Developing Systems for the Rapid Modeling of Team Neurodynamics

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Abstract. Cognitive Neurophysiologic synchronies (NS) are a low level data stream derived from EEG measurements that can be collected and analyzed in near real time and in realistic settings. We are using NS to develop systems that can rapidly determine the functional status of a team with the goals of being able to assess the quality of a teams' performance / decisions, and to adaptively rearrange the team or task components to better optimize the team. EEG-derived measures of engagement from Submarine Piloting and Navigation team members were normalized and pattern classified by self-organizing artificial neural networks and hidden Markov models. The temporal expression of these patterns were mapped onto team events and related to the frequency of team members' speech. Standardized models were created using pooled data from multiple teams and were used to compare NS expression across teams, training sessions and levels of expertise. These models have also been incorporated into software systems that can provide for rapid (minutes) after training feedback to the team and provide a framework for future real-time monitoring.

Keywords: Collaboration, EEG, Neurophysiologic synchrony.

1 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 [1]. One of the challenges for studying team cognition in real-time is the development of unobtrusive and relevant measures of team performance that can be practically implemented in real-world environments [2].

We have explored using the simultaneous expression of EEG-derived cognitive measures by different members of a team as an alternative to verbal communication streams for constructing teamwork models. In this approach the values of a cognitive measure at a particular point in time are aggregated across the team members into a vector that is then clustered / classified by artificial neural network (ANN) technologies [3,4]. This results in a series of patterns termed Neurophysiologic Synchronies (NS) which are defined as the second-by-second quantitative co-expression of the same neurophysiologic / cognitive measures by different members

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of the team. The cognitive measures we have modeled include High Engagement and High Workload which have been derived from EEG data streams [5]. We have reasoned that if NS expression is a meaningful dynamic construct then their expression should:

1. Be sensitive to long and short-term task changes;
2. Relate to some established aspects of team cognition, yet reveal something new;
3. Be usable as well as useful;
4. Distinguish novice / expert performance; and,
5. Be sensitive to the effects of training.

Prior studies have documented the dynamics of NS expression in response to long and short term changes in the task [4]. In those studies the NS models were generated individually for each training session, i.e. they were autologous models. While those modeling approaches were useful research tools there were limitations for their practical application to training activities. First, as new models had to be created for each task and team it was difficult to compare across sessions / teams or levels of expertise as the pattern designations changed for each new model. Also, without standardized models it would be difficult to begin to extend this analysis to real-time team modeling. In this study we have developed models using pooled data from multiple teams to develop a generic set of models that remove these limitations.

2 Tasks and Methods

2.1 Submarine Piloting and Navigation (SPAN)

These studies were conducted with navigation training tasks that are integral components of the Submarine Officer Advanced Course at the US Navy Submarine School, Groton, CT. The task 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 the adaptive team training. Such events in the SPAN 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.

Each SPAN session contains three segments. It begins with a Briefing segment where the overall goals of the mission are presented along with information on position, contacts, weather, sea state, etc. Major participants during the Briefing are the Navigator, the Contact Coordinator along with the Captain, Instructor and / or Evaluator.

The Scenario is an evolving task and is more dynamic than the Brief containing easily identified processes of teamwork along with others which are less well defined. One of the more obvious processes is the regular updating of the ship's position termed 'Rounds'. Here, three navigation points are chosen, usually visually, and the bearing of each to the boat is rapidly measured and plotted on a chart.

Interleaved with these deterministic events are situations that arise due to new ship traffic, increased proximity to hazards, equipment malfunctions, reduced visibility or similar events. In contrast to the regular updating of the submarine's position, these events can be regarded as perturbations to the regular functioning of the team and indicate interesting points where the resilience of the team may be tested. Some events appear rapidly like a man overboard, while others evolve over 5-10 minutes and are based, in part, on previous decisions.

In the Debrief section there is open discussion of what worked, what other options were available, and long and short term lessons. The Debrief is the most structured part of the training with team members reporting in order, beginning with the Navigator. Within this reporting structure there is often overlapping or underlying nested structures where specific events within the Scenario are discussed.

