A Neurophysiologic Approach For Studying Team Cognition

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INTRODUCTION

The integrated thinking of a team is often described by the dynamic construct of team cognition which reflects the interrelated cognitions, behaviors and attitudes that contribute to team performance (Warner et al, 2005). An important goal for studying team cognition 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 for better optimization. One of the challenges for achieving this goal is the development of unobtrusive and real-time measures of team performance that can be practically implemented in environments where real-world tasks are performed (Salas et al, 2008).

Communication streams, a natural product of teamwork, are a potential data source for unraveling the dynamics of team cognition. Communication streams contain structures that evolve over time as individuals in a team gain experience (Garrod & Doherty, 1994), they have content relevant to the tasks, and they have process or flow components (Cooke et al, 2008). They also possess the characteristic of long memory i.e. what is being discussed currently has temporal conversational antecedents. Communication analysis however, is laborious with estimates of upwards of 30 hours of coding needed for each hour of dialog being analyzed and is therefore difficult to apply to real-time analysis of team cognition. But communication may not be the only unobtrusive data stream available for studying team cognition in near real-time and in real-world environments.

Neuronal synchronization (synchronous oscillatory brain activities) and cognitive neurophysiologic synchronization (the second-by second quantitative co-expression of the same neurophysiologic / cognitive measure) between brains may provide another avenue. Brain activity in individuals (within brain) can be synchronized by visual or auditory streams where different brain rhythms become entrained by the frequencies of the stimuli. More recently these approaches have been extended to between brain activities where neural synchronization has been observed between guitarists playing duets. Still, these activities are being entrained by external auditory signals (Lindenberger et al, 2009).

In this study we explored whether similar methods could be expanded to document changing aspects of team performance in real time. We hypothesized that as members of a team performed their duties each would exhibit varying degrees of cognitive components such as attention, workload, or engagement and the levels of these components at any one time might reflect aspects of team cognition.

Rather than focusing on neurophysiologic markers such as P300 or N400 which appear and disappear rapidly in response to a large variety of stimuli, we sought broader markers of cognition such as engagement or workload that would be expected to persist over longer periods of time during team activities. For future real-time studies of team cognition it would also be useful if those markers could be generated rapidly from EEG-data streams.

One system that satisfied these criteria was the wireless EEG headset system developed by Advanced Brain Monitoring, Inc (ABM) which has demonstrated feasibility for acquiring high quality EEG in real-world environments. This system uses an integrated hardware and software solution for acquisition and real-time analysis of the EEG and delivers continuous readouts of levels of engagement (EEG-E) workload (EEG-WL).

TASKS AND METHODS

Tasks

The task we have studied is a high fidelity Submarine Piloting and Navigation (SPAN) simulation that contains dynamically programmed situation events which are crafted to serve as the foundation of adaptive team training. Such events in the SPAN include encounters with approaching ship traffic, the need to avoid nearby 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.

Each SPAN session begins with a briefing detailing the navigation mission. This is followed by the simulation which can last from 60 – 120 minutes or more. This is followed by a debriefing session that helps teams monitor and regulate their own performance based on the dimensions of teamwork. .This teamwork task requires not only the monitoring of the unfolding situation and the monitoring of one's work with regard to that situation, but also the monitoring of the work of others. Three teams and 13 SPAN sessions have been studied at the Submarine Learning Center in Groton, CT.

Methods

EEG

The ABM. B-Alert system contains an easily-applied wireless EEG system that includes intelligent software designed to identify and eliminate multiple sources of biological and environmental contamination and allow real-time classification of cognitive state changes even in challenging environments. The 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. ABM B-Alert® software acquires the data and quantifies alertness, engagement and mental workload in real-time using linear and quadratic discriminant function analyses (DFA) with model-selected PSD variables in each of the 1-hz bins from 1-40hz, ratios of power bins, event-related power (PERP) and/or wavelet transform calculations.

