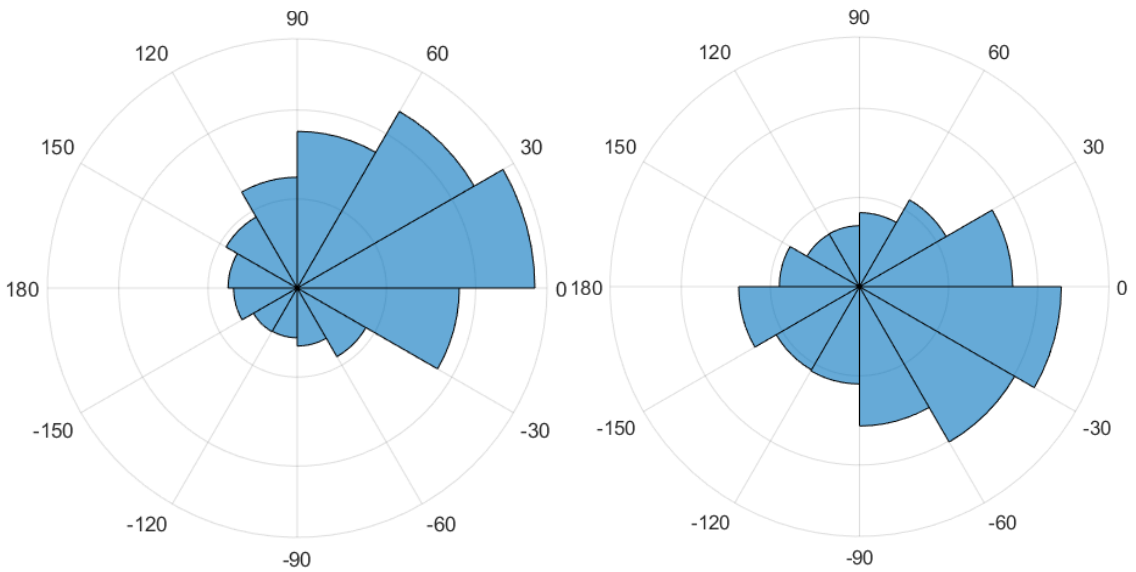

Figure 2. Polar histograms for all antagonistic trials, with the Ant$_{in\text{-}anti}$ condition in the left, and the Ant$_{anti\text{-}in}$ condition in the right. The bins had a size of 30º.

3.3. Amplitude and period

First, a paired sample t-test with factor Chair (levels *char1* or *Chair2*) was performed to ensure that the characteristics of the chair and/or participants did not systematically affect the period or amplitude of the movements. These tests revealed no significant effects for any of the variables, which meant that the rest of the analysis ignored differences in between the participants sitting in right and left chairs.

A two-way ANOVA of repeated measures with factors Coupling Type (*Cooperative* or *Antagonistic*) × Instruction (*Same* or *Opposite*) was performed to test the potential effect of instructions and coupling in the amplitude and period of the movements of the participants. The ANOVA for the amplitude was significant for factor type of coupling ($F_{(1, 19)} = 11.62$, $p<0.001$, with a strong effect $\eta_p^2 = 0.21$) with significantly smaller amplitudes in the *Cooperative* trials (8.87 cm ± 2.82 cm) compared to the *Antagonistic* trials (9.98 cm ± 2.53 cm). The main effect of instruction was also significant ($F_{(1, 19)} = 35.66$, $p<0.001$, with a strong effect $\eta_p^2 = 0.15$). This was due to a significant effect of the interaction ($F_{(1, 19)} = 37.92$, $p<0.001$, with a strong effect $\eta_p^2 = 0.14$). Post hoc analysis of this interaction revealed that the amplitude only differed significantly between the two instructions in the *Antagonistic* trials, with on average the participant with the *Opposite* instruction moving at 19% larger amplitude compared to the participant with the Same instruction (see Table 1 for the values).

For the median of the period (see Table 1 for values) the ANOVA revealed a main effect for Instruction ($F_{(1, 19)} = 9.569$, $p<0.001$, with a small effect $\eta_p^2 = 0.01$), with the *Same* instruction (1.34 sec ± 0.20 sec) significantly slower than the *Opposite* instruction (1.31 sec ± 0.21 sec). Factor Type of coupling was also significant ($F_{(1, 19)} = 12.61$, $p<0.001$, with a medium effect $\eta_p^2 = 0.11$) with *Cooperative* trials (1.39 sec ± 0.18 sec) significantly slower than *Antagonistic* trials (1.27 sec ± 0.21 sec). There was no Type of coupling × Instruction interaction effect.

Table 1. Mean and standard deviation of median of the amplitude and the period for instructions Same (in-phase pattern) and Opposite (antiphase pattern) in Cooperative and Antagonistic trials.

Amplitude	Cooperative	Antagonistic
Same	8.84 cm ± 2.76 cm	9.10 cm ± 2.16 cm
Opposite	8.90 cm ± 2.90 cm	10.86 cm ± 2.58 cm
Period		
Same	1.40 sec ± 0.18 sec	1.28 sec ± 0.20 sec
Opposite	1.37 sec ± 0.18 sec	1.26 sec ± 0.22 sec

3.3. Antagonistic trials classification

Antagonistic trials produced unique dynamics, which lead to polar histograms where the RP was spread all over the place. The instructed antagony led to a wide diversity of dynamical patterns that emerged and switched within trials as well as between trials. Therefore, in this section we take a more detailed look at such antagonistic trials with the intention to provide an overview of the specific dynamics that emerge inside these trials.

To exemplify this, eight exemplary antagonistic trials are presented in figures 3 and 4. The top figures of figure 3 represent situations in which one member of the dyad achieved the desired outcome: either antiphase (left panel) or in-phase (right panel). Note that in these situations there is a low degree of perturbations meaning that there was a phase lock throughout the trial in between the two participants (as also exemplified by power spectrums covering a small range of frequencies, please see figure 3.b). In figure 3c an example of a trial that converged to an 'in-between' pattern (-90º) is presented. Note that this situation also seems quite stable, as the participants seem to achieve a state of phase lock (again characterized by power spectrums that span over a small range of frequencies), eventually fluctuating moderately around -90º. Finally, figure 3d presents a situation where no stabilization happens. The downward phase wrapping in the RP time series indicates that in this specific trial the right participant oscillated at a faster tempo than the left participant did. This is also evident from the two power spectra that do not overlap, with the power for the right participant concentrated in faster frequencies than the left participant does. It is important to note that in these trials the participant moving faster was always the one that had the instruction opposite. Thus, in certain trials the participants with the instruction *opposite* tend to move faster than the ones that received the instruction *same*.

The exemplary trials in Figure 4 display another class of situations that radically differ from the ones shown in Figure 3. In contrast to the situations presented in figure 3, in which a same dynamic (either phase wrap or one of the other three) dominated throughout the trial, these trials were characterized by different dynamics that emerged throughout the development of the trial. They were characterized by brief moments of stabilization followed by phase wrap, followed by another moment of stabilization or even slow drifts between different patterns. In contrast with the other situations, these trials seem to be marked by continuous adaptations as each participant struggled to achieve her/his incongruent desired outcomes. This is shown in the power spectrums, which display a large span of frequencies (the trials above were characterized by the opposite) the wide variety of behaviors that express the struggle of the two members of the instructed antagony.

Thus, after this initial inspection, four different categories for these trials were created: 1) *Winner*: when the stabilization of the dyadic pattern occurred around either in-phase or antiphase (figure 3a and b). 2) *Intermediate patterns*: when the coupling stabilized around 90º or -90º RP (figure 3c). 3) *Phase wrap*: relative phase constantly changing, with no stabilization whatsoever (figure 3d). 4) *Shifting*: the participants switch between patterns 1, 2 and/or 3, as they struggle over the trial. The *shifting* trials were the most diverse of the four categories and represented the majority of trials, being quite different in between each other, as shown by figure 6. What all had in common is that the pattern present seems to change greatly throughout the trial, showing temporally the dynamics of one or the other three categories before some kind of perturbation happened, shifting to another dynamic. Thus, the behavior was shifting through different patterns, which is why the category was called shifting. This category had around 50% of antagonistic trials. The *Winner* and *Intermediate* trials were the other two most common, with the *Phase Wrap* trials being the less common. See table 2 for the exact percentage of trials in each category.

