Objective Measures of Situational Awareness Using Neurophysiology Technology

Conference Paper · January 2006

Chris Berka
Advanced Brain Monitoring

Daniel J Levendowski
Advanced Brain Monitoring

Gene Davis
Advanced Brain Monitoring, Inc.

Kelly S. Hale
Draper Laboratory

Objective Measures of Situational Awareness Using Neurophysiology Technology

Chris Berka, Daniel J. Levendowski
Gene Davis and Melissa Whitmoyer

Advanced Brain Monitoring, Inc.
2850 Pio Pico Drive, Suite A Carlsbad, CA USA 92008
chris@b-alert.com

Kelly Hale and Sven Fuchs

Design Interactive, Inc.
1221 E. Broadway, Suite 110 Orlando, FL USA 32765
kelly@designinteractive.net

Abstract

A key aspect within net-centric warfare is situational awareness (SA), where operators consolidate data into an understanding of 'the big picture' that dynamically updates as the situation changes. While many measures of SA exist, including explicit, implicit, and subjective measures, none of these metrics support the dynamic, real-time assessment of cognitive processes associated with SA. Instead, they rely on behavioral outcomes (i.e., task performance) and/or self- or observer-based assessments to capture operator SA. This paper presents evidence for the feasibility of developing a real-time system that uses neurophysiological methods to assess SA of individuals. By leveraging neurophysiology technologies, it may be possible to develop more objective SA metrics than those currently used.

Neurotechnology has been used to characterize human information processing in laboratory settings where measures are taken under controlled conditions that are not representative of operational environments. Thus, there are numerous challenges that must be overcome to create a robust methodology for capturing consistent high quality EEG signatures in real-time during the performance of complex tasks. This paper presents preliminary evidence supporting the feasibility of developing a system that provides event-locked data extraction from EEG in real-time to measure aspects of individual SA based on single events (i.e., perception of an element, response to an element). Specific time-locked potentials are generated by neuronal networks in relation to behaviorally significant events. EEG data were acquired during a simulated Naval Command task using an integrated hardware and software solution for acquisition and real-time analysis of the EEG. An easily applied wireless sensor headset suitable for operational applications was used in combination with a novel analytical approach to identify and quantify EEG signatures for single events and global cognitive state changes.

Event-related potentials (ERPs) were measured as time-locked to presentation of stimuli or to the time of an operator response. Several key events were identified in the Naval Command task as relevant to operator SA, including correct or incorrect identification of incoming aircraft, distinguishing between a chat question that required a response and one that was simply informative, and distinguishing between hostile tracks that entered weapon range and were responded to in a timely manner and those that were not responded to in the allotted time (i.e., not perceived crossing weapon range). Preliminary data acquired from 8 participants suggests that distinctive neural signatures can be characterized for each of these events.

1. INTRODUCTION

A key aspect within net-centric warfare is situational awareness (SA), where operators consolidate data into an understanding of 'the big picture' that dynamically updates as the situation changes. While many models and definitions of SA exist, Endsley's (1995b) information processing model of SA is the most commonly cited definition (Uhlarik & Comerford, 2002). Using this approach, SA is defined as consisting of three levels: perception of elements within the environment, comprehension of elements, and prediction of future events (Endsley, 1995b). Current measures of SA include explicit measures, implicit measures and subjective measures (Uhlarik & Comerford, 2002). However, none of these metrics support dynamic, real-time assessment of cognitive processes associated with SA, and instead rely on behavioral outcomes (i.e., task performance) and/or self- or observer-based assessments to capture operator SA.

By leveraging neurophysiology technologies it may be feasible to develop more objective SA metrics than those currently used. Early evidence for the efficacy of leveraging physiological sensors for gauging SA has been demonstrated by Pancerella et al. (2003). In this study, an adaptive awareness and decision-making tool was developed which uses an agent-based infrastructure that monitors human state (i.e., heat flux, skin temperature, galvanic skin response (GSR), and heart rate) and the environment to direct personal and small group awareness and decision-making. Doser et al. (2003) also reported a real-time physiological SA evaluation technique in a collaborative team environment. In this study, real-time signal analysis of electrocardiogram (EKG), electromyelograph (EMG), GSR, respirometer and pulse oximeter provided information that characterized emergent and desirable group behavior and improved task performance. Specifically, events of interest (e.g., cooperation, conflict, leadership), when time synchronized and compared to heart rate data, showed evidence of group cooperation (Doser et al., 2003).

Although these studies show promise for using physiological sensors to detect personal and small group awareness, efforts to date have not yet leveraged brain sensors such as electroencephalography (EEG) to characterize the cognitive states associated with situational awareness. Real-time neural signatures could potentially be identified to measure different components of SA, including perception and comprehension, thereby capturing the "state-of-mind" (Perla et al., 2000) associated with each SA component. Event-related brain potentials (ERPs) synchronized to presentation of stimuli or to the time of an operator response could prove valuable in the real-time detection of neural signatures of SA. Specific time-locked potentials are generated by neuronal networks in relation to behaviorally significant events. In the case of discrete events, such as those relevant for perception, ERPs are analyzed in short epochs that are time-locked to the event (Bressler, 2002).

One major challenge is to translate the concept of SA into a real-time metric that can be used to drive dynamic interface adaptation. Endsley (1995a) notes that instead of measuring the activities performed to achieve SA, one should measure the result of these activities. However, to drive system mitigation, one must capture specific errors in SA in real-time. In several studies reported by Endsley (1999), the majority (> 70%) of SA-related errors were based on errors in perception. Given that perception is required before the operator can attain understanding of the environment from which they predict future events, ensuring perception (i.e., that relevant data is presented and perceived by operators in an efficient manner) is a first – if not the most important – step in optimizing SA.