The data processing begins with the 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). Most of the studies to date have used the High EEG-E and EEG-WL metrics. Simple baseline tasks are used to fit the EEG classification algorithms to the individual so that the cognitive state models can then be applied to increasingly complex task environments, providing a highly sensitive and specific technique for identifying an individual's neural signatures of cognition in both real-time and offline analysis. 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, quantifying mental workload in military simulation environments, distinguishing spatial and verbal processing in simple and complex tasks, characterizing alertness and memory deficits in patients with obstructive sleep apnea, and identifying individual differences in susceptibility to the effects of sleep deprivation.

Neurophysiologic synchronies

The neurophysiologic synchronies (NS) that we are studying can be thought of as the second-by-second quantitative co-expression of the same neurophysiologic / cognitive measures by different members of the team.

In prior studies analyzing the dynamics of problem solving with individuals we used the raw EEG-E and EEG-WL data streams (Stevens et al, 2007, 2008). Studying team processes using these EEG measures however, requires a normalization step, which equates the absolute levels of EEG-E of each team member with his/her own average levels. This allows the identification not only of whether an individual team member is experiencing above or below average levels of EEG-E or EEG-WL, but also whether the team as a whole is experiencing above or below average levels.

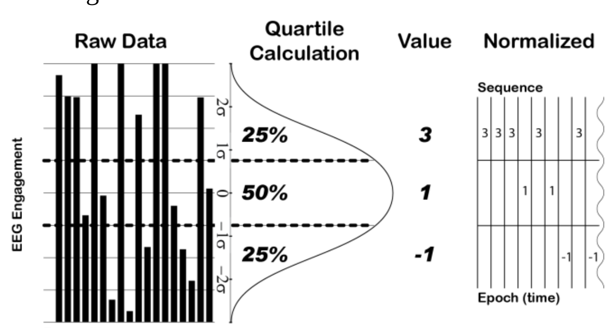

Figure 1. Normalization of Neurophysiologic Measures into Quartile Ranges.

In this normalization process (outlined for one individual in Figure 1) the EEG-E levels are partitioned into the upper 25%, the lower 25% and the middle 50%; these are assigned values of 3, -1, and 1 respectively, values chosen to enhance subsequent visualizations.

The next step combines these values at each epoch for each team member into a vector representing the state of EEG-E for the team as a whole, (this is shown for a team of 3 persons in Figure 2). These vectors can then be used to train unsupervised artificial neural networks that classify the state of the team at any point in time (Stevens et al, 2010). In this process the second-by-second normalized values of team EEG-E for the entire episode are then repeatedly (50-2000 times) presented to a 1 x 25 node unsupervised artificial neural network. During this training a topology develops such that the EEG-E vectors most similar to each other become located closer together and more disparate vectors are pushed away. The result of this training is a linear series of 25 team EEG-E patterns that we call neurophysiologic synchrony patterns.

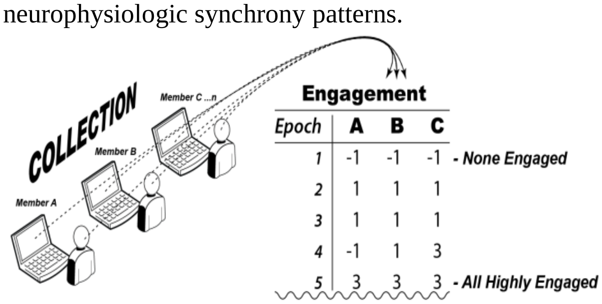

Figure 2. Creation of Team Performance Vectors. While the process is illustrated for three-member teams it can be expanded to include larger teams.

The first set of data is from an experienced submarine navigation team that conducted a 2 hr 45 minute SPAN session. Three crew members were fitted with the ABM B-Alert EEG headsets, the Quartermaster on Watch (QMOW), the Contact Coordinator (CC) and the Officer on Deck (OOD).