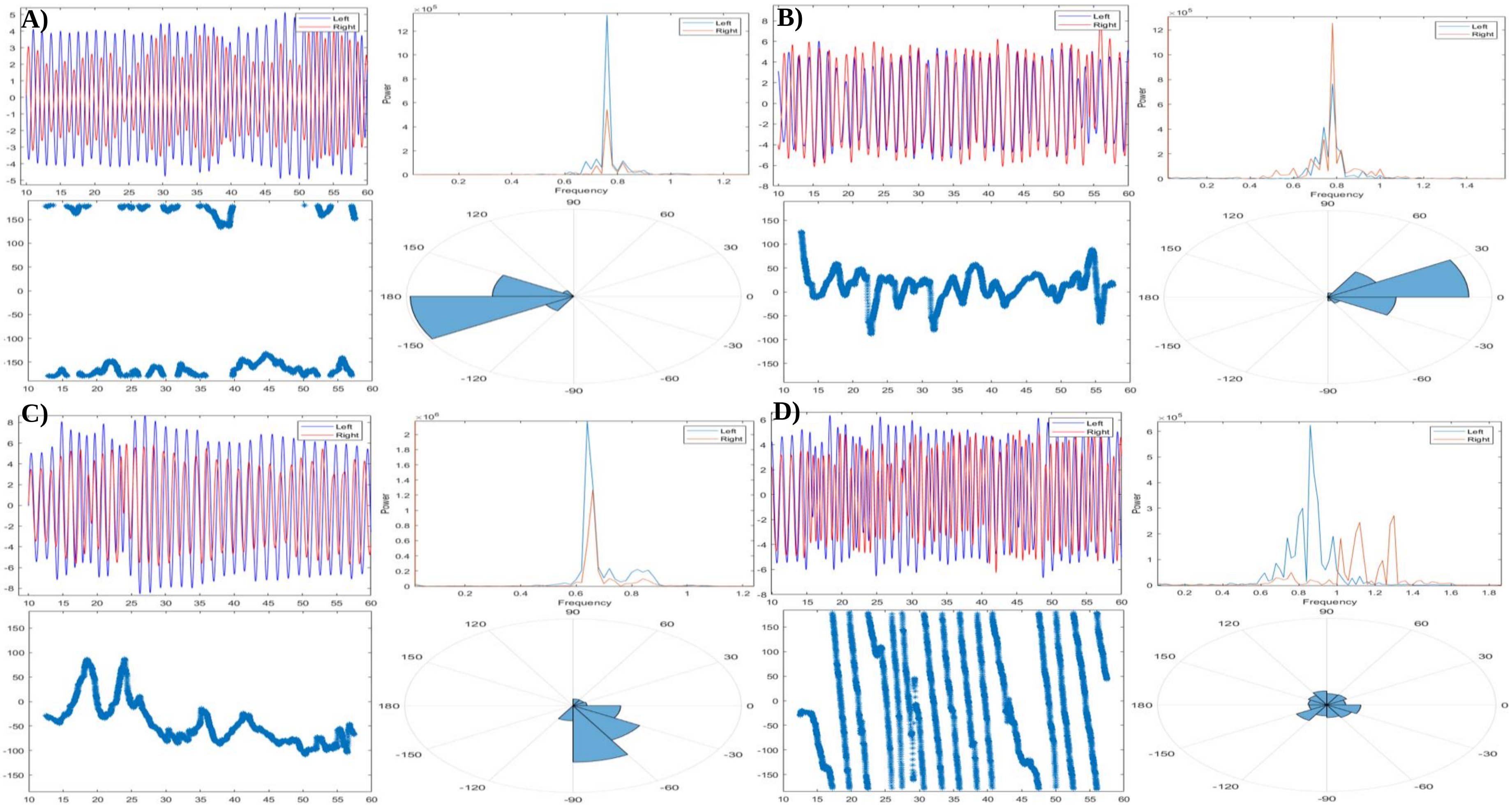

Figure 3. Examples of antagonistic trials analysis, each including time series of the two rocking chairs; spectral analysis; relative phase time series and polar histograms of the trials. The categories are a) Winner antiphase instruction; b) Winner inphase; c) Intermediate and; d) Phase wrap.

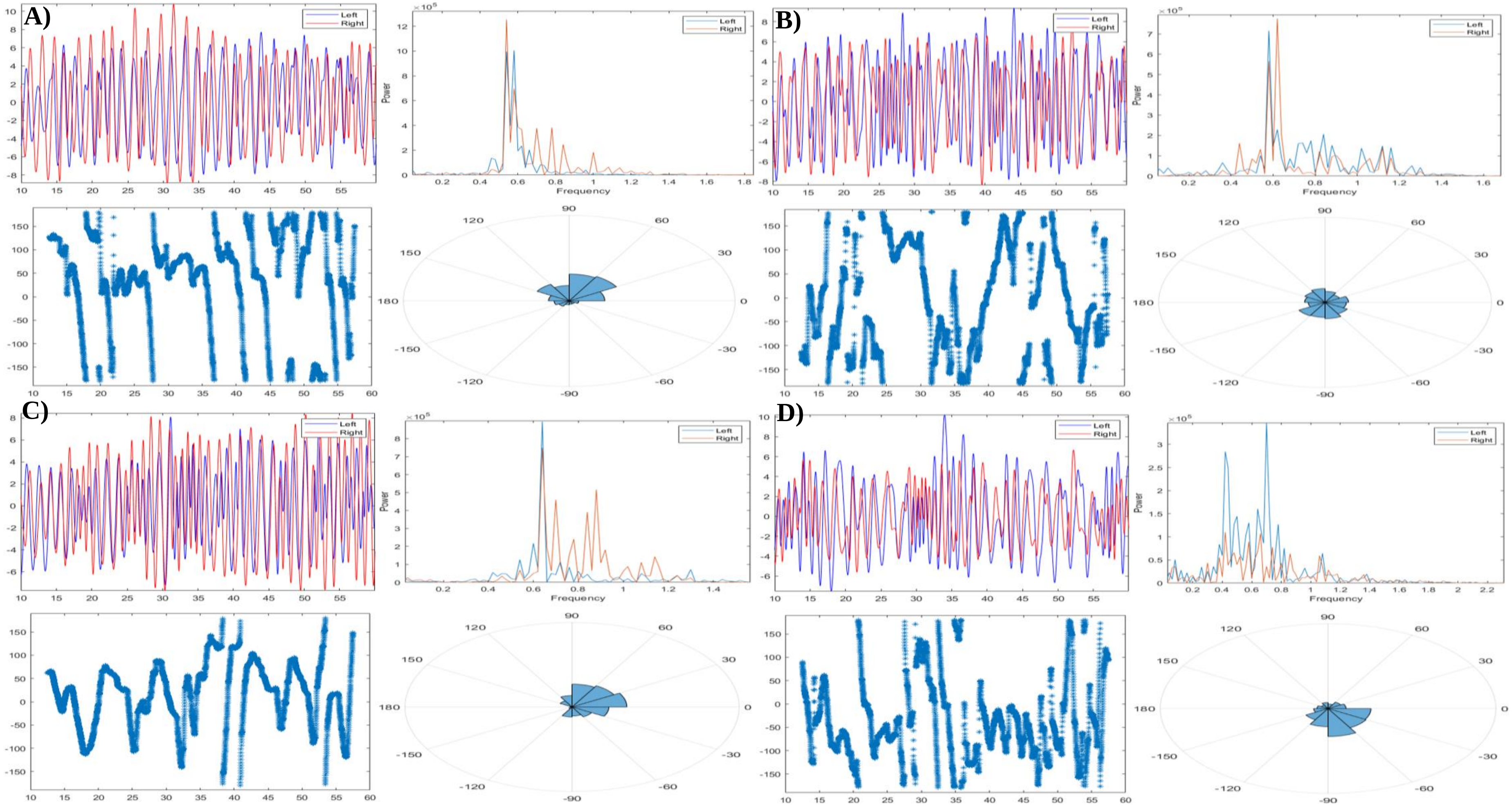

Figure 4. Examples of antagonistic trials analysis for the category shifting, each including time series of the two rocking chairs; spectral analysis; relative phase time series, and polar histograms of the trials.

Table 2: Percentage of the 80 trials for each antagonistic condition (In-anti; Anti-in) that were classified in four categories.

	Winner	*Intermediate*	*Phase wrap*	*Shifting*
In-anti	16,00%	17,50%	12,50%	53,75%
Anti-in	18,75%	23,75%	12,50%	45,00%

4. Discussion

In this study, pairs of participants either performed a rhythmical interpersonal coordination task under instructions that either constrained them to *cooperate* or coupled them in an *antagonistic* way, which we assume represents a competitive 'attacker-defender' interaction. While the cooperative scenario implies congruent intentions for the pair-members (in the present study operationalized by congruent instructions: *Same-Same* and *Opposite-Opposite),* the antagonistic scenario involves incongruent, conflicting intentions (in the present study operationalized by incongruent instructions: *Same-Opposite* and *Opposite-Same*). Results from the cooperative trials were completely in line with other studies in the literature that found increased coordinative variability in the antiphase trials compared to the in phase trials[1,11,12,34,35].

Central to the present study though, was the idea that two participants can be coupled by antagonistic intentions (that oppose each other) rather than congruent intentions (which characterize typical cooperative behaviors). Compared to cooperative trials the antagonistic trials generally showed a higher variability in the performance variable and involved slightly faster oscillatory movements. Based on coupled oscillator dynamics with repulsive vs attractive couplings, we expected to find increased occurrence of 'intermediate' interpersonal patterns towards 90º relative phase (i.e., quarter cycle phase difference). Overall, higher occurrence was observed for intermediate patterns deviating from the canonical in-phase and antiphase patterns, as indicated by the distribution of relative phase values in figure 2. Somewhat surprisingly though, this distribution suggested that the 'attacker' (i.e. *opposite* instruction, instructed to produce an antiphase pattern) generally tended to *lag* in time rather than *lead* in time, which was in contrast to our expectations. At the same time, the 'attacker' appeared to produce around 19% larger movement amplitudes (see table 1). Thus, results of the antagonistic scenarios yielded a variety of strategies for how pairs solved the 'conflict of intentions'. In the subsequent paragraphs, we discuss these findings and their implications in more detail.

4.1. Cooperative vs antagonistic trials: Movement variability and overall behavior.

In antagonistic trials (trials with incongruent intentions), the movement was more variable than in cooperative trials. This supports the idea that antagonistic coupling (principle of opposition[14]) produces increased fluctuations and variability as the two participants cannot achieve their respective desired outcomes at the same time. This may have led participants to try breaking the stability more frequently as a strategy to achieve their desired pattern, logically implying increased variability in the individual parameters as well as in the interpersonal coordination characterized by relative phase.

Furthermore, in antagonistic trials the movement of the individual participants was faster and had larger amplitudes than in cooperative trials. This is consistent with studies in team sports that show that the distance covered and the time spent at high intensity running by players increases with high-level opposition[36,37] as well as on competition compared to training settings[38,39]. Thus, higher antagonistic coupling, as a feature of competitive settings seems to boost participants' range of movement as well as their speeds. More specifically, the participant instructed to produce an antiphase pattern (i.e., 'attacker') seems to generate larger and faster oscillations than the participant instructed to perform an in-phase pattern.

4.2. Interpersonal patterns.

What is relevant from the previous section is that competitive patterns seem to deviate from the in-phase and antiphase patterns (as displayed in figure 4) having relative phases in other values as well. Consistent with the idea that the attractive force was stronger (see Appendix for further information) it seems that the RP mainly stayed in values from the range of 90º to 0 (or -90º and 0º). Thus following the modeling, it seems that attractive force was slightly higher pushing the pattern to stay around these values. Note that the RP also stayed near antiphase for at least some of the dyads in the $Ant_{anti\text{-}in}$ phase condition, which made the bin for 180º-210º be above chance. This could have happened because some dyads had a clearly a more successful participant sitting in the left chair than in the right chair (one of the participants possibly had better interactive skills[40], which could be modeled by increasing one coupling term in relation to the other). Modeling data seem to support such an inference, but this hypothesis should be tested experimentally. Furthermore, as shown in figure 4, the $Ant_{anti\text{-}in}$ trials concentrated around values in between 0º and -90º (right leading in time) while for the $Ant_{in\text{-}anti}$ trials this was in between 0º and 90º (left leading in time), indicating that the 'attacker' generally tended to *lag* rather than lead in time. Thus, these results are the opposite of what the modeling results predicted.

