Team Neurodynamics
by The
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Neurophysiologic Collaboration Patterns During Team Problem Solving

Ron Stevens,
Trysha Galloway,
UCLA/IMMEX
Project Culver City,
California

Chris Berka
Advanced Brain Monitoring
Carlsbad, California

Marcia Sprang
Placentia-Yorba Linda
Unified Sch. Dist.
Anaheim, California

Abstract. We have explored using neurophysiologic collaboration patterns as an approach for developing a deeper understanding of how teams collaborate when solving time-critical, complex real-world problems. Teams of three students solved substance abuse management simulations using IMMEX software while measures of mental workload (WL) and engagement (E) were generated by electroencephalography (EEG). Levels of high and low workload and engagement were identified for each member at each epoch statistically and the vectors consisting of these measures were clustered by self organizing artificial neural networks. The resulting cognitive teamwork patterns, termed neural synchronies, were different across six different teams. When the neural synchronies were compared across the team members of individual teams segments were identified where different synchronies were preferentially expressed. Some were expressed early in the collaboration when the team members were forming mental models of the problem, others were expressed later in the collaboration when the team members were sharing their mental models and converging on a solution. These studies indicate that non-random patterns of neurophysiologic synchronies can be observed across teams and members of a team when they are engaged in problem solving. 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.

Keywords. Collaboration, Teams, Problem Solving, EEG, Neurophysiologic synchrony.

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 such activities as 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 more frequently in action phases and others in transition periods [1-5]. Closely related to team processes are dynamic emergent 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 complex teamwork tasks. This however would seem to be an important contribution to the goal of better understanding the construct of team cognition.

Our hypotheses for this study 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 explored these hypotheses using EEG measures of mental workload and engagement.

TASKS AND METHODS

IMMEX Substance Abuse Simulations (SOS)

The collaboration task is an IMMEX™ problem set called SOS [8-10]. These are a series of substance abuse simulations that are cast in a reality show format. 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 content areas with 48 specific contents items covering subject history, behavior, medical data and conjecture, plus 39 help pages related to content items. These 600+ content items are divided into two major areas, social and scientific, 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. For the current studies, 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 which category of evidence is more 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 Student A selects data from the timeline and reports information from General Health, Anecdotes and Cell & e-mails (i.e. the social perspective), Student C selects data from all the other science categories and reports them to the group (the science perspective) and the third person (Student 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).

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].

Experimental Protocol

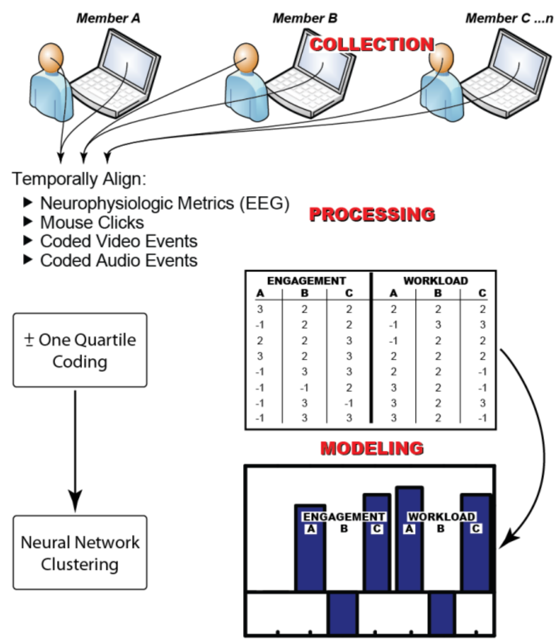

Figure 1. Outline of Experimental Protocol

The overall data flow is shown in Figure 1 and is organized into data Collection, Processing, Modeling and Analysis modules. The teams perform the SOS collaborative tasks as described above while EEG is being collected at 256 Hz from 6-electrode portable headsets. The data Collection initiates 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. Alignment accuracies of 10 milliseconds are typical.

The values of WL and E are then 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) used for baselining the subjects. Also from this figure it is apparent that the subjects expend more WL in a teamwork situation than they did when performing the task individually. This may relate to the process cost of collaboration discussed by others (16).

