Operational Brain Dynamics: Data Fusion Technology for Neurophysiological, Behavioral, and Scenario Context Information in Operational Environments

Don M. Tucker and Phan Luu

Electrical Geodesics, Inc., Eugene, Oregon
NeuroInformatics Center, University of Oregon, Eugene, Oregon
dtucker@egi.com

Abstract. Classical laboratory studies of human performance have always required some form of data integration, such as the synchronization of stimulus display, behavioral accuracy, and reaction time. Studies of performance in operational environments have typically been limited in the precision of behavioral observations. As improved digital informatics have expanded the laboratory data acquisition from a few bytes to terabytes, there has been a similar expansion in both the opportunities and the challenges for data fusion.

Keywords: EEG, information systems, brain activity, neuroergonomics.

1 Introduction

An advanced window on human neurophysiological function has been opened by dense-array (256-channel) electroencephalography (DA-EEG). The improved sampling of the brain's electrical fields has been combined with improved physics models of the human head to allow accurate estimates of the electrical source activity of specific brain networks, such as the ventromedial frontal cortex or posterior cinguate cortex, that are known to be required for effective attention and cognition in demanding military environments. Recent advances in dermal bond hydrogel technology have improved DA-EEG signal quality even in high noise high movement operational environments such as mounted vehicle platforms. Advances in computer vision have allowed inobtrusive capture of critical details of behavior, such as head and eye tracking, in operational as well as laboratory environments with the millisecond accuracy required for fusion with electrophysiological data. At least in simulator environments, the instrumentation of the simulator software allows precise timing and description of events in the simulated operational context. With improved video recognition and sensor technologies, the information on operational contexts is also expanding. Advances in high-performance computation have allowed powerful mathematical algorithms such as independent components analysis and directed components analysis to separate unique sources of variance in the fused data streams. We describe a net-centric, distributed-parallel informatics architecture for increasing the bandwidth of the instrumentation and fused analysis of neurophysiological, behavioral, operational scenario events.

D.D. Schmorrow et al. (Eds.): Augmented Cognition, HCII 2009, LNAI 5638, pp. 98–104, 2009.

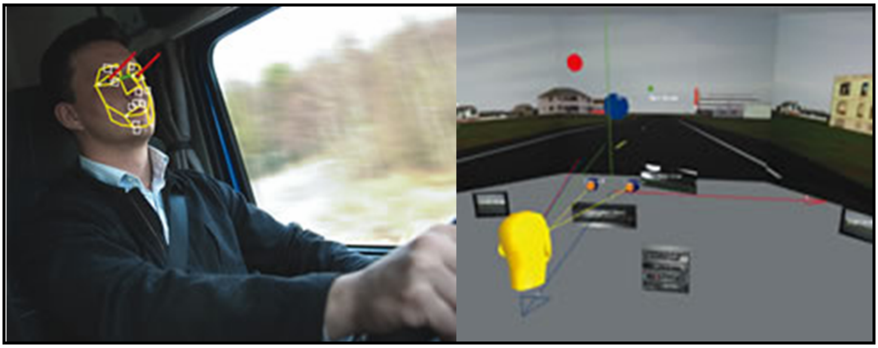

Fig. 1. Tracking of a subject's gaze with free head movement in a 3D environment

The immediate objectives of the proposed project are to: 1) implement a mobile, field-deployable hardware and software platform (AmpServer) capable of integrating and synchronizing the acquisition of neurological (high-density electroencephalography and near-infrared spectroscopy), behavioral (head- and eye-tracking), and autonomic (e.g., EKG) data during field operations, and 2) adapt and refine advanced artifact-cleaning and pattern classification methods to identify and separate the relevant data signals.

Under the DARPA Augmented Cognition program, EGI developed methods for real-time data acquisition and analysis to integrate dense array (256-channel) EEG with head and eye tracking information from infrared video. Under the DARPA/NGA Neurotechnology for Intelligence Analysts program, EGI developed methods for real-time recognition of visual system responses that indicate that an analyst has detected a military target in a rapid (10/sec) stream of visually presented satellite images. Under the ONR Human Performance Training and Education program, EGI has developed methods for assessing the neural mechanisms in the development of expertise during training.

