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Modeling the Neurodynamics of Submarine Piloting and Navigation Teams

Final Report

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Summary

The goal of this 18-month project was to validate and extend a framework for the continuous and quantitative modeling of the neurodynamics of Submarine Piloting and Navigation teams. This research was performed in support of the Defense Advanced Research Agency ARPA Order Nr. Q978-00 issued by U.S. Army Aviation and Missile Command under contract No. W31P4Q-12-C-0166 (Lt Col William D. Casebeer, Program Manager).

The studies reported indicate that the use of EEG technologies coupled with nonlinear dynamical modeling approaches, provides a viable approach for studying teamwork over minutes to hours and perhaps longer time scales. The studies show that it is possible to create a structure of symbols from the cognitive relationships of different team members such that the short and long-term relationships among those symbols represents a collection of teamwork structures that change over time. The structure of the neurophysiologic data streams is dynamic and multifractal with short-term persistence and longer-term correlations. The structure changes in response to major changes in the task, can be disrupted by internal and external perturbations to the task and team, and reveals novice / expert differences. Furthermore, team training factors, including training type and level of team experience, simultaneously impact team neurophysiology and communication in related ways.

Challenges remain before this technology becomes routine, but as these capabilities mature we believe these models will accelerate our understanding of the workings of real teams performing real tasks in real environments.

Introduction

The continuous navigation of a submarine is a complex, dynamic activity requiring a team that is highly trained, organized and cognitively ready. The training mechanisms used to develop these skills include a rigorous program of high fidelity simulations and open-water experiences. Nevertheless mishaps do occur, leading to the need to develop a deeper understanding of the ways in which successful submarine teams operate and create operational resilience. This proposal brought together multiple lines of research to develop such methods.

The task is not easy, as like most forms of social coordination, teamwork is complicated, complex and noisy. It is complicated as teams generally form around tasks that are too difficult for individuals to accomplish alone and require a diversity of experience and expertise. It is complex in the circular causality and feedback among multiple systems and sub-systems involved. For instance, neurophysiological events give rise to speech and other forms of inter-person communications which in turn affect subsequent speech and behavior. It is also complex in the sense that behaviors emerge in teams that often could not be predicted beforehand; i.e. the whole can be greater than the sum of its parts. Finally, teams are noisy in the sense that as the team develops consensus many actions may occur that are peripheral to the immediate task.

These properties of being complicated, complex and noisy pose challenges for evaluating teams and at some point seemingly simple questions like 'How is this team doing?' become difficult to answer, particularly if the goal is to capture quantitative measures of team improvement over time. Part of the challenge is that unlike the performance evaluations of individuals there are few measures and models for rapidly comparing across teams. This is particularly true with teams of diverse experience, like those involved in Submarine Piloting and Navigation (SPAN), who are performing real-world tasks where errors may be infrequent and do not directly correspond to failure.

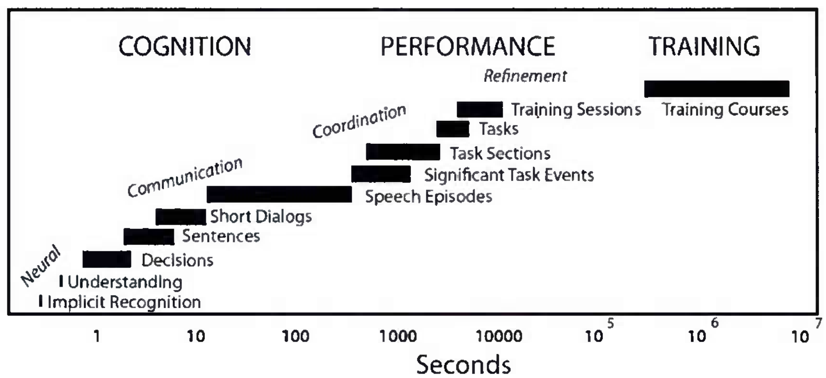

Figure 1. Levels and scales of teamwork events. This figure depicts different neural, behavioral, cognitive and social components of teamwork along a temporal scale from milliseconds to months. The bar lengths approximate the average times of each component. Not shown are reciprocal interactions within and across the different levels of activity. (Adapted from Stevens, Gorman, Amazeen, Likens & Galloway, 2012).

Submarine Piloting and Navigation (SPAN) is a required training component of the Submarine Officer Advanced Candidacy (SOAC) course where junior officers are trained to become ship's captains and navigators. Each SPAN session contains three segments. First there is a Briefing where the goals of the mission are presented with information on their position, the contacts in the area, weather, and sea state. The Scenario follows and is a more dynamic evolving task containing easily identified processes of teamwork along with other processes less well defined. A regular team activity that repeats every three minutes is the visual and / or electronic updating of the ship's position. This activity allows the position of the submarine to be known in relation to the intended course and nearby potential hazards. The SPAN simulations include encounters with approaching ship traffic, the need to avoid shoals, changing weather conditions and instrument failure. 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.

In a typical SPAN training sequence, neural events of 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.

Methods, Assumptions and Procedures

In this study we described and validated an information and organization-centric framework for team neurodynamics that can be applied in many teaming environments. The idea was that raw EEG data streams once converted into symbolic data streams of cognitive measures, may contain statistical regularities representative of the task and team actions at any point in time. In this way, the second-by-second sequence of symbols (termed Neurodynamic Symbols or NS) that arise during teamwork may contain information relating to team performance much in the way that words in a sentence or the codons in nucleic acids convey information. Fluctuations in the mix of symbols may help identify 'interesting periods' of team organization that are relevant to teamwork and if so, the frequency, duration, and magnitude of these fluctuations could then be quantified by measuring the Shannon entropy across segments of the data stream.

For this 18-month project a multidisciplinary team of investigators was assembled to validate these hypotheses and the overall team neurodynamics modeling approach, and to extend its usefulness by linking the findings with robust and realistic evaluations of submarine tactical performance. The five components of the project are briefly described below.

Neurodynamic Models of Team Adaptations and Agility (R. Stevens, Ph.D., The Learning Chameleon, Inc., UCLA, PI).

Neurophysiologic models were created of teams operating in naturalistic settings that captured their dynamic responses to changing task requirements and environments. Symbolic representations of the levels of EEG-derived cognitive markers were created that showed the cognitive levels of each team member in the context of the rest of the team members and also in the context of the second-by-second task activities. Momentary variations in the symbol distributions of these data streams identified periods of significance to the team which could be quantitated by a moving window of entropy approach. The dynamics of these fluctuations ranged from periodic to chaotic and varied in magnitude, frequency and duration depending on the task segment, the team activities and team experience. These findings are developed into an integrated neurodynamic model of information flows during teamwork that is applicable to many forms of teams and tasks.

Team Communication Metrics and Fractal Communication: A Latent Semantic Approach (J. Gorman, Ph.D. Texas Tech University).

Whereas team neurophysiology provides a physically-grounded index of teamwork, the behavioral expression of domain-relevant knowledge through team communication provides a cognitive-behavioral window on teamwork. For these studies Dr. Gorman and associates analyzed team communication content using Latent Semantic Analysis (LSA). Briefly described, LSA is a mathematical/statistical method for representing and analyzing semantic knowledge within a domain of discourse and is based on the theory that knowledge is reflected in the contextual usage of words within meaningful discourse. For the current study, they constructed a semantic space representing nautical navigation knowledge to analyze SPAN communications and then began establishing linkages between the semantic knowledge extracted from these communication streams and the neurodynamic data streams.

Multifractal Structure of Neurodynamic Data streams for Predicting Team Stability (N. Amazeen, Ph.D. Arizona State University).

Multifractal properties are commonly observed in human physiology and behavioral systems, and those properties appear to vary in response to abnormal conditions. One implication of those physiological findings is that multifractal properties may present a general tool for the detection of "healthy" and "unhealthy" systems. If true, then multifractal tools may be beneficial for monitoring the "health" of a team. A second implication from those findings – and fractal theory, in general – is that it should be possible to measure at one level of activity (e.g., neural level) and learn about activities at other levels of analysis (e.g., team-level behavior). In the current project these investigators found supporting evidence for these hypotheses.

A Robust and Realistic Model of Submarine Tactical Team Performance. (J. Lamb, Naval Submarine Medical Research Laboratory, C. Lamb, URS Federal, Inc. R. Steed, UpScope Consulting).

