Nonlinear Dynamics, Psychology, and Life Sciences, Vol. 17, No. 1, pp. 67-86.

The Organizational Neurodynamics of Teams

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Abstract: *Our objective was to apply ideas from complexity theory to derive expanded neurodynamic models of Submarine Piloting and Navigation showing how teams cognitively organize around task changes. The cognitive metric highlighted was an electroencephalography-derived measure of engagement (termed neurophysiologic synchronies of engagement) that was modeled into collective team variables showing the engagement of each of six team members as well as that of the team as a whole. We modeled the cognitive organization of teams using the information content of the neurophysiologic data streams derived from calculations of their Shannon entropy. We show that the periods of team cognitive reorganization (a) occurred as a natural product of teamwork particularly around periods of stress, (b) appeared structured around episodes of communication, (c) occurred following deliberate external perturbation to team function, and (d) were less frequent in experienced navigation teams. These periods of reorganization were lengthy, lasting up to 10 minutes. As the overall entropy levels of the neurophysiologic data stream are significantly higher for expert teams, this measure may be a useful candidate for modeling teamwork and its development over prolonged periods of training.*

Key Words: teamwork, entropy, neurodynamics, EEG

INTRODUCTION

Teams have been described as complex dynamic systems that exist in a context, develop as members interact over time, and evolve and adapt as situational demands unfold (Kozlowski & Ilgen, 2006). From the perspective of complexity science, teams can be thought of as self-organized flows of information that span biological processes and broader societal activities. As team members interact, these often turbulent flows of information organize periodically around a common goal only to change form again as the task and environment evolve.

In the context of the teams of which they are a part, members continually modify their actions in response to the changing actions of others resulting in dynamic synchronizations of information that can be observed

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across different systems and subsystems, including verbal (Drew, 2005), gestural (Ashenfelter, 2007), postural (Shockley, Santana & Fowler, 2003), functional (Gorman, Amazeen, & Cooke, 2010), physiologic (Guastello, Pincus & Gunderson, 2006) and, more recently, neurophysiologic (Dumas, Nadal, Soussignan, Martinerie, & Garnero, 2011; Stevens, Galloway, & Berka, 2009; Stephens, Silbert, & Hasson, 2010). Most of these studies have consisted of two-to-three person teams performing coordination tasks or tasks in controlled settings. Our goal is to expand these ideas to larger real-world teams where the information flows are longer and expertise develops at multiple scales.

Teams, like many complex systems, are thought to operate at a level of self-organized criticality between random and highly organized states (Bak, Tang, & Wiesenfeld, 1987). That tenuous but significant state has also been called the edge of chaos, a feature that allows teams to adapt to both momentary disruptions, such as environmental perturbations, and more permanent alterations, such as changes in task requirements. In this way, effective teamwork is characterized as the continuous effort involved in stabilization of an inherently unstable system (Gorman et al., 2010; Treffner, & Kelso, 1999). At the 'sweet spot' of organization, a team demonstrates both stability and flexibility through supportive co-regulation and adaptive team member interaction.

In keeping with the dynamics of self-organized criticality, patterns of interaction (speech, motion, neurophysiologic changes, etc.) and activity can change spontaneously and qualitatively with the flow of the task, and perturbations to teamwork patterns are characterized by fluctuations away from and back toward stable states across multiple levels of analysis. In a typical training sequence, neural events that span seconds unfold in the context of communication events of tens of seconds that over time comprise longer, minutes-long, team coordination events, the outcome of which influences subsequent neural events. In that structure, we see the circular causality that is characteristic of a complex system. When aggregated across training sessions, the tasks in which teams engage provide the framework for structured formal training. The training sequence depicted in Fig. 1 spans nearly seven orders of magnitude of seconds over a 10-week course; a weakness in the literature is the lack of integrated models of team organization that capture the linkages across these subsystems and time scales. Such integrated models could better inform why some teams function better than others. Are certain teams more cognitively flexible and able to more rapidly enter and exit organized neurophysiologic states? Can these abilities be taught, and if so, how? Longitudinal extensions of these models could be capable of both predicting teamwork breakdowns and suggesting routes for teams to regain their rhythm once it is lost.

Nonlinear dynamical systems (NDS) is a theoretical and methodological approach for understanding complex systems and the linkages within and across subsystems in a manner that deemphasizes material substrate in favor of observed behavior patterns. NDS is a set of mathematical formalisms that can be used to understand the time evolution of physical, behavioral, and cognitive systems, including sudden, developmental transitions in those systems as they evolve. One feature that differentiates dynamical models from conventional models is their applicability for describing the behavior of highly complex, multilevel systems that could not readily be characterized using a linear approach. A second feature is the emphasis on characterizing variability as an integral part of the system rather than as error.

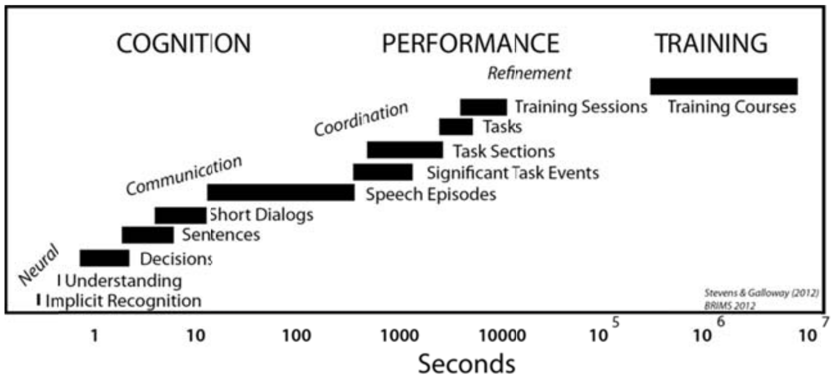

Fig. 1. Time scales of team training.

