Nonlinear Dynamics, Psychology, and Life Sciences, Vol. 14, No. 3, pp. 265-289.

Team Coordination Dynamics

Jamie C. Gorman[1], *Arizona State University*
Polemnia G. Amazeen, *Arizona State University*
Nancy J. Cooke, *Arizona State University*

Abstract: *Team coordination consists of both the dynamics of team member interaction and the environmental dynamics to which a team is subjected. Focusing on dynamics, an approach is developed that contrasts with traditional aggregate-static concepts of team coordination as characterized by the shared mental model approach. A team coordination order parameter was developed to capture momentary fluctuations in coordination. Team coordination was observed in three-person uninhabited air vehicle teams across two experimental sessions. The dynamics of the order parameter were observed under changes of a team familiarity control parameter. Team members returned for the second session to either the same (Intact) or different (Mixed) team. "Roadblock" perturbations, or novel changes in the task environment, were introduced in order to probe the stability of team coordination. Nonlinear dynamic methods revealed differences that a traditional approach did not: Intact and Mixed team coordination dynamics looked very different; Mixed teams were more stable than Intact teams and explored the space of solutions without the need for correction. Stability was positively correlated with the number of roadblock perturbations that were overcome successfully. The novel and non-intuitive contribution of a dynamical analysis was that Mixed teams, who did not have a long history working together, were more adaptive. Team coordination dynamics carries new implications for traditional problems such as training adaptive teams.*

Key Words: order parameter, control parameter, perturbations, stability, long-range correlation.

TEAM COORDINATION DYNAMICS

There are many examples of tasks that are too complex to be accomplished by an individual working alone and, instead, require a team that is composed of people with different skills. Simply assembling a collection of highly trained experts is not enough, however, because teams have to coordinate

[1] Correspondence concerning this paper should be addressed to Jamie C. Gorman, Cognitive Engineering Research Institute, 5810 S. Sossaman Rd. #106, Mesa AZ, 85212. E-mail: jgorman@cerici.org

their activities. One example is a surgical team that consists of highly trained team members, including a chief and assisting surgeon, an anesthesiologist, and circulating and scrub nurses. No matter how much they know as individuals, surgical teams fail if they do not interact effectively as a team. Nevertheless, traditional explanations of team coordination have focused on the aggregate knowledge of a team's members.

Teams must not only interact effectively during routine procedures, but they must also be able to adjust their coordination to meet the changing demands of their environment. If the surgical team always coordinates in a static, unchanging fashion, regardless of how appropriate it is for a particular situation, then the result is potentially fatal. Teams must be able to change their coordination to meet the exigencies of the current situation. Nevertheless, team coordination has traditionally been measured with variables such as mean behavior that do not capture the dynamics of team coordination.

In this paper, we present an approach that goes beyond the aggregate-static concept of team coordination by focusing on the dynamics. The objectives of this paper are to: (a) point out limitations of the traditional, aggregate-static approach to team coordination; (b) develop an alternative dynamical approach for studying team coordination; (c) report the results of an experiment in which we analyze team coordination using our dynamical approach; and (d) discuss the implications for team coordination research and training adaptive teams.

Traditional Approaches to Team Coordination and Their Limitations

The traditional approach to team coordination views effective coordination as the product of a shared mental model. A mental model is a representation that allows an individual to describe, explain, and predict the behavior of a system (Rouse & Morris, 1986). It is believed that through common, overlapping knowledge, individual mental models sum to form a shared mental model (Cannon-Bowers, Salas, & Converse, 1993). Relevant to team coordination, it is further believed that the development of a "shared" mental model allows team members to anticipate each other's needs in order to coordinate implicitly, without the need for explicit interaction (Entin & Serfaty, 1999; Stout, Cannon-Bowers, Salas, & Milanovich, 1999).

What it means to share a mental model varies from completely identical to complementary models. To quantify a shared mental model, the knowledge taken from one team member can be compared to the knowledge taken from another team member for commonality (Langan-Fox, Code, & Langfield-Smith, 2000). Common knowledge is aggregated into a pooled estimate, independent of team member roles. The limitation of taking this aggregate approach is that differences in relations between team member roles do not factor into the aggregate. Consider the surgical example: the aggregate assumption means that a more effective team has nurses, doctors, and an anesthesiologist with more knowledge in common. But should we expect the doctors and the nurses to know the same things? The reason for putting together a team of specialists is to maximize specialty knowledge and communication of that knowledge, rather than common knowledge. Further, even if the doctors and nurses share the same mental model of the task, but interact poorly, then as a team they may not be able to perform the task.

In addition to being aggregated across team members, traditional measures of team coordination are aggregated across time, producing a static measure of coordination. For example, team coordination has been studied in dynamic task environments by looking at communication events averaged over time (e.g., anticipation ratios; Entin & Serfaty, 1999; MacMillan, Entin, & Serfaty, 2004). This practice suggests that a mean coordination pattern is the norm and deviations are not structured but random (e.g., Wang, Klienman, & Luh, 2001). Similarly, single observer ratings over long periods of aircrew task performance have been used to judge overall quality of coordination (e.g., Brannick, Prince, Prince, & Salas, 1995). In the surgical example, this suggests that the team performs the "average" behavior in any situation. However, fluctuations may be revealing of important trends; behaviors that look the same on average may actually differ in important ways (e.g., an increasing trend versus a decreasing trend versus a sinusoidal oscillation). More important than the average behavior is how that behavior is tied to the dynamics of the task environment (Manser, Howard, & Gaba, 2008). For example, the surgical team that coordinates the same way during a routine procedure and during a procedure anomaly (e.g., sudden drop in heart rate) could lose their patient.

It is precisely the details of mutual adjustment to a changing environment that are needed to capture team coordination. Thus, the dynamics of team member interaction and the types of environmental dynamics to which the team is subjected must both be considered. Tools of nonlinear dynamical systems (NDS) are appropriate because they give us more than an aggregate concept of coordination and allow us to observe significant differences in patterning that can be washed out by static measures such as the mean behavior.

Team Coordination Dynamics

Guastello and colleagues (e.g., Guastello & Guastello, 1998; Guastello, Bock, Caldwell, & Bond, 2005; Guastello & Bond, 2007) have investigated the dynamics of group coordination. Groups differ from teams because their members perform the same functions. Guastello, et al.'s paradigm is based on a task from game theory: the intersection game. The intersection game is similar to a four-way traffic stop at which drivers must decide who goes through next. The drivers are not told explicitly in what order they should proceed. In the laboratory version, four group members must decide the order in which they should lay down playing cards to match an unspoken "coordination rule" set by experimenters (e.g., that a higher card must follow a lower card). After each hand, the group receives feedback regarding how closely they matched the coordination rule, and then another hand is played. Over a series of hands, a stable equilibrium state (a point attractor) matching the coordination rule is reached. When the coordination rule changes, then re-acquisition of a new point attractor occurs. It has been observed that groups transfer coordination learning to new rules and that acquisition of the new coordination rule is faster than the original rule.

The intersection paradigm clearly is not static because it focuses on how groups learn to implicitly coordinate over time. However, there are features of this paradigm as currently formulated that limit its usefulness for studying the dynamics of team coordination. First, because the paradigm focuses on groups with homogeneous members, it does not matter who lays down a particular card or when group members interact (Guastello et al., 2005; Guastello & Guastello, 1998). Second, the interpretation of coordination learning as reaching a stable equilibrium state (point attractor) may be an artifact of slow sampling rate; within each hand there may be interesting, higher-dimensional dynamics occurring. Another interpretation is that the group is matching its coordination dynamics to environmental dynamics, but the environment itself is not very dynamic (i.e., the slowly changing coordination rule). If the environment were more dynamic, then coordination learning may appear to be a more complicated attractor (e.g., a limit cycle), as the team continuously matches its coordination dynamics to those of the changing environment. We will employ a highly dynamic task environment in which the goal of achieving a fixed coordination strategy (a point attractor) would be highly unstable. We will look for different attractors using a data extraction method called attractor reconstruction.

