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Toward a quantitative description of the neurodynamic organizations of teams

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The goal was to develop quantitative models of the neurodynamic organizations of teams that could be used for comparing performance within and across teams and sessions. A symbolic modeling system was developed, where raw electroencephalography (EEG) signals from dyads were first transformed into second-by-second estimates of the cognitive Workload or Engagement of each person and transformed again into symbols representing the aggregated levels of the team. The resulting neurodynamic symbol streams had a persistent structure and contained segments of differential symbol expression. The quantitative Shannon entropy changes during these periods were related to speech, performance, and team responses to task changes.

The dyads in an unscripted map navigation task (Human Communication Research Centre (HCRC) Map Task (MT)) developed fluctuating dynamics for Workload and Engagement, as they established their teamwork rhythms, and these were disrupted by external changes to the task. The entropy fluctuations during these disruptions differed in frequency, magnitude, and duration, and were associated with qualitative and quantitative changes in team organization and performance. These results indicate that neurodynamic models may be reliable, sensitive, and valid indicators of the changing neurodynamics of teams around which standardized quantitative models can begin to be developed.

Keywords: Teamwork; Neurodynamics; Entropy.

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

These properties of being complicated, complex, and noisy pose challenges for evaluating teams, and at some point, seemingly simple questions like "How is this team doing?" become difficult to answer, particularly if the goal is to capture quantitative measures of team improvement over time. Part of the challenge is that unlike the performance evaluations of individuals, there are few measures and models for rapidly comparing across teams. This is particularly true with teams of diverse experience, who are performing

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real-world tasks where errors may be infrequent and do not directly correspond to failure (Schmidt, Keeton, Slack, Leveton, & Shea, 2009).

We have proposed that neurodynamics may provide a platform for developing quantitative models of team organization and perhaps performance (Stevens, 2012; Stevens, Galloway, Wang, & Berka, 2012). It is not surprising that neurophysiologic activities are the underpinnings of the social coordination dynamics described above, yet it is only recently that their evolving dynamics in real-world teamwork settings have begun to be modeled (Dodel et al., 2011; Dumas, Nadal, Soussignan, Martinerie & Garnero, 2010; Stephens, Silbert, & Hasson, 2010; Stevens, Galloway, Berka, & Sprang, 2009).

Compared with other teamwork modeling approaches like shared mental models (Entin & Serfaty, 1999), team cognition (Cooke, Gorman, & Kiekel, 2008), and macrocognition (Warner, Letsky, & Cowen, 2005), neurodynamics have the advantages of: (1) Speed—Neurodynamic measures can be modeled and reported within seconds; (2) Specificity—The signal spectra of different electroencephalography (EEG)-defined cognitive measures are distinct and can be modeled independently; (3) Diversity—Different EEG cognitive measures may have different temporal dynamics that could enable the reconstruction of the teaming process in new and more understandable ways; (4) Tools—Portable, high temporal resolution EEG units are becoming widely available. This has led to the idea of "team neurodynamics", which we have defined as the (often nonlinear) dynamics resulting from the quantitative co-expression of an EEG-defined cognitive marker by different members of a team (Stevens et al., 2012; Stevens, Gorman, Amazeen, Likens, & Galloway, 2013).

In this study, we describe an information and organization-centric framework for team neurodynamics that can be applied in many teaming environments. The idea was that raw EEG data streams, once converted into symbolic data streams of cognitive measures, may contain statistical regularities representative of the task and team actions at any point in time. In this way, the second-by-second sequence of symbols (termed neurodynamic symbols or NSs) that arise during teamwork may contain information relating to team performance much in the way that words in a sentence or the codons in nucleic acids convey information (Salem, 2011; Schneider, Stormo, Gold, & Ehrenfeucht, 1986). Fluctuations in the mix of symbols may help identify "interesting periods" of team organization that are relevant to teamwork and if so, the frequency, duration, and magnitude of these fluctuations could then be quantified by measuring the Shannon entropy across segments of the data stream (Shannon & Weaver, 1949).

HYPOTHESES

The guiding hypotheses for this study were:

1. EEG-derived NS streams from dyads have a dynamic structure.
2. Contextual disturbances in the task result in modified team neurodynamics.
3. The changing distributions of neurodynamic symbols in the data streams can be quantitatively described by Shannon's entropy.
4. The neurodynamics of different EEG-defined cognitive measures are dissimilar.

METHODS

Participants

Fifteen 11th and 12th grade students (six male and nine female) from advanced placement chemistry classes were the experimental subjects. Informed consent, allowing the students to participate in the study and to have their images and speech made available for additional analysis, was obtained from the parents.

The Edinburgh Map Task

For these studies, a well-defined but open-ended task for two persons was used, which allowed the collection of detailed speech, mouse clicks, and video. This task was a two-person problem-solving/navigation exercise based on the Edinburgh Map Task corpus (Doherty-Sneddon et al., 1997). In the Map Task (MT), two team members sat facing one another and each had a sketch map with several landmarks on it. The two maps were similar, but not identical and the students could not see each other's map. One person, the instruction giver (Giver, abbreviated G), had a path printed on the map and attempted to verbally guide the other person, the instruction follower (Follower, abbreviated F) in drawing that path on the F's map. The resulting dialog was unscripted and fluent and contained easily identified short-term goals. The task was not timed and the participants did not receive feedback on the quality of their performance.

To support the collection of video and audio streams, the drawing by the F was performed on a computer using Adobe Acrobat standard drawing and erasing tools. Both the G and the F were fitted with a 9-electrode EEG units (Advanced Brain Monitoring, Inc., Carlsbad, CA, USA, described below) and seated in front of a computer configured with Morae Software (Techsmith, Inc., Okemos, MI, USA), which simultaneously logged EEG, audio, video, and the F's mouse clicks. This configuration supported the temporal alignment of speech, mouse movements, and neurophysiologic measures. Samples of four teams' work that are highlighted in this paper are shown in Figure 1 A–D, where the labels indicate the performance epochs when a navigation point was reached. In Figure 1B, for example, four major deviations of the F from the G's path were seen between epochs 66–92, 134–232, 372–500, and 680–750. A scoring system was used to rate the performances with points deducted for drawing inaccuracies. In this system, a Bad Miss, where the route went on the wrong side of a marker, was scored as –2, while a Good Miss, where the edge of a feature was clipped or if the route was taken too widely (i.e., > ½ the height of a feature), was scored as –1.

