Team Neurodynamics
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Mapping Neurophysiologic Synchrony Attractor States and Entropy Fluctuations during Submarine Piloting and Navigation

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Abstract: Our objective was to apply ideas from complexity theory to derive expanded models of Submarine Piloting and Navigation (SPAN) showing how teams cognitively respond to task changes and how this was altered with experience. The cognitive measure highlighted was an electroencephalography (EEG)-derived measure of engagement (EEG-E) that was modeled into a collective team variable termed neurophysiologic synchronies of engagement (NS_E) thus showing the engagement of each of 6 team members as well as the engagement of the team as a whole. We show that the dominant NS_E patterns were different for novice and experienced teams, and that experienced teams used a larger repertoire of potential NS_E patterns. Estimates of the Shannon entropy of the NS_E data streams provided a quantitative history of NS_E fluctuations which were associated with the efficiency of the SPAN teams in updating the ship's position.

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

INTRODUCTION

Nonlinear dynamics (NLD) is a general theoretical approach for understanding complex systems. When teamwork is viewed as a complex adaptive system there are multiple non-linear dynamic concepts that can be applied including self-organization, attractors, phase shifts, instabilities, entropy perturbations, and intrinsic dynamics (Cooke et al, 2009; Gorman et al, 2010). The result is a view of teamwork where individuals are rich dynamic systems with the state of each member depending on the state of others.

The goal of this study was to apply these ideas to neurophysiologic models of Submarine Piloting and Navigation (SPAN) teams to analyze how the teams reorganize themselves in response to changes in the task; and to derive insights into the differences between novice and experienced SPAN teams. The measures used, termed Neurophysiologic Synchronies (NS), are symbolic collective team variables derived from team members' EEG data streams. They represent the relative levels of engagement (NS_E) of each person on the team as well as the team as a whole. Previously we have shown that NS are dynamic variables whose expression during SPAN teamwork was sensitive to short and long-term changes in the task and perhaps based on the experience of the team (Stevens et al 2009, 2010b). In this study we apply NLD approaches to expand this view to provide quantitative associations between NS_E expression and team performance.

TASKS AND METHODS

Submarine Piloting and Navigation Task

The studies were conducted with navigation tasks that are integral training components of the Submarine Officer Advanced Course (SOAC) at the US Navy Submarine School, Groton, CT. SPAN a high fidelity simulation that contains dynamically programmed situation events. There are task-oriented cues to guide the mission, team-member cues that provide information on how other members of the team are performing / communicating, and adaptive behaviors that help the team adjust in cases where one or more members are under stress or are not familiar with aspects of the unfolding situation. The teams contain 11-12 members in positions Officer on Deck (OOD), Navigator (NAV), Assistant Navigator (ANAV), Contact Coordinator (CC), Fathometer (FATH), Helm (HELM), Quartermaster on Watch (QMOW), Radar Operator (RAD), Recorder (REC), Periscope Operator (SCOPE) and Captain (CAPT) and / or Instructor (INST).

Twenty-one SPAN sessions were conducted where EEG was collected from three to six persons. The data reported here was derived from twelve of those sessions selected as: 1) persons in the same six crew positions were being monitored by EEG, 2) the same individuals repeated in the same positions across 2-5 training sessions over multiple days, and 3) the sample contained three Junior Officer teams and three experienced submarine navigation teams; these are termed SOAC and SUB teams respectively.

Each SPAN session begins with a Briefing outlining the mission goals and providing information on position, contacts, weather and sea state. The Scenario segment is more dynamic and contains easily identified processes of teamwork along with others which are less well defined. One process is the regular updating of the ship's position termed 'Rounds'. Here, three navigation points are chosen, often visually, 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 1 minute mark. The Recorder (REC) counts down to the 'fix' and logs the data. Interleaved with these deterministic events are situations arising from new ship traffic, increased proximity to hazards, equipment malfunctions or reduced visibility. In contrast to the regular updating of the submarines' position, these events are more perturbations to the regular functioning of the team, providing points where the resilience of the team may be tested. Some events are rapid like a man overboard, while others evolve over 5-10 minutes and can be based on previous decisions.

Electroencephalography (EEG)

The B-Alert® system contains an easily-applied wireless EEG system that includes intelligent software that identifies and eliminates multiple sources of biological and environmental contamination and allows second -by-second classification of cognitive state changes such as engagement (Berka et al, 2007). The data processing uses eye-blink decontaminated EEG files containing second-by-second calculations of the probabilities of High EEG-Engagement (EEG-E), Low EEG-E, Distraction and High EEG-Workload (EEG-WL) (Levendowski et al, 2001, Berka et al, 2004). In this study we focus on the probability (from 0 to 100%) of High EEG Engagement (EEG-E) which is related to information-gathering, visual scanning and increased attention.