After two collisions in 2012, the Submarine Force undertook a substantial self-assessment effort. One of the findings was a widespread deficit in the ability of submarine watch teams to work together effectively. The fact that the submarine community did not have a consistent, formal model for teamwork for tactical teams to aspire to, nor did it have the structure to help them improve, was identified as the principal reason for this deficit. One response to these findings was the development of the Submarine Team Behaviors Tool (STBT) by the Naval Submarine Medical Research Laboratory (NSMRL). This tool is designed to formalize what has traditionally been a subjective assessment of a team's ability to work together effectively. The tool provides a structure and a language, that addresses team performance from a behavioral perspective in real-time and in real (operational) settings. It is a standardized rubric from which to consistently assess teamwork.

Submarine Bridge Trainer Data Collection. (C. Berka, Advanced Brain Monitoring, Inc.).

The experimental design for data acquisition required simultaneous EEG monitoring and recording for 6 team members. Synchronized and simultaneous data collection from multiple participants, such as the teaming experiment conducted, imposes a variety of challenges that usually compound proportionally with the number of individuals and teams involved. Teaming experiments, therefore, require the seamless, unobtrusive integration of physiological data acquisition which becomes a key necessity for the unbiased and efficient execution of the tasks. The hardware / software EEG data collection system developed by Advanced Brain Monitoring, Inc., provides these capabilities and was used for the data collection in the Submarine Bridge Trainer at the Submarine Learning Center.

Hypotheses. Our hypotheses were:

1) That cross-subject and subject independent neurodynamics models of SPAN will accurately reflect team expertise and simulation performance.
2) Sequential content measures determined by Latent Semantic Analysis (LSA) will reveal novice / expert differences in communication that are linked with neurophysiologic dynamics.
3) Quantitative nonlinear dynamical (NLD) measures of team neurodynamics will be positively correlated with higher performing teams.
4) Multifractal analysis of neurophysiologic data streams will help predict team stability during times of stress.
5) Short term significant fluctuations in team neurodynamics will be associated with identifiable team practices.

Results and Discussion

The science of teamwork research is poised to undergo a significant shift to a more dynamic and quantitative representation of teams and teamwork, due in part to the efforts of the researchers on this project. The studies conducted by this group are foundational for the development and validation of frameworks for the quantitative modeling of the second-by-second dynamics of real teams, performing real tasks in real settings. As illustrated by the list of publications, the research team made particular efforts to conduct focused research studies that would facilitate publication of the results. Rather than duplicate published results, salient findings from the research papers have been assembled into a series of Research Highlights aligned with each of the above hypotheses. Within each Research Highlight are the publication abstracts of the relevant papers as well as a short excerpt of notable findings as a way of introducing each study. Additional information is available at www.teamneurodynamics.com.

This section begins with a brief overview of the development of Neurodynamic Symbols (NS), the primary analytic data source for modeling.

The B-Alert® system by Advanced Brain Monitoring, Inc. 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 (Berka et al, 2007). The 9-channel wireless headset includes sensor site locations: F3, F4, C3, C4, P3, P4, Fz, Cz, POz in a monopolar configuration referenced to linked mastoids. B-Alert® software acquires the data and quantifies engagement (EEG-E) and mental workload (EEG-WL) in real-time using linear and quadratic discriminant function analyses with model-selected PSD variables in each of the 1-hz bins from 1 – 40 Hz, ratios of power bins. Descriptions of the submarine navigation team data collected for this study are described below along with a discussion of the challenges and limitations encountered in this study.

Linear sequences of NS constitute the primary data source for dynamically modeling teams. To generate these symbols we equated the absolute levels of EEG-E (for instance) of each team member with his/her own average levels over the period of the particular task. This allowed the identification of whether an individual team member was experiencing above or below average levels of EEG-E and whether the team as a whole was experiencing above or below average levels. As previously described (Stevens et al, 2011) in this normalization process the EEG-E levels were partitioned into the upper 33%, the lower 33% and the middle 33%; these were assigned values of 3, -1, and 1 respectively, values that were chosen to enhance visualizations of the symbols. The next step combined these values each epoch (second) for each team member into a vector representing the state of EEG-E for the team as a whole; these vectors were used to train artificial neural networks (ANN) to classify the state of the team at any point in time (Stevens al, 2009, 2011). In this process the second-by-second normalized values of team EEG-E for a single performance (or multiple performances when across team models were being generated) were repeatedly (50-2000 times) presented to a 1 x 25 node unsupervised ANN. The result of this training was a series of patterns called Neurodynamic Symbols of Engagement (NS_E) that showed the relative levels of EEG-E for each team member each second. The collection of NS symbols forms the cognitive state space and the linear sequence of these symbols during a performance constitutes the primary data source for neurodynamic analysis.

The framework described is information centric in the sense that EEG measures are converted into a symbolic alphabet where each symbol represents the levels of cognitive markers of each team member and the team as a whole. Symbol expression is updated each second as team cognition evolves in parallel with the task providing a unique temporal perspective (and history) of how the team and its members responded to periodic routines and unexpected challenges. A large diversity of symbols in a segment of the data stream, e.g. approaching random, has few structural trends and little information; while a limited mixture of symbols would have more structure and as a consequence, more information. The frequency, magnitude and duration of these periods are seen as quantitative fluctuations in the Shannon information entropy in the neurodynamics symbol streams (Shannon & Weaver, 1949). The entropy of the symbol stream can be derived over a sliding history window where the entropy was first measured over the initial 100 sec. Then at subsequent seconds the window was shifted removing the first symbol and appending a new one at the end; the entropy was then re-calculated. As described below, the result is a profile of the shifting neurodynamic organization of a team throughout a performance.

Hypothesis 1: Cross-subject and subject independent neurodynamic models of SPAN will accurately reflect team expertise and simulation performance.

Stevens, R.H., Gorman, J.C., Amazeen, P., Likens, A., and Galloway, T. (2013). The Organizational dynamics of teams. Nonlinear Dynamics, Psychology and Life Sciences 17, No. 1, pp. 67-86.

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 1) occurred as a natural product of teamwork particularly around periods of stress; 2) appeared structured around episodes of communication; 3) occurred following deliberate external perturbation to team function; and 4) 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.

Excerpt. Using across-team models neurodynamics models the performances of novice and expert submarine navigation teams were shown to have significant differences in the entropy levels of the Neurodynamic Symbol for Engagement (NS_E) data streams. High NS entropy in this context refers to teams acting fluidly whereas low NS entropy refers to team more rigid in their cognition. When aggregated across six SOAC and six experienced boat teams, the neurodynamic entropy values were significantly different (SOAC, 4.08 ± 0.12 vs. Experienced, 4.22 ± 0.01, $p < 0.001$). These differences were easily identified by the more rugged NS_E entropy profiles of the SOAC teams when compared with the expert navigation teams (Figure. 2A). One interpretation is that expert teams are better able to rapidly sample from possible solutions to problems encountered in the training scenarios. That ability may result in more agile behavior, a broader range of strategies and avoidance of periods where a team becomes 'locked into' a particular interpretation / strategy.

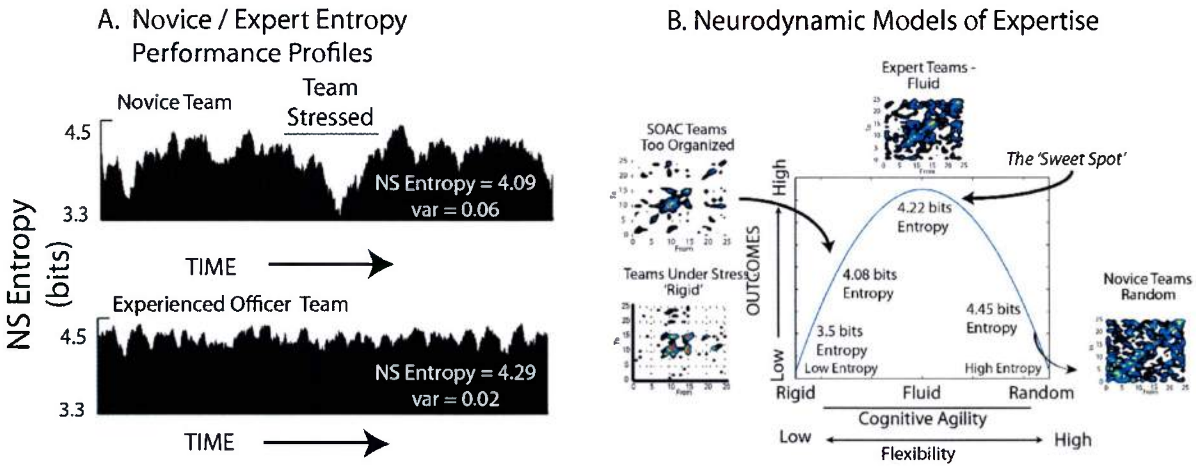

Figure 2. Novice / expert team dynamics. A) The NS_E entropy dynamics of a SOAC and an expert SPAN team. B) A neurodynamic performance model relating team flexibility and performance outcomes. NS entropy is expressed either numerically, or visually in transition matrices. Higher entropy levels were associated with diffuse transition maps and data streams with a greater symbol variety.

