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Tracing Neurodynamic Information Flows during Teamwork

Ronald Stevens¹ *The Learning Chameleon, Inc., IMMEX/UCLA and*
Trysha Galloway *The Learning Chameleon, Inc.*

Abstract: *The goal of this study was to evaluate different neurodynamic representations for their ability to describe the interactions of team members with each other and with the changing task. Electroencephalography (EEG) data streams were collected from six crew members of a submarine piloting and navigation team while they performed a required training simulation. A representation of neurodynamic organization was first generated by creating symbols every second that showed the EEG power levels of each crew member. The second-by-second expression of these symbols continuously varied with the changing task, and the magnitude, duration and frequency of these variations could be quantitated using a moving window of Shannon entropy over the symbol stream. These changes in neurodynamic organization (i.e. entropy) were seen in the alpha, beta and gamma EEG frequency bands. A representation of team members' synchrony was created by measuring the mutual information in the EEG power levels for fourteen dyad combinations. Mutual information was present in the gamma EEG band, and elevated levels were distributed throughout the task. These discrete periods of synchrony were poorly correlated at zero lag with either changes in the team's neurodynamic organization, or speech patterns.*

Key Words: team neurodynamics, synchrony, EEG, entropy, mutual information, teamwork

Abbreviations Used: Electroencephalography (EEG), Submarine Piloting and Navigation (SPAN), Neurodynamic Symbols (NS), Mutual Information (MI), Individual Entropy (IE), Navigator (NV), Assistant Navigator (AN), Quartermaster (QM), Radar Operator (RD), Contact Manager (CM), Officer on Deck (OD), Recorder (REC).

INTRODUCTION

Oscillation-based neurodynamic connectivity is a property that scales from the millisecond levels of neuronal spike trains during stimulus encoding (Schneidman, Bialek & Berry, 2003) through the larger scales of sensory-based computations and across-brain network interactions, leading to synchronized

¹ Correspondence address: Ron Stevens, The Learning Chameleon, Inc., IMMEX/UCLA, 5601 W. Slauson Ave. #184 Culver City, CA 90230. E mail: Immexr@gmail.com

observable actions and behaviors (Onkin, Karunasekara, Kayser, & Panzeri, 2015; Sporn, 2012). A challenge for teamwork research is to develop neurodynamic models of teams over these time scales that are useful for understanding and predicting team behavior, yet are also sufficiently detailed mechanistically to support robust theory building and team training interventions.

One approach would be to conceptualize the neurodynamic responses of a team as hierarchies of fast and slow variables (Flack, 2012). Slow variables as the name suggests, arise from mechanisms that naturally integrate over faster microscopic dynamics, and represent some average of the noisier activities below. As neurophysiologic hierarchies are transitioned upward from faster scales to slower scales what is lost in the mechanistic details of neuronal spike generation and propagation is gained by tighter relationships with more easily-recognized, observer-defined variables such as team coherence, flexibility or resilience (Stevens, Galloway, Lamb, Steed, & Lamb, 2015).

Electroencephalography is often the tool of choice for studying team neurodynamics in natural settings. EEG is the recording of electrical activity of the brain at different regions along the scalp and the rhythmic patterns in the electrical oscillations from different brain regions contain signals representing complex facets of brain activity (Buzaki, 2006). EEG has traditionally been viewed as a tool for studying individual cognition in the milliseconds to seconds range. There is no *a priori* theoretical reason, however for not extending this to include teams operating over minutes or hours in military, educational and healthcare environments.

At the millisecond to seconds' range of neurophysiologic scales, markers of social coordination occur during common human-human interactions (Tognoli & Kelso, 2015). Using high spectral EEG, multiple neuromarkers of social coordination have been described in the 9-12 Hz frequency range which have maximal activity at different EEG scalp locations. These markers include the 10.9 Hz phi complex which is modulated by intentional coordination (Tognoli, Lagarde, De Guzman & Kelso, 2007), and the medial left and right mu EEG components in the alpha wave (9 - 11 Hz), and beta wave (15 - 20 Hz) frequencies which may represent activities associated with the human mirror neuron system (Oberman, Pineda & Ramachandran, 2007; Pineda, 2008).

Less is known about the slower variables of team neurodynamics, i.e. in the minutes to hours range. Neurodynamic organization and synchronization is an information-based dynamical construct that describes the team-task interactions at the seconds, minutes and hours scales in the context of the underlying neurophysiology (Stevens, Gorman, Amazeen, Likens & Galloway, 2013). These information and organization constructs are derived from team-wide symbolic representations of EEG amplitude dynamics as teams perform tasks (Stevens & Galloway, 2014, 2015) and are intended to bridge the gap between the fast neurophysiologic and slow observational variables of teamwork.

Describing the role of different neurodynamic representations with regard to team function, performance and synchrony depends, in part, on relating neurodynamic organizations with ideas on the form(s) of synchrony being

observed. Burgess (2013) recently distinguished four different forms of across-system synchronizations that have relevance for brain hyperscanning studies. These include: (a) coincidental synchrony when non-coupled events occur simultaneously, an example being checkout lines in a store; (b) external entrainment, an example being musicians playing in time to a metronome; (c) driven synchrony where the behavior of one individual drives the behavior of others, i.e. an audience listening to a lecture; and, (d) reciprocal synchronization as seen in the repetitive speaker-listener couplings described by Baess et al., (2012), and Dumas, Nadal, Soussignan, Martinerie and Garnero (2010).

In this paper we consider team neurodynamic interactions in the context of four different hierarchies and scales. First is the temporal scale; our modeling scheme encompasses times from momentary EEG oscillations through changes associated with large-scale task segments lasting an hour or more. The second is the scale of EEG frequencies. Many moment to moment acts of human cognition occur in the 1-40 Hz range where activities in different frequency bands are associated with different processing pathways such as sensory processing or neuromodulation (Buzaki, 2006). Outside the previously mentioned alpha and beta wave-associated social coordination markers, little is known of how the immediate task context is represented by a team across these frequencies. A third context is the region of the brain being monitored, with different EEG sensor locations being differentially receptive to activities associated with multiple functional networks. A final context is the interaction hierarchy of the team with the evolving task requirements driving the team collaboration activities.