The neuropsychological tasks used to build the algorithm, and subsequently used to individualize the algorithm's centroids were presented using proprietary acquisition software. The algorithm was trained using EEG data collected during the Osler maintenance of wakefulness task (OSLER) (Krieger et al., 2004), eyes closed passive vigilance (EC), eyes open passive vigilance (EO), and 3-choice active vigilance (3CVT) tasks to define the classes of sleep onset (SO), distraction/relaxed wakefulness (DIS), low engagement (LE), and high engagement (HE), respectively.

Simple baseline tasks were used to fit the EEG classification algorithms to the individual so the cognitive state models can be applied to increasingly complex task environments. These methods have proven valid in EEG quantification of drowsiness-alertness during driving simulation, simple and complex cognitive tasks and in military, industrial and educational simulation environments (Levendowski et al, 2002, Stevens et al, 2007, Berka et al, 2005).

Data Normalization and Modeling

In this study we created standardized ANN models using pooled data from multiple teams which allowed the comparison of NS_E expression across teams, training sessions and levels of expertise (Stevens et al, 2011). First, the EEG data streams for each person on the team were normalized and combined into vectors describing the EEG-E levels of each person. They were used to train an unsupervised artificial neural network (ANN) that generates 25 NS patterns representing the engagement status of the team. Each pattern has histograms showing the relative EEG-E level of each person. An example for a six person team is shown in Figure 1where persons 3 and 5 showed high levels of a cognitive measure and the remaining were low. In a NS data stream the expression of these patterns represents second- by-second fluctuations of the engagement by different members of the team.

A topology develops during this training where similar vectors cluster together and more disparate vectors are pushed away (Figure 2). For instance, NS_E Patterns 1-5 represent times where most of the team members had low levels of EEG-E; while, NS_E Pattern 24 represents times where most team members had high EEG-E.

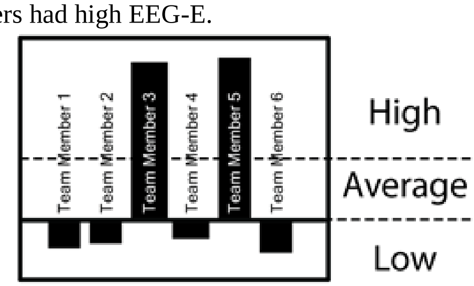

Figure 1. Expression of a Generic NS Measure by Members of a Six-person Team.

The 25 NS_E Patterns shown in Figure 2 constitute the *state space* of the system, i.e. the possible NS_E levels across the six members of the team.

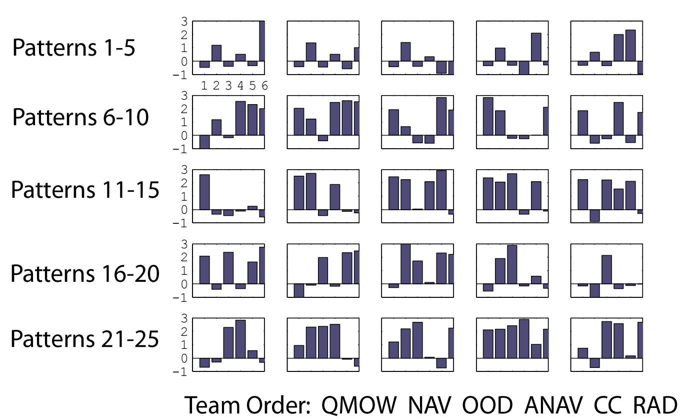

Figure 2. ANN Pattern Classifications for NS_E. The NS are numbered 1-5, 6-10, and etc. row wise.

RESULTS

The starting hypothesis was that many of the second-by-second changes in team engagement would be small. With the linear architecture of the self-organizing ANN and the resulting topology of the NS_E symbols this would be reflected in transition matrices (a plot of the NS_E being expressed at time t vs. that at time t+1) as movement around a diagonal. Larger state space shifts may reflect the teams' response to the evolving teamwork or external changes to the task.

