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Neural signatures of team coordination are revealed by multifractal analysis

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The quality of a team depends on its ability to deliver information through a hierarchy of team members and negotiate processes spanning different time scales. That structure and the behavior that results from it pose problems for researchers because multiply-nested interactions are not easily separated. We explored the behavior of a six-person team engaged in a Submarine Piloting and Navigation (SPAN) task using the tools of dynamical systems. The data were a single entropy time series that showed the distribution of activity across six team members, as recorded by nine-channel electroencephalography (EEG). A single team's data were analyzed for the purposes of illustrating the utility of multifractal analysis and allowing for in-depth exploratory analysis of temporal characteristics. Could the meaningful events experienced by one of these teams be captured using multifractal analysis, a dynamical systems tool that is specifically designed to extract patterns across levels of analysis? Results indicate that nested patterns of team activity can be identified from neural data streams, including both routine and novel events. The novelty of this tool is the ability to identify social patterns from the brain activity of individuals in the social interaction. Implications for application and future directions of this research are discussed.

Keywords: Team coordination; Multifractal; EEG; Complex systems.

Teamwork is a fundamental activity that is observed across business, educational, sports, and military settings. Across all of these settings, the best teams demonstrate the same essential characteristics: They coordinate their activities in diverse ways and are able to switch quickly between performing routine tasks and trouble-shooting unforeseen interruptions. One of the features of teams that makes them productive can also make them difficult to analyze: Teams are hierarchically arranged, with individuals working in smaller, specialized units that are themselves nested within larger units. This complex nested structure is well suited to fulfilling work goals because responsibilities are distributed across specialty groups whose members need only focus on a portion of the overall team task. However, that same nested structure poses problems for traditional approaches to team cognition and performance due to the reliance on comparisons of measured performance that are aggregated across individuals. With nested structures, the challenge is to decide on a

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particular level of aggregation—a small ensemble or the entire team—a task that becomes nearly impossible if individuals are differently grouped for different purposes. In the current work, we explore the benefits of a dynamical systems approach to team hierarchies and demonstrate a method by which to capture the nested character of team performance.

THE NESTED NATURE OF TEAMS

Familiarity with nearly any organizational chart reveals the nested structure of teams. Figure 1 depicts the hierarchical organization of a hypothetical marketing department with a board of directors and chief executive officer (CEO) at the top and various teams, individuals, and physiological processes situated at lower levels. The department is divided into east and west divisions, with brand management and marketing strategy teams nested within each of those geographically identified sub-teams. At each subsequent level of the hierarchy, there is further evidence of nesting: Brand management contains publications, communications, and event planning teams, which are each composed of different ensembles of individuals. Often, individuals contribute to more than one sub-team, resulting in a very complicated branching structure.

The nesting continues at scales smaller than the individual: Just as individuals can be nested within organizational teams, so are physiological processes nested within individuals, producing a physiological extension of the hierarchy commonly considered in team research (Cooke, Gorman, Myers, & Duran, 2013). Physiological processes vary considerably over a workday and contribute to ebbs and flows in an individual's—and, by extension, a team's—productivity. Some obvious examples include processes related to neural, cardiac, and respiratory activities. Inclusion of those physiological processes in our organizational chart increases substantially the levels of influence that contribute to a full understanding of team performance and is a natural step in the evolution of team study.

The reason for situating physiological processes within the team concept may be obvious as various

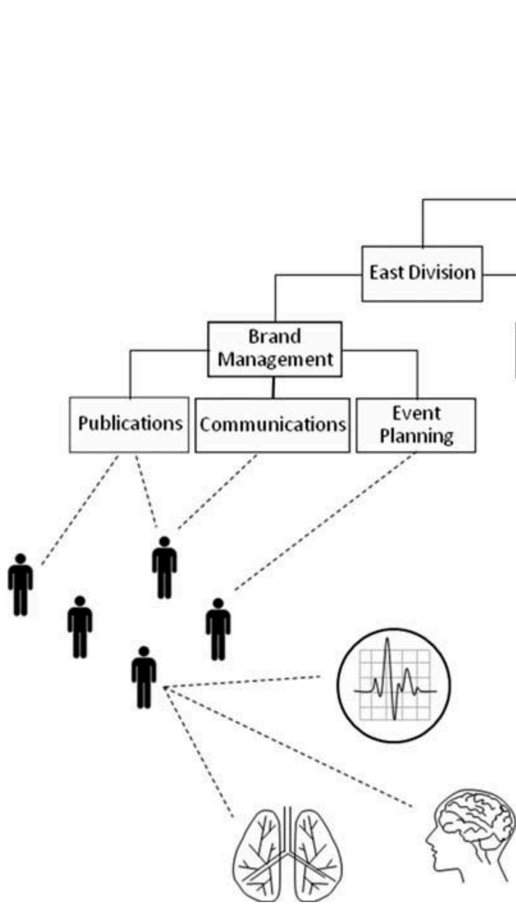

Figure 1. Organizational chart of a hypothetical marketing team. Tracing from the top to the bottom of the figure reveals the hierarchical structure typical of team organization and shows that there are many levels at which to assess team performance.

neural measurements, such as electroencephalography (EEG), magnetoencephalography (MEG), and functional magnetic resonance imaging (fMRI), have come to play a prominent role in many areas of psychological science. Even within the area of cognition, researchers use these brain imaging techniques to look for neural correlates for cognitive processes such as attention (e.g., Coull, 1998), decision-making (Sanfey, Rilling, Aronson, Nystrom, & Cohen, 2003), episodic and working memory (e.g., Cabeza, Dolcos, Graham, & Nyberg, 2002; Paulesu, Frith, & Frackowiak, 1993), and lexical processing (Joubert et al., 2004). One challenge that these researchers face is situating specific processes and events within specific neural structures or patterns (Gonzales-Castillo et al., 2012). Our intention here is not to question the utility of brain imaging techniques in the study of human behavior as that argument is beyond the scope of the current work and has been discussed extensively elsewhere (Uttal, 2001). Instead we offer the possibility that, in at least some instances, neural studies may suffer as a result of the assumption that brain activity exclusively reflects intraperson dynamics and, more specifically, individual cognitive processes. An alternative way of thinking is that brain dynamics also reflect, and may be inseparable from, the situation or context in which individuals are embedded. The precedence for that assumption stems from the study of interperson coordination in the context of dyads (e.g., Schmidt, Carello, & Turvey, 1990) and teams (Gorman, Amazeen, & Cooke, 2010).

A common means of studying interperson behavior is to require individuals to perform a simple task, such as swinging their legs or rocking chairs together (e.g., Richardson, Marsh, Isenhower, Goodman, & Schmidt, 2007; Schmidt et al., 1990). In the prototypical experiment, participants are required to jointly maintain some pattern—such as a zero-degree phase relationship between their effectors—over the course of an experimental trial. The overwhelming finding is that when the participants are coupled in some way (e.g., watching each other's movements), their movements become synchronized, sometimes in surprisingly complex ways (e.g., Fine, Gibbons, & Amazeen, 2013; Marmelat & Delignières, 2012; Richardson et al., 2007). One conclusion that may be drawn from those findings is that individual behaviors reflect the dynamics of the ensemble; that is, group-level constraints are detectable in individual behaviors. To that end, there is growing support for the idea that individual neural activity reflects the quality of coordination between two people (e.g., Hasson, Ghazanfar, Galantucci, Garrod, & Keysers, 2012; Tognoli, Lagarde, DeGuzman, & Kelso, 2007). For example, neural oscillations appear coupled when musicians play the same melody (e.g., Lindenberger, Li, Gruber, & Müller, 2009). We will expand upon this concept in the present study by testing whether team-level information can be extracted from the physiological (neural) behavior of individual team members.

THE TRADITIONAL APPROACH TO STUDYING TEAMS

For decades, researchers have studied team cognition and team coordination using the concept of a shared mental model (e.g., Entin & Serfaty, 1999; Rouse & Morris, 1986; Uitdewilligen, Waller, & Pitariu, 2013). Simply put, an individual team member builds a hypothetical cognitive construct, a mental model, that represents her own knowledge of the task at hand. She uses that mental model to interpret and organize information, make predictions about future events, and control her own behavior. Similarities across the mental models of team members are considered advantageous, as they allow team members to coordinate via anticipation rather than explicit interaction. In the extreme case, all team members possess the same knowledge; in the less extreme case, knowledge among team members is at least complimentary or overlapping. The team's shared mental model is considered to be an aggregate, or summation, of the individual mental models (e.g., Entin & Serfaty, 1999). In that light, a common approach to training that builds from the shared mental model perspective is the use of cross-training (e.g., Cannon-Bowers, Salas, Blickensderfer, & Bowers, 1998), in which team members are trained in the positions of other team members with the goal of developing a shared knowledge structure.