While our focus is on understanding team performance under single trial conditions, our studies target moments when teams need to adapt. Adaptation is a common and multi-faceted teaming construct which can be thought of as a modification of team behavior in response to changes in the operating environment. There can be planned adaptations which represent natural, large scale changes in the task cycle like the briefing and debriefing task segments. Adaptation at smaller scales would include the continuous variation in the amount of automaticity versus executive control, or trading speed for accuracy as teams' shape behaviors to the unfolding task demands (Guastello et al., 2013).

The goal of this study is to evaluate different neurodynamic representations for their ability to describe the interactions of the team members with each other and with the changing task requirements. These representations were calculated each second for each of the 1-40 Hz EEG frequency bins and included: (a) the EEG power averaged across the six team members; (b) the mutual information (MI) of team dyads, and (c) neurodynamic entropy fluctuations developed from symbolic representations of the EEG power levels of all crew members. We describe these dynamics in a case study context of a six-person submarine navigation team where each team member had specialized responsibilities yet needed to coordinate activities with the other team members. Central questions for this research area are how the neurodynamic properties of an individual scale into those of the team, and whether information-theory

approaches can begin to provide quantitative measures of the changing dynamics of teamwork.

METHODS

Submarine Piloting and Navigation

Submarine Piloting and Navigation (SPAN) simulations are required exercises for Junior Officers in the Submarine Officer Advanced Candidacy course at the US Navy Submarine School. SPAN sessions contained three performance segments: Briefing, Scenario, and Debriefing. In the Briefing the team reviewed the environmental conditions and other ships in the area, and statically established the submarine's position. The Scenario was the training part of the navigation simulation where events included: encounters with approaching ships, avoiding shoals, changing weather conditions and instrument failure. The Debriefing was an after-action review where all team members participated in critical performance discussions.

The experimental SPAN teams included six crew members: the Navigator (NV) and Assistant Navigator (AN) with overall task accountabilities; the Officer on Deck (OD) who was on deck with a lookout; the Contact Manager (CM) who visually identified and kept track of other ship traffic and noted contacts of concern; the Quartermaster (QM) who maintained the ship's position; and the Radar operator (RD) who identified other ships in the area and helped with navigation; (Other people were "satellite" team members but were not directly involved in the team processes analyzed here).

The team performance studied had a Briefing of 289s, a Scenario of 3074s and a Debriefing of 992s. Embedded within the simulation were short and long-term perturbations that disrupted team rhythm, the largest being when the Assistant Navigator paused the simulation for ~4 min. for discussions with the crew.

Electroencephalography

The X-10 headsets from Advanced Brain Monitoring, Inc. were used for data collection. This wireless EEG headset system included sensor site locations: F3, F4, C3, C4, P3, P4, Fz, Cz, POz in a monopolar configuration referenced to linked mastoids; bipolar derivations were included which have been reported to reflect sensorimotor activity (FzC3) (Wang, Hong, Gao & Gao, 2007), workload (F3Cz, C3C4; Roux & Uhlhaas, 2014) and alpha wave components of the human mirror neuron system (Oberman et al., 2007). Embedded within the EEG data streams of the team members were eye blinks which were automatically detected and decontaminated using interpolation algorithms contained in the EEG acquisition software (Berka et al., 2004). These interpolations represented ~5% of the simulation time and in previous studies have not significantly influenced the detection of team neurophysiologic activities which occurred throughout the performances (Stevens & Galloway, 2014; Stevens et al., 2012). The EEG values were computed each second at each sensor for the 1 – 40 Hz frequency bins by the B-Alert Lab[®] software.

Neurodynamic Data Modeling Approaches

The goal was to develop neurodynamic data streams that had internal structure(s) with temporal information about the organization, function and performance of teams, in this study, a six person SPAN team. The different modeling approaches are outlined in Fig. 1, and illustrate a single frequency and sensor channel model (i.e. 10 Hz frequency from the CzP0 channel). As there are 14 sensor channels and forty 1 Hz frequency bins for each channel, this modeling was repeated 560 times.

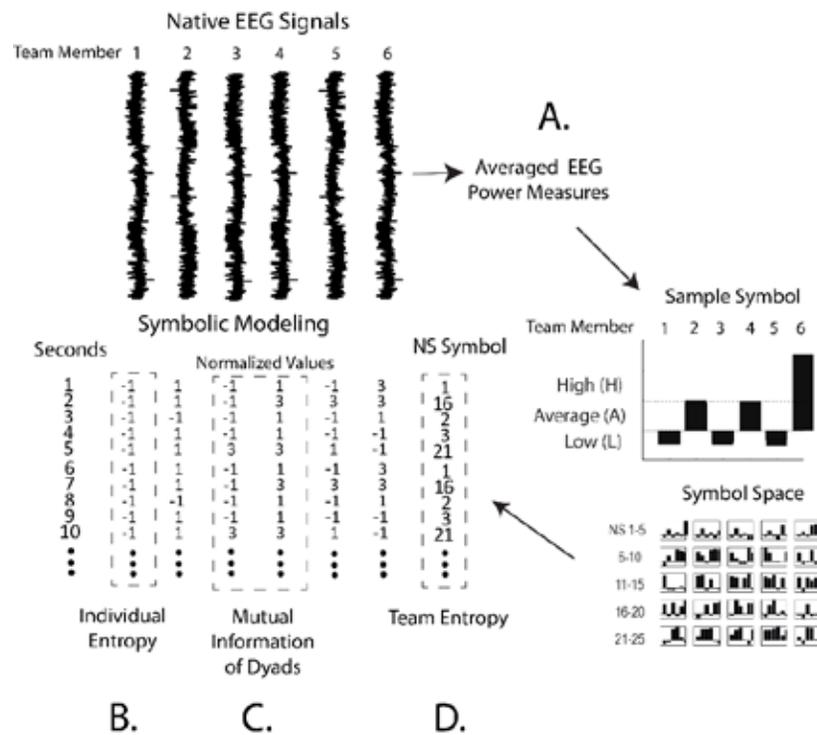


Fig. 1. Derivation of neurodynamic variables of teamwork. (A) The first variable is a measure of EEG power levels averaged across team members. (B) The second variable results from the transformation of an individual’s EEG power levels into a performance-normalized symbolic representation. The time-averaged Shannon entropy of this symbol stream results in a variable termed Individual Entropy (IE). (C) The second-by-second normalized EEG values from dyad pairs can be used to calculate the mutual information dynamics. (D) The symbolic EEG power values of the six-person crew can be aggregated each second into a single neurodynamic symbol representing the distribution of EEG power levels of the team.