Neurotechnology has been used to characterize human information processing in laboratory settings where measures are taken under controlled conditions that are not representative of operational environments. Thus, there are numerous challenges that must be overcome to create a robust methodology for capturing consistent high quality EEG signatures in real-time during the performance of complex tasks. This paper presents data acquired using a system designed to assess neurophysiological indices of SA from individuals performing a complex Naval Command simulation program. The long-term goal of this work is to develop a real-time system that can assess SA of individuals and teams, using EEG to detect second-by-second fluctuations in the EEG that are related to cognitive state changes while capturing perception-related cognitive processing signatures in ERPs. These EEG metrics will be integrated with system-monitored performance metrics and used to identify and characterize operator SA in real-time. If accurate and reliable metrics for objectively monitoring SA can be confirmed, the system will be programmed to employ intelligent mitigation strategies to enhance SA and improve performance. Figure 1 presents the model system.

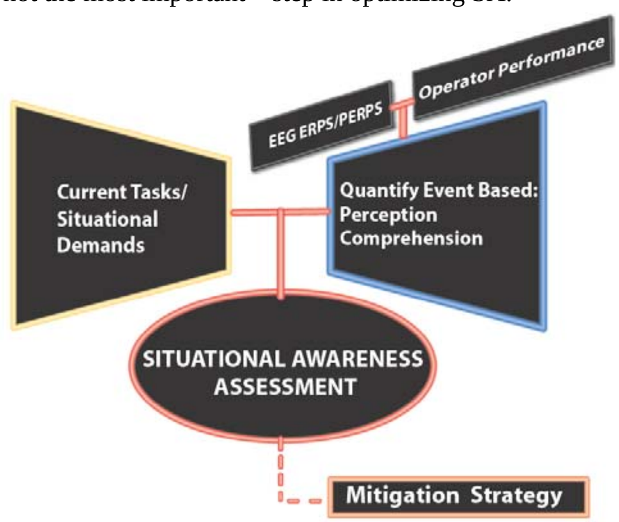

Figure 1: Integrated EEG-SA & mitigation model

Tracking and analysis of system events through an event-based approach allows for better context-sensitivity, as cognitive gauges can now be related to individual events or display objects, thereby providing the much needed context for how and where mitigations should be applied. In such an approach, each system event would be associated with increases or decreases in the cognitive state of interest (e.g., when a new entity appears on the screen, participants should perceive this change and act accordingly). The tracking of system events can be integrated with the development of an event-based EEG metric of SA that can be used to drive adaptive mitigations.

An integrated hardware and software solution for the acquisition and real-time analysis of the EEG was developed to facilitate event-locked data extraction from EEG in real-time to measure aspects of individual SA based on single events (i.e., perception of an element, response to an element) as well as a more global metric of SA. The system includes an easily applied wireless sensor headset suitable for operational applications (see Figure 2). The methods include a novel analytical approach that employs linear and quadratic discriminant function analyses (DFA) to identify and quantify EEG signatures for single events and global cognitive state changes. The cognitive states identified include workload, distraction, drowsiness and task engagement with model-selected variables that may include combinations of the power in each of the 1-hz bins from1-40hz, ratios of power bins, event-related power and/or wavelet transform calculations. This unique modeling technique allows simultaneous selection of multiple EEG characteristics across brain regions and spectral frequencies of the EEG, providing a highly sensitive and specific method for monitoring neural signatures of cognition both in real-time and off-line analysis.

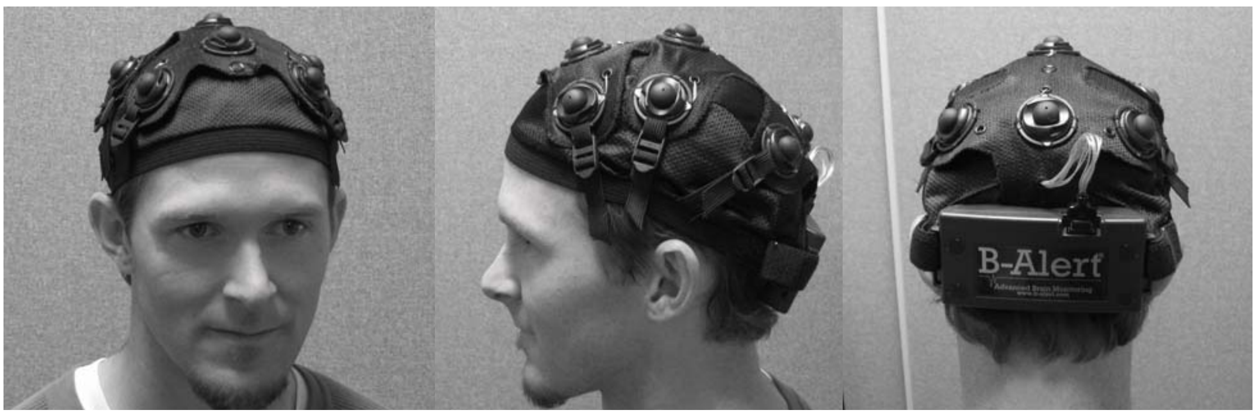

Figure 2: Wireless sensor headset

This method has previously been successfully applied to classify 1-sec or 0.5-sec segments of EEG to identify drowsiness-alertness (Levendowski, Berka, Olmstead, & Jarvik, 1999; Levendowski et al., 2001) mental workload (Berka et al., 2004; Berka et al., 2005c), spatial and verbal processing in simple and complex tasks (Berka et al., 2005a) characterize alertness and memory in patients with sleep apnea (Berka et al., 2005a; Westbrook et al., 2004) and to identify individual differences in susceptibility to the effects of sleep deprivation (Berka et al., 2005b). The model system has also been successfully integrated into real-time, closed-loop automated computing systems which implement dynamic regulation and optimization of performance during a driving simulation task and in the Aegis C2 and Tactical Tomahawk Weapon simulation environments (Berka et al., 2005a; Berka et al., 2005b; Berka et al., 2005c).