For several years Stevens and colleagues have been studying the neurodynamics of teams in order to detect patterns of neural organization and have been developing models using symbolic representations of EEG-derived levels of Engagement that are termed Neurophysiologic Synchronies (NS) (Stevens et al., 2011; Stevens, Galloway, Wang, & Berka, 2011; Stevens & Gorman, 2011). Those prior studies have shown that the symbolic NS data streams contain information regarding the current and past cognitive states of the team, and this is shown by the unequal expression and organization of NS symbols during different periods of the task. A challenge confronting us now is to determine how those NS pattern dynamics can be modeled in the context of changing task demands and across different timescales and levels of teamwork analysis. Based on prior results, we hypothesized that as teams experienced changes in the dynamics of the task or encountered perturbations to the normal flow of teamwork, the organization of NS data streams would fluctuate in a corresponding way and the degree of organization could be quantified by the entropy levels in the data stream, with low entropy indicating a greater degree of organization of team neurophysiologic state and high entropy less organization. In this study, we describe team organization in terms of these entropy fluctuations in the NS data stream and begin to link them with team experience, team communication, and natural and external perturbations in the task environment.

METHOD

Participants

The data sets for these studies were collected with IRB approved protocols from Junior Officer Navigation teams who were enrolled in the Submarine

Officer Advanced Candidacy (SOAC) class at the US Navy Submarine School. The reported data were derived from 12 Submarine Piloting and Navigation (SPAN) simulation sessions that were selected from a total of 21 as: a) persons in the same six crew positions were being monitored by EEG, b) the same individuals repeated in the same positions across 2-5 training sessions over multiple days. The six members of the teams that were fitted with the EEG headsets were the Quartermaster on Watch (QMOW), Navigator (NAV), Officer on Deck (OOD), Assistant Navigator (ANAV), Contact Coordinator (CC), and Radar (RAD). Additional persons participating in the SPAN who were not fitted with the headsets were the Captain (CAPT), Fathometer reader (FATH), the Helm (HELM), and multiple Instructors or Observers (INST).

Procedures

Submarine Piloting and Navigation sessions are required high fidelity navigation training tasks, and each session contains three segments, beginning with a Briefing in which the overall goals of the mission are presented. The Scenario is a dynamically evolving task containing both easily-identified and less well-defined teamwork processes. The Debriefing following the Scenario is the most structured part of the training; it is a topical discussion of what worked and what other options may have been available along with long- and short-term lessons.

One regularly-occurring process during the Scenario is the periodic updating of the ship's position, termed 'Rounds'. In taking Rounds, three navigation points are chosen, and the bearing of each from the boat is measured and plotted on a chart. This process occurs every three minutes with a countdown from the one-minute mark, where the Recorder logs the data (Fig. 2A). A sample navigation task is diagrammed in Fig. 2B: The submarine (whose route is indicated by the black circles with time offsets) was being steered northward (up) and its position is identified by number at different times (epochs or seconds). The submarine encountered an outbound ship (~ epoch 850), an inbound merchant (~ epoch 2100), and an outbound merchant (~ epoch 2100), each requiring changes in course or speed to avoid collision. In Fig. 2A, the top team showed a regular progression of the five-step sequence, being irregular at only two points (gray). The second team showed a more disrupted Rounds process.

Quantitative internal and external outcome measures are generally not available from SPAN as formative and summative feedback is a group process in the style of Total Quality Management (Ahire, 1997). We have attempted to develop an internally-derived outcome measure from the frequency or completeness of the Rounds sequences.

The regularity of the Rounds countdown, along with possible deviations, was obtained from the speech of the Recorder. When only three (or fewer) steps of the Rounds sequence were completed, or when an entire Rounds sequence was missed, it often indicates a team that is experiencing difficulty. The outcome measure is simply the percentage of completed Rounds sequences.

For instance, during the SPAN performance E2S1 in Fig. 2A 12 of 15 (80%) possible rounds sequences were completed, whereas the SPAN performance T4S2 only contained eight completed of 17 possible Rounds sequences.

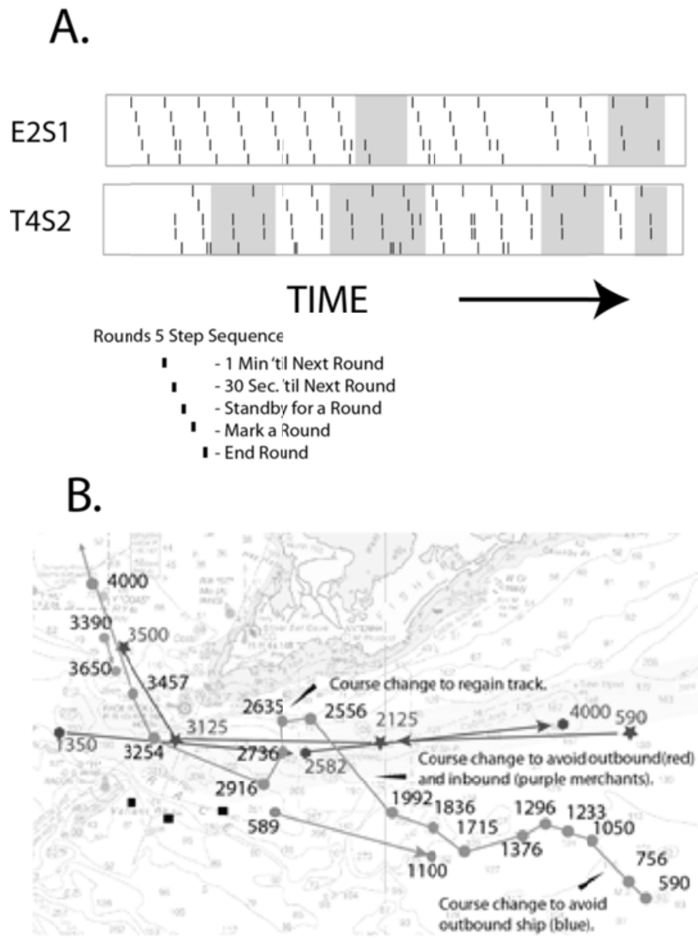

Fig. 2. Components of SPAN tasks. A: The sequence of Rounds is shown for two SPAN teams. B: The numbers on the tracks indicate the position of the submarine and other traffic during the simulation; the submarine's track is shown by the black circles beginning at 590 seconds.