2.2 EEG Metrics

The EEG data acquired from the wireless headset developed by Advanced Brain Monitoring, Inc. uses an integrated hardware and software solution for acquisition and real-time analysis of the EEG [5, 6]. It has demonstrated feasibility for acquiring high quality EEG in real-world environments including workplace, classroom and military operational settings. The 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.

To monitor "mental workload" (WL) and "engagement" (E) using the B-Alert model EEG metrics, values ranging from 0.1-1.0, are calculated for each 1-second epoch of EEG. 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.

2.3 Experimental Protocol

In prior studies analyzing the dynamics of problem solving with individuals we used the raw EEG-E and EEG-WL data streams [7]. Studying team processes using these

EEG measures requires a normalization step, which equates the absolute levels of EEG-E or EEG-WL of each team member with his/her own average levels. This allows the identification of whether an individual team member is experiencing above or below average levels of EEG-E or EEG-WL and whether the team as a whole is experiencing above or below average levels. As described previously (Stevens et al, 2010a) in this normalization process the EEG-E levels are partitioned into the upper 33%, the lower 33% and the middle 33%; these are assigned values of 3, -1, and 1 respectively, values chosen to enhance 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; these vectors are used to train unsupervised artificial neural networks to classify the state of the team at any point in time. In this process the second-by-second normalized values of team EEG-E for the entire episode are 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 series of 25 patterns that we call NS Patterns that show the relative levels of EEG-E for each team member on a second-by-second basis. A profile of a generic NS Pattern is shown in Figure 1 for a six person team. Here, team members 3 and 5 have above average levels of this neurophysiologic measure and the other team members are below average.

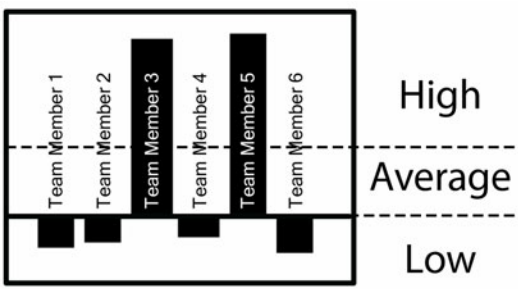

Fig. 1. Expression of a generic NS measure by members of a six-person team

NS Pattern expression can be thought of as output symbols from hidden states of a team, and if so the sequence may give additional information about those states. Hidden Markov modeling (HMM) would seem an appropriate approach for such modeling. The NS data stream for the combined team data was segmented into sequences of 10 to 240 seconds generating NS symbol arrays. HMMs were trained using these arrays assuming 5 hidden states as we have performed previously for modeling problem solving learning trajectories [8]. Training was for 500 epochs and resulted in a convergence of 0.0001. Next the most likely state sequence through the performance was generated by the Viterbi algorithm. The outputs of this subsequent modeling of NS Pattern streams by HMM are termed NS States.

3 Experimental Results

3.1 Detection of Long and Short-Term Task Changes by Autologous and Heterologous NS Models

For the generation of heterologous ANN and HMM models EEG-E data was pooled from 8 SPAN sessions from different experienced and novice navigation teams. This resulted in 31,450 team training vectors (~ 5.5 hours of teamwork) which were used as the training set. For all these sessions the position of each of the team members in the training vector was the same. This order was QMOW = Quartermaster on Watch in position 1, NAV = Navigator in position 2, OOD = Officer on Deck in position 3, ANAV = Assistant Navigator in position 4, CC = Contact Coordinator in position 5, and, RAD = Radar in position 6.

