

Interactive Neuro-Educational Technologies (I-NET): Development of a Novel Platform for Neurogaming

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Abstract. The advances in sophisticated, immersive and highly engaging video gaming technology have resulted in the introduction of “serious gaming” as platforms for training. A virtual environment that mimics reality as closely as possible is an effective instructional medium and also serves as a performance improvement/evaluation platform. However, the current methodologies suffer from several limitations: 1) conventional qualitative evaluation techniques that are removed from the trainee’s actual experience in both time and context 2) open loop platforms fail to support adaptive training and scenarios or leverage repeatability to accelerate training 3) failure to adapt to individual’s current psychophysiological state, limiting skill acquisition rates 4) multi-person tasks that lack tools for objective assessment and prediction of team cohesion or performance. As part of our initiative to invent a suite of Interactive Neuro-Educational Technologies (I-NET), we have developed a Neurogaming platform that will help resolve many of these limitations.

Keywords: EEG, Neuroergonomics, Neurosensing, Augmented Cognition.

1 Introduction

Advances in the fields of computer graphics and artificial intelligence, combined with the availability of sophisticated multi-core gaming hardware have resulted in the application of “serious gaming” as platforms for training simulations in industry, academia and military. The virtual environment provides a safe, controlled and cost effective setting to educate and evaluate users without the dangers associated with real life scenarios, especially for some industrial and military applications. The military has been a strong proponent of the gaming technology and uses sophisticated simulators for enhancements in training, safety, as well as to analyze military maneuvers and battlefield positions [1,2]. The “Educate to Innovate” campaign launched by the President of the United States in 2009 aimed at harnessing the power of interactive games to improve technological, mathematical, scientific and engineering abilities of American students. A wide variety of games were thus introduced in order to provide engaging exercises, improve retention of complex concepts, and create a rewarding learning experience for students [3]. Although this new generation of training technology is engaging and popular, it represents only an initial step towards a true revolution in creating successful instructional delivery systems.

Conventional methods for evaluating instructional design such as subjective reports, performance metrics and expert observations are mostly qualitative in nature and are removed from the trainee's experience in both time and context. Optimized environments that leverage brain-behavior relationships are known to improve the efficiency of learning (Neuroergonomics theory, [4,5]). Increasing evidence suggests that physiological correlates of attention, alertness, cognitive workload, arousal, and other fundamental constructs essential to training can be identified to further improve learning efficacy. The convergence of recent advances in ultra-low power consumer electronics, ubiquitous computing and wearable sensor technologies enables real-time monitoring of these cognitive and emotional states providing objective, timely, and ecologically valid assessments of psychophysiological states associated with learning. Our previous work has revealed specific EEG correlates of the stages of skill acquisition in simple learning and memory tasks, as well as in more cognitively complex and challenging test environments. Unique event-related EEG signatures detected during various stages of skill acquisition were evaluated to assess participants' ability to reflect aspects of learning across tasks and environments [6,7,8]. Such quantitative assessments will enable guidance of the user through distinct stages of skill development as well as provide timely evaluation and mitigation to improve the efficiency of learning.

Practice is accepted as a ubiquitous strategy to accelerate skill development. Repetition alone however, does not ensure success and repeated poor technique can lead to performance deficiencies and/or stress injuries. Instructional strategies and feedback are believed to be critical in accelerating skill learning. Recent investigations have suggested that skill learning may be dependent upon the availability of cognitive resources including attention and working memory and that the speed and efficacy of learning may be affected by either state or trait differences in these cognitive capacities [9,10]. Closed-loop and adaptive training platforms that incorporate real time sensing of cognitive and emotional state of the trainee (Neurosensing) and tailor the information delivery to an individual's or team's evolving skill level can considerably enhance the learning experience [11,12]. We have successfully employed similar closed-loop systems previously in implementing EEG-based drowsiness alarms in a driving simulator [13] and EEG-workload based Aegis radar and Tactical Tomahawk Weapons simulations [14], however the physiological thresholds and mitigations employed were specific to the application and not transferable to a general training platform.