Our approach, which is inspired by Haken's synergetics (1977), is to capture coordination at the team level where it fundamentally resides (as opposed to aggregating a score) and to observe how that team coordination evolves under different conditions and environmental dynamics. Capturing coordinated behavior explicitly at the team level requires specification of an *order parameter* that captures the current state of coordination and allows for fluctuations over time under varying task conditions. Changes to the order parameter occur in the context of changes in a *control parameter* and in response to *perturbations*. In the remainder of this section, we describe the order parameter, control parameter, perturbations, and NDS methods that are appropriate for the study of team coordination.

Order Parameter

Dynamical modeling of any system requires the identification of an appropriate level of analysis for the behavior of interest that captures the interactions of system components. In the field of motor coordination, for example, the relative phasing φ of two components (limbs) is a well-known order parameter that characterizes monofrequency coordination patterns and has given rise to over two decades of research on coordination dynamics (Amazeen, Amazeen, & Turvey, 1998; Fuchs & Jirsa, 2008; Haken, Kelso, & Bunz, 1985; Kelso, 1984; 1995).

To capture coordination at the team level, we developed a team coordination order parameter, κ. The components of coordination (e_i) that rest at the level just below the level of analysis (the team level) are functions that each team member performs individually but that the team assembles dynamically. The value of κ depends on the timing of interactions among the components of coordination. The relative onset times of three-component coordination is given by:

$$E \equiv e_1 < e_2 < e_3 \qquad (1)$$

The components e_1, e_2, and e_3 are not arbitrary but are relations between different team member functions. In the present paper, the e_i are defined as specific types of communications performed by three team members: Information (e_1); Negotiation (e_2); and Feedback (e_3). Only one temporal order satisfies E. However, variability within the temporal order specified by *E* captures fluctuations in team coordination. Relative to E, the time intervals ($e_3 - e_1$) and ($e_3 - e_2$) are the metrics for calculating κ:

$$\kappa = \frac{e_3 - e_1}{e_3 - e_2} \qquad (2)$$

The numerator and denominator in Eq. 2 are both time intervals (e.g., seconds); therefore, κ is a dimensionless quantity. κ indicates qualitative differences in coordination:

$$\kappa \text{ state} = \begin{cases} \text{uncoordinated} & \text{if } \kappa < 1 \\ \text{indeterminate} & \text{if } \kappa = 1 \\ \text{coordinated} & \text{if } \kappa > 1 \end{cases} \qquad (3)$$

$\kappa > 1$ indicates that the component events have occurred in the proper order, $\kappa < 1$ indicates that the component events have not occurred in the proper order (e.g., e_2 occurs before e_1), and $\kappa = 1$ is the coordination boundary. The dynamics of team coordination result from variations within and between κ states. Later, we present the method of generating and analyzing the dynamics of κ using a repetitive team task in which three components of coordinated action (i.e., Information à Negotiation à Feedback) are required for each repetition. Next, we describe two ways in which we will influence κ variability and, thus, team coordination dynamics.

Control Parameter

One way in which variations in κ can be influenced is through the manipulation of a control parameter, whose continuous scaling is accompanied by discontinuous (qualitative) change in the value of the order parameter. Group member familiarity, which has been studied previously using Guastello's paradigm (Guastello et al., 2005), can be treated as a control parameter. We will examine κ dynamics at the extremes of team member familiarity: with team members who are either familiar or unfamiliar with each other.

Perturbations

A second way in which we will influence κ variability is by perturbing team coordination. Perturbations are informative because a team with unstable coordination dynamics may not recover from the perturbation, whereas a team with stable coordination dynamics will recover. In the present study, we will examine κ with respect to perturbations called roadblocks, which are environmental threats to coordination that teams must overcome.

Nonlinear Dynamics Methods

Dynamical similitude is the idea that systems with different material substrates can have the same dynamics. We capitalized on dynamical similitude between team coordination and more frequently studied dynamical systems in order to select appropriate NDS methods.

We have suggested that team coordination is not a point attractor. It is continuously evolving and effortful. Team coordination can be thought of as a balancing act in which the team must continuously match its dynamics to the demands of the environment in order to remain stable. Drawing on dynamical similitude, stabilization of an unstable system is found in Center of Pressure (COP) postural dynamics (e.g., Collins & De Luca, 1993) and manually balancing an inverted pendulum (Treffner & Kelso, 1999). In those dynamical systems, the globally stable state is resting in a horizontal position on the ground. However a metastable state emerges as the active components of the system (e.g., posture; hands) actively counter the forces that pull the upright human, or pendulum, to the ground. Similarly, team coordination can be thought of as the stabilization of an inherently unstable system by the effortful component of the system: team member interaction. The globally stable state is uncoordinated, which naturally results if the team members do not interact or do not interact effectively. A metastable coordinated state is achieved by the mutual effort of the interacting team members to coordinate their actions to the changing demands of the environment. Techniques used for analyzing these types of systems include attractor reconstruction (Abarbanel, 1996), stability analysis (Rosenstein, Collins, & De Luca, 1993), and long-range correlation (Hurst, 1951). We do not provide the details of those analytical techniques in this paper but will identify a general framework for their application to team coordination dynamics:

Attractor reconstruction (Abarbanel, 1996) was used to embed our (scalar) κ time series (**κ**) in an appropriate multidimensional space in order to examine the dynamics (the attractor). We did not necessarily expect differently-sized attractors for different teams. However, we used the vectors of the reconstructed attractor to estimate the largest Lyapunov exponent (λ_1; Wolf, Swift, Swinney, & Vastano, 1985; Rosenstein et al., 1993) in order to evaluate team coordination stability. $\lambda_1 < 0$ is indicative of more stable team coordination, and $\lambda_1 > 0$ is indicative of unstable team coordination; $\lambda_1 \approx 0$ is indicative of parallel trajectories or flow (Kantz & Schreiber, 1997). We expected $\lambda_1 > 0$ for unstable teams whose behavior was easily disrupted by roadblock perturbations.

Long-range correlation was examined by analysis of the Hurst exponent (H; Hurst, 1951), which measures dependence over time scales (Beran, 1994; Eke, Herman, Kocsis, & Kozak, 2002). Our assumption was that fluctuations in k would exhibit different types of long-range correlation. $H > 0.5$ indicates a persistent (positively-correlated) process; $H < 0.5$ indicates an antipersistent (negatively-correlated) process; and $H = 0.5$ indicates a random process with independent observations. COP trajectories are persistent over shorter time scales, as people spontaneously “drift” from upright posture, but antipersistent over longer time scales as the standing person “corrects” to an upright posture (Collins & De Luca, 1993; see also Treffner & Kelso, 1999). Riley, Wong, Mitra, and Turvey (1997) characterized postural drift as exploratory: the short-term drift provides information about the standing person’s relationship to the environment (exploration) that their body acts on in the long-term.

We will also use the term “exploration” instead of “drift” to characterize persistent team coordination. Like COP trajectories, we propose that team coordination can exhibit exploration-correction but that the boundary between exploration and correction differs depending on the qualities of the team. In the current study, we propose that the transition from exploration to correction depends on the familiarity of team members.

The Current Study

We analyzed the κ order parameter by manipulating the team familiarity control parameter—completely familiar (Intact) versus completely unfamiliar (Mixed)—in a three-member Uninhabited Air Vehicle (UAV) simulator. The goal of a UAV team is to coordinate in order to take reconnaissance photographs of ground targets. Roadblocks were introduced in order to perturb the UAV teams’ coordination dynamics. The UAV task is highly dynamic because the conditions under which targets are photographed are never identical and because roadblock perturbations introduce unexpected changes into the task environment. Ideally, coordination should vary with changes in the task environment (i.e., κ should fluctuate). However, we also expect different patterns in the **κ** series depending on team familiarity. Counter to the traditional assumption that team coordination is a static phenomenon, we hypothesized that mean **κ** would not reveal significant differences but that differences would be captured in the **κ** dynamics.