These and other results were expanded into a teamwork performance model relating NS entropy levels and the degree of team organization (Fig. 2B). The x-axis plots low / high levels of neurodynamic entropy and relates them to the cognitive organization of the team from rigid to random (y-axis) and team performance. Junior Officers (lower left), especially when performing under stress or uncertainty showed tightly-organized state transitions and low entropy levels, equivalent to the usage of only 9 of the 25 NS symbols. Experienced, but not yet expert teams still showed restricted state transitions, but the mean entropy levels of these teams increased. With more experience the entropy levels and the diversity of the state transitions further increased. From performance metrics and evaluator ratings, this stage would approximate the 'sweet spot' of team function. To the right are very inexperienced teams which showed the highest entropy but were generally rated by evaluators as the lowest performers; here the NS entropy levels approached those of randomized NS data streams. The model 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 (Bak, Tang & Weisenfeld, 1987).

Stevens, R. H. & Galloway, T., Campell, G., Berka, C. & Balthazard, P. (2013). How Tasks Help Shape the Neurodynamic Rhythms and Organizations of Teams. In Proceedings of HCII 2013 Las Vegas, NV.

Abstract. We have modeled neurophysiologic indicators of Engagement and Workload to determine the influence the task has on the resulting neurodynamic rhythms and organizations of teams. The tasks included submarine piloting and navigation and anti-submarine warfare military simulations, map navigation tasks for high school students and business case discussions for entrepreneurial / corporate teams. The team composition varied from two to six persons and all teams had teamwork experience with the tasks. For each task condition teams developed task-specific neurodynamic rhythms. These task-specific rhythms were present during much of the task but could be interrupted by exogenous or endogenous disturbances to the team or environment. The effects of these disturbances could be rapidly detected by changes in the entropy levels of the team neurodynamics symbol streams. These results suggest the possibility of performing task-specific comparisons of the rhythms and organizations across teams expanding the opportunities for rapid detection of less than successful performances and targeted interventions.

Excerpt. The neurodynamics are shown for one anti-submarine warfare team (ASWT) where the major task segments Search, Track and Attack have been identified (Fig. 3). For these teams, across team NS-WL models were developed by pooling the NS vectors from four performances and then testing teams individually against this model. The NS maps for EEG-WL showed that that NS 1 and 25 had twice the expression of the remaining symbols. These symbols represented periods where the ATO & SO had high EEG-WL levels and the Pilot had low (i.e. [ATO,SO]↑P↓) (e.g. NS 1) or the combination [ATO,SO] ↓P↑ (e.g. NS 25). From the perspective of teamwork these NS_WL patterns are consistent with what would be expected from the task as the ATO & SO work closely together once contact is made while the pilot needs less second-by-second coordination with the other members while flying to the initial location, or when changing the search area. Entropy fluctuations were present in the three major task segments that corresponded to identifiable simulation events like in Fig. 3C.1.a where the sonar instrument was malfunctioning and needed repair. During that period the predominant NS_WL symbols were NS 3-10 indicating periods where all team members had average or below average EEG-WL.

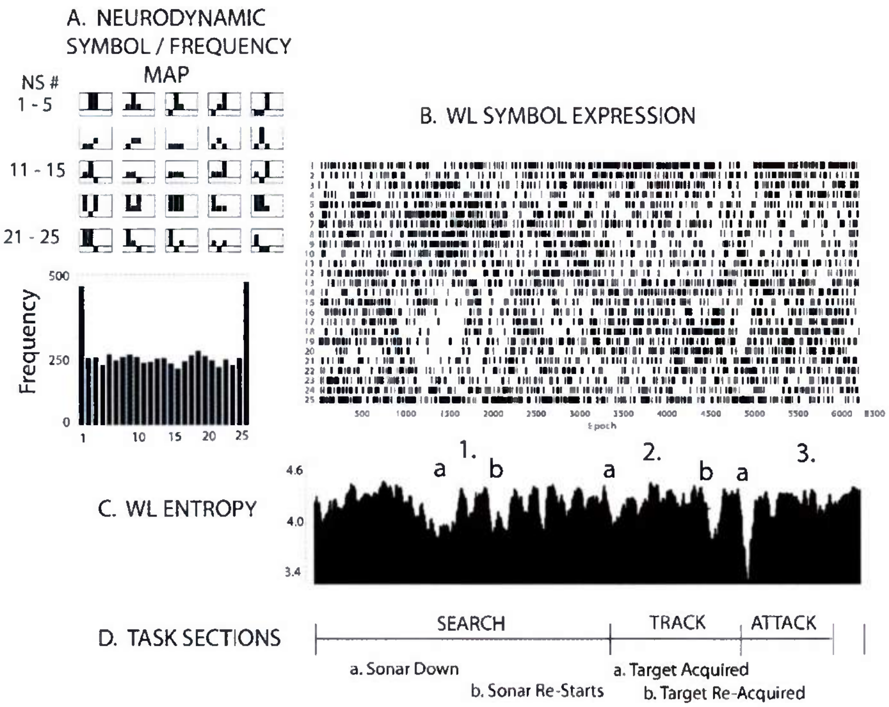

Figure 3. Linking NS symbols (A) with temporal NS expressions (B), entropy fluctuations (C) and segments of the task (D).

Hypothesis 2: Sequential content measures determined by Latent Semantic Analysis (LSA) will reveal novice / expert differences in communication that are linked with neurophysiologic dynamics.

Gorman, J.C., Martin, M., Dunbar, T., Galloway, T., Stevens, R.H. (2013). Analysis of Semantic Content and Its Relation to Team Neurophysiology during Submarine Crew Training. Foundations of Augmented Cognition Lecture Notes in Computer Science Vol. 8027, 2013, pp 143-152.

Abstract. A multi-level framework for analyzing team cognition based on team communication content and team neurophysiology is described. The semantic content of team communication in submarine training crews is quantified using Latent Semantic Analysis (LSA), and their team neurophysiology is quantified using the previously described neurophysiologic synchrony method. In the current study, we validate the LSA communication metrics by demonstrating their sensitivity to variations in training segment and by showing that less experienced (novice) crews can be differentiated from more experienced crews based on the semantic relatedness of their communications. Cross-correlations between an LSA metric and a team neurophysiology metric are explored to examine fluctuations in the lead-lag relationship between team communication and team neurophysiology as a function of training segment and level of team experience. Finally, the implications of this research for team training and assessment are considered.

Excerpt. We constructed a SPAN semantic space to extract semantic content metrics from transcribed SPAN communications to help determine whether team training and experience impact the cognitive-behavioral and neurophysiological levels in similar ways. We hypothesized that if these levels interact during team training, then the linkage between them should fluctuate depending on training conditions. We specifically predicted that if team neurodynamic entropy and team communication are linked, then related changes in both would be caused by differences in training type and team experience. On the other hand, if they are not linked, then changes in one level of analysis should not be concomitant with changes in the other as a function of either training type or team experience.

In constructing a semantic space, LSA takes as input a body of text and represents it as a matrix of frequency co-occurrence of unique terms (e.g., words) by documents (e.g., paragraphs). LSA assumes that lower-dimensional (i.e., latent) semantic factors can be found to account for the frequency co-occurrence between words and documents in the high-dimensional input matrix.

