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Quantifying synergies in two-versus-one situations in team sports: An example from Rugby Union

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Abstract Collective behaviors in team sports result in players forming interpersonal synergies that contribute to performance goals. Because of the huge amount of variables that continuously constrain players' behavior during a game, the way that these synergies are formed remain unclear. Our aim was to quantify interpersonal synergies in the team sport of Rugby Union. For that purpose we used the Uncontrolled Manifold Hypothesis (UCM) to identify interpersonal synergies that are formed between ball carrier and support player in two-versus-one situations in Rugby Union. The inter-player angle close to the moment of the pass was used as a performance variable and players running lines velocities as task-relevant elements. Interpersonal synergies (UCM values above 1) were found in 19 out of 55 trials under analysis, which means that on 34% of the trials, the players' running line velocities contribute to stabilizing the inter-player angle close the moment of the pass. The strength of the synergy fluctuates over time indicating the existence of a location effect during attack phases in Rugby Union. UCM analysis shows considerable promise as a performance analysis tool in team sports to discriminate between skilled sub-groups of players.

Keywords Uncontrolled manifold · Team sports · Interpersonal coordination

Introduction

A major challenge is how to describe and explain interpersonal behavior that is grounded on the behavior of two (or more) independent entities (e.g., players). Rugby Union is a performance context characterized by intense physical contact between players. According to the rules of the game, defenders are allowed to tackle attackers, pull them to the ground, and recover ball possession for their team. Moreover, attacking players cannot pass the ball forward with the hands, i.e., the support players must remain behind the ball carrier acquiring a relative position (characterized by an interpersonal angle between the players) that allows them to receive the ball while running. In team sports such as Rugby Union a common effective tactical strategy is to manufacture ball possession situations with numerical superiority (e.g., the ball carrier and support player against only one defender). To manufacture such situations the players must create a functional synergy, which occurs when components of a system behave as a whole, contributing to the development of a specific task (Kelso, 2009). Thus by definition synergies are context-sensitive functional groupings of elements that are temporarily assembled to act as a single coherent unit (Kelso, 2009). The Uncontrolled Manifold Hypothesis (UCM) was arguably the first elaboration to explicitly link the coordination of a multi-

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component system to the variability structure of its individual components (Schoner, 1995).

The aim of this study was to apply the UCM as a proposed methodology to identify and measure the influence of synergies in team sports. This method has been in existence for some time, but here we seek to apply it to a new realm (the realm of social systems, and particularly in team sports). In this sense it is a novel application of the UCM method.

A brief introduction to synergies

We postulate that synergies are a mechanism that supports interpersonal coordination in team sports. A general feature of coordination is the requirement of a mutual dependency among system components, with a consequent compression of degrees of freedom (d.f.) which led them to behave as whole (Kelso, 2009; Kelso & Engstrom, 2006; Kelso, 2009; Kugler & Turvey, 1987). Degrees of freedom (i.e., d.f.) are structurally diverse elements of a movement system that are free to vary. Synergies have been proposed as a solution for the global control of a movement system, rather than to control each component as a single entity (i.e., the d.f. problem; Bernstein, 1967). Individual components are temporarily coupled to form a synergy and thus the control of the system is achieved through the mutual compensation of the variability of each component (Bernstein, 1967; Riley, Richardson, Shockley, & Ramenzoni, 2011).

While the synergies concept was originally applied in attempts to solve an intrapersonal control problem, the concept has since been extended to interpersonal coordination. Interpersonal coordination that occurs between people is nested on intrapersonal synergies (e.g., bimanual, bipedal) that orchestrate each subject's movements (Schmidt & Richardson, 2008). As such one can evoke the notion that people intentionally and unintentionally coordinate with others based on visual information couplings (Richardson, Marsh, & Schmidt, 2005; Schmidt, Richardson, Arsenault, & Galantucci, 2007). Interpersonal coordination can be measured by changes in interpersonal distances, mediated by different sources of visual information such as segmental motion information based on another's limb motion (to allow anticipatory compensation), or a more global motion information based on the rate of optical expansion due to the other's movements (Meerhoff, De Poel, & Button, 2014). Hence, visual information (segmental and global) is the primary language via which the "interactive capacity" of the system is shared, helping to sustain each individual's potential to couple to each other and form a synergy.

Three layers of analysis are necessary to describe the emergence of synergies: (i) at the lowest layer are the single entities, which are independent entities with no causal link between them. Independency in this sense means that the action of one entity does not influence the action of the others (i.e., the atomism level from Kugler & Turvey, 1987); (ii) at the highest layer are the task and environmental constraints which bound each single entity's behavior. To meet the demands imposed by task and environmental constraints the "independent" entities must coordinate to behave as a single unit; (iii) when this is achieved a middle layer is formed. It is the dynamic relation between the lowest and the highest layers that enables coordinative structures (or synergies) to be formed (Kelso, 2009a, b; Kugler & Turvey, 1987).

