Developing Systems for the Rapid Modeling of Team Neurodynamics

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ABSTRACT

Cognitive Neurophysiologic synchronies (NS) are the quantitative co-expression of a particular neurophysiologic measure across members of a team. Our goal is to use NS expression to develop systems that can rapidly determine the functional status of a team to be better able to assess the quality of a teams' performance / decisions, and to adaptively rearrange the team or task components to optimize the team. One of the challenges in this effort is the development of standardized models of NS expression that can be used with incoming EEG data streams to avoid the need for single-trial modeling. In this study we show how such models can be built for teams of three to six members and validate the approach for neurophysiologic measures of engagement (EEG-E) and workload (EEG-WL). These models were used to compare NS expression across teams, training sessions and levels of expertise. They 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.

ABOUT THE AUTHORS

RON STEVENS, PH.D. Professor and a member of the Brain Research Institute at the UCLA School of Medicine. He directs the internet-based IMMEX problem solving project which has engaged over 150,000 students and teachers in computational education and professional development activities that span elementary school through medical school. Recently Dr. Stevens received the 'Foundations of Augmented Cognition' award from the Augmented Cognition Society. His interests include using machine learning tools and electroencephalography (EEG) to model the acquisition of scientific problem solving skills.

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ADRIENNE BEHNEMAN is a Project Manager at Advanced Brain Monitoring. Since 2007, she has played a key leadership role in the Accelerated Learning, RAPID and ANITA projects. She is interested in the development of neuroscience-based tools to enhance training and education. Her current focus is on researching the psychophysiology of expertise in domains including marksmanship, deadly force decision making and team function, as part of the Accelerated Learning project.

PETER WANG is the programming director for the IMMEX™ Project. During the past twenty years he has jointly developed hundreds of online scientific problem solving and data mining applications.

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INTRODUCTION

One of the challenges for developing adaptive training approaches for teams is the creation of unobtrusive and relevant measures of team performance that can be practically implemented and rapidly modeled in real-world environments (Salas et al, 2008).

We have been studying whether the simultaneous expression of EEG-derived cognitive measures by different members of a team could be used to complement verbal communication streams for constructing such teamwork models. In this approach the values of a cognitive measure at any point in time are aggregated across the team members into a vector that is then clustered / classified by artificial neural network (ANN) technologies (Stevens et al, 2009; Stevens et al, 2010a). The result is a series of symbolic patterns termed Neurophysiologic Synchronies (NS) defined as the second-by-second quantitative co-expression of the same neurophysiologic measure by different members of the team. The cognitive measures we have modeled include High Engagement and High Workload which have been derived from EEG data streams (Berka et al, 2007). If NS are meaningful constructs then their expression should:

1. Be able to be collected and analyzed in real-world situations;
2. Be sensitive to long and short-term task changes;
3. Relate to some established aspects of team cognition, yet reveal something new;
4. Be extensible to future teams;
5. Distinguish novice / expert performance; and,
6. Be sensitive to the effects of training.

Our initial studies used a single-trial approach for developing NS models, i.e. the data from a single performance was used for deriving the ANN models for that performance. These studies were informative and generated validation data for criteria 1-3 described above but there were challenges in extending these models to address criteria 4-6. As new models were created for each task, comparisons across teams or levels of experience were difficult as the ANN designations changed due to the probabilistic assignment of vectors to specific nodes. Also, without standardized models it was difficult to begin extending this analysis to real-time team modeling.

One way of developing standardized models would be to combine the performances from multiple teams with differing experience creating standardized (or generic) models. It is not intuitive whether this approach would be successful. Standardized datasets due to their larger size may not be sensitive to some combinations of NS across members of some teams due to their unique expression by that team. Conversely, separate single-trial models may not have the repertoire of EEG-E combinations to allow meaningful comparisons across teams. There is also a validation challenge when developing standardized models: what will be the comparison standard?

In this study we hypothesized that models derived from datasets pooled from multiple team performances of a task might share sufficient similarity to allow the accurate modeling of subsequent performances. To help validate the models and enable quantitative comparisons across teams we have measured the temporal dynamics of the entropy or ‘amount of mix’ in the resulting symbolic data streams. The assumption was that there would be statistical regularities in the NS data stream that are representative of many requirements of the task. This would be similar to the redundancy in English where as much as half the letters or words are controlled by the statistical structure of the language (Shannon & Weaver, 1964).