Fifteen sessions were collected from 10 different student combinations. The average time to complete the task was 834 ± 374 (SD) seconds and the paired *t*-test between the first and second performances was not significant ($t = 1.46$, $p = .19$ df = 6). The higher-ranked teams took longer (986 vs. 843 seconds) than the lower-ranked teams, but again, the difference was not significant ($t = 1.44$, $p = .17$, df = 12).

Much of the performance time (72%) was spent in dialog with the G speaking nearly twice as much as the F across the sessions; the average words per session was (1725 ± 872 (SD)), and the unique words were (250 ± 69 (SD)). In all scenarios, the G provided the majority of the directions as expected (Figure 2, DIR). During the questioning (Q) and answering (A), the F in some teams asked more questions while in others, there was more balance in the Q and A. We used a form category coding scheme for describing the utterances, which was based on that of Urban, Bowers, Monday and Morgan (1995) and described previously (Stevens et al., 2009). The percent of different speech actions are similar to those described by Louwerse and Crossley (2006).

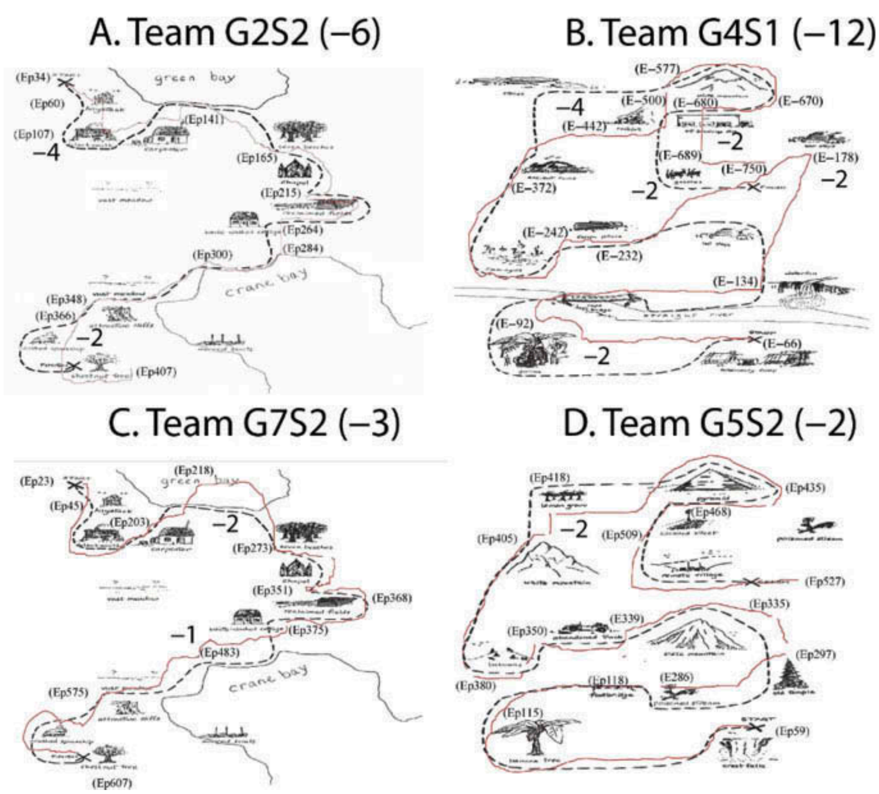

Figure 1. Sample MT performance measures. In panels A–D, the dotted line shows the path of the Giver's map and the solid line that drawn by the Follower. The heading above each figure is the team and session and the numbers in brackets are the overall points deducted. In each figure, there are numeric notations where individual points were deducted. An expanded version of this figure can be found in the supplemental materials at http://dx.doi.org/10.1080/17470919.2014.883324

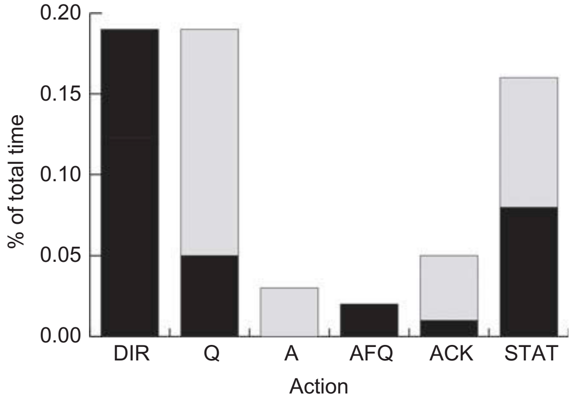

Figure 2. Proportion of time teams spent in speech activities. This figure shows the proportion of time that 11 teams spent in different speech activities where DIR = directions, Q = questions, A = answers, AFQ = answer following question, ACK = acknowledgement, STAT = statement. The contributions of the Giver are shown in black and those of the Follower are shown in gray.

Electroencephalography

The Advanced Brain Monitoring, Inc., 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 nine-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 proprietary software (Davis & Lumicao, 2004).

Embedded within the EEG data stream from each team member are eye blinks, and the algorithms used by ABM for calculating EEG automatically detect and decontaminate the EEG streams by a process of interpolation. As the interpolation represents ~5% of the simulation time, they are not likely to overly influence the calculations of EEG-engagement (EEG-E), EEG-workload (EEG-WL), or further neurodynamic analysis.

The next data processing layer extracts second-by-second calculations of the probabilities of High EEG-E, Low EEG-E, Distraction, and High EEG-WL using proprietary algorithms of ABM (Davis & Lumicao, 2004; Levendowski et al., 2001). The neuropsychological tasks used to build the algorithm and 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 (Krieger & Ayappa, 2004), eyes closed passive vigilance, eyes open passive vigilance, and three-choice active vigilance tasks to define the classes of sleep onset, distraction/relaxed wakefulness, low engagement, and high engagement. Simple baseline tasks were used to fit the EEG classification algorithms to the individual so that the cognitive state models could then be applied to increasingly complex task environments, providing a sensitive and specific technique for identifying an individual's neural signatures of cognition in both real-time and offline analysis.