As important as perception/comprehension of individual system events is as a prerequisite for developing SA, it does not capture its entire scope. A dynamic, objective measure of global SA may be more suitable for monitoring ongoing information processing including the accumulation of data and interpretation of that data within the environmental context. Power spectral changes in EEG frequency bands have also been demonstrated as relevant to several cognitive processes that are also related to SA (including attention, workload and overall task complexity) and may thus increase the chance of capturing the development of the “big picture” (Dennehy & Deighton, 1997) of the situation. EEG metrics have also been identified that may be useful in monitoring skill acquisition by providing objective evidence of the levels of expertise acquired as automaticity develops (Berka et al., 2004).

One important aspect of global SA is operator expertise (Laxmisan, Malhotra, Keselman, Johnson, & Patel, 2005; Stanton, Chambers, & Piggott, 2001). As an individual becomes more familiar with a specific set of inputs and behavioral responses required, less mental effort is required, and more attention can be allocated to perceiving and comprehending changes in the environment that define the current situation. An operator that has not yet trained to the level of automaticity is subject to frequent periods of mental overload that may substantially reduce SA. A global metric of SA may adequately capture this variance due to expertise, as it would be independent of specific events (e.g., perception of a track) and instead reflect an operator's overall understanding of the current situation.

2. METHODS

2.1. Participants

EEG was acquired from eight healthy participants at the Advanced Brain Monitoring human subjects testing facility. The study protocols were approved in advance by an independent review board, the Biomed IRB (San Diego, CA). Each subject provided written informed consent before participating.

2.2. Naval Command Task Simulation

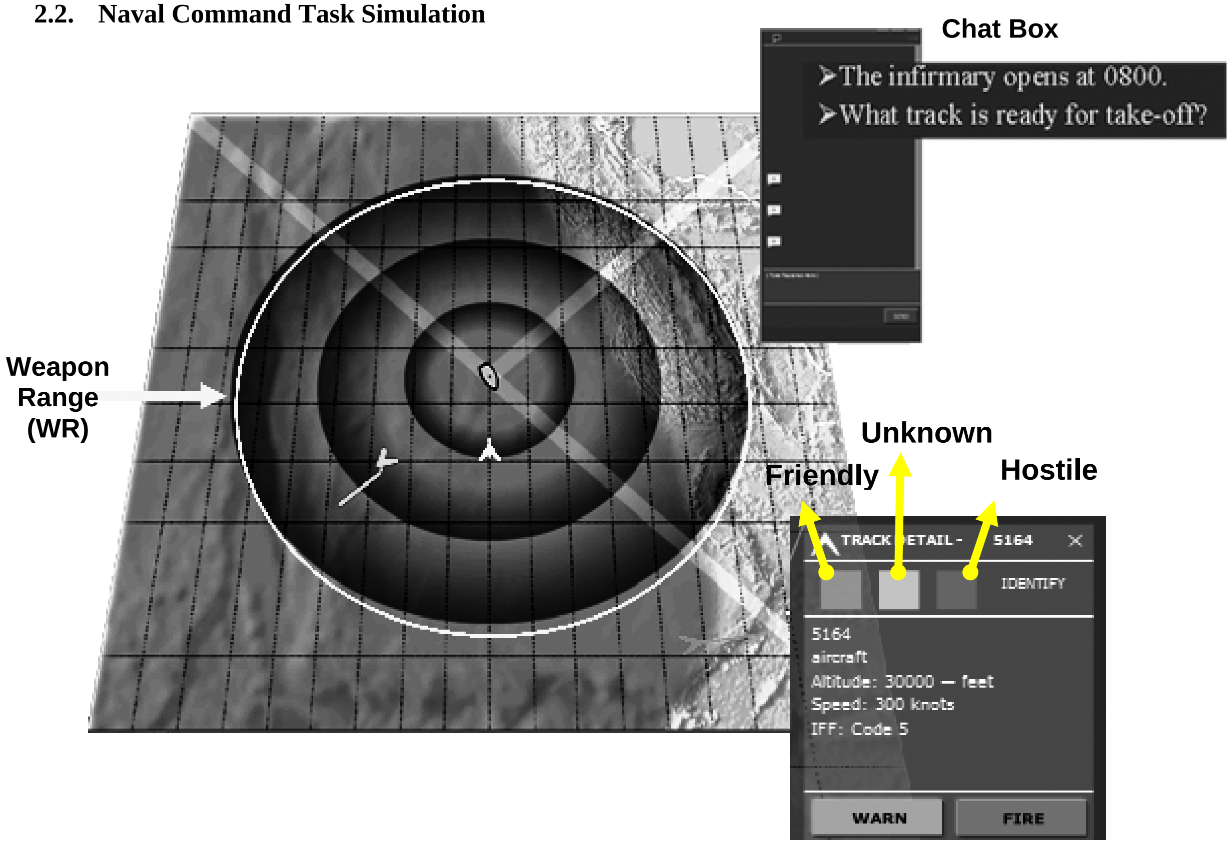

Figure 3: Naval command simulation weapon range, chat box, and tracks.

