Mapping Cognitive Attractors onto the Dynamic Landscapes of Teamwork

Ronald H. Stevens[1] and Jamie C. Gorman[2]

[1] UCLA IMMEX Project 5601 W. Slauson Ave. #272, Culver City, CA 90230, USA
[2] Psychology Department, Texas Tech University, Lubbock, TX 79409, USA
immex_ron@hotmail.com, jamie.gorman@ttu.edu

Abstract. The objective of this study was to apply ideas from complexity theory to derive new models of teamwork. The measures include EEG-derived measures of Engagement and Workload obtained from submarine piloting and navigation (SPAN) teams and communication streams from Uninhibited Air Vehicle Synthetic Task Environments (UAV-STE). We show that despite large differences in the data streams and modeling, similar changes are seen in the respective order parameters in response to task perturbations and the experience of the team. These changes may provide a pathway for future adaptive training systems as both order parameters could conceivably be modeled and reported in real time.

Keywords: Complexity, Teamwork, EEG, Neurophysiologic synchrony, Nonlinear dynamics.

1 Introduction

Teamwork is complicated, complex, and noisy. The ecological perspective of teamwork described by Cooke et al. [1] draws on this complexity to describe a dynamic view of the team, its' members, and the environment. Patterns of interaction and activity qualitatively emerge with the flow of the task, and perturbations to the teamwork and these patterns are characterized by fluctuations away from stable states. In this paper the concept of 'attractor landscapes' is proposed as a methodological approach to describe, explain, and visualize the dynamics of teamwork. In this approach individuals are not viewed as passive entities but rather as comprising a system capable of rich dynamics with the state of each member depending, in part, on the state of others. This synchronization of cognitive and communication components across the team provides a higher order system with its own dynamic properties as each individual attempts to achieve synchronization by adjusting his or her internal state or overt behavior in response to the evolving task and the state or behavior of the individuals with whom he or she is interacting.

How can we begin to model these adjustments and what can we learn that's new from these models? One approach is nonlinear dynamics which is a general theoretical approach for understanding complex systems and the linkages within and across subsystems independent of their specific behavioral or material substrate.

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When teamwork is viewed as a complex adaptive system there are multiple non-linear dynamic concepts that can be applied including self-organization, attractors, phase shifts, recurrence, entropy perturbations, and intrinsic dynamics.

This paper describes methodologies for modeling and visualizing teamwork in the context of cognitive attractors. The principles are organized around Haken'ssynergetics [2] and the developmental framework described and Smith [3]:

- *Define a level of analysis.* A recurring question for most teamwork research is determining the criteria for when, or if, a particular measure has been aggregated to an appropriate level and is being modeled at an appropriate temporal resolution. An appropriate team level of analysis may be influenced by variability in individual level properties from below and by organizational properties from above.
- *Identify patterns in behavior and define the order parameter.* There are many possible degrees of freedom of team member interaction. An order parameter—a collective variable—is a relatively low-dimensional variable that captures qualitative changes in teamwork. That is because the order parameter integrates team interactions that fluctuate critically at critical task points. Knowledge of the intrinsic constraints of team member interaction at critical task points can *a priori* define an order parameter, or, in application, we may distinguish patterns by introducing different manipulations (perturbations).
- *Describe the attractors of the system.* A dynamical system defined over teamwork is continuous, but it will have both repelling and attractive regions of its state space. In phase space the attractors define the qualitative changes in the stable teamwork patterns. The attractor landscape can be traversed by scaling a control parameter, which is an extrinsic parameter nonspecific to the order parameter, but which leads to qualitative change in the behavior of the order parameter.
- *Capitalize on dynamical similitude.* Dynamical models may or may not exist for a given order parameter and attractor landscape. If a model does not exist, then we may capitalize on dynamical similitude, which means simply that systems with different material substrates can share the same dynamics (e.g., teamwork and the dynamics of balance).
- *Identify phase transitions in teamwork:* Phase transitions are qualitative changes in dynamics due to changes in control parameters. Phase transitions occur when the underlying pattern of interaction shifts to another pattern under predictable conditions and may facilitate the identification of perturbations and antecedents to changes in the teams' dynamics.

2 Methods and Results

We highlight two approaches / tasks that draw on this framework and illustrate the advantages and challenges of applying a nonlinear dynamic approach to teamwork. The first approach models teamwork using neurophysiologic measures of the engagement of each person on submarine piloting and navigation (SPAN) teams. This is an empirical, exploratory study where the data stream is a set of non-numeric symbols called Neurophysiologic Synchronies (NS) that represent the relative levels of engagement of each person on the team [4-6].