The first variable was the native EEG power values averaged for the six team members. The simple averaging of an EEG marker (i.e. power levels at a frequency) across members of a team is particularly useful for identifying when all team members had elevated or depressed levels of a particular EEG marker. The limitation of this approach is that the relationships between team members, their individual roles and the immediate context do not factor into such an aggregate. Also, periods where all team members had high or low marker levels can be infrequent, especially in more experienced teams, (Kolm, Stevens & Galloway, 2013) and focusing on them would ignore the other synergistic links among team members expected at the neurodynamic level.

Treating data from multiple time series symbolically is another approach that has been used for discovering interesting data patterns in temporal data streams (Daw, Finney & Tracy, 2003; Lin, Keogh, Lonardi & Chiu, 2003).

To generate Neurodynamic Symbols (NS) for six person SPAN teams, each second the absolute levels of one EEG frequency bin (i.e. 10 Hz or 39 Hz) of a team member was equated with his/her own average levels over the period of the task. This identified whether at a particular time point an individual team member was experiencing above or below average levels of an EEG marker and whether the team as a whole was experiencing above or below levels. Classifying the set of symbols over entire performances (i.e. including Briefing and Debriefing segments) provided neurodynamic models encompassing a comprehensive set of task situations and loads (Fishel, Muth & Hoover, 2007).

As previously described (Stevens et al., 2013), in this process the EEG power in the 1 – 40 Hz frequency bins were partitioned into the upper 33%, the lower 33% and the middle 33%, which were assigned values of 3, -1, and 1 respectively. These values were chosen for data visualization purposes and can also be used symbolically for modeling Mutual Information (MI). The next step combined these values for each team member into a six-value vector which was ordered into a six histogram NS; a sample NS is shown toward the right in Fig. 1. These symbols showed the EEG 1 – 40 Hz frequency bin levels for each person in the team and situated them in the context of the levels of the other team member(s); these symbol combinations also represented the probability distribution of the team's response to the changing task stimuli.

These vectors, which were generated each second, were classified by a pre-trained artificial neural network into a symbol space and assigned a symbol number. This neural network was originally trained using an unsupervised artificial neural network architecture containing 25 output nodes and using performance data from six additional SPAN team performances (i.e. the training set). Similar neural network training protocols using several hundred nodes have shown that the neurodynamic relationships among the members of the team are persistent and can be adequately modeled with a symbolic space of 25 – 36 nodes.

The SPAN performance data that was used for creating the team entropy, termed NS Entropy, was a linear sequence of the twenty-five symbols, one for

each second of the task (Fig. 1d). This symbolic stream contained a neurodynamic history of the team as described by a particular EEG frequency bin from a particular scalp electrode. The procedure was then repeated for the remaining 39 frequency bins and at each sensor site. The next challenge was to determine the statistical properties of the long, internally structured data streams and relate them to individual and team actions during training (Wallace, 2013). As described below these symbols can be plotted over time for single or multiple EEG frequencies to provide visual representations of the changing neurodynamics of the team's performance.

Quantitative estimates of the NS Entropy were derived by calculating the Shannon entropy of the NS symbol stream over a moving window of time. In this procedure the Shannon entropy was calculated for the first 100 seconds of data and then each second the window was shifted by one second, a new symbol added to the end, and the entropy re-calculated. High levels of entropy represent a less organized team neurodynamically while lower entropy levels indicate a more organized team as fewer NS symbols are represented in the 100s time window.

Short and long-term changes in team entropy levels identify fluctuating periods of team neurodynamic organization but they provide little information about the degree of neurodynamic synchrony and the possible roles of these synergistic interactions during teamwork; mutual information descriptions help supply this data. Mutual information is a measure of the mutual dependence of two variables, or how much knowing the value of one variable decreases the uncertainty of the value of the other. MI has been widely used for evaluating information representations, transmissions, and content in single neurons and populations of neurons in stimulus-responses paradigms (Schneidman et al., 2003; Onken, Karunasekara, Kayser & Panzeri, 2014), as well as for reverse engineering gene regulatory and other complex networks (Villaverde, Ross, Moran & Banga, 2014). We wished to determine the relationships between MI and NS Entropy measures during teamwork, particularly as to whether they were complementary or redundant. The representations used for calculating the MI of dyads were the symbolic EEG neurodynamic state representations (i.e. -1, 1 and 3) shown in Fig. 1C. In all studies a moving average window approach for MI data reporting was used as described above for NS Entropy, to directly compare the temporal changes and to relate the two measures to task events.

The final variable was the Individual Entropy (IE) levels (Fig. 1B) that was calculated by treating the normalized EEG values symbolically and then calculating Shannon's entropy over a 100s moving window. Individual Entropy values can be thought of as the neurodynamic organizations as individuals perform their task work, as well as their teamwork. If MI represents one aspect of teamwork, then MI vs. IE comparisons might provide a way of differentiating periods of teamwork vs. task work. Effect size statistics were calculated using the MES toolbox written for MATLAB and described by Hentschke and Stuttgart (2011).

RESULTS

Descriptive Characteristics of Neurodynamic Measures

The frequency profiles of the team-averaged EEG power, team NS Entropy, and the average MI of thirteen dyad pairs is shown in Fig. 2. The total EEG power showed what would be an expected EEG profile of normal individuals with the highest power at lower frequencies which then decreased towards the 40 Hz frequency bin. This inverse relationship reflects the scale-free nature of EEG power and frequencies. The NS Entropy profile showed a trough in the 8-12 Hz bins which then decreased further until 28 Hz where it levelled. Randomizing the neurodynamic symbol stream prior to calculating the NS Entropy increased the entropy to 4.42 and removed the fluctuations seen in the non-randomized data profile. Unlike the NS Entropy profile, the MI profile was low from 1-10 Hz, and then steadily increased until 40 Hz.