The objective of the Naval Command simulation was to monitor and identify incoming aircraft (called "tracks") within a given area of responsibility, to respond appropriately based on a given set of rules of engagement, and to interact with the system (i.e., simulated team members) via chat and auditory communications (see Figure 3). The operator was required to identify these tracks as friendly, unknown, or hostile, and proceed according to instructions given. Visual chat and auditory messages were also presented throughout the scenario; some required responses while others were purely informative. Participants were instructed that their first priority was always to protect their own ship from hostile threats that entered weapon range by engaging tracks (i.e., firing upon hostile tracks that entered weapon range).

Participants were given 3 practice sessions including introductory instructions and three practice scenarios on the task to allow training-to-criterion: 1) Common Operating Picture (COP; just visual stimuli); 2) COP + CHAT communications; 3) COP + CHAT + AUDIO communications. The practice sessions were designed to be incrementally more difficult with the final practice of each set representative of the moderate task level. Upon completion of the practice sessions, two 15-minute scenarios were presented: one at a moderate level and one at a high level of complexity (complexity dependent on number of tracks and communications). The order of presentation of the high and moderate scenarios was counterbalanced across participants.

2.3. EEG System

All participants wore the wireless sensor headset (Figure 2) including the following bi-polar sensor sites: F3-F4, C3-C4, Cz-PO, F3-Cz, Fz-C3, Fz-PO. Bi-polar recordings were selected to reduce the potential for artifacts that can be problematic for applications that require ambulatory conditions in operational environments. Limiting the sensors (seven) and channels (six) ensured the sensor headset could be applied within 10 minutes. The sensor montage was selected after conducting experiments using monopolar recordings and selecting the montage and channels that provided the best mental workload discrimination across subjects, tasks and conditions.

Identification and decontamination of spikes, amplifier saturation and environmental artifacts and computation of the power spectral density were completed using procedures previously described (Berka et al., 2004). Two new wavelets procedures were also applied to these data to detect excessive muscle activity (EMG) and to identify and decontaminate eye blinks. Once the artifacts are identified in the time-domain data, the EEG signal was decomposed using a wavelets transformation. Thresholds were developed for application to the wavelet power in the 64 – 128 Hz bin to identify epochs rejected due to excessive EMG. The wavelets eye blink identification routine used a two-step discriminant function analysis applied to the absolute value of the 0-2, 2-4, 4-8, 8-16, and 16-32 Hz wavelet coefficients from the 50th, 40th, 30th, 20th and 10th data points before and after the target data point in FzPOz and CzPOz. The DFA classified each data point as a control, eye blink or theta activity. Multiple data points that were classified as eye blinks were then linked and the eye blink detection region established based on a fixed distance before the start (e.g., 50 data points) and after the end (e.g., 50 data points) of the blink. Decontamination of eye blinks was accomplished by computing mean wavelet coefficients for the 0-2, 2-4 and 4-8 Hz bins from nearby non-contaminated regions and replacing the contaminated data points. The EEG signal was then reconstructed from the wavelets bins ranging from 0.5 to 64 Hz. Zero values were inserted into the reconstructed EEG signal at zero crossing before and after spikes, excursions and saturations. EEG absolute and relative power spectral density (PSD) variables for each 1-second epoch using a 50% overlapping window were then computed. The PSD values were scaled to accommodate the insertion of zero values as replacements for the artifact.

EEG metrics (values ranging from 0.0-1.0) for "engagement" and "mental workload" were calculated for each 1-second epoch of EEG using quadratic and linear discriminant function analyses of model-selected EEG variables derived from power spectral analysis of the 1-Hz bins from 1-40Hz. Event-related potentials (ERPs) and Power event-related potentials (PERPs) were derived based on time-locking to a specific event of interest (e.g. correct identification of a track, opening a chat message, responding to a hostile track moving into the weapon range). Time-locked events were then averaged within or across participants to establish templates for neural signatures associated with the key events related to SA.

3. RESULTS

3.1. Data Reduction

As a preliminary approach to developing a global SA-EEG metric, previously validated metrics for task engagement and mental workload were calculated for each 1-second epoch of EEG. Event-related potentials (ERPs) and Power event-related potentials (PERPs) were derived from the moderate task scenario based on time-locking to the events that were identified as relevant to SA. Time-locked averages were computed to characterize neural signatures for either the one-second following a stimulus event or for the one-second prior to a specified response event.

Several task conditions were selected for ERP/PERP comparison, including: correct vs. incorrect identification of friendly, hostile or unknown tracks, reading a chat message that was informative vs. one that asked a question, and speed of response (0-3 seconds or 4-6 seconds) to a hostile or unknown track moving into the weapon range. Time-locked events were then averaged within or across participants to establish the templates for neural signatures.

3.2. Classifications of EEG-Engagement and EEG-Workload

Figure 4 presents the average EEG-engagement and EEG-workload levels for the three introductory segments, for each level of practice for the COP only, the COP-CHAT, and the COP-CHAT-AUDIO training sessions, and for the moderate and high complexity level scenarios. As expected, both engagement and workload on average decreased as participants gained expertise in the simulation environment. This expertise effect typically overshadowed the incremental increases in difficulty in the practice scenarios. In addition, the EEG engagement and workload provided objective confirmation of the level of task difficulty in the moderate vs. the high complexity scenarios. These data replicate previous findings suggesting that EEG metrics may prove useful in monitoring skill acquisition by providing objective evidence of the levels of expertise acquired as automaticity develops (Berka et al., 2004).