Measures

The Advanced Brain Monitoring, Inc. (ABM), B-Alert® system contains an easily-applied wireless EEG system that includes intelligent software designed to identify and eliminate multiple sources of biological and environmental contamination and allow real-time classification of cognitive state changes even in challenging environments. The nine-channel wireless headset includes sensor site locations F3, F4, C3, C4, P3, P4, Fz, Cz, and POz in a monopolar configuration referenced to linked mastoids. ABM B-Alert® software acquires the data and quantifies alertness, engagement, and mental workload in real-time using proprietary software (Berka, Levendowski, Cvetinovic, Petrovic, & Davis, 2004). Data processing begins with the eye-blink decontaminated EEG files that contain second-by-second calculations of the probabilities of High EEG-Engagement (EEG-E) and High EEG-Workload (EEG-WL). Simple baseline tasks are used to fit the EEG classification algorithms to the individual so that the cognitive state models can then be applied to increasingly complex task environments. The EEG-E metric is an approximation of the multiple ways in which the term Cognitive Engagement has been reported in the literature. For instance, it has been used to describe the amount of cognitive processing that a learner applies to a subject (Howard, 1996) or as something that has to be broken during a task so that a learner can reflect on his or her actions (Roberts &Young, 2008). It shares similarities with alertness or attention and can be visual or auditory. It is analogous to the EEG-rhythm-based attention measures that are often associated with alpha power dynamics (Jung, Makeig, Stensmo, & Sejnowski 1997; Kelly, Docktree, Reily, & Robertson, 2003; Huang, Jung, & Maekig, 2007). Operationally, precise cognitive terms will be difficult to associate with EEG-derived measures of cognition in the context of teamwork, and functional associations will need to be derived empirically.

Analytic Procedures

Neurophysiologic methods can extend the use of speech for modeling team dynamics by providing “in the head” measures of team dynamics (Warner, Letsky, & Cowan 2005). As team members interact and perform their duties, each would be expected to exhibit varying degrees of cognitive states such as attention, workload, or engagement. We assume that the levels and patterns of variability of these components across team members reflect aspects of team cognition. Rather than focus on neurophysiologic markers, such as P300 or N400 that rapidly appear and disappear in response to many stimuli, we have used EEG-Eor EEG-WL which tend to persist longer across teams.

Neurophysiologic synchrony models were developed by first aggregating the second-by-second EEG-E levels from each team member into a six-unit vector. We used an unsupervised artificial neural network (ANN) with a linear, competitive architecture to extract from these vectors collective team variables termed neurophysiologic synchronies of engagement (NS_E) that showed the engagement of each of six team members as well as of the team as a whole (Stevens, Galloway, Wang, & Berka, 2011). ANN classification of these second-by-second vectors created a symbolic state space that showed the possible combinations of EEG-E across members of the team. Figure 3 shows three symbols that illustrate the diversity of EEG-E levels across team members. They are samples from the 25 symbols in Fig. 4A.

Established dynamical models of agents interacting with the environment can be described using a set of state variables and the position the system occupies in the state space. In our system, the different NS symbols can be thought of as the state variables, and the position of the system at any point of time is indicated by the pattern of NS state transitions. We consider that pattern of transitions, over both shorter and longer time steps, to be a dynamical attractor.

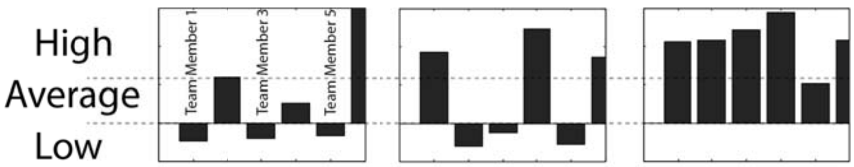

Fig. 3. Three NS symbols resulting from artificial neural network classification. Each bar in the different symbols represents the EEG-E activity levels of one team member.

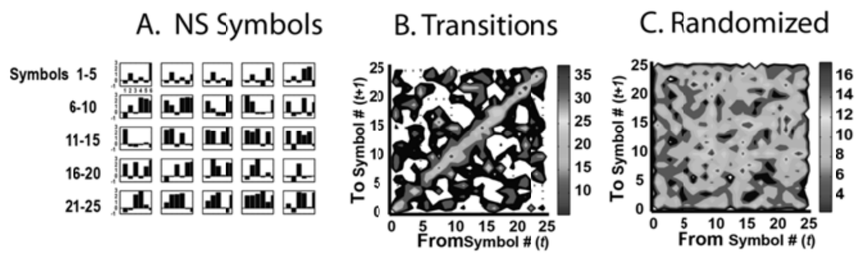

Fig. 4. Developing the dynamics of neurophysiologic synchrony attractors by the set of state variables and their transitions from *t* to *t*+1. A: The activity level of the twenty-five NS state variables can be tracked over time using a (B) neurophysiologic synchronies state transition matrix. C: The transition matrix resulting from the randomization of the NS data stream in B.

For ANN training, we used a linear architecture of nodes on the initial assumption that most second-by-second state transitions would be local changes among individual team members and that larger team shifts would be indicative of team re-organization. The linear architecture of the ANN ensured that the most similar states were proximal and that differences were more distal. This configuration should result in a diagonal line in a second-by-second transition matrix if most transitions were local and in a dispersed map if they were more distributed. Transition matrices plot the NS symbol number being expressed at time t against the NS symbol number expressed the next second (i.e. $t + 1$). The numbers at each transition are summed over the performance, and the totals are shown by the heat maps. The transition matrix of the NS_E data stream showed a prominent diagonal indicating that many of the second-by-second changes in the NS state were small (Fig. 4B). When the NS_E data stream was randomized, the structure, or information, in the NS data stream was lost (Fig. 4C).