Two metrics derived from the geometrical interpretation of the LSA semantic space are (1) the vector length of a piece of discourse and (2) the cosine between two pieces of discourse. These metrics were used to analyze the semantic content and semantic relatedness of team communication during SPAN. The vector length of a piece of discourse (e.g., an utterance; "Recommend steering course 178 to regain track.") is the Euclidean norm of the vector, created by summing the semantic space vectors of the words in the discourse, plotted in the semantic space. The vector length measures the amount of semantic content (cf. domain-specific knowledge) a piece of discourse contains relative to the domain of discourse, as represented by the SPAN semantic space. The cosine between any two pieces of discourse (e.g., any two utterances; any two training segments; any two complete transcripts; etc.) is the vector dot product between two vectors plotted in the semantic space. The correlation between two vectors can be shown to be the cosine of the angle joining them (e.g., independent, perpendicular vectors have cos [90°] = 0, and they are completely uncorrelated). Hence, the cosine measures the degree of semantic relatedness, or correlation, between any two pieces of discourse.

Hierarchical clustering of the scenario cosine matrix using average between-groups linkage revealed that more experienced and less experienced teams clustered together based on the semantic relatedness of their communications (Figure 4).

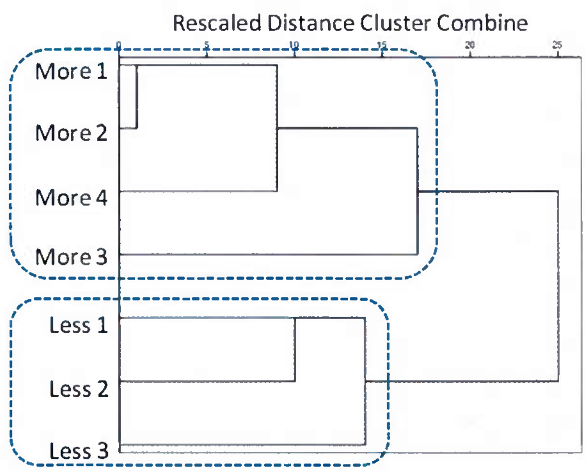

Figure 4. A hierarchical clustering of the LSA cosine matrix from the Scenario training segment (More = More Experienced Team; Less = Less Experienced Team).

Hypothesis 3: Quantitative nonlinear dynamical (NLD) measures of team neurodynamics will be positively correlated with higher performing teams.

Stevens, R. H. & Galloway, T., (2014). Toward a Quantitative Description of the Neurodynamics Organizations of Teams. Social Neuroscience Vol. 9:2, 160-173.

Abstract. The goal was to develop quantitative models of the neurodynamic organizations of teams that could be used for comparing performance within and across teams and sessions. A symbolic modeling system was developed, where raw electroencephalography (EEG) signals from dyads were first transformed into second-by-second estimates of the cognitive Workload or Engagement of each person and transformed again into symbols representing the aggregated levels of the team. The resulting neurodynamic symbol streams had a persistent structure and contained segments of differential symbol expression. The quantitative Shannon entropy changes during these periods were related to speech, performance, and team responses to task changes. The dyads in an unscripted map navigation task (Human Communication Research Centre (HCRC) Map Task (MT) developed fluctuating dynamics for Workload and Engagement, as they established their teamwork rhythms, and these were disrupted by external changes to the task. The entropy fluctuations during these disruptions differed in frequency, magnitude, and duration, and were associated with qualitative and quantitative changes in team organization and performance. These results indicate that neurodynamic models may be reliable, sensitive, and valid indicators of the changing neurodynamics of teams around which standardized quantitative models can begin to be developed.

Stevens, R. H. & Galloway, T., (2014). Teams Reorganize Neurodynamically When They Sense Loss of Control. In Proceedings of HCII 2014 Crete Greece

Abstract. Perturbations to the normal flow of teamwork arise externally through changes in the environment or internally as a result of the team's processes / decisions. We used quantitative neurophysiologic models of the rhythms and organizations of teams to examine the effects of these two classes of perturbations on team neurodynamics. Electroencephalographic (EEG) signals from dyads were transformed into cognitive workload estimates and then into neurodynamic symbols (NS) showing the second-by-second workload of each individual as well as the team. Periods of changing cognitive organizations were identified by a moving average smoothing of the Shannon entropy of the NS data stream and related to team speech, actions and responses to external and internal task changes. Dyads performing an unscripted map navigation (HCRC Map Task) developed fluctuating NS dynamics around the construct of workload which were disrupted by external task perturbations or when the team became confused or uncertain of their progress. Importantly, we detected no significant neurodynamic fluctuations associated with periods when the team made mistakes and did not realize they made the mistake. These results indicated that neurodynamics reorganizations occurred in teams in response to multiple types of perturbations, but primarily when the team perceived difficulties.

Excerpt. The task for these studies was a two-person problem solving / navigation exercise based on the Edinburgh Map Task corpus (Doherty-Sneddon, Anderson, O'Malley, Langton, Garrod & Bruce, 1997). In the task two team members sat facing one another and each had a sketch-map with several landmarks on it. The two maps were similar, but not identical and they could not see each other's map. One person, the instruction giver (Giver or G), had a path printed on the map and attempted to verbally guide the other person, the instruction follower (Follower or F) in drawing that path on the Follower's map. The resulting dialog was unscripted and fluent and contained easily identified short-term goals.

The detailed neurodynamics of one MT team performance is illustrated in Fig. 5 which highlights the major features seen in other teams. Here team performance (Fig. 5A), is linked with the lengths of speech transactions (Fig. 5B), the NS_WL Entropy profile (Fig. 5C), and the NS_E Entropy profile (Fig. 5D). This was one of the lower performing teams with mistakes occurring on five occasions (indicated by the negative numbers in bold italic). Two significant mistakes were made in the first 232 epochs (the numbers in parentheses) where the Follower went to the wrong side of the palm trees and then later made a large path deviation towards the upper right corner before re-aligning with the intended path.

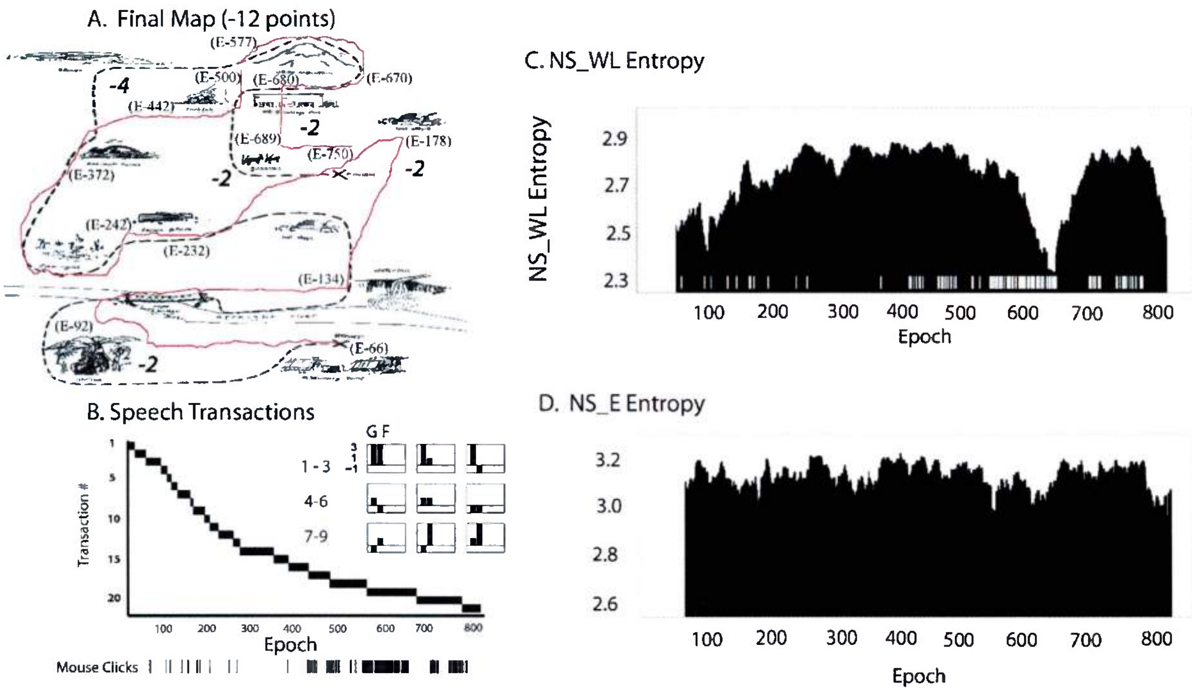

Figure 5. Linking the neurodynamics of Entropies with speech, and map task events (Performance G4S1). A) The final map showing the places where points were deducted; B) The timing of the team's speech transactions with the Follower's mouse clicks shown below; C)

Histogram plot of NS_WL Entropy (black) and mouse clicks (white); D) Histogram plot of NS_E Entropy.