Hypothesis 1

Analysis of mean **κ** will fail to reveal familiarity differences.

Guastello et al. (2005) found that complete unfamiliarity resulted in the biggest disruption of group coordination. Building on that result, we hypothesized that mixing team membership would serve to disrupt team coordination just enough to enable the Mixed teams to find better coordination patterns. That hypothesis is similar to a hill climbing algorithm in which the system is jostled from a local maximum in order to find a global maximum (Busemeyer, Swenson, & Lazarte, 1986). Conversely, without this disruption, we expect that the Intact teams would rigidly correct to the same coordination dynamics.

Hypothesis 2

Because they are more rigid, Intact teams should exhibit corrective coordination dynamics (antipersistence; *H*) that Mixed teams do not.

Although rigidity may be appropriate for a totally stationary, unchanging environment, rigid coordination (i.e., ending up with the same coordination dynamic regardless of changing task conditions) becomes unstable in the face of a dynamic task environment. To the degree that team coordination dynamics do not match the dynamics of the task environment, teams become unstable with respect to the current coordination demands.

Hypothesis 3

Because they are less rigid, Mixed teams should have more stable coordination dynamics than Intact teams, as indexed by λ_1.

Due to the inverse theoretical relationship between recovery from perturbation and stability, teams with higher stability should also overcome more roadblocks. The relationship between stability and the dynamics of the environment can be captured by the correlation between stability and number of roadblock perturbations overcome.

Hypothesis 4

The number of roadblocks overcome should be negatively correlated with λ_1, i.e., more stable teams overcome more roadblocks.

METHOD

Participants

Forty-five three-person teams (135 participants) were recruited for participation from Mesa, AZ and surrounding areas. None of the three team-members had any prior experience working together. Participants ranged in age from 18 to 58 (M = 26) and 96 were male. Participants were randomly assigned to one of three team member roles (described below) and one of two familiarity conditions (Intact or Mixed). The experiment occurred over two sessions. Twenty of the 45 teams from the first session were assigned to new teams (Mixed) for the second session. The remaining 20 teams were Intact. Five teams did not return for the second session. One Intact team was dropped due to poor team performance, which was defined as greater than two standard deviations below the grand mean of team performance; N = 39 teams. Participants were

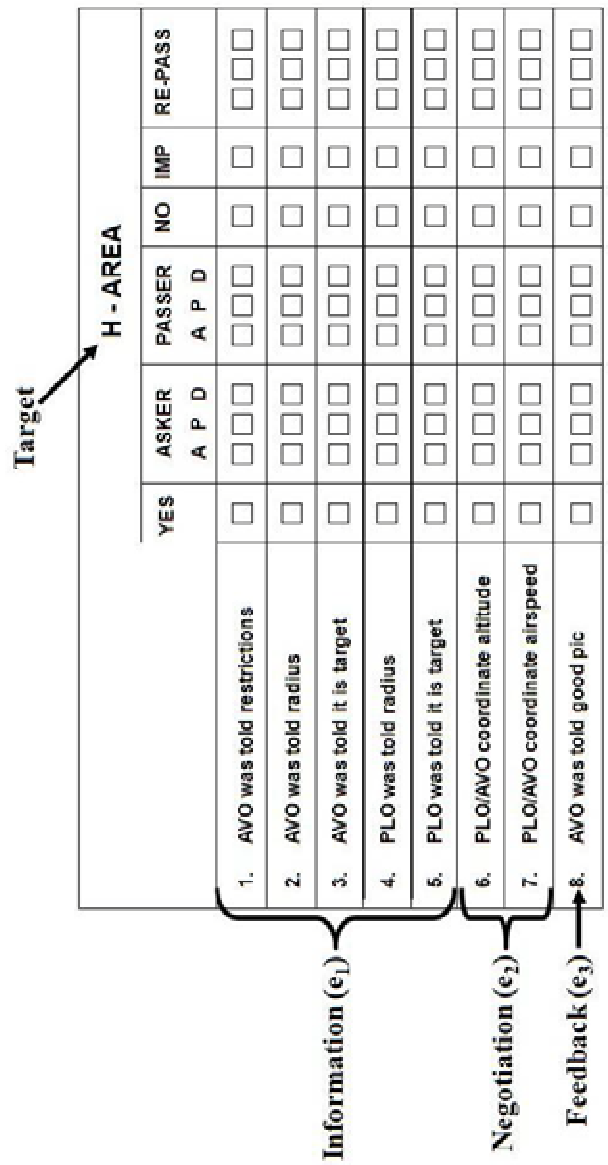

Fig. 1. Coordination log interface for one target; check boxes were used to record timestamps for the coordination components: Information (e_1), Negotiation (e_2), and Feedback (e_3).

paid $30 after the first session and $70 after the second session. A $100 bonus was paid to each member of the highest performing team.

Materials and Apparatus

The experiment was conducted in a UAV synthetic task environment (Cooke & Shope, 2005). This experiment was part of a larger study, details of which can be found in Cooke et al. (2007). The UAV team's task was to take reconnaissance photographs of ground targets over a sequence of 40-minute simulated missions. There were 11-12 targets per mission. The three team members each had a different role: pilot, navigator, or photographer. Each of the three team members was seated at a workstation that consisted of three computer monitors, a keyboard, and a mouse. Each team member's monitors displayed both role-specific (different for each team member) and common (the same for each team member) information regarding vehicle speed, altitude, and course bearing. The three workstations were located in the same room. Team members wore aviation quality, noise-canceling headsets and communicated by holding down push-to-talk buttons. After each mission, teams received performance feedback based on how many targets were successfully photographed, the amount of resources used (e.g., fuel, film), and the number of UAV warnings or alarms (e.g., low fuel).

As teams photographed each target, their communications were monitored by an experimenter for specific interactions using coordination logging software (see Fig. 1). Specific interactions for each target corresponded to the components (e_i) of coordination as described in Eq. 1: navigator providing *information* about the target (e_1); pilot and photographer *negotiating* UAV speed and altitude for the target (e_2); and photographer providing *feedback* on the status of the target photograph (e_3). When these interactions occurred for each target the experimenter checked the appropriate box. The timestamps associated with these interactions were used to calculate a κ for each target using Eq. 2.

During each mission, an experimenter presented the team with a situation awareness roadblock (Cooke, Gorman, & Rowe, 2009; Gorman, Cooke, & Winner, 2006). The roadblock was a novel change in the task environment that disrupted team coordination (i.e., e_1 à e_2 à e_3) during routine task performance (e.g., taking a photograph). Roadblocks were related to enemy activity, the appearance of unmarked targets on the navigator map, or communication glitches. These roadblocks mimic unwanted sources of novelty in actual UAV operations that operators must overcome. In the communication glitch, for example, communications were cut from one team member to another for five minutes, such that communication had to be rerouted through the other team member to overcome the roadblock. The number of roadblocks successfully overcome (scored "yes/no" as judged by experimenters) was recorded. Number of roadblocks overcome for each session was calculated for each team.

Procedure

Participation occurred across two sessions. Session 1 consisted of five UAV missions. This was followed 3 to 13 weeks later by Session 2, which consisted of three UAV missions. Teams who returned for Session 2 were either Intact (same team members) or Mixed (different team members). Retention interval was also manipulated in this experiment but its analysis is not relevant to the current experimental questions.

Coordination was logged for each target of each mission, and **κ** series were generated across all Session 1 and Session 2 targets. Roadblock perturbations were introduced during each mission in order to measure the total number of roadblocks overcome by each team during each experimental session.