For the second approach Gorman et al [7-8] developed a team coordination order parameter for three-person Uninhabited Air Vehicle (UAV) teams and in the resulting dynamical model the scaling of a control parameter, team-member familiarity, revealed qualitative changes in team coordination dynamics whereby team mixing resulted in a more stable attractor.

2.1 Submarine Piloting and Navigation (SPAN)

The goal of this project is to use neurophysiologic measures to rapidly determine the functional status of a team in order to assess the quality of a teams' performance / decisions and to adaptively rearrange the team or task components to better optimize the team. In this study the ideas of self-organization and attractor landscapes have been applied to derive new insights into the differences between novice and expert SPAN teams. The SPAN simulations contain dynamically programmed situations events that are crafted to serve as the foundation of the adaptive team training. Each SPAN session begins with a Brief presenting the goals of the mission. The more dynamic Scenario segment follows and contains easily identified processes of teamwork along with others which are less well defined. The Debrief follows and is highly structured with team members reporting on their overall performance. As shown previously [4, 6], there are often major shifts in NS expression at the junctions of these segments. The cognitive measure being studied is an EEG-derived measure of Engagement (EEG-E) defined by Advance Brain Monitoring's B-Alert® system [9, 10].The hypotheses of this study were:

- Multiple attractor basins (attractors) for engagement exist for SPAN teams; and,
- Some attractors are favored over others depending on the control patterns (i.e. task environment and team experience).

The B-Alert® system contains an easily-applied wireless EEG system that includes intelligent software that identifies and eliminates multiple sources of biological and environmental contamination and allows second – by -second classification of cognitive state changes such as Engagement. The EEG data streams for each person on the team are normalized and combined into vectors describing the EEG-E level of each person. They are used to train an unsupervised artificial neural network (ANN) that generates 25 NS clusters (symbols) representing the Engagement status of the team [4-6]. Each cluster displays a histogram showing the relative EEG-E level of each person. An example for a six person team is shown in Figure 1where persons 3 and 5 have high levels of a cognitive measure and the rest are low.

A topology also develops during this training where similar vectors cluster together and more disparate vectors are pushed away. For instance, NS_E Patterns 1-5 represent times where most of the team members had low levels of EEG-E while NS_E Pattern 24 represents times where most team members had high EEG-E. In a NS data stream the expression of these patterns represents second – by – second fluctuations of the engagement by different members of the team and provides an order parameter for these studies. The control parameter(s) for this study are team expertise and the task divisions (i.e. Brief, Scenario & Debrief).

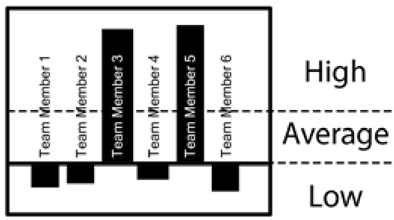

Fig. 1. Expression of a generic NS measure by members of a six-person team

The starting assumption was that many of the second-by-second changes in team NS_E would be small which would result in local transitions between NS_E Patterns. With the linear architecture of the self-organizing ANN this would appear in transition matrices as movement around / along a diagonal line. The thickness of the diagonal line confirms that there are transitions in local neighborhoods and these are more common than more distant transitions.