In the shared mental model, the implication of summation is that the behavior of any one team member is relatively independent of the behavior of other teammates. This assumption creates a problem of shared variance in a nested structure, particularly if individuals belong to multiple sub-teams. In the example depicted in Figure 1, the same individual may contribute to both publications and communications, but not event planning, in the brand management unit. An alternative to the shared mental model is a dynamical approach in which characteristics of a team (knowledge, performance, process) emerge from interactions among team members. Treating the interactions as primary downplays the role of particular individual traits and knowledge and highlights the exchange of information that characterizes teams at all levels (Cooke et al., 2013). The difference with the shared mental model approach can be made more concrete through empirical demonstrations. For instance, a comparison of the aforementioned cross-training with "perturbation training", in which team members were forced to interact with each other in unexpected ways in response to novel situations, revealed that more adaptive teams developed with this latter, dynamical strategy (Gorman, Cooke, & Amazeen, 2010). We propose that shifting emphasis to the primacy of interactions among team members will allow us to capture the nested structure of teams and large organizations.

A DYNAMICAL SYSTEMS APPROACH TO NESTED TEAM COGNITION

A dynamical systems approach to team cognition involves recognizing the fact that while individual behavior affects team performance, teams exhibit bidirectional influence, with individuals being constrained by the team's goals and intentions just as they contribute to them. This bidirectional influence, called circular causality, is a hallmark characteristic of a complex system (Haken, 1996). For the company depicted in Figure 1, a particular subset of individuals, perhaps those on the board of directors, have formulated a mission statement for the company, but then that mission statement acts as a constraint on even the board of directors' individual decisions and daily behaviors. This circular causality occurs at all scales: The company's mission statement affects the activities of the east and west divisions and all of the individual teams nested within them. At each level, team decisions affect the behavior of individuals and team behavior is affected by individual behaviors and decisions. That same structure can be applied within individuals: Physiological processes function to support the individual as a whole and are, in turn, constrained by the individual's behavior. For example, respiration and cardiac activity are essential support systems for life but can be affected by a stressful event experienced by the individual. Research supports the interdependency of whole body, cognitive, and physiological processes. For example, decreases in heart rate variability are associated with a stressful work environment (Chandola, Heraclides, & Kumari, 2010), and increases in EEG activity are associated with engagement in cognitive tasks (e.g., Berka et al., 2007). In contrast, psychologists have known that autonomic responses, like changes in heart rate, have a profound effect on cognitive processes ever since Yerkes and Dodson (1908) first found that arousal produced U-shaped performance functions in a discrimination learning task. Contemporary researchers have found similar results indicating that certain forms of exercise both enhance and deteriorate cognitive performance, depending on the intensity and duration of the exercise (Brisswalter, Collardeau, & René, 2002).

A dynamical systems approach to team cognition also entails recognition that the influence among team members is an ongoing and dynamic, not static, process. Team behavior commonly changes over time as team members are confronted with new information or challenges. Dynamical systems tools are designed to capture the temporal evolution of any process, with the main objective being to uncover temporal patterns not readily captured from outcomes or other static measures (e.g., mean, variance). There are a large number of dynamical models that could be used to describe team behavior. One dynamical method, called attractor reconstruction, was used to characterize team coordination dynamics from communication data (Gorman, Amazeen, et al., 2010). A second dynamical measure, called the Hurst exponent, was used to characterize long-range correlations in those team coordination data. A more sophisticated form of that method, called multifractal analysis, will be used here to analyze the nested patterns of behavior inherent in teams. We will provide details about multifractal analyses following an introduction to fractals below. The same feature that poses fundamental problems to traditional analyses, which are based upon partitioning sources of variability, is foundational to multifractal analysis, which thrives on nested patterns of variability.

FRACTALS AND MULTIFRACTALS

Fractals are spatial or temporal geometric structures that have self-similar structure at multiple levels of analysis (Mandelbrot, 1983). The concept of self-similarity refers to the characteristic that the spatial or temporal features of an object or time series, respectively, observed at a small scale, resemble the features observed at a large scale. An accessible example of spatial self-similarity can be seen in the structure of a tree (Figure 2a). Tracing the trunk upward from the ground, one observes that the tree forks into two branches; following one of those branches reveals another fork into another two branches. One of the assumptions that we will make in applying a fractal analysis to teams is that hierarchical team structure resembles this tree's structure: in some sense, the interaction of team members in small groups resembles small group interaction within larger groups. The same approach can be applied to time series data, with an emphasis on timing characteristics: teams have the

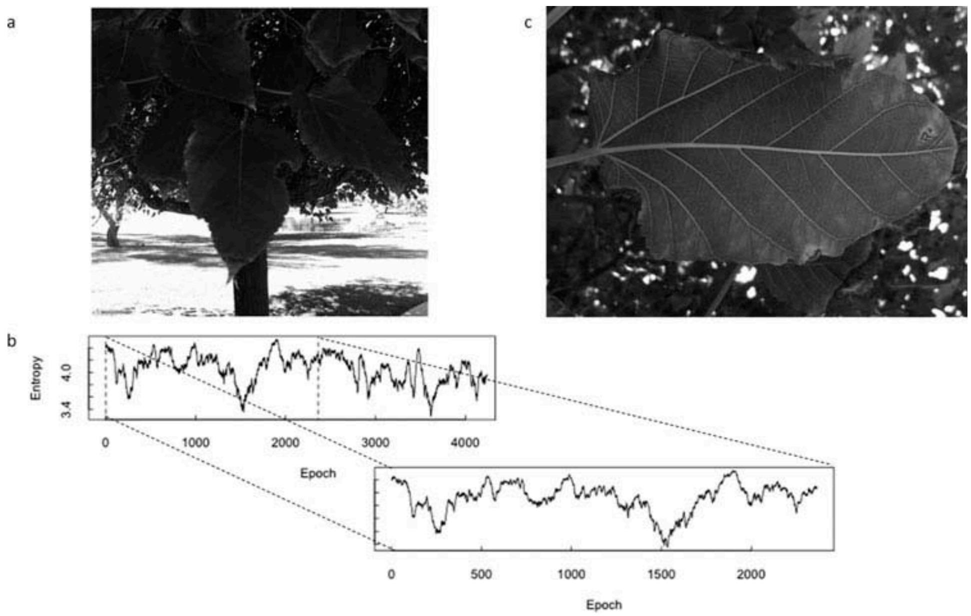

Figure 2. (a) A picture of a tree demonstrating the fractal property of self-similarity. (b) A sample entropy time series. Magnifying one portion of the top time series reveals another very similar time series and represents the concept of statistical self-affinity, i.e., the time series looks the same at large scales as it does at small scales. (c) A picture of the vein structure found in a leaf. This illustrates the concept of multifractality—the fractal structure of the leaf differs from that of the tree, despite being part of the same structure.

potential to demonstrate similar patterns of fluctuation over both short and long time scales (Figure 2b). The paradigmatic example of such fluctuations is that of the heartbeat, in which self-similarity over time is the defining characteristic of a healthy heart beat and deviations from that fractal patterning are indicative of life-threatening conditions such as cardiac arrhythmia (random variation) or congestive heart failure (periodicity) (e.g., Gieraltowski, Zebrowski, & Baranowski, 2012; Goldberger et al., 2002; Peng et al., 1995).

The suggestion from these studies is that fractal properties are a general characteristic of smoothly running systems, in which the nested physiological and/or cognitive components interact efficiently (Van Orden, Holden, & Turvey, 2003). Fractals have been used to make categorical distinctions between healthy and unhealthy people with Parkinson's (e.g., Hausdorff, 2009) and Alzheimer's (e.g., Woyshville & Calabrese, 1994) diseases and to predict performance patterns in perceptual tasks such as visual search (e.g., Stephen & Anastas, 2011) and weight estimation of a wielded object (e.g., Stephen, Arzamarksi, & Michaels, 2010). In the present study, we will test the hypothesis that these findings extend beyond the individual to team performance. Gorman, Amazeen, et al. (2010) demonstrated preliminary support for that hypothesis using one index of fractal scaling, the Hurst exponent.