Apart from antagonistic interaction, other aspects may induce lead-lag relationships, such as delta-amplitude asymmetries. Such asymmetries can potentially obscure coupling effects, which already happened in a study by de Poel et al.[41]. In a bimanual task focused on the attentional effect on relative phase, the authors found that the hand leading in time was the opposite than modeling had predicted for attentional asymmetries. This effect was attributed to the differences in amplitude found in their data, as past results[42,43] suggested that amplitude differences made the oscillator with smaller amplitudes lead in time. Similarly, in our study there were statistical differences in amplitude in between the two performers. The participants with instruction *Opposite* (antiphase) had on average 1.76 cm wider movements (19.34% bigger movement) than the ones with the *Same* (in-phase) instruction. This could have explained the inverted results found in this study, as the participants with *Same* instructions could have led as its amplitude was consistently smaller than participants with *opposite* instruction. Future research could test this hypothesis with a study that forces the oscillation to have certain amplitudes, which will eliminate the differences in amplitude present in this study[44].

4.3. Various behaviors for 'conflict of intentions'.

The classification of the behaviors observed in the antagonistic trials revealed a variety of strategies to deal with the 'conflict of intentions' in the task. As presented in table 2, roughly 50% of these trials converged more or less into a constant behavioral pattern. These trials could be classified as *Winner* (the dyad converges mainly towards either the 0º or the 180º RP pattern), *Intermediate* (the dyad arrives to a pattern around 90º RP) or *Phase Wrap* (the behaviors of the participants fail to reach a phase lock, constantly drifting in one direction). In that line of reasoning, for these trials the power spectrum of the oscillatory movements concentrated in a narrow frequency band. This characteristic behavior can be conceptualized as the pair reaching some kind of agreement, thus being stable around in-phase or anti-phase (one is the *Winner*), or to an *Intermediate* pattern (the two oscillators arrived at a state of continuous repelling-attracting balance). In a similar vein, for *Phase Wrap* trials participants fail to achieve locking in the same movement frequency (see section 2.4 for clarification on what phase wrap is). It is important to note, that the participant moving faster in these trials was always the one with the *opposite* instruction. Thus, these trials seem to be consistent with a strategy where the attacker was willing to 'draw' (no one could achieve their desired outcome) rather than losing.

On the other hand, the other 50% of trials adhered to category *Shifting*, for which behavior was characterized by a lack of a stable pattern in the interpersonal state, indicated by highly variable '*shifting'* between the above three behaviors. This was apparent from the capricious time courses of the relative phase and power spectrum spanning over a larger range of frequencies (figure 6). Such behavior reflects that the dyadic behavior cannot be in a pattern that is desirable for both participants at the same time as well as a willingness to perturb the system towards their desired state. Hence, within a competitive rally or trial the odds may constantly shift[15], switching rapidly between brief instances clearly in favor of the 'attacker' (around antiphase), clearly in favor of the 'defender' (around in-phase), etc. This is achieved by momentary perturbations: e.g., the attacker manages to break away from the in-phase by generating a perturbation such as a smaller or quicker cycle.

If we consider the in-phase pattern representing a 'victory' for the 'defender' while the antiphase pattern will represents a 'victory' for the 'attacker', modeling results will suggest the defender had an advantage over the attacker as 0º is a more stable steady state than 180º. However, data in the literature, as well as data from this study suggests that this is not completely true. First, previous research regarding attacker-defender interactions in 1v1 dribbling situations[45] show that dribbles are successful for even 50% of the trials for each dyad. On the other hand, in our data *Winner* category trials were dominated by 0º patterns, but they only represented 17% of the trials (please see table 2). What seems to be more supported is the occurrence of out of phase patterns (not in 0º or 180º[21,22,28,45,46]), and increase fluctuations [26,27,28]. Similarly, in our data *Intermediate* category trials were as common as *Winner* category trials, while *Shifting* category trials with increased fluctuations, dominated (please see table 2 for further details). Thus, the dynamic and conflictive nature of antagonistic coupling produces a wide variety of solutions for antagonistic situations.

4.4. Antagonistic coordination in natural settings

Thus, the present study supports the idea that antagonistic coupling generates deviations from traditional canonical patterns of coordination. Similarly, studies on racket sports[21,22,24] and two studies on defender attacker interactions in team sports[28,45]) found clear deviations from the typical in-phase and antiphase pattern. In racket sports studies, stabilization occurred near to 90º and/or 270º RP also having the in-phase or antiphase pattern as a stable behavior, while in basketball[45] and football[28] successful attacking situations were related with a coordination pattern around 60º RP. Furthermore, studies centering on conflictive conversation between individuals (discussions) found deviations from traditional in-sync patterns, when associated with negative and positive emotions[47] and head movements[48,49]. Although due to methodological differences the results could not be directly comparable, these studies further suggest that conflict poses a set of specific constraints which produce the emergence of novel and unique interpersonal coordination patterns.

5. Conclusion

This study provided a novel experimental test of antagonistic coupling in a rhythmical task. In conclusion, antagonistic coupling led to coordination patterns that deviate from the in-phase and antiphase patterns that are typically present in cooperative interactions. Furthermore, introducing incongruent instructions in the experimental design led to specific novel adaptations, like modulations in movement amplitude, or increase willingness to perturb the system. Thus, antagonistic coupling imposes a unique set of constraints that produce a unique set of behavioral patterns. As such, the present study clearly demonstrates that situations of competitive interaction do not imply the same dynamics as cooperative interaction.

We contend that more research on antagonistic coupling would enrich the coordination dynamics approach by complementing traditional cooperative studies. Additionally, the research of such situations and their unique constraints as well as according phenomena could enrich the available data in antagonistic interactions, such as combat sports, attacker-defender interactions in team sports, and individual antagonistic sports (e.g. racket sports).

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Appendix 1: Simulation outcomes

In this section, modelling outcomes following Kelso et al. [13] will be presented to exemplify how antagonistic coupling affects rhythmical coupled behavior. This specific way of modelling follows the formula presented below:

$$\ddot{x} + (\alpha x^2 + \beta \dot{x}^2 - \gamma)\dot{x} + \omega^2 x = (A + B(x + \mu_1 y)^2)(\dot{x} - \mu_1 \dot{y}) \quad [1]$$

$$\ddot{y} + (\alpha y^2 + \beta \dot{y}^2 - \gamma)\dot{y} + \omega^2 y = (A + B(y + \mu_2 x)^2)(\dot{y} - \mu_2 \dot{x}) \quad [2]$$

Such that x, $\dot{x}$ and $\ddot{x}$ represents the position, velocity and acceleration, respectively, of oscillator one, while the $y, \dot{y},$ and $\ddot{y}$ represent the position and velocity of oscillator two. On the other hand, α, β, γ, ω^2, A and B represent constants. Constants α, β, control the nonlinear damping of the individual oscillators, while γ controls the linear damping of such oscillators. Furthermore, ω^2 controls the period of oscillation. Finally, the values of A and B, as well as the relation in between them, controls the stability of the system. In symmetrical attractive settings (when the behavior of the two oscillators attract each other) this means that changing the relation in between A and B controls if the system is in a bi-stable (0 º and 180 º) or a mono-stable (0 º) regime. Following Kelso et al.[13], the novelty of this modelling comes from parameter μ. Such parameter, when set to a negative value in one oscillator, allows generating a repulsive force, which makes for a repulsive-attractive coupling, which can be used to model antagonistic coupling.

In the modelling outcomes presented in figure 5 parameters are set to be α= 8, β= 0.5, γ= 4, ω^2=2*π, *A*=0.5, and *B*= 0.5; with the repulsive force exerted by the first oscillator ($\mu_1 < 0$). This way of modelling will make cooperative situations have a mono-stable regime, with a frequency of oscillation of 1 Hz and an amplitude of oscillation near to 1.

In figure 5 three modelling results are presented. Figure 1a presents a symmetrical situation were the repulsive and the attractive force are equal ($|\mu_1|=|\mu_2|$). Such a situation has an attractor around 90º, which does not appear in usual cooperative modelling. Note that in this case the participant leading is the one that is exerting a repulsive force (oscillator 1). Furthermore, assuming that the oscillator with the attractive force is the ‘defender’, which is trying to produce an in-phase steady state, decreasing the repulsive force in relation to the attractive force should make the system stabilize around 0º. As expected when decreasing μ_1 to 0.9 we found an attractor around 20º (see figure 1b), with the oscillator exerting the attractive force still leading. By further reducing the repulsive force (to 0.5 this time), the phase gets nearer to 0º stabilizing around 7.5 degrees (please see Figure 1c), with the oscillator leading been the one that is exerting a repulsive force. It is important to note, that for all these cases the one that is leading in time (the oscillators cycle which is starting before) is the oscillator exerting the repulsive force (‘the attacker’).