Speech dynamics were seen in this team that were associated with segments of dialog called transactions. Transactions are sub-dialogues that accomplish one major step in the plan for achieving the task. A typical transaction gets the Follower to draw one route segment on the map. For instance, the phrases "(G) Do you have Abandoned Truck? (F) Ya, (G) You should end at the K of the Abandoned Truck" is an example of a transaction. Figure 5B plots the time for each transaction (solid blocks) with the individual mouse clicks used for drawing shown below.

Early transactions were short (< 20 seconds) and seemingly effective as indicated by the few mouse clicks. Around epoch 200 the average length of the transactions began to lengthen (~ 45 seconds) as the team realized that they were far off course (see Fig. 5A near E-178). Details from the transcript gave little indication that the team felt that there were performance problems at this time.

The NS_WL Entropy levels began the performance around 2.7 bits representing a restricted use of the available symbols and then increased over 300 seconds reaching an average of 3.02. These dynamics were seen when starting the problem in 5/15 performances and have been observed in other teamwork situations.

Most Map Task performances also showed context-related NS_WL Entropy dynamics that began when the Follower had difficulty drawing with the mouse. This contextual change in the task was an unintended consequence of having the Followers draw their paths on a computer overlay of the map and resulted in a large number of mouse clicks (Fig. 5C). When this occurred it disrupted the transaction times (Fig. 5B) and resulted in a decrease in NS_WL Entropy. For team G4S1 this occurred near epochs 550-700.

Hypothesis 4: Multifractal analysis of neurophysiologic data streams will help predict team stability during times of stress.

Likens, A., Amazeen, P., Stevens, R. H., Galloway, T., Gorman, J.C., (2014). Neural Signatures of Team Coordination are revealed by Multifractal Analysis. Social Neuroscience 9:3, pp 219-234.

Abstract. 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.

Excerpt. 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. Figure 6 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. 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. Gorman, Amazeen, et al. (2010) interpreted the finding of $H > 0.5$ for the most adaptive teams as a team-level exploration of solutions to unexpected problems.

Figure 6 demonstrates the benefit that the employed approach provided to the project. The black "+" symbols that superimpose the graph near Epoch 2,000 each correspond to a unique scaling exponent. The region near Epoch 2,000 was one in which the team experienced a significant increase in stress resulting from decreased visibility. Near the onset of that event, Figure 6 shows a marked decrease in the magnitude of scaling exponents to a range typical of corrective behavior. However, as the team progressed through the problem, the scaling exponent increased towards a value thought to denote persistent behavior typical of a smoothly running system.

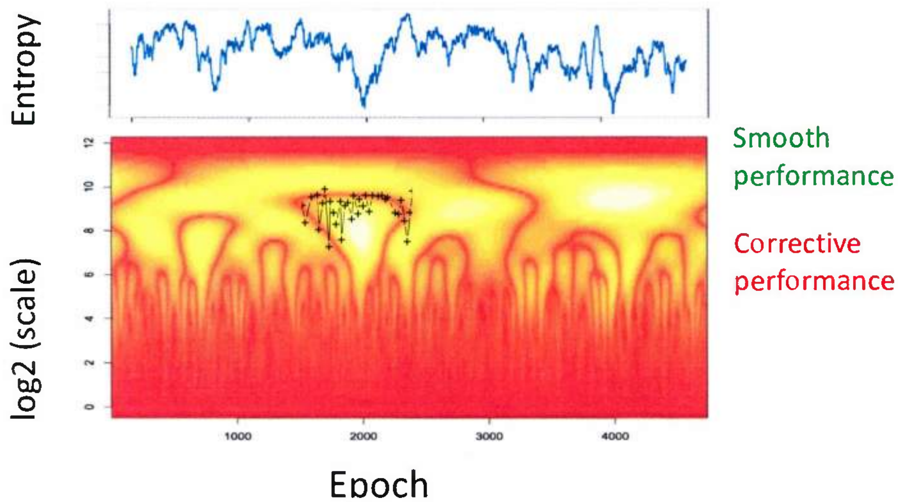

Figure 6. NS_E entropy times series for team T2 and accompanying CWT representation. The CWT is superimposed by scaling exponent trend near a time of stress. Scaling exponents at the outset correspond to corrective or anticorrelated behavior. Scaling exponents increase throughout as the team manages the incident and assuages the stress. Note that the scaling exponents indicated by "+" do not share a common scale with the wavelet plot but are superimposed for demonstration purposes.

Hypothesis 5: Short term significant fluctuations in team neurodynamics will be associated with identifiable team practices.

Kolm, J., Stevens, R.H., Galloway, T., (2013). How Long Is the Coastline of Teamwork? Foundations of Augmented Cognition Lecture Notes in Computer Science Vol. 8027, 2013, pp 162-171

Abstract. A five-state Markov model is proposed for group and team operation and evolution that has a stronger basis in neurodynamics, greater descriptive accuracy and higher predictive value than many existing models. The derivation of this model from the symbolic analysis of normalized EEG activity during assigned team and group tasks is discussed, as are observations on team and group dynamics which emerge from the model. The predictive value of the model is shown when applied to independent data from submarine crew evolutions. Observations are offered on team dynamics which show the five-state model and its accompanying state transitions to be necessary and sufficient to describe both linear and non-linear team dynamics, and to begin unifying these traditional and new approaches in a straightforward way.

Lamb, C., Jones, E., Steed, R., & Stevens (2013). A Robust and Realistic Model of Submarine Tactical Team Performance. Proceedings, Sub Tech, 2013

Abstract. As the U.S. Undersea Force looks to future challenges of ensuring our access to critical world regions, denying our adversaries' access and maneuver, and exerting influence worldwide, it will require teams with the ability to conduct simultaneous engagements in several emerging missions. This shift in mission role, from traditional to new and disruptive mission areas, along with progressively more complex sensor, navigation, and combat systems, will stress the problem solving capacity of crews. The objective of this research is to develop a multidisciplinary model of engaged and resilient tactical teams which can then be used to assess, develop, and improve team performance. Our research has indicated that, in addition to technical skills, deliberate and effective team practices are necessary to manage the wide variety of simultaneous and increasingly complex problems that occur during tactical operations.

Stevens, R. H. & Galloway, T., (2013). Towards the Development of Quantitative Descriptions of the Neurodynamic Rhythms and Organizations of Teams. Proceedings of the Human Factors and Ergonomics Society Annual Meeting Vol. 57 (1), pp 134-138

Abstract. The goal was to begin developing quantitative approaches for modeling the neurodynamic rhythms and organizations of teams. Raw EEG signals from team members were first transformed into estimates of cognitive workload and transformed again into neurodynamics symbols showing the second-by-second workload of each individual as well as the team. Periods of increased or decreased symbol organization in the data streams were hypothesized to reflect periods of increased or decreased organization around the cognitive construct of workload. These segments were identified by a moving average smoothing of the Shannon entropy over the length of the performance and then related to team speech, actions and team responses to endogenous and exogenous task changes. Two-person teams in an unscripted map navigation task developed a common, dominant coordination dynamic for workload whose rhythm was disrupted by exogenous changes to the task. The entropy fluctuations during these disruptions differed in magnitude and duration within and across performances and were associated with qualitative and quantitative changes in team organization. Similar results were obtained with three and six person teams on other complex tasks. These results indicate that neurodynamic measures may be reliable, sensitive and valid indicators of the changing neurodynamics of teams around which standardized quantitative models can be developed.

Stevens, R. H. (2014) Team Neurodynamics. Encyclopedia of Information Science and Technology. In Press.

Abstract. Team neurodynamics is the study of the changing rhythms and organizations of teams from the perspective of neurophysiology. As a discipline, team neurodynamics is located at the intersection of collaborative learning, psychometrics, complexity theory and neurobiology with the resulting principles and applications both drawing from and contributing to these specialties. This article describes the tools for studying team neurodynamics and shows the potential of these methods and models for better understanding team formation and function. The models developed are reliable, sensitive and valid indicators of the changing neurodynamics of teams around which standardized quantitative models can begin to be developed. The technology is intended for documenting how rapidly / well teams are progressing towards proficiency and expertise and for understanding why some teams function better than others.

