Toward Cognitive Two-Way Interactions in an Immersive Virtual Reality Environment

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ABSTRACT

The use of Immersive Virtual Reality Environments (iVREs) for training and rehabilitation purposes is growing in popularity. An emerging topic in iVRE program development, particularly programs aimed at cognition enhancement, is implementing two-way interactions between the user's cognitive state and the iVRE to achieve maximal effects. This process incurs several outstanding challenges. For example, although recent advances in electroencephalography (EEG) have revealed a number of neural correlates/signatures for a variety of operationally-relevant cognitive states (e.g., attentiveness, fatigue), most if not all of these neuromarkers have not been validated in iVREs. The current paper addresses this gap by describing efforts to achieve high quality EEG signals in an iVRE with millisecond-time synchronization between the two systems. To achieve these goals, we evaluated several mobile EEG systems, incorporated off-the-shelf hardware, and developed custom software to effectively implement the EEG devices into the Physical and Cognitive Operational Research Environment (PhyCORE), an iVRE located at the Naval Health Research Center in San Diego, California. As a result, the PhyCORE can now provide cognitive information about human subjects through on-line monitoring of brain activity patterns. Equipped with this capability, the PhyCORE is ready for further development of individualized training and rehabilitation programs based on the subjects' cognitive states as assessed in real-time and in a real-life environment. The technical challenges and solutions described herein can be easily generalized and adapted for other iVREs, and represent a critical step toward optimization of the human-machine interaction.

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INTRODUCTION

Immersive Virtual Reality Environments (iVRE) have been extensively developed and widely deployed for a variety of purposes, including performance training and injury rehabilitation (Cheung, Tunik, Adamovich, & Boyd, 2014; Chou, Weingarten, Madden, Song, & Chen, 2012; de Oliveira et al., 2012; Karutz & Bailenson, 2015; Slater, 2014). The goal of performance training programs is for subjects to enhance and then transfer their acquired knowledge, skills, and abilities into the real world; for injury rehabilitation, the aim is to restore degraded skills, functions, and abilities that are, in turn, transferable into the real-life environment. Efforts toward achieving these goals have historically focused on the naturalistic presentation of stimuli as well as methods for interacting with these stimuli; however, iVRE program effectiveness depends on more than these features alone.

An emerging trend, particularly among iVREs designed to enhance cognitive performance, is to incorporate two-way interactions between subjects' brain states and the iVRE (Chou et al., 2012; Fouad, Amin, El-Bendary, & Hassanien, 2015; Gramann, Ferris, Gwin, & Makeig, 2014; Gruzelier, 2014a, 2014b, 2014c; Mak & Wolpaw, 2009; van Boxtel & Gruzelier, 2014). Cognitive two-way interactions have been made possible through recent discoveries of neural correlates/signatures for a variety of cognitive functions and brain states as measured through electroencephalography (EEG; Bohil, Alicea, & Biocca, 2011; Nimmrich, Draguhn, & Axmacher, 2015; Parasuraman, 2003). That is, through EEG-based analyses of brain electrical activities that occur in direct response to specific sensory, cognitive, or motor events (i.e., event-related potential, ERP), a variety of metrics have been established for indicating such mental states as workload, fatigue, alertness, and attentiveness. Most if not all of these metrics, however, have not been validated in iVREs.

Although greatly promising, the implementation and use of EEG technologies in iVREs presents many challenges. Unlike conventional applications of EEG systems (e.g., in laboratory or clinical settings where subjects refrain from movements and ambient electrical interference is minimized), iVREs are inherently dynamic, often require subject movement, and therefore produce considerable physiological, mechanical, and electrical noise. Technology developers have attempted to overcome these challenges by designing EEG systems that promote subject mobility and feature innovative devices for reducing the impact of unavoidable interference on signal quality. To date, however, there is very little research available which documents and evaluates the processes required for achieving robust mobile EEG recordings in an iVRE (Callan, Durantin, & Terzibas, 2015; Lin, Wang, Wei, & Jung, 2014).