Synergies and team sports an example from Rugby Union

According to coordination dynamics theory, a functional synergy is grounded on complementarity between stability and variability (Kelso & Engstrom, 2006). Stability can be conceptually defined as the system resilience to external perturbations (Kelso & Engstrom, 2006), while variability is a general feature of human movement system which affords adaptability to perform in an ever-changing context (Glazier, Wheat, Pease & Bartlett, 2006). The complementary nature between stability and variability is what drives a system to achieve the same task goal through different paths. Some components of a system must vary the way they interact to stabilize task-specific *performance variables* which can be defined as a goal that ideally remains stable (Black, Riley, & McCord, 2007). The manner in which some task-relevant elements co-vary (the d.f. that participate in a task, e.g., players' velocities, interpersonal distances, distances to goal, etc.) becomes crucial to stabilize specific performance variables (Riley et al., 2011).

In order for us to apply this general theoretical concept to a specific sports example such as Rugby Union, one significant challenge is to identify the process by which system components vary to stabilize task specific performance variables. An important question is: What are the *performance variables* (that need to remain stable) and *task-relevant elements* (that need to vary) that contribute to this complementarity? For instance, one performance variable that is relevant to game play can be the relative position of two team-mates in a defensive line (measured with angles or interpersonal distances between them) that should remain relatively stable during a phase of active play (see Passos, Araujo, Davids, Gouveia, Milho, & Serpa, 2008).

The principle of abundance may offer a mechanism through which the evolution of synergies in team sports can be understood. In a system blessed with abundance, "all the elements (i.e., Degrees of Freedom) always participate in all tasks, assuring both stability and flexibility of the performance" (Latash, Scholz, & Schoner, 2002, p. 27). Functional synergies arise in team sports due to a huge (but limited) set of combinations between system elements. In other words, all d.f. contribute to the formation of a synergy but some might have more participation than others. By definition, a functional synergy is suited to the situation in which it is formed (situation specific). A key aspect of synergies is that they should not necessarily simply adapt to different situations. Due to context dependency, synergies may assume different functions using some of the same components (e.g., using the legs to walk and jump) and the same function using different components (e.g., getting closer to the try line using different ball carriers). The timeframe over which the synergy acts must also be considered because players' co-adaptive behavior becomes more relevant to success close to decision moments (e.g., the moment of the pass) than at other moments (Passos, Cordovil, Fernandes, & Barreiros, 2012).

The three research questions we set out to answer are: (i) How to confirm that two independent units (such as the players) form a synergy; (ii) How to measure the "strength" of the synergy between the players; (iii) How to display whether that candidate synergy contributes to the performance of a task. To address these questions we assumed that interactive behavior can be expressed by the players' relative position, measured via the angle between players, which is a coordinative variable previously identified in other studies in Rugby Union (Passos et al., 2008, 2009). The angle between ball carrier and support player is a crucial variable which affords the support player to receive a pass from the ball carrier while running, a paramount issue to the attackers in Rugby Union. The inter-player angle can be used to identify moments of stability (low variability) and also critical regions (high variability) due to a mutual behavioral dependency between opposing players. Within these critical regions the angle variability is constrained by the relative velocity of the players (Passos et al., 2008, 2009). To support this relation there is a formal mathematical model of the player's interpersonal angle and player's relative velocity (for further details please see Araújo, Diniz, Passos, & Davids, 2014). Stabilizing angle values means reducing the variance between both players' relative positions, highlighting an affordance for passing and receiving the ball. Hence, we hypothesized that both attacking players adjust velocities to each other to stabilize the angle value close to the moment of the pass. Despite the task constraint that the ball carrier does not (continuously) see the support player, he/she needs to acquire a position that affords him/her to successfully perform a pass to the support player, and thus a reciprocal compensation can occur between them. However, we assumed that adjustments to the support player's velocity are largely dependent upon changes in the ball carrier's running line velocity rather than vice versa.[1] In order to investigate this hypothesis we applied the UCM (Black et al., 2007; Latash et al., 2002; Riley et al., 2011; Scholz & Schoner, 1999).

[1] Which raises an important and underdeveloped point in the synergy literature: how reciprocal does the compensation have to be? We acknowledge an anonymous reviewer for raising this question.

The Uncontrolled Manifold (UCM) Hypothesis

By definition "The UCM approach is a geometrical approach that seeks to discover the structure of variance in multi-degree-of-freedom task spaces in which all degrees of freedom have a common metric. The structure of variance in that space is interpreted in terms of its meaning for task variables" (Schoner & Scholz, 2007). In other words the UCM hypothesis assumes that controlling a motor task is related to stabilization of a performance variable (i.e., a task goal). When this hypothesis is confirmed a sub-space is created, known as the UCM, which is a geometrical "object" containing all combinations of task-relevant elements which lead to the same value for a performance variable (Black et al., 2007; Klous, Danna-dos-Santos, & Latash, 2010; Schoner & Scholz, 2007).

The main question underlying the UCM is whether movement variability contains a certain variance structure correlated to the task performance (Rein & Suppl 1-M5, 2012). By mapping the variability of supposed task-relevant elements to the variability of a performance variable, hidden structural features are exposed (Rein & Suppl 1-M5, 2012). Task-relevant elements can be any quantity whose interaction is predicted to influence the system performance outcome and the performance variables are those which are necessary to achieve a task (Schoner & Scholz, 2007). With the choice of variables comes a choice of metrics. UCM requires a common metric of the task-relevant elements for the construction of the variance sub-space (Schoner & Scholz, 2007). According to these authors, if for instance we choose to use an angular velocity and an angular position as task-relevant elements, even though they cannot be measured by the same metrics (one being in radians per second, the other in radians) the computation is still possible. Nevertheless, the interpretation of such a computation does not make sense, because when we move forward to discuss the data, it is somewhat ambiguous to argue that there is more variance along a velocity axis than along a position axis (Schoner & Scholz, 2007).