The process presented here is an initial step towards a dynamic training system that will adaptively incorporate the psychophysiological state of the user in order to optimize training. The interactive training platform we intend to develop incorporates three modules: 1) Event-locked extraction of physiological metrics, 2) Closed-loop mitigation of tactical scenarios based on real time physiological metrics, and 3) Real time evaluation and mitigation of team neurodynamics. This paper presents a pilot study addressing the first module: event-locked extraction of physiological metrics. We will then discuss work done to address Modules 2 and 3, and how the three modules may be integrated into an adaptive training platform to increase training efficacy in individuals and teams. The platform was developed as part of our initiative to invent a suite of Interactive Neuro-Educational Technologies (I-NET) to accelerate skill learning and novice-to-expert transition.

2 Methods

2.1 Participants

Twenty-three participants (10 females and 13 males, mean age 25.87 years, range 19-40 years) were recruited from local colleges and newspaper/online advertisements. All participants had normal or corrected to normal vision and reported no history of neurological problems. No participants that had undergone formal marksmanship training were admitted to the study. Informed consent was obtained from all participants in accordance with the guidelines and approval of the Biomedical Research of America Institutional Review Board.

2.2 Data Acquisition

Electroencephalographic (EEG) and Electrocardiographic (EKG) data were collected using the wireless B-Alert® X10 EEG sensor headset developed by Advanced Brain Monitoring (ABM). Nine Ag/AgCl EEG electrodes were located at F3, Fz, F4, C3, Cz, C4, P3, POz, P4, according to the international 10-20 system. All EEG channels were referenced to linked reference electrodes located behind each ear on the mastoid bone. EKG was recorded with electrodes placed on the clavicle and opposite lower rib. Data was sampled at 256 Hz.

2.3 Paradigm

The popular military gaming platform - Virtual Battle Space 2 (VBS2), Tactical Warfare Simulation running on Real Virtuality 2 simulation engine, developed by Bohemia Interactive was used to create the gaming scenarios. In collaboration with Laser Shot Inc., we developed five custom combat scenarios using VBS2. The scenarios had realistic settings and contexts in which participants (acting as soldiers) were required to make deadly force decisions. In order to mimic reality as closely as possible, the game room was equipped with life-size projection of threats, stereo sound delivered via earbuds and other paraphernalia found in the battlefield environment. The participant used a demilitarized “airsoft” replica of an M4 rifle that interacted with the game using a wireless laser-based training system from Laser Shot Inc. The M4 was mounted with an EOtech holographic weapon sight, or red dot scope, commonly used in combat environment for quick target acquisition. Sandbags were provided to support the weight of the weapon, to both simulate combat firing procedures and reduce the effect of muscle fatigue on performance.

Participants were initially given marksmanship instructions (power point presentation) and requested to undergo a set of training tasks. Training addressed the fundamentals of marksmanship (aiming, breath control, trigger control, etc.), and the Rules of Engagement applicable in the testing scenarios. Five testing scenarios were administered in a randomized order for each subject. Each scenario was set in a unique environment that replicated typical fire fighting situations for soldiers (e.g., checkpoint, market, etc. in Afghanistan). In order to avoid excessive fatigue in participants, the scenarios were designed from a fixed point of view and lasted only 3-4 minutes. Throughout the scenario a mixture of enemy and friendly units, both stationary and moving, appeared at varying distances. Participants were instructed to evaluate threats and eliminate all enemy units as quickly as possible.

2.4 Data Analysis

ABM B-Alert® software was used to acquire, filter and analyze the physiological signals transmitted by the headsets in real time. The software identifies and eliminates multiple sources of environmental and physiological contamination such as power frequency hum, eye-blinks, EMG, etc. as well as other artifacts such as spikes, excursions, saturations, etc. using patented wavelet based signal processing algorithms. The software also incorporates patented algorithms for real-time classification of EEG based Engagement and Workload. These metrics are calculated using quadratic and linear discriminant functions that analyze Power Spectral Densities (PSD) of EEG frequency bins ranging from 1-40 Hz on a second-by-second basis [15]. Simple baseline tasks (completed on a prior study visit) were used to fit the EEG Engagement and Workload algorithms to the individual, so that the cognitive state models provide a highly sensitive and specific technique for identifying an individual's neural signatures of cognition.