To establish cognitive two-way interactions in any iVRE, it is necessary to first demonstrate the capability to capture, analyze, and apply relevant ERP metrics under germane conditions. Of course, this critical step depends largely on the quality of EEG signals obtained in the system. There also exists the critical need to achieve millisecond-time synchronization between the two systems as required for correlating brain states with subject performance or using brain activity patterns to drive the program. In this paper, we address these considerations by discussing the processes by which we integrated and evaluated the performance and potential utility of three unique mobile EEG systems within an iVRE known as the Physical and Cognitive Operational Research Environment (PhyCORE, Figure 1; Bartlett, Sessoms, & Reini, 2013). Located at the Naval Health Research Center (NHRC) in San Diego, California, the PhyCORE is a state-of-the-art system for evaluating programs associated with military performance training, injury rehabilitation, and physical fitness assessment, as well as for testing the effects of military gear and equipment on human performance. The integration of mobile EEG technologies into the PhyCORE was intended to enhance these programs by providing a mechanism for capturing and comparing subjects' cognitive states and functions in real time and in a realistic, but highly controlled dynamic environment. Ultimately, the mobile EEG addition would provide the necessary foundation for further development of individualized training and rehabilitation programs based on cognitive two-way interactions between subjects and the PhyCORE. The processes and challenges associated with integrating these technologies are described herein, to include our process for validating the three mobile EEG devices, as well as our methodology for synchronizing the mobile EEG and the PhyCORE with millisecond accuracy.

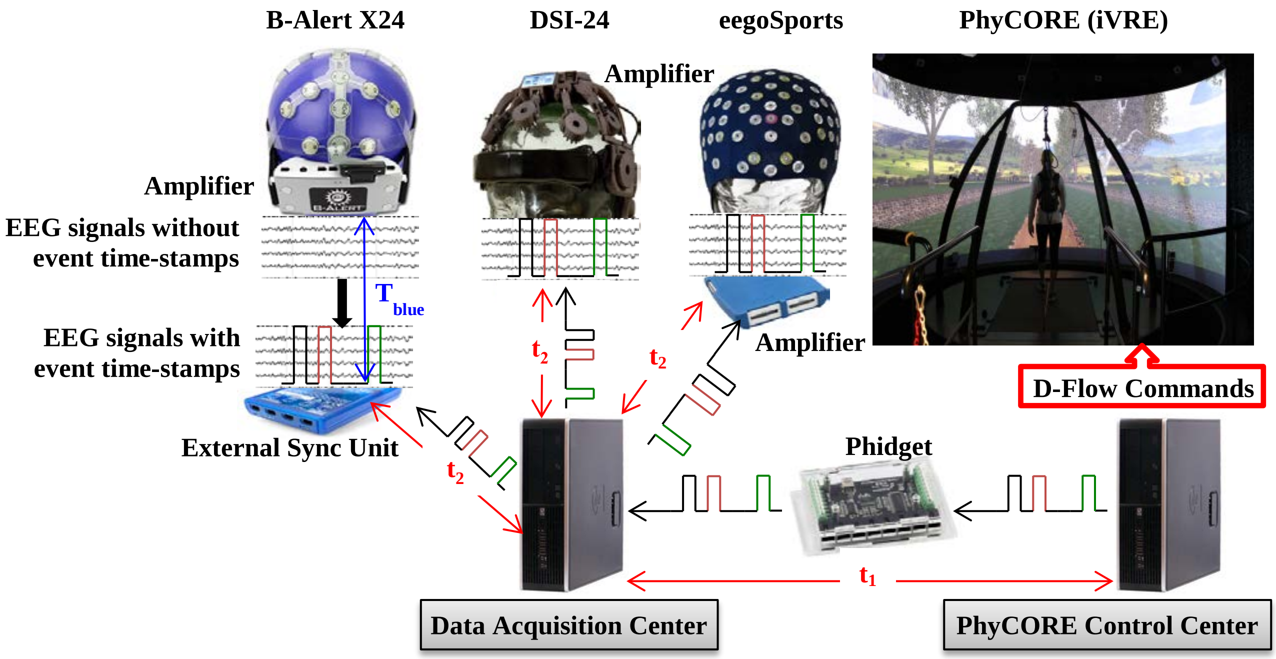


Figure 1. Technical Approaches for Integrating the Mobile EEG Systems into the PhyCORE

MATERIALS AND METHODS

The Physical and Cognitive Operational Research Environment (PhyCORE)