Learning, or performance, seen as action regulation inherently emphasizes the need to adjust behavior according to both internal states and external demands, requiring different learning and memory systems; these systems reflect cybernetic constraints on action control. Learning, adaptive performance, and memory naturally arise from these action regulation processes. Two complementary cortico-limbic-thalamic circuits have been identified, each providing a unique strategic control on the learning process [1]. The ventral limbic circuit is made up of the anterior cingulate cortex (ACC) and the medial nuclei of the thalamus, with input from the amygdala. This ACC-based circuit is triggered by exogenous feedback, and leads to rapid changes in learning in response to new information, discrepancies with expectations, and threat. It is involved in the early stages of learning, whenever new tasks must be learned, or when routine actions and a priori knowledge are no longer appropriate for current demands [2-4]. The dorsal limbic circuit is centered on the posterior cingulate cortex and anterior ventral nucleus of the thalamus, with input from the hippocampus. It is involved in the later stages of learning and expert performance [5], when consolidation of information into long-term memory is important [2]. In these late stages, a contextual model is fully formed, and minor changes that are consistent with the contextual model can be made with minimal attention demands.

Human research in our laboratory with DA-EEG measures has yielded results largely consistent with this model. For example, we have observed greater ACC activity, as assessed through source analysis of the scalp-recorded EEG, when expectancies were violated [6], under particularly challenging performance demands [7,8], and following errors and negative feedback [9]. Moreover, increased anxiety was associated with the modulation of ACC engagement [10]. In contrast, we observed greater activity associated with the PCC circuit during the later stages of learning [11], after extensive practice [7,8], and in expert versus novice performance. Extension of these findings to realistic operational environments will help in identifying individual differences and contextual events that impact these fundamental self-regulatory mechanisms and enhance or impede adaptive performance.

2 Method

Significant technological advances have been made in the field of eye tracking. This project uses the state-of-the-art Smart Eye eye-tracking system. The Smart Eye system is completely unobtrusive (i.e., remote and not head mounted), and measures eye and head movements given the inputs from up to four cameras at 60 fps (see Figure 1). Head movement is measured to an accuracy of 0.5 degrees (rotation). The accuracy of the computed gaze-vector is 1 degree. The Smart Eye system allows us to track saccades and fixation within a 210-degree field of view. Pupillometry and a video stream with the image analyst's gaze position overlaid on the scene camera video, are also available as output. Additional benefits include flexible camera-mount positions, fast camera calibration, and handling of occluded cameras.

EGI, in collaboration with Smart-Eye engineers, has integrated the Smart-Eye system into our EEG acquisition platform. Because of the unobtrusive nature of this technology as well as the importance of understanding behaviors during performance we propose to employ it for tracking of attentional focus in a complex field environment. Integration of data acquisition from multiple sensors can be enabled through use of a common, network-capable, software architecture. Currently, EGI employs a software application called AmpServer for our dense-array EEG system. AmpServer has the capability to control multiple amplifiers, if they are all connected to the same machine and the bandwidth for all amplifiers are within the limits of Firewire technology. If the bandwidth requirements exceed the limits and the application requires integration of multiple amplifiers on the same machine, then multiple Firewire cards can be utilized. AmpServer currently is developed on Mac OS X but can be modified to run on Linux or Vista (when it is stable) with minor to moderate work. AmpServer can be made to support non-EGI amplifiers provided the amplifiers are stable and control and interface protocols are documented (see Figure 2).

With AmpServer as the platform, anyone can write client applications (on any platform) to access the raw data being broadcast by AmpServer. Alternatively, NetStation (EGI's acquisition software) can be used as the client.

The importance of electroencephalography (EEG) for tracking a human operator's cognitive state is well established. Moreover, our understanding of real-time brain