The studies in this report have used the High EEG-E and EEG-WL metrics. The two metrics have different functional properties and are poorly correlated; over six team member combinations, the average value of R was –.19 ± .24. EEG-E is related to processes involving information gathering, visual scanning, and sustained attention while EEG-WL is correlated with objective performance and subjective workload ratings in tasks of varying difficulty. Like all EEG-derived measures of cognitive activities, EEG-E and EEG-WL are approximations of the many different ways Engagement and Workload are described in the literature. Engagement, for example, has been used to describe the amount of cognitive processing a learner applies to a subject (Howard, 1996), or as something that has to be broken during a task so that a learner can reflect on his/her actions (Roberts & Young, 2008). It shares similarities with alertness or attention, can be visual and/or auditory, and can be elevated through a variety of activities such as inducing cognitive dissonance, posing argumentative questions requiring the development of a supportable position, and causing learners to generate a prediction and rationale during a lesson. To some extent, we have to accept the premise that precise terms will be difficult to associate with different EEG-derived cognitive measures and that functional associations will need to be empirically derived in the context of the task.

Across the MT sessions in our study, there were no differences between the overall EEG-WL levels of the G (mean (M) = .66, standard deviation (SD) = .09) and F (M = .66, SD = .09), $t(32) = .53$, $p = .60$, or the overall EEG-E levels of the G (M = .42, SD = .15) or F (M = .45, SD = .05), $t(32) = –.84$, $p = .40$).

RESULTS

For studying team processes, we chose a symbolic approach for combining the data rather than directly using two concurrent EEG data streams; this lets the current status of the team as a whole to be represented by a single symbol. To generate these symbols, we equated the absolute levels of EEG-WL or EEG-E of each team member with his/her own average levels over the period of the particular task. This allowed the identification of whether an individual team member was experiencing above or below average levels of EEG-WL and whether the team as a whole was experiencing above or below average levels. As previously described (Stevens, Galloway, Wang, Berka, & Behneman, 2011), in this normalization process, the EEG-WL levels were partitioned into the upper 33%, the lower 33%, and the middle 33%; these were assigned values of 3, –1, and 1, respectively, values that were chosen to enhance visualizations of the symbols. For instance, the symbol in Figure 3A shows a situation where the EEG-WL of G was high and that of F was low; in the text, this is represented as G^h F^l.

The next step combined these values at each epoch for each team member into a vector representing the state of EEG-WL for the team as a whole; these vectors were used to train artificial neural networks (ANNs) to classify the state of the team at any point in time (Stevens et al., 2009; Stevens, Galloway, Berka, & Behneman, 2011). In this process, the second-by-second normalized values of team EEG-WL for a single MT performance (or for multiple performances when across team models were being generated) were repeatedly (50–2000 times) presented to a 1 × 9 node unsupervised ANN. The result of this training was a series of patterns, which we call NS patterns, that show the relative levels of EEG-WL (or EEG-E) for each team member on a second-by-second basis.

During the training process, a topology is developed whereby similar EEG-WL vectors become adjacent through short-range excitatory interconnections, while the more disparate vectors are inhibited and co-locate further away. The output of the ANN training is a symbolic state space showing the possible combinations of EEG-WL across members of the team for a performance. The resulting ANN topology for these studies is shown in Figure 3B, where NS #1 (upper left corner) depicts a time where both G and F expressed above-average levels of EEG-WL (i.e., G^h F^h). In NS #2 & #3, the EEG-WL expression of F decreased, and at NS #6

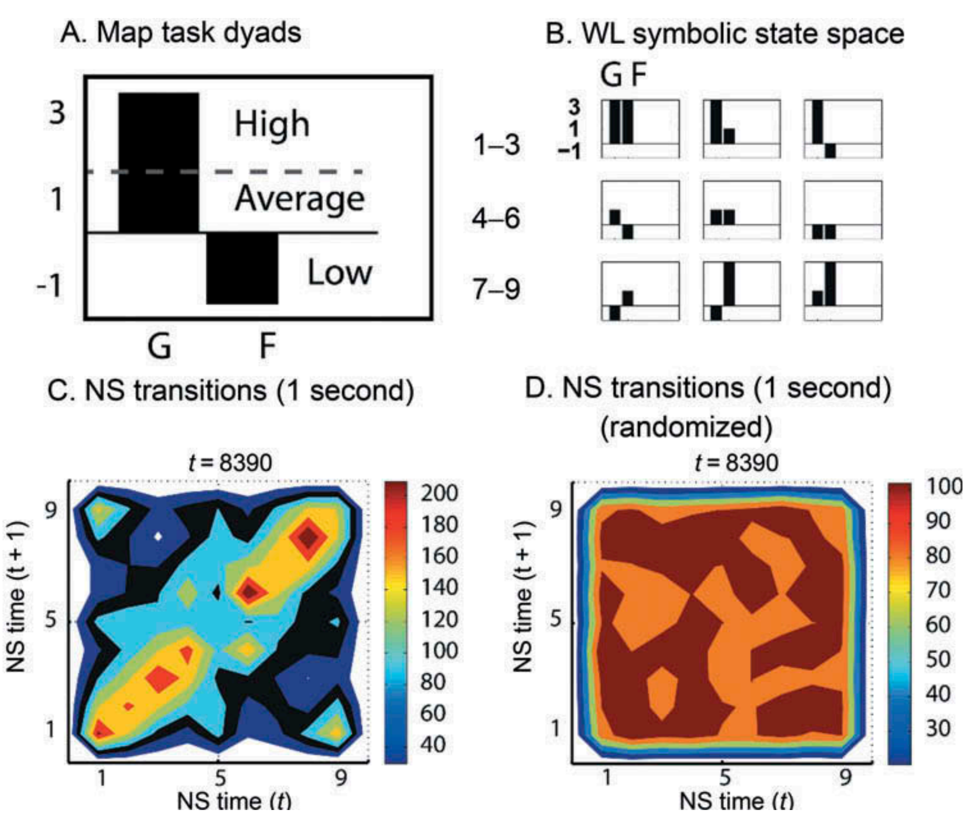

Figure 3. Structural properties of NS streams. (A) Levels of EEG-WL were extracted from raw EEG signals and partitioned into high, average, and low categories (G = Giver, F = Follower). (B) An ANN-generated nine-symbol state space map shows the possible combination of EEG-WL levels. (C) The transition frequencies are shown from the time *t* symbol number (x-axis) to the time *t* + 1 second symbol number (y-axis). (D) The symbol stream in (C) was randomized before creating the transition map.

the NS represented the state G^{l} F^{l}. This topology helps interpret the structure and dynamics of NS data streams, particularly when teams with more than two members are involved. The primary data source for further analysis was the second-by-second sequence of NS symbols which for EEG-WL and EEG-E are abbreviated NS_WL and NS_E, respectively.