An External Sync Unit (ESU) was used to synchronize the physiological signals with events in the game as well as user responses (rifle shots). Synchronization in the windows environment is dependant on the windows task scheduler and cannot guarantee an upper bound for user level tasks. The ESU is a general purpose data integration platform that can synchronize multi-source digital data (serial and/or parallel port protocols) with physiological signals from B-Alert® headsets acquired via Bluetooth protocol to millisecond level precision. ABM's automated analysis tools were used to extract various performance metrics in order to identify, 1) psychophysiological states associated with learning and skill acquisition, 2) cognitive factors that influence decision making, and 3) relevant physiological measures that distinguish top performers.

The analysis of Event Related Potentials (ERPs) offer excellent temporal resolution for tracking the flow of information from sensory processing, detection and identification of relevant objects and decision-making. ERPs and Event Related Engagement / Workload / Heart Rate were derived by time-locking to the presentation of the test bed stimuli (one-second post-stimulus), and to the one second epochs prior to and following user shots. ERPs were then plotted for the two seconds surrounding each shot (one second pre-shot, one second post-shot), at each sensor site and for each single trial shot event. Single trial ERP waveforms were averaged within and then across participants to compute grand means. Before averaging, data that included artifact such as eye blinks, excursions or excessive muscle activity were rejected on a trial-by-trial basis using automated in-house software [15].

As a normalization step, single trial event-related Engagement / Workload / Heart Rate data were z-scored to each individual's average level of each metric. This allows the identification of whether an individual was experiencing above or below average Engagement / Workload / Heart Rate in relation to a given event.

3 Results

3.1 Event Related Potentials

Fig.1 below illustrates the averaged time series at the vertex (Cz) for missed shots (shots that did not hit a target) versus kill shots (shots that hit and killed an enemy

target). Greater positivity from 875 ms to 250 ms before the shot distinguished kill shots from missed shots. Peak amplitude preceding kill shots was significantly greater than the peak amplitude preceding missed shots ($t(22) = 2.92, p < .01$). Eighteen of the 23 subjects (78%) showed this distinction, with peak amplitude preceding kill shots on average $5.37 \mu\text{V}$ greater than the peak amplitude preceding missed shots. This appears similar to findings reported by Konttinen and Lyytinen, 1998 [16], in which pre-shot slow potential positivity was associated with increased rifle stability. Alternatively, the pre-shot positivity for kill shots could be associated with target identification and recognition with a greater attenuation to enemy targets preceding kill shots (and presumably absent preceding missed shots). All subjects exhibited a characteristic *post-shot* positive potential beginning at the time of the shot and peaking between 100 and 250 ms post-shot. This initial positive component was most clearly seen in the central channels, and did not differentiate shot types (e.g., missed shots versus kill shots). However a late positive component differentiated missed shots from kill shots as early as 250 ms post-shot and was sustained for windows in excess of 900 ms post-shot. Maximal miss/kill differences were seen in central and parietal channels, and varied from 490-850 ms post-shot. Peak amplitude of the late positive component (between 490-850 ms post-shot) was significantly higher following kill shots than following misses ($t(20) = 4.84, p < .0001$). The peak amplitude of the late component following kill shots was on average $7.39 \mu\text{V}$ greater than the peak amplitude following missed shots. This later positivity is likely a P300 or Late Positive component, possibly in response to the visual cue of the enemy death in the simulation environment (absent in the case of missed shots).

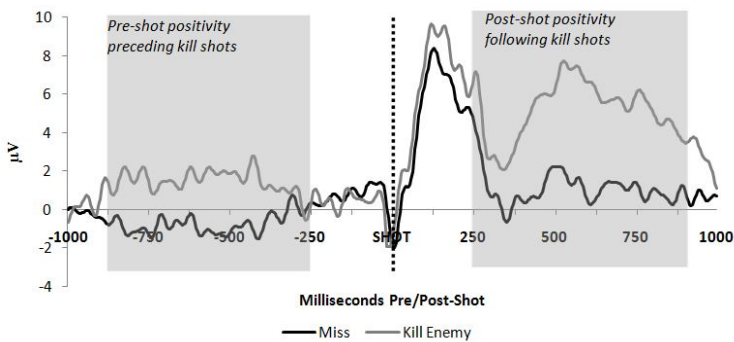


Fig. 1. Grand mean ($n=23$) ERP waveforms for missed shots versus shots that killed an enemy, at vertex site (Cz), for one-second pre- and post-shot

3.2 Other Event Related Metrics

EEG-Engagement one second pre-shot distinguished missed shots from those that killed an enemy (see Fig.2(a)). Below average engagement was associated with missed shots. This difference did not reach statistical significance ($P=0.07$), however suggests differing neurophysiologic states for the preparation of successful versus

unsuccessful shots. A subsample of subjects ($n=6$) had instances of “friendly fire” (shooting a civilian or comrade). Fig.2(b) shows normalized EEG-Engagement and EEG-Workload in the one second pre-shot, averaged for those six subjects.