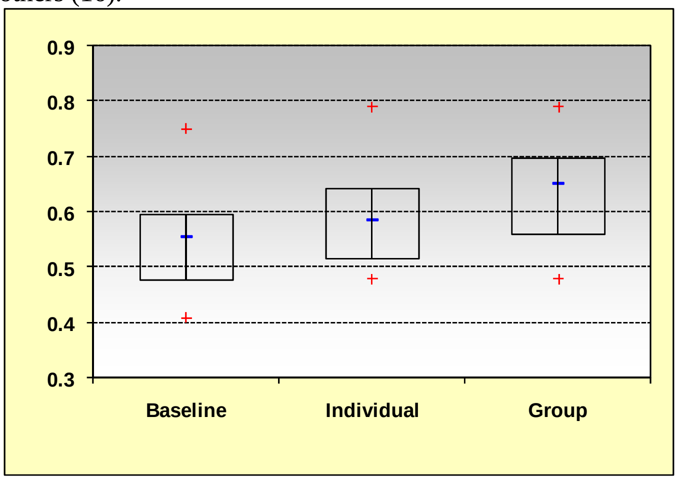

Figure 2. EEG-WL Levels During Baseline, Individual and Group Conditions. The levels of WL were calculated for 15 individuals on a 3-CVT task, during an individual performance of an SOS problem, and during a 3-person team performance.

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. 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.

EXPERIMENTAL RESULTS

Team Events During a Sample SOS Collaboration Session

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 six 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. Representative pattern profiles are shown in Figure 3 B. The most common synchrony was represented by node 14 and consisted of epochs where all members were engaged and working at moderate levels. Other common synchronies were nodes 23, 4, and 2 where one of the members was either not working hard or not highly engaged.

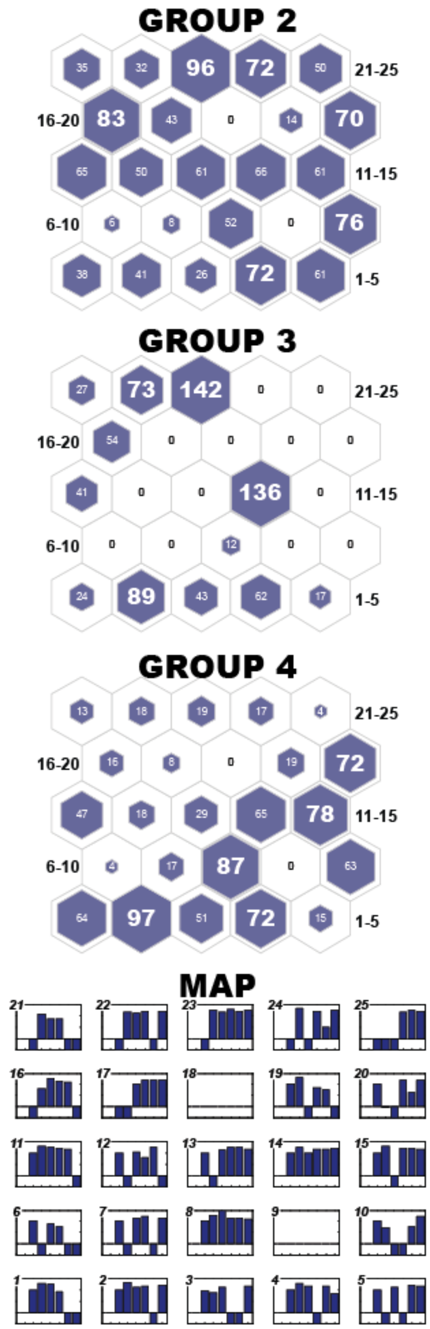

Figure 3. Neural Synchrony Patterns across Teams. A self organizing ANN was trained with the collaboration performances of 5 teams and retested with the individual performances. The numbers in the hexagons reflect the number of times the pattern was repeated during the task.

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 team member A was minimally engaged (i.e. node 23). Group 4 in contrast showed few epochs clustered at node 23 and instead showed more epochs at nodes 10, 15 and 20 where the common feature was low engagement of Team Member B.

Do Common Neurophysiologic Patterns Have Collaborative Significance?