In that study, researchers recorded communication patterns from three-member teams (pilot, navigator, and photographer) while they performed a simulation task involving an uninhabited air vehicle (UAV). Some teams, called intact teams, were composed of team members who had worked together on that task previously, and other teams, called mixed teams, were composed of team members who had worked on that task before but never worked together. The researchers used perturbations—abrupt, momentary disruptions, such as a lapse in communication—to gauge the flexibility of each team in responding to unpredictable problems. They found that mixed teams exhibited more fractal behavior and more successful recovery from perturbations. This finding was the motivation for "perturbation training", mentioned earlier (Gorman, Cooke, et al., 2010). In that follow-up study, perturbations were manipulated explicitly during training in order to determine their role in producing a more adaptive team. In retrospect, the result was not surprising because mixed teams relied more heavily on ongoing interactions rather than on a shared mental model that they may have developed in concert with other teammates who were then replaced.

A global analysis of fractality, such as that performed by Gorman, Amazeen, et al. (2010), reveals whether a team is, like the heart rate of a healthy individual (e.g., Peng et al., 1995), a smoothly operating, functional system (Kello, Beltz, Holden, & Van Orden, 2007; Van Orden et al., 2003). In nature, however, it is rare to observe a monofractal system, in which the same scaling features are evident at all levels of analysis. The tree in Figure 2a can be used to illustrate this concept: although both the branches and veins that run through the leaves of the tree are both fractal, they differ structurally (Figure 2c). We expect that human systems, which demonstrate tremendous complexity, are more like the tree than the (mono-)fractality that has been reported repeatedly in the literature (Van Orden et al., 2003; Wagenmakers, Farrell, & Ratcliff, 2004). Humans and human teams are far more likely to exhibit different fractal patterns at different levels of analysis (from neural to social) rather than a single pattern across all scales. Multifractal indices relax the assumption of self-similarity but also make it possible to detect scaling differences across levels of analysis. Using terminology employed by others in this field (e.g., Ihlen, 2012; Ihlen & Vereijken, 2010), the distinction between monofractal and multifractal processes reflects the difference between time-independent and time-dependent processes, respectively. We expect that the self-similar characteristic of (multi-)fractal systems will allow us to observe characteristics of team behavior in processes both smaller than and larger than the team. In the current study, we will focus on demonstrating the feasibility of this approach using the brain activity of individual team members to reveal team-level processes.

CURRENT STUDY

In the current study, we will use multifractal analysis to extract team-level behavior from brain activity signals of individual team members. We expect changes in scaling features, across levels of analysis, to correspond to regions of organization that characterize important team experiences, including both the performance of routine tasks and responses to (unexpected) perturbations. Data were taken from a larger study of team neurodynamics (Stevens, Galloway, Wang, & Berka, 2012, Stevens, Galloway, et al., 2013) involving EEG synchronization data generated by Submarine Piloting and Navigation (SPAN) trainees at the Naval Training Academy in Groton, Connecticut. The data were ideal for our purposes because of the presence of hierarchies in both team structure and routine procedures. The training team and its members were constrained by the rules and procedures of the US Navy and, more specifically, the training protocols of the Submarine Learning Center. The training exercise itself was divided into three distinct events called Briefing, Scenario, and Debriefing. Even within those major events were arranged other, smaller and rhythmically occurring events, such as the "taking of Rounds" (described in Method) during the Scenario. Furthermore, significant changes in the team's neurophysiology and speech patterns have been reported at the junctions between these major training segments (Stevens et al., 2012). We therefore expected changes in scaling features across levels of analysis to correspond to regions of neurophysiologic organization that characterize important team experiences, including both the performance of routine tasks and responses to (unexpected) perturbations.

METHOD

In this study, we analyzed data from a single team for the purposes of illustrating how team-level behavior may be captured through rigorous examination of temporal characteristics observed at the level of the individual. Although the EEG data that we collected required little post processing prior to implementation of our multifractal analysis, generation of the audio transcripts against which we compared our output was time and labor-intensive, restricting the data sets available. Therefore, the focus of this paper is to demonstrate the feasibility and utility of our approach.

A brief description of the data collection/manipulation methodology is presented here, but a full description of the data appears in Stevens et al. (2012).

Participants

Analyzed data were collected from one SPAN team that was composed of six male trainees who occupied the positions of Navigator, Assistant Navigator, Contact Manager, Quartermaster of Watch, Radar, and Officer of the Deck. The team had worked together on one prior simulation exercise, but all members were experienced submarine personnel taking part in a 6 month training program that readies them for promotion. The analyzed team was representative of all teams that were tested, and there was a complete audio transcript along with instructor comments and assessments of stressful events. With a complete data set for that one team, variation over time could be linked to specific events experienced by the team.

Task

Each SPAN session is a high-fidelity simulation composed of three distinct sections: Briefing; Scenario; and Debriefing. During the Briefing, trainees learned about the objectives of the mission and other factors relevant to task performance (e.g., weather, ship traffic). During the Scenario, trainees engaged in the regular mission and encountered a number of unforeseen events that forced the team to reorganize their activities. For example, a loss of visibility due to fog forced the team to consult other navigation equipment in order to determine the ship's positions. Other perturbations were equipment malfunctions or reports of a man overboard. A significant rhythmic feature of the Scenario was the "taking of Rounds", in which teams regularly reported on the ship's position in a structured manner every 3 minutes. The team members discussed various aspects of the Scenario during the final section, the Debriefing. The Debriefing section was highly structured, with team members reporting in turn.

EEG data collection and transformation

The main challenge of analyzing the synchronization of EEG signals from multiple individuals was to condense the signals into a single time series that preserves significant features. Gorman, Amazeen, et al. (2010) solved that problem by creating a coordination parameter that captured the essential interactions between three team members and revealed key differences in performance between teams that were not evident in traditional summary statistics.

In the current study, the raw data were 54 data streams—nine EEG leads from each of six team members. Simple summation would effectively cancel out the variability, leaving no information about changes in behavior. Stevens and colleagues (Stevens et al., 2012; Stevens, Gorman, Amazeen, Likens, & Galloway, 2013) approached the challenge of condensing EEG data by first deriving temporal estimates of engagement, a measure of attention to the task at hand for individual SPAN team members. Estimates of EEG-derived Engagement (EEG-E) were generated using the B-Alert® EEG system, and are based on individual EEG activity, primarily in the range of 1–40 Hz (Berka et al., 2007). They merged the individual engagement series into one time series using an artificial neural network model that classified the collective activity of the teams as one of 25 neurodynamic symbolic patterns of engagement (NS_E), essentially ordering them from least activity across all team members to greatest activity. Figures 3a and

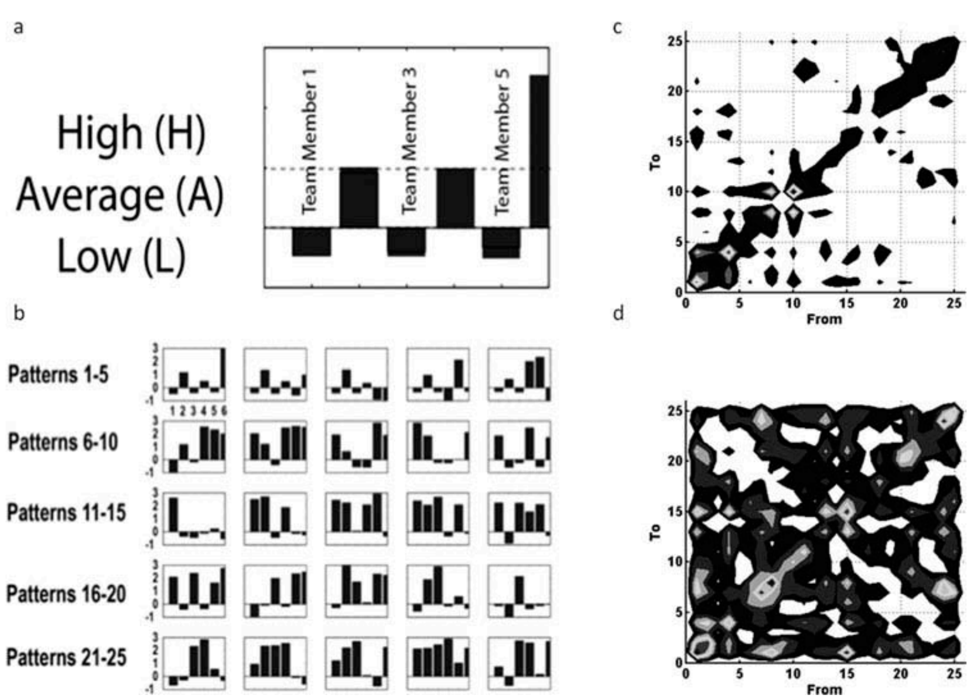

Figure 3. An artificial neural network was used to identify 25 characteristic patterns of engagement across six team members. Those engagement categories were essentially ordered from least activity (pattern 1) to greatest activity (pattern 25) across team members. (a) A generic depiction of one engagement category that depicts engagement level for the six team members. (b) Activity of the six team members across all 25 team engagement categories at one point in time. (c) Transition matrix with a small amount of clustering, mostly on the diagonal. (d) Transition matrix with a large amount of clustering that is widely distributed across the plot.