RESULTS

The data in Fig. 4 indicated there was structure in the NS_E symbol stream. The goal was to build an organizational model of navigation teams by extracting the information contained in the NS data stream and relating it to the task, team performance and expertise, team communication, and internal and external task perturbations.

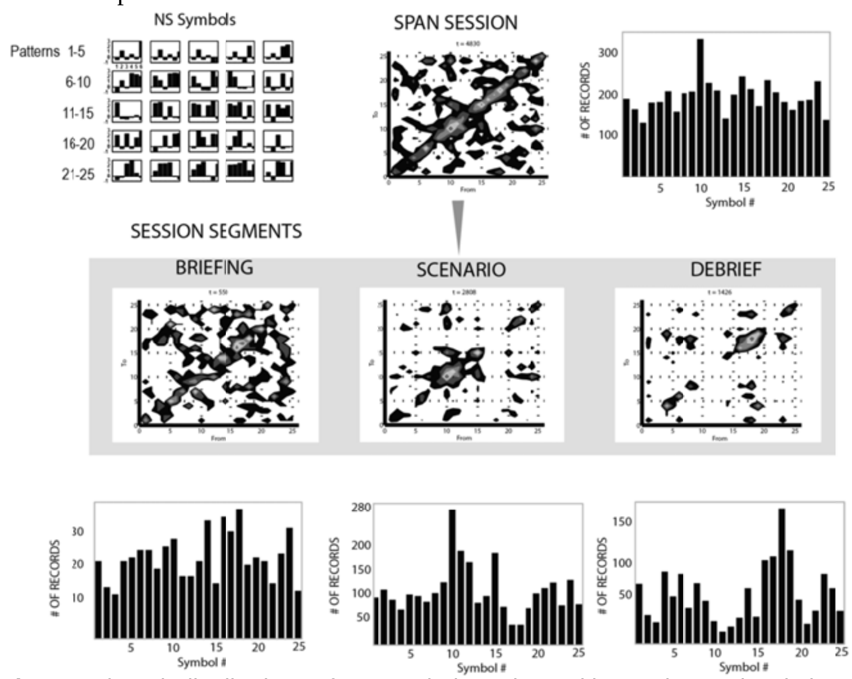

Fig. 5. Sub-task distributions of NS symbols and transitions. The top level shows the transition matrix and expression of the twenty-five NS symbols for the SPAN performance by a SOAC team. The matrices and histograms below show similar data for the three major segments of the task.

Capturing Task-Induced Shifts in NS Distributions

We used the three-part structure of the SPAN task in the first study to determine how team organization at a neurodynamics level was influenced by the task. Figure 5 shows the NS symbol frequencies and transition matrices for a SPAN performance that had been decomposed into periods representing the Briefing, Scenario, and Debriefing segments. The greatest heterogeneity in NS expression was seen with the entire SPAN session. Each SPAN segment was more restricted in NS symbol expression, with the Scenario and Debriefing segments showing more complementary rather than overlapping NS distributions. The most frequent NS symbols were also highlighted in the NS transitions suggesting the persistence of symbol expression. From the NS distributions, there were few periods in any of the Scenario segments where all team members simultaneously and persistently had high levels of engagement; referring to the NS symbol map; that condition would have been represented by NS_E symbols 14, 15, 21, and 24. Instead, the dominant symbols were those where the majority of the team members had low E (i.e., NS_E symbols 10 & 11). Overall, the patterns of NS expression suggest that qualitative re-organizations of the team occur with changes in task demands.

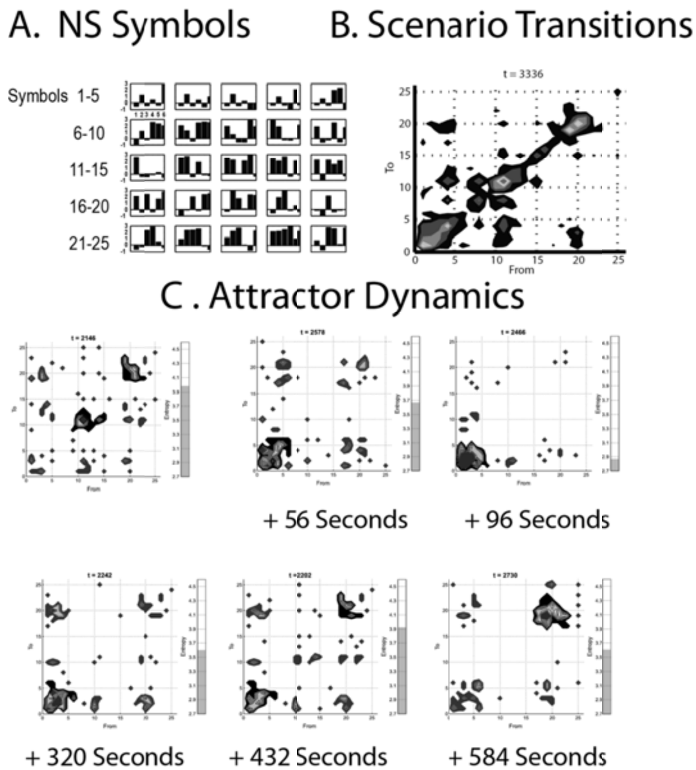

Fig. 6. NS_E transition matrix sampled at different points over a 584 second period of a SPAN Debriefing. Second-by-second dynamics of this and other SPAN performances can be found at www.teamneurodynamics.com.

Dynamics of NS Attractor Formation and Dispersion

The fact that the most frequent NS in each task segment lie on the diagonal suggests NS state persistence but offers little about how the activities change from one persistent state to another. From a dynamics perspective, natural questions include how rapidly these states develop and disperse and how long they persist. Figure 6 tracks the NS_E (state variable) transitions of the team from time *t* (X axis) to time *t* + 1 (Y axis) during one SPAN Debriefing segment.