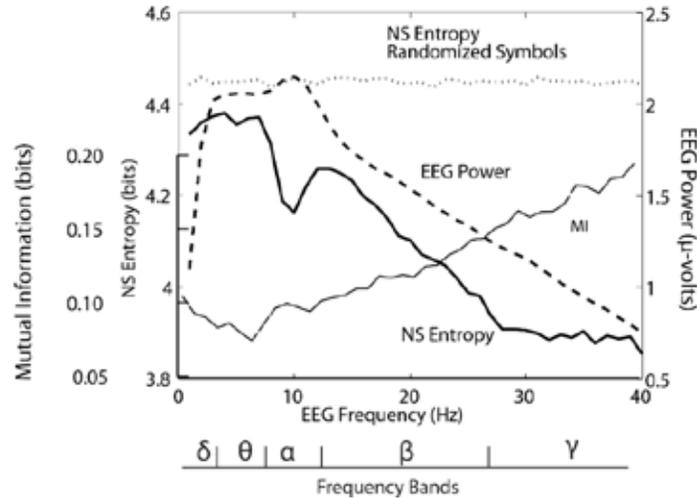


Fig. 2. Spectral properties of neurodynamic measures. The power-frequency distributions for EEG power, mutual information and NS entropy were constructed from the EEG CzP0 channel data streams as described in the Methods.

Differential Encoding of Neurodynamic Organizational Information across EEG Frequencies

The first studies examined whether the 10 Hz and 39 Hz EEG frequency bins contained equivalent information regarding the teams' dynamics. The 10 Hz frequency bin was selected based on the prominent NS Entropy trough at this frequency in the power spectrum. The 10 Hz frequency bin was also of interest as multiple EEG social coordination markers have been defined in this alpha wave bin (Tognoli & Kelso, 2015). The 39 Hz frequency bin was selected as this gamma

wave bin showed the lowest NS Entropy levels in Fig. 2, indicating the highest degree of team neurodynamic organization. This increased neurodynamic organization in the gamma wave region has been seen with other team-task combinations, suggesting a broader role for these frequencies in team activities (Stevens & Galloway, 2015). For these studies we sequentially plotted the symbols from the 10 Hz (Fig. 3B) or 39 Hz (Fig. 3D) NS data streams that were modeled from the EEG CzP0 channel.

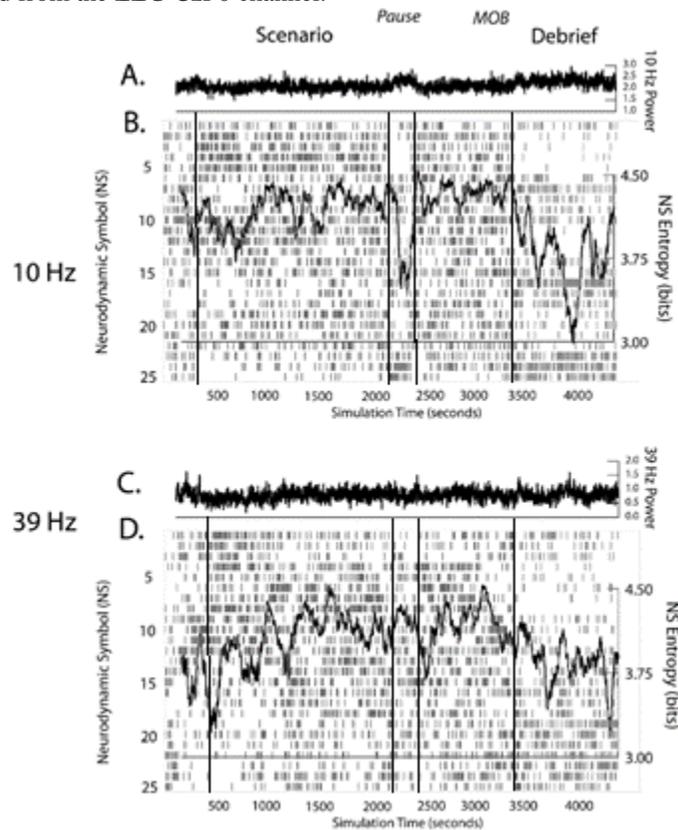


Fig. 3. Neurodynamic expression maps. The two major segments of the task, the Scenario and Debriefing are labeled and color-coded, along with the period where the Assistant Navigator paused the simulation (*Pause*), and when there was a Man Overboard (MOB) incident. The CzP0 channel power spectrum was averaged across the six team members for the 10 Hz (A) and 39 Hz (C) frequency bins. The symbol maps for 10 Hz (B) and 39 Hz (D) plot the second-by-second expression of the 25 NS. The Shannon entropy levels were calculated from the NS data streams with the traces overlaid on the NS maps. Randomizing the NS data streams prior to entropy calculations increased the 10 Hz entropy from 4.11 bits (SD = 0.28) to 4.45 bits (SD = 0.003); $\eta^2 = 0.40$, CI₉₅ [0.39, 0.42].

The dominant feature in both of these plots was the non-uniform expression of the twenty-five symbol states and the changes that occurred at the Scenario-Debriefing junction. During the Scenario at 10 Hz NS # 2-5 and NS #10-12 were the most frequent symbols while NS # 16-25 were only sporadically expressed. At the start of the Debrief this expression pattern reversed with NS # 16 and 24 - 25 dominating. Referring to the state space in Fig. 1 this symbol reversal represented a change from low to high team-averaged 10 Hz power levels. The NS expression in the 39 Hz frequency bin showed similar symbol reversals at the Scenario-Debriefing junction involving a switch from NS # 4-8 (Scenario) to NS # 18-24 (Debriefing), representing an overall increase in gamma wave power. The changing symbol expressions at the Scenario - Debrief task junctions were rapid (seconds) indicating that NS expressions are dynamically responsive to task changes.

While the overall trend from lower power in the Scenario to higher power levels in the Debriefing were similar for both the 10 Hz and 39 Hz data streams, cross-tabulation analyses indicated that the 10 Hz and 39 Hz symbol expressions in the Scenario and Debriefing were significantly different, (Scenario, $\chi^2=656$, $df = 24$, $p < 0.001$; Debriefing, $\chi^2=398$, $df = 24$, $p < 0.001$) and that the correlations between the NS entropy levels were moderate (Scenario, $r = 0.22$; Debriefing, $r = 0.23$).