Different NS_E Attractors Exist for SOAC & SUB Teams during SPAN Scenarios

The Scenario segment of SPAN simulations is where the navigation task is performed. The NS_E transition matrices with a 1 second lag are shown in Figure 3 for pooled data from six SOAC and six SUB SPAN sessions during the Scenario. The diagonal line shows the persistence and local transitions of NS_E patterns with the more frequent transitions shown by the higher contours. The dominant pattern for SOAC teams was centered near NS_E 10 & 11. From Figure 2, this was where half of the team members had low EEG-E. We designate these NS_E patterns as *attractors* as they are states of engagement that the team often persists in / returns to. The attractors for SUB teams clustered near NS_E 22-25 with the majority of the team members showing high EEG-E. A second attractor centered near NS_E 15 where again most of the team showed above average EEG-E. Cross tabulation analysis showed the two groups of teams were significantly different from one another ($\chi2$ = 298, df = 24, p <0.001). The SUB teams also showed more minor transitions as evidenced by the darker background contours throughout the matrix.

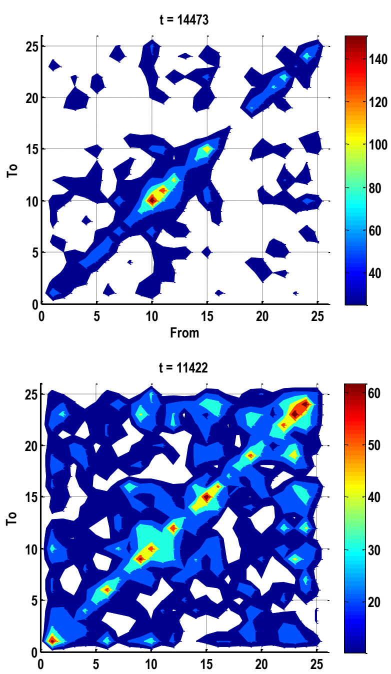

Figure 3. NS_E Transition Matrices for SOAC (top) and SUB (lower) Teams during the Scenario. The samples included data from six SOAC (14,473 epochs) and six SUB (11,422 epochs) SPAN sessions.

SOAC and SUB NS_E Attractors Change at Task Boundaries

Transition matrices of both SOAC and SUB teams created from the Debriefing segments of SPAN sessions showed restricted NS_E Pattern expression that were significantly different from the Scenario segment (SOAC Scenario / Debrief $\chi2$ = 1362, df = 24 p<0.001; SUB Scenario Debrief $\chi2$ = 391, df = 24, p<0.001), and different from each other (SUB vs SOAC $\chi2$ = 360, df = 24, p<0.001) confined around the diagonal (Figure 4). The main attractors during the debriefing showed that the SUB teams switched to overall low levels of engagement while the SOAC teams two groups showed transition patterns that reflected different overall engagement levels of the team. Those of the SUB teams (NS_E 5,8 & 11) represented periods where many of the team members had below levels of EEG-E, while those of SOAC teams (NS_E 14, 18) represented periods of above levels of EEG-E for the team .

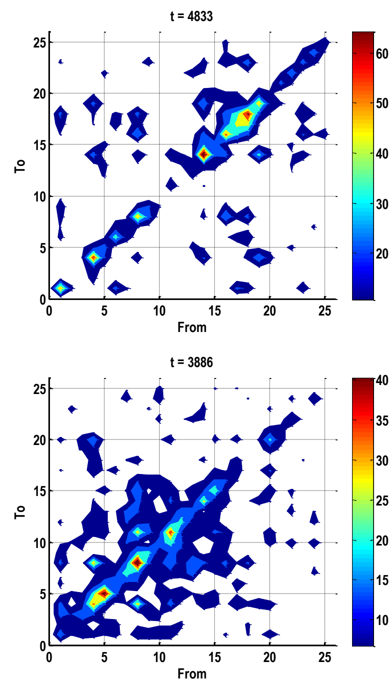

Figure 4. NS_E Transition Matrix for SOAC (top) and SUB (lower) Teams during the Debrief. The samples included pooled data from six novice (4,833 epochs), and six expert (3,886 epochs), SPAN teams.

Capturing a Quantitative History of Attractor Instabilities with Shannon Entropy

While transition matrices help identify preferred transitions, a more quantitative measure of the teams' attractor stabilities / instabilities would be useful for linking with other metrics of teamwork. As the NS_E patterns are symbolic, one approach would be to calculate the Shannon entropy of the NS_E data stream (Shannon, 1951). The idea of *entropy* is derived from information science and is a measure of the level of uncertainty or "amount of mix" in a symbol stream. Calculated entropy is expressed in terms of bits and the maximum entropy that we could expect from the 25 NS_E patterns would be log2 (25) or 4.64. As expected from the transition matrices, the SUB teams had higher entropy than the SOAC teams in the scenario.