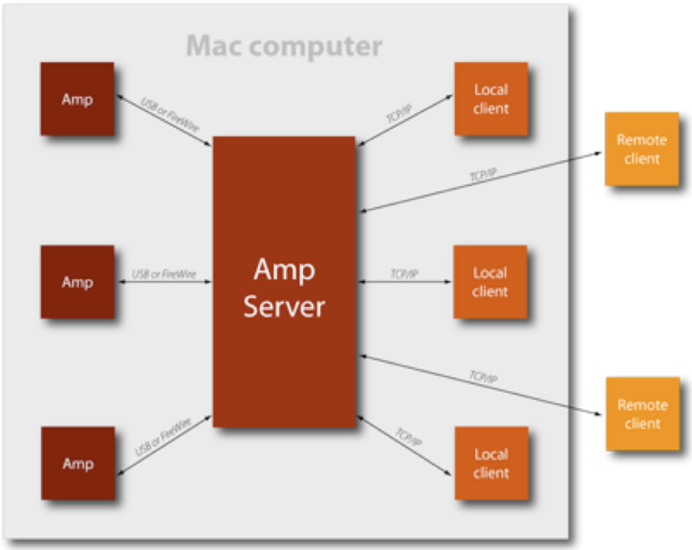

Fig. 2. Schematic of AmpServer architecture

activity is crucial in fulfilling the goal of monitoring performance to facilitate the mitigation of cognitive bottlenecks through dynamically modifying system behavior. Non-brain activity in continuous EEG severely masks and hampers the detection and interpretation of brain activity. Sources of non-brain activity include physiological artifacts, electromagnetic interference, and amplifier noise. The effectiveness of metrics derived from EEG to measure cognitive performance is severely diminished given the multitude of these artifact and noise sources. It therefore becomes both a crucial necessity as well as a major challenge to parse brain activity from the raw EEG signal in real time, while carefully minimizing the distortion of the actual brain activity components.

In a related effort (Luu et al., this volume), we developed a framework for detecting and extracting physiological artifacts due to ocular (i.e. eye blinks and movements) and cardiac activity from the recorded EEG in real time. Within this framework, the integration of continuous electrocardiography (EKG) as well as head and eye tracking enhances the robustness and stability of the artifact removal procedure. Both EKG and head and eye tracking have become ubiquitous in operator performance measurement environments.

Although Independent Component Analysis (ICA) has demonstrated the ability to cleanly separate ocular from brain activity, its reliance on computationally intensive higher-order statistics precludes its use in real-time applications. These higher order statistics can only be reliably calculated on long epochs, and exposes another drawback of ICA in that it is assumed that the measured EEG is derived from a limited set (equal to the number of EEG sensors) of spatially stationary brain and artifact generators over the entire epoch. Methods based on Principal Components Analysis (PCA), employing only computationally simpler second–order statistics, can be applied for artifact removal in real time. Special care is needed to ensure their effectiveness, as the reliance of PCA on orthogonal topographies has an important drawback. Existing PCA artifact removal methodologies can be classified as either methods that remove artifacts without considering brain activity, or techniques that attempt to separate artifact and brain activity. As part of our artifact removal framework, we propose a hybrid method that harnesses our ability to monitor and evaluate the temporal evolution of artifact activity. By identifying, selecting and segregating time slices of EEG data from contaminated and artifact-free epochs, we derive separate, finely detailed topographies for the artifact and brain activity in the signal, enabling a much cleaner removal of artifact contamination without distortion of the brain activity measurements. The integration and synchronization of head and eye tracking with EEG acquisition is essential for extracting eye (and head) movement artifacts effectively. By employing a separate EKG trace, we can cleanly extract cardiac artifacts, even in the presence of spike activity emanating from brain sources.

3 Results

In a series of eight studies investigating the effects of stress in simulated flight and a task analogous to pilots executing instructions from air traffic control we found that many people experienced stress-induced decrements in performance, particularly as task difficulty increased. However, others experienced no ill-effects of stress and for some people performance actually improved, despite equal levels of task difficulty. A unitary arousal model or the Yerkes-Dodson quantitative model [12], which associated performance with levels of difficulty and arousal, thus cannot explain these differences in performance under stress. Instead, we observed that *qualitative* differences in the emotional response to stress best accounted for these findings. Our results indicated that several factors influenced emotion response to stress. The following are particularly important to our understanding of the effects of stress in operational environments:

1. Context: Predictability of the stressor was related to decreased anxiety.
2. Experience: Early exposure to a stressor (i.e., when learning a new task) was related to increased anxiety, larger stressor-condition performance decrements, and lower levels of competency after two weeks of training.
3. Appraisal: Both experimental manipulation and participants' own appraisals of the stressor were predictably related to emotion response to stress.
4. Trait differences: When emotion responses to stress were most variable (due to differences in predictability of the stressor and appraisal manipulations), trait anxiety and behavioral inhibition were predictive of emotion responses to stress, but did not directly predict stressor-condition performance.