Lamb, C., Lamb, J., Stevens, R., Caras, A., (2014). Team Behaviors and Cognitive Cohesion in Complex Situations. In Proceedings of HCII 2014. Crete Greece

Abstract. Our research has indicated that, in addition to technical skills, deliberate and effective team practices are necessary to manage the wide variety of simultaneous and increasingly complex problems that occur during tactical operations. This paper looks at team performance from two aspects, the first is observable team behaviors and the second is from two objective measures of team interactions. The combined results point toward a fuller understanding of team dynamics that can be applied to assessment, improvement, and prediction of team performance in operational situations.

Excerpt. The Periodicity of Rounds: Every three minutes during SPAN simulations the position of the submarine is updated by a process called 'Rounds'. During Rounds the bearing and / or distance to charted markers are plotted on a chart and the intersection of the lines 'fixes' the submarine's position. The periodicity of the Rounds process is shown in Figure 7A for one team where there were twenty-three Rounds cycles. The times between Rounds were regular with the twenty-three cycles spanning 4635 seconds. Exceptions were noted around epochs 1280 and 4230 where in both cases the first Round was discarded as the fix seemed inaccurate and then a second Mark Round was performed. There was also one Rounds sequence near 4470 seconds which took 315 seconds. The mean time between Rounds cycles was 177 ± 48 seconds.

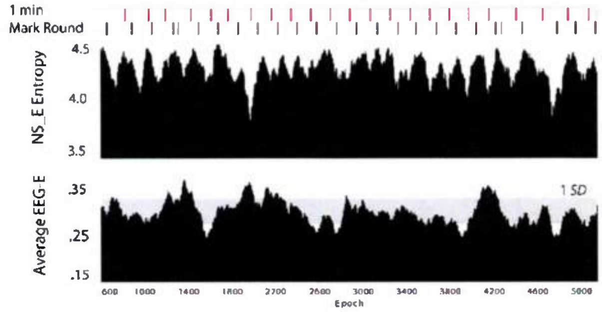

Figure 7. Periodicity of rounds sequence (*top*), NS_E Entropy fluctuations (*middle*), and EEG-E (*bottom*).

A similar periodicity was observed in the fluctuations of the NS_E Entropy (Figure 7B bottom) with at least twenty-one easily identifiable peaks that were closely aligned with each Rounds cycle, the 'Mark Rounds' in particular. A 100-second moving average of the EEG-E values of the team members did not show the same periodic structure (Fig. 11C), and the moving average levels of EEG-E and NS_E Entropy were uncorrelated (R = - 0.12).

With the large number of Rounds-associated NS_E Entropy fluctuations we compared the NS_E Entropy in the ten seconds prior to and after a Mark Round call, with the NS_E entropy of the remaining performance. Periods of Mark Rounds had elevated NS_E Entropy levels compared with non-mark Rounds periods (4.32 ± 0.08 vs. 4.24 ± 0.18, $P < 0.001$).

Data Collection and Technical Challenges

ABM staff involved with the study traveled to Newport, RI and Groton, CT on 1 and 3 occasions, respectively. Over the course of the four visits, a total of 27.5 sessions were completed with a total of 72 participants. The table below illustrates the breakdown of sessions and new participants per visit.

Data Acquisition. One of the main requirements for the teaming setup is the synchronization between the subjects. The majority of offline analysis in teaming tasks involves comparing the EEG characteristics in response to events faced by the subjects in the team.

The teaming protocol for desktop computers was developed using our External Sync Unit (ESU). The ESU is a data acquisition and timer module interfaced to the PC via the USB port that communicates with our wireless data acquisition devices. By bypassing the windows operating system, the ESU enables millisecond level synchronization of the data from the subjects in the team. The desktop networking architecture follows similar protocols for tablets, wherein periodic and unique beacons are sent to all subject computers for synchronization. The beacons are however, distributed via a proprietary serial port network; each ESU in the network will receive the beacon via its serial port. In addition, the ESU timestamps the beacons and the acquisition software stores them alongside the EEG data in the EDF file. The transmitting computer (i.e. technician's computer) also has an interface to send custom comments, as markers, to all the computers in the team. These custom comments are converted to ASCII format and saved in the EDF file for offline processing. The custom comments provide a robust way to extract points of interest from the synchronized data without further alignment or processing.

The laptops connect to ABM headsets via Bluetooth and acquire and store data in compatible EDF format. The typical setup involves the following steps:

- One laptop is assigned to each subject, and each is given a subject ID prior to the start of acquisition. The same laptop is used to test the scalp-electrode impedance and then to administer the baseline tasks referred to as the Alertness Memory Profiler (AMP).
- Once each team member has completed their AMP, all laptops are linked together using the serial port network.
- The data acquisition is then initiated once the team is ready to start their training scenario. The acquired data will be stored in EDF format in the laptop memory, which can be accessed at a later point.

A B-Alert X10 system was used and EEG data from 9 sites (POz, Fz, Cz, C3, C4, F3, F4, P3, and P4) were recorded with a sampling rate of 256 samples per second. The EEG signals were first filtered with a band-pass filter (0.5-65Hz) before the analog to digital conversion, and then the sharp notch filters were applied to remove environmental artifacts from the power network. A number of artifacts in the time-domain EEG signal, such as spikes caused by tapping or bumping of the sensors, amplifier saturation, or excursions that occur during the onset or recovery of saturations, were automatically detected and removed. Eye blinks and excessive muscle activity were identified and decontaminated by an algorithm based on wavelet transformation.

Study Procedures. Of the ~14 team members involved with the training scenario, a maximum of 6 per team participated in each study session. The sizes of the teams were based on the positions of interest and the willingness of the participant in that position to participate in the study. The positions of interest included the Officer of the Deck (OOD), Navigator (NAV), Assistant Navigator (ANAV), Radar, Contact Coordinator (CC), and the Quarter Master (QMOW).

After consent, each participant was fitted with an EEG system and a technician performed an impedance check to ensure good electrode to scalp connection. Afterwards, each participant was administered a 15 minute AMP session which included 5 minutes each of the 3-

Choice Vigilance Task (3-CVT), Visual Psychomotor Vigilance Task (V-PVT), and Auditory Psychomotor Vigilance Task (A-PVT). This step is required to obtain ABM's proprietary B-Alert cognitive state metrics and cognitive workload during the teaming sessions.

Signal Processing, Artifact Detection and Decontamination. Artifacts are automatically detected and decontaminated in the time-domain EEG signal. Artifacts include spikes, saturation, excursions, eye blinks, and excessive muscle activity (EMG). For each of these artifacts, data points with 0 μV are inserted, starting at the last zero crossing prior to and ending at the first zero crossing after the artifact. A 60 Hz notch filter is applied to all EEG data. Three sets of filtered EEG data are then derived using a 0.5 Hz 256th order high-pass finite impulse response (FIR) filter, a 4 Hz 640th order FIR high-pass filter and a 7 Hz infinite impulse response (IIR) low-pass filter. To obtain faster computations, both high-pass filters are realized by subtracting the output of the corresponding low-pass filter from the original signal.

Identification of eye blinks in the EEG without the use of a reference EOG channel is achieved by filtering the fast component of the FzPOz channel with a 7 Hz IIR low-pass filter, applying cross-correlation analysis to the filtered signal using the positive half of a 40 □V 1.33 Hz sine wave as the target shape, and applying thresholds to the outputs from the cross-correlation analysis. Minima and maxima analysis in each direction from the point of maximum correlation is used to identify the data points corresponding to the range between the start and end of each eye blink. Once eye blink ranges have been determined, the 0.5 Hz high-pass filtered EEG signal from each channel is decontaminated by replacing the data points in the eye blink region with the corresponding data after application of the 4 Hz filter.