Dynamical Systems Algorithms

Programs for attractor reconstruction, the largest Lyapunov exponent, and Hurst exponent were developed in Matlab, a mathematical programming language, using algorithms that are widely available in the NDS literature (see Kantz & Schrieber, 1997 for a general overview of the algorithms). The method of attractor reconstruction (Abarbanel, 1996) was used to reconstruct a dynamical attractor for each **κ**. The algorithm has two steps: (a) identification of the time delay τ at which the observations of **κ** are maximally independent and (b) using the τ-lagged coordinates of **κ** to identify the embedding dimension d_E. We estimated τ as the first local minimum of the average mutual information (AMI) function (Fraser & Swinney, 1986) and d_E as the number of τ-lagged coordinates at which the percentage of false nearest neighbors (FNN; Kennel, Brown, & Abarbanel, 1992) reached zero or a global minimum. We used the vectors from each team's reconstructed attractor to calculate λ_1 using Rosenstein et al.'s (1993) algorithm (see also Kantz, 1994).

We used rescaled-range analysis (*R/S*; Hurst, 1951) to estimate *H*. Following the procedure used for postural and inverted pendulum balancing dynamics (Collins & De Luca, 1993; Treffner & Kelso, 1999), we tested for two (exploratory: $H > 0.5$; and corrective: $H < 0.5$) linear regions, separated by an inflection point. The inflection point was estimated by refitting H with increasing time scale in order to identify the first minimum R^2 for each **κ**, which is the inflection point (Treffner & Kelso, 1999). When an inflection point was identified, separate H estimates were obtained for the linear regions before (short-region H) and after (long-region H) the inflection point.

RESULTS

In order to ensure the quality of the components of **κ**, the inter-rater reliability of the time-stamped coordination components of the coordination log (Fig. 2) were evaluated. Independent logs were obtained for a subset of UAV missions ($N = 35$) by having an independent experimenter log DVD recordings of those missions. The Intraclass correlation coefficient indicated good reliability, $ICC = .67$, F (3511, 3511) = 3.05, $p < .001$.

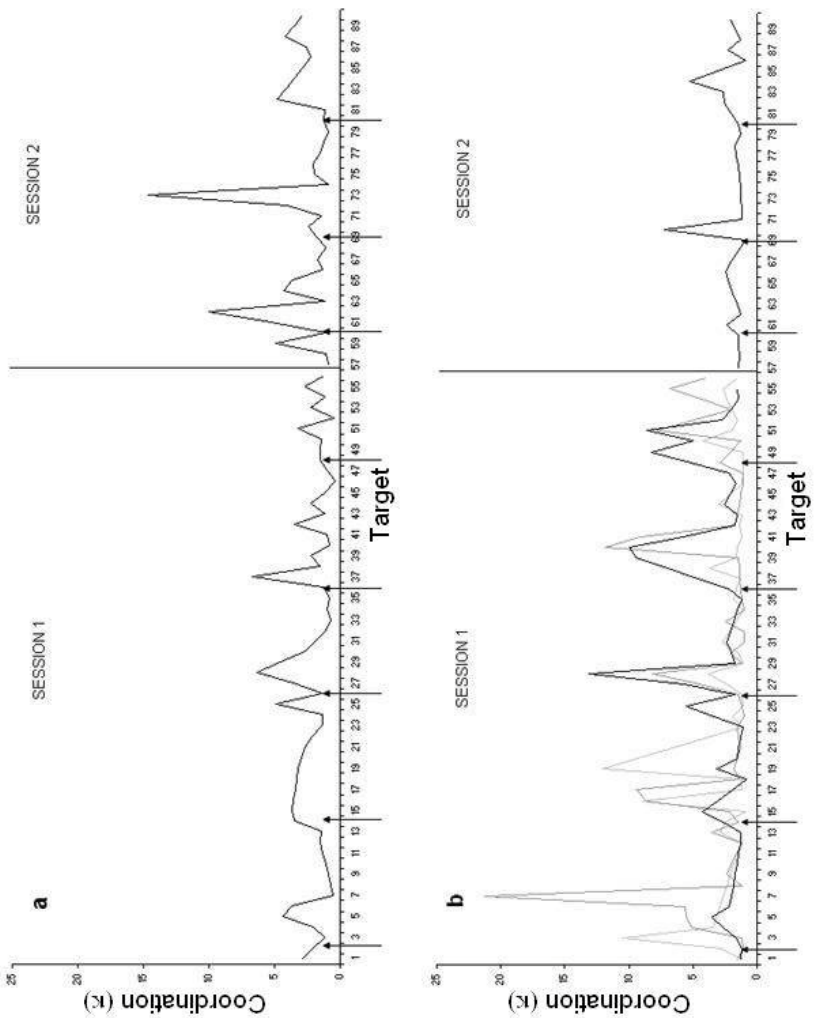

Fig. 2. Representative **κ** series for (a) Intact and (b) Mixed teams; three Session 1 **κ** series for Mixed teams, graphed using differently shaded lines, come from each of the original Session 1 teams. Vertical arrows indicate the introduction of roadblock perturbations.

Representative **κ** series over Session 1 and Session 2 are plotted in Fig. 2. Note that there is one **κ** for Session 1 for the Intact teams (Fig. 2a) and there are three **κ** for Session 1 for the Mixed teams (Fig. 2b). This is because in Session 1, prior to the change in familiarity, each Mixed team member came from a different team; all three teams from which team members came are depicted in Fig. 2b. During Session 2, there was only one **κ** for each team. Our analyses will focus on Session 2 in order to compare Intact to Mixed team coordination dynamics.

The arrows on the abscissa of Fig. 2 correspond to the introduction of roadblock perturbations. In response to the roadblocks, the **κ** demonstrated large, brief fluctuations. Notice that (for Session 2) these fluctuations tended to be larger for Intact teams than for Mixed teams. This trend suggests that roadblock perturbations did not affect the **κ** trajectory for Mixed teams (stable dynamics) as much as for Intact teams (unstable dynamics). Inspection of the **κ** series were followed by analysis of mean **κ** over time in order to determine if these differences were captured by a traditional analysis.

Traditional Analysis

For Session 2, mean **κ** for Intact teams (M = 3.63, SD = 2.99) was not significantly different than mean **κ** for Mixed teams (M = 6.00, SD = 9.82), t (37) = -1.01, *ns*. Thus, the static approach did not reveal any significant differences between Intact versus Mixed team coordination.

Dynamical Analyses

To match the order of hypotheses in the introduction, the dynamical results are presented in the following order: attractor reconstruction; Hurst analysis; and stability analyses.

Attractor reconstruction was performed on each Session 2 **κ** series. Time lag (M = 2.10, SD = 1.12) and dimensionality (M = 4.72, SD = .92) did not differ between Intact and Mixed teams, $t(37)$ = -.55, *ns* and $t(37)$ = 1.18, *ns*, respectively. However the time evolution of trajectories as captured by the attractors of Fig. 3 indicated very different dynamics. Intact teams had more complicated coordination dynamics than Mixed teams. Intact team coordination was focused on a small part of phase space, departures from which were met by corrections back to this familiar part of the space (Fig. 3a). The Mixed team attractor was comparatively simple and could be characterized as continuous exploration of a wider range of phase space (Fig. 3b).