Our goal was to develop neurodynamic measures that have structures which convey information regarding the organization, function, and performance of teams. Structure in this context refers to a pattern of relationships among entities which in our studies consist of a series of symbols representing the neurodynamic state of the team around a particular construct like EEG-WL.

The short-term structure in the neurodynamic data streams of the entire MT data set (8980 epochs) is shown in Figure 3C. This transition diagram plots the NS being expressed at time t vs. that expressed 1 second later (i.e., $t + 1$). The nonrandom arrangement of the NS in the data stream is seen by comparing this figure with one where the NS data stream was randomized prior to plotting the transitions (Figure 3D). The NS data structure was highlighted by the diagonal, suggesting a short-term persistent component. The thickness of the diagonal indicates there were also transitions from NSs to their immediate neighbors on the linear ANN topology map. The transitions on the diagonal were also expressed at different frequencies, with the NS #8–NS #8 transition being particularly frequent, while the NS #5–NS #5 transitions were less common. Thus, within the data stream, some NS repeats were more common than others and these differences may have significance (i.e., information) regarding the performance.

Fluctuations in the mix of symbols in the second-by-second data stream were then used to identify these possible "interesting periods" of team organization. These fluctuations were detected and quantified by measuring the Shannon entropy (Shannon & Weaver, 1949) of the symbol stream over a sliding history window, where the entropy was first measured over the initial 70 seconds. Then, at subsequent seconds, the window was shifted removing the first symbol and appending a new one at the end, the entropy was then recalculated. In this context, if a segment of the data stream had a random mix of nine NSs, the entropy would be 3.17, while if the symbol number in this data stream was restricted to only five of the nine (i.e., more symbol persistence or organization), the NS_WL entropy level would drop to 2.32 (Figure 4A and B). The working range of NS entropy values that we have found in this study are shown in the shaded rectangle.

The entropy values themselves provide no information on the nature of the organization, only that there was

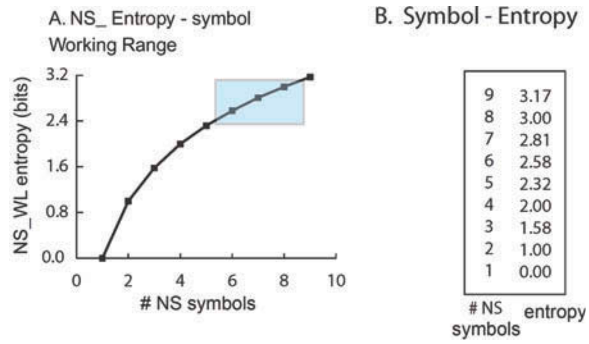

Figure 4. Properties of NS_WL entropy. (A) The bits of NS_WL entropy are plotted against the number of symbols they represent; the shaded panel shows the range of values observed. (B) A tabular representation of panel A.

greater or lesser organization. The organizational specifics of these segments, however, can be deduced from the symbolic state space maps like those in Figure 3B.

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

The dynamics are temporally plotted for each speech transaction defined as sub-dialogues that accomplish one major step in the plan for achieving the task. A typical transaction gets the F to draw one route segment on the map. For instance, the phrases "(G) Do you have Abandoned Truck? (F) Ya, (G) You should end at the K of the Abandoned Truck" are an example of a transaction. Figure 5B plots the time for each transaction (solid blocks) and below this are the individual mouse clicks used by F when drawing.

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

The NS_WL entropy levels began the performance around 2.7 bits (or about 6.5 symbols), representing a

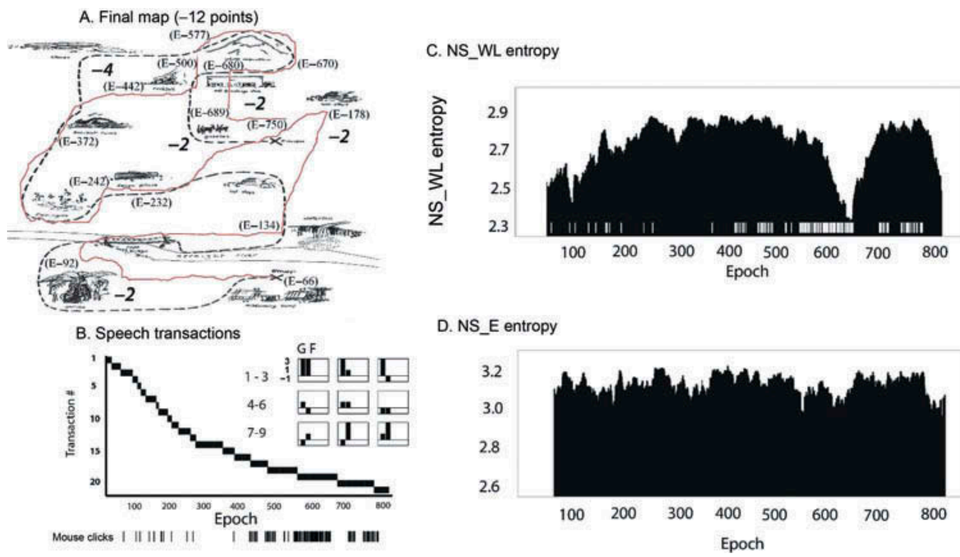

Figure 5. Linking the neurodynamics of EEG-WL and EEG-WL with speech and MT events (Performance G4S1). (A) The final map showing the places where points were deducted; (B) The timing of the teams' speech transactions with the Follower's mouse clicks shown below; (C) Histogram plot of NS_WL entropy (black) and mouse clicks (white); (D) Histogram plot of NS_E entropy. An expanded version of this figure can be found in the supplemental materials at http://dx.doi.org/10.1080/17470919.2014.883324

restricted use of the symbol space, and then increased over 300 seconds, reaching an average of 3.02 bits. These early-session dynamics were seen in 5/15 MT performances, and have also been seen in other teamwork situations; they may suggest a team establishing a rhythm.

