Can Neurophysiologic Synchronies Provide a Platform for Adapting Team Performance?

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Abstract. We have explored using neurophysiologic patterns as an approach for developing a deeper understanding of how teams collaborate when solving time-critical, complex real-world problems. Fifteen students solved substance abuse management simulations individually, and then in teams of three while measures of mental workload (WL) and engagement (E) were generated by electroencephalography (EEG). High and low workload and engagement levels were identified at each epoch for each team member and vectors of these measures were clustered by self organizing artificial neural networks. The resulting patterns, termed neurophysiologic synchronies, differed for the five teams reflecting the teams' efficiency. When the neural synchronies were compared across the collaboration, segments were identified where different synchronies were preferentially expressed. This approach may provide an approach for monitoring the quality of team work during complex, real-world and possible one of a kind problem solving, and for adaptively modifying the teamwork flow when optimal synchronies are not frequent.

Keywords: Collaboration, EEG, Neurophysiologic synchrony.

1 Introduction

A current challenge in studying collaborative teamwork is the measurement of team cognition and the separation of it from aspects of individual cognition [16]. Research on teamwork and cooperative behaviors often adopts an input-process-output framework (IPO). In this model the interdependent acts of individuals convert inputs such as the member and task characteristics to outcomes through behavioral activities directed toward organizing teamwork to achieve collective goals. These activities are termed team processes and include goal specification, strategy formulation, systems and team monitoring, etc [15].

Much of this teamwork research has made use of externalized events focusing on *who* is a member of the team, *how* they work together and *what* they do to perform their work. The studies often rely on post-hoc elicitation of the subjective relationships among pertinent concepts. There have been fewer studies looking at the *when* of teamwork interactions although the dynamics of team function are known to be complex [4] with temporal models of teamwork suggesting that some processes transpire

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more frequently in action phases and others in transition periods [1-5]. Closely related to team processes are dynamic states that characterize properties of the team that vary as a function of team context, inputs, processes and outcome. Emergent states describe cognitive, motivational and affective states of teams and can serve both as outputs and inputs in dynamic IPO models. When viewed this way, the focus shifts to when and how fast activities and change occur, and the variables move from amounts, dependencies and levels to pace, cycles and synchrony [6].

One framework for studying the *when* of team cognition is macrocognition [7] which is defined as the externalized and internalized high-level mental processes employed by teams to create new knowledge during complex collaborative problem solving. External processes (processes occurring outside the head) are those associated with actions that are observable and measurable in a consistent, reliable, repeatable manner. Internalized processes are those that cannot be expressed externally and are generally approached indirectly through qualitative metrics like think aloud protocols or surrogate quantitative metrics, (pupil size, EEG metrics, galvanic skin responses). To our knowledge, there have been no reports linking neurophysiologic correlates of internalized processes across members of a team as they engage in teamwork tasks. This however would seem to be an important contribution to the goal of better understanding the construct of team cognition.

Our hypotheses is that as members of a team perform a collaborative task each will exhibit varying degrees of cognitive components such as attention, workload, engagement, etc. and the levels of these components at any one time will depend (at least) on 1) what that person was doing at a particular time, 2) the progress the team has made toward the task goal, and 3) the composition and experience of the team. Given the temporal model of team processes, some of the balances of the components across team members may also repeat as different phases of the task, like data acquisition, or communication are repeatedly executed. In this study we have directly tested these hypotheses using EEG measures of mental workload and engagement.

2 Tasks and Methods

2.1 IMMEX Substance Abuse Simulations (*SOS*)

The collaboration task is an IMMEX™ problem set called *SOS* which are a series of substance abuse simulations cast in a reality show format [8-10]. The case begins with a short introduction to a person who may / may not be abusing drugs. The challenge for the student is to gather sufficient information about this person to answer the question "Should this person seek help, and if so, from whom?" The primary interface is a timeline that covers up to twelve specific events (such as health, job, social school, etc. related activities) and drilling down into this interface provides information in eleven areas with contents covering subject history, behavior, medical data and conjecture, and help. These 600+ content items are divided into social and scientific areas allowing the student to gather information from many perspectives. Prior modeling studies have shown that ~20% of the students use science-only approaches, ~40% will use social approaches, and ~40% will use a combination of the two. This task provides a convenient mechanism for the division of teamwork (i.e. social vs. scientific evidence), as well as a potential source of conflict within the group as to what evidence is important relative to the decision.