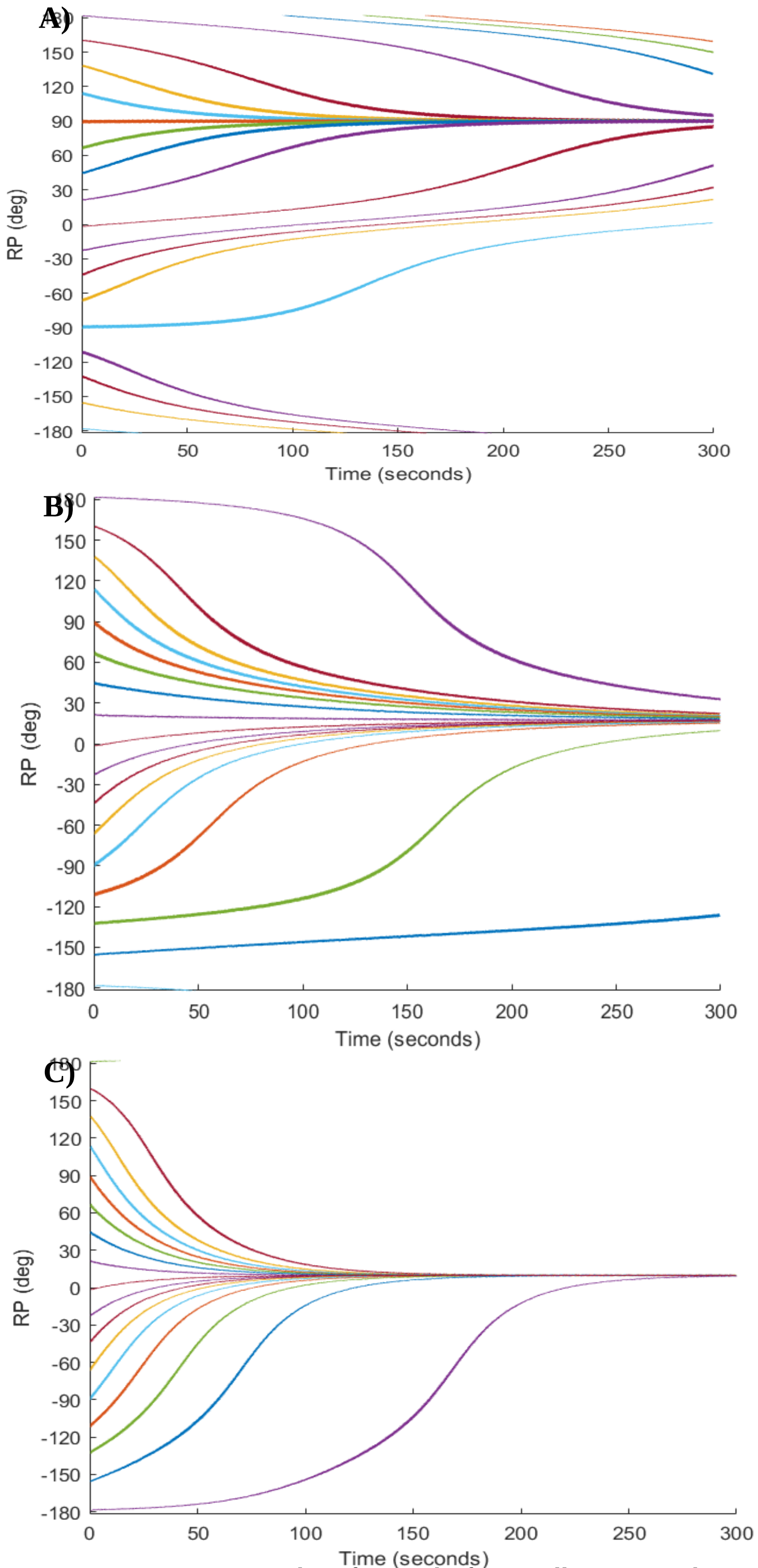

Figure 1. In these figures the first oscillator exerts the repulsive force. Furthermore, the repulsive force introduced in this way of modelling was a) equal to the attractive force, b) half the attractive force and c) two times bigger than the attractive force.

Chapter 4: Hegemonic struggle in team sports

Illustrating changes in landscapes of passing opportunities along a set of competitive football matches

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Abstract

This study aims to illustrate the landscape of passing opportunities of a football team across a set of competitive matches. To do so positional data of 5 competitive matches was used to create polygons of pass availability. Passes were divided into three types depending on the hypothetical threat they may pose to the opposing defense (penetrative, support, and backwards passes). These categories were used to create three heatmaps per match. Moreover, the mean time of passing opportunities was calculated and compared across matches and for the three categories of passes. Due to the specificity of player's interactive behavior, results showed heatmaps with a variety of patterns. Specifically the fifth match was very dissimilar to the other four. However, characterizing a football match in terms of passing opportunities with a single heatmap dismisses the variety of dynamics that occur throughout a match. Therefore, three temporal heatmaps over windows of 10 min were presented highlighting on-going dynamical changes in pass availability. Results also display that penetrative passes were available over shorter periods than backward passes that were available shorter than support passes. The results highlight the sensibility of the model to different task constrains that emerge within football matches.

Keywords: Landscape of affordances, passing, football, team analysis, outplay principle

1. Introduction

During a football match, players adjust their decisions and actions to each other's as they play over the hegemony of the game[1,2] (also called dominance[3]). We assume that a team with greater hegemony will be more threatening and this threat can be characterized by how each team explores the space that is temporarily free of opponents; allowing to either keep the ball possession, progress towards the goal or create a goal scoring opportunity[4]. To do so, the players' decisions and actions are highly influenced by prospective information that emerges in the course of the players' interactive behavior, i.e. a temporary open gap in the opponent defense[5]. Thus, this information continuously suggests not only *what* to do, but also *when*, *where*, and *how* to do it, highlighting ongoing possibilities of action[6,7,8].

This flow of prospective information is dynamically evolving over time[9], as it is influenced by the changing positioning of the players (respective to the field boundaries, proximity to the goal, and their teammates and opponents)[6,7,10], as well as the players' capability to perceive what the others can do[5,7,11,12]. Thus, passing opportunities emerge, persist, and dissolve within a limited space–time window[13], and greatly depend on the players' interactive behavior. For instance, the interaction between the ball-carrier and the off-ball players is determinant to create passing channels at a given moment. On one hand, the ball carrier's attunement to relevant information (e.g., relevant passing lines) influences how open an environment is for his/her teammates. On the other hand, the presence of several potential pass receivers, increases a player unpredictability regarding the actions to perform, creating additional difficulties to the opposing team[14]. The rich set of individual and environmental constraints that can arise in a football match influences the availability of a diverse set of potential actions (some menacing whereas others are not), which can be conceptualized as a landscape of potential actions[15]. Previous research addressed this issue and created a landscape of passing opportunities in football which was based on the analysis of a single match[16,17]). Results revealed the key areas on field providing most opportunities for penetrative passes[16] and also support and backward passes[17] on a single competitive football match. Moreover, a heterogeneous space–time spread of passing opportunities across the entire field was displayed, which highlighted the specificity of player's interactive behavior during the course of a match. However, these previous research works has some limitations some of them we aim to address now: (1) instead of a single match analysis, on the current research work the dynamics within and in between a set of five competitive football matches was analyzed; (2) the current research work drove us to the need of analyzing the images created by the heatmaps beyond visual inspection. Therefore, to allow a more objective analysis we used a technique called Earth Mover's Distance (EMD), which quantifies the differences between the heatmaps of the five matches under analysis. (3) Finally, the dynamics of the landscapes within each match were studied. To do so, temporal heatmaps were created which allows to identify how the threat (for the defense) caused by the different types of passing opportunities changed during the course of a match.

Despite a relevant initial contribution of the previous research work, to the authors' knowledge, there is still a gap in the literature concerning the depiction of off-ball players' actions, and how they are affected by specific constrains (i.e. playing against different teams; possibility to receive different types of passes; changes on passing possibilities along time). Beyond the influence of these specific constraints, is it possible to depict a similarity on player's interactive behavior along a set of matches? Aiming to answer this question, the main goal of this study was to identify the landscapes of passing opportunities because of spatio-temporal windows that emerge due to the interactive behavior between off-ball players, defenders, and the ball carrier during different football matches.

2. Methods

2.1. Data acquisition

The data analyzed corresponds to five matches of the Spanish second division respective to the 2017/18 season, focusing on one team and five of its competitors. Over these matches, the team under scope had 20 participating players. The data corresponds to bi-dimensional (*x* and *y*) coordinates of each player of both teams recorded at 25 fps by an opto-tracking system. The data was recorded and provided by Footovision (Paris, France), complemented by game events (e.g., passes, shots, fouls…). This study received institutional ethics approval from Faculdade de Motricidade Humana, University of Lisbon. It is worth noting that we analyzed performance that did not require identification of individual performers.

2.2. Algorithm description

The algorithm evaluates passing opportunities for: (1) the players' current position and (2) to the players' estimated position a second later (taking into account the player current velocity) as long as the velocity was higher than 2 m/s. This analysis was only carried on when the ball was in play. Based on the ball carrier and support player's current and estimated positions, two potential passing lines were created[16].

Afterwards, aiming to evaluate if these passing opportunities were actually available, defensive coverage areas were defined based on the defending players' running line velocities[18] (see[19] for a similar approach to the one taken to create these areas). Using the velocity of each player, a matrix was created that corresponded to each turning capability in such a way that each player velocity on percentile 90 was set as the point with the lowest turning capability (40º) and a velocity of 0 m/s was stablish as the highest turning capability (360º)[18]. These turning capabilities were then used to create coverage areas (see Algorithm 1;[17]) that were used to calculate the time each defender will take to arrive to each point of the potential passing line assuming that the player will take a second to arrive to the end of the area. When the velocity of a player was under 1.5 m/s we used this value instead of the actual velocity of the player. With this, unrealistic situations were defenders did not cover any space were avoided.

If the player could arrive to any point of the line before the ball, the pass was consider to be intercepted (see Algorithm 1). If the pass was available, a polygon was defined as the area that is temporarily available to perform a pass, with the ball carrier, the receiver and the two nearest defenders as its vertexes. In the absence of any defensive player, the sideline was used as an alternative. Based on player's positional data this polygon was updated every 0.2 s. In this study the ball was considered to move at a constant 10 m/s speed. While this value was chosen for illustrative purposes, it is important to acknowledge that ball speed is a dynamic parameter (as it depends on the ball carrier passing ability, match context and even field conditions) and that it can, and should be, fine-tuned by the end-user.

Algorithm 1 *Calculation of the interception of passing lines.

Input: Position of the players in the attacking team, Position and Velocity of players in the defensive team, Ball velocity and Matrix of velocities corresponding to the players' angles

Output: Line intercepted or not.

```
for k players in the defensive team do
    αk= α corresponding to the value of the matrix of velocity nearest to vk
    αvelocity=tan⁻¹(Vyk/ Vxk)
    α1:200= αvelocity- (αk/2): αvelocity+ (αk/2)
    for n 200 points do
        xn = xk + vtotal · sin(αn)
        yn = yk + vtotal · cos(αn)
        if vtotal< 1.5 m/s do
        xn = xk + 1.5 · sin(αn)
        yn = yk + 1.5 · cos(αn)
        end if
        Define interception lines through points (xk, yk) and (xn, yn) to the end of the field.
        if the interception lines cross the passing line do
            Interception_vector= player k to point of interception.
            Reference_vector= player k to point n.
            Ball_vector= ball carrier to point of interception.
            Interception_time= | Interception_vector |/| Reference_vector |
            Ball_time= |Ball vector|/Ball velocity
                If ball_time> interception_time do
                    The passing line was intercepted.
                end if
        end if
    end for
end for
```

2.3. Pass categorization: the outplay principle

Some actions taken by attacking players in football are more threatening than others. For instance, to increase the chances to shot at goal, the ball carrier must perform passes that outplay as many opponents as possible[20]. By ‘outplay’ we mean the defending player’s that after a pass were further away from the own goal than the ball. Therefore, this *outplayed principle* is proposed in order to categorize the different types of passes that could be used to create a landscape model of passing opportunities in football. This principle expresses the number of opponents a ball carrier has in between her/him and their own goal[21,22]. Passes that outplay more opponents have been shown to be correlated with the number of goals scored[23,24], are therefore, more threatening but are also generally more risky[3,25].

