Team Neurodynamics

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INTRODUCTION

The ubiquity of teamwork in the workplace makes its optimization imperative, from the initial selection and training of teams to the on-the-job formative guidance and feedback. 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 which 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-team 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 is greater than the sum of its parts. Finally, teams are noisy in the sense that many actions may occur that are peripheral to the immediate task as the team develops consensus, shared mental models and shared situation awareness.

Unlike the performance evaluations of individuals where estimates of ability are common, there are few measures and models for rapidly and quantitatively comparing team process skills to help direct this guidance and feedback. Without the objectivity of quantitative measures of team processes it is difficult to approach deeper contextual understandings of team concepts like robustness and resilience, and even seemingly simple questions like 'How is this team doing?' can become difficult to answer.

The guiding hypothesis for this research is that when Electroencephalography (EEG) data streams from multiple team members are converted into symbolic representations of cognitive measures statistical regularities representative of the task and team actions can be isolated. In this way, the second-by-second sequence of symbols (termed Neurodynamic Symbols or NS) that arise during teamwork contain information relating to team performance much in the way that words in a sentence or the codons in nucleic acids convey information (Schneider, Stormo, Gold & Ehrenfeucht, 1986; Salem, 2011). This article provides supporting evidence for this hypothesis.

BACKGROUND

It is not surprising that neurophysiologic events are the underpinnings of the social coordination dynamics seen in teams, yet it is only recently that their evolving dynamics in real-world teamwork settings have begun to be modeled (Stevens, Galloway, Berka & Sprang, 2009; Stephens, Silbert, & Hasson, 2010; Dumas, Nadal, Soussignan, Martinerie & Garnero, 2010; Dodel, Cohen, Mersmann, Luu, Forsythe, and Jirsa, 2011, Stevens, Galloway, Wang, Berka, 2012; Stevens, 2012). Equally important has been the extension of the neurophysiologic studies of teams from the relatively short and controlled environments with repetitive tasks, to continuous monitoring in real-world settings with longer-lasting tasks. Advances in both areas have led to the emerging field of team neurodynamics.

Electroencephalography is often the tool of choice for studying team neurodynamics. 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. While EEG has traditionally been viewed as a tool for studying individual cognition in the milliseconds to seconds range, multiple investigators are extending this range to include teams operating over minutes or hours in military, educational and corporate environments.

Two complementary approaches are steering these efforts. The first seeks to establish linkages between specific neuromarkers and different behavioral, cognitive or emotional states; an example is the phi complex that may distinguish states of effective and ineffective social coordination (Tognoli, Lagarde, DeGuzman, & Kelso, 2007). These high spectral EEG neuromarkers show a topology consistent with the neuroanatomical location of the human mirror neuron system that is activated during intentional social coordination. Unlike EEG signatures that appear and disappear in response to many stimuli (e.g. P300), neuromarkers like the phi complex exist at a higher level of abstraction and are more targeted to subsets of behaviors. Such neuromarkers may not be precise analogs of the multiple ways that can be used to describe interactions or aspects of cognition but are close enough approximations to be useful for a better understanding of teamwork.

Such use of previously defined EEG neuromarkers for Engagement (EEG-E) or Workload (EEG-WL) (Berka, Levendowski, Cvetinovic, Petrovic, Davis, 2004) has been the approach used by Stevens et al (Stevens, Galloway, Berka, Behneman, Wohlgemuth, Lamb & Buckles, 2011; Stevens, Galloway, Wang, & Berka, 2012, Stevens, 2012, Stevens, Gorman, Amazeen, Likens & Galloway, 2013) to investigate team neurodynamics in settings as diverse as Submarine Piloting and Navigation by Navy teams and high school students scientific problem solving (Stevens & Galloway, 2014). The EEG system developed by Advanced Brain Monitoring, Inc. acquires the data from teams and quantifies the levels of engagement (EEG-E) and mental workload (EEG-WL) using proprietary model-selected PSD variables from each of the 1-Hz bins from 1 - 40 Hz. The two metrics have different functional properties and are poorly correlated; over six team member combinations the average R was -0.19 ± 0.24 . 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.

MODELING THE COMPLEX NEURODYNAMICS OF TEAMWORK

Compared with other teamwork modeling approaches like shared mental models (Entin & Serfaty, 1999), team cognition (Cooke, Gorman & Kiekel, 2008) and macrocognition (Warner, Letsky & Cowan, 2005), neurodynamics has the advantages of: 1) Speed – Neurodynamic measures can be modeled and reported within seconds; 2) Specificity – The signal spectra of different 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 dynamics resulting from the quantitative co-expression of an EEG-defined cognitive marker by different members of a team (Stevens et al., 2012; Stevens et al., 2013).

Complex systems theory is often used to understand how heterogeneous individuals and systems interact and evolve over time; it is based on the assumption that complex phenomena consists of groups of mutually linked elements. Given the complexity of the teamwork systems, the underlying neurophysiologic measures, and the nature of real-world tasks, a nonlinear dynamical analytic framework would seem an appropriate guiding framework. The resulting dynamical teamwork models are based around an information and organization-centric framework. 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. Unlike other teaming models that are specific for a particular task or related series of tasks, these models can be applied in many teaming environments.

Approach and Results

The overall idea is that (EEG) data streams from multiple team members once converted into symbolic data streams of cognitive measures, may contain statistical regularities representative of the ongoing task and team actions. 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).

Data from multiple time series can be difficult to manipulate, but when treated as symbols instead of numeric points it often becomes easier to mine them 7 more pages are available in the full version of this document, which may be purchased using the "Add to Cart" button on the publisher's webpage:

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