Within each training segment there were shorter scale (30-150s) blocks of more restricted NS symbol expressions which were associated with decreased NS Entropy. The most obvious example was between 2148 – 2382s when the Assistant Navigator paused the simulation for discussions with the crew. This resulted in a significant neurodynamic reorganization in the 10 Hz frequency bin characterized by increased expression of NS #24 & #25 (i.e. increased 10 Hz power levels). This neurodynamic reorganization was not seen at the 39 Hz EEG frequency bin. This result illustrates a third point, information about the team performance may be distributed across the 1-40 Hz EEG frequency power spectrum of the CzP0 channel.

A comparison of Fig 3B and 3D indicates a useful characteristic feature of the team NS entropy. Irrespective of whether the team as a whole was expressing low (as in the Scenario) or high (as in the Debrief) power levels of an EEG marker, the NS Entropy provided a consistent and quantitative measure of this organization. Second, unlike EEG power levels which decrease with increasing frequency, the degree of neurodynamic organization is uniform across the EEG frequency spectrum meaning that quantitative comparisons can be made in response to specific events or task segments across frequencies.

The contrasting 10 Hz and 39 Hz NS symbol expressions and entropy levels during the Pause suggested that different EEG frequencies from the same scalp location carry different information about the team's neurodynamic organization. To broadly estimate the relatedness of the neurodynamic organizations in the different EEG frequency bands a frequency by frequency correlation was conducted of NS entropy at the CzP0 channel. Each second the NS Entropy levels of the current 1-40 Hz frequencies were correlated with the entropy levels of the

remaining thirty-nine EEG channels. Also shown is a correlation plot when the NS data stream was randomized before calculating the NS Entropy. The correlations were not diffuse across the frequency channels but highlighted areas of increased correlation in the 8-12 Hz, the 16-22 Hz, and the 32-40 Hz frequency bins. Consistent with the data in Fig. 1, the NS Entropy in the 10 Hz frequency bin was poorly correlated with that in the 39 Hz bin.

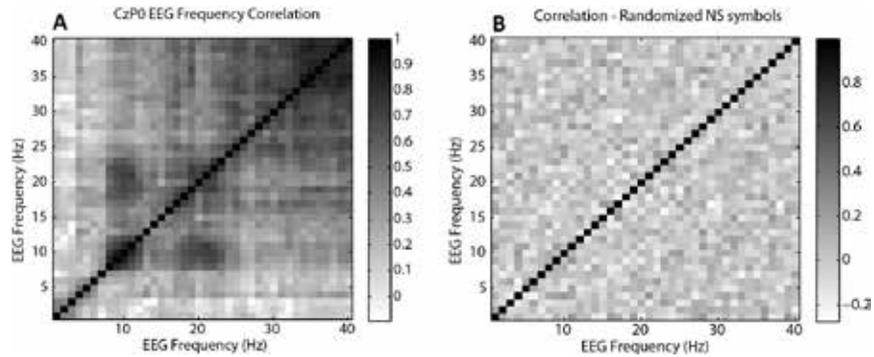


Fig. 4. Across-frequency correlations of NS Entropy: (a) Correlations for the NS data stream resulting from data modeling of the CzP0 EEG values; (b) Correlations when the twenty-five symbols in the data stream were randomized before calculating the NS entropy levels.

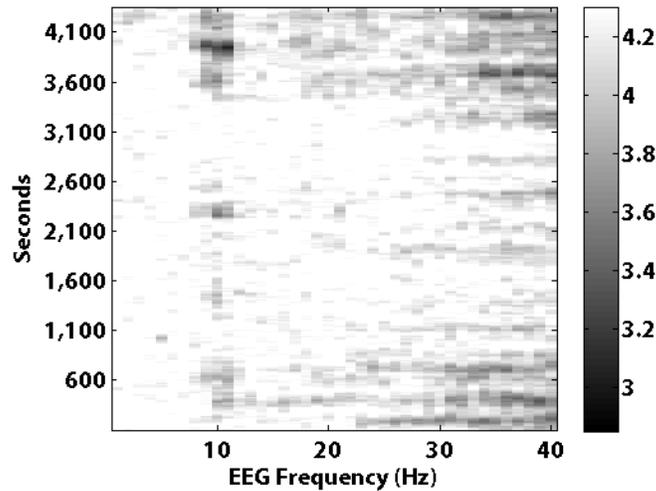


Fig. 5. Temporal-frequency plot of NS Entropy. This figure plots the NS entropy levels vs time and EEG frequency.

The frequency-NS Entropy relationships for each second of the performance are shown in Fig. 5. Viewed from above, the times of decreased NS Entropy (i.e. increased team neurodynamic organization) appeared darker. During the first 800s there were consistent organizations (i.e. reduced entropy) in the 8-11 Hz and also the 16-40 Hz bins with the lowest NS entropy in the higher EEG frequencies. This data is consistent with the reduced NS symbol expression and entropy levels seen at both the 10 Hz and 39 Hz frequency bins in Fig. 2 during the first 900s. The NS Entropy levels then increased across all frequencies as the team engaged in their navigation duties until ~ 2200s when the Assistant Navigator paused the simulation which resulted in decreased entropy levels primarily in the 8-11 Hz frequency bin. After the Pause, variable regions of decreased NS entropy occurred throughout the performance until the Debriefing at 3365s.

Mutual Information Dynamics across Team Dyads

The next studies transited from documenting the team's neurodynamic organizations to synchronizations among the team members. Fourteen team dyads were created from the six member crew and the mutual information dynamics were calculated for the performance, the dyads are shown in decreasing order of MI (Fig. 6). In contrast to the NS entropy expressions in Fig. 3, the MI expressions were more discrete. The dyads with the highest MI levels were generally those containing the QM, the RD or the NV as one of the crew pairs, and the differences between the highest to the lowest dyad levels showed a moderate effect size (NV-QM $M=.51, SD=0.13$ vs CM-AN, $M=0.44, SD=.02$; $\eta^2=.16$, $CI_{95}=[.14-.17]$).