The Hurst analysis employed the use of multiple time scales to estimate long-range correlation in the **κ** series. Seven **κ** series (five Intact and two Mixed) were dropped from the Hurst analysis because they were critically shorter (two fewer time scales) than the rest and so could not be considered in the same analysis as the other (n = 32) **κ** series. [Note: N = 39 for all other analyses.] For testing the exploration-correction hypothesis, a value of $H > 0.5$ was used to test for exploration before the inflection point and $H < 0.5$ was used to test for correction after the inflection point. Mean H values across teams in each condition are depicted in Fig. 4. Intact teams demonstrated a clear inflection point (M = 14.12 targets, SD = 4.10, mean R^2 = .96). For those teams the short-region H exhibited exploration (M = .91, SD = .06), $t(13)$ = 27.20, $p < .001$

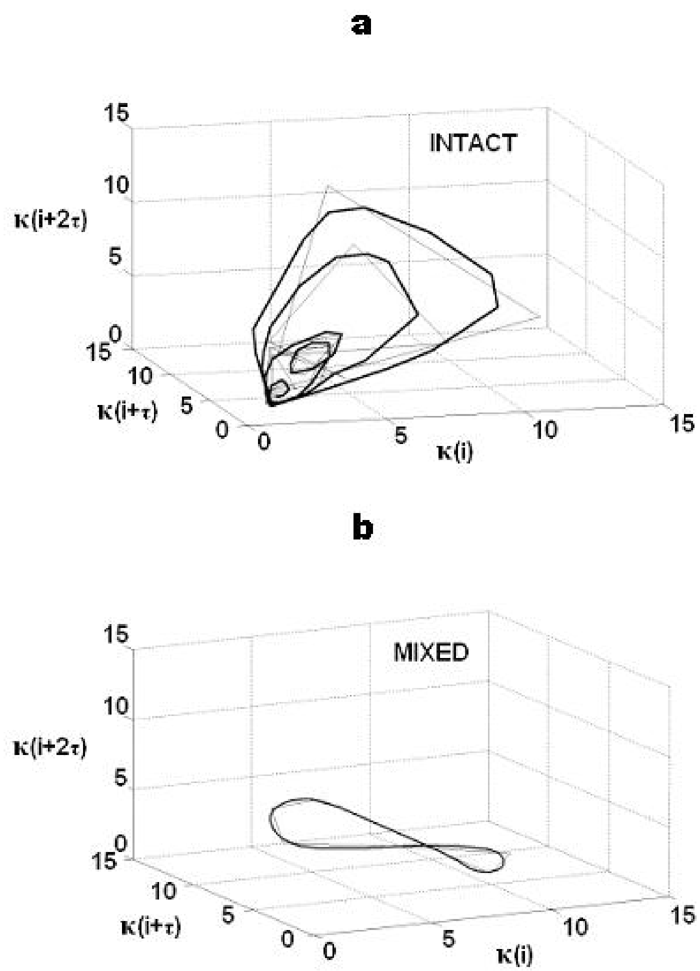

Fig. 3. Reconstructed attractors from (a) Intact and (b) Mixed team coordination.

(one-tailed), $d = 7.27$ and the long-region H exhibited correction ($M = .34$, $SD = .29$), $t\ (13) = -2.01$, $p < .05$ (one-tailed), $d = -.54$. That is, Intact teams used a strategy that was exploratory across small time scales and corrective across long time scales. That pattern supports the interpretation of Fig. 3 and mimics the standard finding for COP dynamics and manual control of inverted pendulums. In contrast, Mixed teams demonstrated no clear inflection point and a single-region $H > 0.5$ over all timescales ($M = .80$, $SD = .07$), $t(17) = 18.16$, $p < .001$ (one-tailed), $d = 4.34$. Thus, Mixed teams displayed only exploration, as ob-

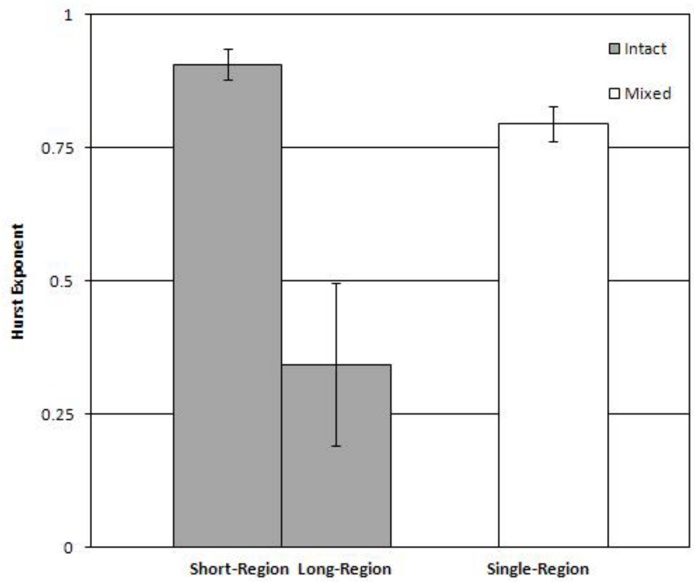

Fig. 4. Mean Hurst exponents for Intact and Mixed teams (95% confidence intervals).

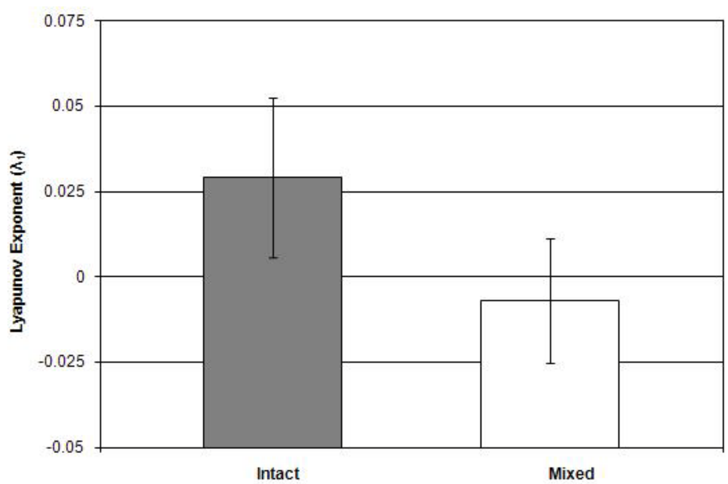

Fig. 5. Mean Intact and Mixed largest Lyapunov exponents λ_1 (95% confidence intervals).

served in Fig. 3. The possibility remains that an inflection point, and a corrective strategy, may exist for Mixed teams at time scales that are larger than the longest sampling window in the experiment.

Mean λ_1 values across teams in each condition are depicted in Fig. 5. A value of $\lambda_1 = 0$ was used as the null hypothesis. Intact teams demonstrated unstable coordination dynamics ($M = .03$, $SD = .05$), $t(18) = 2.45$, $p < .05$ (two-tailed), $d = .56$. Mixed teams were not significantly different from $\lambda_1 = 0$ ($M = -.01$, $SD = .04$), $t(19) = -.74$, *ns*, but an independent samples *t*-test revealed that Mixed teams were more stable than Intact teams, $t(37) = 2.39$, $p < .05$ (two-tailed), $d = .79$. As was suggested by the $\boldsymbol{\kappa}$ series of Fig. 2 and indicated in the attractors of Fig. 3, the exploratory dynamics exhibited by the Mixed teams' attractor were more stable in this highly dynamic UAV task environment than were the corrective dynamics of Intact teams.

Validity Tests

How was stability, or lack of stability, related to the dynamics of the task environment? Environmental change was experimentally introduced using the roadblock perturbations. In order to ensure the quality of the roadblock data, inter-rater reliability of judgments of roadblocks overcome was evaluated. Independent ratings were obtained from a subset of UAV missions ($N = 35$) by having an independent experimenter rate DVD recordings of the missions. The Intraclass correlation coefficient indicated good reliability, $ICC = .86$, $F(33, 33) = 7.24$, $p < .001$.

There was a significant negative correlation between stability and number of roadblocks overcome, $r(37) = -.36$, $p < .05$. As expected, teams with higher stability (i.e., more negative λ_1) also overcame more roadblocks. This result supports the common notion from the dynamical literature that the ability to handle dynamical uncertainty in the environment is related to maintaining stable coordination dynamics.

