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Interpersonal Pattern Dynamics and Adaptive Behavior in Multiagent Neurobiological Systems: Conceptual Model and Data

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ABSTRACT. Ecological dynamics characterizes adaptive behavior as an emergent, self-organizing property of interpersonal interactions in complex social systems. The authors conceptualize and investigate constraints on dynamics of decisions and actions in the multiagent system of team sports. They studied coadaptive interpersonal dynamics in rugby union to model potential control parameter and collective variable relations in attacker–defender dyads. A videogrammetry analysis revealed how some agents generated fluctuations by adapting displacement velocity to create phase transitions and destabilize dyadic subsystems near the try line. Agent interpersonal dynamics exhibited characteristics of chaotic attractors and informational constraints of rugby union boxed dyadic systems into a low dimensional attractor. Data suggests that decisions and actions of agents in sports teams may be characterized as emergent, self-organizing properties, governed by laws of dynamical systems at the ecological scale. Further research needs to generalize this conceptual model of adaptive behavior in performance to other multiagent populations.

Keywords: action, constraints, decision making, multiagent dynamics, self-organization

Studies of behavioral neurobiology have tended to favor closed systems analyses, typical of traditional scientific methods founded on a determinate world view (Glimcher, 2005). Consequently, theories of decision making, planning, and action in motor behavior have typically been founded on the notion that humans construct mental models or representations to frame strategic problems (Maule, Hockey, & Bdzola, 2000). These frameworks suggest that neurobiological behavior occurs through the development of extensive and highly differentiated knowledge structures mapped into memory circuits to expedite functional performance (e.g., Anderson's ACT* theory, 1983; Araújo, Davids, Sainhas, & Fernandes, 2002; Hodgkinson, Maule, & Bown, 2004). In a determinate world, uncertainty is reduced through individuals testing the causal mapping of related phenomena in closed systems. In the early decades of the last century, a challenge to a determinate view of the world was raised by quantum physics and taken up later in the social, psychological, and behavioral neurosciences (Glimcher).

As a consequence, the concept of indeterminacy has begun to gain credence in many open-systems analyses of neurobiological behavior, which have incorporated environmental constraints on action (e.g., Davids, Button, Araújo, Renshaw, & Hristovski, 2006; Gigerenzer, Todd, & ABC Research Group, 1999; Hastie, 2001; Schall, 2001, 2004). Indeterminate systems portray a certain amount of behavioral unpredictability. In such systems, behavior is not an outcome sustained by a single cause–effect relation. Rather, work in neuroscience suggests that behavior always contains a certain degree of uncertainty that is impossible to eliminate, supporting the assumption that humans perceive, make decisions, and act in an indeterminate world (Glimcher, 2005). These developments in the natural sciences have raised important questions for traditional closed-systems modeling of rational decision making, planning, and action founded on classical utility theory used to analyze economic systems (e.g., Bar-Eli, Lurie, & Breivik, 1999; Ranyard, Crozier, & Svenson, 1997).

Indeterminacy has influenced planning and design of robotic platforms and artefactual control systems. Traditional sense, model, plan, act principles are being complemented by behavior-based control approaches in engineering systems to produce complex controllers of multiple agents operating in unpredictable, dynamic environments, such as during terrain exploration, process manufacturing, and playing in robocup soccer competitions (e.g, Mataric, 1998). Some research has shown how insights on self-organizing collectives could be implemented in the design of control systems for multiagent interactions (e.g., Davids et al., 2006; Di Paolo, 2002; Paine & Tani, 2005; Sumpter, 2006). For example, indeterminacy features strongly in the development of *situated robotics,* a design platform for multiagent robotic and artificial intelligence systems informed by theories of neurobiological perception, planning, and action to support dynamic interagent interactions in complex performance environments.

A theoretical rationale for modeling decisions and actions of interactive agents in complex organizations can also be framed in ideas from evolutionary biology, complexity sciences, ecological psychology, and nonlinear dynamics (e.g., Araújo, Davids, Bennett, Button, & Chapman, 2004). These ideas propose that perception, cognition, decision making, and actions emerge as each individual agent in a complex system interacts with other agents and can be revealed in humans through studying their behavioral interactions in specific performance contexts. In multiagent dynamical systems, such as work organizations and sports teams, a most

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important source of information constraining the perceptions and actions of individuals is provided by other interacting agents (e.g., Marsh, Richardson, Baron, & Schmidt, 2006). Collective agent performance contexts of sports provide a particularly useful testing ground for indeterminacy of adaptive behavior to understand how emergence of cognition, decision making, and actions supports intentional behavior in complex, adaptive neurobiological systems functioning in such dynamic environments (see also Araújo, Davids, & Hristovski, 2006; Turvey & Shaw, 1995, 1999; van Orden, Holden, & Turvey, 2003).

Emergence is a collective property of any open system (e.g., an attacker–defender dyadic system in team sports), not uniquely possessed by any of the individual parts (i.e., the players), that leads to the spontaneous appearance of coordinated patterns of behavior (Kauffman, 1995). From this viewpoint, emergent coordination tendencies are a collective property of dynamic systems of interacting agents (e.g., dyadic attacker–defender dyads in team sports such as rugby union). As Kauffman pointed out, "No vital force or extra substance is present in the emergent, self-reproducing whole. But the collective system does possess a stunning property not possessed by any of its parts" (p. 24). These ideas are harmonious with outcomes of work by Richardson, Marsh, Isenhower, Goodman, and Schmidt (2007) who suggested that in everyday behavior, an individuals frequently coordinate their own decisions and actions with the decisions and actions of other individuals. These interpersonal coordination tendencies underlie performance in everyday activities such as dancing, rowing a canoe, or merely walking and talking with friends. Although coordination of this sort is sometimes intentional and explicitly achieved through physical contact (e.g., when individuals are playing a ball game), it can also be unintentional and occur throughout a visual interaction. From a dynamical systems perspective, visually mediated interpersonal coordination tendencies, despite being intentional or unintentional can be understood as a self-organized process (Richardson et al.).

Although the experimental design Richardson et al. (2007) used was based on noncompetitive intentional and unintentional coordination tasks, it is clear that these ideas have implications for the study of multiagent interpersonal dynamics in competitive performance settings. In this article, our purpose is to conceptualize and test a model of interpersonal dynamics that can be used to describe emergent decision making, planning, and actions in multiple agents engaged in competitive tasks within performance contexts like team sports. For this purpose, we examined the model's utility by investigating the pattern forming dynamics of multiagent interactions that evolved in during 1:1 subphases ubiquitous to most team sports.

A Conceptual Model to Describe Dyadic System Dynamics in Rugby Union

Emergent dynamics of component interactions in complex adaptive systems under constraints have been studied for some time (see Bak & Chialvo, 2001; Kauffman, 1993; Sumpter, 2006). Kauffman's modeling of evolutionary processes from the perspective of spontaneous self-organizing system dynamics provides valuable insights on interpersonal dynamics in complex social systems (e.g., industrial organizations, academic institutions, team games). Self-organizing dynamics lead to system behaviors that evolve over time without little direct external influence (e.g., a coach's prescriptive instructions) and are only sustained by information created by the interactions amongst system agents (e.g., the players in team games). In such systems, varied patterns of behavior can emerge as individual agents coadapt their actions to achieve specific outcomes or goals. Coadaptation occurs when system agents make behavioral adjustments to functionally adapt to the behaviors of other agents. Rich interpersonal interactions can spontaneously emerge when previously uncorrelated agents or processes suddenly become interconnected and entrained under constraints (Guerin & Kunkle, 2004; Juarrero, 1999; Kauffmann, 1995). The process of coadaptation has been used to explain how sophisticated biological systems evolve and adapt their behaviors and morphological structure to satisfy evolutionary constraints. The latter include local constraints posed by neighboring agents that are manifested in variability in (a) system developmental trajectories over time, (b) the rate of progression of such developmental processes, and (c) the cessation of specific developmental processes. Research has demonstrated how these evolutionary constraints might lead to changes in system outcomes over time (Kauffman, 1993).