TASKS AND METHODS

Tasks

The studies described were conducted with navigation tasks that are integral training components of the Submarine Officer Advanced Course (SOAC) at the US Navy Submarine School, Groton, CT. Submarine Piloting and Navigation (SPAN) simulations are high fidelity tasks that contain dynamically programmed situation events 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. 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. Twenty-one SPAN sessions were conducted where EEG was collected from three to six persons. The data reported here was derived from twelve of those sessions selected as: 1) persons in the same six crew positions were being monitored by EEG, 2) the same individuals repeated in the same positions across 2-5 training sessions over multiple days. The six members of the teams that were fitted with the EEG headsets were the Quartermaster on Watch (QMOW), Navigator (NAV), Officer on Deck (OOD), Assistant Navigator (ANAV), Contact Coordinator (CC), and Radar (RAD).

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 with model-selected PSD variables in each of the 1-hz bins from 1 - 40 Hz, 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) (Berka et al, 2004, 2007). The studies in this report have used the High EEG-E and EEG-WL metrics. The two metrics have different functional properties in response to different tasks and the two data streams are poorly correlated with one another; when averaged over six members of one SPAN team the R was -0.19 ± 0.24 with an R^2 of 0.09 ± 0.05 (Mean & SD). The neuropsychological tasks used to build the algorithm, and subsequently used to individualize the algorithm's centroids were presented using proprietary acquisition software. The algorithm was trained using EEG data collected during the Osler maintenance of wakefulness task (OSLER) (Krieger et al., 2004), eyes closed passive vigilance (EC), eyes open passive vigilance (EO), and 3-choice active vigilance (3CVT) tasks to define the classes of sleep onset (SO), distraction/relaxed wakefulness (DIS), low engagement (LE), and high engagement (HE).

Simple baseline tasks were 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 (Berka et al, 2004, 2007; Stevens et al, 2007).

Neurophysiologic Synchronies

The neurophysiologic synchronies (NS) that we are studying are the second-by-second quantitative co-expression of the same neurophysiologic / cognitive measures by members of the team. We have developed a four-step modeling approach with the outputs of each step providing a different perspective of team neurodynamics. The four steps outlined in Figure 1 are: A) Data Normalization; B) Unsupervised Artificial Neural Network Clustering; C) Hidden Markov Modeling (HMM), and; D) NS Data Stream Entropy.

For the generation of generic ANN and HMM models EEG-E data was pooled from 8 SPAN sessions (31,450 team training vectors or ~ 8 hours of teamwork) which were used as the training set. The position of each of the team members in the training vector was the same as described above. The team highlighted in Figures 3-5 was not part of the training set.

The first step (A), data normalization, equated the absolute levels of EEG-E or EEG-WL of each team member with his/her own average levels over the period of the task. This identified whether a team member was experiencing above or below average levels of EEG-E or EEG-WL; and, whether the team as a whole was experiencing above or below average levels.

As described previously (Stevens et al, 2010a) 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 chosen to enhance visualizations. The next step (B) combined 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 were used to train ANN to classify the state of the team at any point in time (Stevens al, 2010a).

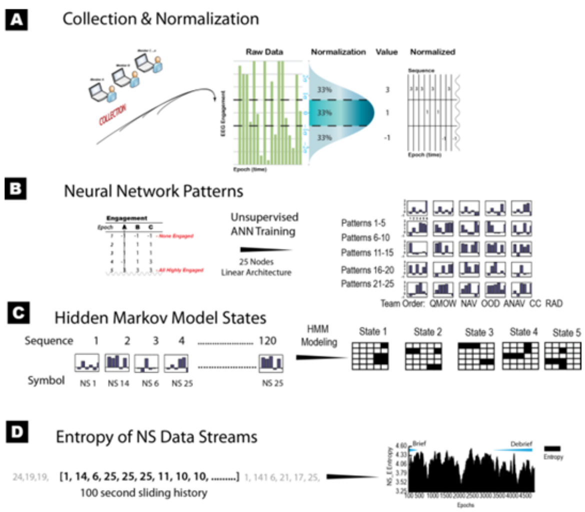

Figure 1. Layered Analytic Model for Detecting and Describing Neurophysiologic Synchronies.