Surrogate Analyses

Surrogate analyses are conducted to address the possibility that the observed dynamics were an artifact of short time series (Delignieres, Deschamps, Legros, & Caillou, 2003) or occurred randomly. Observed $\boldsymbol{\kappa}$ were compared to randomly shuffled surrogates of the observed $\boldsymbol{\kappa}$. Surrogate analysis (Theiler, Eubank, Longtin, Galdrikian, & Farmer, 1992) is a bootstrapping method that represents a more stringent null hypothesis for presence of significant dynamical structure than comparison to a theoretical value alone (e.g., $H > 0.5$; $\lambda_1 = 0$). Ten randomly shuffled surrogates were generated for each $\boldsymbol{\kappa}$. Each surrogate had the same marginal statistical properties (mean, variance) as its parent $\boldsymbol{\kappa}$ but was randomly sequenced. Single-region *H* (inflection points were not estimated) and λ_1 estimates were compared for all observed and surrogate $\boldsymbol{\kappa}$. Two paired-sample *t*-tests (one for *H* and one for λ_1) were conducted. The observed *H* values ($M = .80$, $SD = .08$) were significantly larger than the mean surrogate values (*M* = .74, *SD* = .03), $t(38) = 5.59$, $p < .001$ (one-tailed), $d = .90$. The absolute values of the observed λ_1 (*M* = .04, *SD* = .04) were also significantly larger than the mean absolute surrogate values (*M* = .02, *SD* = .02), $t(38) = 2.97$, $p < .01$ (two-tailed), $d = .48$. Therefore the observed dynamics were not artifacts of short or noisy $\boldsymbol{\kappa}$.

DISCUSSION

Team coordination has traditionally been studied from an aggregate-static approach. This approach, however, fails to capture important changes in team coordination as teams adjust to meet the changing demands of their environment. In the current study we examined team coordination using principles of NDS. We hypothesized that team coordination *should* exhibit important changes in variability based on changes in team member familiarity and perturbations; averaging coordination behavior over time should wash out these influences. An order parameter (κ) was used to capture the target-to-target variability in team coordination. In support of Hypothesis 1, average κ failed to reveal differences between Intact and Mixed teams. The aggregate-static approach thus failed to reveal differences that were captured using NDS methods.

The Hurst analysis was used to calculate long-range correlations, specifically patterns of exploration and correction, in κ. The analysis revealed that Intact teams displayed exploration and correction, but Mixed teams displayed only exploration. Corrective behavior was demonstrated graphically in Fig. 3a: the Intact attractor focused on a relatively small region of phase space, and when Intact teams did depart from this region, they subsequently corrected back to this small region of phase space. The Mixed attractor of Fig. 3b encompassed approximately the same proportion of phase space as the Intact attractor, but was comparatively simple: the Mixed attractor resembled a periodic dynamic that consistently explored the phase space without correcting back to a preferred region. Thus, Intact teams were rigidly bound to a particular range of κ that Mixed teams were not. This result provides support for Hypothesis 2.

The exploration-correction hypothesis was based on the dynamics of stabilization, similar to COP trajectories (e.g., Collins & De Luca, 1993) and manual control of inverted pendulums (e.g., Treffner & Kelso, 1999). The exploration-correction of the Intact teams was more similar to standard findings in the stabilization literature than the exploration-only dynamics of the Mixed teams. Treffner and Kelso (1999) described a “jiggling” and “running” strategy for the manual control of an inverted pendulum, which produces exploration-correction dynamics similar to those of the Intact teams. In the jiggle-run strategy, a human controller jiggles the bottom of the pendulum in an attempt to stabilize the pendulum in an upright position. Eventually, balance at the jiggle-point is lost and an episode of running occurs. During running, the controller corrects back to a central location at which a new bout of jiggling occurs. The jiggle-run strategy does not produce stable, fixed point dynamics but chaotic and intermittent dynamics, which are unstable. Treffner and Kelso (1999) did not describe a run-only strategy for manual control of an inverted pendulum. However, using their language the simple periodic dynamic of the Mixed teams could be interpreted as a controlled run that explores the same amount of phase space as the Intact teams, but results in more globally stable coordination dynamics.

We checked the stability of those dynamics by calculating the largest Lyapunov exponent, λ_1. Consistent with the patterns of stabilization, the controlled exploration of the Mixed teams was more stable than the corrective dynamics of the Intact teams, as indexed by λ_1. This result provides support for Hypothesis 3. By continuously exploring, the Mixed teams were better able to maintain stability as they adapted to the dynamics of the task environment, namely, roadblocks. Based on existing dynamical literature and theory we hypothesized that this higher stability would be correlated with a greater number of roadblocks overcome. In support of Hypothesis 4, λ_1 was negatively correlated with number of roadblocks overcome indicating that more stable teams (i.e., Mixed teams) overcame more roadblocks.

The dominant view in the shared mental model literature is that the teams who worked together longer (i.e., Intact teams) should have coordinated more effectively (Smith-Jentsch, Kraiger, Cannon-Bowers, & Salas, 2009). However, the Mixed teams exhibited greater flexibility and adaptability; this was obviously not accomplished by a prolonged period of working together. A more plausible explanation is that the process of mixing team members jostles team coordination from a locally-optimal attractor, moving teams through a coordination attractor landscape (see below) to find a more globally-optimal coordination attractor. This is similar to concepts from both computational modeling and motor learning. In computational modeling, a method called hill climbing is used to shake up a settled system resulting in a more globally-adaptive solution. Relatedly, it is common in the motor learning literature to introduce variability in the execution of a task to improve transfer following skill acquisition. In this case the result was the more flexible, yet stable, team coordination dynamics exhibited by the Mixed teams. But will mixing team membership always result in more effective team coordination? The answer may be “no” if the task has only one fixed solution that needs to be followed like a recipe (e.g., Malone & Crowston, 1994).

We have argued that teams must not only be able to interact effectively under routine conditions; they must also be able to adjust their coordination to meet the changing demands of their environment. One could argue, however, that if the task is highly routine (e.g., following a check list), then a team that is well-rehearsed and does not deviate from procedure can coordinate more effectively than a newly formed team that has to relearn the procedure each time team membership changes. Thus, for a totally fixed, unchanging task, mixing team membership could be detrimental to team coordination. Although the idea of a totally fixed environment is somewhat of a straw man, mixing group membership has been found to disrupt group coordination even in a slowly evolving task environment (Guastello et al., 2005), which is likely closer to reality than a totally fixed environment. The current results have greater applicability to changing (dynamic) task environments. In the next section we consider the implications for training teams to perform at a high level under both routine and novel task conditions.

Implications for Training Adaptive Teams

The traditional approach suggests training interventions that focus on building a shared mental model to improve coordination. However the evidence shows that teams or groups whose membership is based on the same view of the world will tend to display rigid behavior regardless of changing environmental demands (e.g., "groupthink;" Janice, 1972; see also Katz, 1982). Those observations are theoretically aligned with our result that mixing team members leads to more adaptive team coordination. Counter to the traditional approach, our mixing results suggest that interventions that "jostle" team coordination into new patterns improve coordination by allowing teams to escape rigid patterns and ultimately become more flexible and adaptive. We hypothesize that this can be accomplished not just by mixing team members, but also by directly multiplying the amount and types of coordination experiences to which the team is exposed using perturbations.

In the current study, we created flexible teams by changing team membership and we probed their flexibility by introducing roadblock perturbations, but we have been developing training strategies for creating flexible teams without the need for changing team membership by introducing perturbations during task acquisition. We have been conducting UAV team training experiments in which perturbation training is compared to traditional team training (e.g., cross-training for a shared mental model; Cannon-Bowers, Blickensderfer, & Bowers, 1998). Following training, the teams must perform under both routine and novel situations. Our results thus far indicate that perturbation training methods are superior to training methods that focus on development of a shared mental model for training adaptive teams and with no loss in routine performance (Gorman, Cooke, & Amazeen, in press).