3b depict the classification procedure, showing the engagement level for each of the six team members at a particular moment in time for a sample pattern (Figure 3a) and the 25 classified patterns (Figure 3b). Changes in activity over time were tracked using a transition matrix (Figures 3c and 3d), with Patterns 1–25 plotted along the horizontal axis at time t and plotted along the vertical axis at time $t + 1$. The distribution of activity in the transition matrix indicated the distribution of patterns over time, with well-defined clusters indicating persistence of certain patterns (along the diagonal) or transition pathways (off the diagonal) and greater homogeneity (Figure 3d) indicating widespread use of patterns and transition pathways over time.

We quantified the distribution of activity over time by calculating the Shannon (1951) entropy in sliding, 100-second windows or epochs.[1] That resulted in a time series of 4243 observations from a training session that lasted about 1.3 hours (Figure 4a). The classic use of Shannon entropy was to quantify the amount of disorder in a system in terms of the bits of information needed to fully describe that system. Low entropy indicates a highly ordered system (Figure 3c, well-defined clusters in the transition matrix), and high entropy means that the system is less ordered (Figure 3d, greater homogeneity in the transition matrix). Shannon entropy has also been used to quantify the distribution of activity in state space grids derived from peer interactions (e.g., Dishion, Nelson, Winter, & Bullock, 2004; Hollenstein, 2007), where conversion from symbolic to ratio data is desired for further analyses. In the context of our data, low entropy suggests that the team is highly organized (rigid, in the extreme) and high entropy suggests that the team is randomly organized or transitioning, perhaps due to lack of task structure or the occurrence of a recent perturbation toward which a team-level response has not yet taken place. Low and high entropy states were observed in less and more experienced teams, respectively, in Stevens (2012).

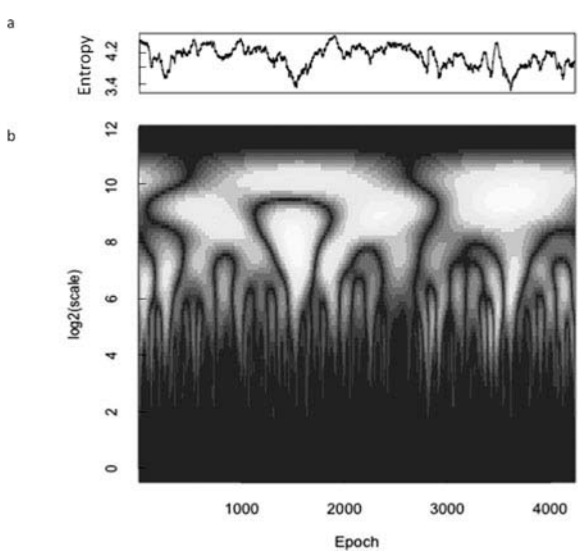

Figure 4. (a) A sample NS_E entropy time series. (b) The CWT of the series depicted in (a). Nesting patterns can be clearly observed viewing the CWT from top to bottom.

Time series analysis

There are many detailed accounts of fractal analysis in the literature (e.g., Eke, Herman, Kocsis, & Kozak, 2002), and so we will refrain from providing a full account of the various techniques. However, as an aid to interpreting the results, we orient the reader to common fractal indices called *scaling exponents.* Mandelbrot (1983) introduced the notion of a scaling exponent to describe self-similarity in natural phenomena. The Hurst exponent, H, which is commonly used in a number of scientific fields, provides an estimate of correlation over time scales (Beran, 1994; Eke et al., 2002). Figure 5 depicts the standard interpretation of H along its entire range, 0 to 1. The midpoint, $H = 0.5$, is indicative of a random process in which data points are uncorrelated with each other.

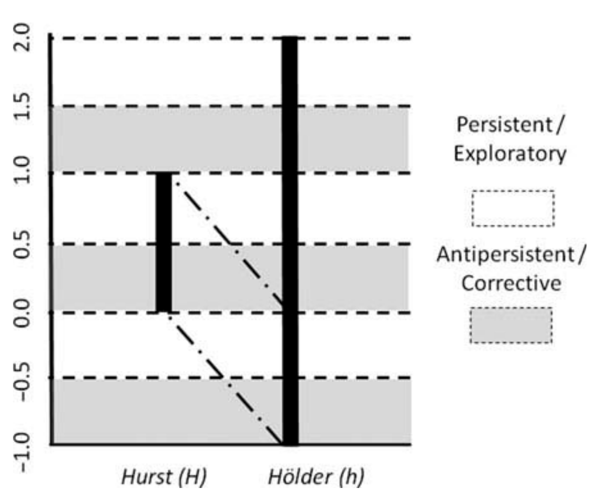

Figure 5. Hurst and Hölder exponents along with interpretative ranges. Diagonal connecting lines represent the relationship, $h = H - 1$, between the Hurst and Hölder exponents.

[1] The 100-second window preserved critical characteristics of the time series. Windows larger than 100-seconds decreased the resolution of entropy changes, and substantially smaller windows (e.g., 30 seconds) introduced meaningless fluctuations. For these categorical data, entropy ranged in value from $\log_2(1) = 0$ to $\log_2(25) \sim 4.64$.

The lower half of the range, $0 < H < 0.5$, identifies an antipersistent (negatively correlated) process that is often interpreted as corrective behavior (e.g., in teams, Gorman, Amazeen, et al., 2010; to maintain upright posture, Collins & Deluca, 1993). The upper half of the range, $0.5 < H < 1$, identifies a persistent (positively correlated) process thought to be a sign of exploration (Collins & Deluca, 1993; Riley, Wong, Mitra, & Turvey, 1997; Treffner & Kelso, 1999; Stephen, Arzamarski, & Michaels, 2011). Gorman et al. (2013) interpreted the finding of $H > 0.5$ for the most adaptive teams as a team-level exploration of solutions to unexpected problems.

Technically, the Hurst exponent, H, should only be used to characterize processes whose variance characteristics remain stable over time. We used multifractal analysis in the present study because we expected that variance characteristics might change over time. For that reason, we used the localized scaling exponent, the Hölder exponent, h, which is related to H by the following equation: $h = H - 1$ (Scafetta, Griffin, & West, 2003). Figure 5 depicts both H, along its range from 0 to 1, and h, along its range from −1.0 to 2.0. Note that h exists beyond the range of both H and the values given by the conversion equation. Figure 5 provides the standard interpretation of h and the categorical relation to the more commonly used H.

Multifractal analysis is a generic term for a set of techniques that all serve to characterize how fractality changes across the levels of analysis in a time series (Ihlen, 2012). Time-based methods, such as *multifractal detrended fluctuation analysis* (MFDFA), are excellent for characterizing the (multi-)fractal characteristics of a time series, but the potential for application is limited due to an inability of that method to localize variation in scaling with respect to time. *Wavelet transform modulus maxima* (WTMM) provides an estimate of variability in the form of time-localized estimates of fractal scaling (Muzy, Bacry, & Arneodo, 1993; Struzik, 2001). That property made it a good choice for locating team responses with respect to important events in time. In this section, we present a summary of WTMM but refer interested readers to more detailed treatments (e.g., Mallat, 1999; Percival & Walden, 2000).

The first step of the WTMM analysis is to perform a continuous wavelet transform (CWT) of the time series. The CWT detects the similarity between the time series and small, finite waveforms called *analyzing wavelets* (syn. *wavelets* or *wavelet filters*). The choice of an analyzing wavelet is nontrivial and should be based on the characteristics of the time series. We used the second derivative of the Gaussian function Figures 6a–c, dark curve) as the analyzing wavelet because its symmetric properties are ideal for signals that possess sharp peaks and step-like properties called *singularities* (Ashenfelter, Boker, Waddell, & Vitanov, 2009; Muzy et al., 1993; Scafetta et al., 2003), as observed in our entropy time series. Once selected, the analyzing wavelet is compared to a large region of the time series (e.g., one-fourth the length of the series, as depicted in Figure 6a), and a measure of correlation called the *wavelet coefficient* is computed. The window of comparison is shifted by one time-step until correlations are computed for the length of the time series using that large comparison window. The process is repeated at all scales (Figures 6b and 6c) as the width of the wavelet and the analyzing window are decreased by an integer amount until the width of the analyzing wavelet accommodates only two or three data points.