Hence, the passing opportunities were divided on three categories: (1) *penetrative pass*, a passing opportunity to a player that outplays more opponents than the ball carrier; (2) *support pass*, a passing opportunity to a player that outplays the same opponents than the ball carrier; and (3) *backward pass*, a passing opportunity to a teammate which outplays less opponents than the ball carrier (please see Fig. 1 for a detailed explanation).

Moreover due to the level of threat that might cause to the opposing team, it was hypothesized that different passes (based on the outplay principle[24]) may create different landscapes of passing opportunities, and due to specific task constraints that characterize each match, they could vary across different matches.

Finally, following the rationale that players are more willing to perform *penetrative* passes (as they will receive a higher reward for them) and these passes are more threatening and risky than the other two, we hypothesized that *penetrative* passes opportunities were available for shorter periods than *support* or *backward* passes.

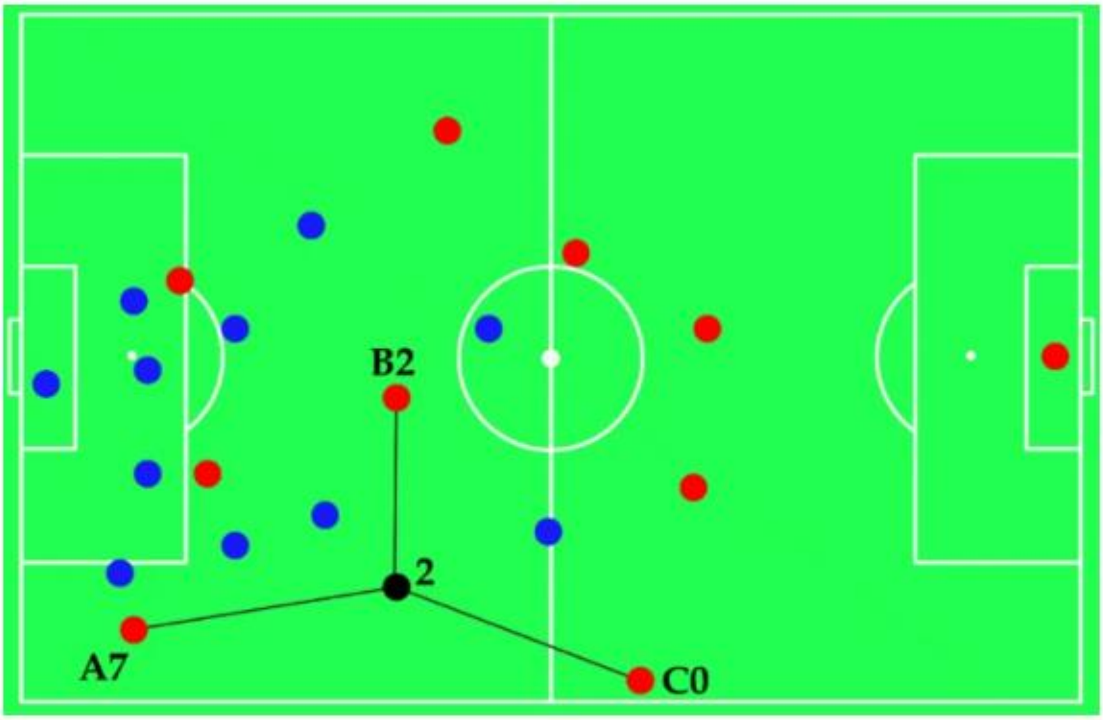

Figure 1. Blue dots correspond to the defensive team players, while the red dots represent the attacking team players. The black dot corresponds to the ball carrier. The numbers near each red dot (i.e., attacking player) corresponds to his/her outplay opponents. Letter A corresponds to a penetrative pass, as the attacking player (and potential receiver) outplays more opponents than the current ball carrier. Letter B corresponds to a support pass as the attacking player (and potential receiver) outplays the same number of opponents as the current ball carrier. Letter C corresponds to a backward pass as the attacking player (and potential receiver) outplays less opponents than the current ball carrier.

2.4. Data repository

Additionally, we created a repository [https://github.com/luisjordana/landscape-passing-opportunities] including 3 min of data, as well as Matlab routines, including algorithms 1 and 2, and others that can be used to load and process the data, run the algorithm and create similar videos and heatmaps as the ones presented in this article.

2.5. *Data analysis*

2.5.1. Landscapes of passing opportunities

To define the landscape of passing opportunities, heatmaps were built by overlapping the different polygons available throughout a match. For the heatmaps to express how long a given area was under potential passing opportunities, the obtained count values were divided by the data set's sampling rate (or frequency). Thus, and considering the color scale used, dark blue means that no passing opportunities were available, whereas dark red means that passing opportunities were available for more than 100 s per match.

A heatmap was built for each of the five matches and each of the three types of potential passes previously defined (*penetrative, support* and *backward*). To allow comparisons through the matches, the field dimensions were normalized to 105 m × 70 m.

Furthermore, to analyze the dynamics of these landscapes, heatmaps were created to characterized consecutive periods of a match. While the size of the time window and the update rate depend on the specific necessities of each team, a 10-min sliding window was chosen for illustrative purposes. For instance, for the first half of the 4th match, exemplar heatmaps of penetrative passing opportunities with time windows of 10 min were created. Three of these heatmaps are presented to show the dynamical evolution of these landscapes. On these heatmaps the color scale was adjusted to have dark red in the areas that were under potential passes for 30 s.

Additionally to go beyond a visual inspection, the heatmaps of the five matches for each type of pass were compared using the Earth Mover's Distance (EMD; please see[26] for further explanation of this method). This method provides a measure of similarity between two images[27], with lower values meaning high similarity and vice versa. As an EMD output we created a colored matrix where the coldest colors (i.e., blue, green) display a high similarity between heatmaps, whereas the warmest colors (i.e., yellow, orange, red) display a low similarity between heatmaps.

Algorithm 2

Input: Position and Velocity of players in both teams, Outplay players by the attacking team, Matrix of velocities corresponding to the players' angles, and Ball carrier.

Output: Matrix of results (R), and Defenders(D).

h=1

for j players in the team do

if ballcarrier equal to j do

R_j =ballcarrier

end if

if Passing line is not intercepted* do

$Defender_h$ =defensive player nearest to one side of the passing line.

If there is no defender on this side do

$$D_h = \frac{X_{ballcarrier} + X_{player_j}}{2}$$

end if

$Defender_{h+1}$=defensive player nearest to the other side of the passing line.

If there is no defender on this side do

$$D_{h+1} = \frac{X_{ballcarrier} + X_{player_j}}{2}$$

end if

h= h+2

If $player_j$ outplay> ballcarrier outplay do

R_j =penetrative

end if

if $player_j$ outplay= ballcarrier outplay do

R_j =support

end if

If $player_j$ outplay< ballcarrier outplay do

R_j =backward

end if

end if

end for

	1^{st} match	2^{nd} match	3^{rd} match	4^{th} match	5^{th} match	Total
Penetrative passes	1.19 ± 1.00 s	0.97 ± 0.88 s	1.03 ± 0.97 s	0.95 ± 0.97 s	0.93 ± 1.02 s	1.00 ± 0.98 s
Support passes	1.59 ± 1.30 s	1.45 ± 1.31 s	1.54 ± 1.43 s	1.45 ± 1.29 s	1.60 ± 1.47 s	1.52 ± 1.39 s
Backward passes	1.43 ± 1.17 s	1.15 ± 0.91 s	1.10 ± 0.89 s	0.97 ± 0.78 s	1.00 ± 0.83 s	1.13 ± 0.97 s
Total	1.34 ± 1.13 s	1.15 ± 1.04 s	1.21 ± 1.18 s	1.17 ± 1.17 s	1.16 ± 1.15 s	1.26 ± 1.08 s

Table 3. Mean and standard deviation of the time that the passing opportunities were available per match and type of pass. The values are presented in seconds.

2.5.2. Time of passing opportunities analysis

The time that each potential pass was available was calculated over the five matches. From this information, it is possible to calculate the mean duration of passing opportunities per match and by type of pass (please see Table 1 for further details).

2.5.3. Statistical analysis

Aiming to analyze if the mean duration for passing availability differs across the different type of passes as well as across the five matches (i.e. two factors, Match x TypeOfPass), a two-way ANOVA was performed using Rstudio (Rstudio 1.138; RStudio, Inc., Boston, MA). It is important to note that since the distribution of passing availability is not normal (with most cases concentrated in shorter pass durations, but with a long tail), a requirement for properly implementing an ANOVA, a logarithmic transformation was implemented. After this transformation, q-q plots and residual plots where consistent with a normal distribution with homogeneity of variances. Furthermore, the factors were found not to be collinear.