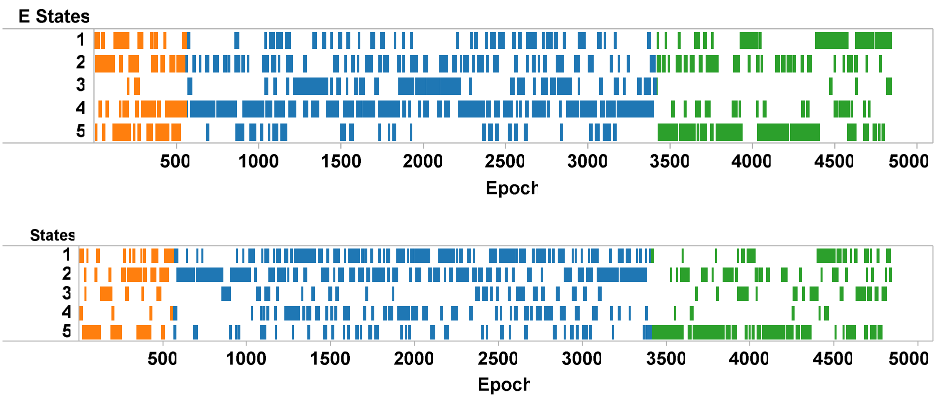

Fig. 2. Comparison of NS_E expression when modeled with autologous (top) or heterologous (bottom) ANN and HMM models. The data is shown for a Junior Officer navigation team at the early part of their SPAN training. The dark portion in the middle is the Scenario segment and the lighter portions to the left and right are the Brief and Debrief segments respectively.

Figure 2 compares the NS_E States following autologous and heterologous modeling of the same SPAN performance. Both models showed the NS_E state transitions at the Scenario / Debrief junction (epoch 3390) and at epoch 4400 of the Debrief. They also both showed a long period at the beginning of the scenario (epochs 590 – 1000) where a single state predominated and a period (3100 – 3385) at the end of the scenario where the same state predominated. These task-junction transitions have been observed in ten different SPAN sessions where autologous and heterologous modeling was conducted in parallel.

Another validation approach was to compare the Shannon entropy of the NS Pattern data streams obtained from each model. This metric is derived from information science and measures the level of uncertainty in a data stream [9]. The top of Figure 3 is a scatter plot of the levels of Shannon entropy for the NS_E values obtained from autologous and heterologous NS_E models. The histograms below the scatter plot highlight the peaks and valleys in entropy and show a strong concordance across both NS_E data streams. Combined, these data indicate that the heterologous NS_E models provide a close approximation of those obtained with autologous modeling.

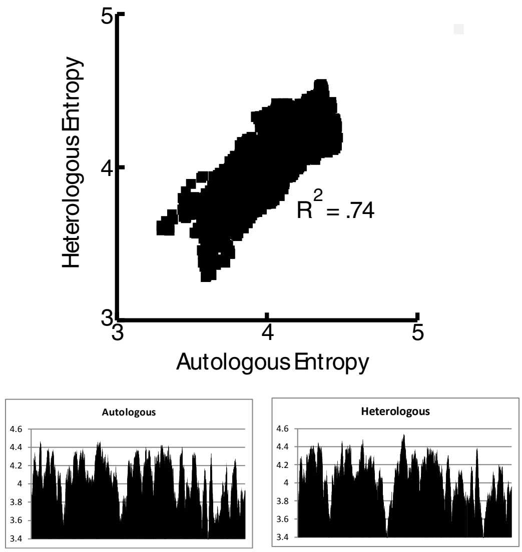

Fig. 3. Comparison of the Shannon entropy of NS_E Pattern expression from autologous (lower left) or heterologous (lower right) models. The top figure shows a scatterplot of the entropy from the two data streams.

3.2 Mapping NS_E Patterns to NS_E States for the Heterologous Models

In addition to documenting changes in NS expression in response to the changing task it is important to relate these changes to the cognitive measure itself. One result of the hidden Markov modeling is an emission matrix that maps different NS Patterns to NS States. This mapping provides a cognitive context across team members for the state changes associated with task events. These relationships are summarized in Figure 4 for NS_E Patterns and States. Each of the five (numbered 1-5) NS States is represented by a gray box containing the numbered NS Patterns most often associated with each State.

As expected from the complexity of the modeling, the associations of different NS Patterns with each NS State were not simple. In general however, NS E States 3 and 4 represent where many of the members of the team showed low EEG-E levels. The transition probabilities between these two states are very low (<0.03) suggesting that they are not subsets or close dynamic neighbors of each other. NS_E State 2 was the most frequently expressed NS E State and we refer to this as the normal operating mode (NOM) of the teams, as it is mainly expressed during the Scenario and less so during the Debrief. It is also a state where many of the team members expressed high

EEG-E. There are strong reciprocal transition probabilities between NS_E State 2 and NS_E State 1 (another state of high EEG-E expression), and lower probabilities with NS_E State 5.