This training process resulted in 25 sets of histograms that show the degree of EEG-E by each team member (Figure 3). For instance, NS # 12 NS represents times when all three team members showed below average levels of EEG-E. As discussed earlier (Stevens et al, 2009a) this does not necessarily mean that they were not engaged in the task, just that they were not externally engaged, i.e. they could have been more thoughtful or introspective. NS #22 identifies times when all three team members were highly engaged, while NS #25 represents times when the QMOW and the OOD showed above average levels of EEG-E while the CC showed below average levels.

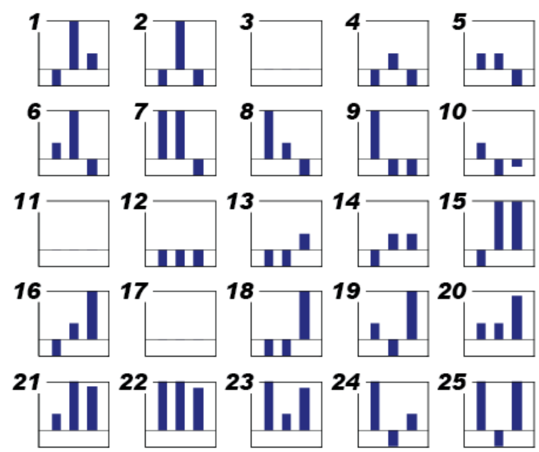

Figure 3. NS Classification Patterns. The input vectors were from a three person expert SPAN team who performed a 160 minute piloting and navigation simulation. The NS represented in each classification are shown by histograms showing the degree of engagement for each team member.

RESULTS

The dynamics of NS expression by an experienced team were visualized by plotting the second-by-second expression of each of the NS patterns as shown in Figure 4. Here a bar mark is inserted for each of the 9684 epochs that represents the NS being expressed at each second.

Audio files were collected that allowed the second-by-second reconstruction of the teamwork discussions. The task began following a briefing period of 221 seconds and lasted until epoch (second) 6651. At epoch 7012 the debriefing period began. Routine events during the simulation included the updating of the ship's position every three minutes, making decisions regarding encounters with other ships and generally satisfying the goals of the mission. Labeled above the figure are several non-routine events that also occurred during the simulation which included a man overboard event

(MOB), a period where the submarine skipper paused the simulation to address the team (Skipper Break) and a short Break after the simulation and before the Debriefing session began.

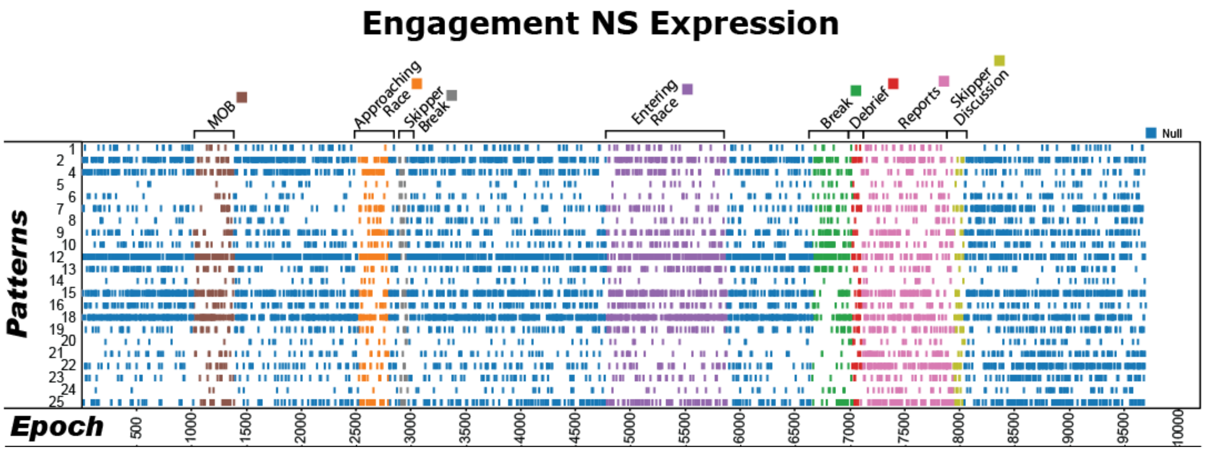

Figure 4. EEG-E Neurophysiologic Synchrony and NS State Expression for an Experienced Navigation Team.