The transition matrices in Fig. 6 are sequential snapshots of the system at times following the first frame when an attractor region around NS symbols 1-4 began to form. As this activity increased, the smaller transition regions around NS symbols 20 and 11 began to disperse, and by 96 seconds the activity in the region of NS symbols 1-4 dominated. This area remained stable for the next two minutes (until 320 seconds) and then began to disperse with the appearance of new transitions around from NS 1 *to* NS 20. This area was stable for the next two minutes, and there were reciprocal *from -> to* transitions across NS symbols 1 and 20. Two possible interpretations are: (a) that this is a periodic attractor or (b) that the pattern represents a sequence of attractors that that form or dissolve with changes in task demands. After approximately two more minutes (at 584 seconds), the activity around NS 20 dominated. This sequence of attractor formation is informative because whereas most NS transitions are local, as indicated by the diagonals in Figs. 4 and 5, phase transitions often begin by temporary transitions far from the diagonal of the transition matrix.

Though a symbolic representation of the state of the team is useful for characterizing team neurodynamics, it is not the best tool for quantifying team neurodynamics. Although there are methods for the quantitative representation of symbols (Daw, Finney & Tracey, 2003), we chose to perform a moving average window approach to derive numeric estimates of Shannon entropy of the NS symbol stream. Shannon entropy is the informational content of the symbol stream measured by the number of binary decisions (calculated in bits) required to represent the symbol stream at a given point in time (Shannon & Weaver, 1949). The NS entropy measure captures the distribution of activity across the state space. In terms of team cognition, low entropy may be interpreted as a highly-ordered team neurophysiologic state, whereas high entropy would correspond to a more random mix of team neurophysiologic states. The maximum entropy for 25 randomly-distributed NS symbols is $\log_2 (25) = 4.64$. In comparison, an entropy value of 3.60 would result if roughly half (12) of the NS symbols were randomly expressed. To develop an entropy profile over a SPAN session, the NS Shannon entropy was calculated at each epoch using a sliding window of the values from the prior 100 seconds. Windowing over longer periods decreased the resolution of entropy changes, whereas smaller windows (e.g. 30 seconds) increased the potential for false positives. An interesting feature of the attractor sequence in Fig. 6 was the changing levels of entropy in the NS data stream, which are shown by the bar to the right of each frame. Periods of low entropy were associated with changes in the shape of the attractor. Our work represents a preliminary step in the use of entropy and its dynamics to understand the real-time organization of team cognition. More information is needed on what drives teams to these areas of high organization, and whether this organization is beneficial to the team.

NS_E Dynamics Are Not Uniform

The previous neurodynamic models are expanded in Fig. 7 for another SPAN team session. This sequence of figures illustrates the transformation of sequences of NS symbols into a quantitative measure of the data stream organization. Figure 7A shows the second-by-second expression of the 25 NS_E symbols. Figures 7B and 7C show the attractor states associated with different entropy fluctuations of the NS data stream. As with most SPAN performances, the expressions of the NS symbols were not uniform but changed over time, particularly at the task junctions (indicated by the arrows. For instance, NS_E symbols 13-18 were poorly expressed during the Scenario but dominated in the Debriefing.

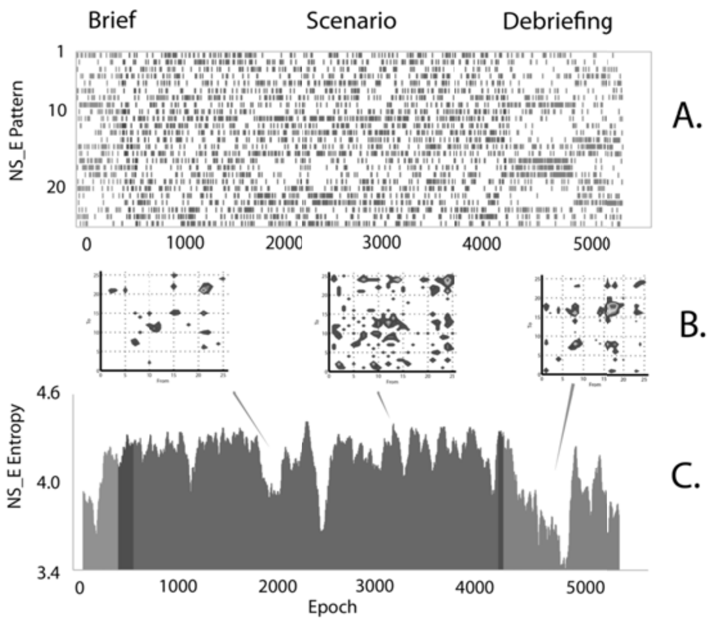

Fig. 7. Multiple representations of NS_E neurodynamics. A: The second-by-second expression of individual NS_E symbols. B: The transition matrices for NS_E show the NS_E symbols being expressed at the regions indicated in the entropy profile (C). During periods of low entropy (~epochs 1900 & 2400) few of the 625 potential (i.e. *from* 25 symbols *to* 25 symbols) NS symbol transitions were used by the team during a 100 second window.

The variations in the NS_E entropy levels were complex, with longer fluctuations covering minutes. Nested within these larger fluctuations were smaller and shorter fluctuations (i.e. the NS entropy streams appeared fractal). We are currently exploring the fractal nature of these entropy streams using other dynamical analysis techniques (Likens, Amazeen, Gorman, Stevens, & Galloway, in preparation).