The inspiration to use UCM in the present work came from Riley and colleagues who proposed that functional synergies support the existence of interpersonal coordination in team sports (Riley et al., 2011). Accordingly, we also applied the proviso that only systems that demonstrate reciprocal compensation among elements may be called synergies (Latash et al., 2002). The variance along the UCM expresses a reciprocal compensation between task-relevant elements (e.g., players' velocities to stabilize a performance variable), whereas the variance perpendicular to the UCM expresses changes the task-relevant elements that do not contribute to stabilizing the performance variable. By calculating the ratio between compensated and uncompensated variance we measure the UCM and consequently the functional synergies. The UCM is a "control hypothesis" about a selected performance variable whose value the system assumes to stabilize (Latash et al., 2002, pp. 28).

In summary, players reciprocal movement adjustments characterizes coupling grounded on perceptual information (e.g., visual) contributing to the compression of d.f. and consequently stabilizing a performance variable. In team sports players' mutual dependency is achieved due to temporary compressions of d.f. compensation which are the necessary features to the emergence of functional synergies. These features may be found in team sports players' interactive behavior, which is why we decided to analyze players interpersonal synergies using the UCM approach.

Methods

Twenty-four national academy level Rugby Union players (14–15 years old), participated in this study. The players were randomly assigned into eight sub-groups or triads (two attackers vs. one defender). The instructions to both attackers were "Your goal is to avoid the defender and score a try" and the instruction to the defender was "Your goal is to prevent a try from being scored." To limit fatigue, each triad performed only nine trials (i.e., ball carrier, support player and defender), shifting roles on each set of three trials. There were no restrictions concerning either the ball carrier's initial side position (right hand side or left hand side) or the number of passes to be performed (Passos et al., 2012). Only complete trials that resulted in a successful pass to the support player and a consequent try being scored (N = 55 out of 72) were used for data analysis.

The task was performed on a grass field with 5 m width and 22 m depth. All trials were recorded using a single video camera at 25 Hz. TACTO v8.0 software was used to manually digitize the displacements of the players (Cordovil et al., 2009; Fernandes & Malta, 2007; Nema, Schweizer, von Hoff, & Guerreiro, 2009). Players were tracked using a working point between the feet on the ground. A MATLAB routine with Direct Linear Transformation (DLT) was used to transform the virtual coordinates into real coordinates using six calibration points representing known distances of a 22 m by 5 m playing field dimensions (Abdel-Aziz & Karara, 1971).

The first step was to select a relevant performance variable of the two-versus-one situation in Rugby Union. The candidate performance variable was the players' relative positions approaching the moment of the pass. To measure the players' relative position we used an angle between ball carrier and support player, from the beginning of the trial until the moment of the pass, which was defined by the moment the ball leaves the hand of the ball carrier (Passos et al., 2012). The discretization in time of this angle continuously describes the interactive behavior between ball carrier and support player. The inter-player angle (hereinafter shown as θ) was calculated with a vector from the support player to the ball carrier and an imaginary horizontal line parallel to the try line (for a more detailed description please see Passos et al., 2009). The coordinates (x, y) of each player position on plane of the game field are obtained from video capture data (Fig. 1).

In Fig. 1, the zero crossing point identifies the moment when the support player was side by side with the ball carrier (meaning that both players are at the same distance from the try line). Positive θ values signaled that the ball carrier was closer to the try line than the support player. All calculations based on data captured from video were performed at 25 Hz, corresponding to the same frequency of the video frame rate.

UCM procedure

It is necessary to present here a detailed description of how to compute the UCM for the purposes of analysing synergies in sports groups. As previously suggested, interpersonal coordination can be achieved by stabilizing a value of a performance variable. For that to happen some task-relevant elements, here defined as the ball carrier and support player running line velocities, develop compensatory movements that create variability which is the basis to stabilize a performance variable. Plotting the velocity of the ball carrier and the support player for each trial will create a subspace within a state space of task-relevant elements (e.g., players running line velocities; see Fig. 2).