The ideas behind coadaptive moves under constraints in evolutionary systems have considerable relevance to the understanding of interpersonal dynamics at different levels of complex multiagent collectives because of the scale invariance of key properties exhibited by such systems. Many complex systems in nature display self-similarity at different levels because of their fractal characteristics (e.g., Solé, Manrubia, Benton, Kauffman, & Bak, 1999). In informal terms, fractal systems comprise component parts, which are smaller copies of the whole system. Because of the fractal nature of complex systems, the principle of universality implies that the local interactions of constituent components in subsystems can emulate the global interactions of the whole system at critical points in environmental exchanges (Bak & Chialvo, 2001; van Orden et al., 2003). These ideas imply that regardless of whether one is studying global patterns of interactions of all agents in an organization or the local interpersonal dynamics of two key individuals constrained to function in a subsystem, behavior is an emergent property of each system's dynamics.

Modeled as dynamical systems, multiagent systems such as sports teams also exhibit important characteristics such as complexity and metastability (i.e., partially coordinated tendencies in which individual coordinating elements are neither completely independent [local segregation] nor fully linked in a fixed mutual relation [global integration]; Oullier & Kelso, 2006) because of the potential for interactions to emerge between system components (i.e., performers) over time (e.g., an attacker and a defender are two components of a dyadic system in 1:1 subphases; Guerin & Kunkle, 2004; McGarry & Perl, 2007; Passos, Araújo, Davids, Gouveia, & Serpa, 2006; Schmidt, O'Brien, & Sysko, 1999). The behavior of metastable complex systems is influenced by multiple variables that may produce multiple effects leading to such systems being poised in dynamically stable states and open to constraint.

Complex systems are bounded by two categories of constraints that alter the decisions and actions of agents over time. These include first order contextual constraints (Juarrero, 1999; e.g., a specific environmental constraint that decreases randomness in behavior and simultaneously increases the potential of the system to explore new sources of information). In team sports, such as football, rugby union, and basketball, the relative positioning of an attacker with the ball and a marking defender near an important target area (e.g., a goal, tryline, basket) is a typical 1:1 situation. The actions and decisions of dyadic subsystems of team games, comprising an attacker and a defender, are externally regulated by boundaries of the information fields geared by first order constraints, such as performance area dimensions, interpersonal distance between players, boundary markings, and rules of the game. These constraints increase the likelihood that specific actions will emerge, such as an attacker selecting a particular running trajectory to make a score instead of running randomly across the field or a defender committing to a tackle at a specific location approximate to the try line in rugby union.

But interacting agents in organizations also operate under social constraints, and behavior can emerge out of fluctuations created by the dynamics of the interdependent agents in the system. Self-organization tendencies of complex social systems lead to the emergence of second order constraints on behavior (Juarrero, 1999). Self-organization occurs because complex systems have a predisposition to organize and display specific coordination tendencies sustained by information resulting from the interactions amid system agents (e.g., interactions of the players in team games). Under this type of constraint, random interactions between system components can alter into more organized forms of interactions as one key system parameter (a control parameter) changes in value. When a critical control parameter value is achieved, rich variations in behavior in complex systems can emerge. A *control parameter* has been defined as any variable that can lead a system through a variety of different patterns or states (see Kelso, 1995). Near the critical state (i.e., a state to which a system evolves so that it is poised for a transition; Bak, 1996) interactions between agents and nearest neighbors can become correlated, in a type of domino effect, capturing global system interactions and leading to a sudden reduction from multiple options to one. In the critical state, a slight change in circumstances characterizing near neighbor interactions will break the balance of equally poised options leading to a transition in system order. Criticality provides the platform for a functional mix of creativity and constraint to support decision making in dynamic performance environments. It affords opportunities for rich and varied patterns of behavior to emerge, which can fit newly arising circumstances. Therefore, in complex organizations, the probability of an event depends on and is altered by the localized emergent interactions of agents, a process known as conditioned coupling (van Geert, 1994). Over time, the actions of social system agents become systematically related and their intentions do not make sense if separated from each other's actions, an idea with profound implications for studying decision making in organizations (Kauffmann, 1993).

Coadaptation and System Evolution as a Model of Emergent Decision Making in a Rugby Union Dyad

These insights of Kauffman (1993), Kelso (1995), Juarrero (1999), and Marsh et al. (2006) led us to conceptualize how behavior may emerge from two agents mutually entrained in a subsystem (e.g., attacker–defender dyad) in the performance context of the team sport of rugby union. In our model, we characterized an attacker–defender dyad in team games as a complex dynamical system displaying chaotic features (i.e., nonlinear behavior, unpredictable outcomes, sensitivity to initial conditions) with three attractor states toward which system components might converge over time. Kauffman defined an attractor state as "a set of points or states in state space to which trajectories within some value of state space converge asymptotically over time" (p. 177). State space is a vector space where any dynamical system (e.g., an attacker–defender dyadic system in team sports) can be defined at any point (Abarbanel, 1996). For example, in the team sport of rugby union, these ideas suggest that attractors in dyads may be defined as preferred states of coordination to where a system converges over time (e.g., a try being scored by an attacker, a successful tackle by a defender). Despite different individual constraints, both agents in a dyadic subsystem in the team sport of rugby union (i.e., the players) are attracted to the space available in front of them. Despite the individual trajectories that each player may adopt, the subsystem will always converge toward the three attractor (i.e., preferred) states mentioned previously. In the initial stable state of the subsystem, the defender starts closest to the try line and if the attacker passes the defender, the subsystem organization is destabilized. For example, when a try occurs, the dyad structural organization changes or the connection between the agents changes (i.e., nonphysical to physical; e.g., when an effective tackle happens, when a tackle occurs and the attacker passes the defender).

A critical feature observed in chaotic systems is the divergence of trajectories in state space because of sensitivity to initial conditions (Ruelle, 1978), signifying that slight differences in the performance contexts may lead to substantial differences in subsequent behavior of the system (Kauffman, 1993; Brown, 1995). In rugby union, each agent's behavior is initially regulated by first-order contextual constraints such as the performance area dimensions and boundary markings, the rules of the game, and each player's personal goals (i.e., attackers are seeking to score tries and defenders aim to successfully tackle opponents to stop them scoring tries at a basic level). During the approach phase in 1:1 subphases of rugby union, there exists a relative independence of both players' decisions and actions, and one player's actions will not directly affect the actions of another in a dyad. But, to achieve their personal tactical performance goals (e.g., score a try, defend the try line), the flow of trajectories pulls the players in this dynamical system toward a region in state space where the dyadic system is poised for a transition, the so-called region of self-organized criticality.

In practical terms, the agents' interactions attract each other (because of decreasing interpersonal distance) to a critical region of the field where the decisions and actions of each player no longer remain independent. A decrease in interpersonal distance is inversely associated with each player's relative dependence and characterizes the 1:1 performance context in rugby union. The implication is that as players get closer to each other (i.e., because of a decrease of interpersonal distance), the decisions and actions of each individual player in the dyad become more dependent on decisions and actions of the immediate opponent in the dyad. Because of the emergence of second-order constraints, attacker–defender behavioral dependence is an emergent property of dyadic systems, which means that a new behavioral repertoire becomes available to the dyad functioning as a system.