Enhanced and upgraded from the traditional extended version of the Computer Assisted Rehabilitation Environment (CAREN, Motekforce Link, Amsterdam, The Netherlands), the PhyCORE consists of a 9-foot diameter platform that can be programmed to move in six degrees of freedom independently or simultaneously. At the platform center is a dual belt treadmill that runs the length of the platform and has integrated force plates under each belt to measure ground reaction forces (ForceLink, Culemborg, The Netherlands). The platform is surrounded by a 180-degree wide and 9-foot tall curved screen, with motion capture cameras to track movement of the subject. Subjects can thus be immersed in a 3D virtual environment within which multimodality sensations (visual, auditory, vestibular, and olfactory) can be experienced and controlled by the subject or the experimenter. The movement of the platform and the sensory stimulations are synchronized to form a real-life environment with real-time actions (Bartlett et al., 2013). The PhyCORE thus provides an ideal iVRE for assessing the performance of mobile EEG systems with regard to noise reduction/elimination and addressing the millisecond time synchronization challenge.

Mobile EEG Systems

Currently, numerous mobile EEG systems are available on the market. To determine which of these systems to integrate into the PhyCORE, we considered a host of decision criteria, including but not limited to:

- Ease of use
- Durability of the hardware
- Resilience to electrical noise interference (signal-to-noise ratio)
- Stability of the acquired brain signals

- Capability of accepting external event timing markers
- Efficiency and reliability of the data acquisition and analysis software

Based on an extensive literature review, site visits to the vendors, and general technical inquiries, we selected the following three mobile EEG systems for testing:

1. B-Alert X24 mobile EEG system (20 EEG wet sensors, Advanced Brain Monitoring Inc., Carlsbad, CA)
2. DSI-24 mobile EEG system (19 EEG dry sensors, Wearable Sensing, San Diego, CA)
3. eegoSports 64 mobile EEG system (61 EEG wet sensors, ANT Neuro, Enschede, The Netherlands).

To integrate these EEG systems into the PhyCORE, the first task was to establish digital communication pathways through which the recorded EEG signals could be accurately time-stamped with events occurring inside the iVRE. Critical factors to consider for successful integration included (a) the mechanism by which the PhyCORE Control Center sent out event signals, (b) the process by which each EEG system received event time markers, and (c) calibration of the established digital signal pathways for timing accuracy and jittering estimation. Our approaches for overcoming these technical challenges are presented in the Results section.

Experimental Design

Twelve healthy volunteers participated in this study (7 females, 5 males, age range: 21-40 years). All procedures were approved by the NHRC Institutional Review Board, and the research was conducted in compliance with all applicable federal regulations governing the protection of human subjects (Protocol NHRC.2014.0017).

Subjects reported individually to NHRC's PhyCORE laboratory. They were informed that they would be fitted with three different mobile EEG headsets and undergo similar testing trials on the PhyCORE while wearing each device. After donning each headset, an impedance check was performed in accordance with each vendor's impedance test utility tool to ensure that all channels had satisfactory connections. Following testing of each device, subjects completed a brief survey that evaluated their levels of comfort and pain (scale of 1-10), to include opportunity for written comments on their experience. Short breaks (10-20 minutes) were taken between testing conditions, in addition to a 1-hour lunch break. The entire experiment tended to last about 8 hours.

Testing trials consisted of classical auditory and visual oddball experiments performed under two conditions: (a) subjects sitting still on a chair located on the stationary PhyCORE platform and with a corresponding visual display showing a stationary nature trail scene; and (b) subjects walking at a self-selected pace on the PhyCORE treadmill and with a corresponding visual display of a dynamic nature trail scene that flowed in sync with subjects' walking speed. Preceding each testing trial, a baseline assessment of subjects' EEG activity was acquired while subjects sat with their eyes open and then closed for 2 minutes each.

For the auditory oddball paradigm, a series of bird chirps were presented through the surround sound speakers as the frequent stimulus, with toad croaks as the rare stimulus. For the visual oddball paradigm, a series of bird images were displayed at the center of the screen as the frequent stimulus, with toad images as the rare stimulus. Presentation of frequent to rare stimuli occurred at a 4:1 ratio. The stimulus duration was 0.5 s and the stimulus interval was varied pseudo-randomly between 1.5 s and 2.0 s. The rare stimuli were presented pseudo-randomly following presentation of 2 to 10 frequent stimuli. A total of 250 (200 frequent, 50 rare) and 500 (400 frequent, 100 rare) stimuli were presented in each session for the sitting and walking conditions, respectively, which corresponded to about 10 minutes for each sitting trial and about 20 minutes for each walking trial. For all trials, subjects were instructed to count silently the total number of frequent stimuli and report this total at the end of each session.