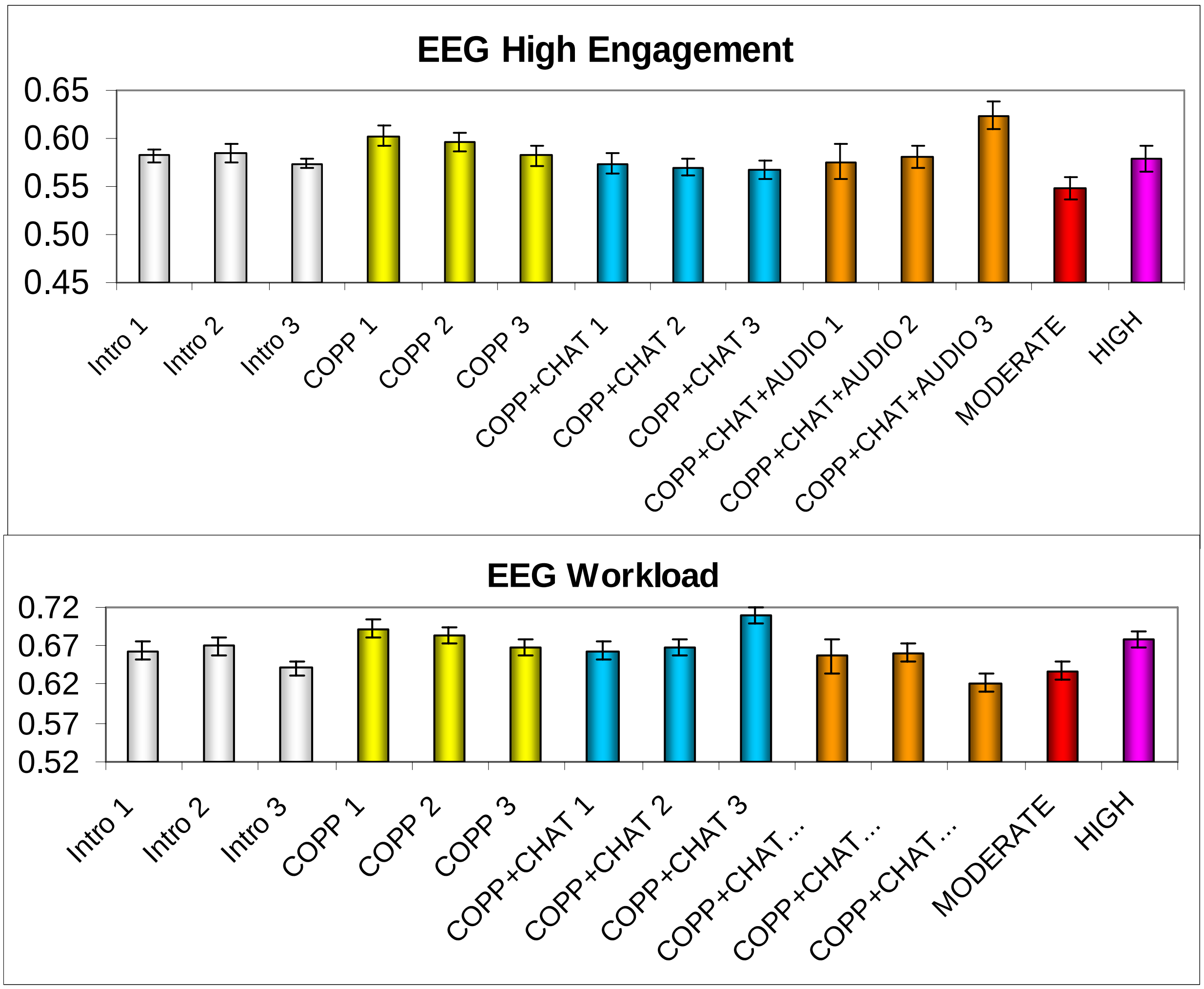

Figure 4: Mean (±SEM) EEG-engagement and EEG-workload for Introduction, Training and Moderate and High testing scenarios

3.3. ERPs and PERPs Associated with Correct and Incorrect Track Identification

Figure 5 presents the grand averaged PERPs derived from one second of EEG prior to identification of friendly, hostile and unknown tracks sorted into correct vs. incorrect identification to allow generation of distinctive neural signatures for correct and incorrect responses. The difference between the correct and incorrect identification occurring primarily in the EEG theta bands was clearly evidenced across trials and participants. This distinction suggests that a relatively simple real-time algorithm could be implemented to monitor errors in identification and could also be used to drive mitigations aimed at improving performance.