Despite the many different trajectories available to rugby union players, second-order contextual constraints that emerge during this phase typically box the attacker–defender subsystem toward one of three possible attractor states: (a) Physical contact takes place but the attacker does not pass the defender and initial system organization is preserved. However, the type of connection between the dyad agents changes (from nonphysical to physical), resulting in the system entering a new phase in the self-organizing, emergent process. (b) Physical contact takes place and the attacker passes the defender. Because of physical contact, the type of connection between the dyad agents changes, but the main difference between this new emergent state and the previous one is that a change in within-system organization occurs and the attacker is now the player closest the try line. Or (c) the attacker passes the defender without physical contact and the connection between the two players remains nonphysical. However, the dyad undergoes a phase transition because the players' within-system structural organization changes with the attacker now closer than the defender to the try line.

This conceptual modeling shows how cognition, decision making, and action in dynamic performance environments may emerge because of shared interactions by coupled system agents. Self-organization under constraints is characterized by system agents becoming systematically reorganized in qualitatively novel ways with changes in connection type or structural organization among components of the system (Juarrero, 1999). This conceptualization of the dynamics of interpersonal interaction in the performance context of team games led us to empirically investigate the conceptual model in a study of dyadic system behavior in 1:1 subphases of rugby union.

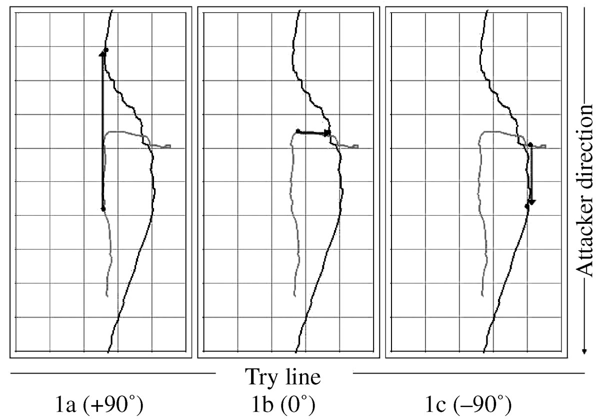

FIGURE 1. Defender–attacker vector with the attacker trajectory represented with a black line and the defender trajectory represented with a gray line. Three different positions (1a, 1b, and lc for angles of 90°, 0°, and −90°, respectively) of the collective variable, which is represented by the continuous black arrow, are shown.

Model Measurement

To study interpersonal dynamics of decision making and action in attacker–defender dyads in team sports, we first identified a collective variable that accurately described dyadic system behavior: a vector connecting each agent in the dyad. The values for this collective variable were calculated from the angle between the defender–attacker vector and an imaginary horizontal line parallel to the try line with the origin in the defender's position. This analysis method resulted in an angle close to 90° before the attacker reached the defender and close to −90° if the attacker successfully passed the defender, with a zero crossing point emerging precisely when the attacker reached the defender (see Figure 1). As a result of the players' interactions, the defender–attacker vector will change over time, with the values of this angular relation providing a potential collective variable to capture system behavior.

Next, we plotted the first derivative of the collective variable over time. The aim of this calculation was to analyze the rate of change of the relative positioning between an attacker and defender in a dyadic system. When an attacker achieves greater relative velocity of movement than a defender, the first derivative values increase with the distance to the minimum (i.e., 0°/s). Alternatively, when a defender's relative velocity is greater than an attacker's, the first derivative values tend toward the minimum. When there are no differences between the players' relative positions, the first derivative values tend toward 0.

We hypothesized that the divergence of running speed (i.e., players' velocity) between attacker and defender in the region before the zero crossing point is a key constraint on the stability of the dyad, leading the system to one of the attractor states previously identified. This prediction was sustained by experiential knowledge of the performance context of rugby union as well as by the expertise of elite coaches (e.g., John Haggart, Otago Highlanders, New Zealand Super 14s team defense coach, personal communication, August, 2005).

We also incorporated the use of nonlinear dynamical tools to analyze dyadic system behavior over time. Brown (1995) demonstrated how dynamic behaviors of a system can be illustrated using phase space plots (i.e., a representation of the state of the behavior of the dynamic system in state space; N. Stergiou, Buzzi, Kurz, & Heidel, 2004). Consequently, we followed the method suggested by Stergiou et al. to examine the dynamic behavior of a system from time series data in which researchers investigate the structural characteristics of that time series. To achieve our aim, we needed to plot the system state space. Juarrero (1999) defined *state space* as a representation of a system's current potential: Each possible state of the system is represented as an intersection of coordinates, a point or region in two, three, or, more likely, multidimensional space (i.e., where a system's dynamical behavior is represented by multiple variables). At any instant in time, the relative positioning of both agents in a dyad could be represented in state space by a single point. After a small time interval, each player's position will slightly alter due to his or her actions, which implies that the representative point can move to a new point in system state space. Over time, the movement of the representative point along a succession of new points can be traced by a smooth line displaying the trajectory of the dyadic system in state space. These plots allowed us to observe the functional structure for the three visually different possible states of the system and to identify patterns in the evolution of the continuous flow of the system.

Because of the nonlinear nature of our time series, we decided to use statistical methods of analysis appropriate for analysis of outcomes of nonlinear dynamical systems, such as approximate entropy (ApEn). Pincus (1991) suggested that parameter estimation methods such as ApEn could be used as a tool to measure the complexity of a system and also as a measure of regularity or predictability of a time series. In line with these ideas, we calculated ApEn for each time series observed in the movements of attackers and defenders in the dyads. The decision to use ApEn instead of other nonlinear tools such as the Lyapunov exponent and correlation dimension was made on the basis of previous work by Stergiou et al. (2004), who suggested that the former provided a greater level of statistical accuracy in studying behaviors of neurobiological systems in which a mix of stochastic and deterministic processes are typically observed (see van Orden et al., 2003).

Method

In the present study, the method for studying interpersonal interactions of 1:1 attacker–defender dyads in the team sport of rugby union was based on techniques articulated by Passes et al. (2006). Participants were 8 male rugby players aged 11–12 year *(M* age = 11.6 years) with an average of 4.0 years of rugby practice (*SD* = 0.5 years). We decided to investigate such young players to prevent the confounding effects of expertise and different amounts of learning from contaminating the data (cf. Zanone & Kelso, 1994). The participants had competed at the highest national competition levels for their age group. Despite this level of experience, the emergent patterns of behavior that they displayed were not the result of prelearned sequences established through years of training because these players had not had enough time in practice to assimilate and stabilize such prelearned sequences. Because of their age-related experience levels, the behavioral patterns of the players can be considered emergent properties of the interpersonal interactions in the dyads (cf. Schmidt et al., 1999). To plot players' interactions, we designed a task that simulated a subphase of the team sport of rugby union with the least number of players involved (i.e., the ubiquitous 1:1 situation near the try line). In this subphase, an attacker needs to run beyond a defender to score a try, whereas a defender needs to keep the attacker and ball in front of him or her. The experimental task was performed on a field of 5 m width $\times$ 10 m depth. To prevent contaminating effects of fatigue on performance, we decided to observe each dyad for three trials, allowing us to observe responses of 48 different dyads.

To capture players' movements, two digital video cameras were used to record trajectory motion data. The angle between the cameras varied between 60° and 120° to record motion data (Bartlett, 1997). For image treatment, we used the software TACTO 7.0, digitized at 25 frames per second (Fernandes & Malta, 2007). Artificial neural networks (ANNs) were used as a procedure to transform the extracted coordinates into real-world coordinates (see Passes et al., 2006). An ANN is an information processing system with parallel distribution and a tendency to store experimental data to make it available for future use (Haykin, 1994; Smith, 2001; Stergiou & Siganos, 1996).