From the density of the marks, some NS like # 12 and #18 were frequently expressed during the task. Similar to previous results, others like NS # 7 and #'s 21-25 were more frequent in the debrief section indicating that NS expression is sensitive to changes in the task.

Such second-by-second mappings of NS are useful for the retrospective viewing of the dynamics of NS expression but on their own would seem too insensitive for practical training applications. We then extended these studies by examining possible 'long memory' properties of the NS data stream. As discussed by Gorman (2005) long memory refers to long-range autocorrelations of some process such as communication where what is currently happening has prior antecedents. Recent autocorrelation studies of NS data streams suggested that there may be a temporal component to NS expression over both short (seconds) and longer (minutes) periods of time (Stevens et al, 2009b). In this way the different NS being expressed over time might be viewed as output symbols from a hidden state(s) of a team, and if so the sequence may give some information about the hidden states the team is passing through. Hidden Markov modeling (HMM) would seem an appropriate approach for such modeling.

The NS data stream for the experienced submarine navigation team was segmented into sequences of 10 to 240 seconds generating NS symbol arrays. HMM were trained using these arrays assuming 5 hidden states as we have performed previously for modeling problem solving learning trajectories (Soller & Stevens, 2007). Training was for 500 epochs and generally resulted in a convergence of 0.0001. Next the most likely state sequence through the performance was generated by the Viterbi algorithm.

The transition matrix derived from the HMM training is shown in Figure 5.

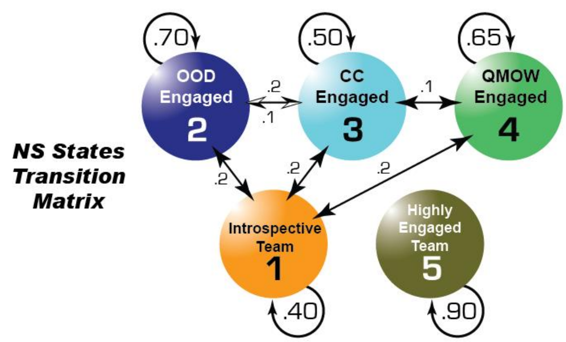

Figure 5. Transition Matrix for the SPAN Expert Team HMM.

State 1 represents and introspective / non-engaged State and States 2-4 represent where one of the team members shows above average of EEG-E while the others remain average or below average. State 5, which is mainly expressed during the debrief, represents a highly engaged team. The transition probabilities show that each state has a high probability of persisting which accounts for the autocorrelations observed earlier. It is also interesting that the transition probability between

States 1 & 5 is very low indicating that such large swings in the team's EEG-E are not common.

This data stream of NS 'States' was then plotted for each second of time and greatly accentuated the changing NS dynamics at the task / debrief junction indicating that large-scale shifts can be detected (Figure 6 *top*).