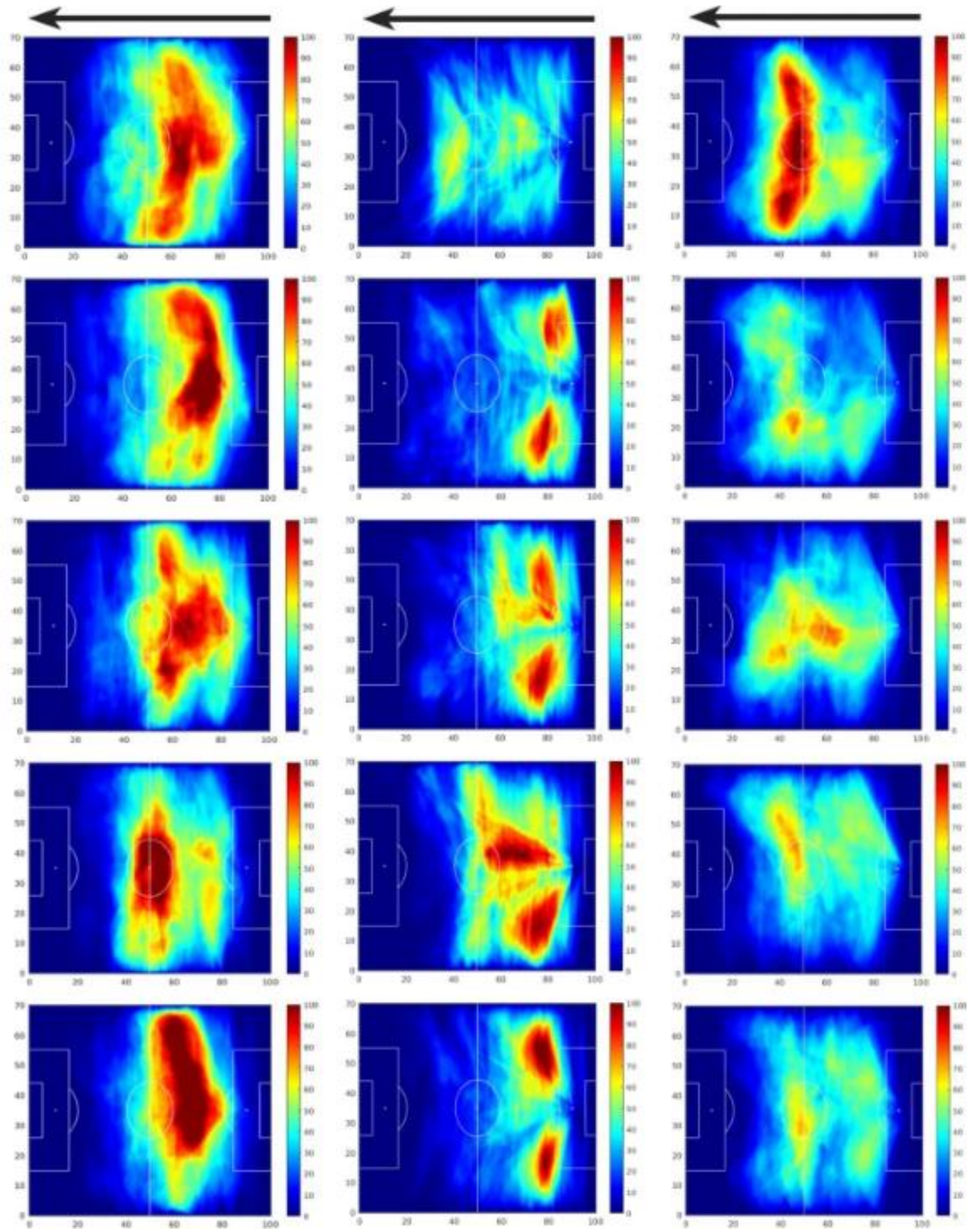

Figure 2. Landscape of passing opportunities for penetrative (left), support (middle), and backward (right) of the five matches. Darker blue indicates areas of the field that did not have any passing opportunities available in the course of the match, while colors nearer to dark red indicate a higher amount of passing opportunities available on that area of the field. The black arrow on the top indicates the attacker direction.

3. Results

The power of the effect is quantified by the eta squared (η^2) statistic, with values near 0.01 meaning the effect was small, 0.06 medium, and 0.14 high[28]. To asses uncertainty the 95% confidence intervals regarding these power of the effects were provided. In case there was a significant effect of a factor and/or the interaction, a Tukey post hoc analysis was run to analyze the main effects and/or interactions between the two factors, providing information on which specific matches and/or type of passes differ. For all tests performed, the level of significance was $p < 0.05$.

3.1. Videos

Three short videos that illustrate the landscapes of each type of passing opportunity were provided as supplementary material. These videos can be access in the Github repository where the data is stored, in the folder of results. The top part of Videos 1–3 displays an animation of player's displacements during a match, as well as the polygons that were created which identifies each passing opportunity. The bottom part of Videos 1–3 displays the heatmaps that illustrates the landscapes of passing opportunities along time. These videos correspond to (1) Penetrative Passes, (2) Support Passes, and (3) Backward Passes.

3.2. Landscapes of passing opportunities

The obtained heatmaps for the five matches and three types of passes are displayed in Fig. 2. It is important to highlight the variety of landscapes that emerged over the matches. As displayed by the warmest colors (i.e., yellow, orange, red), *penetrative* (Fig. 2, left column) and *support* passing opportunities (Fig. 2, middle column) are mostly concentrated in the midfield (mainly for *penetrative* passes) and own side of the field (from the attackers perspective; mainly for support passes). *Backward* passing opportunities (Fig. 2, right column) are scattered more across the field and, with the exception of the first match, are not concentrated on any particular area of the field.

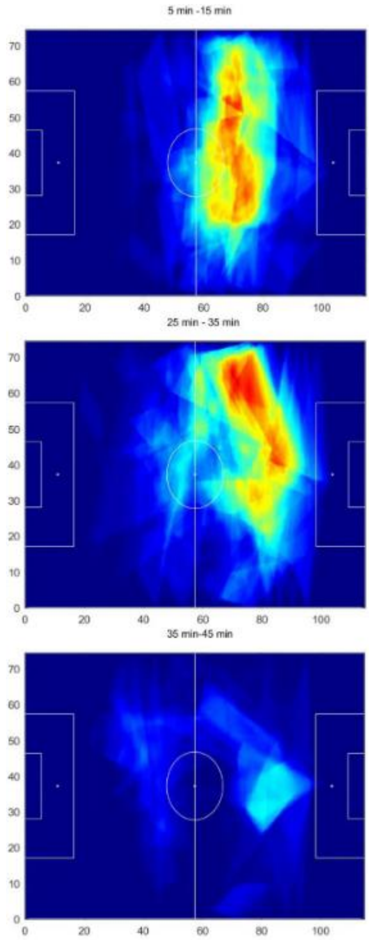

Figure 3. Three heatmaps of 10 min each of the first half of the 4th match representing minutes 5 through 15 (top figure), 25 through 35 (mid figure), and 35–45 (bottom figure). In these heatmaps the dark red area represents areas that were under potential passes for 30 s or more.

In Fig. 3 three 10-min windows heatmaps are shown for the 4th match which highlight how a team's offensive dynamics fluctuate throughout a match. While between the 5th and 15th minutes opportunities were created in both the right and center regions of the field (top figure), between the 25th and 35th minute (i.e. 20 min later) diagonal penetrative passes from the center to the right were predominant as passes concentrated more in the right side of the field (center figure); lastly, in the time period from the 35th and 45th minutes we can see that pass frequency drops drastically (bottom figure).

3.3. Heatmaps analysis with Earth Mover's Distance (EMD)

EMD results revealed that while *backward* passing opportunities (Fig. 4 on the right) are similar over the five matches, *penetrative* (Fig. 4 on the left) and *support* passing opportunities show more diverse patterns (Fig. 4 on the middle). All the squares in the *backward* passing matrix are near dark blue, meaning that the landscapes are very similar across the five matches. On the other hand, the warmest colors on the fifth match of the *penetrative* and *support* passing opportunities matrix is indicative that this fifth match is very dissimilar to the other four (please see the last line of Fig. 4 on the left and middle respectively).

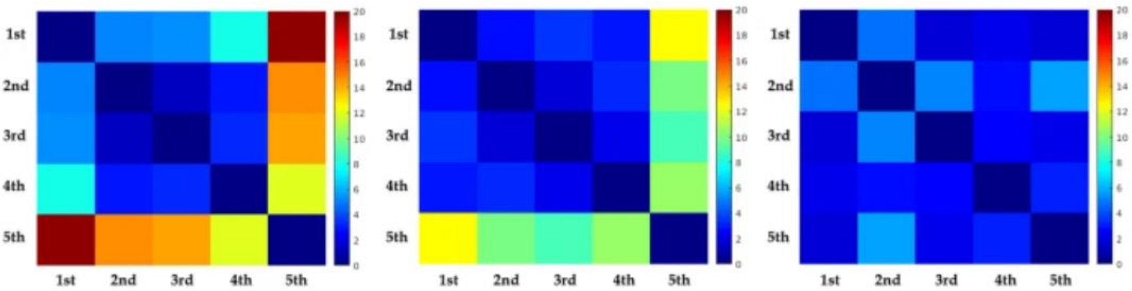

Figure 4. Matrix expressing values of EMD's for Penetrative, support, and backward passing opportunities respectively. Colors nearer to color dark blue indicate more similarity in between the landscapes while colors nearer to strong red indicate more dissimilarity.

3.4. Duration of passing opportunities

The ANOVA revealed a significant effect for the factor TypeOfPass ($F_{(2,16132)} = 376.80$, $p < 0.001$; *Penetrative:* 1.00 ± 0.98 and *Support*: 1.52 ± 1.39 s, *Backward:* 1.13 ± 0.97), with a medium effect power($\eta^2 = 0.045$, 95%, CI 0.04–0.05). Post-hoc results showed that on average the possibilities to perform a *penetrative* pass had less time available than the opportunities to perform a *backward* pass, which in turn had less time available than the opportunities to perform a *support* pass.

The ANOVA analysis highlighted a significant effect of the factor Game on the mean passing availability ($F_{(4,\ 16132)} = 28.07$, $p < 0.001$; 1st: 1.34 ± 1.13 s, 2nd: 1.15

± 1.04 s, *3rd*: 1.21 ± 1.18 s, 4th: 1.17 ± 1.17 s and 5th: 1.16 ± 1.15 s), with a low power effect ($\eta^2 = 0.007$, 95%, CI 0.004–0.009), with the post-hoc analysis revealing that the first match had potential passes available for longer periods, while the remaining matches did not differ between them.

Additionally, there was a significant effect of the interaction between the two factors ($F_{(8, 16132)} = 5.06$, $p < 0.001$), with a low power of the effect ($\eta^2 = 0.003$, 95%, CI 0.001–0.004). A post hoc analysis showed that *penetrative* and *backward* passing opportunities were available for longer periods in the first match than in the other four matches. Furthermore, the difference between *backward* and *penetrative* passes was only significant over the three first matches. Finally, *support* passing opportunities were similar between all five matches. Table 1 displays the exact time the passing opportunities were available per match, and type of pass.