In this process the second-by-second normalized values of team EEG-E for the entire episode were repeatedly (50-2000 times) presented to a 1 x 25 node unsupervised ANN. The result was a series of 25 patterns that we call neurophysiologic synchrony patterns that show the relative levels of EEG-E for each team member on a second-by-second basis (Figure 2).

In Step C the sequences of NS Patterns were viewed as output symbols from hidden states of a team and HMM were developed to characterize these states. The NS data stream for the combined team data was segmented into sequences of 120 seconds and HMMs were trained with these sequences assuming 5 hidden states as previously performed when modeling problem solving learning trajectories (Soller & Stevens, 2007). 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 the modeling of NS Pattern streams by HMM are termed NS States.

While ANN Pattern and HMM State changes help identify transition points and preferred patterns, a quantitative measure of the teams' dynamics would be useful for comparing across teams or with other teamwork metrics (Step D). As the NS Patterns are symbolic, one approach is to calculate the Shannon entropy of the NS data stream (Shannon, 1951).

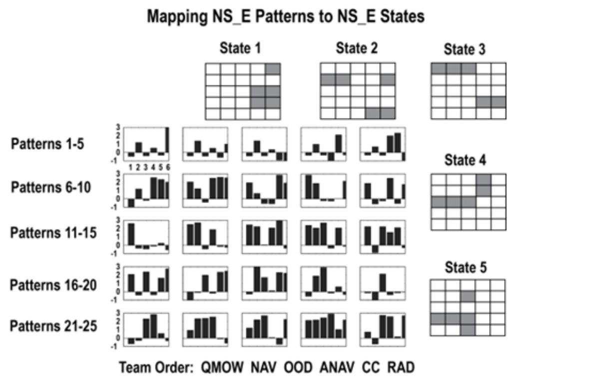

Figure 2. Team NS_E Profiles after ANN Training. The center histograms show the 25 NS Patterns obtained after ANN training. The order of team members associated with each histogram bar is shown below. The surrounding matrices map the NS_E Patterns to the NS_E States from HMM modeling.

The idea of entropy is derived from information science and is a measure of the level of uncertainty or "amount of mix" in a symbol stream. Calculated entropy is expressed in terms of bits and the maximum entropy that we could expect from the 25 NS Patterns if they were randomly distributed would be log2 (25) or 4.64. For comparison, and entropy value of 3.6 would result were only 12 of the NS Patterns randomly expressed.

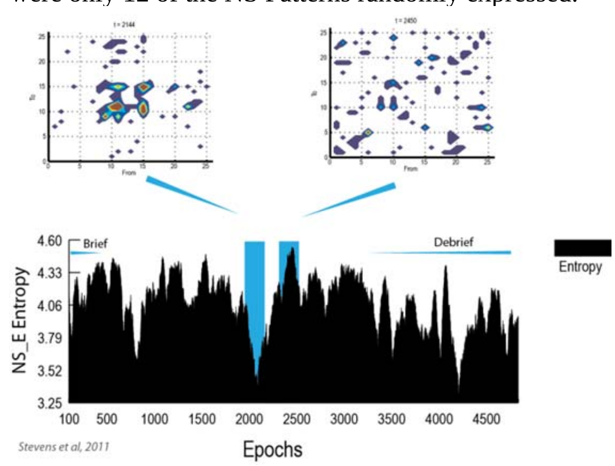

Figure 3. NS_E Entropy Profile for a SPAN Team. This figure shows the Shannon entropy for NS_E at each epoch over a sliding window of the prior 100 seconds. Above the entropy profile are the transition matrices for the two highlighted 120 second periods. These transition matrices show the NS_E Patterns at times t and t+1.

To develop an entropy profile over a SPAN session the NS Shannon entropy was calculated at each epoch using a sliding window of the values from the prior 100 seconds. The idea was that as teams entered and left periods of organization the entropy would fluctuate as fewer or more of the 25 NS_E patterns were expressed. This relationship is shown in Figure 3.

RESULTS

Figure 4 compares the NS_E States following single-trial and generic 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 single-trial and generic modeling was conducted in parallel.