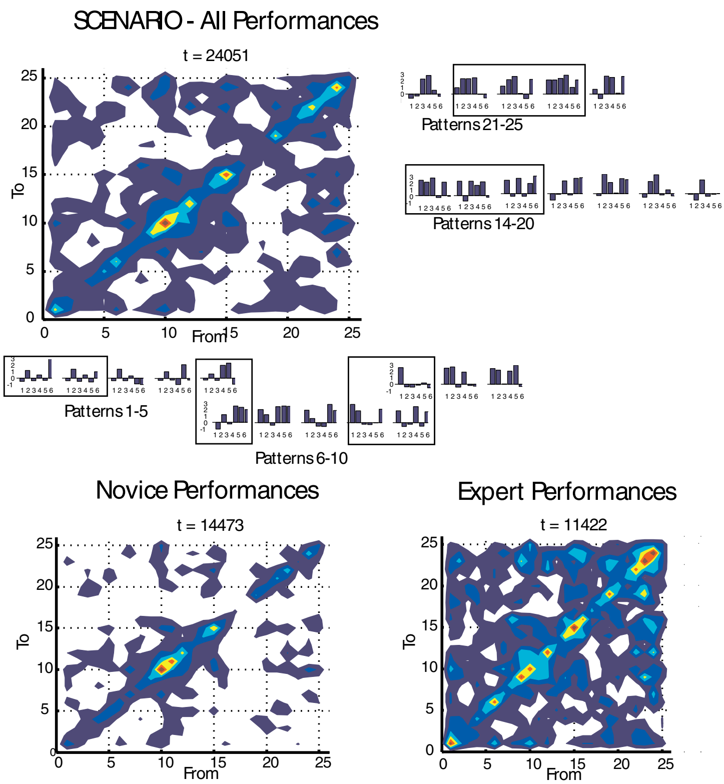

Fig. 2. NS_E transition matrices during the scenario segments of novices (left) and experts (right). The top figure shows the transition matrix of the combined dataset of five novice and five expert SPAN performances. Surrounding this figure are the 25 NS_E patterns resulting from ANN clustering. The boxes highlight patterns that are frequent in the matrix. The figures below show only the Scenario data for the novice (left) and expert (right) teams.

For novices, the areas with more frequent transitions were centered on NS_E Patterns10-11. Referring to Figure 2, these patterns were where many of the team members had low EEG-E. The most frequent patterns / transitions for experts clustered near NS_E 15 where most of the team showed above average EEG-E. A second cluster (attractor) centered near NS_E 22-25 where again the majority of the team showed high EEG-E. The expert teams also showed more minor transitions than novices as evidenced by the darker background contours throughout the matrix.

For both novice and expert groups the Debriefing segments showed transition matrices with restricted patterns of NS_E expression confined around the diagonal (Figure 3). The two groups however, showed reverse pattern of NS_E expression with those of the expert team members representing below levels of EEG-E, while those of the novices representing above levels of EEG-E for many team members.

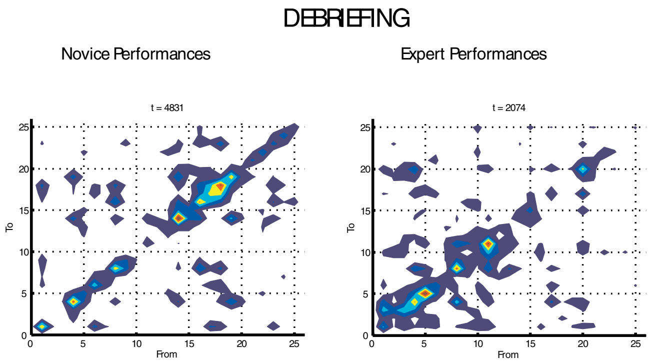

Fig. 3. NS_E transition matrices during the Debriefing of novices (left) and experts (right)

To capture the attractor dynamics of the NS_E Patterns transition matrix movies were created for each team where movie frames were updated every 8 seconds over a background history window of the prior 90 seconds. Two frames are shown in Figure 4 for the novice team T4S2. The left frame (epoch 1586) was where there was confusion in the team about contacting / avoiding another ship. Here the team oscillated between two attractors centered near NS_E 14-16 and NS_E 9-11. The right frame shows a period of diffuse attraction.

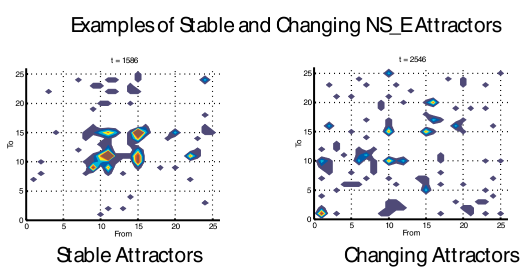

Fig. 4. Examples of stable (left) and changing (right) NS_E attractor states

2.2 UAV Team Coordination Dynamics

In the UAV task [11] three team members (a pilot, a navigator, and a photographer) interact over headsets to fly a simulated UAV over targets in order to take reconnaissance photos. This task is performed over a series of 40 min missions, each consisting of 11-12 targets. Each team members' computer work station displayed information specific to that team-member role as well as general flight information (e.g., current heading, altitude, and speed). Team members were seated in the same room with their backs to each other such that they only communicated verbally over the headsets. In this section we describe the methodological strategy for studying team coordination dynamics in this UAV task as well as results using that approach. We do so by summarizing the research originally reported in [7, 8], following the framework described in Section 1.