Although the body is adapted to respond with little or no ill effect to the acute mobilization of physiological distress reactions, it is clear that chronic or repeated activation of threat systems can have adverse long-term physiological, cognitive, and affective health effects [13]. Over the short-term, such reactions can also be maladaptive when individuals fail to flexibly regulate threat systems in the face of changing circumstances (e.g., when the threat no longer exists) or when the situation precludes fight or flight (e.g., work environments). Assessment of the autonomic stress response in complex, operational environments via EKG and EMG sensors in an integrated platform will provide a greater understanding of how these autonomic changes interact with the engagement of neural self-regulatory systems, such as the anterior, ventral limbic system under perceived threat. Head and eye-tracking measures will further clarify the attentional response to stress by tracking gaze duration and eye fixations. This information can indicate, for example, if one performer is more easily distracted under stress, rapidly shifting fixations across irrelevant information, whereas another performer is able to shift attention systematically to relevant information in a goal-directed fashion.

4 Discussion

The implementation of an integrated information environment for both behavioral and electrophysiological observations allows novel approaches to real-time measurement of human brain activity in operational environments. Key features of this implementation are single-trial data measures (rather than averaged event-related potentials) and exact precision of timing of high-bandwidth data streams. The technical capacities now available with video head and eye tracking and dense array EEG are well suited to the challenges of neuroergonomics in operational environments.

References

1. Gabriel, M., Burhans, L., Talk, A., Scalf, P.: Cingulate Cortex. In: Ramachandran, V.S. (ed.) Encyclopedia of the Human Brain, pp. 775–791. Elsevier Science, Amsterdam (2002)
2. Gabriel, M.: Functions of Anterior and Posterior Cingulate Cortex During Avoidance Learning in Rabbits. Prog. Brain Res. 85, 467–483 (1990)
3. Gabriel, M., Sparenborg, S.P., Stolar, N.: An Executive Function of the Hippocampus: Pathway Selection for Thalamic Neuronal Significance Code. In: Isaacson, R.L., Pribram, K.H. (eds.) The Hippocampus, pp. 1–39. Plenum, New York (1986)
4. Poremba, A., Gabriel, M.: Amygdalar Efferents Initiate Auditory Thalamic Discriminative Training-Induced Neuronal Activity. J. Neurosci. 21, 270–278 (2001)
5. Keng, E., Gabriel, M.: Hippocampal Modulation of Cingulo-Thalamic Neuronal Activity and Discriminative Avoidance Learning in Rabbits. Hippocampus 8, 491–510 (1998)
6. Frishkoff, G.A., Tucker, D.M., Davey, C., Scherg, M.: Frontal and Posterior Sources of Event-Related Potentials in Semantic Comprehension. Brain Res. Cogn. Brain Res. 20(3), 329–354 (2004)
7. Poulsen, C., Luu, P., Davey, C., Tucker, D.: Dynamics of Task Sets: Evidence from Dense-Array Event-Related Potentials. Cog. Brain Res. 24, 133–154 (2005)
8. Poulsen, C., Luu, P., Tucker, D., Scherg, M., Davey, C., Frishkoff, G.: Electrical Brain Activity during Task Switching: Neural Source Localization and Underlying Dynamics of Scalp-Recorded Potentials. Poster presented at the Tenth Annual Meeting of the Cognitive Neuroscience Society, New York, NY (March 2003)
9. Luu, P., Tucker, D.M., Derryberry, D., Reed, M., Poulsen, C.: Electrophysiological Responses to Errors and Feedback in the Process of Action Regulation. Psychol. Sci. 14(1), 47–53 (2003)

10. Poulsen, C., Luu, P., Crane, S.M., Quiring, J., Poolman, P., Tucker, D.M.: Neural Mechanisms of Self-Evaluation in Anxiety and Depression (in preparation)
11. Luu, P., Tucker, D.M., Stripling, R.: Neural Mechanisms for Learning Actions in Context. Brain Res. 1179, 89–105 (2007)
12. Yerkes, R.M., Dodson, J.D.: The Relation of Strength of Stimulus to Rapidity of Habit-Formation. J. Comparat. Neurol. Psychol. 18, 459–482 (1908)
13. McEwen, B.S.: The Neurobiology of Stress: From Serendipity to Clinical Relevance. Brain Res. 886, 172–189 (2000)