The hypothesis that task-relevant elements stabilize a performance variable can be empirically demonstrated by computing two quantities (Black et al., 2007): (i) the variance along the UCM (i.e., compensated variance); (ii) the variance perpendicular to the UCM (i.e., the uncompensated variance). The variance along the UCM expresses a reciprocal compensation between player's velocities to stabilize the performance variable θ. Variance perpendicular to the UCM, expresses changes in players' velocity that do not contribute to stabilizing the performance variable θ (i.e., low θ variability values) with values close to "optimal." By calculating a ratio UCM between compensated and uncompensated variance (i.e., var_{comp}/var_{uncomp}) we compare which of these variances is higher

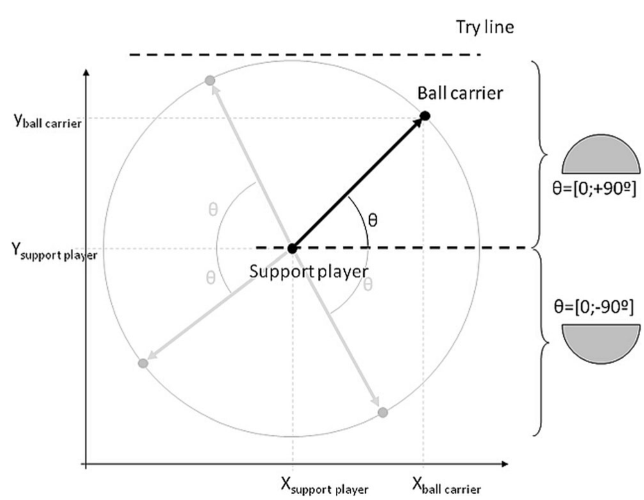

Fig. 1 Diagram depicting the calculation of inter-player angle (θ)

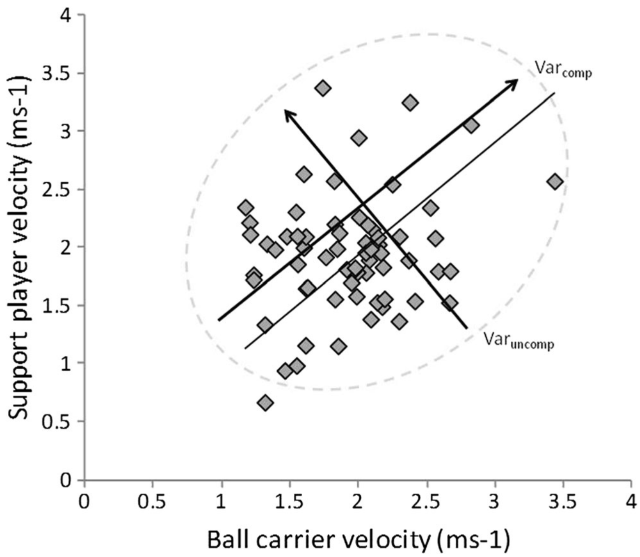

Fig. 2 Running line velocities subspace (an example from trial data)

and consequently quantify the functional synergies. This means that for UCM values >1, a synergy exists; and for UCM values <1, there is no synergy.

The UCM was evaluated in time for each trial, requiring a discretization of the model using discrete time points (t). Correspondingly, the duration of each trial and the corresponding total number of time points N for each trial is defined by the moment in time when the ball carrier passes the ball, and therefore, the time discretization of each trial is defined by a dataset of time points t varying between frame 1 and frame N, i.e., t=1..N.

The task-relevant elements are defined by the running line velocities of the ball carrier $v_{BallCarrier}$ and support player $v_{SupportPlayer}$, which are computed using the finite difference method from the coordinates of the players' trajectories. The corresponding vector **T** with dimension n=2 for the task-relevant elements, is given at each time point t by:

$$\mathbf{T}^t = \begin{bmatrix} v^t_{BallCarrier} \\ v^t_{SupportPlayer} \end{bmatrix}$$

For the performance variable defined by θ, the corresponding vector **p** of dimension d=1, is given at each time point t by:

$$\mathbf{p}^t = [\theta^t]$$

The reference configuration corresponds to the state of the task-relevant elements designated as $\mathbf{T}^0$ and the performance variable designated as $\mathbf{p}^0$ given by:

$$\mathbf{T}^0 = \begin{bmatrix} v^0_{BallCarrier} \\ v^0_{SupportPlayer} \end{bmatrix}$$

$$\mathbf{p}^0 = [\theta^0]$$

The reference configuration corresponds to the task-relevant elements and the performance variable values retrieved at the moment of the pass backwards, such that t=N. At each time point, linear approximations were assumed between small changes in magnitude of the task-relevant elements and the performance variable with respect to the reference configuration. Based on a Jacobian matrix $\mathbf{J}(\mathbf{T}^0)$ of the system evaluated at the reference configuration that describes how small changes in the output of the task-relevant elements are reflected in the magnitude of the performance variable, the corresponding linear approximation is given at each time point by:

$$\mathbf{p}^t - \mathbf{p}^0 = \mathbf{J}\left(\mathbf{T}^0\right).\left(\mathbf{T}^t - \mathbf{T}^0\right)$$

The Jacobian matrix $\mathbf{J}(\mathbf{T}^0)$ is formalized as a matrix of partial derivatives of the performance variable with respect to the relevant task elements. In the present study, obtaining the Jacobian of the systems is not available by differentiation since no analytical kinematic model of the system is available relating the performance variable and the task-relevant elements. Furthermore, the apparent output of the performance variable may not be independently tested for each task-relevant element to infer its contribution to the Jacobian, given that while the players are performing the trial task it is not feasible to independently perturb the player's velocities and observe the corresponding change in θ. Therefore, the estimate of the Jacobian matrix was here obtained using a linear multiple regression method based on the methodology presented by Klous et al., (2010). Considering the dimensionality d=1 for the performance variable, n=2 for the task-relevant elements and t=N, this method assumes the form given by:

$$\left(\theta^t - \theta^0\right) = K_1.\left(v^t_{BallCarrier} - v^0_{BallCarrier}\right) + K_2.\left(v^t_{SupportPlayer} - v^0_{SupportPlayer}\right)$$