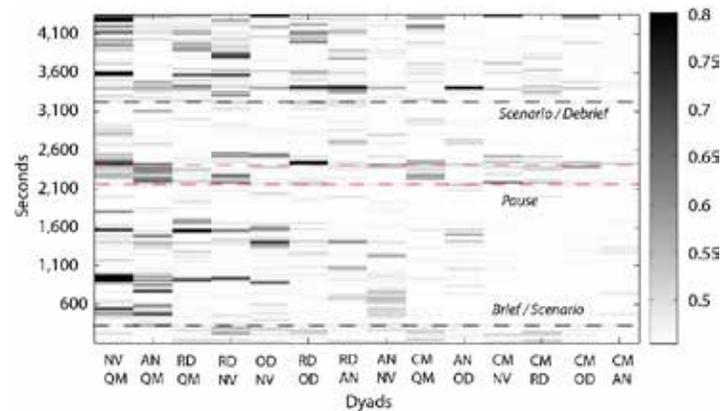


Fig. 6. Mutual information of team dyads. The mutual information dynamics of fourteen dyad pairs from the six-person crew were calculated and plotted in the order of decreasing mutual information.

Once again the Pause interval was interesting neurodynamically and provided an opportunity to compare MI dynamics with the speech patterns of the crew. Prior to the Pause the speech was distributed across the crew. Speech during

the first half of the Pause was dominated by the AN and punctuated with the REC (who was not wearing an EEG headset) (Fig. 7A). The segments where the crew members were speaking during the Pause is shown in Fig. 7A.

From Fig. 7 the Pause region was one where most dyads showed increased levels of MI, some of which extended beyond the simulation suspension. Figures 7B and 7C show the MI dynamics at the beginning and end of the Pause. The MI of the CM-NV and the RD-NV rose shortly after the pause, followed by the AN-QM dyad. The other MI increases shown during the Pause interval were associated with the NV-AM and CM-QM dyads. These increases are interesting as most of the crew involved (i.e. CM, QM, NV) did not speak during this time. Shortly after the break, there was a strong MI peak from the RD-OD dyad at a time when the OD did not speak, and the RD spoke sporadically.

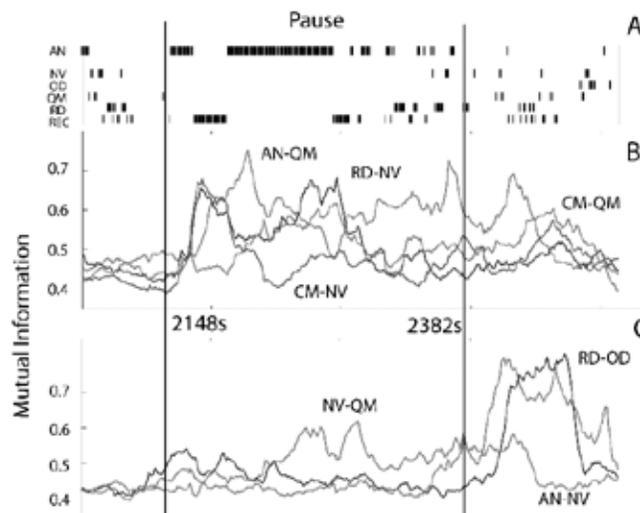


Fig. 7. Temporal dynamics of dyad MI and speech flow during the Pause. (A) The top panel plots when the different team members were speaking. Panels B and C plot the MI for the team dyads. The dyads have been separated into two groups representing dyads with increased MI during the Pause (B) or after the Pause (C). The MI for the AN-NV, the AN-CM and the AN-OD which had the lowest levels from Fig. 6 are not shown.

Initially we thought that elevated MI might represent times when there were significant NS Entropy decreases resulting in a negative correlation between the two measures. A performance-wide comparison was made using averaged NS Entropy data across all EEG channels and frequencies, and the MI levels from each of the dyads in Fig. 6. Like NS Entropy, the overall MI fluctuated with peaks occurring between 850-1050s and 1340-1550s and during the Pause interval between 2148-2382s (Fig. 8a). While there seemed to be a concordance between

the two measures during the Pause interval, there was no correlation at zero lag (Fig. 8b). Cross-correlation analysis at positive or negative lags revealed more significant negative correlations ($r \sim -0.2$), particularly with earlier time lags (Fig. 8b).

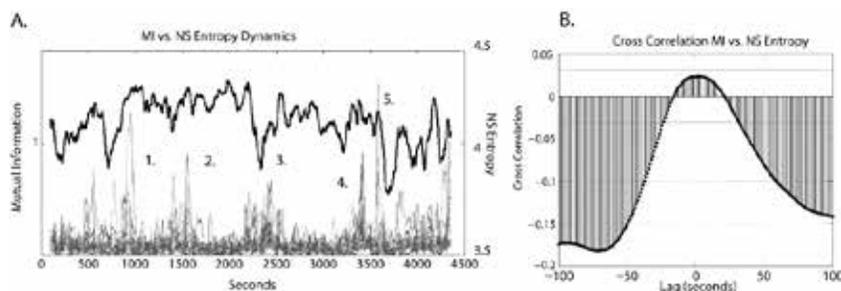


Fig. 8. Dynamical comparisons of NS entropy and mutual information. The team NS Entropy was averaged across all frequencies and all sensors, and the mutual information values were averaged across the fourteen dyad pairs in Fig. 6. The numbers represent performance events surrounding those time periods. (1) The team was having difficulty remembering the sequence of buoys to use when establish the ship's position. (2) The team was preparing for a turn into difficult waters with other ship traffic. (3) The simulation Pause called by the Assistant Navigator. (4) The Man Overboard event. (5) Beginning of the Debriefing segment.

A second set of correlations were made, using the 1-40 Hz averaged NS entropy and MI from the different EEG channel sensors (Fig. 9). While the levels of NS entropy and MI clustered differently for the monopole (e.g. Fz, F3, F4, C3, C4, P0, P3 and P4) and bipole EEG channels, the decrease in NS entropy was associated with an increased value for MI. The highest MI levels were associated with the parietal and central sensor locations while the frontal and midline sensors had lower MI levels.

The negative correlation ($r = -.7$, $p < 0.003$) between MI and NS entropy levels supports the hypothesis that performance wide, increased MI was associated with the periods of decreased NS entropy. To associate the MI and entropy dynamics more closely, in our final studies, we compared the MI dynamics with the dynamics of the individual (i.e. single person) entropy from each of the persons in the dyad. Individual entropy levels might be expected to show periods of symbol persistence in response to both their individual task activities, e.g. when the radar operator was determining the position of other ships, as well as team-wide activities, e.g. sharing this information with the team. Mutual information being a dyad-based metric might be expected to be more restricted to person-person interactions.