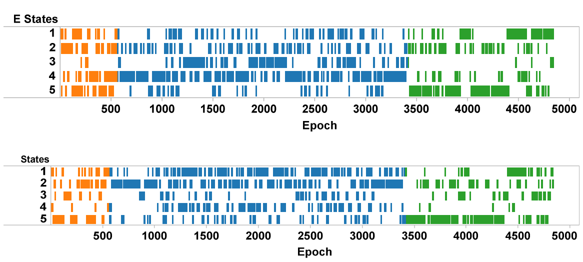

Figure 4. Comparison of NS_E State Expressions when Modeled with Single Trial (top) or Generic (bottom) ANN and HMM Models. The dark portion in the middle is the Scenario segment and the lighter portions to the left and right are the Brief and Debrief segments.

Another validation approach compared the Shannon entropy of the NS Pattern data streams from each model. This metric is derived from information science and measures the degree of uncertainty in a data stream (Shannon, 1951). A scatter plot of the NS_E Shannon entropies from the single-trial and generic NS_E models was highly correlated (R = 0.86, R^2 = 0.74). The line graph below shows the co-fluctuations of the two entropy streams. The overall NS_E entropies of the single-trial and generic were also similar (Mean ± SD = 4.073 ± 0.23 and 4.071 ± 0.22). Combined, these data show a strong concordance between the generic and single-trial NS_E models.

NS_E Expression across Teams and SPAN Sessions

One question that can be approached with the generic NS_E models is: How, consistently are different NS_E States used across teams and / or training sessions. Figure 6 shows the frequency distribution of NS_E for an expert (E2) and two Junior Officer teams (T4 and T5). Each performed two simulations; an additional Junior Officer team performed a single session (T1). The NS_E frequencies were separated into the Scenario, Debrief and Briefing segments based on prior studies (such as Figure 2) that have shown there are often dynamic NS_E shifts at these segment junctions.

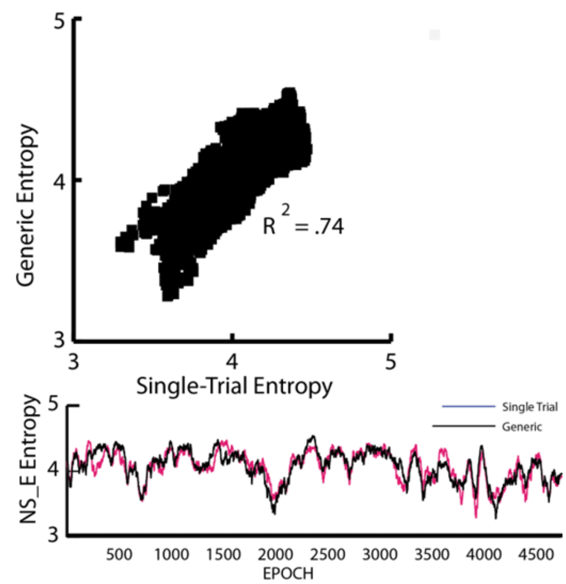

Figure 5. Comparison of the Shannon Entropy of NS_E Pattern Expression from Single Trial or Generic Models. The top figure shows a scatterplot of the entropy from the two data streams; below is a line chart comparing the second-by-second fluctuations.

For most teams the dominant NS_E States during the Scenario segment were 1 and 2. Referring to Figure 2, these states represent where most of the team was highly engaged. These appeared to represent the normal operating mode for SPAN teams as their expression was 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 T1 was different with NS_E State 4 dominating. Referring to Figure 2, this state was one where many of the team members' had low EEG-E. 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.

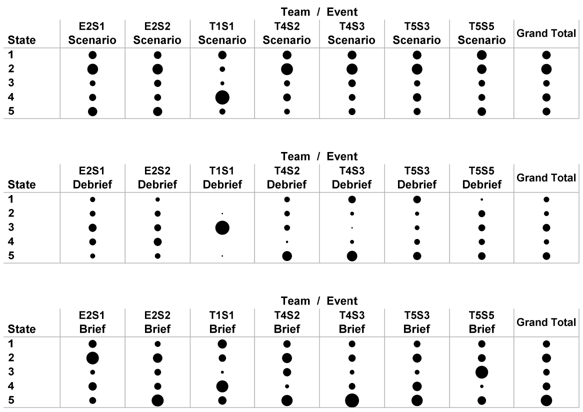

Figure 6. Team NS_E State Distributions Across Teams and Sessions.