Dependent Variables

As stated, the values for this collective variable were calculated on the basis of the relative position of the players as presented in Figure 2 and the trigonometric definition of sine. The collective variable is defined at time (*t*) by

$$\theta_{(t)} = \arcsin\left(\frac{y_{attacker} - y_{defender}}{\sqrt{\left(x_{attacker} - x_{defender}\right)^2 + \left(y_{attacker} - y_{defender}\right)^2}}\right)_{(t)}$$

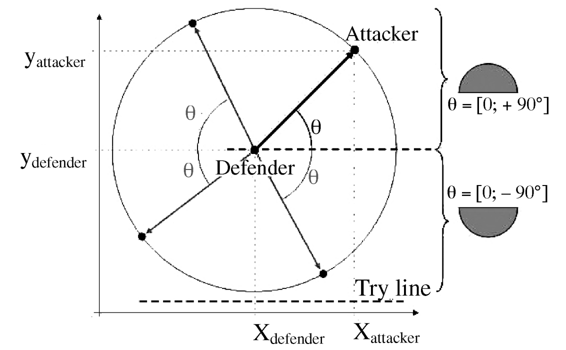

FIGURE 2. Diagram of the calculation of the collective variable.

With this method, the angle would be close to 90° before an attacker reaches a defender and close to −90° after an attacker successfully passes a defender. The zero crossing point occurs exactly at the moment when an attacker reaches the defender's position on the field (see Figure 1). We made this choice because if no obstacle to progression on the performance field is present, attackers in team games will choose the shortest trajectory from their current position to a try line. Therefore, angle values closer to 90° signified that attackers remained on an imaginary straight line perpendicular to the try line, which indicated whether one player in the dyad was closer to the try line than the other. A decrease in angle values signaled that the attacker was attempting to break system stability and pass the defender. After a zero crossing, a decrease in angle values occurred, signifying that an attacker was approaching the try line at a faster rate than a defender in the dyad. However, when an attacker passed the defender, two events could occur: (a) There was no contact between players or (b) contact between the players occurred. Therefore, a continuous decrease in angle values, up to approximately −90°, reflected that the attacker passed the defender and moved toward the try line without further contact, increasing interpersonal distance values and decreasing the distance to the try line. This behavior of the angle value over time was typically associated with try scoring outcomes from the dyadic system. However, fluctuations in angle values over time would be observed when contact between the players occurred. This fluctuation could stop when a tackle occurred or, alternatively, when an attacker managed to avoid contact with a defender.

If the angle values never reach 0°, this system behavior signifies that the attacker did not pass the defender, an outcome usually associated with an effective tackle by the defender.

First Derivative Analysis

The analysis of the first derivative data for each performance situation allowed us to characterize the rate of change of relative position between attacker and defender when three different performance outcomes were observed in the dyadic interactions: (a) when an attacker destabilized the dyad to successfully score a try, (b) when a defender successfully tackled the attacker to maintain system stability, and (c) when a defender unsuccessfully tackled an attacker. This value is obtained using central finite differences approximation of derivatives, for a given time t and a time increment Δt. The first time derivative of the collective variable is

$$\frac{d\theta_{(t)}}{dt} = \frac{\theta_{(t+\Delta t)} - \theta_{(t+\Delta t)}}{2 \cdot \Delta t}$$

We used a time increment of 0.04 s on the basis of the time increment between the images of the video captured at 25 frames per second.

The first derivative of the collective variable was plotted as a function of time, and this procedure allowed us to analyze how quickly the players changed their relative positions over time. If the values remained at 0 m/s, this outcome signified that there were no changes in the players' relative position. On the contrary, any change in the players' relative positions led to fluctuations in the first derivative values. An increase in the magnitude of first derivative fluctuations may be interpreted to suggest that the system was approaching a self-organized state of criticality poised for a transition. A sudden decrease in first derivative values meant that the players were changing their relative positions quickly. This situation is consistent with observations of clean try situations. Every time the first derivative values got closer to 0 m/s, this value signaled that the players maintained their relative positions. This situation is usually consistent with successful tackles where defenders are able to counterbalance the attacker's decisions and actions. To observe this behavior of the system, we plotted data for time on the x axis and first derivative data on the y axis. The lowest value achieved is the inflection point, signifying the moment when an attacker passed a defender.

Phase Space Plot

The phase space plot is a representation of the behavior of the dynamic system in the state space (Stergiou et al., 2004). To plot the state space of rugby dyads, we calculated values of defender–attacker vectors (i.e., the collective variable) on the x axis and their first derivative (i.e., x′) on the. y axis. According to Brown (1995), phase space is a graphic depiction that can be used to identify the existence of chaotic attractors in a time series, and this procedure is valuable to reconstruct the shape of chaotic attractors for visual inspection, even in the presence of substantial noise. A *chaotic attractor* refers to a set of points to where a dynamical system can converge over time that displays sensitivity to initial conditions. Because of this feature in dynamical systems, the effects of small amounts of variability on system behavior are amplified. Once sufficiently amplified, the variability determines the system's large-scale nonlinear behavior and the outcome then becomes more unpredictable. The use of these nonlinear tools allows a variability and complexity analysis for each coordination pattern. Phase space displays the structural characteristics of each coordination pattern. The trajectories performed in phase space could acquire distinctive shapes. In this study, our focus was on the pattern display, such as when it was random (e.g., no clear pattern due to high variability and increased complexity) or more periodic (e.g., when clearly it is possible to observe the beginning and the end of each time series). More periodic patterns signify less complexity because of few constraints influencing system behavior.

Approximate Entropy

ApEn measures the logarithmic probability that a data time series displays similar features in any subsequent incremental comparison within the state space of an observed system (Pincus, 1991). Approximate entropy can be defined as “a specific method to determine complexity that can quantify the regularity or predictability of a time series” (N. Stergiou et al., 2004, p. 76). This measure of the complexity of system behavior was calculated over the values of the collective variable using MATLAB software (Version 6.5.0.180913a). To calculate ApEn, as suggested by N. Stergiou et al. in all studies of neurobiological action, the two input parameters, *m* (i.e., the number of observation windows to be compared) and *r* (i.e., the tolerance factor for which similarity between observation windows is accepted) presented values of $m = 2$ and $r = 0.2$. Higher values of ApEn (i.e., close to 2) signified more complexity and less regularity and predictability, whereas lower values of ApEn signified less complexity and more regularity and predictability.

In this study, collective variable time series data associated with each trial have different lengths, which necessitate a normalization procedure to allow comparison of their ApEn values. For this purpose, original time series data were normalized with a set of random time series that were calculated to provide the maximum value of ApEn. For each trial, and because ApEn values are asymptotically normal (Pincus, 1991), 100 normally distributed random time series were generated with the same data length as the original time series. A ratio was calculated, defined by the ApEn for the original time series divided by the average of the ApEn values in the random time series. The obtained ratio corresponded to a normalized ApEn value that was suitable to be compared among collective variable time series with different data lengths.

Dedicated routines were written in MATLAB for this purpose, using some functions written by Kaplan and Staffin (2009).

Results

In the present study, we examined patterns of interpersonal dynamics in 1:1 attacker–defender dyads in rugby to test a

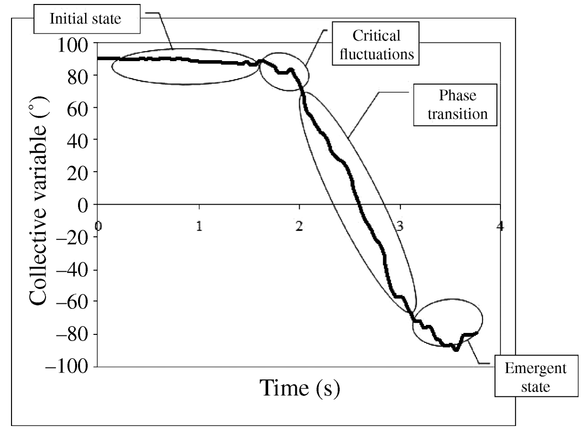

FIGURE 3. Four phases of a self-organized process with the angle of defender–attacker vector values in degrees (black line): initial state phase, critical fluctuations phase, phase transition phase, and emergent phase.

conceptual model of emergent decision making and action, which self-organize under constraints.