Most MT performances also showed context-related NS_WL entropy dynamics occurring when the F had difficulty drawing with the mouse. This contextual change in the task was an unintended consequence of having the Fs draw their paths on a computer. Occasionally, the mouse drawing was delayed due to the microprocessor overload caused by both the EEG acquisitions as well as the video recording, and during these delays, the users often repeatedly clicked the mouse. Segments with large numbers of mouse clicks are easily visualized (Figure 5C); this occurred near epochs 550–700 for this team. When this occurred. it disrupted the transaction times (Figure 5B) and changed the organization of the team, as reflected by the decreased NS_WL entropy.

Entropy values, on their own, indicate that there are changing system dynamics, but they do not indicate the nature of the changes; this step requires a temporal mapping of the NS expression. Figure 6A shows the NS_WL entropy profile aligned with the sequential mouse clicks (Figure 6B) and NS_WL symbol expression (Figure 6C), where a mark indicates which NS is being expressed at each second. During the first 200 seconds, there was an overexpression of NS #6 and #4 (52% and 55% of the total performance numbers, respectively) which, referring to the nine-symbol state space, represented periods where the EEG-WL of both G and F was low (G^{l} F^{l}, NS #6) or where G was average and F was low (G^{a} F^{l}, NS #4), i.e., the team was not working hard.

This was directly confirmed from the moving average profiles of the raw EEG-WL in Figure 6C and D, where, for much of this time, both team members were 1 SD below the means (indicated by the gray bars).

Between epochs 600 and 700, when the NS_WL entropy was lowest, the total EEG-WL moving average values of the F exceeded 1 SD, while those of the G were average/below average; again, these values correspond to NS #8 & #9, which predominated during this period.

The dynamics for a second performance are shown in Figures 7 and 8. This was one of the more successful teams with only two points being deducted (Figure 1D). Around epoch 185, the F began having drawing difficulties, which were paralleled by a temporary lengthening of the speech transaction time (Figure 7A) and a decrease in the NS_WL entropy (Figures 7B). The profile of the entropy for EEG-E, NS_E entropy, (Figure 7C) did not show a similar decrease at this time.

In Figure 8, the NS_WL entropy profile in panel (Figure 8A) has been shaded to highlight periods where there was no speech (light gray), where G was speaking (dark gray) or where F was speaking (black). With the

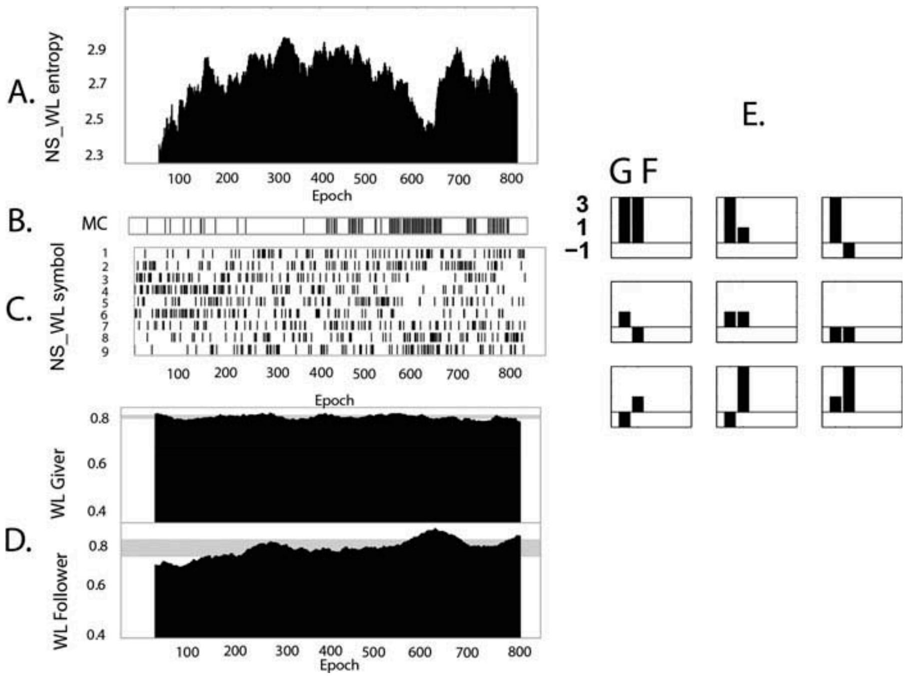

Figure 6. Dynamics of NS WL metrics for team G4S1. (A) This panel plots the NS_WL entropy levels using a 70 second backward moving average; (B) This panel plots the individual mouse clicks of the Follower; (C) The expressions of individual NS_WL symbols are plotted each second; (D) This panel plots the EEG-WL levels for the Giver (top) and the Follower (bottom) using a 70 second backward moving average; (E) The NS_WL symbolic state space is shown for comparisons with panel C.

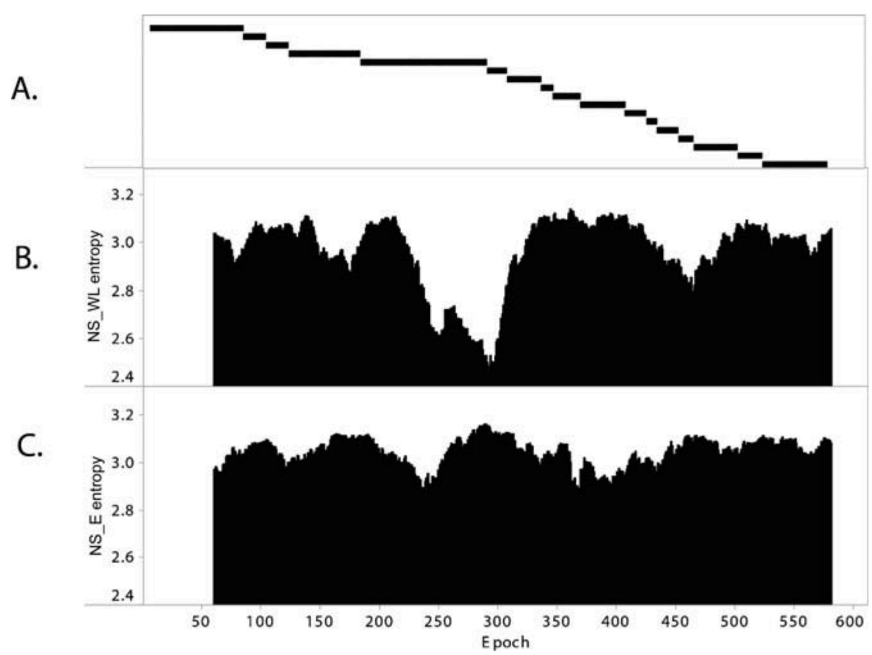

Figure 7. Linking NS_WL and NS_E entropies with speech transactions (Performance G5S2). (A) The timing of the teams' speech transactions; (B) Histogram plot of NS_WL entropy, and; (D) Histogram plot of NS_E entropy.