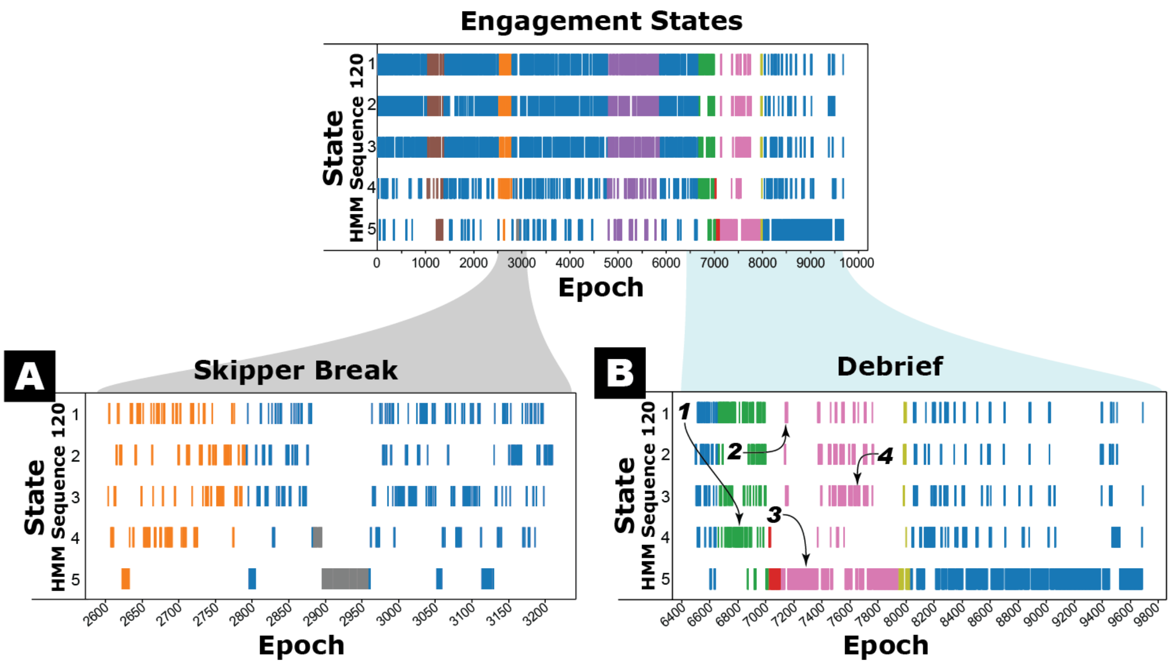

Figure 6. Expression of NS States Derived from the SPAN Expert Team. The NS data stream displayed in Figure 4 was segmented into 60 second sequences and these sequences were used to train a 5 state HMM model. *Above:* The top figure shows the NS State expression at each epoch. *A Left:* The gray section indicates the Skippers' discussion. *B Right:* The green color indicates a break after the Task where the team was joking with the research staff (1). Red highlights the onset of the debrief with team reports occurring during the pink section.

We next wished to determine whether such transitions could be detected during shorter time periods. These analyzes focused on non-routine periods of the simulation starting with the Skipper Break where the Skipper paused the simulation when the team was having difficulties approaching a hazardous section of water. (Figure 6 *left*).

Within a second the NS expression switched from the dominant States 1, 2 and 3 to State 4 and then State 5 where most members showed high levels of EEG-E, i.e. the team became externally engaged. After the short talk the team went back to the dominant expression of States 1-3 which represent a more introspective state of the team.

A second period is highlighted in Figure 6B for this in-depth analysis and this was the junction between the end of the simulation, through a short break, and into the debrief section (epochs 6400-9600).

Here the onset of the break is not as clearly demarcated by state transitions as it was with the Skipper Break. Instead as the team stands down they begin joking with the research staff (labeled as 1) and States 2 & 3 stop being expressed. A larger transition occurred when the debrief started and this was dominated by State 5, an externally aware mode. This section was followed by individual team member reports (labeled 3) which were generally State 5. For 30 seconds one team member criticized the team for excessive talking. During this time (labeled 2), the NS States switched to 1-3 and then returned to State 5 when this person finished speaking.

While these modeling approaches are informative, there are several challenges for their practical application to training activities. First, as new models have to be created for each task and team it would be difficult to make comparisons across models / teams as the ANN node and HMM state designations would likely change given the probabilistic assignment of vectors to specifically numbered nodes and states. For instance whereas NS State 5 represents an engaged team for the data shown in Figures 4 - 6 the training of new models could shift these designations to another state. Also, without standardized models it would be difficult to extend this analysis to real-time team modeling.