Entropy Fluctuations can be Associated with Conversation Episodes

Patterns of NS_E entropy fluctuation can last for considerable more time than it takes to utter a question or sentence, suggesting that if an association exists between NS expression and speech, then it may be organized around higher-level discourse units. These higher-level discourse units may be similar to the “episodes” described by Salem (2011). Episodes consist of mutually constructed sequences of behavior. When conversation is described as an episode, it is based on the premise that individuals initially construct messages to be consistent with their perceptions and then evolve these messages in ways that are linked to those of others. The episode may evolve until it is mutually satisfactory to all, or it might continue into another episode. It can be thought of as a discussion around a central theme or topic.

Figure 8 shows detailed NS entropy mapping of episode shifting in the Debriefing segment of one SPAN performance. There were two major discussion topics: one from epochs 4171 to 4800 and a second from epochs 4800 to 5285. In the first segment, the team engaged in a discussion about why the submarine deviated around a merchant, and, in the second segment, the OOD asked the team if they understood his overall plan. During the first topic the NS_E entropy steadily dropped until closure was reached. The entropy rapidly increased and again slowly declined as closure on the second major topic was reached. Importantly, these fluctuations in entropy and the attractors observed in the above studies were natural products of teamwork and lack causality in that we can only infer what induced them.

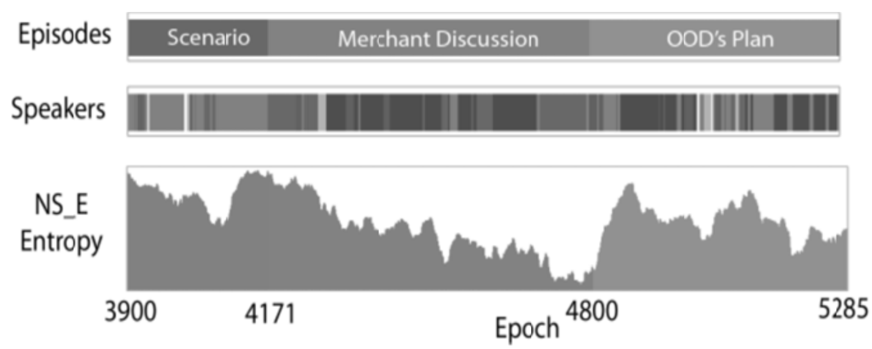

Fig. 8. NS entropy organizes around conversational episodes or topics. The Episodes bar shows the major discussion episodes of the Debriefing. The Speakers bar is color coded to periods when there were different speakers. The NS_E entropy variability shows the entropy profile.

NS_E Entropy Fluctuations Occur Around Perturbations to the Task

There were two instances when the SPAN Scenario was externally paused while the Captain or Navigator addressed the navigation team with concerns and recommendations. The NS_E profile for one of these events is shown in Fig. 9. Coincident with the pause was a gradual decline in NS_E entropy while the team re-organized itself, and at the conclusion of the discussion is observed a rapid shift up to the prior, less-organized team state.

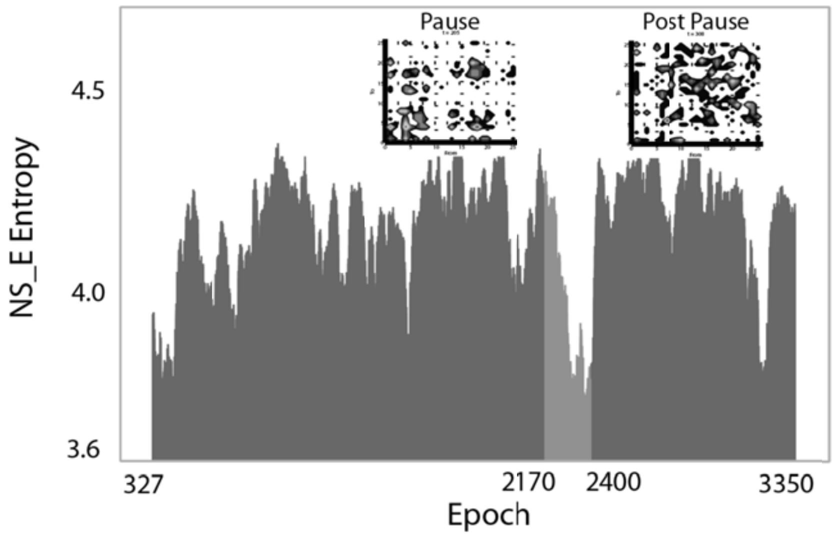

Fig. 9. Perturbation of the SPAN task induces team reorganization. During the period highlighted, the simulation was in pause and the attractors were more organized than after the pause.

Linking NS_E Entropy Fluctuations with Team Performance

Many of the findings described in previous sections are brought together in Fig. 10, which provides a framework for linking NS_E entropy with team performance. Figure 10 shows the NS_E transition matrix, the overall NS_E entropy, a profile of the entropy fluctuations, and the output of the Rounds performance metric for a more experienced (SUB) and a SOAC team. The expert team session in Fig. 10A showed mostly regular and complete five-step Rounds countdowns and also had the highest overall NS_E entropy. There was a more patterned background in the transition matrix and a relatively smooth NS_E entropy profile. The Rounds sequence patterns were more irregular for team SOAC 2 where individual steps, and occasionally complete Rounds sequences, were missed as indicated by the gray boxes. Irregularities often indicate stressful conditions like making a turn, avoiding traffic or equipment failures (Stevens, Galloway, Wang & Berka, 2011). This team also had lower overall NS_E entropy levels with more fluctuations and showed a more restricted transition matrix. There was a positive correlation between the regularity of Rounds taking, which is an internal performance metric, and the levels of NS_E entropy (Fig. 10B).

These findings were explored using NS_E comparisons between Experienced (SUB, *n*=6) and SOAC (*n*=6) navigation teams. Three different comparisons were made (Table 1): The first was across the average NS_E entropy levels where Experienced teams had significantly higher levels of entropy. The second comparison indirectly measured the degree of organization represented in the transition matrices. This was performed by comparing the file sizes of the transition matrices of the different SUB and SOAC performances. The idea was that since PNG files provide lossless compression, the most organized performances will have the smallest file size. This approach also showed a more highly organized state by the SOAC teams. The third approach entailed recurrence quantification analysis, a tool for extracting temporal structure in noisy, coupled dynamic systems by quantifying the points in time that a system revisits similar states (Webber & Zbilut, 2005). As shown in Table 1, the SUB and SOAC teams were significantly different by this measure, with the SUB teams showing fewer recurrences than the SOAC teams.