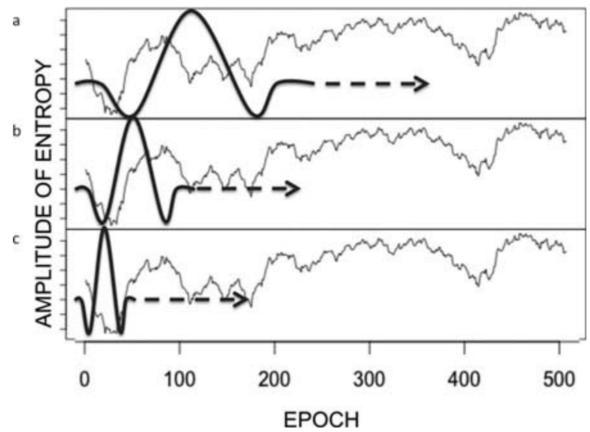

Figure 6. A depiction of the CWT algorithm. Three scale levels are illustrated. The wavelet is compared to a section of the time series before being translated and being compared to other sections of the time series. The scale is decreased and the comparing–translating procedure continues.

We will discuss additional details of the analysis where relevant in the Results section: (1) the time by scale graph of the time series (Figure 4b) is useful for identifying nested structure visually; (2) the multifractal spectrum (Figures 7a and 7b) quantifies the local fractal scaling exponent, with a greater range in the spectrum indicative of multifractality; and (3) the time series of local exponents (Figure 7b) demonstrates change over time and can be compared to audio transcripts to interpret team reactions to important events.

RESULTS

Multifractal analysis generates both graphical and quantitative outputs. To report our results, we will

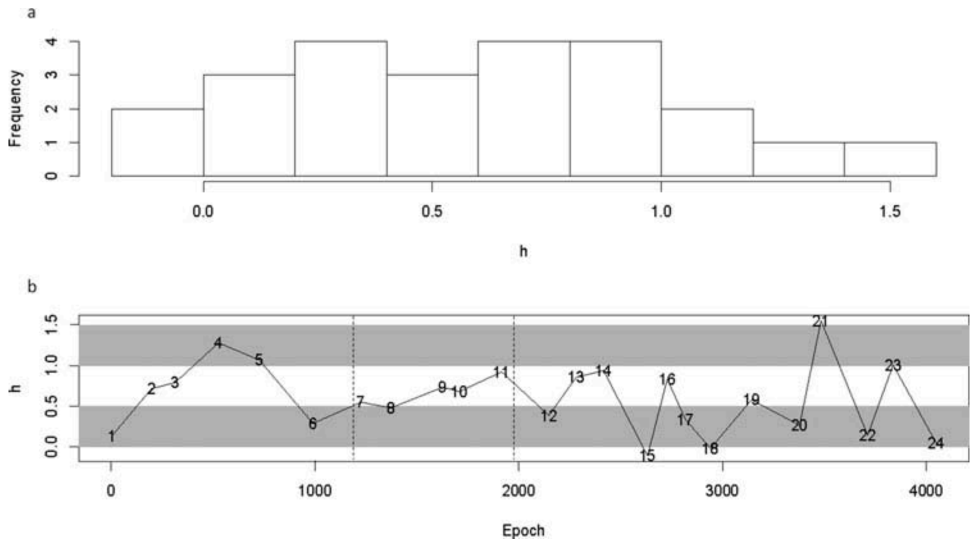

Figure 7. (a) A histogram of local fractal scaling exponents. The distribution represents a broad range of exponents indicative of both antipersistent and persistent behavior, as expected when a series is multifractal. (b) Fractal scaling exponents plotted over time (epoch). This figure illustrates how scaling exponents change over time and in response to important team events. Gray bands indicate when the team is engaged in corrective or antipersitent behavior. White bands indicate when the team is engaged in exploratory or persistent behavior. Vertical dashed lines demarcate when the team experienced a high amount of stress.

describe the graphical output and then provide relevant quantitative support for graphical interpretations. As an example, Figure 4a depicts a time series of NS_E entropy (M = 4.07, SD = 0.23) for the target SPAN team. Notice that entropy varied considerably from one epoch to the next, sometimes generating sharp peaks or step-like changes. Some changes in the waveform extend over a long period of time, such as the arc-shaped trend that spans from approximately Epoch 200 to 1500. Other, more rapid, changes are nested within those slower oscillations and give the waveform its "noisy" appearance. That high degree of variation is expected from the dynamic nature of SPAN training sessions and is a prototypical example of the type of time series one might expect to exhibit fractal or multifractal behavior. Monofractal detrended fluctuation analysis (DFA) supported the intuition that the time series was fractal, $H \approx 1.01$ (Peng et al., 1994). Therefore, even though the starting point for this analysis was individual NS_E, analysis of NS_E entropy indicates that global behavior of the team was persistent/exploratory.

Graphical interpretation

Figure 4b depicts the output of the CWT of the time series, a scale (vertical axis) over time (horizontal axis) plot that shows the relative magnitude of wavelet coefficients. Given the gray scale shading scheme chosen here, bright spots in Figure 4b indicate a high degree of similarity (i.e., correlation) between the analyzing wavelet and the time series. Contiguous bright regions reflect similar patterns of entropy fluctuation that persist across scale and time. We believe that those regions characterize significant events. Darker regions represent a lack of similarity and also serve to delineate the correlated regions, that is, to identify transitions between significant events.

Closer examination of Figure 4b reveals several important features: Most notable are the multiple branching patterns that indicate nesting. Notice that the bright region at the largest scale (around Epoch 1500, $\log_2$scale = 11) branches into two smaller regions that continue to branch at ever smaller scales. The fact that the branching bright regions are connected in the vertical direction implies that rapid changes (at the smaller scale) exist concurrently with and are nested within slower changes (at the larger scale). That branching feature is indicative of a fractal system. However, because the same pattern does not persist across all scales, the fractality appears to be scale-dependent or multifractal.

It is also notable that multiple bright regions exist at the largest scale; that is, even in the most abstract sense, team behavior changes over the course of the experimental session. A dark line in the vicinity of Epoch 2800 delineates two *regions of organization* at the largest scale that are nevertheless segregated all of the way down to the smallest scales. Comparison with the session transcripts indicates that this time corresponded to an event change that was experienced by the team: the shift from Scenario to Debriefing. We can use the same process to identify and interpret regions of organization at other levels of analysis. A rhythmic event, apparent from alternating bands of light and dark, persists across nearly the entire graph at approximately $\log_2$scale = 6. Comparison with the audio transcripts indicated that this nearly-periodic structure corresponded with the taking of Rounds, which was highly regimented but not quite the same from one instance to the next.

Perhaps the most promising feature of multifractal analysis is its use not in monitoring routine events but in identifying unplanned, surprising events. Note in Figure 4b the existence of a bright, delineated region centered near Epoch 1500 and $\log_2$scale = 8. That region is located within the Session but is clearly separated and appears to disrupt events at multiple levels of analysis, including the periodic taking of Rounds. Comparison to audio transcripts indicates that the team experienced a considerable amount of stress resulting from reduced visibility. The situation was further complicated by a communication breakdown and confusion over the course correction needed to avoid a vessel in the near vicinity. We explore all of these graphical features quantitatively in the next section.

Quantitative results

We identified the likelihood of multifractal scaling in the NS_E data stream using the CWT graphical output of Figure 4b. Quantitative analysis of the multifractal spectrum further supports that claim. A histogram of the local scaling exponents is depicted in Figure 7a. As expected, local scaling exponents were sufficiently varied to constitute a broad spectrum typical of multifractal processes. In the mean (M = 0.60; SD = 0.42), the team's behavior was exploratory (see Figure 5), no doubt based on their experience of problem-solving during the Scenario. That finding is in agreement with the DFA-calculated global Hurst exponent that was reported earlier. However, the histogram identifies that behavior crossed both the corrective and exploratory ranges, justifying the need for a more fine-grained analysis to characterize the team's behavior.

A plot of h over time (Figure 7b) supports that observation: h clearly changes over time, particularly near important mission events. We used a number count to identify that the value of h changed 23 times over the course of the experimental session. Dashed vertical lines highlight one region of organization that we identified earlier (near Epoch 1500). The change in h near Epoch 1300 marks the beginning of that region and corresponds with a shift toward random behavior (h = 0.54). As the team navigated the submarine near a contact in the fog, activity heightened, and team behavior—as measured by NS_E entropy—became more exploratory/persistent, as marked by the increase in h from the random range (h = 0.54) to a local maximum at h = 0.92. In words, team exploratory behavior increased throughout the event until the team resolved the situation, at which time, the team oscillated between exploratory and corrective patterns for the remainder of the scenario.