Most dyads showed both elevated MI and decreased IE during the simulation Pause segment and also at the Brief-Debrief junction (Fig. 10). There were also multiple examples where there was decreased IE with little MI and periods with increased MI and little IE. The performance-wide correlations were generally low (≤ 0.2) at zero lag.

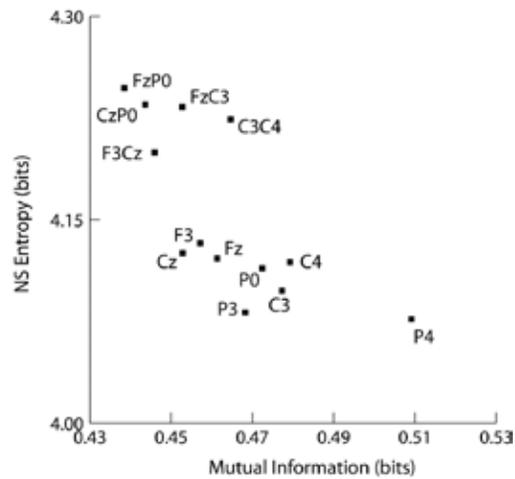


Fig. 9. Relationships between mutual information and NS Entropy at different EEG channels.

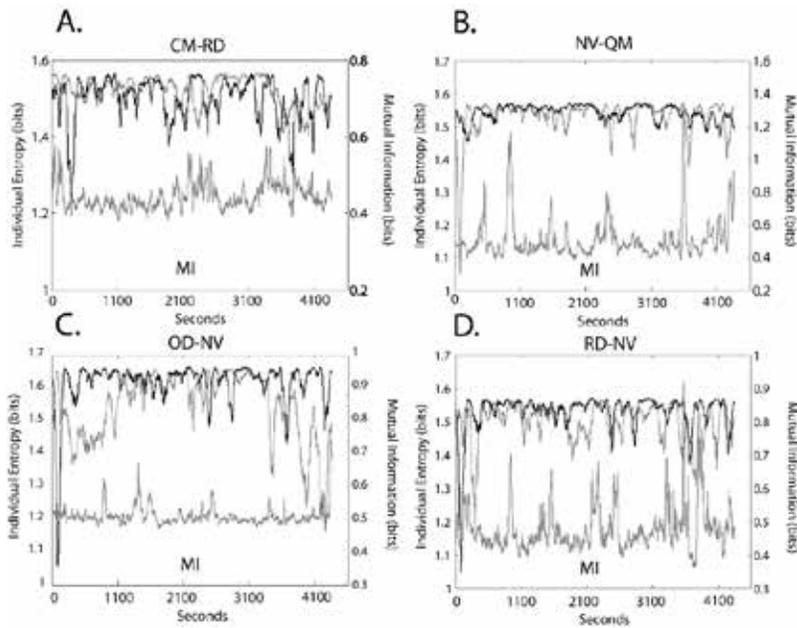


Fig. 10. Dynamics of dyad MI and the individual entropy of the team members. The MI for the dyads CM-RD (A), NV-QM (B), OD-NV (C) and RD-NV (D) are plotted with the IE of each of the members. The MI values are the lower scale values.

DISCUSSION

The first goal of this study was to derive a better understanding of the dynamical relationships between the different neurophysiological representations of the teams' EEG data streams. The second goal was to determine how the changing dynamics of these variables related to team responses to different task events. These objectives are part of a larger effort to develop a framework for team neurodynamics that bridges the micro-scale changes of neurophysiologic signals with speech and larger-scale observable behaviors.

Constructing such team representations requires high levels of abstraction. We reduced the degrees of separation from the native EEG signals to useful abstractions by building on existing neurodynamic structures with nested spatial and temporal levels. In this way, some teamwork measures such as neurodynamic entropy had slower (minutes-tens of minutes) temporal dynamics (Stevens & Galloway, 2014) than faster (seconds-minutes) mutual information measures of dyads (Stevens & Galloway, 2015), or speaker-listener neurophysiologic couplings that change over tens to hundreds of milliseconds (Dumas et al., 2010; Stephens, Silbert & Hasson, 2012).

NS Entropy may be the most versatile of the three neurodynamic measures studied as it describes a quantitative measure of teamwork related to team organization. The idea behind neurodynamic organization is that the team becomes dynamically entrained by the evolving task and these entrainments result in neurodynamically persistent states. These states can be visualized in symbol maps and quantitated by fluctuations in NS Entropy. NS Entropy is uniquely suited for identifying neurodynamic organizations as irrespective of whether the team as a whole was expressing high or low levels at a particular EEG frequency. The NS Entropy provides a consistent and quantitative measure of this organization. Unlike EEG power levels which decrease with increasing frequency, the degree of neurodynamic organization is uniform meaning that quantitative across-frequency comparisons can be made in response to specific events or task segments. By normalizing the symbol representations across the entire performance including the Briefing and Debriefing as well as the Scenario, quantitative comparisons can be made across teams, team experience and training protocols with less need for standardized models or baseline comparisons. Finally, we have generated similar NS Entropy models with teams consisting of two to six members performing a variety of tasks indicating the scaling potential (Stevens & Galloway, 2015).

These properties have helped describe changes in a team's neurodynamic organization associated with small and large task changes, often during periods of stress. For instance, while dyads of high school students performed a map navigation and drawing exercise, the largest entropy drops occurred when the follower briefly lost control of the mouse while drawing (Stevens & Galloway, 2014, 2015). Similarly, in submarine navigation teams, the magnitude and persistence of NS Entropy declines were the greatest when there were adverse task conditions (fog, current, or other ship traffic) which caused the teams to

deviate from their planned course of action. Early studies have also shown that the NS Entropy levels during the Scenario were higher for experienced teams (i.e. boat navigation teams) than for junior officer teams undergoing training to become navigators and boat operators (Stevens et al., 2013), and more recently, a positive correlation was seen between the NS Entropy levels and team resilience as measured by an observational instrument recently adopted by the submarine fleet (Stevens et al., 2015).