To develop an entropy profile over a SPAN session the NS_E Shannon entropy for one SOAC team was calculated at each epoch using a sliding window of the values from the prior 100 seconds. The idea was that as teams entered an attractor state the entropy would decrease as fewer of the 25 NS_E patterns would be expressed (Figure 5).

To relate the fluctuations in entropy with the attractor states of the team, transition matrix movies were created that updated every 8 seconds over a background of the prior 100 seconds (www.teamneurodynamics.com). Two transition matrices are shown in Figure 5 for team T4S2. The left (epochs 2044 - 2144) was where there was confusion about contacting / avoiding another ship and the team was oscillating between two attractors centered near NS 14-15 and NS 9-11. The right matrix shows an uneventful time period (epochs 2350 - 2450).

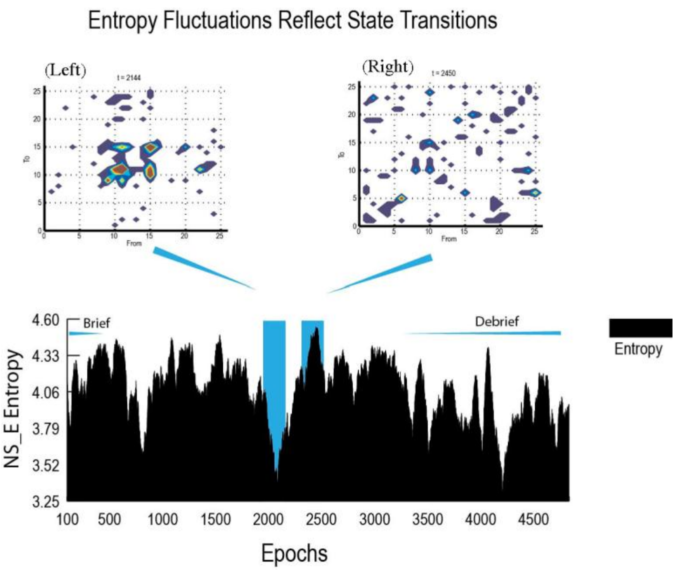

Figure 5. NS_E Entropy Profile for Team T4S2. This figure shows the teams' Shannon entropy at each epoch over a sliding window of the previous 100 seconds. Above the entropy profile are the transition matrices for the two highlighted 120 second periods.

Linking NS_E Entropy, Transition Matrices with Rounds Accuracy

SPAN simulations have the advantage of high ecological validity as they are realistic simulations and required components of the SOAC curriculum. A limitation of SPAN from a research perspective however is there are not detailed performance scoring criteria and most performance issues are raised and discussed during the Debriefing. A possible proxy for a performance score would be the regularity by which Rounds are conducted. This periodic updating of the submarines' position is conducted every three minutes with a 5-step countdown during the last minute. The regularity of this countdown, along with possible deviations, can be obtained from the speech of the REC who is responsible for the countdown. Figure 6 shows the Rounds sequence for 5 SPAN sessions. All teams had periods where the rhythm of Rounds was broken. These periods are highlighted by gray boxes. These irregularities can be caused by making a turn, avoiding traffic or overloading of the team; they often indicate stressful conditions (Stevens et al, 2011).

The SPAN sessions are listed in the order of decreasing overall NS_E entropy. Also shown in Figure 6 are the transition matrices for each session as well as a second-by-second NS_E entropy profiles. The two SUB team sessions, E1S1 and E1S2 mostly showed regular and complete 5-step Rounds countdowns. These sessions also had the highest overall NS_E entropy which was evident in 1) the more patterned background of the transition matrices and, 2) the less jagged profile of the NS_E data stream. The Rounds sequence patterns were more irregular for SOAC teams T4S2 and T5S5 where steps, and occasionally a complete Rounds sequence were omitted. These teams showed more restricted transition matrices and more prominent attractor basins than did the SUB teams. The NS_E entropy profiles also contained more peaks and troughs.

Another expert team E4S2 began the Scenario with four effective fixes and then started having difficulties conducting regular rounds. This example indicates there are likely levels of expertise.