A second event of interest noted earlier was the transition between Scenario and Debriefing. In Figure 7b, point 17 corresponds to the dividing line (near Epoch 2800) on the CWT graph (Figure 4b). The localized exponent (h = 0.33) at that point identifies a corrective pattern of behavior, as may be expected during a change in task. In fact, corrective behavior appears to have played a more dominant role during the Debriefing section as 42% of scaling exponents were corrective during the Debriefing compared to 23% during the Scenario.

A third event that was readily identified in Figure 4b was the taking of Rounds. Transcript data shows that the Rounds occurred roughly every 3 minutes (180 Epochs). That corresponds with the average interval (M = 175.93; SD = 61.05 Epochs) between changes in h, identified in Figure 7b as the space between adjacent numbered points.

Surrogate analysis

The final step in our analysis is a surrogate analysis that provides a test of the null hypothesis that the observed multifractal structure is spurious, arising from a process that is monofractal or random rather than multifractal (Ihlen, 2012; Ihlen & Vereijken, 2010). In the current context, the most appropriate surrogate test is a comparison of the multifractal spectrum width, $h_{\max} - h_{\min}$, of the observed series with the confidence interval of an average surrogate spectrum derived from many shuffled time series. Following Ihlen and Vereijken (2010), we used an iterated amplitude-adjusted Fourier transform that maintains any monofractal characteristics while eliminating interscale interactions. Multifractal analysis of 100 surrogate time series revealed spectrum estimates for the shuffled series with the following characteristics: M = 1.55; SD = 0.29; 95% CI = [1.49, 1.61]. The spectrum width of the intact series (1.67) exceeds the upper limit of the 95% confidence interval of the shuffled average. On the basis of this surrogate test, we can conclude that the results represent a time-dependent intermittent process.

DISCUSSION

Across a large variety of behavior settings, teams are likely to exhibit hierarchical structure, whether it is as complex as the organizational chart depicted in Figure 1 or as simple as a team of individuals assembled to accomplish a single goal. In this study, we analyzed a team whose structure was between those two extremes, a naval training team whose behavior was constrained from above by the rules and procedures of the US Navy and the Submarine Learning Center and was influenced from below by the physiological fluctuations and cognitive decisions of individual team members. A novel aspect of our analysis was the decision to analyze team behavior via the brain activity of individual team members. We discovered that significant events experienced by the team could be extracted from EEG patterns collected at the level of individual neurophysiology, a method that was successful, in large part, due to the complex, interactive, nested quality of the team's structure and behavior. We believe that this study was the first to analyze simultaneously multiple levels of analysis from neural activity to team activity and from momentary events to whole experimental sections.

The finding that team-level experiences could be identified from the neural recordings taken from individual team members is both novel and promising. Over the past two decades, reports of fractal processes in physiological (e.g., Goldberger et al., 2002) and cognitive (e.g., Van Orden et al., 2003) systems have been used to support the notion of the human body as a system of vastly interconnected and interacting subsystems. A logical evolution of that thought process follows from the extension of interperson coordination dynamics to the level of dyads. Relative phase dynamics, such as those described in the introduction, were first studied at the intraperson level (Amazeen, Amazeen, & Turvey, 1998; Amazeen, Schmidt, & Turvey, 1995; Kelso, 1984) before being extended to the interperson level (Richardson et al., 2007; Schmidt et al., 1990). Similarly, (mono-)fractal scaling first observed at the level of the individual has, in two recent studies, been demonstrated across individuals (Gorman, Amazeen, et al., 2010; Marmelat & Delignières, 2012). We have expanded on those findings by exploring how those fractal patterns changed across time and levels of analysis. Just as a single exponent did not adequately describe response times in individuals (Ihlen & Vereijken, 2010), a single scaling exponent did not capture fully the team behavior we analyzed. Instead, a range of scaling exponents was needed, and the scaling exponents that made up that range co-occurred with meaningful team-level events. Surrogate analysis was used to verify that the series was multifractal rather than monofractal or random (see Ihlen & Vereijken, 2010).

Our contention is that the current findings support the conception of teams as highly interconnected, dynamical systems. Given that fractal and multifractal properties are recognized as markers of health in physiological systems (e.g., Peng et al., 1995), those same properties may also be useful in assessing the general "health" of a team (i.e., its adaptability and responsiveness to the changing environment). Fractal patterning in an electrocardiogram is used as an indicator of overall bodily health. Deviations from fractal in either direction indicate serious health problems: cardiac arrhythmia if the patterning is random and congestive heart failure if the patterning is periodic (Peng et al., 1995). Within the team domain, Gorman et al. (2010) showed that the teams best able to recover from perturbations were those teams that exhibited self-similarity in communication patterns, albeit at a single, global scale of analysis. More recently in the physiological domain, researchers have found that multifractal properties also distinguish between healthy and unhealthy heart behavior (Ivanov et al., 2001). The current findings—and those earlier mono- and multifractal findings—suggest that multifractal measures may also provide team coordination researchers with important diagnostic information. Our future interest is in understanding how fractal properties characterize team health, not just at the global level but also on a moment-by-moment basis and without the need to reference session transcripts. Such research might reveal reliable changes in fractal properties that are associated with healthy and unhealthy team behaviors.

We readily acknowledge that a current point of contention in the literature is whether the occurrence of fractal patterning indicates a smoothly running, functionally healthy system (e.g., Peng et al., 1995; Van Orden et al., 2003; see criticisms in Wagenmakers et al., 2004). Fractal patterning in reaction time data has been interpreted as a system whose cognitive, motor, respiratory, and cardiac components are functioning in concert with the intention of the experimental participant to respond as quickly as possible (Van Orden et al., 2003). Other researchers point to an over-reliance in the literature on more primitive methods for determining fractality and a disconnect between data analysis techniques and the psychological phenomena of interest (e.g., Wagenmakers et al., 2004). Certainly, monofractal methods set up an all-or-nothing scenario that is difficult to overcome. Greater promise comes from multifractal methods that allow for identification of regions of organization that correspond to the team's psychological experiences and observable behaviors in complex and realistic environments like those required by SPAN training.

We believe that an additional limitation of previous studies has been the reliance on logical argument to explain the impact on the entire system of an effect that is only observed, measured, and analyzed at one level (e.g., heart rate). With the method used here, we were able to measure at one level—the level of brain activity (cortical regions, to be specific)—and watch the dynamics emerge at the level of social interaction. The output of our multifractal analysis (see Figure 4b) highlighted significant events at multiple levels of analysis simultaneously. Infrequent changes, such as the transition between the Scenario and Debriefing, were identified in the same analysis as frequent, rhythmic events, such as the taking of Rounds. We were also able to detect disruptions to the team's behavior (e.g., team confusion at Epoch 1500). That simultaneous, multi-level analysis would not have been possible with monofractal analysis of any type of data due to the assumption of a single scaling region at all levels of analysis and across time. The success of this multifractal tool in identifying multiple scaling regions suggests that other phenomena, previously thought of as fractal, may also be found to be more complex when submitted to a multifractal analysis.

Application of multifractal methods

The concepts and tools that we have used in this study appear to be a promising combination for exploring the idea that individual physiology reflects the elusive quality of nestedness in teams. Still, many questions remain regarding the utility of our approach as a general method for studying team performance. Our first goal will be to demonstrate this finding in other teams in the same data set and then to test for generalizability across teams of different sizes in different contexts and with different types of data. We will build upon the findings of fractality in both interperson motor coordination (Marmelat & Delignières, 2012) and team communication (Gorman, Amazeen, et al., 2010) to investigate time- and level-sensitive phenomena. Even for researchers who are not interested in team or social processes, we argue that multifractal analysis is a way to see more macroscopic details of systems that are often measured more microscopically. The use of EEG and other brain imaging techniques has become more popular in the social sciences (Uttal, 2001). An ongoing challenge is to relate neural-level phenomena to behavioral experiences and cognitive reports (Gonzales-Castillo et al., 2012). Multifractal analysis gives us an additional tool by which to identify events of interest to social scientists from the brain imaging data that they collect.