EEG Data Offline Analysis

Data from the 12 subjects were analyzed off-line following completion of the data collection phase. An automated set of procedures for evaluating the EEG data quality was developed to process data recorded with each EEG system using EEGLAB (Delorme & Makeig, 2004) running on a MATLAB platform (MathWorks, Natick, MA). Both Wearable Sensing and ANT Neuro provided plug-ins for importing raw data into EEGLAB. Advanced Brain Monitoring (ABM) provided an independent program, the B-Alert Lab, to process their raw data. To evaluate data quality consistently across the three EEG systems, an additional MATLAB program was developed to extract the

ABM raw data and import them into EEGLAB. After importing these data into EEGLAB, the following automated procedures were applied to the data recorded from all three EEG systems:

1. Trimming: All data were trimmed 1 second before and after the event markers of session start and session end. The events of session start and end were sent manually to the EEG event channel by having the experimenter push a button on a wireless game controller connected to the D-Flow software.
2. High-pass filtering: Data were high-pass filtered with a zero-phase shift Finite Impulse Response (FIR) filter (1.0 Hz cut-off, -6dB).
3. Electric power line noise cleaning: The 60 Hz electrical noise was cleaned with an adaptive algorithm (CleanLine, an EEGLAB plug-in) instead of with a notch filter, as the algorithm did not generate dips on the EEG signal as often seen with a notch filter. The total power of the 60 Hz reduction for each channel was used to compare the resilience of each EEG system with electrical power line noises.
4. Low-pass filtering: Data were low-pass filtered with a zero-phase shift FIR filter (50.0 Hz cut-off, -6dB).
5. Referencing: Data were referenced to the average of the two mastoid or earlobe electrodes (M1 and M2).
6. Removing bad channels: A channel was considered bad if any of the following criteria were met: (a) a flat-line segment longer than 5 s, (b) maximal amplitude larger than 100 mcV, (c) signal-to-noise ratio higher than the channel population mean by 4 standard deviations, or (d) correlation coefficient below 0.8 to the robust estimate of the other channels. The number of removed channels was used to indicate the yielding rate of each EEG system.
7. Removing artifacts: Non-stationary high variance signals, usually originating from muscle activities, were removed by using Artifact Subspace Reconstruction (ASR, an EEGLAB plug-in).
8. Independent Component Analysis: EEG signals were decomposed using the extended infomax algorithm in EEGLAB to separate sensory-evoked components from other brain activity and artifact components.
9. Removing artifact components: Artifact components isolated from the ICA were automatically removed with Multiple Artifact Rejection Algorithm (MARA), a supervised machine learning algorithm that runs with EEGLAB to identify components originating from eye/muscular artifacts and loose electrodes.
10. Data epoching: Data were segmented into epochs (-400 ms pre-stimulus to 800 ms post-stimulus) corresponding to the frequent and rare auditory or visual stimuli.
11. Measuring ERP: EEG data in same epochs in each channel were averaged to yield ERPs using the ERPLAB (Lopez-Calderon & Luck, 2014).
12. Grand average ERP: ERPs from each channel were averaged across all 12 subjects to yield the grand average ERPs using our in-house developed MATLAB programs.
13. Statistical analysis: The grand average ERPs were used to compare the signal quality recorded from the three EEG systems.

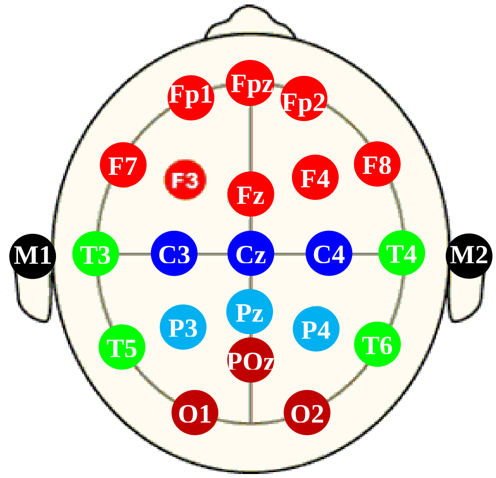


Figure 2. Sensors Common to the Three Systems
Red, frontal; blue, central; green, temporal; light blue, parietal; dark red, occipital. Note: POz is not available in DSI-24.