onset of drawing difficulties, as indicated by the increasing mouse clicks (Figure 8B), there was little speech, and NS_WL entropy first rose and then steadily declined. During this reorganization, the NS_WL symbol expression switched from predominantly NS #1 and #2 to NS #6, 7, and 8, representing a switch from a pattern where

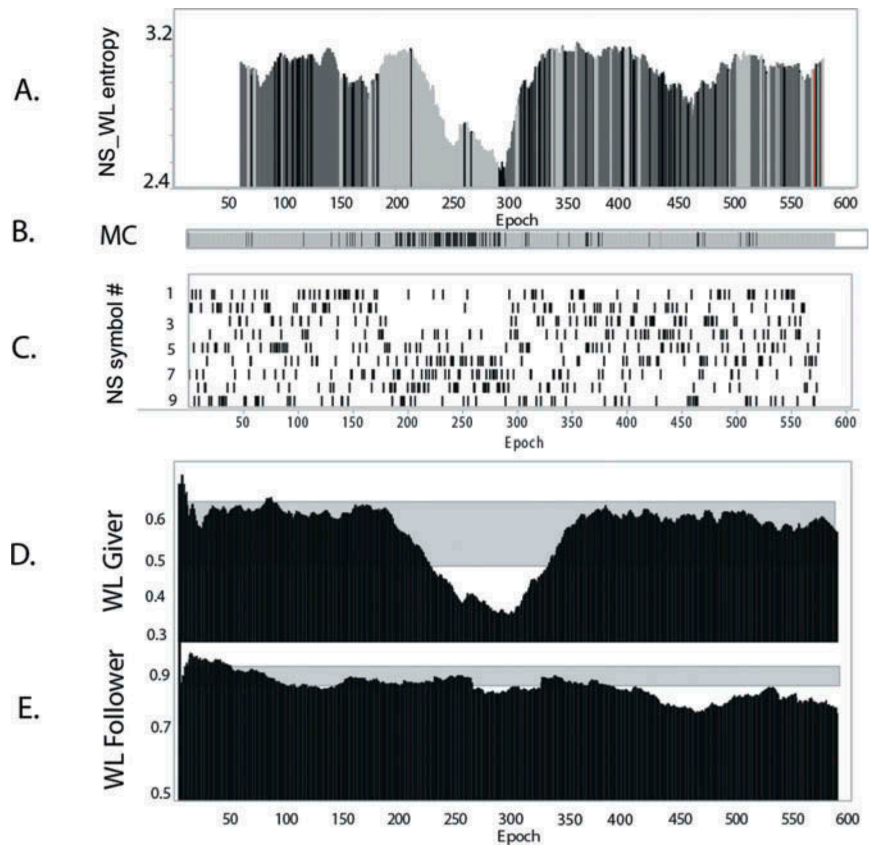

Figure 8. Dynamics of EEG-WL metrics for team G5S2. (A) This panel plots the NS_WL entropy levels using a 70 second backward moving average. The lighter areas are the periods when there was no speech; (B) This panel plots the individual mouse clicks of the Follower. (C) The expression of individual NS WL symbols are plotted each second; (D, E) These panels plot the EEG-WL levels for the Giver and the Follower using a 70 second backward moving average.

both members had high/average EEG-WL levels to one where G had below average EEG-WL levels; this pattern was repeated in the EEG-WL profiles of the G and F. A plot of the raw EEG-WL levels for G and F confirmed the symbolic interpretation (Figure 8D and E).

This pattern of NS switching was also repeated across the other performances where there were drawing difficulties and excessive mouse clicks that were paralleled by a decrease in NS_WL entropy (Figure 9). Higher frequencies of NS #6 to #9 were seen during the drawing disturbances, while the remaining epochs had higher frequencies of NS #1 to #5; these differences were significant (Chi-square = 47.4, df = 8, $p < .001$).

Lastly, we analyzed the relationship between session-aggregated NS_WL entropy levels and task performance. As described in the "Methods" section, the Human Communication Research Centre (HCRC) MT performances can be quantified by the degree of

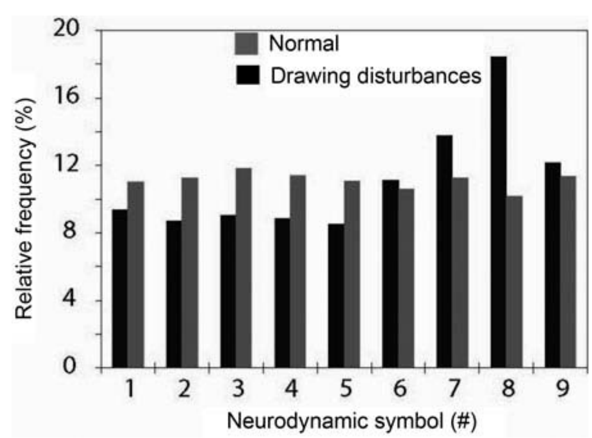

Figure 9. Differential distribution of NS_WL symbols during task contextual changes. The epochs associated with drawing difficulties were extracted from the NS data streams (n = 576 epochs) and the NS frequencies compared with those of the remaining data (n = 4086 epochs).