Experimentally, students log on to IMMEX™ and individually perform a *SOS* simulation so that each can develop a mental model of the problem space, and so that individual levels of EEG-related workload and engagement can be determined. Two students then log on to a second *SOS* problem set where Member A selects data from the timeline and reports information from General Health, Anecdotes and Cell & e-mails (i.e. the social perspective), Member C selects data from all the other science categories and reports them to the group (the science perspective) and the leader (Member B) integrates the information and decides when to make a decision, and what the decision will be. The time allowed is 30 minutes (a time constraint).

2.2 EEG Metrics

The EEG data acquired from the wireless headset developed by Advanced Brain Monitoring, Inc. uses an integrated hardware and software solution for acquisition and real-time analysis of the EEG. It has demonstrated feasibility for acquiring high quality EEG in real-world environments including workplace, classroom and military operational settings. The system contains an easily-applied wireless EEG system that includes intelligent software designed to identify and eliminate multiple sources of biological and environmental contamination and allow real-time classification of cognitive state changes even in challenging environments. The 9-channel wireless headset includes sensor site locations: F3, F4, C3, C4, P3, P4, Fz, Cz, POz in a monopolar configuration referenced to linked mastoids. ABM B-Alert® software acquires the data and quantifies alertness, engagement and mental workload in real-time using linear and quadratic discriminant function analyses (DFA) with model-selected PSD variables in each of the 1-hz bins from 1-40hz, ratios of power bins, event-related power (PERP) and/or wavelet transform calculations.

To monitor "mental workload" (WL) and "engagement" (E) using the B-Alert model EEG metrics, values ranging from 0.1-1.0, are calculated for each 1-second epoch of EEG. Simple baseline tasks are used to fit the EEG classification algorithms to the individual so that the cognitive state models can then be applied to increasingly complex task environments, providing a highly sensitive and specific technique for identifying an individual's neural signatures of cognition in both real-time and offline analysis. These methods have proven valid in EEG quantification of drowsiness-alertness during driving simulation, simple and complex cognitive tasks and in military, industrial and educational simulation environments, quantifying mental workload in military simulation environments, distinguishing spatial and verbal processing in simple and complex tasks, characterizing alertness and memory deficits in patients with obstructive sleep apnea, and identifying individual differences in susceptibility to the effects of sleep deprivation [11-13].

2.3 Experimental Protocol

The data flow (Figure 1) is organized into Collection, Processing, Modeling and Analysis modules. The teams perform the *SOS* collaborative tasks while EEG is being collected at 256 Hz from 6-electrode portable headsets. The data Collection initiates

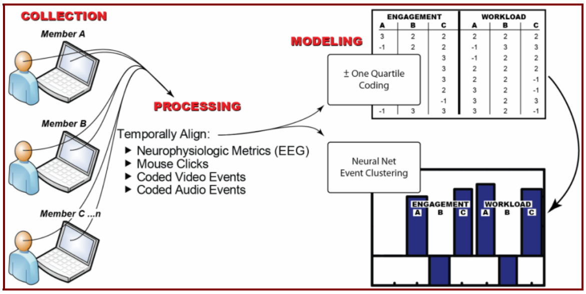

Fig. 1. Outline of Experimental Protocol

with the start of the *SOS* simulations on the time synchronized computers of the two team members. The computers also run Morae (Techsmith, Inc.) which records a video and audio trace of each participant and generates logs with timestamps of mouse clicks screen refreshes, etc. The Processing module aligns the EEG logs containing the second-by-second WL and E values from each of the three team members and interleaves them with mouse clicks logs and video/audio logs.

The values of WL and E were determined for the individual performances of each student, as well as for each student during the collaboration event. As shown in Figure 2, IMMEX tasks are complex eliciting more WL from the students than on a 3-choice vigilance task (3-CVT) baseline task. The subjects also expend more WL in a teamwork situation than they did when performing the task individually, which may relate to the process cost of collaboration discussed by others [16].

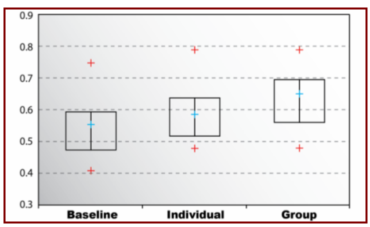

Fig. 2. EEG-WL Levels During Baseline, Individual and Group Conditions. The levels of WL were calculated for 15 individuals on a 3-CVT task, during an individual performance of an SOS problem, and during a 3-person team performance.