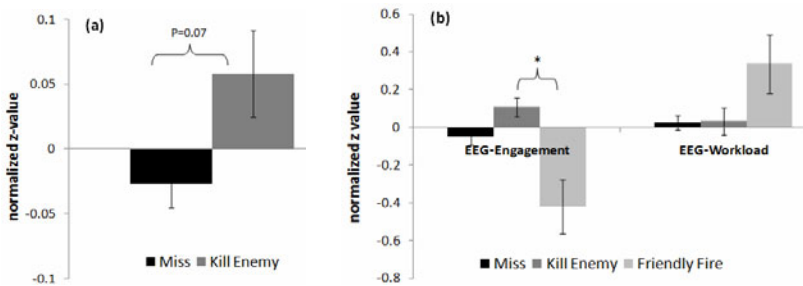


Fig. 2. (a) Grand means for normalized (within individuals) EEG-Engagement in the one second preceding missed shots versus kill shots ($n=18$; performance outliers removed). (b) Group means for the six subjects that had instances of friendly fire errors. Normalized EEG-Engagement and EEG-Workload in the one second pre-shot for misses, kills, and friendly fire.

Friendly fire errors were marked by below-average EEG-Engagement (about 0.4 standard deviation *below* average), and above average EEG-Workload (about 0.3 standard deviation *above* average). EEG-Engagement preceding friendly fire errors was significantly lower than EEG-Engagement preceding shots that killed an enemy ($t(4) = 2.92, p < 0.05$). No other differences reached significance. Due to the low number of friendly fire errors in the dataset, these results are only relevant to the six subjects that made this type of error and may not generalize across a larger population. A test bed with a greater number of civilians or comrades (or with enemy and friendly forces that are harder to distinguish from each other) would provide better opportunity for studying the neurophysiology associated with that type of error.

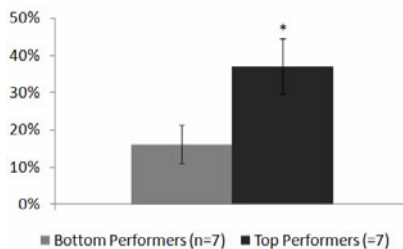


Fig. 3. Average percent pre-shot Engagement across all shots, for bottom vs. top performers

3.3 Top vs. Bottom Performers

Each of the thirteen VBS2 performance metrics were z-scored to the population (23 subjects), and then aggregated into a summary performance measure to determine the overall top ($n=7$) and bottom ($n=7$) performers. Pre-shot EEG-Engagement,

EEG-Workload, and HR (raw values; not normalized within individuals) were compared between the two groups. Fig.3 illustrates that top performers had nearly 2 times higher pre-shot EEG-Engagement than bottom performers ($t(12) = -2.32$, $p < 0.05$). This finding highlights the importance of Engagement in the combat pre-shot state.

4 Discussion

In this study we developed a platform which allows for event-locked extraction of physiological metrics in a tactical training environment. Our preliminary results suggest that physiological signatures may distinguish elements of good and poor performance that could be used to accelerate the efficiency of learning in individuals and to improve performance of teams. The interactive training platform under development incorporates three modules: 1) Event-locked extraction of physiological metrics, 2) Closed-loop mitigation of tactical scenarios, based on real time physiological metrics and 3) Real time evaluation and mitigation of team neurodynamics. The study presented above addresses the first module. Below, we discuss efforts taken to address the second two modules.