To produce meaningful comparisons, the channels common to all three EEG systems were used for final statistical analyses and reporting results in this report. A total of 20 channels were included (see Figure 2).

RESULTS

Integration of EEG Systems into the PhyCORE

One of the key challenges of integrating the EEG systems into the iVRE was achieving the highest possible accuracy in event timing synchronization, which depended heavily on how the event signals were transmitted from the event generators and how the signals were received by the EEG systems. From the receiving end, this challenge became complicated due to the inherent design differences among the mobile EEG systems, as each device had unique methods for achieving mobility and synchronizing external events with the EEG signals. As illustrated in

Figure 1, in the B-Alert X24, EEG signals were acquired in the headstage unit and transmitted via Bluetooth to an External Sync Unit for time-marking of EEG signals. The time-stamped EEG signals were then streamed into the Data Acquisition Center through a USB cable. However, the initial use of a Bluetooth transmission prior to time-marking created a time delay (T_{blue}, Figure 1) of approximately 35 ms and jittering of 20 ms for this device as reported by the manufacturer. In contrast, the external event signals for both the DSI-24 and the eegoSports 64 were sent directly to an EEG amplifier through a cable connected to the event generator (PhyCORE Control Center, Figure 1). Thus, for these devices, EEG signals were time-stamped prior to their wireless transmission to the data acquisition computer. This method effectively eliminated T_{blue} as found with the B-Alert X24.

From the event generator, events such as platform movement, treadmill speed, and stimulus presentation were all programmed and produced with a software program called D-Flow (Motek Medical, Amsterdam, The Netherlands). By design, D-Flow does not communicate with the computer's parallel ports. Therefore, to send PhyCORE event time stamps to the EEG systems, a 1018 Phidget I/O Board (Phidgets Inc., Calgary, Alberta, Canada) was used to receive event time stamps through a USB cable. The Phidget I/O Board sent the event time markers to a PCI-based digital I/O board residing in the computer of the Data Acquisition Center. Only then could the event time markers be relayed to the EEG systems through the parallel ports. Inevitably, this event timing transmission method created a systematic delay (T_{sys}) in time-stamping the EEG signals ($T_{sys} = t_1 + t_2$, Figure 3). This systematic time delay was independent of the design of the EEG systems and was therefore consistent for all three devices. Using this approach, the total delay in event timing for the DSI-24 and eegoSports 64 was T_{sys}. For the B-Alert X24, the total delay was $T_{sys} + T_{blue}$ (equivalent to $t_1 + t_2 + T_{blue}$).