Collective Variable

Results are presented in two levels of analysis: (a) identification of several phases of a self-organization in attacker–defender dyadic systems in rugby union and (b) description of three visually different outcome situations that could emerge from an attacker–defender behavior in rugby union. In graphical format (Figure 3), four phases of a self-organized process can be identified in the data: (a) the initial state of order, (b) the critical fluctuation phase, (c) a phase transition, and (d) the emergent state.

The different curve shapes observed (See Figure 4) allowed us to classify three visually different situations, and this graphic displayed exemplar data from analysis of one trial each when (a) a clean try where contact between an attacker and a defender did not occur, (b) an unsuccessful tackle occurred and the attacker passed the defender, and (c) an effective tackle was made by the defender moving the attacker backwards.

The initial state of order was characterized by an approach phase with the maintenance of defender–attacker horizontal angle values because the attacking players kept the running line straight. In the critical fluctuations phase, there was evidence that a decrease in interpersonal distance led to some changes in running line, with the attacker aiming to avoid contact with the defender and using technical skills to explore the subsystem’s stability, provoking some fluctuations in angle values. These changes in running line can be construed as evidence of perturbations within the dyadic system because of local interpersonal interactions. This is an emergent process constrained by the information field created by a decrease in interpersonal distance between the attacker and

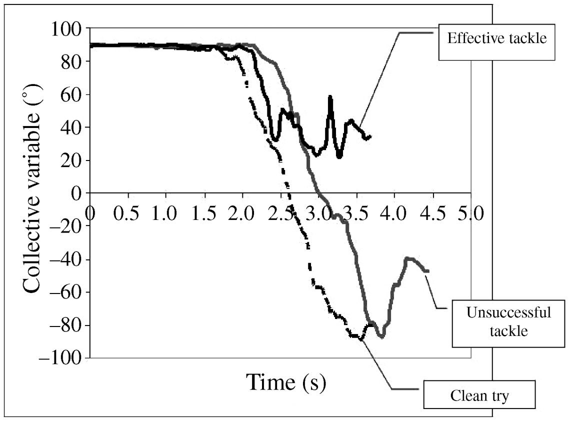

FIGURE 4. Three different situations shown with angle of defender–attacker vector values in degrees: clean try situation (black dashed line), unsuccessful tackle (gray line), and effective tackle (black line).

defender. Figure 4 shows that during a clean try, the approach phase finished at 1.6 s and 88.62° of the collective variable values; during an unsuccessful tackle by the defender, the approach phase finished at 2.12 s and 89.45°; and last, during an effective tackle, the approach phase finished at 2.08 s and 86.23°. In a range from 0 to 90°, a difference of 3.22° in the values of the collective variable that characterized system initial conditions (see Figure 4) corresponded to a 3.5% difference. This sensitivity to relative differences in initial conditions led to huge differences in the final outcomes of dyadic interactions.

As stated previously, a continuous decrease in defender–attacker horizontal angle values after zero crossing signified that a try occurred (see Figure 4, black dashed lines). Fluctuations (i.e., variations) in angle values signified that contact between the players took place. This interpretation was sustained by the assumption that the attacker (after a zero crossing) followed a straight line trajectory as the fastest way to get to the try area, a decision that led to angles values close to −90°. However, in tackle situations, when a defender's actions put an attacker on the floor, the angle value usually remained approximately at −50° (see Figure 4, gray line). Last, in effective tackles (see Figure 4, black line), the horizontal angle never reached 0°, signifying that the attacker never passed the defender.

As we have already noted, the openness of the dyadic systems and their sensitivity to initial conditions led to differences in the final reorganization of the system: (a) data in Figure 4 (see black dashed line) illustrate how the system was attracted to lower values of collective variable, to a zero crossing and then continuously decreasing to approximately −90°, which meant that the attacker passed the defender and a new state of subsystem order emerged; (b) in Figure 4 (see gray line), data show how the system was attracted to lower values of the collective variable, to zero crossing and after that decreasing in a nonlinear fashion until the final values close to −50°, signifying once again that an attacker passed a defender; and (c) these values of the collective variable suggested that contact between players took place in Figure 4 (see black line), the lowest values of the collective variable never reached 0°, illustrating that a successful tackle occurred and an attacker never passed the defender.

First Derivative Analysis

Figure 5 displays exemplar data (collective variable and first derivative) from analysis of a single trial when (a) a clean try occurred without contact between an attacker and a defender (Figures 5A and B), (b) an unsuccessful tackle was made in which the attacker passed the defender (See Figures 5C and D), and (c) an effective tackle was made which stopped the attacker from passing the defender (See Figures 5E and F). In the exemplar clean try situation (See Figures 5A and B), the majority of dyadic activity occurred between 1.5 and 2.5 s after the initiation of the trial. Within this time interval, there was no zero crossing and the inflection point occurred at 2 s with a value of −600°/s. For the unsuccessful tackle situation in which an attacker passed a defender (See Figures 5C and D), we observed several zero crossings between 2 and 2.8 s after trial initiation, followed by a period with no zero crossings between the 2.9 and 3.5 s. During this period, the inflection point occurred at 3.3 s with a value of −400°/s.

In the effective tackle (See Figures 5E and F), exemplifying when an attacker did not pass a defender, we observed several zero crossing situations. It was not possible to identify a single inflection point, although the slowest value achieved was −300°/s. Changes in first derivative values observed in this study may have been due to attackers changing the running line to avoid being tackled by the defender. Every time the values neared 0° the players' relative positioning remained stable. In these situations, the defender maintained system stability by successfully counterbalancing the attackers' decision and actions, an example of coadaptive moves in the interpersonal dynamics of the dyad. Alternatively, when values were far from 0°, players had altered their relative positions. In these situations the attacker had the ability to increase locomotion velocity to create the fluctuations needed to destabilize the system, allowing him to pass the defender. If the attacker and defender velocity values were close, the relative position of each player did not undergo a substantial change. The players could annihilate each other's actions as occurred in an effective tackle (See Figures 5F). However, if the players' relative positioning changed because of an attacker's velocity being higher than the defender's, then the attacker passed the defender as in a clean try situation or even in an unsuccessful tackle when the attacker passed the defender (See Figures 5A and B and 5C and D, respectively).

Based on the collective variable graphics, we identified the moment when the attacker decided to advance and pass the defender. At this point, the collective values suddenly