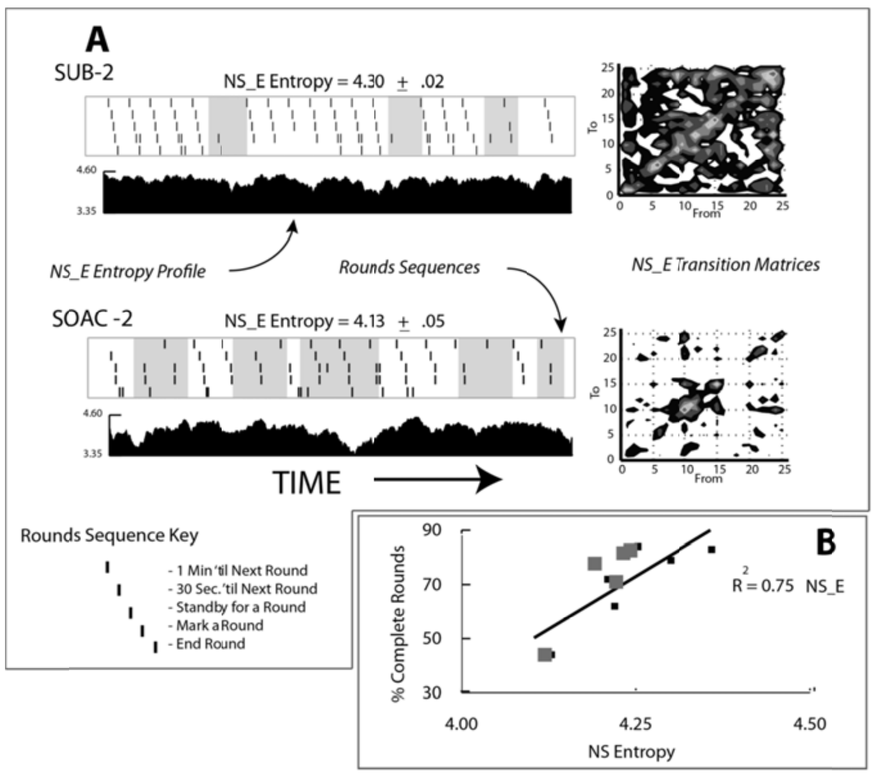

Fig. 10. Entropy fluctuations and sequencing of the Rounds. The sequences of Rounds for a representative experienced (SUB) and SOAC team are plotted above the NS_E entropy profiles. To the right are the overall transition matrices for the Scenario segment. Figure 10B plots the output of a performance metric, the taking of Rounds, against the overall NS_E entropy levels for the Scenario segments of three SUB and three SOAC SPAN teams.

Table 1. Comparisons between Experienced (SUB, n=6) and SOAC (n=6) navigation teams.

	NS_E Entropy	*Transition Map Size (bytes)*	*Percent Recurrences*
Expert	4.22 ± 0.01	15,072 ± 2,232	1.05 ± 0.62
SOAC teams	4.08 ± 0.12	12,068 ± 2,807	3.2 ± 1.60
Significance	$p < 0.001$ Kruskal-Wallis test	$p < 0.04$ Wilcoxen	$p < 0.007$ *t*-Test (independent)

These results indicate that, on the average, experienced teams have fewer periods of decreased NS entropy, or the decreases have a shorter period or amplitude, suggesting a less organized state than the SOAC teams.

DISCUSSION

The results presented in this paper show that the NS symbol streams contain multiple levels of structure that relate to the functioning of SPAN teams. At the simplest level, the NS_E entropy values, and presumably the sequence of NS_E symbols, are not random but have a structure. Part of the structure is imposed by the modeling system, where the linear architecture of the unsupervised ANN is designed so that similar symbols are located nearby and more different symbols are located further away. We took advantage of this architecture to show that many of the second-to-second changes in the EEG-E levels of the team occur in local neighborhoods. This does not mean that the NS_E transitions off the diagonal are noise. Instead, they may signal the onset of a significant shift across the state space. The dynamics of these shifts were interesting because they often exhibited reciprocal transitions across two NS symbols resulting in a four-point transition matrix pattern as illustrated in the 320 second and 432 second panels of Fig. 6. Few of these off-axis transitions persisted longer than several minutes, and the system eventually stabilized on or near diagonal transition, which would seem to be the attractors of the system. This is further suggested by the association of different attractors with different segments of the task.

A second level of structure was the fluctuations in the NS_E entropy stream. The periods of team cognitive re-organization identified by entropy fluctuations: (a) occurred as a natural product of SPAN teamwork (Figs. 7 and 10), (b) appeared linked with episodes of communication (Fig. 8), and (c) were associated with external perturbations to teamwork (Fig. 9). Evidence is beginning to accumulate suggesting that periods of intensity or stress contribute to the natural decreases in NS_E entropy. These decreases indicate not only a change in organization but increased organization. There is a substantial psychology literature on the importance of conflict on the synchronization of group communication and interactions (Pincus, 2009). Most relevant for this study are the physiological synchronizations in personal relationships characterized by conflict. Such conflict causes structural changes in interpersonal dynamics by shifting the individuals and groups into a more organized (i.e. rigid) state of thinking and acting. This parallels our findings of periods of increased team organization being associated with increased team stress due to visibility, the number of contacts in the vicinity, restricted maneuverability, etc., (Stevens et al., 2011). Though the SUB navigation teams encountered simulation events similar to those of SOAC teams, their increased training or experience did not cause interruptions or restrictions to the flow of cognitive information among the team members.