The values of WL and E were then normalized for each team member by statistically partitioning them into the upper quartile, the lower quartile, and the half in the middle representing high, low and average levels of WL and E. These partitions were assigned the values 3, -1, and 2 and were combined for each of the members of the team to create training vectors (Figure 1, Modeling) for training self organizing artificial neural networks (ANN) as previously described [8,9]. This process results in patterns of WL and E measures across the members of the team on a second by second time scale. We define these epochs of alignment as neurophysiologic synchronies.

3 Experimental Results

3.1 Team Differences in Neurophysiologic Patterns of Collaboration

We first examined the performances of five collaboration groups to identify common and dissimilar neural synchronies (i.e. combinations of WL and E across team members) across teams. An example of this analysis is shown in Figure 3 where an ANN was trained with the neural synchronies from 5 different groups. The output from such an analysis is a series of ANN nodes each representing a synchrony with a different profile of neurophysiologic indicators. After training, twenty three of the twenty five nodes contained between 37 and 562 epochs with different patterns of neurophysiologic synchrony of WL and E. The most common synchrony was represented by nodes 14 and 8 which consisted of epochs where all members were engaged and working at moderate to high levels. This may represent the nature of the IMMEX task itself which requires more workload than simpler image identification tasks [18]. Other frequent synchronies were nodes 23, 4, and 2 where one of the members was either not working hard or not highly engaged.

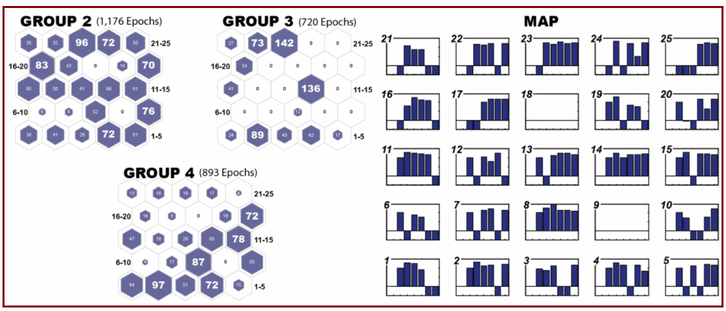

Fig. 3. Neural Synchrony Patterns across Teams. A self organizing ANN was trained with the collaboration performances of 5 teams and retested with the individual performances. The numbers in the hexagons reflect the number of times the pattern was repeated during the task.

When the different teams were tested on this combined ANN they showed significant differences in the proportions of neural synchronies being expressed. Group 3 for instance showed a pattern of synchronies restricted to only half of the neural network nodes. Many of the epochs reflected times where the whole team was engaged or working, or where only Team Member A was minimally engaged (i.e. node 23). Group 4 in contrast showed a greater diversity of neurophysiologic synchronies. There were few epochs clustered at node 23 and instead showed more epochs at nodes 1 and 2 where the common feature was low engagement of the Team Leader, and nodes 10, 15 and 20 where Team Member B was not engaged. Group 2 was more diverse still showing similarities with both Group 3 (i.e. node 23) and Group 4 (i.e. nodes 4, 10 and 13).

3.2 Do Common Neurophysiologic Patterns Have Collaborative Significance?

During collaboration effective teams execute processes that often occur in a cyclical fashion depending on task demands. In a second set of studies we tried to determine if the different patterns of WL and E expression across the team had significance vis a vis the collaboration event. Most team tasks, including the IMMEX problem solving tasks, can be separated into segments consisting of mental model formation, mental model sharing and integration, and mental model consensus and revision. These can be further divided into behavioral episodes relating to team processes. Figure 4 shows the task breakdown for one collaborative team (Group 2) (1178 epochs or seconds duration). The tasks included the reading of the task and initial discussions, explorations of the problem space, deriving a consensus regarding the decision, etc. We have highlighted these tasks by the different stages of mental model formation, sharing and integration, and convergence and revision. The epochs reflecting different team synchronies were temporally aligned with the collaborative events. The most common synchrony (113 epochs) showed limited mouse click activity, all three members were experiencing elevated WL and the Team Leader and Member C were highly engaged.