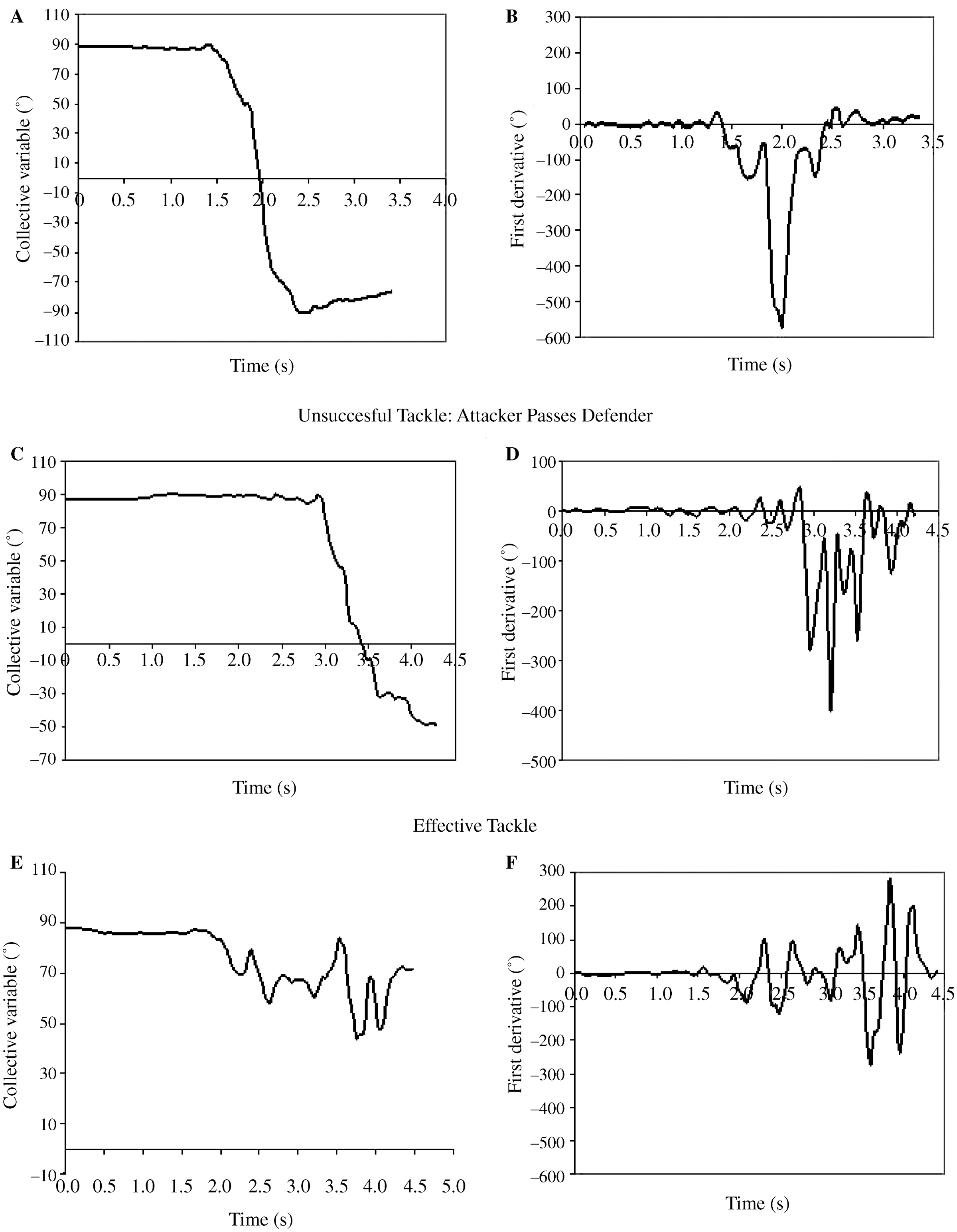

FIGURE 5. (A) Collective variable shown as clean try, (C) tackle but the attacker passed the defender, and (E) effective tackle. (B) First derivative shown as clean try, (D) tackle but the attacker passed the defender, (F) and effective tackle.

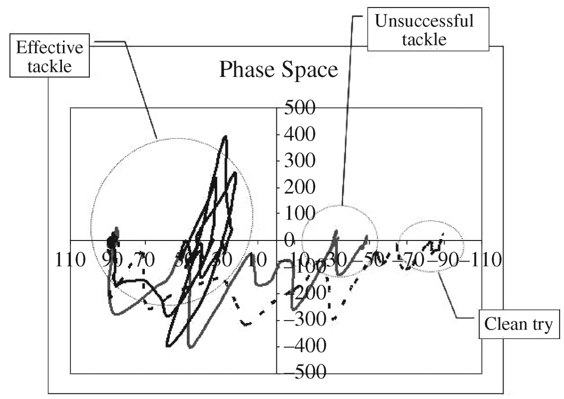

FIGURE 6. Phase space plot where the *x* axis represents the defender–attacker vector values (i.e., collective variable) and the *y* axis represents the first derivative. Black line represents an effective tackle, gray line represents a tackle where the attacker passes the defender, and the black dashed line represents a clean try when no contact occurred.

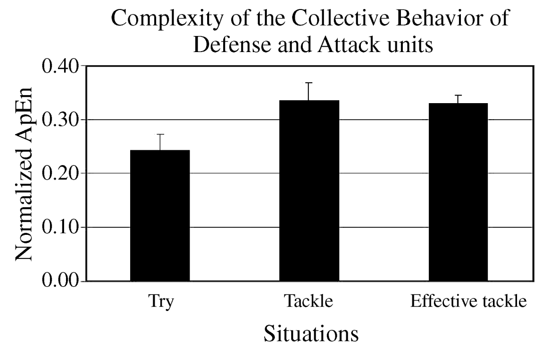

FIGURE 7. Mean and standard error bars of the normalized approximate entropy (ApEn) for each situation.

decreased until the zero crossing (in a clean try and tackle context in which the attacker passed the defender) or the first inflection point (in the effective tackle).

Phase Space Analysis

In these plots, each of the curves is an exemplar representative of specific dyadic system performance outcomes (i.e., a try, an unsuccessful tackle, an effective tackle). From the plots, three visually different structures in state space can be observed: (a) a try situation (See Figure 6, black dashed line) where the collective variable achieved values close to $-90°$ degrees, (b) a tackle took place but the attacker passed the defender (See Figure 6, continuous gray line) and the collective variable values stayed between 0 and $-50°$, and (c) when the attacker did not pass the defender (i.e., when an effective tackle took place; see Figure 6, continuous black line) and the collective variable values remained positive in the neighborhood of 50°. In these trials, we observed that in a dyadic system, slight differences in initial conditions (see Figure 4) led to major differences in the final system state. The systems exhibited huge differences in emergent trajectories. The try situation (Figure 6, black dashed line) ended after the system flowed to almost the entire range of collective variable values. In the tackle situation (See Figure 6, continuous gray line), the system trajectory ended on the right side of the graph after zero crossing, contrary to an effective tackle (Figure 6, continuous black line) where the loop remained on the left side of the graph. These findings show how a dyadic system in rugby union can behave as a chaotic attractor. A second observation is that the attacker–defender subsystem in this team game exists in a high dimensional state space, meaning that the system can be influenced by a huge number of variables (e.g., physical and physiological characteristics of dyad members, emotions and cognitions, game states, weather conditions, playing surface).

Because of the nonlinear characteristic of the time series data and in accordance with observations by Stergiou et al. (2004), the statistical properties of the curves could be described with measures of complexity such as ApEn. In this study, we eschewed the use of descriptive or inferential statistics involving measures such as values for the mean and standard deviation of a variable because they could bias hidden important features in the data such as signal variability, which is paramount to characterize the complexity and regularity of a given time series.

Approximate Entropy Analysis

According to Stergiou et al. (2004), ApEn values typically range from 0 to 2. Values close to 0 are consistent with greater periodicity and less complexity.

Figure 7 displays the normalized ApEn for each of the three performance outcomes, with standard error bars included. As illustrated, there was a tendency for greater values of ApEn in unsuccessful tackles, which indicated the presence of more irregularity and complexity compared with clean try situations, which demonstrated lower ApEn values, indicating more regularity and periodicity.

We used a nonparametric test to compare normalized ApEn means of the three performance outcomes (i.e., clean try, unsuccessful tackle, effective tackle). The test presented a borderline level of statistical significance (Kruskal-Wallis, $p = .053$) as displayed in Table 1.

From the normalized ApEn values for the three situations, an interesting feature is that system complexity increased with the level of physical contact between the interacting agents in the dyad. Dyadic trajectories in clean-try situations were more periodic, more regular, and less complex than both of these tackle situations. In rugby dyads, the nonlinearity of decisions and actions of each player, as a result of decreasing interpersonal distance, decreased the probability

TABLE 1. Nonparametric Test Comparing Approximate Entropy (ApEn) by Performace Outcome

	Normalized ApEn			
Situation	*n*	*M*	*SD*	Kruskal-Wallis
Clean try	20	0.24	0.133	5.89
Unsuccessful tackle	23	0.34	0.154	5.89
Effective tackle	4	0.33	0.031	5.89

of a time series (e.g., collective variable values) displaying similar features in comparisons within state space.