4. Discussion

Visually inspecting the obtained landscapes enables the interpretation of game patterns that may characterize a team's performance. For example, we may suggest that the team under analysis had difficulties to create opportunities to pass within the opposing midfield, since most of passing opportunities were created in its own midfield. Specifically, *backward* passing opportunities were more spread over the field than the other two types of passes that are concentrated on a certain area of their own side of the field (expressed by the warmer colors in Fig. 2, left and middle columns). This supports the idea that within a football match, the set of (game) constraints[29] influence the dynamics of player's co-positioning. Consequently, there are some areas of a football field that are over-used compared to others, suggesting that opportunities for action and the threat that those actions may cause (e.g., a *penetrative* pass) are not homogeneously spread across the space.

Concerning heatmaps similarity, EMD results revealed that most matches displayed quite similar landscape patterns of passing opportunities, which means that the player's spatial configuration of the team under analysis was able to maintain similar patterns of passing opportunities. For instance, landscapes of *backward* passing opportunities displayed the highest similarity between the five matches under analysis. A similar result was achieved for the first four matches regarding the penetrative and support passes opportunities. However, the fifth match demands a more detailed explanation. On the 5th match the EMD results displayed a low similarity of penetrative and *support* passing opportunities when compared with the remaining four (please see Fig. 4). Perhaps these results were due to the opponent team adopting a high defensive pressure strategy[30] which decreases the space available to create these passing opportunities. Consequently, the heatmaps display a high concentration of *penetrative* and *support* passing opportunities in a short area of the field (please see Fig. 2 left and middle columns, bottom heatmap) which may led to a different landscape.

However, characterizing a football match in terms of passing opportunities with a single heatmap that covers the whole game dismisses the variation in dynamics that occur throughout a match (identical to the smoothing effect of temporal averaging). The analysis of the heatmaps with shorter temporal windows may enable to identify changes in the landscapes of passing opportunities that emerge during the course of a match and how they evolve with time. For example, in the 4th match it was possible to observe the transitions of penetrative passing opportunities from a spread area in the midfield to one area where the passing opportunities concentrated in the right side of their own midfield. As the first half ends, passing opportunities drastically drop, as opportunities for penetrative passes vanish in most areas of the field (please see Fig. 3). This example depicts transitions within the landscape of *penetrative* passing opportunities which allows to characterize the dynamics of the most threatening areas that arise along a football match.

Regarding the mean time that passing opportunities were available, there were differences over the matches and for the different type of passing opportunities. The first match had longer mean times for their potential passes than the other four (that did not differ between them). This is probably due to an opposing player receiving a red card on the 63rd minute, which means that the opponent team played with one player less for approximately half an hour, which demands an adjustment on his team spatio-temporal configuration. Consequently, these adjustments may create additional difficulties to the team to defend and close passing opportunities but also to regain ball possession and create passing opportunities. Thus, this landscape model reinforces the notion that disturbances in a team initial configuration (e.g., a sent off player) alter players interactive behavior which consequently lead to changes in the time that a passing opportunities were available. It is noteworthy that this difference only happens for *backward* and *penetrative* passes passes and not for *support* passes, which suggests that this type of passing opportunities were less affected by the team defense capabilities and strategies.

Concerning *penetrative* passing opportunities been available for less time than *support* or *backward* passes (for the first three matches); these may be because *penetrative* passes will place the ball onto an off-ball player that is outplaying more opponents than the ball carrier, which is hypothetically more dangerous for the defending team than a *support* or a *backward* pass[3]. This theoretical threat may increase the defenders' willingness to intercept passing opportunities, which consequently decreases the time that *penetrative* passing are available compared to *backward* or *support* passes. However, this should mean that *support* passing opportunities had less time available than backward passes. Nevertheless, the results revealed otherwise, which could be explain by a possible increased pressure to recover ball possession close to the opposing goal[7,31]. This could explain the results of the fourth and fifth match, with no significant differences between the time that *backward* and *penetrative* passing opportunities were available. This was possibly due to a high defensive pressure of the opposing team.

Differences in the time that passing opportunities were available, as well as visual differences in the landscapes of passing opportunities accordingly with the different type of passes, led us to suggest that this landscape model is sensible to changes in game constrains. Such changes are the defensive pressure of the opposing team, a red card shown to an opposing player, or other events that may change players' spatio-temporal configuration allowing to identify the most vulnerable areas of the field. From an applied perspective, this landscape model provides relevant information for performance analysis and team technical staff about the passing opportunities that have been created by both teams (i.e., potential receivers and opponent players) as well as in which areas of the field and for how long those passing opportunities were available.

Regardless of the promising results, this model suggests three issues for further research: (1) so far the model assumed that all the players are technically and tactically equal. An issue for further research is to add individual technical characteristics to shape each player passing opportunities on a competitive match; (2) the outplay principle to categorize passes requires an accuracy improvement. *Penetrative* passes are not the only that can increase the probability of a goal as *backward* passes can also help in scoring goals[32]. This is especially relevant close to the opposing goal, where a pass *backwards* that creates a better angle to score could be a better decision than *penetrative* passes that leave the receivers in a worst angle to shoot to the goal. In this regard, it is important to keep in mind that previous research have shown that the location of the goal was a relevant task constrain in Futsal[33]; (3) currently a constant ball speed was assumed. As 'real' balls do not fly with constant speed, this could be leading to under or overestimation of the passing opportunities available and should therefore be reformulated (please see[34], for a possible solution).

Based on ball carrier and off-ball players spatiotemporal interactions this landscape model depict the passing opportunities that emerge in the course of a football match. The landscapes of passing opportunities varied through different matches, especially for support and penetrative passes. Hence we may conclude that this model is sensitive to task constrains and to the uncertainty related with the uniqueness of each football match, at least regarding the landscape of passing opportunities. Nevertheless, it was possible to show evidence that due to player's interactive behavior some matches exhibit more similarity than others do, as displayed by the EMD results.

Having the heatmaps as an output provides visual information regarding the areas of the field where more passing opportunities were available and for how long they last. Additionally by creating temporal heatmaps it was possible to identify how the threat (for the defense) caused by the different types of passing opportunities fluctuates in space and time during the course of a match. As expected, the different type of passing opportunities were available for different time windows. For different reasons penetrative and backward passing opportunities last less than *support* passing opportunities.

Finally, we reinforce that this is a methodological driven research, thus we do not aim for a generalization of results, but rather a generalization of the method usability. The outputs of this landscape model provides information that could be relevant to a post-match report shortening the gap between performance analysis team and the technical staff.

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Chapter 5. Discussion: Final remarks and issues for improvements

1. General remarks.

In this thesis, important issues for the hegemonic struggle in antagonistic sports, as well as the cooperative and antagonistic coordination dimensions were studied. Regarding the cooperative coordination dimension, the UCM method was employed to measure the synergetic behavior of a defensive unit (the four defensive players of a line). The results suggest that the defensive line maintains its structure under a tighter control than its position in the field, with Unsuccessful Defensive Plays (UDO) having a tighter control than Successful Defensive Plays (SDO). In the case of Antagonistic coordination, our results show that these situations are characterized by increase fluctuations, unique intermediate states (not present in cooperative situations), and constant switching behavior. All this highlights the uniqueness of such situations, which calls for more research in antagonistic situations, with models and expectations specifically created for such situations. Finally, a tentative to illustrate the hegemonic struggle of five football games was employed in the form of a landscape of possibilities for action. Such illustration was centered on passing opportunities of one of the two teams. The heatmaps created could help characterizing how the struggling is unfolding during matches. In the following sections, and to serve as a closure for this thesis, a few key points and limitations of the past chapters are discussed.

2. Cooperative coordination within teams

To our knowledge, in this thesis the UCM was employed for the first time to study a group of players rather than just a dyad[1,2]. As shown on chapter two the method is perfectly equipped for doing this, providing important information about the behavior of such multilevel synergy. In fact, the method was originally developed to study redundant systems with a lot of degrees of freedom, rather than dyads. In a situation where the task elements and performance variables are clearly defined, such a methodology should be able to tell us which performance variables are under a tighter stabilization. We suggest that this kind of multilevel synergetic analysis is desirable over other analysis were coupled elements are studied and hierarchically organized[3].

A method like the UCM, in contrast with other measures like the relative phase, allows for relating the variability of the elemental variables in the sphere of the performance variable. Therefore, it provides with a direct proof of the existence of synergies, while other methods only provide measures of synchronization. The used of the UCM also allowed to see to what degree the unit is controlling the performance variable, which in our study was related to performance. In this regard, we show that the units were keeping their position in the field under less control compared to their structure. Moreover, the performance variables were under tighter control when failing compared to when succeeding, thus emphasizing that success in team performance is more related to the control of variability rather than to the reduction of such variability.

The biggest limitation with the methodology employed was relate with the selection of the performance variable and the reference values. The decision of the reference values is always an issue, as the reference values will radically change the results of the method[4]. This happens because the method works by constructing a UCM space (similar to some specific axis) which is necessarily dependent on where the origin is built and so on. In this thesis, we assume that the behavior of the defensive unit was converging towards the configuration present on the end of the plays, but future research should study different reference values and its effects on the results of the method.

Regarding the performance variables, the stretch index and the centroid are stablish measures that have been used to measure synchronization in team sports. However, there is some doubts that these measures are related to the actual performance of football teams during games. Despite these doubts, there are studies that show that the centroids and stretch index behavior is related to performance. Furthermore, these two variables represent two different elements that globally define the unit, its position in the field, and its structure. Thus, we believe that the variables were related to performance (as show by the results of our article), and allow to study different possible process by which synergies may form.

In the future new performance variables that are directly related to performance should be developed, but to our knowledge, such measures are not (so far) available in literature. Mathematical defining such a performance variable should also allow for a formal definition of the UCM, in contrast to the method used in this thesis where the performance variable was defined using multiple regression analysis. This definition is especially useful to define reference values, as the performance variables is clearly related to the task relevant elements. In addition, the method was developed to work with such non-linear mathematical definitions, which makes it an advisable solution when available. Nevertheless, using a multiple regression method is still a valid way of applying the UCM[5], and it can have its own advantages when working with multilevel synergies (in which models are not available).

3. Antagonistic coordination in between opponent athletes

Our results using a simple antagonistic task show unique dynamics compared to cooperative coupling. First, we see the emergence of intermediate steady state (near 90º or 270º) that are not present in normal cooperative situations. Second, the antagonistic trials only had around 17% of the trials with normal in-phase or anti-phase steady states. In comparison, only two of the 80 trials in the cooperative conditions show any other pattern to in-phase or anti-phase. Finally, the classification of the trials show diverse conflictive situations that lead to a variety of results. The majority of trials were dominated by unstable behavior that kept switching between different steady states. All this highlights that such antagonistic situations radically differ from synergetic situations.