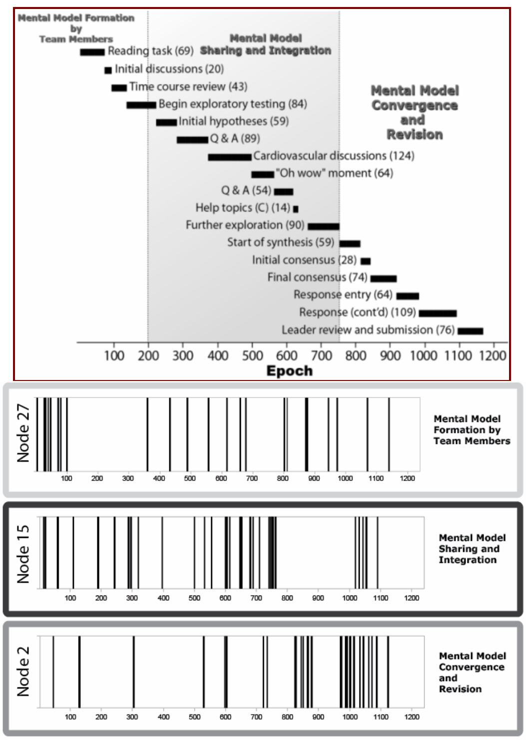

Fig. 4. (Top) Team Behaviors during a Sample *SOS* Collaboration Session. The numbers in parentheses indicate the number of epochs for each task. (Bottom) Selective expression of neurophysiologic synchrony patterns during different segments of the collaboration task.

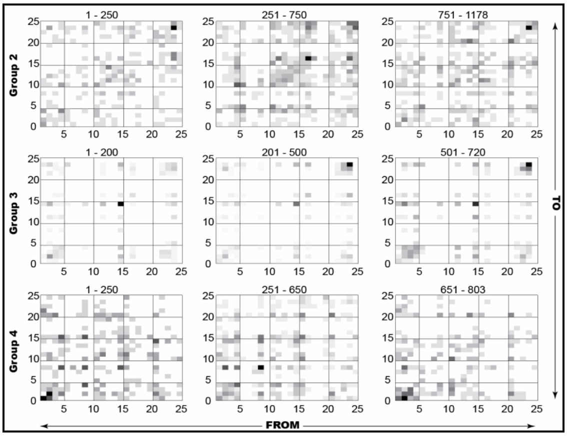

Fig. 5. Temporal Analysis of Nodal Transitions. A nearest neighbor correlation analysis was performed for the beginning, middle and end of the collaborations for three groups. The diagrams show the transitions from one nodal pattern (X-axis) to another (Y-axis).

This profile was present throughout the collaborative task and may reflect a common feature of this team's interaction. In this regard, examination of the video log indicates that interactions between the leader and team member A were less frequent than interactions with team member C. Neurophysiologic synchronies identified by other neural network nodes were more selectively expressed during the task with some being preferentially expressed during the mental model forming stage whereas others were more prevalent during the mental model convergence and revision stage (chi square = 1291, p=< 0.001).

A second approach examined the autocorrelations of the synchronies with a time lag of 1, i.e. a sequential nearest neighbor analysis asking 'If a synchrony pattern is being expressed, what pattern is likely to follow next?' The diagrams in Figure 5 are called From >To diagrams and indicate the transition from a node on the X axis to a node on the Y axis. Similarly, to determine how a node was arrived at, a Y value can be traced across the X axis. Figure 5 shows such an analysis for Groups 2, 3 and 4. To relate the correlations to different stages of the collaborative task, the analyses were repeated for the early, middle and late epochs of the teamwork as indicated by the epoch numbers above each diagram. Group 2 showed the lowest From-> To correlations (-.14, .19 and -.25 for the early, middle and late epochs), had the lowest proportion (12%) of synchronies where all members were simultaneously engaged and working (i.e. nodes 8 and 14), and also took the longest to complete the task. The most frequent patterns were where the E of Team Member A was low while the other members were fully engaged and working. Group 3 showed the most restricted pattern of synchrony, had the highest From->To correlations and the highest proportion of synchronies (19%) where all members were fully engaged and working. The transition from Node 14 to 14 dominated early during the collaboration, and transited to a Node 23->23 transition indicating a state where the engagement of Team Member A was reduced while the others were engaged and working. The autocorrelations were .77, .58 and .75 respectively for the early, middle and late epochs of the collaboration.