There are numerous applications for multifractal techniques in both research—where a particular manipulation might be implemented in response to a change in the team's coordination dynamic—and in real-world settings, including both educational training settings and business or military scenarios. One distinct advantage that our method has over current monitoring methods is the multi-level aspect of the analysis. While humans can detect the nested quality of an event—a conversation, for example, that is centered on a topic but is characterized by information exchange, punctuated by tangential mini-conversations—it is far more difficult to write a machine algorithm that can simultaneously detect all of those details. With multifractal analysis, the promise is that we can see simultaneously multiple events occurring at multiple levels of analysis and respond accordingly.

Recent successes in combining time series analysis techniques with statistical techniques, such as vector error correction modeling (e.g., Stephen, Anastas, & Dixon, 2012), suggest that it may be possible to study when, how fast, and to what extent perturbations experienced at one level diffuse to other levels of analysis. For example, a medical emergency experienced by one individual could lead to either a momentary disruption of the team or overall system collapse, depending on how that perturbation is absorbed by the system. The same argument occurs in the opposite direction: a change in company directive has the potential to either change the behavior of all individuals in the company (for better or worse), or it may not even be perceived by individuals at the lower levels of the organization, again, depending on how information ripples through the system.

A significant aspect of these analyses is the potential for real-time implementation. The time required to execute our entire process, from data collection of individual EEG to identification of significant team events, required a small fraction of the time required to transcribe audio recordings and release them (particularly for classified data). Real-time information about team health would make possible interventions that can alter the course of behavior, possibly in advance of lengthy adverse events. Eventually, monitoring personnel may be able to detect perturbations on the fly as well as the level of analysis at which the perturbation occurred and the contagion of that perturbation to other levels. Although we currently rely on transcripts to interpret the significance of the events that we have identified, the fact that we can identify events analytically in a matter of seconds means that we can determine in (essentially) real time that significant events have occurred and, if necessary, formulate a timely intervention or response.

From description to prediction

The application of our method to real-time situations is tantamount to transitioning from a descriptive analysis to a predictive one. That transition requires the ability to detect if and when a meaningful change occurs in the scaling exponent. A similar problem was explored in Gorman, Hessler, Amazeen, Cooke, and Shope (2012), who investigated real-time changes in Lyapunov exponents (a measure of stability) in team communication patterns as indicators of perturbations. The solution they presented was the establishment of a baseline measure of the team's communication dynamics using an initial data sample to estimate mean parameter values and confidence intervals. Significant change in team behavior was evidenced when Lyapunov exponents, calculated in real time, exceeded the confidence interval. A similar method could be explored with the present analysis using a pointwise estimate of scaling behavior, similar to the one discussed in Robertson, Farrar, and Sohn (2003), to calculate average scaling exponents and confidence intervals. Scaling exponent values that subsequently exceed the confidence interval could be interpreted as a reliable change in team dynamics with only 5% error. This procedure assumes sufficient stationarity in team behavior, but baseline values could be updated for nonstationary data sets. Using this procedure, either in real time or after data collection has occurred, allows for a principled approach to the prediction of changes in team dynamics. Interestingly, researchers from engineering fields have considered several ways of classifying the mechanical condition of tools from pointwise scaling estimates (e.g., Zhu, Wong, & Hong, 2009), but those methods have not yet been evaluated for application to human behavior. For our specific purposes, developing those methods would aid in real-time implementation and potentially obviate the need for post hoc comparison of EEG and transcript data.

CONCLUSION

The already prevalent and ever-increasing role of teamwork in organizational settings demands new and better techniques for capturing and characterizing team behavior. Team research may have been hindered by the fact that traditional analysis techniques and concepts that build from the shared mental model are at odds with the nested character of team performance. The problem of nestedness in teams may be resolved by adopting a dynamical systems approach in the study of team behavior. Theoretical concepts, such as circular causality (Haken, 1996) and self-similarity (Mandelbrot, 1983), are inherent in that approach and make possible the conception of teams as complex systems whose component interactions span many levels of analysis. A further implication is that probing any one of those levels should reveal valuable information about levels both smaller and larger than the level of observation. Our application of multifractal analysis to individual physiological data shows that variation in multifractal properties is associated with the organizational behavior of teams.

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REFERENCES

Amazeen, P. G., Amazeen, E. L., & Turvey, M. T. (1998). Dynamics of human intersegmental coordination: Theory and research. In D. A. Rosenbaum & C. E. Collyer (Eds.), *Timing of behavior: Neural, computational, and psychological perspectives* (pp. 237–248). Cambridge, MA: MIT Press.

Amazeen, P. G., Schmidt, R. C., & Turvey, M. T. (1995). Frequency detuning of the phase entrainment dynamics of visually coupled rhythmic movements. *Biological Cybernetics, 72*(6), 511–518.

Ashenfelter, K. T., Boker, S. M., Waddell, J. R., & Vitanov, N. (2009). Spatiotemporal symmetry and multifractal structure of head movements during dyadic conversation. *Journal of Experimental Psychology: Human Perception & Performance, 35*(4), 1072–1091.

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

Berka, C., Levendowski, D. J., Lumicao, M. N., Yau, A., Davis, G., Zivkovic, V. T., . . . Craven, P. L. (2007). EEG correlates of task engagement and mental workload in vigilance, learning, and memory tasks. *Aviation, Space, and Environmental Medicine, 78*(Suppl 1), B231–B244.x.

Brisswalter, J., Collardeau, M., & René, A. (2002). Effects of acute physical exercise characteristics on cognitive performance. *Sports Medicine, 32*(9), 555–566.

Cabeza, R., Dolcos, F., Graham, R., & Nyberg, L. (2002). Similarities and differences in the neural correlates of episodic memory retrieval and working memory. *NeuroImage, 16*(2), 317–330.

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: The*

Journal of the Human Factors and Ergonomics Society, 40(1), 92–101.

Chandola, T., Heraclides, A., & Kumari, M. (2010). Psychophysiological biomarkers of workplace stressors. *Neuroscience & Biobehavioral Reviews, 35*(1), 51–57.

Collins, J. J., & DeLuca, 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., Myers, C. W., & Duran, J. L. (2013). Interactive team cognition. *Cognitive Science, 37*, 255–285.

Coull, J. T. (1998). Neural correlates of attention and arousal: Insights from electrophysiology, functional neuroimaging and psychopharmacology. *Progress in Neurobiology, 55* (4), 343–361.

Dishion, T. J., Nelson, S. E., Winter, C. E., & Bullock, B. M. (2004). Adolescent friendship as a dynamic system: Entropy and deviance in the etiology and course of male antisocial behavior. *Journal of Abnormal Child Psychology, 32*(6), 651–663.

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: The Journal of the Human Factors and Ergonomics Society, 41*(2), 312–325.

Fine, J. M., Gibbons, C. T., & Amazeen, E. L. (2013). Congruency effects in interpersonal coordination. *Journal of Experimental Psychology: Human Perception & Performance, 39*, 1541–1556.

Gieraltowski, J., Zebrowski, J. J., & Baranowski, R. (2012). Multiscale multifractal analysis of heart rate variability recordings with a large number of occurrences of arrhythmia. *Physical Review E, 85*, 1–16.

Goldberger, A. L., Amaral, L. A. N., Hausdorff, J. M., Ivanov, P. C., Ch., I. P., Peng, C.-K., & Stanley, H. E. (2002). Fractal dynamics in physiology: Alterations with disease and aging. *Proceedings of the National Academy of Sciences, 99*, 2466–2472.

Gonzalez-Castillo, J., Saad, Z. S., Handwerker, D. A., Inati, S. J., Brenowitz, N., & Bandettini, P. A. (2012). Whole-brain, time-locked activation with simple tasks revealed using massive averaging and model-free analysis. *Proceedings of the National Academy of Sciences, 109*(14), 5487–5492.

Gorman, J. C., Amazeen, P. G., & Cooke, N. J. (2010). Team coordination dynamics. *Nonlinear Dynamics in Psychology and Life Sciences, 14*(3), 265–289.

Gorman, J. C., Cooke, N. J., & Amazeen, P. G. (2010). Training adaptive teams. *Human Factors: The Journal of the Human Factors and Ergonomics Society, 52*(2), 295–307.

Gorman, J. C., Hessler, E. E., Amazeen, P. G., Cooke, N. J., & Shope, S. M. (2012). Dynamical analysis in real time: Detecting perturbations to team communication. *Ergonomics, 55*, 825–839.

Haken, H. (1996). *Principles of brain functioning. A synergetic approach to brain activity, behavior and cognition.* Berlin: Springer.

Hasson, U., Ghazanfar, A. A., Galantucci, B., Garrod, S., & Keysers, C. (2012). Brain-to-brain coupling: A mechanism for creating and sharing a social world. *Trends in Cognitive Science*, *16*(2), 114–121.