To identify an order parameter at the appropriate level of analysis (i.e., the team level), the functions that each team member performs just below that level of analysis were first identified. Recordings of previous UAV team communication revealed three primary functions: (1) the navigator sends target *information* (I) to the pilot; (2) the pilot and photographer *negotiate* (N) an appropriate airspeed and altitude; and (3) the photographer provides *feedback* (F) on the status of the target photograph. Team members dynamically combine these functions in a specific order via communication to photograph each target (I→N→F). To measure how this pattern of behavior changes over time, timestamps of these specific interactions at each target were collected. The coordination order parameter, called κ, is shown in Equation 1.

$$\kappa_t = \frac{\mathrm{time}(F_t) - \mathrm{time}(I_t)}{\mathrm{time}(F_t) - \mathrm{time}(N_t)} \qquad (t = 1, 2, \ldots \#\,\mathrm{targets}) \tag{1}$$

Because time cancels in the numerator and denominator of Equation 1, κ is a dimensionless (unit-free) measure of the relationship across the three primary functions at each target. Relative to the temporal arrangement of the components of coordination, κ> 1 is coordinated, κ < 1 is uncoordinated, and κ = 1 is indeterminate. Figure 5 shows κ trial series for (a) Intact and (b) Mixed (these terms are described below) team coordination dynamics. As shown in Figure 5, the κ order parameter fluctuates at the critical task points, which were defined as the targets themselves, as well as unexpected perturbations called roadblocks [7].

Although there has been over two and a half decades of research on coordination dynamics [12, 13, 14, 15], there was no previous research on *team* coordination dynamics. Therefore, dynamical similitude was employed to describe the attractors of UAV team coordination dynamics. If the globally stable attractor of team coordination was coordinated, then team members would never have to interact. To meet the demands of a continuously changing environment, however, team members have to interact. Like a balancing act, team coordination is continuous and effortful because it is the stabilization of an inherently unstable system [7]. Existing dynamical models of similar processes are found in postural dynamics (i.e., standing up straight; [16]) and manually balancing an inverted pendulum [17]. In those systems, the globally stable state is lying in a horizontal position on the ground; however, a metastable state emerges as the active components counter the forces that are pulling the upright human or pendulum toward the ground [7]. Based on dynamical similitude, then, the team coordination attractor may be summarized as follows: The globally stable state is uncoordinated. However, a metastable coordinated state emerges as team members interact to counter environmental forces (i.e., constantly varying task demands) that pull them toward the uncoordinated state.

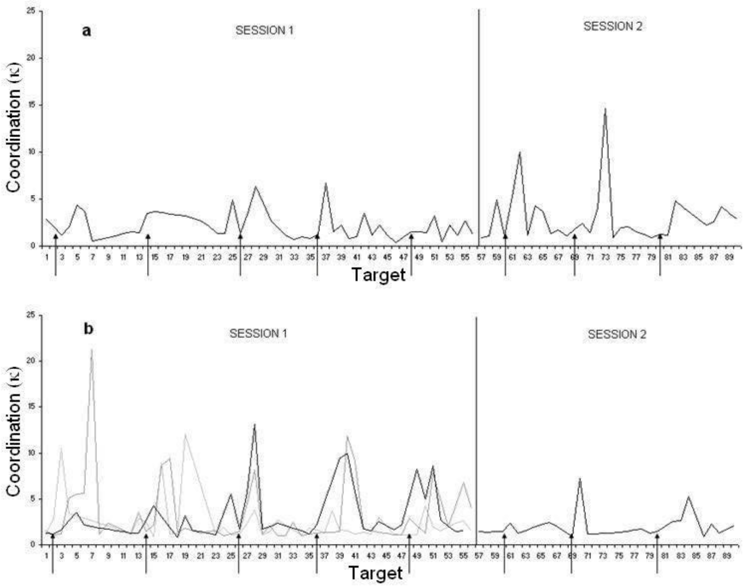

Fig. 5. Examples of κ fluctuations at critical points in the task: critical targets are indexed on the x-axis and roadblock perturbations are indexed by arrows on the x-axis (reprinted from [7])

The UAV team coordination dynamics were evaluated in an experiment in which team membership either stayed the same or changed following a retention interval [7]:After initially acquiring proficiency in the UAV task with one set of team members, participants would go away during a retention interval and, upon returning, either continue to work with the same members (Intact) or with completely different members (Mixed). (Participants maintained their same role on the team in both conditions.)The scaling of this team familiarity control parameter revealed qualitatively different team coordination dynamics.