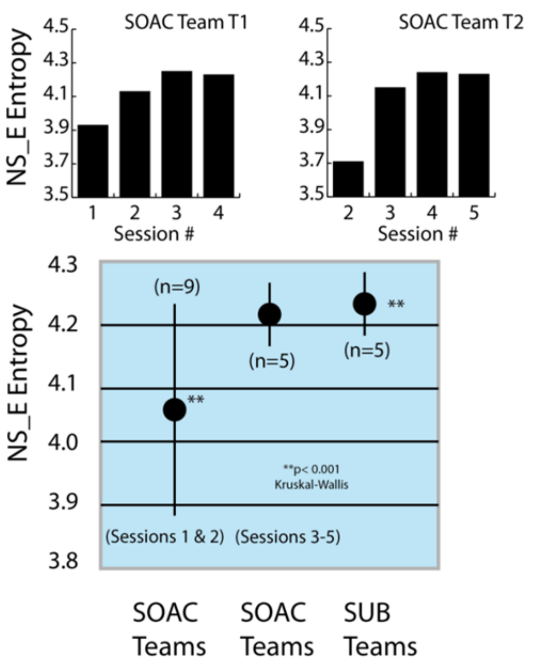

Figure 7. NS_E Entropy Levels for SOAC and SUB Teams.

While the above comparisons showed differences across sessions and teams the lack of resolution made it difficult to make quantitative assessments across teams or comparisons between teams with different levels of experience, like SOAC vs. experienced submarine (SUB) teams. In other studies an examination of the predominant NS_E Patterns showed that they were different for SOAC and SUB teams (Stevens & Gorman, 2011) and that SUB teams used more of the available NS Patterns than did SOAC teams. This suggested that direct comparisons of the NS_E entropy streams may be a useful indicator of team experience. The NS_E Patterns from 14 SOAC and 5 SUB team sessions were generated by testing the EEG-E data streams on the generic networks. Next, the NS_E entropies were calculated as described in the Methods. SUB teams had the highest levels of NS_E entropy while the lowest entropies were from the first two sessions by SOAC teams. The histograms in the top figure show the progressive increase in NS_E entropy as two of the teams gained experience.

The final studies sought to determine how well generic networks would perform in other teamwork situations. NS have been used to study three-person teamwork including scientific problem solving by high school students (Stevens et al, 2009) as well as NAVAIR Anti-Submarine Warfare Teams (ASWT).

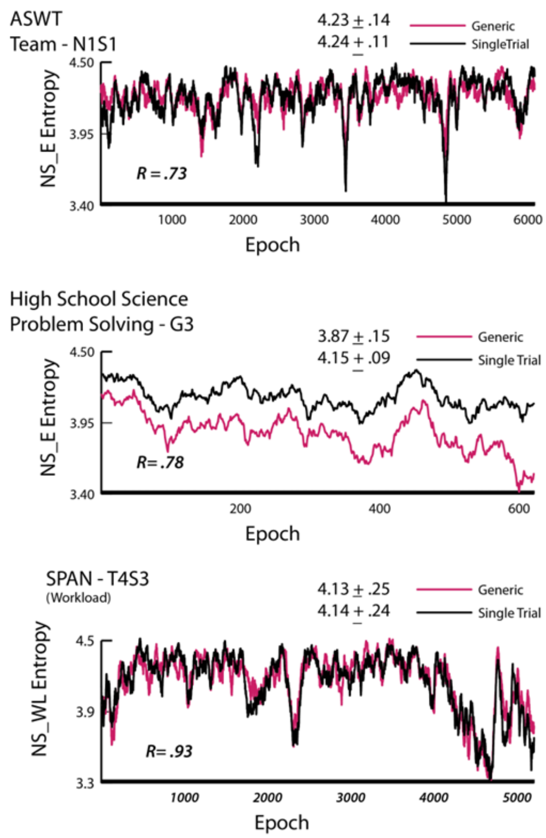

Figure 8. Comparison of Single Trial and Generic ANN NS Entropies. Comparisons of NS_E entropies are made for an ASWT team (top), and a high school scientific problem solving team (middle). The lower figure shows the NS_WL entropy comparisons for a SPAN team.