The characteristics of combat sports, where two fighters try to beat each other, pose an interesting field to study antagonistic situations. However, in contrast with our finding theoretical approaches to combat sports that (unsurprisingly) have not translated into a strong research program refer to combats as an interpersonal synergy[6,7]. Such approaches, imply the idea that a combat can be understood as a situation where two fighters behave as a unit, a combat unit. In this approach, synergies are loosely define as coordination which will mean that fights will be study more like a dance than a struggle between two opposites.

However, we believed that coordination can happen without synergetic behavior (because of antagonistic goals), which means that the loose definition of synergy as simply coordination is not advisable. On the other hand, if the idea is that fighters are acting like a cooperative unit, this framework could only effectively explain practices where two or more fighters train techniques and transitions. Only in these situations, synergies may happen due to cooperation between the two fighters. In actual fights and sparring, fighters have conflicting antagonistic intentions, which should be model and conceptualized differently to cooperative situations. First, because the microscopic elements are not working together (the literal Greek definition of synergy) but rather against each other. Second, because modelling results (see chapter three) show the appearance of unique steady states for such situations. Finally, because our results and the results from the literature suggest that such antagonistic struggles radically differ from synergetic units.

This kind of lose definition of antagonistic situations, has led to repeatedly masking results that are consistent with antagonistic modelling[8] or the incorrect interpretation of intermediate states as been near to in-phase or anti-phase[9,10]. Furthermore, these kind of frameworks may be hampering the progress in fields such as combat sports, by looking for steady states that may be not the relevant and dominant ones in such antagonistic situations. Thus, we suggest that such situations would benefit by modelling and theoretical frameworks specific to them, especially for the ones that highlight their difference with cooperative synergetic situations. That is what we propose to do in chapter 3.

Thus, we applied an adaptation of the HKB model to model such situations. Such adaptation introduces an asymmetry in the coupling in the form of two conflicting or opposing forces. In contrast to the classic HKB who has congruent coupling (two attractive forces), in this case one of the forces kept been an attractive force, while the other one was a repulsive force. This kind of attractive-repulsive seems like a perfect fit to study situations with antagonistic intentions. This type of coupling introduces antagonic forces, two forces that oppose each other, as one will be attracted to the behavior of the other while the other one will be exerting a repulsive force (thus forces that negate each other). Furthermore, the results of our study support the predictions of such a model further highlighting the usability of such a model.

In the case of the conceptual framing of such situations, in this thesis the word antagonistic[11] was used to define the coupling, the type of intentions, these situations and sports. This concept was used over the concept competitive as competitive can be a very blurry concept. For example, competitive sports entail sports as football, combat sports, or racket sports, which contain clear antagonisms. However, competitive sports are also others, such as long jump, Hammer throwing, or ski, which, while clearly competitive, have no antagonistic coordination, or any coordination for all that matters. Furthermore, other sports entail coordinative processes (such as crew rowing) that are competitive, in the sense as they compete against each other, but entail cooperative coordination within the members of a team. This is even true in team sports, where there is competition in between the members of a team, in a twofold sense. First players within a team compete for a spot in the starting team (or more minutes of play), but also in the way that they are cooperatively coordinating within a team to compete against each other, what could perfectly be define as competitive coordination.

Therefore, we believe that the use of antagonistic is a better terminology as antagonistic can be defined as 'acting in opposition; opposing, especially mutually'. Such a term does not lead to ambiguities that can come with the term competitive. In this regard, for those attach to terminologies extracted from the synergetic field, a situation such as the one studied in chapter 3 could be defined as an *antinergy*. If synergy comes from *sun-* (together) and *-ergon* (work; working together), *antinergy* will come from *ant-* (against) and *ergon* (work; working against each other). Thus, the term *antinergy* could serve as a clear opposite to the term synergy, while implying the same macroscopic self-organized emergence of behavior. A possible definition for an *antinergy* will be an antagonistic coordination in between two opposites that leads to some type of unstable and/or metastable macroscopic behavior, as displayed by our model presented on chapter 3.

4. Landscape of passing opportunities

Our study shows the potential of landscape of passing opportunities to depict areas that are over or under use by an attacking team. Specifically, the team under analysis failed to create passing opportunities near the opposing goal. Which probably related to the incapability of the team to generate goals and threatening situations. Furthermore, dividing pass types into *Backward*, *Support*, and *Penetrative* allows differentiating pass opportunities by the threat they pose to the opposing team. Unsurprisingly, *Penetrative* passes were available for longer times when compared with other type of passes. All this suggests that the model was susceptible to constrains that emerge in the development of football games.

However, characterizing a football match in terms of passing opportunities with a single heatmap that covers the whole game dismisses the variation in dynamics that occur throughout a match (identical to the smoothing effect of temporal averaging). The analysis of the heatmaps with shorter temporal windows may enable to identify changes in the landscapes of passing opportunities that emerge during the course of a match and how they evolve with time. This could be useful to stress deficiencies or strength a coaching stuff may want to reinforce in preparation for the next game. For example, in the fourth match it was possible to observe the transitions of *penetrative* passing opportunities from a spread area in the midfield to the right side of their own midfield. As the first half ends, passing opportunities drastically drop, as opportunities for penetrative passes vanish in most areas of the field (please see Fig. 3 in chapter 4). This example depicts transitions within the landscape of *Penetrative* passing opportunities, which allows to characterize the dynamics of the most threatening areas that arise along a football match.

From an applied perspective, this landscape model provides relevant information for performance analysis and team technical staff about the passing opportunities that have been created. This model was created using the interactive behavior among ball carrier and off-ball players (i.e., potential receivers and opponent players) as well as in which areas of the field and for how long those passing opportunities were available. Furthermore, the division of passing opportunities due to the threat they generate (into *Penetrative*, *Support*, and *Retreat*) introduces an element that relates to the threat that passes pose, allowing to study how tactical constrains affect the availability of such passes. Thus, all this suggests the model is sensible to task constrains emerging in the development of the game, been therefore an interesting approach to measure the hegemonical struggle that arises in within football games. However, the model is still in its early stages and still has some limitations.

The first limitation of our approach is that, right now, the model is not physic base. Meaning that players and the ball are assumed to move in a straight line, at a constant speed, and in 2D plane. On contrast in real football games players need to turn to face the trajectory of the ball to try to intercept it[12], accelerating due to their muscular force. Furthermore, the effects of drag and other forces affect the ball movement[13], which also moves in a 3D plane. Moreover, the model does not include the effect of the orientation of the ball carrier[14]. This orientation should affect the passes that are available for the ball carrier, as she/he can only pass the ball with certain angle[14]. Therefore, future improvements of the landscape model will benefit of defining motion models for the movement of players as well the ball, as well as taking into consideration where the player is looking and how this affects the actions available.

Making the model physic base should help us address the second limitation of our model, which is in the definition of pass availability (whether the pass was available or not). In our thesis pass availability was defined as a pass been available or not. However, this will only fully addressed situations where no intrinsic individual variability was present (on behalf of the ball carrier, the receiver, and their opponents) as this will decrease the level of uncertainty present in the task. On the other hand, football is a complex sport with variability been introduced by all the players low predictable behavior. Therefore, we suggest that the next stage will be to convert this model to a probability base one. Consequently the output will be a pass opportunity probability from one to zero, instead of just been the passing opportunity ‘open’ or not. In this way, a physic base model will help in building such a probability model, as it will give a time a player will take to arrive to each point of the line in relation to the time the ball will take[12]. Thus allowing calculating the probability of such a pass arriving to the receiver.

A probability model has another advantage that could help address the third limitation of our model. Such limitation is that all players are treated equally which means that differences in technical (e.g., not all players can see and perform the same passes), tactical (e.g. different position of the players will lead to players taking more or less risk), and physical (e.g. not all players are equally fast) were purposely left out. This can be address by data mining long data sets, which should allow us to give some kind of scores in these categories to the players. On this regard, a probability model is helpful because it has a predictive value. This means that a probability model should allow us to test the success of passes in relation to the probability of such passes arriving (technical quality), the risk players are taking (tactical behavior), and the velocity and acceleration of players (physical behavior).

In any case, this kind of hegemonical approach to football studies could be of interest as they can lead to a better understanding of the dynamics arising inside football games, as well as the characteristics of the members of a football team. On this regard, using temporal landscapes (i.e. spanning specific plays) could help pinpoint specific information that coaches want to transmit to players. Furthermore, these models could be extended to more elements of football games, such as shooting opportunities (an article currently under writing to submit to a journal), dribbles, crosses and even, situations such as pressing opportunities.

5. Conclusion

In conclusion, in this thesis, the hegemonical process that characterizes antagonistic sports was studied. To do so, we study the dimension of coordinative coordination, the dimension of antagonistic coordination, and the actual macroscopic hegemonical behavior emerging from the interaction of these two moments. We believe such a hegemonical approach could serve as valid theoretical approach to study antagonistic sports, such as combat sports, racket sports, and team sports.

To study the dimension of coordinative coordination we study the synergetic behavior of a multilevel defensive unit of a football team using the UCM. This highlights that successful movement is more related with the management of variability than the reduction of such a variability. In addition, the unit under study maintain is position on the field under less control than its structure. Furthermore, it showed the usability of the UCM to study multilevel synergies, as the use of such methodology for interpersonal behavior had only been limited to dyads.

On the dimension of the antagonistic coordination, we study a simple antagonistic rhythmical task to highlight the differences between this dimension and the synergetic dimension. The results highlight that such situations are characterized by increase fluctuations, intermediate steady states (different to in-phase or anti-phase) and behavior that constantly switches. Such a behavior is the result of antagonistic opposing intentions, which highlights the need to conceptualize, model and study such situations as their own unique framework.

Finally, the landscape model was capable of depicting essential elements of the hegemonical struggle arising inside a football game. The team under study had problems generating plays in the near the opposing goal, which was depicted by passing opportunities been uncommon in the opposing field. Furthermore, passes that were more threatening were available for shorter times. Thus, these kind of approaches could serve as a way of studying the underlying dynamics emerging in team sports, serving as a way of enriching the data analyst process in team sports. However, it is important to note that the model is open to great improvements.

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