In this group Team Member A also had the lowest overall WL and E levels and ordered fewer items during the simulation than did the second team member (186 vs. 234 tests ordered). Of the five teams tested, Group 3 was the most effective as judged subjectively from the video logs, as well as objectively with the most rapid solution time (11 minutes), and the final answer.

Group 4 displayed an intermediate diversity of neurophysiologic synchronies compared with the other groups and this was also reflected in the From->To correlations. The dominant nodal patterns were nodes 1, 2 and 8, where node 8 is similar to node 14 with all members are engaged and working, and this constituted 15% of the total number of epochs. During the initial part of the teamwork the time-lagged correlation was .22 indicating a less stable pattern than for Group 3. The major nodal transitions were from nodes 1 to 1 and nodes 2 to 2, and the common feature of nodes 1 and 2 is the decreased WL levels in the Team Leader. During the middle portion of the teamwork the nodal correlations increased to .59 with the dominant repeating nodes being 8 and 4. During task closure the timed lagged correlation dropped to .44 the repeating node 8 transition decreased and the transition from node 2 to node 1 returned. In Group 4, the Team Leader had the lowest overall WL of any of the team members and the second highest E levels.

4 Discussion

This study describes our preliminary efforts at determining if neurophysiologic synchronies can be observed during problem solving teamwork. We define neurophysiologic synchronies as the coordinated expression of different levels of neurophysiologic indicators by individuals of a team as they engage in collaborative activities. In this study we have used the neurophysiologic correlates of workload and engagement as defined by the B-Alert EEG system, although there is no a priori reason that other measures could not be used, or included. The studies to date, while involving only five teams, suggest that patterns of neurophysiologic synchrony can be observed in different teams which may have collaborative significance. An important next step is to link them to other collaboration behaviors, and an important challenge will be determining the granularity to conduct these studies. The enrichment of some patterns at the early and late stages of the teamwork suggests a temporally related contribution which may relate to different aspects of the collaboration task. A more granular approach would be to link the synchronies to common behaviors in IMMEX™ such as the ordering of tests by mouse clicking on menu items or other behaviors such as questioning, responding, etc. Such epoch “tagging” may facilitate categorizing the macrocognitive constructs that are occurring simultaneously such as synthesis, questioning, team consensus, revision / analysis, etc. Neurophysiologic synchronies may also be useful for adaptively establishing or modifying the balance of team members and their degree of participation. Situations where a member is consistently lower in WL and/or E while the other members are fully engaged and working hard may indicate a less effective team member. This may be particularly important as the efficiency of a team is in completing a task (as measured by time to completion) was proportional to the percentage of neural synchronies where all members are both engaged and working. (i.e. nodes 8 and 14). Another possible indicator of effective / ineffective teams may be the persistence of neural synchronization indicated by the degree of correlations between synchronies with a time lag of 1 epoch. These nearest neighbor correlations may indicate that a team state is more stable over a longer period of time, while teams with low or negative From -> To correlations may represent teams where the members are searching for an effective rhythm. The nodal neurophysiologic From -> To correlations may also make this approach amenable to the development of dynamic and predictive models either through Hidden Markov Modeling [9] or through a more dynamical systems approach such as phase space reconstruction [14].

Finally, the studies may also provide a tool for approaching the process cost associated with teamwork. Team workload is a core component of most theories of collaborative and cooperative learning, and is described as the resources available by a team for a task relative to the demands placed on it. As with individuals, team performance is presumed to deteriorate when the task demands exceed available resources. Experimental evidence suggests that this may be so, with the higher the workload of the least-loaded team member, the lower the team performance [17]. Many factors can contribute to the workload of a member of a team and the overall team functioning. At one extreme, the individual may have difficulty with his own task which would lead to individual task overload. Depending on the degree of critical nature of that task for the overall team goal, this may or may not have an effect on team outcome. At the other pole, there may be disruptions in the degree of information sharing leading to negative team performance.

Workload in teams, however, is complex and at its simplest consists of the workload of a team member on his/her individual task within the team (Task Awareness) as well as more of a team process workload (Teamwork Awareness) which relates to the resources required to be an active member of a team. While the ideas of workload and work overload are practically appealing, it has been difficult to derive quantitative measures of them. The results in Figure 2, suggest that the EEG-WL metric may provide a useful measure for this added cost.

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