Three-person NS_E generic ANN and HMM models were prepared from 62,021 epochs of EEG-E data; the data was from six teams of high school students that performed substance abuse science simulations, emotion recall experiments, three-member SPAN teams and brainstorming sessions (Stevens et al, 2010b). First, EEG-E vectors were prepared from an experienced ASWT and were classified by either these generic models, or single-trial models. Similar to the SPAN results shown in Figure 5, the overall NS_E entropies and variances were similar, the correlation between the two data streams was high, and when the two data streams were co-plotted they showed similar temporal dynamics (Figure 8). The high school problem solving team also showed similar dynamics for NS_E when tested on the generic and single-trial models although the overall NS_E entropy level was lower when tested on the generic models. A third generic model was created from the EEG-WL vectors of multiple SPAN teams and the dynamics of the neurophysiologic synchronies for EEG-WL (NS_WL) were compared with those generated from homologous EEG-WL models from the T4S3 SPAN team. The overall correlation coefficient was the highest of the comparisons made in this study. The entropy dynamics of the two data streams co-fluctuated, very similarly.

A final study compared continuous wavelet transformations (CWT) from the generic and single-trial modeling of NS_E entropy streams from the SOAC team shown in Figures 3 and 5 (Figure 9).

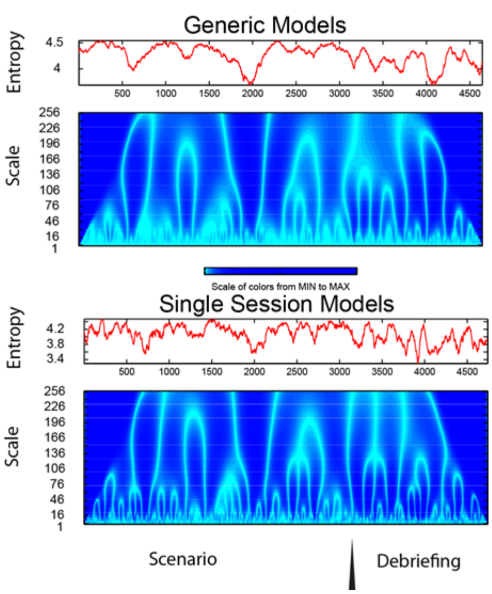

Figure 9. CWT Spectrograms of NS_E Entropy Obtained From Generic or Single-Trial Modeling. The X axis shows the performance epochs with the task segments indicated. The Y axis shows the scale of the wavelet transform. Above each spectrogram are the NS_E entropy profiles.

CWT can be used to produce spectrograms which show the frequency content of a signal as a function of time (Hubbard, 1998). A visual comparison of the two spectrograms showed large scale similarities during the Scenario (for instance near epochs 550, 1250, 2000), 2500). Structural similarities were also seen at smaller scales (scales <46) but were less defined in the Generic model spectrogram. The spectrograms were more disparate during the Debriefing segment. These results suggest that the Generic models are most robust for modeling the Scenario segments of SPAN, but may be less accurate when modeling the Debriefing.

DISCUSSION

Prior to developing and validating the generic NS models only the first three usefulness criteria outlined in the introduction could be approached: We had used NS expression to study teamwork in multiple settings with different size teams (Stevens et al, 2010b); we had demonstrated changing dynamics of their expression over long and short time periods (Stevens et al, 2010a); and, we had shown that these dynamics related to some aspects of speech (Stevens et al, 2009). As shown in this study, with the standardized models we can now begin to compare NS expression across teams, training sessions and levels of expertise.

Validation of the generic 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 (Stevens et al, 2010b). 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 generic and single-trial 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. These entropy profiles highlighted periods of high and low entropy modeled by both approaches. From the NS_E Pattern transition matrices, the periods of low entropy were those where the team was more cognitively organized. The significance of these re-organizations is not clear, but may relate to periods of unusual tension or stress for a team (Stevens et al, submitted). However, the strong concordance in the entropy profiles between the single-trial and generic models provided an additional validation of the sensitivity and specificity of the generic NS_E models.

One of the most interesting and potentially useful findings from the generic models is the differences in NS_E entropy between SOAC teams beginning their training, and experienced SUB teams. These findings may provide an objective, quantitative measure of team proficiency which can be tracked over training or across different training protocols.

The fluctuations in entropy we have observed during the model validations may also provide a rapid readout for how teams respond to different events during a simulation task. To further such studies, we are incorporating these models into software systems that will supply rapid (minutes) after training feedback to teams and provide a framework for future real-time adaptive monitoring and training.

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