The patterns of neurophysiolgic organization could be lengthy, lasting up to 10 minutes, and were often more associated with communication episodes than shorter 'thought units' including sentences, utterances, or who was speaking. In the Debriefing segments, where speech is synchronous and most highly structured, there are intriguing associations between NS_E entropy and episodes of conversation that need to be further explored. These studies, and others being performed with a simpler map tracing task, suggest that the NS organizations are not only speaker or listener responses (Stephens et al., 2010) but also reflect longer periods of deliberation by the team.

In a broad sense, we view teams as real-time dynamical systems that must continuously adapt to changes in task requirements and unpredictable perturbations to remain effective. Of course, some teams are better at this than others, and metrics based on communication analysis and other aspects of team performance have been developed to detect subtle differences in team effectiveness. Importantly, the team neurosynchrony studies presented in this paper revealed expert or novice differences, which typically manifest themselves over relatively long time scales of team development.

We have integrated these data with performances from other teams that we have studied into a model linking NS_E entropy and state transitions with experience and perhaps the development of expertise (Fig. 11). The cognitive organization axis reflects the overall entropy levels and the diversity of transitions in the transition maps. A highly organized team (lower right), as typified by a SPAN team under stress, is shown by tightly-organized transitions and low entropy levels, equivalent to the random usage of only nine of the 25 NS_E symbols. NS transitions pooled from the Scenario segments of six SOAC teams still show restricted transitions, but the mean entropy has increased. As teams progress after their initial training and develop more experience (SUB Teams), the entropy levels and the diversity of the transitions further increase; from the performance metric, this stage would approximate the 'sweet spot' of team function. The data from zero-history student teams who had not worked together (lower left), and were unfamiliar with both the task and domain, showed the highest entropy. Their entropy levels were nearly equivalent to randomized NS_E data streams. As discussed in the Introduction, this hypothesized structure is consistent with the idea that teams, like many complex systems, are thought to operate at an organization level between random and highly-organized, at the so-called edge of chaos or self-organized criticality. From a complexity perspective, Fig. 11 can be thought of in terms of statistical complexity (Crutchfield & Young, 1989), which is the information about the past that is needed to predict the future. In particular, both zero-history and SPAN teams under stress would have low statistical complexity, one being a nearly random process and the other highly organized, whereas experienced SUB teams would have the highest complexity.

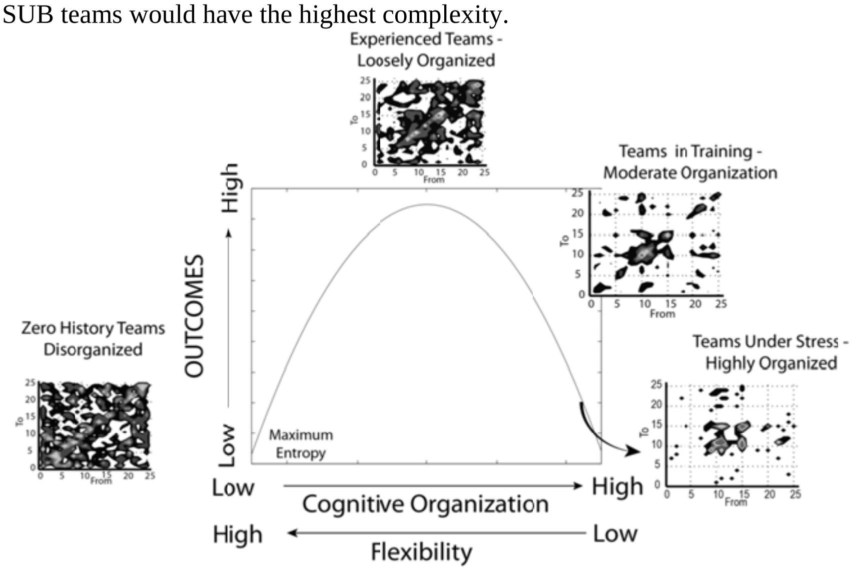

Fig. 11. A model of expertise and the cognitive organization of SPAN teams.

This diversity of organizational states suggests that SPAN teams exhibit a modest range of complex states, not unlike stock market volatility. A normally functioning market is chaotic, and the local variability of the process is heterogeneous in its sources and flows of information. But a market in crisis shows increased coordinated behavior of a large number of agents in the market and a decrease in financial diversity (Sornette, 1998). This additional structure and order in the system process leads to a "crash." Similarly, experienced navigation teams may function closer to the "sweet spot" of organization where the team demonstrates both stability and flexibility in the form of supportive co-regulation. As team neurosynchronies also fluctuate on much smaller timescales, organized around episodes or perturbations within a single task performance, fractal scaling analysis may provide an approach for better defining such sweet spots (Muzy, Bacry, & Arneodo, 1993).

We propose that the studies that we have presented here suggest an avenue for the development of adaptive training systems. A common goal of training activities in complex environments is the ability to rapidly determine the functional status of a team in order to assess the quality of a teams' performance or decisions and to adaptively rearrange the team or task components to better optimize the team. One of the challenges in accomplishing this goal is the development of rapid, relevant, and reliable models for providing this information to the trainers and trainees. With the creation of standardized models of NS_E expression (Stevens, Galloway, Wang, Berka, & Behneman, 2011) it may now be possible to direct real-time EEG streams into our modeling system and rapidly report back the entropy and attractor basin status of the team.

ACKNOWLEDGMENTS

This work was supported in part by The Defense Advanced Research Projects Agency under contract number(s) W31P4Q12C0166, and NSF SBIR grants IIP 0822020 and IIP 1215327. The views, opinions, aor findings contained are those of the authors and should not be interpreted as representing the official views or policies, either expressed or implied, of the Defense Advanced Research Projects Agency or the Department of Defense. Special thanks to Chris Berka, Adrienne Behneman, and Veasna Tan for EEG technical support and assistance with the data collection.

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