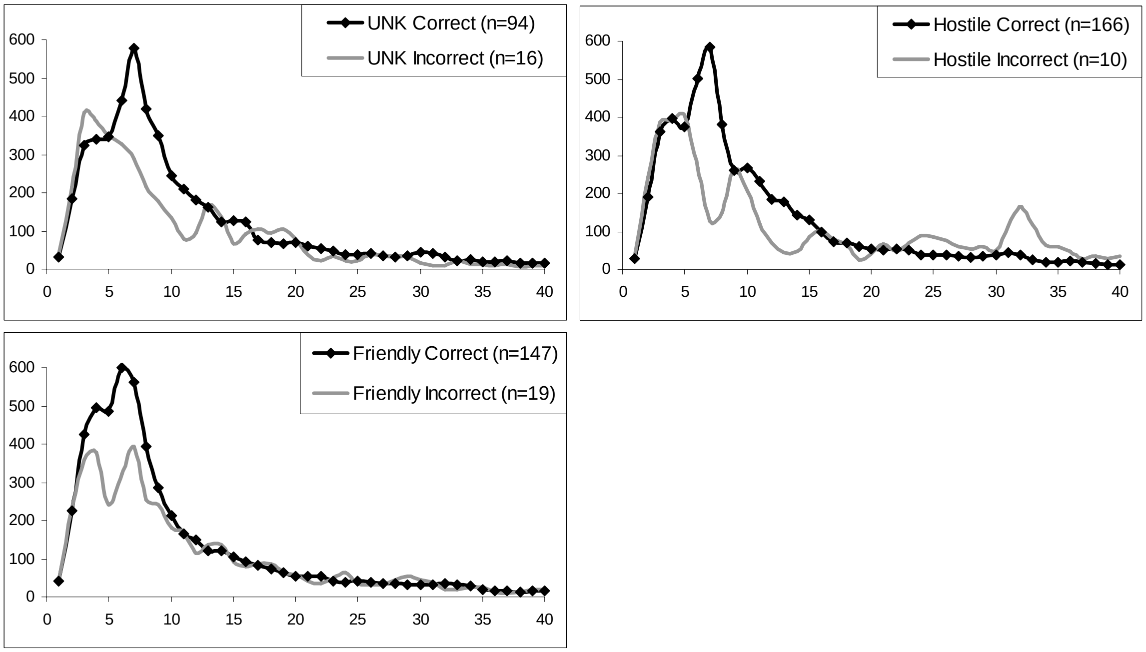

Figure 5: PERPs - Power Event-related EEG recorded one-second prior to the identification of friendly, hostile and unknown tracks sorted by correct and incorrect identifications.

3.4. ERPs and PERPs Associated with Reading Chat Message vs. Question

Figure 6 presents the grand averaged ERPS and PERPS associated with reading a chat message containing information compared to a chat message which asked a question and required a response. The difference in the ERP graph between chat messages and chat questions reveals distinct differences in the late positive components of the ERP—these likely reflect the additional cognitive resources devoted to the processing of the question and the formulation of the response. The PERPs provide evidence that distinctive neural signatures for these events can be identified during a real-time analysis.

FzPO (PERPs): Across Subjects: Reading Message vs. Question

FzPO (ERPs): Across Subjects: Reading Message vs. Question

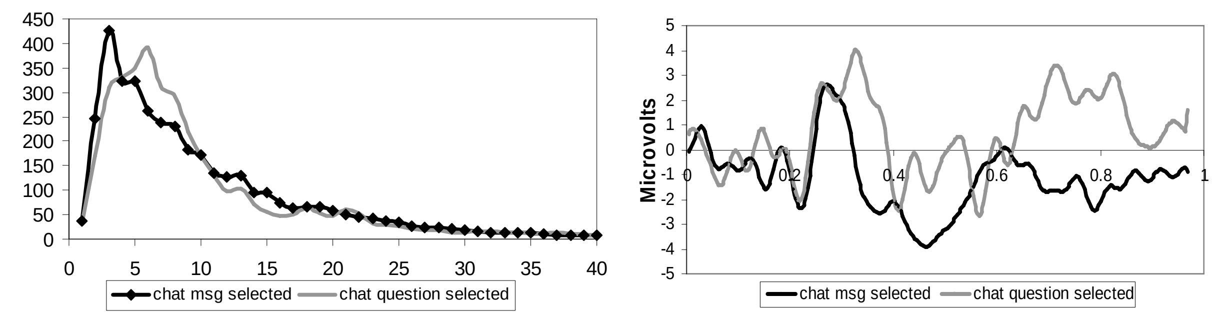

Figure 6: ERPs and PERPs reading message vs. question

3.5. ERPs and PERPs Associated with Responses to Tracks Moving into Weapon Range

Figure 7 presents the ERPs and PERPs associated with the speed of response (0-3 seconds or 4-6 seconds) to a hostile or unknown track moving into the weapon range. The distinctive neural signatures suggest the feasibility of implementing a mitigation to ensure that participants responded to all hostiles in the weapon range as quickly as possible.