4.1 Closed-Loop Mitigation of Tactical Scenarios

The concept of a comprehensive closed-loop module was tested independently in order to incorporate the mitigation parameters and strategy derived through research studies [17]. Automated adaptive training was incorporated based on both physiological (EEG, EKG, GSR) and non-physiological (performance, subjective training, expert observations) metrics. The Synchronous Operational Psychophysiological Sensor Suite (SyKron) developed by the University of Central Florida's ACTIVE laboratory was used to integrate, synchronize, as well as analyze physiological signals from ABM EEG headsets as well as other non-physiological inputs such as performance, subjective rating etc. The data logging and playback features of SyKron were used to facilitate iterative assessment of adaptive mitigation and threshold development. General Purpose Real-Time Mitigation Engine (GPRIME) developed by the Warfighter Human-Systems Integration Laboratory at the U.S. Naval Research Laboratory (NRL) was used to close the loop by providing real time modification of the game. GPRIME is a software platform that can support streaming data from multiple IP addresses, allowing for mitigations to be triggered by data variables streaming from multiple computers on a local network. GPRIME receives processed real-time (or near real-time) physiological inputs along with subjective and/or performance data from SyKron as variables to create Boolean logic (If, And, Or, >, =, etc.) rules that are saved and evaluated in real-time to assess when it is appropriate to perform a mitigation. When the streaming data inputs meet the threshold rules, pre-recorded keyboard and mouse click macros are triggered to modify the training scenario in VBS2.

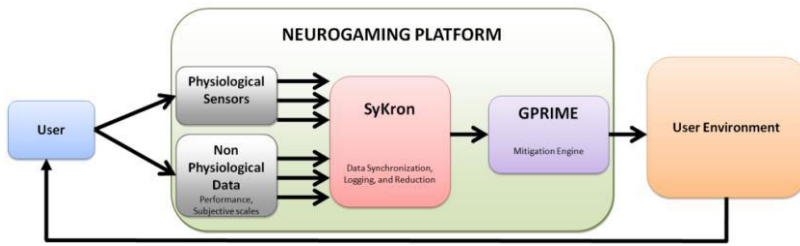


Fig. 4. Closed-loop Adaptive module for real-time mitigation (adapted from Berka et.al, 2010)

4.2 Real Time Evaluation of Team Neurodynamics

In order to develop a tightly controlled platform for investigating team neurodynamics in a simulation environment, we developed a team training module using desktop based simulators. Working with Discovery Machine Inc., ABM designed a three person teaming scenario, called ‘Safe Passage,’ within VBS2. The scenario was designed to evaluate and train team members to work together to successfully complete a team mission, emphasizing team communication and friendly fire avoidance. The primary mission objective of the team was to safely escort a convoy through enemy territory. Team members were assigned individual tasks, each with unique roles essential to meeting the mission’s objectives.

Pilot Study: ABM recruited two teams of three people, with each team performing six iterations of the teaming mission. Each team member was fit with a wireless X10 B-Alert headset which allowed EEG-Engagement, EEG-Workload and Heart Rate to be calculated on a second-by-second basis. All computers were programmed to follow the Network Time Protocol (NTP) such that the physiological parameters, game events, user responses, etc. from all team members were time synchronized for analysis by real-time as well as offline algorithms.

The automated online program developed by Stevens et.al [18, 19] was used to generate EEG-based neurosynchrony (NS) profiles for team performance in real-time. A summary of the layered analytic approach used by the program is as follows: The data flow is organized into collection, processing, modeling and analysis modules. The data collection and processing modules are included in ABM B-Alert software where EEG is decontaminated and Workload (WL) and Engagement (E) values from each of the team members are calculated on a second-by-second basis. The values of WL and E are then normalized and statistically partitioned. The values at each second for each team member are then combined into a vector representing the state of the team (EEG-E) as a whole. A trained 1×25 node unsupervised artificial neural network develops a topology and outputs a linear series of 25 team EEG-E patterns that are termed as neurophysiologic synchronies (NS). A ‘hit’ frequency map showing the number of times each node was expressed during a performance was then created, which when aligned with training context can provide significant insight into team dynamics and potentially be used for real time mitigation of tasks. Predictive models developed using Hidden Markov Modeling by analyzing the correlations and persistence of the NS could also be potentially used to indicate effective/ineffective team compositions. Data analysis for this pilot study is in progress.

The final integrated Neurogaming platform will incorporate automated event logging and synchronization with physiological data and closed-loop mitigations for individuals and teams. Even though the scenarios discussed above were specific to military applications, the scope of the Neurogaming platform can be extended to many other medical, educational and industrial applications.