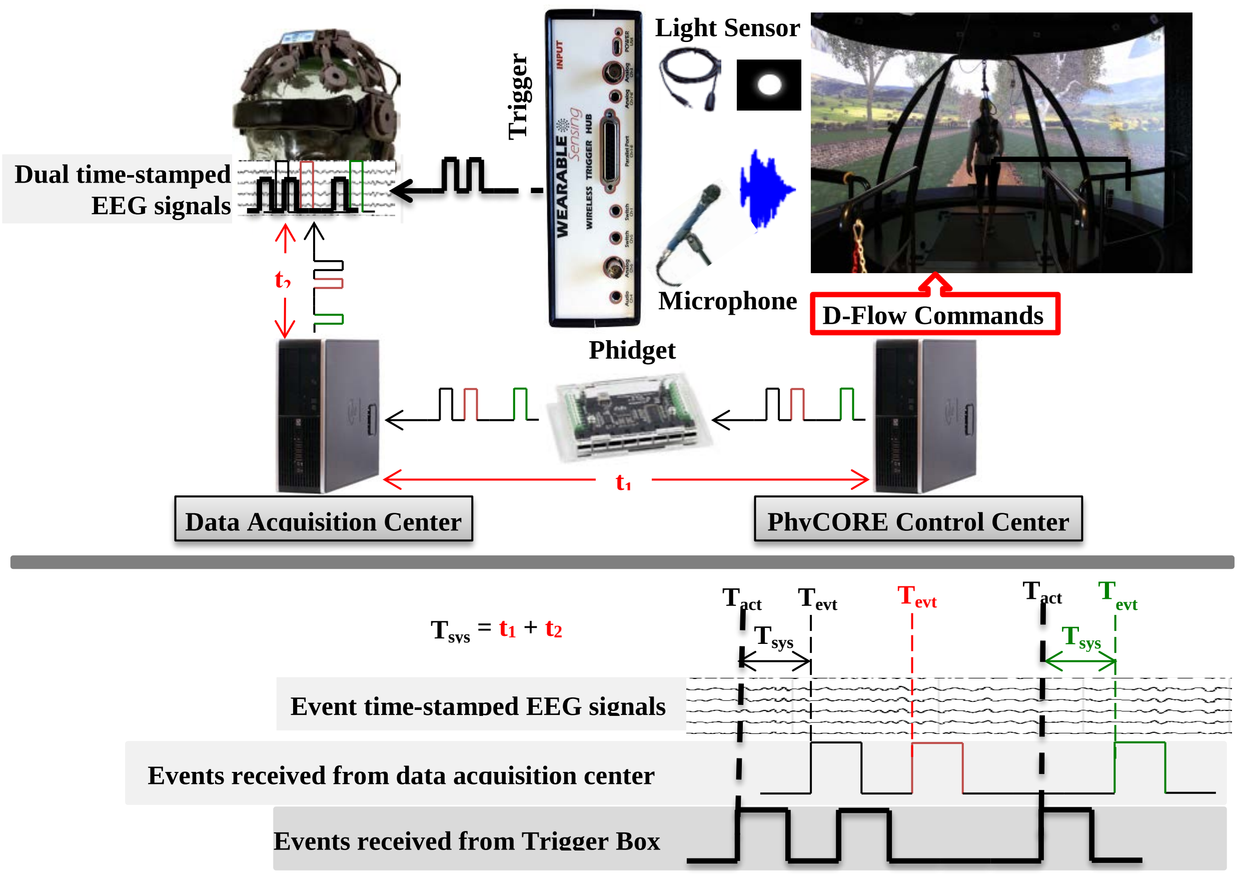
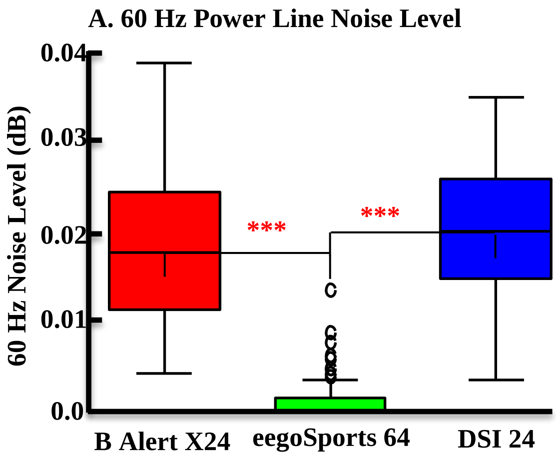


Figure 3. Calibration of Event Time Delays and Jitters

The existence of time delays was viewed as a technical setback; nevertheless, the value of T_{sys} could be measured accurately. As shown in Figure 3, T_{sys} was calibrated using a trigger box manufactured by Wearable Sensing. The actual timing (T_{act}) of the screen's visual display screen or the surround speakers' sound emission was detected by a light sensor or microphone connected to the trigger box. The trigger box then sent the visual or audio event signal to the headstage (Figure 3, top). Simultaneously, the event marker signals that were sent to the EEG system from the

Data Acquisition Center were also sent to the headstage and recorded as T_{evt}. The values of T_{sys} were then measured off-line by calculating the difference between T_{evt} and T_{act} (Figure 3, bottom). The mean values of T_{sys} were 21.9 ± 2.9 SD ms and 30.7 ± 1.9 SD ms for visual and auditory stimulation, respectively. These T_{sys} values were accounted for in EEG data analyses for both the DSI-24 and eegoSports 64 systems. For the B-Alert X24, an additional 35 ms (T_{blue}) was used to compensate for the delay.