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

$$\mathbf{J}\left(\mathbf{T}^0\right) = [K_1 \quad K_2]$$

A critical issue is the multicollinearity of the predictor regression vectors (e.g., the players running line velocities) which 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 may be calculated for each predictor by doing a linear regression of one predictor over the other (Allison, 1999). By obtaining the coefficient of determination r^2 from that regression, the VIF was calculated as:

$$VIF = 1/\left(1 - r^2\right)$$

The variance inflation factor 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) and no upper bound. Higher values of *VIF* reveal higher correlations among predictor variables, leading to unreliable and unstable estimates of the regression coefficients. The UCM subspace was approximated with the null-space of the Jacobian matrix that represents the combinations of task-relevant elements that leave the performance variable unaffected. The null-space is measured by *i*=*n*-*d* basis vectors ε_i, solving the equation:

$$0 = \mathbf{J}\left(\mathbf{T}^0\right).\varepsilon_i$$

For the present study *i*=*n*-*d* =2-1=1, and therefore there is one basis vector ε_1 of the null-space that was computed numerically for each trial using the MATLAB Null function. The vector $(\mathbf{T}^t-\mathbf{T}^0)$ of the deviations of the task-relevant element vector from the reference configuration was resolved into its projection $f_{\|}$ onto the UCM subspace and the component perpendicular $f_{\perp}$ to the UCM subspace, as:

$$f_{\|} = \sum_{i=1}^{n-d} \left(\varepsilon_i^T.\left(\mathbf{T}^t-\mathbf{T}^0\right)\right).\varepsilon_i$$

$$f_{\perp} = \left(\mathbf{T}^t-\mathbf{T}^0\right)-f_{\|}$$

The variance in each of the subspaces var_{comp} and var_{uncomp} normalized by the number of d.f. of the respective subspaces were calculated as:

$$var_{comp} = \sigma_{\|}^2 = \frac{1}{(n-d).N}\sum_{i=1}^{N} f_{\|}^2$$

$$var_{uncomp} = \sigma_{\perp}^2 = \frac{1}{d.N}\sum_{i=1}^{N} f_{\perp}^2$$

The quantification of the functional synergies is obtained by comparing which of these variances is higher, using a ratio *UCM* that evaluates the compensated variance with respect to the uncompensated variance of the subspaces, given by:

$$UCM = \frac{var_{comp}}{var_{uncomp}}$$

In order to meaningfully interpret the UCM results, a methodology was used to quantify the probability that synergies could be created with other configurations of the performance variable dataset. This methodology is inspired by the work of Richardson et al. (2005), which describes the shuffled baselines of synchrony approach applied to the coupling between speakers' and listeners' eye movements. These authors produced a randomized series distribution which is obtained by shuffling the temporal order of the series being analyzed, which is then used as a reference baseline or "at chance" occurrence. In the present work, the developed methodology aims to define a probability of obtaining UCM>1 by a different temporal order (line-up) of the performance variable for a given dataset, i.e., task-relevant elements mutual and reciprocal adjustments may support several configurations of the performance variable values (within the same range). Hence, temporal orders of the performance variable are not required for a synergy to exist. Using the approach from the aforementioned authors, a randomized series distribution is produced by shuffling the temporal order of the performance variable series for each trial dataset. This shuffling corresponds to a surrogate series obtained by the method of Amplitude Adjusted Fourier Transform, which attempts to preserve both the linear structure and the amplitude distribution of the series. Using this series and the same task relevant variables series, a new UCM value is obtained and checked. For different seeds for the randomized series of the same performance variable, occurrence of both UCM>1 and UCM<1 may be observed. Therefore, a probabilistic approach is established using *nr* randomized series distributions for which the number of occurrences of UCM>1 are evaluated. The ratio between this number of occurrences and the total number *nr* of random series distributions used, lead to an estimate for the probability of obtaining UCM>1. For this purpose, an initial value of *nr* is set to 100 and recursively increased in integer multiples (*nr* = 100, 200, 300,…), leading to an evaluation of the probability of obtaining UCM>1 for each number of random distribution series used. The number *nr* of random distributions used is established according to a stabilization criterion for the probability of obtaining UCM>1. This criterion is defined by the slope of the linear regression between *nr* and the probability of obtaining UCM>1 and is met whenever the slope is below a specified slope limit of one degree, consequently interrupting the recursive increase of the number of random distribution series and setting the *nr* value to be used. Additionally, the evolution of the confidence interval for the probability of obtaining UCM>1 with 95% confidence level is evaluated and checked for an expected lower than unit order (10 1) of magnitude for the interval confidence range. The probability of obtaining UCM>1 based on the attained value of *nr* random distribution series is then considered for interpreting the trial dataset value of UCM>1 being obtained based on a different line-up of the performance variable time series. In this regard, high values for the probability of obtaining UCM>1 in the shuffled random distribution series suggest that the UCM>1 value for the trial dataset is obtained by a different line-up of the performance variable, and that a task relevant adjustment may support a synergy with a different line-up (within the same range of values) of the performance variable dataset. Conversely, if low values are achieved for the probability of obtaining UCM>1 in the shuffled random distribution series, it suggests that the UCM>1 value for the trial dataset is obtained only for the current line-up of the performance variable dataset, and thereby that a synergy is obtained due to the adjustment of task-relevant elements for a specific line-up of the performance variable dataset.