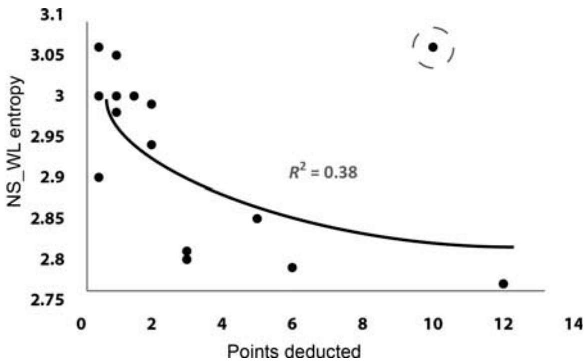

Figure 10. Correlation of team performance and NS_WL entropy levels. The NS_WL entropy levels averaged over each performance are plotted against the number of performance points deducted as determined by two independent raters. The dotted circle indicates an apparent outlier.

coherence between the G and F maps. In Figure 1A, for example, the path deviations around epochs 66–92, 178–232, and 372–442 would all lower the performance rating. Figure 10 plots the MT performance score (i.e., points deducted) for the teams against the resulting levels of NS_WL entropy. The curve shows that higher overall levels of NS_WL entropy were correlated with higher performance. In this analysis, a power law curve was the best fit for the data and the resulting correlation (R^2 = .38) was significant at the 0.01 level. There was one outlier in the data set, which represented a team that performed poorly yet had high NS_WL entropy levels. This correlation was not seen between the points deducted and the levels of the raw EEG-WL for the F (R^2 = 0.02), the G (R^2 = 0.00), or the average Workload of both (R^2 = 0.04).

Finally, in most performances, the neurodynamics of EEG-E were measured in parallel with those of EEG-WL. The overall NS_E entropy level was significantly higher (M = 3.06 ± .03 bits (SD)) than that of NS_WL (M = 3.00 ± .02 (SD) bits, t = 2.8, p = .02). The NS_E entropy levels were not decreased at the beginning of any performances or during periods when the F had drawing difficulties. Where the NS_E entropy fluctuations occurred (see Figures 5D and 7C), they were of smaller magnitude and shorter duration than those observed with NS_WL entropy, and were variably correlated with those of NS_WL entropy when measured at zero lag (r = .1 ± .29, range –.3 to + .5, n = 10).

DISCUSSION

This study describes an information and organization-centric framework for team neurodynamics, which can be flexibly applied across teaming environments. The framework is information–organization-centric, in the sense that raw EEG measures are converted into symbolic data streams from which information about the cognitive organization of the team is extracted.

Our first hypothesis was that NS data streams had structure, a broad term referring to the notion of patterns and relationships of entities. The entities in this study were symbols, which are an abstraction of the quantitative relationships between EEG-defined cognitive variables. One of the motivations for using symbols to describe these relationships is that the same approach can be used with teams of up to 6–8 persons by expanding the member representations within each symbol. The structure we observed was a simple persistent pattern, where many symbols repeated in sequence more often than expected, giving rise to a diagonal in the 1 second lagged transition matrices. The easy identification of this persistent structure also shows one of the advantages of the topology generated using a linear self-organized ANN for deriving the symbolic state space. This topology helped identify a second layer of structure where the next symbol in a sequence was not the exact symbol but one of the proximal neighbors in the state space; this was indicated in the transition map by the broadness of the diagonal. In addition to the “local” transitions, there were more distal transitions, the clearest example being the reciprocal transitions between NS #1 and NS #9. The relative frequencies of the different transitions in the map also provide information regarding the rhythm of the team on the task. For instance, there are relatively few repeating NS #5 symbols suggesting that these were times when the team was in transition. This symbol represents periods where both team members had average EEG-WL levels. The persistent structures that we see do not preclude the existence of more complicated hierarchical, nested, or longer-range structures present in other natural systems like nucleic acids or sentences. They do suggest, however, that there is information within the structure, which can loosely be thought of as messages or “interesting periods”, which may relate to teamwork events that affect the state of the system. This was borne out (1) by developing entropy profiles of the amount of mix of the symbols in the data stream and showing continually fluctuating values and (2) by relating these fluctuations to contextual disturbances (Hypothesis 2).

We found that contextual disturbances to the task had powerful effects on a team’s neurodynamic organizations. These disturbances arose as a consequence of having the Fs draw maps on their computer screens where the mouse would occasionally freeze. There were nine examples of these disturbances, providing multiple opportunities to describe the teams' neurodynamic responses when they encountered them as well as when they recovered from them. As shown in Figures 6 and 8, the changes in the NS symbol expression and the resulting entropy decreases during these periods were initially gradual, often spanning minutes, as the team developed a realization of the changing conditions. Once the mouse difficulties were resolved, the teams' NS_WL entropy levels rapidly (~30 seconds) increased, indicating that changing entropy fluctuations may be a quantifiable team dynamic. The largest magnitude of these drops was ~2.4 bits, which from Figure 4, would correspond to a reduction from the theoretical maximum of 9 NS_WL symbols to around 5.5, representing a shrinkage of about 40% of the state space.

Why do such organizations develop, especially during periods of uncertainty or stress like those experienced by the MT teams? One answer is that it is an energy savings/efficiency device, i.e., self-organization of complex systems often results in a lowering of the number of degrees of freedom and reduced system entropy (Guastello et al., 2013). When one complex system (task) interacts with a second complex system (team), it is difficult to reduce the constraints of the task when difficulties occur, but the degrees of freedom of the interactions of the team members can be reduced by mutually agreeing on a new plan. This is the essence of team safety and resilience, which (Hollnagel, Woods, and Levinson 2006) views resilience as "…how well a system can handle disruptions and variations that fall outside the base mechanisms/models for being adaptive as defined in that system." This means a team will most clearly demonstrate resilience when it encounters a disturbance outside the base task design. The difficulties experienced by the MT teams when drawing, would be such a disturbance and in all instances resulted in a substantial reorganization of the team that was seen as decreased entropy.

The differing frequency, magnitude, and duration of the entropy fluctuations, along with the findings in Figure 10 of a correlation between overall entropy levels and performance, suggests that team neurodynamic entropy may be a measure around which quantitative models of team performance can be developed (Hypothesis 3).

The changing dynamics of NS_Entropy in MT teams parallel those we have observed with military teams performing realistic simulations in ecologic settings (Stevens et al., 2012, 2013). Here the navigation simulations were divided into Briefing, Simulation, and Debriefing segments, i.e., the context of the task was changed by the training protocol. Much like we have seen with the drawing difficulties of MT teams, each of these simulation segments was characterized by different NS distributions reflecting different organizational states of the teams (Stevens et al., 2013) and these changes could be related to other measures like conversation and spatial proximity (Gorman, Martin, Dunbar, Galloway, & Stevens, 2013). The team neurodynamic modeling systems also rapidly detected periods of team uncertainty or stress on the navigation simulations and quantitatively distinguished the performances of expert submarine navigation teams and Junior Officers in training (Stevens et al., 2013).