B. Percent of bad channels (mean % ± SD)

	DSI 24	B Alert X24	eegoSports 64
Sitting	7.42 ± 0.06 ***	6.25 ± 0.06	9.78 ± 0.05 ***
Walking	16.25 ± 0.09	3.96 ± 0.05	3.13 ± 0.05

Figure 4. Noise Sensitivity/Vulnerability

*A. Comparison of 60 Hz power line noise level. B. Bad channels by sitting and walking condition. ***p < 0.001.*

Assessing Noise Sensitivity/Vulnerability of Mobile EEG Systems in the PhyCORE

The massive amount of electrical and physical activity inherent in an iVRE presents a considerable concern when attempting to record EEG activity due to the impact of noise interference on brain signal quality. Generally, there are two types of noise (i.e., artifacts) in EEG signal measurement (Frølich, Andersen, & Mørup, 2015; Onton, Westerfield, Townsend, & Makeig, 2006): (a) non-stereotyped artifacts originating from environmental electrical noise and subject movements, and (b) stereotyped artifacts generated by eye movements, blinks, and heart beats. Overcoming these challenges is a necessity for capturing clean EEG data in iVRE settings.

To address the challenge of power line electrical noise sensitivity/vulnerability for the three mobile EEG systems, we measured the level of 60 Hz components in EEG signals in all recorded data for each system. As shown in Figure 4A, the mean 60 Hz noise level was similar for the B-Alert X24 and DSI-24 systems (0.0206 ± 0.022 dB and 0.0225 ± 0.029 dB, respectively) and was significantly lower in the eegoSports 64 (0.0014 ± 0.006 dB).

To assess the sensitivity/vulnerability of the EEG systems to subjects' body movement noise, we measured the percentage of bad channels (see Methods and Materials) in the sitting and walking experimental conditions. As presented in Figure 4B, there was no significant difference between these two conditions for the B-Alert X24 system. There were, however, significant differences for the DSI-24 and eegoSports 64 systems.

Measuring Behaviorally-Relevant EEG Signals in the PhyCORE

The ultimate goal of implementing EEG systems into an iVRE is to detect behaviorally relevant EEG signals. To this end, we conducted extensive analyses on our data within and across each EEG system. For this paper, we have reported results only from data recorded from the 20 sensors common to all three systems (Figure 2). Two neural activities, alpha oscillations and ERPs, were used to indicate the capability of each EEG system.

Alpha rhythm was present mainly over the parietal regions of the brain when subjects' eyes were closed (i.e., posterior rhythm or Berger effect; Bazanova & Vernon, 2014). When subjects' eyes were open, the amplitude of EEG signals in the alpha band (8–13 Hz) decreased significantly. Therefore, changes in alpha rhythm were a behaviorally-induced brain activity. As shown in Figure 5A, a series of bursts of alpha oscillations were induced immediately after subject's eyes closed, particularly at the sensors located in the posterior cortex regions (e.g., O1, P3, Pz, and POz). Spectral components of EEG signals recorded during eyes open (top) and eyes closed (bottom)