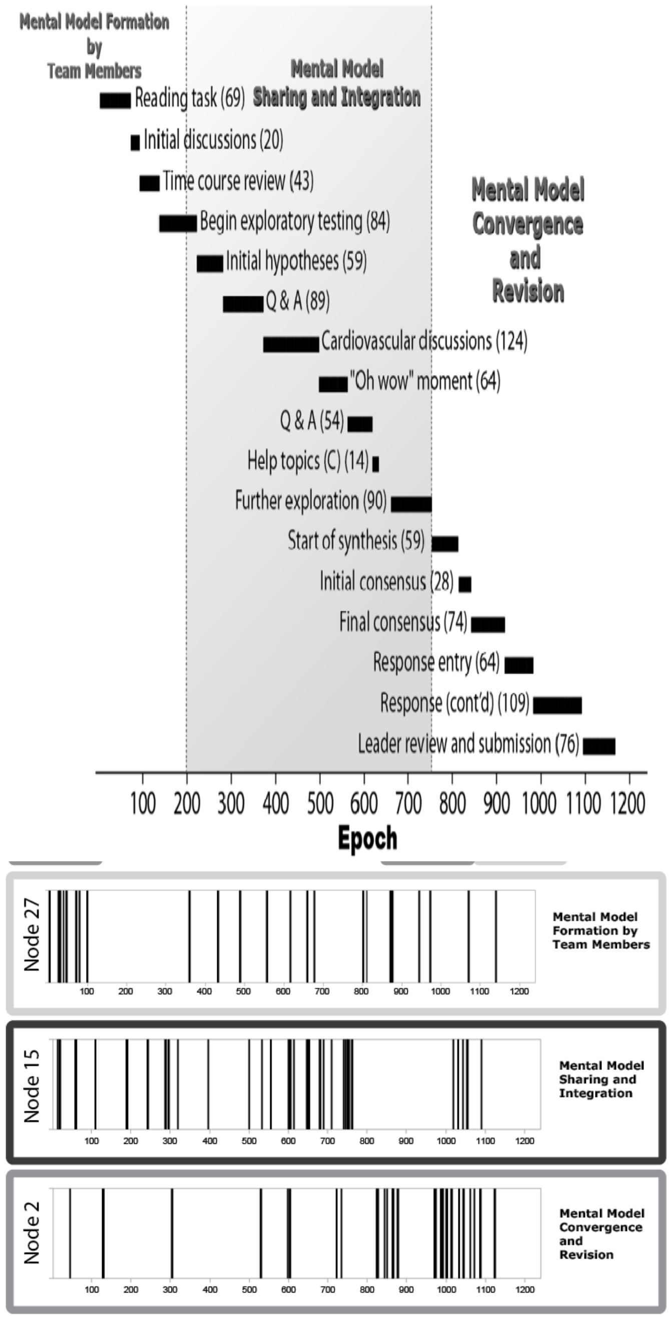

Figure 4. (Top) Team Behaviors during a Sample SOS Collaboration Session. The numbers in parentheses indicate the number of epochs for each task. (Bottom) Selective expression of neurophysiologic synchrony patterns during different segments of the collaboration task.

During collaboration effective teams often 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 members had significance vis a vis the collaboration event. Most team 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.

For these studies a different set of ANN were trained using the single trial of each team on the task. Instead of comparing across teams, the nodes were used to relate different team synchronies to particular parts of the collaborative event. Differences might be expected for instance between the portions of the task where the team was reaching consensus on a solution as opposed to when individual members were gathering data and reporting to the team leader. the most common synchrony pattern (113 epochs) showed limited mouse click activity, all three members were experiencing elevated WL and the team leader and member C were highly engaged. 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 synchronies 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). These are shown in the lower portions of Figure 4.

DISCUSSION

This study describes our preliminary efforts at determining if neurophysiologic collaboration patterns 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 measures of workload and engagement as defined by the B-Alert system, although there is no a priori reason that other measures could be used, or included. For instance, Feldman et al [18] used eye tracking to measure the number, and durations of eye fixations to derive evidence of the sharing of mental models across team members, and such measures could be included with our EEG metrics to expand the vectors for training and testing.

The studies to date, while involving only six teams, suggest that different patterns of neurophysiologic synchrony can be observed across teams and that they are most likely not random. An important next step is to link them to other collaboration behaviors, and an important question is the level of granularity at which to conduct these studies; should it be performed at the levels of minutes, several seconds, seconds, or less? The enrichment of some patterns at the early and late stages of the teamwork suggests a temporally related contribution which may relate to different stages of the collaboration task. Such stages could include the formulation of a search strategy, the derivation of a shared mental model, the changing of hypotheses as key pieces of information are obtained, etc. At a more granular level, one approach could be to link the synchronies to common behaviors in IMMEX™ such as the ordering of tests by mouse clicking on menu items. Preliminary studies indicate that while many neurophysiologic patterns were expressed in the absence of mouse clicks, others were more closely associated with these actions, suggesting an interaction may exist between this synchrony and a form of test ordering. As we refine coding of the collaborative sessions, we will extend this analysis to other behaviors such as questioning, responding, etc. Such "tagging" of the epochs may facilitate categorizing the macrocognitive constructs that are occurring simultaneously such as synthesis, questioning, team consensus, revision / analysis, etc. The nodal neurophysiologic profiles may also be 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].

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 of collaboration.

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