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References

1. Ackerman, R.K.: Navy Researchers Target, Virtually. *Signal* 60(11)
2. Alpert, M.: My Virtual War. *Scientific American.com*. January 22 (2006)
3. Anderson, et al.: Critters in the classroom: a 3D computer-game-like tool for teaching programming to computer animation students. In: *Proceedings in SIGGRAPH* (2007)
4. Kramer, A., Parasuraman, R.: Neuroergonomics: Application of Neuroscience to Human Factors. In: Caccioppo, J.T., Tassinary, L.G., Berntson, G.G. (eds.) *Handbook of Psychophysiology*, 3rd edn., pp. 704–722. Cambridge University Press, New York (2007)
5. Parasuraman, R.: *Neuroergonomics: The Brain at Work*. Oxford University Press, Oxford (2005)
6. Berka, C., et al.: Objective Measures of Situational Awareness using Neurophysiology Technology. In: Schmorow, D., Stanney, K., Reeves, L. (eds.) *Augmented Cognition: Past, Present and Future*, pp. 145–154. Strategic Analysis, Inc, Arlington (2006)
7. Stevens, R., Galloway, T., Berka, C.: Integrating EEG Models of Cognitive Load with Machine Learning Models of Scientific Problem Solving. In: Schmorow, D., Stanney, K., Reeves, L. (eds.) *Augmented Cognition: Past, Present and Future*, pp. 55–65 (2006)
8. Berka, C., et al.: Real-time Analysis of EEG Indices of Alertness, Cognition and Memory Acquired with a Wireless EEG Headset. *International Journal of Human-Computer Interaction* 17(2), 151–170 (2004)
9. Best, J.B.: *Cognitive Psychology*, 3rd edn. West Publishing Company, New York (1992)
10. Solomon, R.M., Horn, J.M.: Post-shooting traumatic reactions: A pilot study. In: Reese, J., Goldstein, H. (eds.) *Psychological Services in Law Enforcement*, pp. 383–393. United States Government Printing Office (1986)
11. Schmorow, D., Stanney, K.M., Wilson, G.F., Young, P.: Augmented cognition in human-system interaction. In: Salvendy, G. (ed.) *Handbook of human factors and ergonomics*, 3rd edn. John Wiley, New York (2005)
12. Stripling, R., Coyne, J.T., Cole, A., Afergan, D., Barnes, R.L., Rossi, K.A., et al.: Automated SAF Adaptation Tool (ASAT). In: *Augmented Cognition Conf.*, pp. 346–353 (2007)
13. Berka, C., Levendowski, D., Westbrook, P., Davis, G., Lumicao, M., Ramsey, C., et al.: Implementation of a Closed-Loop Real-Time EEG-Based Drowsiness Detection System: Effects of Feedback Alarms on Performance in a Driving Simulator. In: *Paper presented at the 1st International Conference on Augmented Cognition*, Las Vegas, NV (2005)

14. Berka, C., Levendowski, D., Ramsey, C.K., Davis, G., Lumicao, M., Stanney, K., et al.: Evaluation of an EEG-Workload Model in an Aegis Simulation Environment. In: Paper presented at the Proceedings of SPIE Defense and Security Symposium, Biomonitoring for Physiological and Cognitive Performance during Military Operations, Orlando, FL (2005)
15. Berka, C., et al.: Real-time Analysis of EEG Indices of Alertness, Cognition, and Memory Acquired with a Wireless EEG Headset. *International Journal of Human-Computer Interaction* 17(2), 151–170 (2004)
16. Konttinen, N., Lyytinen, H., Viitasalo, J.: Rifle-balancing in precision shooting: behavioral aspects and psychophysiological implication. *Scandinavian J. Med. Sci. Sports* (1998)
17. Berka, C., Pojman, N., Trejo, J., Coyne, J., Cole, A., Fidopias, C., Nicholson, D.: Neurogaming: Merging Cognitive Neuroscience & Virtual Simulation in an Interactive Training Platform. In: 1st International Conference on Neuroergonomics Florida (2010)
18. Stevens, R.H., et al.: Can Neurophysiologic Synchronies be Detected during Collaborative Teamwork? In: *Proceedings in HCI International*, San Deigo (July 2009)
19. Stevens, R.H., Galloway, T., Berka, C., Behneman, A.: A Neurophysiologic Approach for Studying Team Cognition. In: *Proceedings in ITSEC* (2010)