Decontaminated EEG is then segmented into overlapping 256 data-point windows called overlays. An epoch consists of three consecutive overlays. Fast-Fourier transform is applied to each overlay of the decontaminated EEG signal multiplied by the Kaiser window ($\alpha = 6.0$) to compute the power spectral densities (PSD). The PSD values are adjusted to take into account zero values inserted for artifact contaminated data points. The PSD between 70 and 128 Hz is used to detect EMG artifact. Overlays with excessive EMG artifact ("EMG") or with fewer than 128 data points ("missing data") are rejected. The remaining overlays are then averaged to derive PSD for each epoch with a 50% overlapping window. Epochs with two or more overlays with EMG or missing data are classified as invalid. For each channel, PSD values are derived for each one-Hz bin ("bin") from 3 Hz to 40 Hz and the total PSD from 3 to 40 Hz ("band"). [1]

EMG is computed by comparing PSD coefficients computed at specific bandwidths against set thresholds derived statistically from the population database maintained by ABM. Three categories of EMG artifacts are computed based on the bandwidth of the artifact: 1) High Freq EMG: frequency bands 70-128Hz, 2) Low Freq EMG: frequency bands 35-40 Hz, 3) Delta Contamination (very low frequency bands 1-3 Hz). Excessive power in each category is compared with thresholds and the outcome from all categories are combined using proprietary logic functions to qualify each epoch with respect to EMG contamination. Epochs with EMG contamination are rejected and not used by the classification algorithms.

For this specific study we fine-tuned the thresholds for noise levels specific to the study, through trial and error methods. This considerably improved the yield of good epochs and enabled us to optimistically salvage considerable amount of data generated in the study. The team continues to put an effort into investigating these EMG thresholds.

B-Alert Classification Model. Individual data was processed offline using the B-Alert Analysis software. Output metrics of interest included the B-Alert measures of engagement and workload. The EEG engagement index is related to information-gathering, visual scanning, sensory load, and sustained attention [1-4]. The four-class quadratic DFA modal was constructed using absolute and relative power spectra variables from sites FzPOz and CzPOz [2]. EEG Workload is correlated with objective performance and workload ratings in tasks related to working memory [2, 5]. The workload classifier was developed using a linear DFA with two classes, low and high mental workload. Similar to the engagement classifier, workload used the absolute and relative power spectra variables obtained using stepwise regression on sites C3C4, CzPOz, F3Cz, FzC3, and FzPOz [2].

Each participant's engagement and workload data was processed into an epoch by epoch output file. Using the beacon timestamps from the Teaming Sync App, relevant events (i.e., debriefing start, session start, mark rounds, etc.) were identified and each individual file was hand aligned with all other team members. Invalid values within the output files were removed and files were sent to Dr. Ron Stevens for further analysis.

During the offline analysis it was discovered that a firmware bug within the ESU was introduced during some of the raw EEG files at the time of the B-Alert acquisition sessions. That is, EEG data that contained missed blocks as a result of participants moving out of the 10 meter range-of- sight required for Bluetooth transmission were being misrepresented due to a data collapse; forcing the output file to shift in time. This ended up misleading the automated offline analysis and causing the 6-member team files to become incorrectly aligned. Fortunately, the teaming platform was created to include multiple redundant time-stamping and synchronization protocols and once the problem was identified, ABM team members were able to undertake the difficult process of re-aligning the files epoch-by-epoch for several teams. Once it was established that the files could be properly realigned, a software tool was created to allow systematic repair of all of the affected data.

The solution was introduced in the analysis software that automatically identified such cases of collapsed data series and adjusted the corresponding epoch orders accordingly. This fix was applied to all data files that contained errors introduced by the firmware bug. The resulting output files for each participant were synchronized based on session/team and the fixed data was sent back to the collaborators for modeling. The firmware issue did not alter the data quality, but rather the correct alignment of data, as we had missed blocks that were not properly accounted for prior to repair.

Regardless of the firmware bug, the data collected as part of this study were of similar quality to prior studies in the SPAN trainer (Table 1).

Table 1. Comparison of artifact from past data sessions with most recent data sessions.

Teaming Data	Session X Subj	Other %	EMG %	MissedBocks %	GoodData %
OLD (2009-2010)	170	5.21	20.00	0.00	75
NEW (inc. REPAIRED; 2012-2013)	164	7.03	23.36	0.16	70

The primary difference from our original studies in 2009/2010 to 2012/2013 was a change in location/training facility. During studies conducted in 2009-2010 in Groton, CT, the OOD was not physically separated from the rest of the simulation team. Starting in November 2012, the simulation took place in the Submarine Bridge Trainer (SBT) located in Newport, RI. The OOD's position in the bridge was separated from the rest of the team; the position up on the bridge simulated a more realistic 360 degree view of the area above water. Fortunately, the OOD's laptop was not physically disconnected from the rest of the teaming platform--signal from the headset to the laptop was able to be carried up into the bridge--and the overall EEG acquisition for all teams during this visit went smoothly. Following the November 2012 visit, the location was changed back to Groton, CT for the three subsequent data acquisitions during 2013 (Table 2). Similar to the Newport location, the SBT was utilized; these sessions were located in a different room and building from the 2009/2010 Groton acquisition. Also similar to the Newport acquisition, the OOD was again separated from the rest of the team. However, this time the signal was not able to pass from the laptop to the OOD sitting up at the bridge and his laptop had to be disconnected from the teaming platform. Overall, we generally had more problems with connection within this simulator and we found that this led to greater issues with missed blocks. When we examine the data quality from the 2013 sessions compared to all preceding sessions (Table 1&2) we see that there is a slightly greater increase in the percent of missed blocks (0.19%) during the Groton 2013 sessions.

Table 2. Comparison of the Groton 2013 sessions with Newport 2012.

Teaming Data	Session X Subj	Other %	EMG %	MissedBocks %	GoodData %
Newport, RI (SBT)	37	6.50	27.00	0.04	66.70
Groton, CT (SBT)	127	7.18	22.30	0.19	70.93

The data quality seen herein is, as these tables show, consistent with past studies in this context, as well as with other ambulatory applications that we have collected in the past--as EMG is the primary driving factor in contaminating EEG in an active moving environment. In other recent applications, with teams sitting around a table discussing and problem solving, we see data quality loss due to EMG is still in the 20-30% range, however we see no missed blocks, as these participants are not moving in and out of range as occurs in the bridge trainer(s) (Table 3).

Table 3. Summary of data quality for similar teaming study.

Teaming data	Session X Subj	Other %	EMG %	MissedBocks %	GoodData %
ESADE 2012	201	7.59	27.86	0.00	65.52

The technical challenges in modeling team neurodynamics fall into two categories: biologic / technical artifacts and degrees of separation from primary data sources. Teams are more than the sum of the individuals and data tolerances that are acceptable for performing research with individuals are not for teams. The unique challenge for teams is the compounding of errors across members of the team. While a 5-10% loss of data signals due to decontamination or data stream repairs may be acceptable for studying the dynamics of individual data streams, such missing data compounds when data streams are combined across 4-6 persons.

Signal loss due to biologic or technical artifacts can arise from biologic sources like blinking and other eye movements or excessive muscle activities. The degree of data loss depends on the number of electrode positions required for deriving the measure of cognition under study, the number of persons in the team and the experimental time. It also depends on the conditions which the task was performed. The Submarine Bridge Trainer Exercises were very stringent data collection environments with required exercises and the team needed to be 'flies on the wall' during the data collection and not adjust headsets during the simulations. Once EEG signals are obtained from team members other challenges include aligning the data with each other and with third-party data sources like audio and video streams.

An average data loss of 7% for each individual would compound to a 42% data loss for a six person team if the losses are not overlapping across the team members. Normally there are overlaps of epochs of lost data so the number can be reduced, but such compounding is a good starting point. Figure 8 explores some of these considerations in more detail with data from one of the SBT teams. This figure plots the % of lost data for each individual on the team as well as the cumulative lost data; lines are plotted for both EEG-E and EEG-WL. The EEG-WL measure is synthesized from more electrodes / frequencies than EEG-E which results in greater data loss. Rapidly the data loss reaches unacceptable levels for this team.

The NS entropy levels are calculated by averaging over a 100 second moving window and so long segments of lost data would result in artificial entropy levels during that period. The next step is to examine the data strings for the number of continuous segments of lost data. Figure 8 shows that team member 4 had a segment of 196 epochs of lost data. For this long a segment the team member is generally dropped from the modeling. The result is a 5-person model for EEG-E only. Where tasks have defined segments like a Brief, Scenario and Debrief it is often possible to isolate the long segment of lost data and perform segment specific modeling.