Results

Numerous different θ values were found at the moment of the pass, which led us to suggest that θ values are situation specific. This implies that one optimal angle of θ does not exist and that players do not restrict themselves to only one coordination solution. Based on the ball carrier's behavior, the support player should simply manage the "depth" between them aiming to have space in front that allows him to receive the ball while increasing velocity (Biscombe & Drewett, 1998). For UCM>1, θ can assume values between 10° and 51°, and for UCM<1, θ can assume values between 7° and 55° (see Table 1). This means that for any θ value between 10° and 51° a synergy might exist or not, it depends on how players' velocities contribute to stabilize θ values.

To summarize thus far, we propose the value of θ close the moment of the pass as a performance variable for a two-versus-one situation in Rugby Union, which captures players' co-adaptive behavior. Players' running line velocities act as task-relevant elements that seem to stabilize θ under functional specific values.

Multicollinearity of the predictor regression vectors was estimated for the players running line velocities for all trials. The *VIF* reveal low values close to the lower bound (1) (mean=1.06; standard deviation=0.09),which are acceptable for the state purpose of low correlations among predictor variables, leading to reliable and stable estimates of regression coefficients.

UCM results

Concerning θ values close to the moment of the pass, the data revealed that 19 out of 55 trials display UCM values >1, which means that 34% of the trials confirm the existence of an UCM. Therefore, a functional synergy is grounded on the adjustments on the running line velocities between ball carrier and support player that stabilize θ values close the moment of the pass. The remaining 36 trials (65%) display UCM values <1 which suggests that players' velocities are stabilizing other performance variables, but not θ values close to the moment of the pass (Fig. 3).

Table 1 θ values close the moment of the pass

	UCM>1	*UCM*<1
θ Mean	26°+/-10	25°+/-16
θ Max	51°	55°
θ Min	10°	7°
θ Range	41°	47°

Probability of getting a UCM>1 with a different configuration of performance variable dataset

A quartile-based scale was used for the analysis of the probability values of getting an UCM>1. For the trial dataset with the UCM>1, results revealed that only two out of 19 trials display a probability below 25%, which suggest that on these two trials the UCM values did not support a different configuration of the performance variable dataset. For eight out of 19 trials, the probability of getting an UCM>1 were between 25% and 50% (suggesting a moderate probability that the trial dataset with UCM>1 support different configurations of the performance variable dataset). For six out of 19 trials the probability of getting an UCM>1 were between 50% and 75% (a strong probability that different configurations of the performance variable values were supported). Finally, for three out of 19 trials the probability of getting an UCM>1 was above 75% (a very strong probability that different configurations of the performance variable values were supported) (Fig. 4).

Figure 5 displays two representative data trials where a synergy exists expressed through the relative positions of the three players (i.e., ball carrier, support player, and defender). There are two features worth noting: First, the maintenance of interpersonal distance between ball carrier and support player throughout each trial. Second, the decrease in interpersonal distance between ball carrier and defender which highlight how the actions of these two opposing players contrive to release the support player to receive the ball and run free towards the try line (Fig. 5).

Figure captions: Black filled line represents the ball carrier trajectory; black dashed line represents the support player trajectory; the gray line represents the defender trajectory

Discussion

In Rugby Union, the ball carrier and the support player's relative position can form a synergy to enable them to beat a defender and advance to the try line in a two-versus-one situation. To describe this relative position we used an interplayer angle defined as θ. However, descriptive statistics of θ (see Table 1) are insufficient to identify whether a synergy of targeted task-relevant elements exists in order to stabilize a specific performance variable. Instead, the UCM approach is a suitable tool to measure functional synergies in team sports because it can describe how the relation between two task-relevant elements (i.e., players' running lines velocity) stabilizes a specific performance variable (i.e., θ values close the