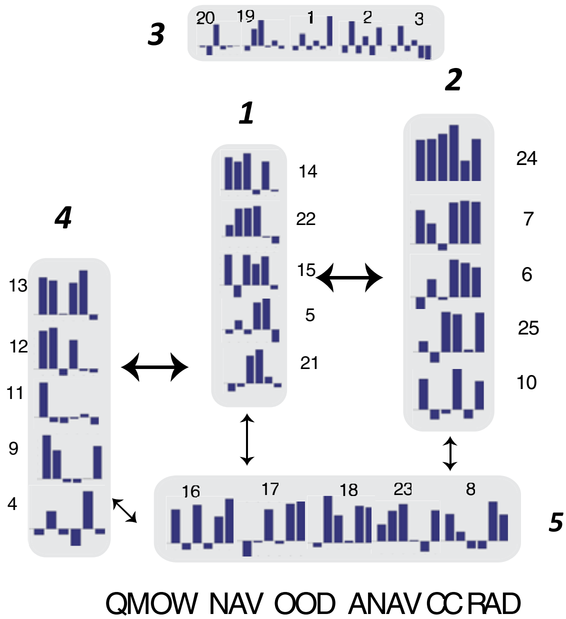

Fig. 4. Mapping of NS_E ANN patterns to HMM states. The team members associated with each bar in the histograms is shown below the figure. QMOW = Quartermaster on Watch, NAV = Navigator, OOD = Officer on Deck, ANAV = Assistant Navigator, CC = Contact Coordinator, RAD = Radar.

3.3 NS_E Expression across Teams and SPAN Sessions

One question that can be approached with the heterologous NS_E models is how consistently different NS_E States are used across teams and / or training sessions. Figure 5 shows the frequency distribution of NS_E for an expert (E2) and two Junior Officer teams (T4 and T5) that each performed two simulations and additional Junior Officer team that performed a single session (T1). The NS_E frequencies are separated into the Scenario, Debrief and Briefing segments of the simulation based on prior studies (such as Figure 2) that have shown there are often dynamic NS_E shifts at these segment junctions. For most teams the dominant NS_E States during the Scenario segment were 1 and 2. Referring to Figure 4, these states represent where most of the team is highly engaged. These appear to represent the normal operating mode for SPAN teams as their expression is diminished during the Debriefing segment and to a lesser extent in the Briefing segment. While there were slight differences in the NS_E State frequencies for E2, T4 and T5 the performance of team T1was different with NS_E State 4 dominating. Referring to Figure 4, this state is one where many of the team members' had low EEG-E.