Although perturbation training has been successful for training adaptive teams, an important question that remains is whether or not the concepts of team coordination dynamics apply to more than just the three-person UAV teams described here. Teams can be much larger than three members and they can form to solve many problems beyond the sequenced command-and-control of the UAV task of the present study. In the remainder of this section we extend the notions of order parameters, control parameters, and NDS methods beyond the three-person UAV teams described here.

Extensions of Team Coordination Dynamics

Order Parameters

The power of the order parameter is that pattern formation at the team level exerts causal constraint on—"enslaves" (Haken, 1977)—the local interactions of the team members. Under Haken's slaving principle, coordination need not be described in terms of independent component behavior because the components are constrained to act as a single functional unit. The order parameter captures patterns that are dynamically assembled at the component level and exhibit coordination at the system level. The patterns revealed in our analyses of κ spanned large timescales of UAV operations (i.e., long-range correlations) across several missions, which suggests that the team members were likely unaware of the patterns exhibited at the level of the order parameter even though their interactions were constrained by those patterns.

Possible extensions of the order parameter concept include the ability to scale quantities like κ to larger team sizes. Although κ was mapped in two dimensions (a slope) in principle it could be mapped to a much higher dimension (a gradient). The traditional view does not scale as teams grow in size because the goal of a shared mental model becomes unreasonable. Alternatively, the slaving principle entails that coordination of system components is captured by the dynamics of the order parameter. Thus coordination across many-component systems can be captured in a relatively low dimension once the order parameter has been identified.

The components of coordination (i.e., e_1, e_2, e_3) for the UAV task were sequenced according to relational constraints, but system components need not be sequenced for the order parameter concept to apply. More generally, coordinated behavior across homogeneous components can produce emergent pattern formation. For instance, although group members are not constrained to interact in a particular sequence, the work by Guastello and colleagues (1998, 2005, 2007) shows that group coordination can exhibit emergent pattern formation as control parameters (e.g., level of verbalization; group familiarity) are adjusted.

Control Parameters

The attractor landscape can be altered as a function of changes in the value of the control parameter. This is demonstrated in Fig, 3, in which the only difference between Intact and Mixed teams was the value of the team familiarity control parameter. In our study, exploration-correction was the most stable attractor for completely familiar teams whereas exploration-only was the most stable attractor for completely unfamiliar teams. The most stable mode was not determined by familiarity but rather the NDS of team interaction. Thelen and Smith (1996) referred to this as the *non-specificity* of the control parameter: team coordination was not encoded in the level of familiarity; the stable pattern emerged strictly from the NDS of the system. This also means that different dynamics may exist at the midpoint between totally intact and totally mixed teams, that is, if we had set the system up differently. These dynamics could be revealed by continuously adjusting, or scaling, the control parameter.

An example of an independent variable (IV) from team coordination research that can be continuously scaled is level of workload. Treated as an IV, increased workload is thought to *cause* teams to shift explicit to implicit coordination (Entin & Serfaty, 1999). Another interpretation is that implicit coordination is more attractive under increased workload and that explicit coordination is more attractive under decreased workload. Treated as a control parameter, continuous scaling of workload may yield new insights into the explicit-implicit coordination distinction. One possibility is the revealing of hysteresis effects (Gilmore, 1981). That is, the transition from explicit to implicit coordination may occur at one level of workload when workload is increased, but the transition back to explicit coordination may not occur at the same level of workload as workload is decreased. The presence of a hysteresis effect is a clear reminder that the coordinated response is not directly specified by the control parameter.

As workload, or any other control parameter, is scaled we must consider that the coordinated response emerges from team member interactions. This calls for appropriate NDS methods to capture coordinated and other team responses that emerge from team member interaction in a dynamic environment.

NDS Methods

Dynamical similitude is the principle that systems with different material substrates can exhibit the same dynamics. This principle can be used to guide selection of appropriate NDS methods for a system that has not been previously analyzed using a dynamical approach. We chose attractor reconstruction, stability analysis, and long-range correlation for this study but other methods may be more appropriate for other team tasks. For example, in addition to team coordination we also study teams that perform collaborative planning tasks and have observed that such teams can exhibit simultaneous, nested threads of interaction suggestive of fractal dynamics (Gorman, Cooke, Amazeen et al., 2009). Fractal dynamics are those found in scale invariant processes, such as the human heartbeat, in which behavior at small time scales resembles behavior at larger time scales, i.e., when you magnify a fractal the pattern looks the same (Eke et al., 2002). An appropriate NDS method for analyzing fractal dynamics of heart rate variability is the power spectral density – the log-log slope of the frequency content of inter-heartbeat intervals. Based on the principle of dynamical similitude, power spectral density is an appropriate NDS method for examining collaborative planning behavior—for example, frequency content by topic—in teams.

A reasonable goal for any team is to continuously achieve a match between coordination dynamics and the dynamics of the environment. To date, all NDS analyses are conducted *post hoc* but there are situations, like the surgical team from the introduction, in which it would be advantageous to identify a team's dynamical patterns in real time. We are currently developing real-time methods for the exponents described in the present study (i.e., H; λ_1) and other exponents such as the power spectral density. Ultimately, real-time NDS methods would allow us to detect and intervene in real time in the case of anomalous matches between team dynamics and environmental dynamics.

Conclusion

It is not enough to simply assemble a collection of experts to accomplish a team task because team members have to coordinate their actions. The team must not only coordinate effectively during routine procedures; they must also be able to adapt to the changing demands of their environment. Tools of NDS are appropriate for understanding team coordination phenomena because they give us more than an aggregate-static snapshot of team-member interaction. The dynamical approach that we have described here may provide new answers for traditional problems such as how to train an adaptive team that aggregate-static approaches do not.

Mark Twain once wrote that "history does not repeat itself, but it often rhymes." Put differently, the present is not the same as the past, but there is an undeniable flow that unifies them into a single coherent history—a rhyme. Like a rhyme, the essence of coordination is in the flow across time of relations across the constituent parts, not the individual parts themselves. The goal of the team coordination dynamics approach is to look for that rhyme.

ACKNOWLEDGMENT

This research was funded by Air Force Office of Scientific Research grant FA9550-04-1-0234 and Air Force Research Laboratory grant FA8650-04-6442; additional support came from National Science Foundation grant BCS 0447039. The authors would like to thank the following individuals who contributed to this research: Dee Andrews, Brian Bell, Christy Caballero, Olena Connor, Janie Dejoode, Preston Kiekel, Harry Pedersen, Steven Shope, and Jennifer Winner. Some of the data reported in this paper were reported in the first author's dissertation and in a technical report (Cooke et al., 2007).

REFERENCES

Abarbanel, H. D. I. (1996). *Analysis of observed chaotic data.* New York: Springer-Verlag.

Amazeen, P. G., Amazeen, E. L., & Turvey, M. T. (1998). Breaking the reflectional symmetry of interlimb coordination dynamics. *Journal of Motor Behavior, 30,* 199-216.

Beran, J. (1994). *Statistics for long-memory processes.* Boca Raton, FL: Chapman & Hall/CRC Press.

Busemeyer, J. R., Swenson, K. N., & Lazarte, A. (1986). Ad adaptive approach to resource allocation. *Organizational Behavior and Human Decision Processes, 38,* 318-341.

Brannick, M. T., Prince, A., Prince, C., & Salas, E. (1995). The measurement of team process. *Human Factors, 37,* 641-651.

Cannon-Bowers, J. A., Salas, E., Blickensderfer, E., & Bowers, C. A. (1998). The impact of cross-training and workload on team functioning: A replication and extension of initial findings. *Human Factors, 40,* 92-101.

Cannon-Bowers, J. A., Salas, E., & Converse, S. (1993). Shared mental models in expert team decision making. In N. J. Castellan (Ed.), *Individual and group decision making* (pp. 221-246). Hillsdale, NJ: Lawrence Erlbaum Associates.