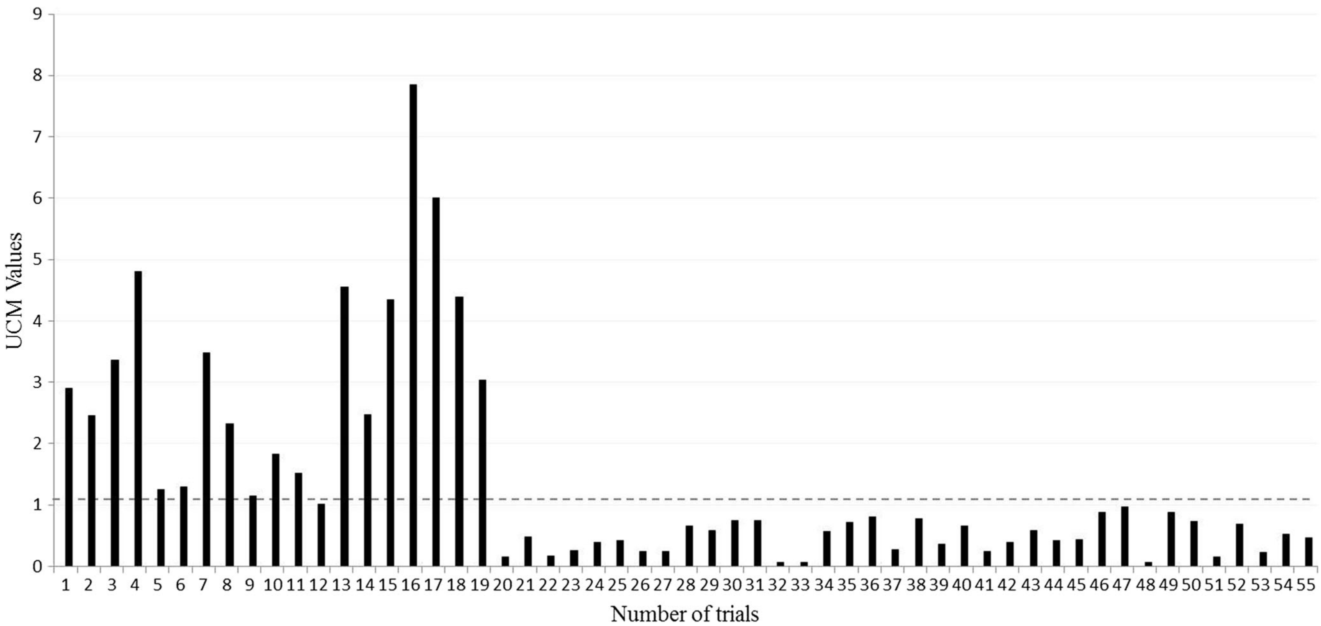

Fig. 3 UCM values for θ close to the moment of the pass

moment of the pass). Despite this novel use of the UCM approach in relation to interactive behavior in team sports other applications of the procedure do exist, the work of Fusaroli and colleagues on linguistic coordination is a suitable example (Fusaroli et al., 2012; Fusaroli, Raczaszek-Leonardi, & Tylen, 2014). Thus, we may suggest that in social systems (as team sports) as long as a reciprocal compensation exists between two task-relevant elements (that use compatible metrics), then UCM can be used.

An important stage was to calculate the probability of getting an UCM>1 with a different configuration of the performance variable dataset. Results revealed that only on two trials the probability of getting an UCM>1 was not supported on a different configuration of the performance variable dataset. This

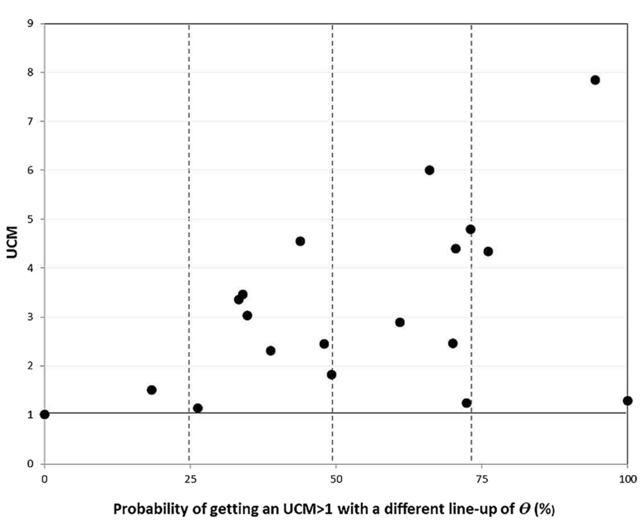

Fig. 4 Probability of getting a UCM>1 with a different configurations of the performance variable values

probability data sustains the hypothesis that the player's velocities reciprocally adjust to stabilize only one configuration of the interpersonal angle values at the moment of the pass. For eight (out of 19) trials results revealed a moderate probability that the UCM>1 support a different configuration of the interpersonal angle dataset. Above 75% there was a strong probability that the formed synergy based on different configurations of the performance variable dataset. These findings indicate that the same adjustment on the player's running lines velocities may stabilize other configurations of data set within the same range of values which reinforces the notion that there is a range of θ values to form a synergy not a specific configuration of θ values. We may conclude that synergies in team sports interactive behavior do not require a temporal order of the performance variable to exist.

We also set out to analyze the coupling strength between trials of the formed synergies. Black and colleagues assume that there is a direct relation between coupling strength and the strength of a synergy (captured with UCM values) (Black et al., 2007). Following this reasoning our results reveal different coupling strengths exist within the dataset. In fact, three different levels of coupling strength can be classified based on the average ($\overline{x}$) and standard deviation (*SD*) of the UCM values (Table 2). The upper limit values for each level, are correspondingly defined by the average $\overline{x} = 3.1 \approx 3$, average plus one standard deviation $\overline{x} + 1.SD = 4.9 \approx 5$ and average plus two standard deviation $\overline{x} + 2.SD = 6.8 \approx 7$.

The data reveal that just over half of the trials (ten out of 19 UCM trials) display a synergy between support player and ball carrier at the moment of the pass with strength of coupling below the average UCM values. Notably, seven trials display a synergy with UCM values above average plus one standard deviation which may be suggested as a "strong" coupling.