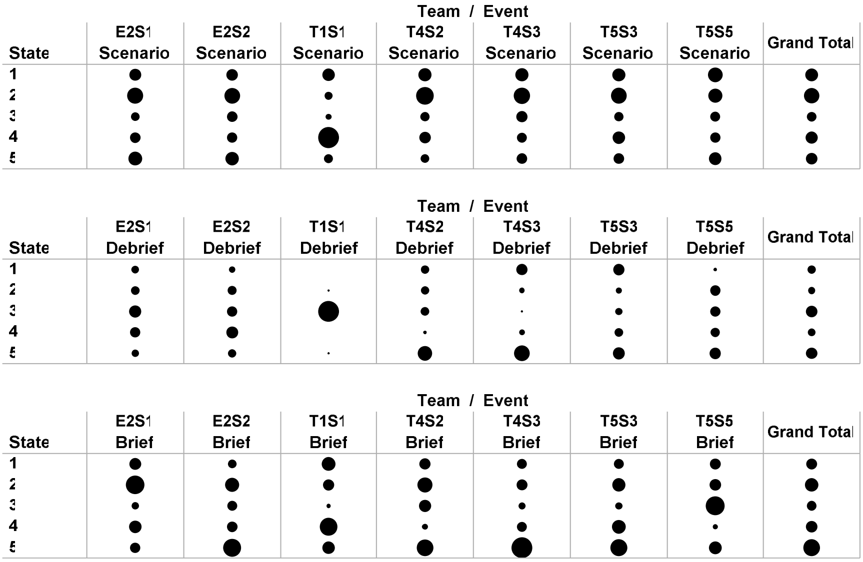

Fig. 5. Team NS_E state distributions across teams and sessions

The differences across teams were larger when comparing across the Debrief and Brief segments. Here there was proportionally higher expression of NS_E States 3 & 4 (teams with low EEG-E) for the expert team and NS_E State 5 for the Junior Officer teams.

3.4 Association of NS_E Expression with Speech

When team members interact the resulting communication stream contains information about knowledge, uncertainty, awareness of the situation, stress and other cognitive states. Their speech provides a detailed and dynamic representation of team cognition and is considered one of the gold standards for studying teamwork.

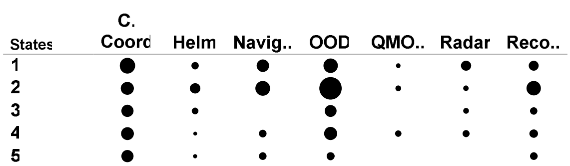

Fig. 6. NS_E expression while team members were speaking

Initial associations between team member's speech and NS_E expression is shown in Figure 6. For these studies we coded the speech of three teams on a second – by – second basis and pooled the data for cross tabulation analysis. The speech condition during the scenario resulted in higher than expected levels of NS_E State 3 while the non-speech condition had higher than expected levels of NS_E State 4. It is not clear if this is significant regarding teamwork as both are States where the overall team

EEG-E is low. The speech condition was eight times more common than the non-speech condition during the Debriefing segment and there were significantly fewer epochs where NS_E State 1 was expressed (data not shown).

Within the Scenario NS_E State expression was variable with NS_E States 1 & 2 preferentially being expressed when the Navigator (Navig), Officer of Deck (OOD) or Recorder (Rec) were speaking; while all five states were equally expressed when the Contact Coordinator (CC) was speaking.

4 Discussion

In our previous studies [3, 4, 10] NS expressions were derived from autologous datasets as we felt that such models may have the greatest sensitivity to small and large changes during the task. Such models were also necessary early in the project as there were few performances and datasets where there were team members in the same navigation positions. With more SPAN performances from Junior Officer and experienced teams we assembled a dataset of nearly 6 hrs. of teamwork and created standardized NS models.

Validation of the heterologous models was approached two ways; one using NS Patterns from ANN clustering of EEG-Engagement levels and one using NS States which provides a temporal component to the NS Patterns [10]. One of the most reproducible features of SPAN performances is the change in NS_E States at the junction between the Scenario and Debriefing. The heterologous and autologous models reproducibly detected these temporal features at this junction indicating an equivalent sensitivity of large task changes. A different form of validation drew on the concept of entropy from information theory which measures the degree of uncertainty in a data stream of symbols. In the present study we determined the entropy of both the autologous and heterologous NS_E data stream at 1 second intervals over a sliding window of the prior 90 seconds. These entropy profiles highlighted periods of high and low entropy modeled by both approaches. The strong concordance between the two models provides an additional validation of the sensitivity and specificity of the heterologous NS_E models.

It is currently difficult to say which model is the ‘right’ model. Heterologous datasets due to their larger size may not be sensitive to some combinations of EEG-E across team members due to their unique expression by a team. Similarly, autologous models may not have the repertoire of EEG-E combinations that would allow meaningful comparisons across teams. From a practical perspective both models seemed adequate for detecting shifts in NS_E expression in association with changes in the task and perturbations to the environment.

Prior to developing and validating the heterologous NS models only the first of the five usefulness criteria outlined in the introduction could be approached. As shown in this study, with the standardized models we can begin to compare NS expression across teams, training sessions and levels of expertise. Most recently these models have been incorporated into software systems that supply rapid (minutes) after training feedback to teams and provide a framework for future real-time adaptive monitoring and training.

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