Discussion

The data from this research program highlighted that there are several ways for systems to achieve the same outcome, which implies that systems have to learn how to deal with performance variability that emerges due to agent interactions. The findings of our research in the performance context of team sports exemplified how Kauffman's (1993) model of coevolving agent adaptation can serve as a sound theoretical basis to observe emergent decision making in the dynamics of interpersonal interactions in multia–gent systems. Specifically, our results suggested how decision making in attacker–defender dyads near the try area in the multiagent performance context of rugby union may be characterized as an emergent process, governed by laws of dynamical systems. These are laws that are common to all dynamical systems and are based on important characteristics such as critical fluctuations, phase transitions, emergent states of order, and multistability at the ecological scale analysis. This level of analysis is appropriate to describe and explain the emergence of players' decisions and actions in team sports such as rugby union. It affords an accurate analysis using an interaction-based approach rather then a traditional individual participant based approach. The data have implications for research on the interpersonal dynamics of agents in complex performance environments involving robotic and engineering systems, commercial companies, academic institutions, and sports teams. Our work suggests how global system structure and organization is an emergent property of local subsystem dynamics, as predicted by Kauffmann (1995). It shows how dynamical systems exploit surrounding constraints to shape the functional, self-sustaining patterns of behavior that emerge in specific performance contexts. Coevolving adaptive behaviors of system components within critical regions of state space are typically emergent because of the evolved coupling between system components (e.g., an attacker and defender in a dyad). In such systems, behaviors can emerge out of fluctuations created by interactions between interdependent constituents of the system (e.g., in sports the moves of an attacker and defender in a 1:1 dyad). Random interactions between system components can alter into more organized forms of interactions as one key system parameter (i.e., control parameter) changes in value. When such self-organizing systems are poised in a state near this value, different types of behavior can emerge depending on the value of the control parameter.

In such complex adaptive systems, because of the emergent nature of information used to support cognition, decision making, and action, it may be difficult to predict or prescribe large sequences of agent interactions in advance. These findings suggest that organizational decision making and planning in multiagent systems such as team sports should be predictive and adaptive in nature and not static and predetermined.

In the present study, susceptibility of global system behavior to localized relations and interactions between agents was revealed by analysis of collective variable values, which showed that small differences in initial conditions could lead to large differences in the final state of the system. Phase space data revealed how slight relative differences in initial conditions led to large differences observed in the dynamics of the interpersonal interactions and outcomes in the dyads. Through the collective variable data plots, we observed that dyadic system behavior was always attracted to a minimum (i.e., zero crossing). In every simulation of the 1:1 subphase of rugby union, it was possible to identify a region of the performance landscape where the players in the dyad were engaged in coadaptive moves in attempting to optimize their relative fitness, the region of self-organized criticality. These findings are consistent with our proposal that the decisions and actions of subsystems in large organizations could be modeled as a chaotic attractor. Therefore, in complex multiagent systems, attractors can be viewed as privileged configurations or states toward which first- and second-order constraints channel the system. System design to enhance adaptive behavior in multiagent collectives should be predicated on a good understanding of the unique first- and second-order constraints that shape system attractors in a particular performance environment. In fact, these constraints could form the basis of realism in designing specific training simulations in team sports. Adaptive behavior for athletes in team sports is self-organized behavior that emerges from the dynamics of the interactions between a structured environment and a player, which are governed by simple control laws under physical and informational constraints (Warren, 2006). In this way, adaptive behavior involves goal-directed action that is tailored to the constraints of specific performance environments.

The importance of environmental information for adaptive behavior was also observed in the critical fluctuations for the trajectories of individual agents in the dyads. Decisions cannot be accurately prescribed in advance in such open, indeterminate systems and ongoing interactions with the environment are necessary to ensure system adaptivity. The observed fluctuations in system behavior reported in Figure 4 expressed how the attacker was varying actions to create information for exploring how to pass the defender. Because of the emergent decision making of the attacker (i.e., when to move forward and pass the defender), a phase transition was characterized by a sudden and continuous decrease in angle values until a zero crossing occurred (where the attacker passed the defender and the defender–attacker horizontal angle reached the minimum value). As suggested by Juarrero (1999), because of changes in connection type (e.g., from nonphysical to physical if contact occurs) or organizational changes within the dyad (because of relative spatial proximity to the try line), the observed phase transition may be interpreted as a new phase of a self-organized process. These findings provide new insights to interpret the role of within-agent variability of decisions and actions in subsystems of collectives.

Another feature of the collective variable data that supports the view of attacker–defender interactions as a self-organizing, coevolving adaptive process is the different shapes of the collective variable patterns. As stated previously, system initial conditions were set from the moment when second-order constraints emerged (i.e., the moment that the player's actions became mutually entrained). This idea signifies that every time a trial was performed, the initial conditions were slightly different (see Figure 4). These slight variations in initial conditions led to different shapes of the collective variable and consequently to different outcomes. Again, this is a key finding suggesting that few outcomes for system behavior can be completely prescribed in advance. The data suggest that complex multiagent systems may be difficult to control with traditional, hierarchical modes of decision making, planning, and management. Further, the more connections between system components, the more challenging it is for an executive mode of control to regulate the precise nature of the interactions between subsystem agents.

The findings of the present study are similar to data reported by Richardson et al. (2007), who found coordination tendencies among participants coupled by visual information demonstrated that intentional and unintentional interpersonal coordination in noncompetitive tasks (e.g., rocking chair movements) was constrained by the self-organizing dynamics of coupled agents as a system. In the present study, system initial conditions, as well the shape of the collective variable, emerged because of agents' interactions toward mutual entrainment, which were sustained by the information fields (i.e., visual information fields maintained by perception-action couplings) created by the system itself. The localized interactions in the 1:1 competitive subphases led to the emergence of self-organized criticality, which benefited the multiagent system (i.e., the team) by creating new options for adaptive behavior (van Orden et al., 2003).

In his modelling of evolutionary systems, Kauffman (1993) named this property *self construction,* a term which adequately captures how interpersonal interactions in attacker–defender dyads can lead to different system outcomes in the performance environment of team sports. Self-construction of decisions and actions is an important process to understand and research in future studies of behavior in complex multiagent systems. This process fits well with robotic design modules based on empowerment and facilitation of individual agents to explore the environment for new information to regulate trajectories. The findings suggest that designers of multiagent adaptive systems should avoid attempting to control the uncontrollable by trying to eradicate variability in decision making and actions of individual agents. Rather, global system performance is more likely to be enhanced by developing the adaptive behaviors of agents. For example, robotic designers could enhance the amount of variability included in training environments, and in team sports, coaches could achieve a similar objective in the training drills that players face during subphase practices. This strategy will provide a platform for agents to learn how to make decisions and perform actions that stabilize or destabilize subsystem interactions so that they may work in a collective manner or independently to achieve task goals.

In the present study, collective variable patterns successfully described the nonlinear interactions that occurred between the agents of the dyadic system. These nonlinear interactions created fields of information that drove the subsystem of agents to a metastable region of self-organizing criticality with three possible states (Kauffman, 1993; Kelso, 1995). In complex organizations, such as team sports, these regions are fertile areas for observing creativity and flexibility in decision making and actions in enhancing performance because of the rich and diverse patterns of behavior that emerge from the localized agent interactions (Bak & Chialvo, 2001).

Specific values achieved by the collective variable revealed the state toward which the dyadic system was being attracted to regions of self-organizing criticality. Because of slight differences in initial conditions, the final state achieved by the system was quite different, again signaling how global organization outcomes are challenging to prescribe in advance.