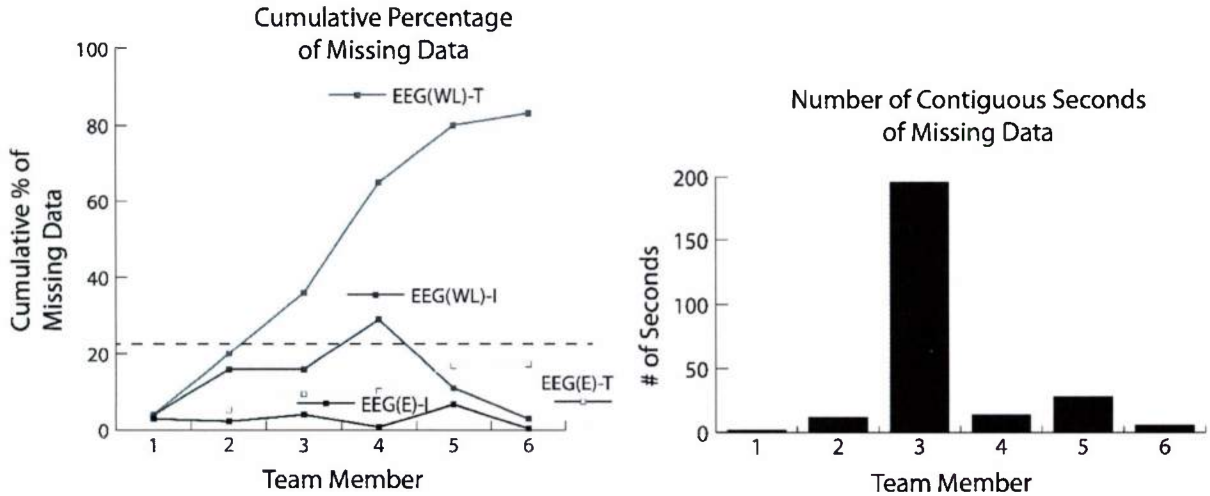

Figure 8. A) Effect of cumulative individual EEG-data loss on overall team data loss. B) Number of contiguous seconds of missing data for each team member.

When these analyses were conducted for the re-synchronized and re-aligned data streams delivered by Advanced Brain Monitoring, Inc. on 3/28/2014 the Engagement and Workload data qualities shown in Table 4 were obtained for the twenty-seven SBT teams. This represents the starting point for subsequent modeling efforts.

Table 4. Distribution of maximum possible team sizes based on EEG – data quality

Prob High Eng			Prob HW		
# of Team Members	# SBT Teams	% of Total SBT Data Collected	# of Team Members	# SBT Teams	% of Total SBT Data Collected
6 Person Team	1	3.70%	6 Person Team	0	0.00%
5 Person Team	7	25.93%	5 Person Team	5	18.50%
4 Person Team	8	29.63%	4 Person Team	6	22.22%
3 Person Team	8	29.63%	3 Person Team	4	14.81%
2 Person Team	3	11.11%	2 Person Team	12	44.44%
No Team	0	0.00%	No Team	0	0.00%

Conclusions and Future Work

A generalizable system has been described for studying team neurodynamics which shows the potential of nonlinear methods and models for better understanding team formation and function. The models developed are reliable, and sensitive indicators of the changing neurodynamics of teams around which standardized quantitative models are being developed. Examples were presented illustrating how such measures can be used to validate team training protocols / and provide a deeper understanding of higher level teamwork concepts like robustness and resilience.

The technology is intended for documenting how rapidly / well teams are progressing towards proficiency and expertise and for understanding why some teams function better than others. With continued refinement and validation, such models would have theoretical and practical implications for understanding teams and teamwork. Theoretically they may provide a framework for defining complex linkages among the flows of information between the biological scales and broader interpersonal scales of teamwork and relating them to the development of team expertise. More practically, the models could provide a standard metric and scale for comparing organizations across teams, training protocols and team composition. They could enable the tracking of team dynamics both short and long-term and help detect phase shifts characteristic of expertise. The ultimate success of these models will be determined by the extrapolation of the neurodynamics findings to everyday group and teamwork activities.

Significant Results were obtained for all objectives and resulted in 12 published articles. Additional manuscripts are under review and will be posted on www.teamneurodynamics.com when published.

Publications

1. Stevens, R.H., Gorman, J.C., Amazeen, P., Likens, A., and Galloway, T. (2013). The organizational dynamics of teams. *Nonlinear Dynamics, Psychology and Life Sciences 17, No. 1,* pp. 67-86.
2. Stevens, R.H., (2013). The emergence of team neurodynamics. Society for Chaos Theory in Psychology and Life Sciences, 20, (2) 7-11.
3. Stevens, R. H., Galloway, T., Campbell, G., Berka, C. & Balthazard, P. (2013). How tasks help shape the neurodynamic rhythms and organizations of teams. *Lecture Notes in Computer Science*, 8027: 199-2008.
4. Gorman, J., Martin, M., Dunbar, S., Galloway, T., & Stevens, R. (2013). Analysis of semantic content and its relation to team neurophysiology during submarine crew training. *Lecture Notes in Computer Science,* 8027: 143-152.
5. Kolm, J., Stevens, R. H., Galloway, T. (2013). How long is the coastline of teamwork? *Lecture Notes in computer Science,* 8027: 162-171.
6. Lamb, C., Jones, E., Steed, R., & Stevens (2013). A robust and realistic model of submarine tactical team performance. Proceedings, SubTech, Norfolk, VA 2013.
7. Stevens, R. H. and Galloway, T. (2013). Towards a quantitative description of the neurodynamics rhythms and organizations of teams. Human Factors and Ergonomics Society 2013 annual meeting presentation, San Diego.
8. Stevens, R. H. & Galloway, T., (2014). Toward a quantitative description of the neurodynamics organizations of teams. *Social Neuroscience* 9:2, 160-173.
9. Stevens, R. H. & Galloway, T. (2014). Teams neurodynamically reorganize when they sense loss of control. In Proceedings of HCII 2014, Heraklon Crete.
10. Likens, A., Amazeen, P., Stevens, R., Galloway, T., Gorman, J. (2014). Multifractal scaling reveals the nested nature of team performance. *Social Neuroscience.* 3: 219-234.
11. Stevens, R., (2014). Team Neurodynamics. Encyclopedia of Information Science and Technology. In press.
12. Lamb, C., Lamb, J., Stevens, R., & Caras, A. (2014). Team behaviors and cognitive cohesion in complex situations. In Proceedings of HCII 2014. Heraklon, Crete.

References

Bak, P., Tang, C. and Wiesenfeld, K. (1987). Self-organized criticality: an explanation of 1 / f noise. Physical 59 (4): 381–384.

Berka, C.D, Levendowski, M., Lumincao, et al (2007). EEG Correlates of task engagement and mental workload in vigilance, learning and memory tasks. Aviation Space and Environmental Medicine. 78(5), B231-B244.

Doherty-Sneddon, G., Anderson, A., O'Malley, C., Langton, S., Garrod, S., & Bruce, V. (1997). Face-to-face and video-mediated communication: A comparison of dialogue structure and task performance. Journal of Experimental Psychology: Applied, 3(2), 105–125. doi:10.1037/1076-898X.3.2.105

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

Shannon, Claude E. (1951). Prediction and entropy of printed English. The Bell System Technical Journal, 30:50-64.

Stevens, R. H. (2012). Charting neurodynamics eddies in the temporal flows of teamwork. In Proceedings of the Human Factors and Ergonomics Society 56th Annual Meeting. October 2012.

Stevens, R. H., Galloway, T., and Berka, C., & Sprang, M. (2009). Can neurophysiologic synchronies be detected during collaborative teamwork? Frontiers of Augmented Cognition: Proceedings: HCI International 2009, D. Schmorrow & I. Estabrook, M. Grootjen (Eds.) LNCS 5638 pp. 271-275. Springer-Verlag, Berlin, Heidelberg, 2009.

Stevens, R., Galloway, T., Wang, P., Berka, C., & Behneman, A. (2011). Developing systems for the rapid modeling of team neurodynamics. Interservice / Industry Training Simulation and Education Conference (I/ITSEC) 2011. Paper No. 11097.

Stevens, R.H., Galloway, T., Wang, P., and Berka, C. (2012). Cognitive neurophysiologic synchronies: What can they contribute to the study of teamwork? Human Factors 54, 489-502.

Stevens, R.H., Gorman, J.C., Amazeen, P., Likens, A., and Galloway, T. (2013). The organizational dynamics of teams. Nonlinear Dynamics, Psychology and Life Sciences 17, No. 1, pp. 67-86.

Stevens, R. H. & Galloway, T., (2014). Toward a quantitative description of the neurodynamics organizations of teams. Social Neuroscience 9:2, 160-173.