We have begun to address these challenges by generating generic ANN and HMM models from the combined performances of 15 different teams on a variety of tasks that included emotion recall, submarine piloting and navigation, brainstorming sessions, map navigation and substance abuse simulations. This resulted in 52,367 team training vectors (~ 14.5 hours of teamwork) which were used as the training set.

We then tested the EEG-E data streams from one expert team and a session of a less-experienced team on these new ANN and HMM models (Figure 7). As expected the expert team again showed a NS State shift, particularly State 4 at the simulation / boundary indicating that the generic models were sensitive to the changes in the task as were the original models. As described in Figure 7, State 4 on the generic models represents a highly engaged team..

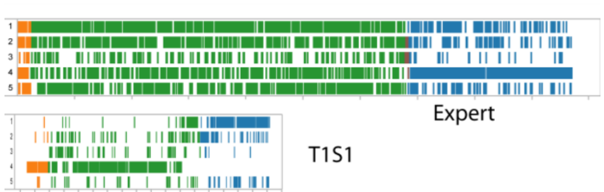

Figure 7. Comparison of an Expert and Novice Session on Generic NS Models. A generic ANN and HMM was trained as described in the text. The dynamics of the experienced team and a novice team were modeled. The colors represent the pre-simulation brief (orange), the simulation (green) and the debriefing sessions (blue). The figures are proportional to the session lengths. State 4 in the generic models represents an engaged team much like State 5 in Figure 6.

The performance of the less experienced team was qualitatively different from the expert team. Here the team seemed more highly engaged (i.e. Sate 4) State 4 during the simulation rather than during the debriefing session.

DISCUSSION

Neurophysiologic synchronies represent a low level data stream that can be collected and analyzed in real time and in realistic settings. Our goal for studying NS expression 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. The neurophysiologic measure we have used for this study is a measure of engagement in the sense that high levels represent a state of external awareness while low levels better represent an introspective state. The current studies were motivated by our earlier demonstration of significant autocorrelations of NS expression over longer time lags (20 sec) suggesting that there may be a temporal component to their expression.

Several examples presented illustrate that the NS States may be a rapid and sensitive indicator of some aspects of team cognition. Both the experienced and novice SPAN teams studied showed sharp changes in NS States at the Task / Debriefing boundary indicating that their expression was sensitive to large changes in the task. While both groups showed these sharp transitions, the nature of the transitions were opposite. For most of the simulation the experienced team expressed more introspective states, (i.e. they were more involved with the task than other events in the room) and switched to a more externally aware state during the debrief and discussion. The novice team however was more externally aware during the task and became more introspective during the debriefing session. Whether these reflect general characteristics of novice / experienced teams awaits further studies.

While the transitions at the Task / Debrief boundary represent long lasting changes, the changes in NS State expression during the Skipper Break and Debrief show that changes can occur quicker and may be able to highlight short term changes in team cognition.

An important question is the size of the segment chosen for creating the HMM models and in studies not shown here it appeared that segments less than 30 seconds may not have sufficient information for developing good models. Possibly the use of overlapping segments would improve the models at these shorter times, but the need for longer segments (60-120 seconds) suggest that long memory effects may exist in the NS data stream (Gorman, 2005).

The usefulness of this approach will depend on the cognitive indicator chosen. In parallel studies we have similarly modeled an EEG-derived measure of workload and the NS (and the derived HMM States) with the same teams show very different dynamics from those described here with EEG-E. An important challenge will be relating the dynamics of any new cognitive measure to the team task to best determine what aspects of team cognition are being measured. It will be important to determine if the characteristics of cognitive measures defined by the performance of individuals map to the performance of teams.

While EEG has traditionally been viewed as a tool for studying individual cognition in the milliseconds to seconds range, the current approaches extend this utility to teams and over periods of minutes.

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Team Neurodynamics

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