Quantitative models for teamwork would have widespread applicability for training, for continued feedback and evaluation, and for increasing the overall resilience of teams. Teamwork is commonplace in most complex environments and the effects of decrements in team performance can range from inconvenient to catastrophic (Merket, Bergondy, & Salas, 1999). While much of the research on team safety has been retrospectively obtained from incident reports, more recently, researchers have begun to adopt a prospective approach to identify factors contributing to effective teams (Lamb, Jones, Steed, & Stevens, 2013). Many of these studies and environments could benefit from an unobtrusive and rapid and quantitative indicator of how a team is performing.

Our current model for describing the neurodynamics of teams is shown in Figure 11, where teams which are operating efficiently and effectively use the available cognitive states without becoming too rigid (i.e., deterministic) or too fluid (i.e., random).

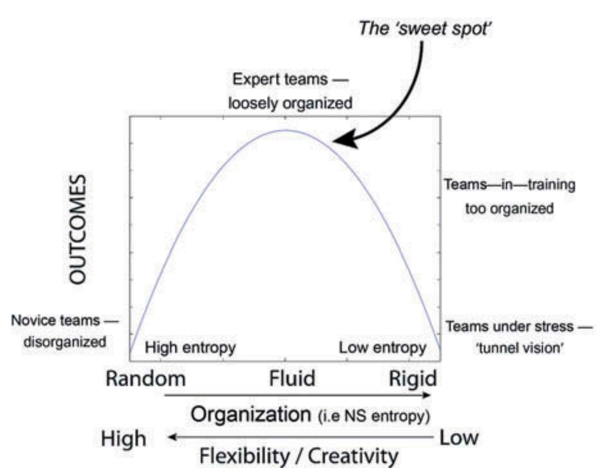

Figure 11. A complexity-based cognitive model for teamwork.

Contextual disturbances to the normal operating rhythm may, depending on team experience, shift the position of the team on this curve as they transiently reorganize to meet these new demands.

The challenges of using entropy as a performance metric for MT (and other team and task combinations) will arise from the exponential nature of the entropy scale and the limited range over which measurements would seem applicable. There was one outlier in our data set where the NS entropy level was very high, but the performance was rated low. This outlier in Figure 10 would be to the far left of the curve (i.e., random) in Figure 11, approaching that of a random performance. In MT, we saw no examples of teams to the far right side of the curve (too organized, deterministic), as we have seen in submarine teams when stressed (Stevens, 2012); this may be due to how importantly the teams viewed the consequences of the performance outcomes, which were high for the submarine navigation teams and low for the MT teams.

From the entropy profiles, there are multiple loci and measures for developing within-task quantitative models from NS_WL entropy fluctuations (Figure 12). The magnitude and duration of the entropy fluctuations have already been mentioned as loci affected by external perturbations, and as shown in Figure 8C, these often represented a succession of incremental changes resulting in a new organizational state of the team. While these states were ones the team had visited before, they now become more persistent, lasting up to several minutes.

The recovery rate is considered as the time needed for the team to return to their normal operating rhythm and organization after a perturbation to the system, and this can be very rapid (up to 4× faster than the entropy decline), returning to maximum entropy within 30 seconds of the removal of the perturbation. Finally, the idea of a tipping point stems from the

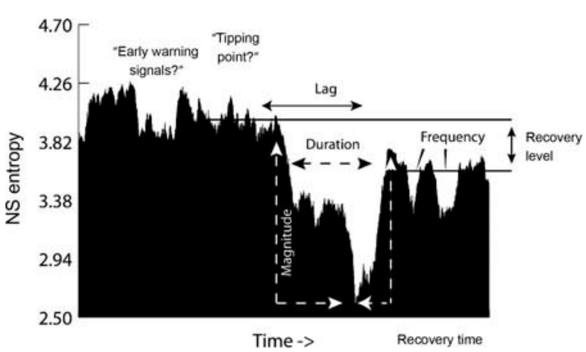

Figure 12. Potentially useful metrics for quantifying NS entropy fluctuations.

work of Scheffer and coworkers (2009) on Critical Transitions. The idea here is that gradual changes to the system, not overtly obvious, increase system fragility to the point that a small additional change propels the team to the tipping point where a transition to an alternative state or regime shift occurs. This may suggest the existence of early warning signals that could provide a predictive horizon, perhaps not for external disruptions like the drawing problems in the MT but for more endogenous perturbations like those seen with military teams.

The above discussions describe *how* neurodynamics can be used in the context of teamwork to develop models of team performance, but an equally important question is: *Why* does it work? How can neurodynamics provide informative team models across teams, tasks, and perhaps time scales? We believe that this results from the hierarchical arrangement of teams with individuals working in smaller, specialized units that are themselves nested within larger units. Recent multifractal analysis (Likens, Amazeen, Stevens, Galloway & Gorman, in press) of the NS_E and NS_WL data streams suggests that the neurodynamic models may capture basic neurologic–cognitive processes that span seconds to hours of the team training hierarchy. Here interbrain coordination dynamics (Hasson, Ghazanfar, Glantucci, Garrod, & Keysers, 2011), become linked across the whole team in response to the task demands and these give rise to the NS entropy fluctuations, which are themselves nested (and fractal) such that the second-by-second changes reflect rapidly occurring team events, while longer-lasting fluctuations parallel larger task segments or significant external perturbations to the team. In this way, the magnitude, duration, and frequency of major NS entropy fluctuations that are summed across a team's performance contribute to the observed performance differences.

A final finding was that the overall NS_E entropy values were higher than those of NS_WL entropy in all teams, and there were no major fluctuations in the NS_E levels directly associated with the drawing difficulties. This suggests that the cognitive organizations we are observing around the construct of EEG-WL are not brain-wide phenomena. This finding that the most revealing team neurodynamics for the MT are seen with EEG-WL is interesting as this is opposite to what we have seen with submarine navigation teams, where the major reorganizations were EEG-E-related (Stevens, 2012). In retrospect, this may reflect the nature of the tasks. According to the EEG developers, EEG-E is related to processes involving information gathering, visual scanning, and sustained attention, and while MT requires substantial computer screen scanning, team members have independent screens with little coordinated image scanning, i.e., viewing remains an individual, not a team task.

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