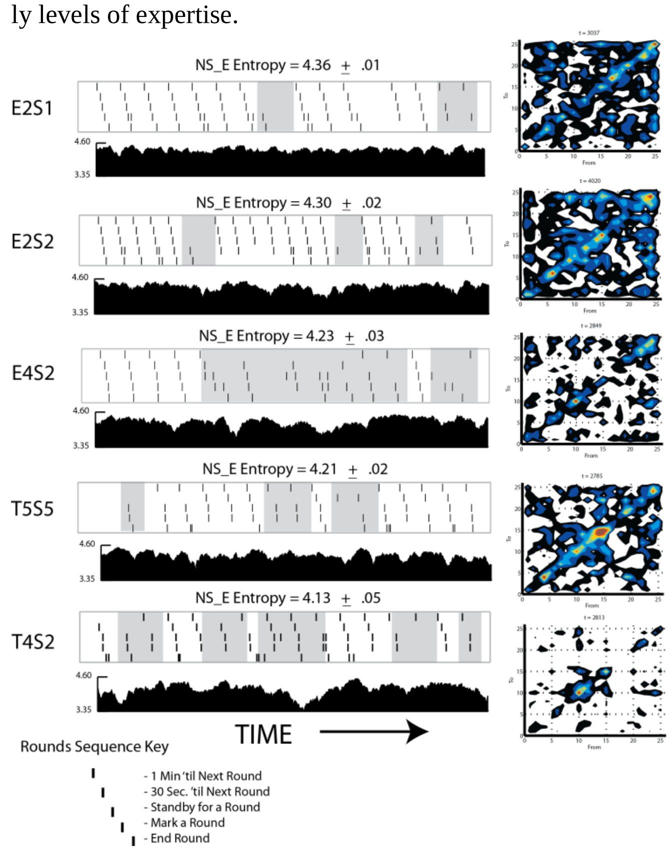

Figure 6. Entropy and Rounds for 5 SPAN Sessions.

DISCUSSION

In this study we have focused on what we are describing as attractor states for NS_E, which are simply preferred patterns of engagement among team members. Our results indicate that the ideas of self-organization and attractor states may be relevant for modeling team cognition and the engagement of teams in that changes in NS_E attractor dynamics occurred across task boundaries and were also sensitive to the effects of team experience.

Conceptually, one of the challenges in approaching a nonlinear description of a system is the definition of order parameters and control parameters. Order patterns are properties of a system that change, often discontinuously, as a result of some external condition. Control parameters are those that can be manipulated to induce instabilities in the system and cause the system to enter into different states. The challenge for the order parameter was to create a collective variable that represented the contribution of each team member at any point in time. The ANN clusters generated from the normalized EEG data streams are symbolic, not numeric which directs the subsequent data analysis approaches (Daw et al, 2003).

One control parameter for the NS_E system is the task. In all SPAN teams we have studied NS_E expression undergoes qualitative shifts at the Briefing / Scenario and the Scenario / Debriefing junctions (Stevens et al, 2010a, 2010b). The state transitions are not just related to the structure of the task as other external perturbations to the team, such as the pausing of the simulation by the boat captain also induce state transitions. While these state transitions are the most obvious in SPAN teamwork, the team also undergoes state transitions as a result of the teamwork / task interaction. In Figure 5, the largest decrease in entropy and the stabilization of the largest NS_E attractor of the performance occurred near epoch 2000 without any external perturbation

The significance of the entropy fluctuations are under investigation and we have begun mapping their expression to other teamwork / task measures and events. It will also be important to determine if there are critical fluctuations as instabilities in the NS_E data stream develop as they may be useful for anticipating an upcoming change in teamwork. Similarly, it will be important to document periods of critical slowing that may provide an indicator of team recovery.

The NS_E attractor and entropy differences resulting from the second control parameter, team experience, begin to highlight some important differences between novice and expert teams. First, the dominant NS_E attractor for the expert team during the Scenario represents a team where more members are engaged / highly engaged than in the novice teams. From the transition matrices, the expert teams seem to use more of the available NS_E patterns possibly indicating a more flexible team and one that does not frequently get locked into a restricted pattern of engagement.

These studies may also suggest an avenue for the development of adaptive training systems. A goal of most training activities in complex environments is to be able to rapidly determine the functional status of a team in order to assess the quality of a teams' performance / decisions, and to adaptively rearrange the team or task components to better optimize the team. One of the challenges in accomplishing this goal is the development of rapid, relevant and reliable models for providing this information to the trainers and trainees. With the creation of standardized models of NS_E expression it may now be possible to direct real time EEG streams into the modeling system and rapidly report back the entropy and attractor basin status of the team.

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