Hausdorff, J. M. (2009). Gait dynamics in Parkinson's disease: Common and distinct behavior among stride length, gait variability, and fractal-like scaling. *Chaos: An Interdisciplinary Journal of Nonlinear Science*, *19*(2), 026113-1–026113-14.

Hollenstein, T. (2007). State space grids: Analyzing dynamics across development. *International Journal of Behavioral Development, 31*(4), 384–396.

Ihlen, E. A. F. (2012). Introduction to multifractal detrended fluctuation analysis in Matlab. *Frontiers in Physiology: Fractal Physiology, 3*, 1–18.

Ihlen, E. A. F., & Vereijken, B. (2010). Interaction-dominant dynamics in human cognition: Beyond $1/f^{\alpha}$ fluctuation. *Journal of Experimental Psychology: General, 139*(3), 436–463.

Ivanov, P. C., Amaral, L. A. N., Goldberger, A. L., Havlin, S., Rosenblum, M. G., Stanley, H. E., & Struzik, Z. R. (2001). From 1/f noise to multifractal cascades in heartbeat dynamics. *Chaos: An Interdisciplinary Journal of Nonlinear Science, 11*(3), 641–652.

Joubert, S., Beauregard, M., Walter, N., Bourgouin, P., Beaudoin, G., Leroux, J. M., . . . Lecours, A. R. (2004). Neural correlates of lexical and sublexical processes in reading. *Brain and Language, 89*(1), 9–20.

Kello, C. T., Beltz, B. C., Holden, J. G., & Van Orden, G. C. (2007). The emergent coordination of cognitive function. *Journal of Experimental Psychology: General, 136*(4), 551–568.

Kelso, J. A. (1984). Phase transitions and critical behavior in human bimanual coordination. *American Journal of Physiology-Regulatory, Integrative and Comparative Physiology*, *246*(6), R1000–R1004.

Lindenberger, U., Li, S. C., Gruber, W., & Müller, V. (2009). Brains swinging in concert: cortical phase synchronization while playing guitar. *BMC Neuroscience*, *10*, 22.

Mallat, S. G. (1999). *A wavelet tour of signal processing* (2nd ed.) Cambridge, MA: Academic Press.

Mandelbrot, B. B. (1983). *The fractal geometry of nature*. New York, NY: Freeman.

Marmelat, V., & Delignières, D. (2012). Strong anticipation: Complexity matching in interpersonal coordination. *Experimental Brain Research, 222*(1–2), 137–148.

Muzy, J. F., Bacry, E., & Arneodo, A. (1993). Multifractal formalism for fractal signals: The structure-function approach versus the wavelet-transform modulus maxima method. *Physical Review E, 47*, 875–884.

Paulesu, E., Frith, C. D., & Frackowiak, R. S. (1993). The neural correlates of the verbal component of working memory. *Nature, 362*, 342–345.

Peng, C.-K., Buldyrev, S. V., Havlin, S., Simons, H. E., Stanley, H. E., & Goldberger, A. L. (1994). Mosaic organization of DNA nucleotides. *Physical Review E, 49*, 1685–1689.

Peng, C.-K., Havlin, S., Hausdorff, J. M., Mietus, B. S. J., Stanley, H. E., & Goldberger, A. L. (1995). Fractal mechanisms and heart rate dynamics: Long-range correlations and their breakdown with disease. *Journal of Electrophysiology, 28*, 59–65.

Percival, D. J., & Walden, A. T. (2000). *Wavelet methods for time series analysis*. Cambridge, MA: Cambridge University Press.

Richardson, M. J., Marsh, K. L., Isenhower, R. W., Goodman, J. R., & Schmidt, R. C. (2007). Rocking together: Dynamics of intentional and unintentional interpersonal coordination. *Human Movement Science, 26*(6), 867–891.

Riley, M. A., Wong, S., Mitra, S., & Turvey, M. T. (1997). Common effects of touch and vision on postural parameters. *Experimental Brain Research, 117*(1), 165–170.

Robertson, A. N., Farrar, C. R., & Sohn, H. (2003). Singularity detection for structural health monitoring using Holder exponents. *Mechanical Systems and Signal Processing, 17*(6), 1163–1184.

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.

Sanfey, A. G., Rilling, J. K., Aronson, J. A., Nystrom, L. E., & Cohen, J. D. (2003). The neural basis of economic decision-making in the ultimatum game. *Science, 300*(5626), 1755–1758.

Scafetta, N., Griffin, L., & West, B. J. (2003). Hölder exponent spectra for human gait. *Physica A: Statistical Mechanics and its Applications, 328*(3), 561–583.

Schmidt, R. C., Carello, C., & Turvey, M. T. (1990). Phase transitions and critical fluctuations in the visual coordination of rhythmic movements between people. *Journal of Experimental Ppsychology: Human Perception and Performance, 16*(2), 227–247.

Shannon, C. E. (1951). Prediction and entropy of printed English. *Bell System Technical Journal, 30*, 50–64.

Stephen, D. G., & Anastas, J. (2011). Fractal fluctuations in gaze speed visual search. *Attention, Perception, and Psychophysics, 73*, 666–677.

Stephen, D. G., Anastas, J., & Dixon, J. A. (2012). Scaling in executive control reflects multiplicative multifractal cascade dynamics. *Frontiers in Physiology, 3*(102), 1–6.

Stephen, D. G., Arzamarksi, R., & Michaels, C. (2010). The role of fractality in perceptual learning: Exploration in dynamic touch. *Journal of Experimental Psychology: Human Perception & Performance, 36*, 1161–1173.

Stevens, R. (2012, October 25). *Charting neurodynamic eddies in the temporal flows of teamwork.* Proceedings of the 56th Annual Meeting of the Human Factors and Ergonomics Society. Boston, MA.

Stevens, R., Galloway, T. L., Wang, P., & Berka, C. (2012). Cognitive neurophysiologic synchronies: What can they contribute to the study of teamwork? *Human Factors: The Journal of the Human Factors and Ergonomics Society, 54*(4), 489–502.

Stevens, R., Galloway, T., Wang, P., Berka, C. Tan, V., Wohlgemuth, T., … Buckles, R. (2013). Modeling the neurodynamic complexity of submarine navigation teams *Computational and Mathematical Organization Theory, 19*(3), 346–369.

Stevens, R., Gorman, J. C., Amazeen, P. G., Likens, A., & Galloway, T. L. (2013). The organizational neurodynamics of teams. *Nonlinear Dynamics, Psychology, and Life Sciences, 17*, 67–86.

Struzik, Z. R. (2001). Revealing the local variability properties of human heartbeat intervals with the local effective Holder exponent. *Fractals, 9*, 77–93.

Treffner, P. J., & Kelso, J. S. (1999). Dynamic encounters: Long memory during functional stabilization. *Ecological Psychology, 11*(2), 103–137.

Tognoli, E., Lagarde, J., DeGuzman, G. C., & Kelso, J. S. (2007). The phi complex as a neuromarker of human social coordination. *Proceedings of the National Academy of Sciences, 104*(19), 8190–8195.

Uitdewilligen, S., Waller, M. J., & Pitariu, A. H. (2013). Mental Model Updating and Team Adaptation. *Small Group Research, 44*(2), 127–158.

Uttal, W. R. (2001). *The new phrenology: The limits of localizing cognitive processes in the brain. (Life and mind: Philosophical issues in biology and psychology)*. Cambridge, MA: The MIT Press.

Van Orden, G. C., Holden, J. G., & Turvey, M. T. (2003). Self-organization of cognitive performance. *Journal of Experimental Psychology: General, 132*(3) 331–350.

Wagenmakers, E. J., Farrell, S., & Ratcliff, R. (2004). Estimation and interpretation of $1/f^{\alpha}$ noise in human cognition. *Psychonomic Bulletin and Review, 11*(4), 579–615.

Woyshville, M. J., & Calabrese, J. R. (1994). Quantification of occipital EEG changes in Alzheimer's disease utilizing a new metric: The fractal dimension. *Biological Psychiatry, 35*, 381–387.

Yerkes, R. M., & Dodson, J. D. (1908). The relation of strength of stimulus to rapidity of habit-formation. *Journal of Comparative Neurology and Psychology, 18*(5), 459–482.

Zhu, K., Wong, Y. S., & Hong, G. S. (2009). Wavelet analysis of sensor signals for tool conditioning monitoring: A review and some new results. *International Journal of Machine Tools and Manufacture, 49*, 537–553.