To examine those differences in Intact vs. Mixed team coordination dynamics, attractor reconstruction [18] was performed on the κ trial series. Attractor reconstruction is a method for unfolding a scalar time series (e.g., Figure 5) into an appropriate dimension in which to view the dynamical system (i.e., the attractor) that produced the time series. As shown in Figure 6a, Intact teams' reconstructed attractor looks quite different than Mixed teams' reconstructed attractor (Figure 6b). In postural (or inverted pendulum) dynamics, short-term drift away from center is countered by long-range correction back to upright. Similar to those dynamics, Intact team coordination dynamics were centered on a small region of the reconstructed space (i.e., the phase space), near the origin (Figure 6). As with postural stabilization, explorations away from this small region of phase space were countered by long-range corrections back to this small, preferred region (i.e., the larger orbits moving away from, and then returning to, the origin in Figure 6a). On the other hand, the Mixed teams did not rigidly correct back to one small region of the reconstructed space: The Mixed team attractor consistently explored more of the phase space, and there was no correction back to a small, preferred region of phase space. Thus, the attractor landscape can be altered with the scaling of a team familiarity control parameter. Accordingly, the observed team coordination dynamics were not *encoded* by the level of familiarity; the scaling of the control parameter simply moved teams through the coordination attractor landscape.

Further analyses revealed that the stability of these attractors (the resistance to perturbation) was significantly correlated with successfully working through roadblock perturbations (denoted by the arrows on the abscissa in Figure 5; see [7] for details) such that higher stability was associated with adapting to unexpected changes in the task environment. Furthermore, the Mixed team attractor was significantly more stable than the Intact team attractor, suggesting that Mixed teams were more adaptive than Intact teams.

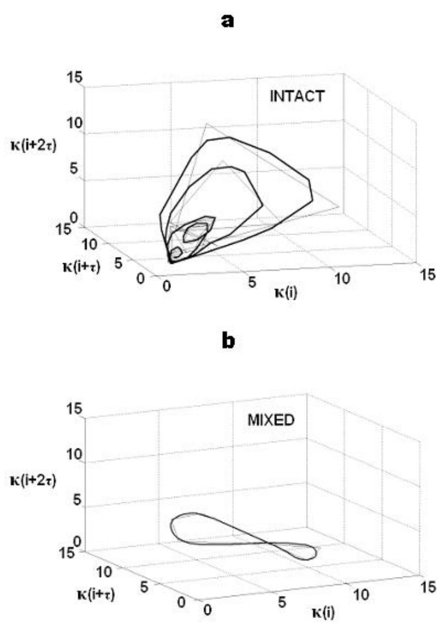

Fig. 6. Intact (a) and Mixed (b) reconstructed attractors (reprinted from [7])

In a following experiment, elements of the I→N→F coordination process of some teams were purposefully perturbed during task acquisition [8]. Though teams in that study were never mixed, those perturbations were intended to simulate the effects of increased interaction experience due to team mixing. As anticipated, this *perturbation training* led to more adaptive teams: Perturbation-trained teams exhibited significantly higher performance under novel task conditions than teams trained using standard methods; namely, cross-training and procedural training [8]. In this way, the

Intact vs. Mixed nonlinear dynamics results led to the development of a new team training method for team adaptation, and those predictions of enhanced team adaptation were borne out in the follow-up team training study.

3 Discussion

A goal of most training activities in complex environments is to be able to rapidly determine the functional status of a team in order to assess the quality of a teams' performance / decisions, and to adaptively rearrange the team or task components to better optimize the team. One of the challenges in accomplishing this goal is the development of rapid, relevant and reliable models for providing this information to the trainers and trainees.

While the two examples in this paper share task similarities, both being realistic and complex teamwork situations, the data streams and modeling approaches are very different. Despite these differences, the results show parallels in response to similar control parameters (Table 1).

Table 1. Model properties of the SPAN and UAV systems

	SPAN	UAV
Data Stream	EEG	Communication
Models	Symbolic	Numeric
Order Parameter	Neurophysiologic Synchronies (NS)	Coordination (κ)
Control Parameter(s)		
a) expertise	Novice / Expert Differences	Learning & Retention Differences
b) perturbations	NS State Changes	κ Fluctuations
Adaptive Models	Near Real-time	Near Real-time

The differences in the cognitive attractors seen in both of the systems with the changing experience of the team could provide a metric for following the efficacy of team training over time. The fluctuations of the order parameter within a task may also provide a pathway for future adaptive training systems as both could conceivably be modeled and reported in real time.

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