The similar findings across teams of different compositions and experience collaborating on different tasks suggest that NS Entropy measurements may be a generic modeling for studying team dynamics. The types of tasks and teams we have studied represent ‘detailed task teams’ with a well described goal and hierarchical definition (Anicich, Swabb, & Galinski, 2014). It will be important to extend these studies to collaborative situations where goals are more ambiguous and compromise is important to further test the generality of the neurodynamic models.

While neurodynamic organization is a useful property for linking across scales of neurodynamic, cognitive and observational measures, the native EEG signals provide theoretical groundings for linking to the neuroscience research base. The links between NS Entropy and native EEG amplitude levels were made symbolically where the expression of different NS were mapped onto a symbol space whose topology was such that symbols representing many team members with below average EEG power levels mapped toward the beginning of the symbol space (NS #1-5) while those symbols representing many team members with high levels mapped toward the end (NS #20-25). This topology resulted from the competitive properties of Kohonen networks used for the model development. This mapping allowed easy identification of high or low average EEG power.

A prominent feature was the change in the teams’ neurodynamic reorganization that occurred at the Scenario – Debriefing junction, a change that occurred at multiple EEG frequencies. The switch from desynchronized (e.g. low power) alpha rhythms during the Scenario to synchronized (high power) alpha rhythms in the Debriefing indicates a reversal in the attentional state of the team. The high degree of Scenario-related alpha desynchronization suggests the team members were closely attending to the unfolding events and activities in the environment. These activities would simultaneously include attention to each of the other team members as well as the task events. During social coordination, vision of the partner substantially desynchronizes alpha rhythms, with the power of the fluctuations reflecting the complexity of behavioral information acquired about the partner (Tognoli & Kelso, 2015). During the Debriefing, much of the team’s attention was directed to the instructor or on the response of a single other team member.

One of the challenges in interpreting the changes in 8-11 Hz rhythms is the presence of other social coordination markers including the phi complex (Tognoli et al., 2007) and the medial, left, and right central mu rhythms that also map between 9 and 11.5 Hz and are suppressed by movement, or imagined movements (Menoret, Varnet, Fargier, et al., 2014; Caetano, Jousmaki & Hari,

2007; Pineda, 2008). In Fig. 5 unequal levels of NS entropy were seen in a band across the 8-12 Hz frequency bins indicating heterogeneity in this region. Whether this represents the differential expression of social coordination markers in this region will require further studies using additional sensor channels during EEG acquisition.

While the amplitude of alpha-band activity is generally suppressed by eye opening, visual stimuli and visually scanning, it is enhanced during more internal tasks such as mental calculation and working memory (Klimesch, Sauseng & Hanslmayr, 2007). Recently the suggestion has been made that simultaneous alpha, beta and gamma-band oscillations are required for unified cognitive operations such as working memory and perception (Palva & Palva, 2007). This hypothesis is particularly interesting in light of the cross-frequency correlations in NS entropy across these bands illustrated in Fig. 4, where the correlations between the alpha and beta band regions were particularly strong.

Information processing in the brain is thought to rely on oscillatory behaviors of distributed brain sites, the simplest being the synchronization and desynchronization of brain rhythms like those of the alpha region described above. Even at rest, cross-frequency couplings occur between different frequencies which may serve as a carrier mechanism for communications across brain regions (Jirsa & Muller, 2013). The evidence for these couplings has largely been obtained in individuals, and whether similar couplings dominate for team-based neurodynamic measures remains an open question. The NS Entropy correlation map shown in Fig. 4 highlighted discrete regions of correlation across frequencies. Two of the regions were the 8-12 Hz alpha region and the 16-22 Hz beta region. The across frequency correlations were similar for these two regions which may not be surprising as the mirror neuron complex contains a component in the beta region along with one in the alpha region (Pineda, 2008). It should be emphasized that the correlations were performed at zero lag and the possibility exists that the correlations would change with a timed-lagged analysis. There were other discrete regions of NS Entropy correlation including the 1-5 Hz (delta) band, a region that has not been identified as having markers of social coordination *per se*, although recent studies have suggested that this region may be associated with motivation and emotional states (Schutter & Knyazev, 2012), and in processing speech utterances over the period of 1-3 seconds (Ghitza, 2012). Also shown in Fig. 4 was a small region of correlation around 28-30 Hz suggesting that NS Entropy correlations may be useful for identifying additional social coordination markers that arise under particular conditions of team activity.

The neurodynamic modeling across EEG sensor locations also showed contrasting dynamics characterized by both quantitative and qualitative differences over the same temporal window. The dynamical differences may relate to the more selective detection of large scale emergent networks such as the sensorimotor, dorsal attention or visual networks by different EEG sensor combinations (Chialvo, 2010; Sporn, 2012). Such network activations in turn may result from the differential interactions among members of the crew. More precise spatial modeling of the cross-frequency couplings by the use of additional EEG

sensors, along with more detailed analyses of the relationships between team neurodynamic metrics and team member speech and other interactions may begin to distinguish between alternatives.

The mutual information of team dyads provided a different perspective of teamwork than did either the NS Entropy of the six-person symbolic representations or the IE of individual team members. Our expectation was that the summed mutual information of the different dyads in a team might account for the neurodynamic symbol entropy that resulted from modeling the overall team. While the peaks of MI were consistently near periods of decreased NS entropy, the correlations (at zero lag) between MI and either of the entropy measures was small and non-significant. Cross-correlations at different time lags showed that the highest correlation between MI and the six-person NS Entropy levels ($r = -0.2$) occurred with a lag of 70s, indicating the need in the future for extended correlation analyses.

Finally, interesting relationships may exist between speech and MI. During the Pause segment, the AN spoke most of the time and while the AN-QM dyad contributed significant MI toward the beginning of the pause, most of the other MI increases resulted from other members of the crew who did not speak. Also, most of the dyad pairings containing the AN had low MI levels, particularly during the Pause interval and the Debriefing. Combined these data suggest there may be an inverse relationship between a person's speech and the MI levels of the dyads this person is a part of, i.e. MI may arise under conditions of synchronic rather than diachronic social coordination activities (Tognoli & Kelso, 2015). It will be particularly important to extend these studies beyond relationships with speech flow, to speech content and speech consistency as we have previously performed with NS entropy (Gorman et al., 2015).

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