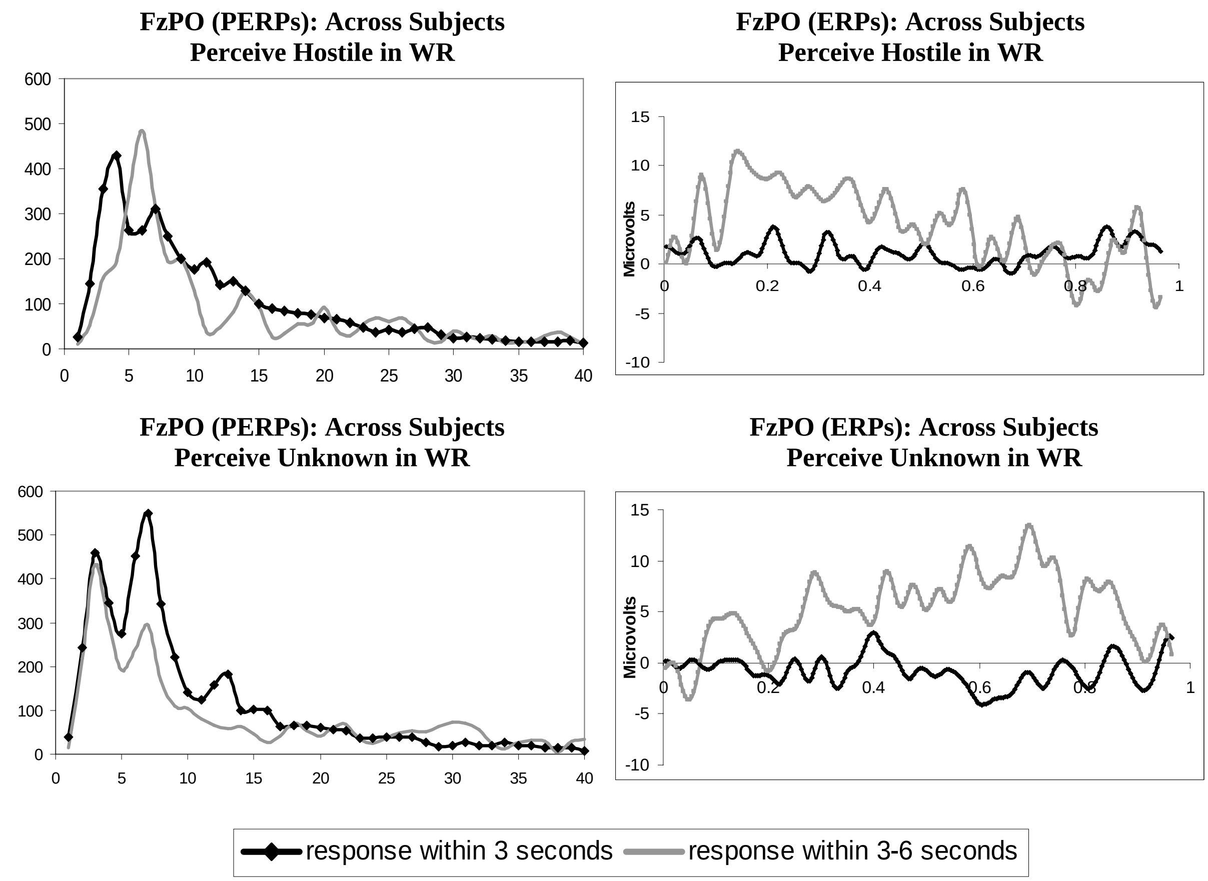

Figure 7: Averaged ERPs and PERPs associated with speed of responding (0-3 seconds or 3-6 seconds) to a hostile or unknown track moving into the weapons range.

4. CONCLUSIONS

4.1. Feasibility of an Event-related, EEG-based System for Characterizing Aspects of SA

These data provide preliminary support for the feasibility of identifying neural signatures that may reflect different aspects of SA. Recent advances in real-time processing of the EEG suggest that once the templates for neural signatures are established, they can be detected and processed in real-time and serve as inputs to drive mitigations and improve operator performance. ERPs synchronized to system events and/or behavioral responses of operators provided distinctive signatures for several of the key SA-relevant events, including correct/incorrect identification of tracks, reading a chat message that was informative (i.e., statement) vs. one that asked a question, and speed of response (0-3 seconds vs. 4-6 seconds) to a hostile or unknown track moving into weapon range. The PERPs revealed differences in the event-related power spectra particularly in the theta band of the EEG (3-7 Hz). Further investigation is required to determine how robust these differences are across subjects and to assess the validity of single trial ERPs and PERPs. This paper presents data from just one channel of EEG (Fz-PO) to illustrate the significant differences in the event-related correlates relevant to SA. Full implementation of a real-time classification model could employ combinations of all six channels of EEG to create more robust neural signature templates that could be identified in a single-trial analysis.

One major challenge of this effort was to translate the concept of SA into a real-time metric that could be used to drive dynamic interface adaptation. In the Naval Command simulation environment, the correct identification of a track as friendly or hostile is an essential element of performing the task. The PERP differences between correct and incorrect identifications in this study suggest neural signatures for comprehension of track identity could be used to drive mitigation (i.e., draw attention when incorrect identifications occur). The EEG signatures relating to participants' delayed responding to hostile tracks entering the weapon zone are particularly relevant to SA in the Naval Command simulation because the primary initiative is the protection of own ship from threatening tracks. Neural signatures for slow responses could readily trigger a mitigation designed to focus the attention of the participant on the threats in the weapon zone.

The present study also revealed detectable differences in neural signatures related to reading a chat message that was informative vs. one that asked a question. These differences appear to reflect the distinction between comprehension of simple information compared to a question that requires additional processing and preparation of a response.

Previous studies suggested that the majority of SA-related errors were based on errors in perception (Endsley, 1999). Thus, incorporating the approach outlined in this paper into a real-time measure that captures missed perceptual events and using this to drive a mitigation should lead to substantially fewer SA-related errors. Once a robust template for correct identification has been established, it may be possible to train the EEG system to indicate times where the operator fails to appropriately identify a track, and when indicated, mitigate the system to enhance operator awareness of potentially incorrect actions (i.e., incorrect identifications).

4.2. EEG Metrics Associated with Skill Acquisition

The EEG engagement and workload data acquired during the training session confirm previous findings suggesting that these EEG metrics may prove useful in monitoring skill acquisition and could provide objective evidence of operators attainment of levels of expertise (Berka et al., 2004). Level of expertise is a critical contributor to SA. Skill development has been described as occurring in stages that are characterized by distinctive amounts of time and mental effort required to exercise the skill the initial cognitive stage of assembling new knowledge, the associative stage where newly assembled procedural steps gradually automate as they are practiced, and the autonomous stage where the task execution is automated and performed with minimal conscious mental effort. During the transition from the cognitive to associative stage, both speed and accuracy increase as subjects become less reliant on the declarative representations of knowledge (Anderson, 1982; Anderson, 1995). Because the key distinction between the second and third stages of skill acquisition is a decrease in mental effort rather than a reliable difference in the accuracy of performance, the addition of the EEG-workload and engagement measures provide evidence of the progression from stage 2 to stage 3. If performance alone is used, no difference is made between people who perform well but require high mental effort and people who perform well with low mental effort.

With the lack of training and limitations of human resources in today's military, objective EEG measures that automatically assess skill acquisition could increase efficiency of training and decrease manpower requirements.
The wireless sensor headset has proven useful in the acquisition of high quality EEG in a number of operational environments, allowing neurotechnology to move out of the laboratory and into the real world (Ververs, Whitlow, Dorneich, Mathan, & Sampson, 2005).