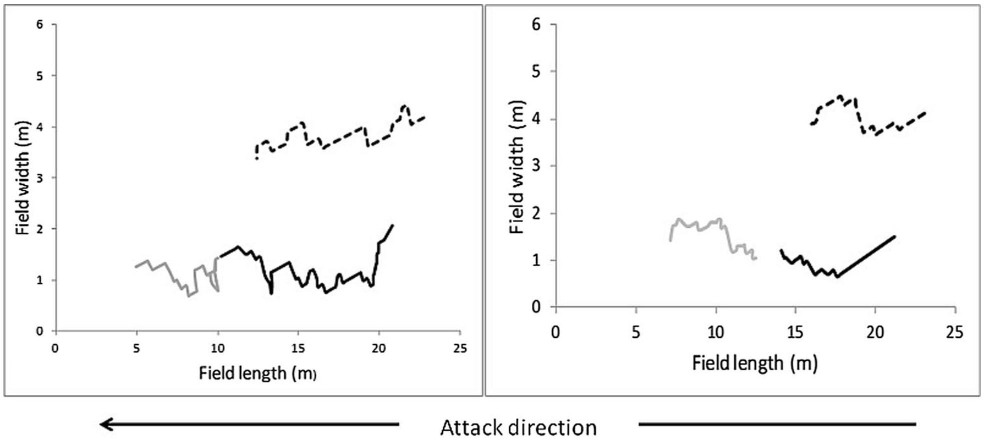

Fig. 5 Players trajectories (x, y) approaching the moment of the pass

These results suggest that if differences exist in the UCM values for the different trials, it is also possible that these differences occur along a trial, meaning that UCM values may change in different moments of the same trial. Black and colleagues also reveal differences in the UCM values for different moments (i.e., initial, middle, final) of a rhythmic cycle movement (Black et al., 2007). Hence, UCM values might change on different time scales, from short and very fast adjustments that occur on each frame of a trial (i.e., 4 ms) but also adjustments that occur on long and slow scales due to learning effects.

Another factor which also should be considered in further research with the UCM on social interactions is the player's expertise level. We suggest different expertise levels may provide different UCM values for the same task. One major difference in expertise levels is the perceptual attunement which is the ability to rely on the most information variables to decide and act (Fajen, Riley, & Turvey, 2009). Learning effects (over long and slow time scales) provide a convergence of the most relevant information variables and consequently an increase in the accuracy of perceptual attunement on interpersonal coordination tasks (e.g., as a two-vs.-one in Rugby Union) which may be the support to form synergies between players. A major issue in a two-versus-one situation in rugby is that the support player aims to have space in front that allows him to receive the ball while running, requiring him to manage the "depth" between himself and the ball carrier. The "depth" between players is managed due to fine adjustments in players running line velocities. Adjustments in the support player running lines velocities are supported by visual information provided by the ball carrier behavior (Black et al., 2007; Schmidt, Bienvenu, Fitzpatrick, & Amazeen, 1998). The strength of an interpersonal coordination synergy is supported by visual information, which means that adjustments in running line velocities are shaped by the visual information provided by players' relative position. Due to practice players may be more fine-tuned to the visual information regarding changes in the other behavior, which provide prospective information that support co-adaptive behaviors than for the information regarding a specific position as the exact moment to perform and receive the pass (Fajen, 2005; Fajen et al., 2009).

Social interactions as team sports are complex, meaning that system behavior is influenced by several variables. Thus the main issue when applying the UCM approach to social systems as team sports concerns identification of criteria that can be used to select the performance variables as well as the task-relevant elements. However, this constraint affords opportunities to test other performance variables and other task-relevant elements. In the present study we delimited our analysis to only one performance solution (i.e., when a pass occurred and a try was scored); however, there are numerous other performance solutions that could and do typically occur when small group dyads are formed (e.g., when a ball carrier fakes a pass and dummies to beat the defender themselves). How other performance solutions impact upon the emergence or decay of synergies between players will be a fruitful topic to future research.

Another important issue for further application of this approach in team sports is the location effect. Black and colleagues stated that variability along the UCM was not uniform across an entire cycle of an interlimb task of moving two hands rhythmically, which means that the strength of the synergy may vary within the movement cycle (Black et al., 2007). We think that the same might happen for a task where two players need to co-adapt to succeed. The non-linear feature of interpersonal coordination tasks may constrain variability along the UCM across an entire trial. This lack of uniformity

Table 2 Classification of coupling strength of rugby synergies

Below $\bar{x}$ $1<UCM<3$	Between $\bar{x}$ and $\bar{x}+1.SD$ $3<UCM<5$	Between $\bar{x}+1.SD$ and $\bar{x}+2.SD$ $5<UCM<7$
10 trials	7 trials	2 trials

leads us to suggest the following issues for further investigation: (i) task-relevant elements stabilize one performance variable but with fluctuations in the synergy strength (i.e., UCM values) across the trial; (ii) task-relevant elements may stabilize different (i.e., two or more) performance variables, that is, in some part of the trial the task-relevant elements may contribute to stabilize θ values, but in other parts of the trial the same task-relevant elements stabilize other performance variables (e.g., players interpersonal distances).

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