By plotting the evolution of the collective variable patterns from the attacker–defender interactions in the present study, it was possible to observe what happens at each moment in time, as well as to characterize the type of phase transition that took place (i.e., changes in system organization or changes in the dyadic components' connection). However, for both situations (i.e., try or tackle), the fluctuations that occurred in the collective variable because of the emergence of second-order constraints led the system to a state of nonequilibrium (i.e., the region of self-organizing criticality) and one of the following situations could emerge: (a) For try situations, the probability of a new state of organization emerging (e.g., attacker reached the try line) increased because of a breaking of symmetry in the initial structure of the dyad (i.e., the attacker was now the player closest to the try line); and (b) for tackle situations, after physical contact takes place and the players fall to the floor, according to the rules of the game the ball must be released; from that moment, the function of each player in this local system is over (i.e., the ball on the floor is available to every player and there is temporarily no defined attacker or defender dyad).

Both situations exemplify the process of self-construction in multiagent interactions and how the information flows drive the collective system to a desegregation of its components. In other words, the defender and attacker created a nonlinear interpersonal relation sustained on information flows that attracted this local dyadic system to its own desegregation, leaving its agents free to merge into other new localized subsystems with other agents (see Kauffman, 1993). These observations illustrate how globalized decision making and actions can emerge to influence the structure and organization of collective artificial systems as agents cooperate and compete with each other in localized emergent subgroupings.

The first derivative data allowed us to analyze the rate of change of relative position between attacker and defender. The data from the present study illustrated how 1:1 dyads in rugby are a self-organizing system with the ability to create the potential that moves the global system to the region of self-organizing criticality (Kauffman, 1993; van Orden et al., 2003). That potential seemed to be predicated on the velocity of each player inside the basin of attraction, which altered the players' relative position (Passos et al., 2008).

Phase space represents all the trajectories that a system can achieve in state space. Despite the potential for a huge number of trajectories to emerge from the players' interactions, typically system behavior always flowed to a low dimensional attractor (whose behavior can be described with reference to two or three variables), captured by the three states previously presented. These data are harmonious with Kauffman's (1993) observations that typically complex systems become boxed into a tiny volume of state space even though their behavior within that small volume is chaotic in the precise sense of high sensitivity to initial conditions. Behaving as a chaotic attractor means that the dyadic system displayed nonlinear characteristics because of context sensitivity, microvariations in the initial state and the consequent interdependence of decisions and actions of both agents involved in the dyad. For similar conditions, the behavior of the collective may be different, although this range of behavioral solutions clustered around a specific pattern. The dynamic patterns that characterized the three possible states formed because of the information flows that arose during performer-environment couplings in the dyad's course of action.

These findings emphasize the importance of indeterminacy in multiagent systems. They are quite different from results obtained in traditional experimental and theoretical paradigms for studying decision making in team sports, which usually focus on the development of internal models to make decisions rather on the agent-environment couplings. Rather, the outcomes of the present study emphasized the view that decision making is a process that emerges under ecological constraints (i.e., boundaries created because of agents interactions; Araújo et al., 2006; Juarrero, 1999). The ApEn value provided a measure of dyadic system complexity, and the results confirmed that system complexity increased with changes in relations between players. In this article, we use the term complex in the systems oriented manner (i.e., to describe systems composed of two or more interacting parts). The data suggested that system complexity increased as the relation between the agents changed (i.e., from nonphysical to physical). It is interesting to note that with decreasing interpersonal distance, more causes emerged (e.g., grasping, tackling, pushing or pulling the attacker), allowing the dyadic system to produce multiple effects (i.e., an attacker's efforts to release the ball with two legs held by a defender, with the defender tackling just one leg or the chest). According to Bar-Yam (2004), these observations are a key feature of increasing complexity in a system's behavior. In addition, the interaction among variables (e.g., grasp power, level of fatigue, fear due to an unsuccessful previous attempt, body contact area with the opponent, relative position of both players at the contact point) that influenced each physical contact situation (i.e., tackle) was unique and thus context dependent. In that line of reasoning, an increase in complexity can make decisions and actions more context dependent.

The results of the present study illustrate how no one specific optimal decision can be prescribed in advance by multiple agents in dynamic performance contexts such as rugby dyads. Inside the collision zone in rugby dyads, the decision when to intercept an attacker actually emerged for defenders, sustained by the informational constraints of the context (e.g., attacker actions). These results are harmonious with ideas from ecological psychology, which advocate an emergent approach to decision making with the necessary information to make appropriate decisions available for collection from the environment (e.g., Araújo et al., 2006; Hristovski, Davids, & Araújo, 2006). Data suggest that information from an attacker's actions is geared by the specific moves of the defender, supporting the conceptualization of attacker–defender dyads as a highly interconnected coadapting system.

Regarding methods for studying adaptive behavior in complex, multiagent neurobiological systems, the present study has shown that the use of techniques such as videogrammetry and artificial neural networks allows the collection of data directly from the performance field in a continuous fashion. Similarly, it has indicated how the use of nonlinear tools such as phase space analysis and measures of complexity such as ApEn can provide a powerful basis for testing different theoretical rationales for modeling interpersonal dynamics in complex organizations conceptualized as dynamical systems sustained by information fields. With this method, it is possible to analyze how a complex interpersonal system searches task and environmental constraints for information, leading to emergent decisions and actions that allow the system to functionally interact with the environment.

For future research, we suggest two levels of analysis: (a) extending this method to situations that involve more agents in subsystem interactions (e.g., subphases of 2:1, 3:2, 4:3) and (b) applying this method of analyzing decision making and actions to other organizational contexts such as artificially intelligent systems. These investigations are required because, as Kauffman (1993) pointed out, with increasing levels of system complexity-that is, as the number of system degrees of freedom increases-the potential for interaction increases and the likelihood of phase transitions increases. Researchers need to understand whether localized subsystems varying in structure exhibit greater tendencies for phase transitions. Regardless of organizational context, one common feature needs to be addressed: the discovery of relevant collective variables.

Last, our model and data showed the value of interpreting variability in the interpersonal dynamics of agent behavior to understand decision-making processes in organizations as complex systems (i.e., systems composed of two or more interacting parts). These findings are harmonious with data from recent research in the behavioral neurosciences highlighting the functional role of variability as organisms adapt to changing environmental constraints, even altering stereotypical sequences of behavior in response (for examples, see Tumer & Brainard, 2007; Faisal, Selen, & Wolpert, 2008). Kelso (1995) proposed how fluctuations are continuously probing complex systems in nature, allowing them to feel their stability and providing an opportunity for them to discover new patterns of behavior. The results indicated how metastability provided a platform for a universal decision-making process for switching between and selection among different states of organization in complex systems. When a multiagent system enters a metastable region, it is a fluctuation that decides which possible trajectory will be selected, not decisions prescribed in advance. Even if we know the initial values and boundary constraints, there are still many states available to a complex system among which it chooses as a result of fluctuations (Prigogine, 1996; see also, van Orden et al., 2003). In organizations such as team sports, fluctuations in interpersonal dynamics can be described by a collective variable whose behavior is governed by nonlinear interactions among complex system agents (e.g., the players in a team game). This point was highlighted by the observation in the present study that at specific values of interpersonal distance with the emergence of second-order constraints, nonlinear interactions among attackers and defenders created information flows that led the system far from equilibrium. A system that is nonlinear, dynamical, adaptive, and evolving because of an embedded interaction with the environment far from equilibrium is poised for a phase transition because of a change in its structural organization or in type of connection among its components. In these cases, fluctuations are the rule and the interpersonal dynamics of interacting agents in organizations will be attracted to one of the available system states. We have argued that such data are harmonious with the model of coevolving adaptation ascribed to evolutionary processes by Kauffman (1993) and that further work is needed to verify this theoretical framework for studying adaptive behavior in a variety of other multiagent systems.

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