5. ACKNOWLEDGEMENTS

This material is based upon work supported in part by the Defense Advanced Research Projects Agency (DARPA) under its SBIR Program. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views or the endorsement of DARPA.

6. REFERENCES

Anderson, J. R. (1982). Acquisition of cognitive skill. *Psychological Review, 89*, 369-406.

Anderson, J. R. (1995). *Cognitive psychology and its implications* (4 ed.). New York: Freeman.

Berka, C., Levendowski, D., Cvetinovic, M., Petrovic, M., Davis, G., Lumicao, M., Zivkovic, V., Popovic, M., & Olmstead, R. (2004). Real-time Analysis of EEG Indices of Alertness, Cognition, and Memory with a Wireless EEG Headset. *International Journal of Human-Computer Interaction*, *17*(2), 151-170.

Berka, C., Levendowski, D., Davis, G., Lumicao, M., Ramsey, C., Stanney, K., Reeves, L., Harkness, S., & Tremoulet, P. (2005a, July). *EEG Indices Distinguish Spatial and Verbal Working Memory Processing: Implications for Real-Time Monitoring in a Closed-Loop Tactical Tomahawk Weapons Simulation.* Paper presented at the 1st International Conference on Augmented Cognition, Las Vegas, NV.

Berka, C., Levendowski, D., Westbrook, P., Davis, G., Lumicao, M., Olmstead, R., Popovic, M. V., Zivkovic, V., & Ramsey, C. (2005b, May). *EEG Quantification of Alertness: Methods for Early Identification of Individuals Most Susceptible to Sleep Deprivation.* Paper presented at the Proceedings of SPIE Defense and Security Symposium, Biomonitoring for Physiological and Cognitive Performance during Military Operations, Orlando, FL.

Berka, C., Levendowski, D., Westbrook, P., Davis, G., Lumicao, M., Ramsey, C., Petrovic, M., Zivkovic, V., & Olmstead, R. (2005c, July). *Implementation of a Closed-Loop Real-Time EEG-Based Drowsiness Detection System: Effects of Feedback Alarms on Performance in a Driving Simulator.* Paper presented at the 1st International Conference on Augmented Cognition, Las Vegas, NV.

Bressler, S. L. (2002). Event-related potentials. In M. A. Arbib (Ed.), *The Handbook of Brain Theory and Neural Networks* (pp. 412-415). Cambridge, MA: MIT Press.

Dennehy, K., & Deighton, C. (1997). Development of an interactionist framework for operationalising situation awareness. In D. Harris (Ed.), *Engineering Psychology and Cognitive Ergonomics* (EAMTP Infocentre Reference: 030317-04 ed., Vol. 1). Aldershot: Ashgate.

Doser, A. B., Merkle, P. B., Johnson, C., Jones, W., Warner, D., & Murphy, T. (2003). *Enabling technology for human collaboration.* (No. SAND 2003-4225): Sandia National Laboratories.

Endsley, M. R. (1995a). Measurement of situation awareness in dynamic situations. *Human Factors, 37*(1), 65-84.

Endsley, M. R. (1995b). Towards a theory of situation awareness. *Human Factors, 37*(1), 32-64.

Endsley, M. R. (1999). *Situation awareness and human error: designing to support human performance.* Paper presented at the High Consequence Systems Surety Conference, Albuquerque, NM.

Laxmisan, A., Malhotra, S., Keselman, A., Johnson, T. R., & Patel, V. (2005). Decisions about critical events in device-related scenarios as a function of expertise. *Journal of Biomedical Informatics, 38*(3), 200-212.

Levendowski, D. J., Berka, C., Olmstead, R. E., & Jarvik, M. (1999, October 25). *Correlations between EEG Indices of Alertness Measures of Performance and Self-Reported States while Operating a Driving Simulator.* Paper presented at the 29th Annual Meeting, Society for Neuroscience, Miami Beach, FL.

Levendowski, D. J., Berka, C., Olmstead, R. E., Konstantinovic, Z. R., Davis, G., Lumicao, M. N., & Westbrook, P. (2001). Electroencephalographic indices predict future vulnerability to fatigue induced by sleep deprivation. *Sleep, 24*(Abstract Supplement), A243-A244.

Pancerella, C. M., Tucker, S., Doser, A. B., Kyker, R., Perano, K. J., & Berry, N. M. (2003). *Adaptive awareness for personal and small group decision making*. Albuquerque, NM: Sandia National Laboratories.

Perla, P. P., Markowitz, M., Nofi, A., Weuve, C., Loughran, J., & Stahl, M. (2000). *Gaming and Shared Situation Awareness* (No. CRM D0002722): The Center for Naval Analyses Corporation.

Stanton, N. A., Chambers, P., & Piggott, J. (2001). Situational Awareness and Safety. *Safety Science, 39*(3), 189-204.

Uhlarik, J., & Comerford, D. A. (2002). *A review of situation awareness literature relevant to pilot surveillance functions.*: US Department of of Transportation Federal Aviation Administration: DOD/FAA?AM-02/3.

Ververs, P. M., Whitlow, S., Dorneich, M., Mathan, S., & Sampson, J. B. (2005). *AugCogifying the Army's Future Warfighter.* Paper presented at the Human Factors and Ergonomics Society 49th Annual Meeting, Orlando, FL.

Westbrook, P., Berka, C., Levendowski, D., Lumicao, M., Davis, G., Olmstead, R., Petrovic, M., Yuksel, Y., Ramsey, C., & Zivkovic, V. (2004). Quantification of Alertness, Memory and Neurophysiological Changes in Sleep Apnea Patients Following Treatment with nCPAP. *Sleep, 27*, A223.