Collins J. J. & De Luca C. J. (1993) Open-loop and closed-loop control of posture: A random-walk analysis of center-of-pressure trajectories. *Experimental Brain Research, 95,* 308-318.

Cooke, N. J., Gorman, J. C., Pedersen, H. K., Winner, J., Duran, J., Taylor, A. et al. (2007). *Acquisition and retention of team coordination in command-and-control.* Technical Report for AFOSR grant FA9550-04-1-0234 and AFRL award number FA8650-04-6442.

Cooke, N. J., Gorman, J. C., & Rowe, L. J. (2009). An ecological perspective on team cognition. In E. Salas, J. Goodwin, & C. S. Burke (Eds.), *Team effectiveness in complex organizations: Cross-disciplinary perspectives and approaches* (pp. 157-182). SIOP Organizational Frontiers Series. New York: Taylor & Francis.

Cooke, N. J., & Shope, S. M. (2005). *Synthetic task environments for teams: CERTT's UAV-STE handbook on human factors and ergonomics methods,* (pp. 46-1-46-6). Boca Raton, FL: CRC Press.

Delignieres, D., Deschamps, T., Legros., A., & Caillou, N. (2003). A methodological note on nonlinear time series analysis: Is the open- and closed-loop model of Collins and De Luca (1993) a statistical artifact? *Journal of Motor Behavior, 35,* 86-97.

Eke, A., Herman, P., Kocsis, L., & Kozak, L. R. (2002). Fractal characterization of complexity in temporal physiological signals. *Physiological Measurement, 23,* R1-R38.

Entin, E. E. & Serfaty, D. (1999). Adaptive team coordination. *Human Factors, 41,* 312-325.

Fraser, A. M. & Swinney, H. L. (1986). Independent coordinates for strange attractors from mutual information. *Physical Review A, 33,* 1134-1140.

Fuchs, A. & Jirsa, V. K. (Eds.) (2008). *Coordination: Neural, behavioral and social dynamics.* Heidelberg: Springer.

Gilmore, R. (1981). *Catastrophe theory for scientists and engineers.* New York: Dover Publications, Inc.

Gorman, J. C., Cooke, N. J., & Amazeen, P. L. (in press). Training adaptive teams. *Human Factors.*

Gorman, J. C., Cooke, N. J., Amazeen, P. L., Hessler, E. E., & Rowe, L. (2009). *Automatic tagging of macrocognitive collaborative processes through communication analysis.* Technical Report for Office of Naval Research grant N00014-05-1-0625.

Gorman, J. C., Cooke, N. J., & Winner, J. L. (2006). Measuring team situation awareness in decentralized command and control environments. *Ergonomics, 49,* 1312-1325.

Guastello, S. J., Bock, B. R., Caldwell, P., & Bond, R. W. (2005). Origins of group coordination: Nonlinear dynamics and the role of verbalization. *Nonlinear Dynamics, Psychology, and Life Sciences, 9,* 175-207.

Guastello, S. J. & Bond, R. W. (2007). The emergence of leadership in coordination-intensive groups. *Nonlinear Dynamics, Psychology, and Life Sciences, 11*, 91-117.

Guastello, S. J. & Guastello, D. D. (1998). Origins of coordination and team effectiveness: A perspective from game theory and nonlinear dynamics. *Journal of Applied Psychology, 83*, 423-437.

Haken, H. (1977). *Synergetics: An introduction.* Berlin: Springer-Verlag.

Haken, H., Kelso, J. A. S., & Bunz, H. (1985). A theoretical model of phase transitions in human hand movements. *Biological Cybernetics, 51,* 347-356.

Hurst, H. E. (1951). Long term storage capacity of reservoirs. *Transactions of the American Society of Civil Engineering, 116*, 770-799.

Janis, I. L. (1972). *Groupthink: Psychological studies of policy decisions and fiascoes*. Boston: Houghton Mifflin.

Kantz, H. (1994). A robust method to estimate the maximal Lyapunov exponent of a time series. *Physics Letters A, 185,* 77-87.

Kantz, H. & Schreiber, T. (1997). *Nonlinear time series analysis.* Cambridge, UK: Cambridge University Press.

Katz, R. (1982). The effects of group longevity on project communication and performance. *Administrative Science Quarterly, 27*, 81-104.

Kelso, J. A. S. (1984). Phase transitions and critical behavior in human bimanual coordination. *American Journal of Physiology: Regulatory, Integrative and Comparative, 15,* R1000-R1004.

Kelso, J. A. S. (1995). *Dynamic patterns: The self-organization of brain and behavior.* Cambridge, MA: MIT Press.

Kennel, M. B., Brown, R., & Abarbanel, H. D. I. (1992). Determining embedding dimension for phase-space reconstruction using a geometrical construction. *Physical Review A, 45,* 3403-3411.

Langan-Fox, J., Code, S., & Langfield-Smith, K. (2000). Team mental models: Techniques, methods, and analytic approaches. *Human Factors, 42*, 242-271.

MacMillan, J., Entin, E. E., & Serfaty, D. (2004). Communication overhead: The hidden cost of team cognition. In E. Salas & S. M. Fiore (Eds.), *Team cognition: Process and performance at the inter and intra-individual level* (pp. 61-82). Washington, DC: American Psychological Association.

Malone, T. W. & Crowston, K. (1994). The interdisciplinary study of coordination. *ACM Computing Surveys, 26,* 87-119.

Manser, T., Howard, S. K., & Gaba, D. M. (2008). Adaptive coordination in cardiac anaesthesia: A study of situational changes in coordination patterns using a new observation system. *Ergonomics, 51,* 1153-1178.

Mohammed, S. & Dumville, B. C. (2001). Team mental models in a team knowledge framework: Expanding theory and measurement across disciplinary boundaries. *Journal of Organizational Behavior, 22,* 89-106.

Riley, M. A., Wong, S., Mitra, S., & Turvey, M. T. (1997). Common effects of touch and vision on postural parameters. *Experimental Brain Research, 117,* 165-170.

Rosenstein, M. T., Collins, J. J., & DeLuca, C. J. (1993). A practical method for calculating largest Lyapunov exponents from small data sets. *Physica D, 65,* 117-134.

Rouse, W. B., & Morris, N. M. (1986). On looking into the black box: Prospects and limits in the search for mental models. *Psychological Bulletin, 100,* 349-363.

Smith-Jentsch, K. A., Kraiger, K., Cannon-Bowers, J. A., & Salas, E. (2009). Do familiar teammates request and accept more backup? Transactive memory in air traffic control. *Human Factors, 51,* 181-192.

Stout, R. J., Cannon-Bowers, J. A., Salas, E., & Milanovich, D. M. (1999). Planning, shared mental models, and coordinated performance: An empirical link is established. *Human Factors, 41,* 61-71.

Theiler, J., Eubank, S., Longtin, A., Galdrikian, B., & Farmer, J. D. (1992). Testing for nonlinearity in time series: The method of surrogate data. *Physica D, 15,* 77-94.

Thelen, E. & Smith, L. B. (1996). *A dynamic systems approach to the development of cognition and action.* Cambridge, MA: MIT Press.

Treffner, P. J., & Kelso, J. A. S. (1999). Dynamic encounters: Long memory during functional stabilization. *Ecological Psychology, 11*, 103-137.

Wang, W-P, Kleinman, D. L., & Luh, P. B. (2001). Modeling team coordination and decisions in a distributed dynamic environment. In G. M. Olson, T. W. Malone, and J. B. Smith (Eds.), *Coordination theory and collaboration technology* (pp. 673-710). Mahwah, NJ: Lawrence Erlbaum Associates.

Wolf, A., Swift, J. B., Swinney, H. L., & Vastano, J. A. (1985). Determining Lyapunov exponents from a time series. *Physica D, 16,* 285-317.