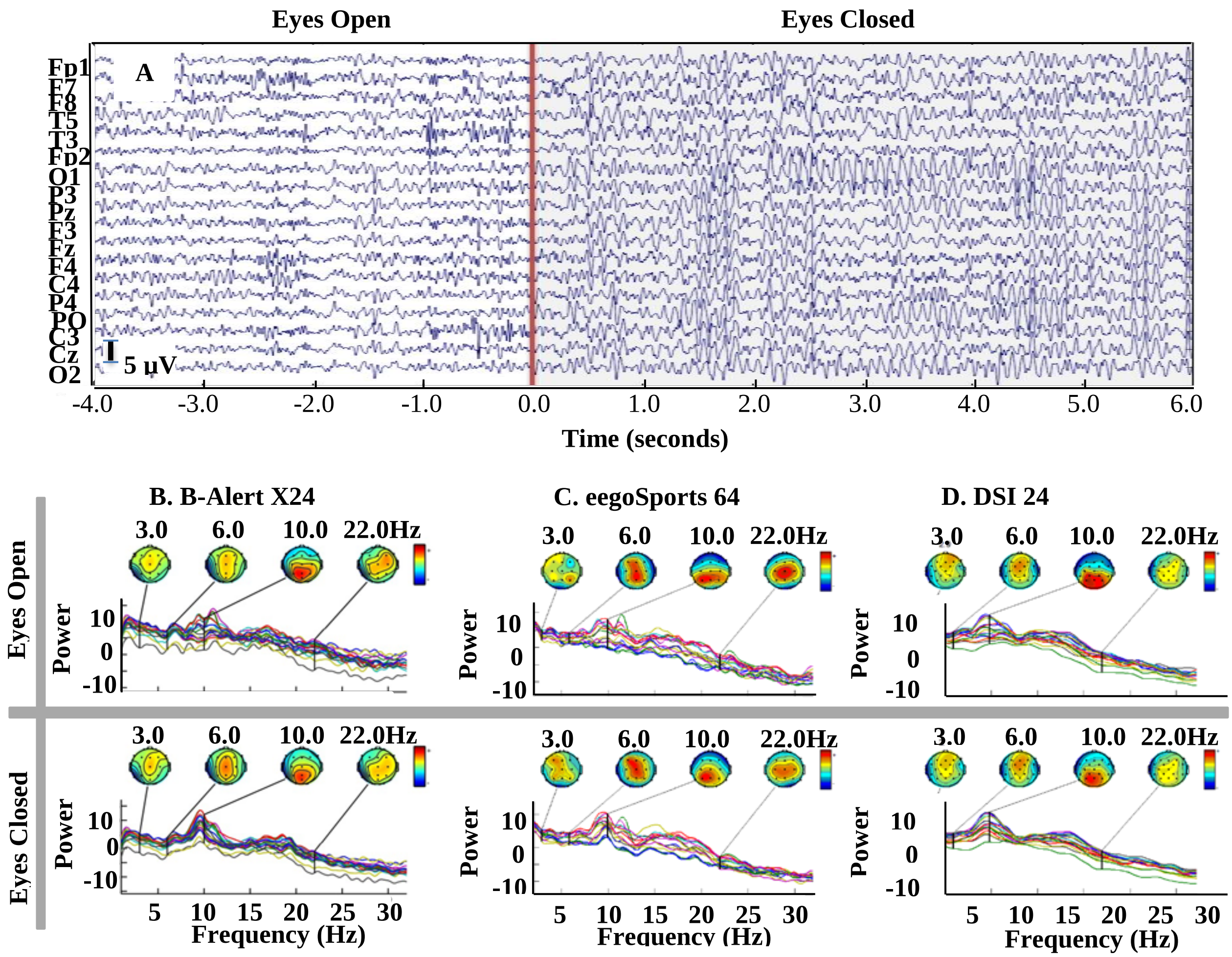


Figure 5. Alpha Rhythm (8–13 Hz) Changes Induced by Closing Eyes

A. EEG traces recorded with the eegoSports 64 system. B-D. Spectral components of the EEG signals. Scalp maps show the distribution of total spectral power across all channels. Line-plots depict the power of spectral components at all frequencies ranging from 2-32 Hz. Note the significant changes that occurred at 10 Hz.

from Subject 12 are shown in Figure 5B-D. During the eyes closed condition, the power of the 10 Hz component was present in more channels with significantly higher magnitude. In both conditions, the 10 Hz components were localized in the posterior regions of the brain. Further analyses across all subjects demonstrated that the alpha rhythm increased significantly for all three EEG systems (detailed data not provided in this report).

ERPs represent the brain's response to sensory stimulations; they are both behaviorally relevant and biologically significant (Jackson & Bolger, 2014; Nidal & Malik, 2014). A short segment of epoched EEG signals in the auditory oddball experiment is shown in Figure 6A, illustrating how ERPs are measured. The averaged responses to the frequent sound stimuli for this session are depicted in Figure 6B, which shows the spectrogram (top) and response magnitude change curve (bottom). A clear ERP peak can be seen at the time between 200-400 ms after sound presentation. The rare sound not only evoked a much stronger ERP peak in the same time period but also induced a period of silence immediately after the ERP peak at about 500 ms after sound presentation (Figure 6C). To compare the ERPs recorded from the three EEG systems, the mean ERP from each sensor was averaged across all 12 subjects to obtain the grand average ERP. The grand average ERPs at electrodes F3 and P4 for the auditory and visual oddball experiments, respectively, are presented in Figure 7. As this Figure illustrates, all three mobile EEG systems were able to record clean and typical ERPs under both sitting and walking conditions in the PhyCORE.

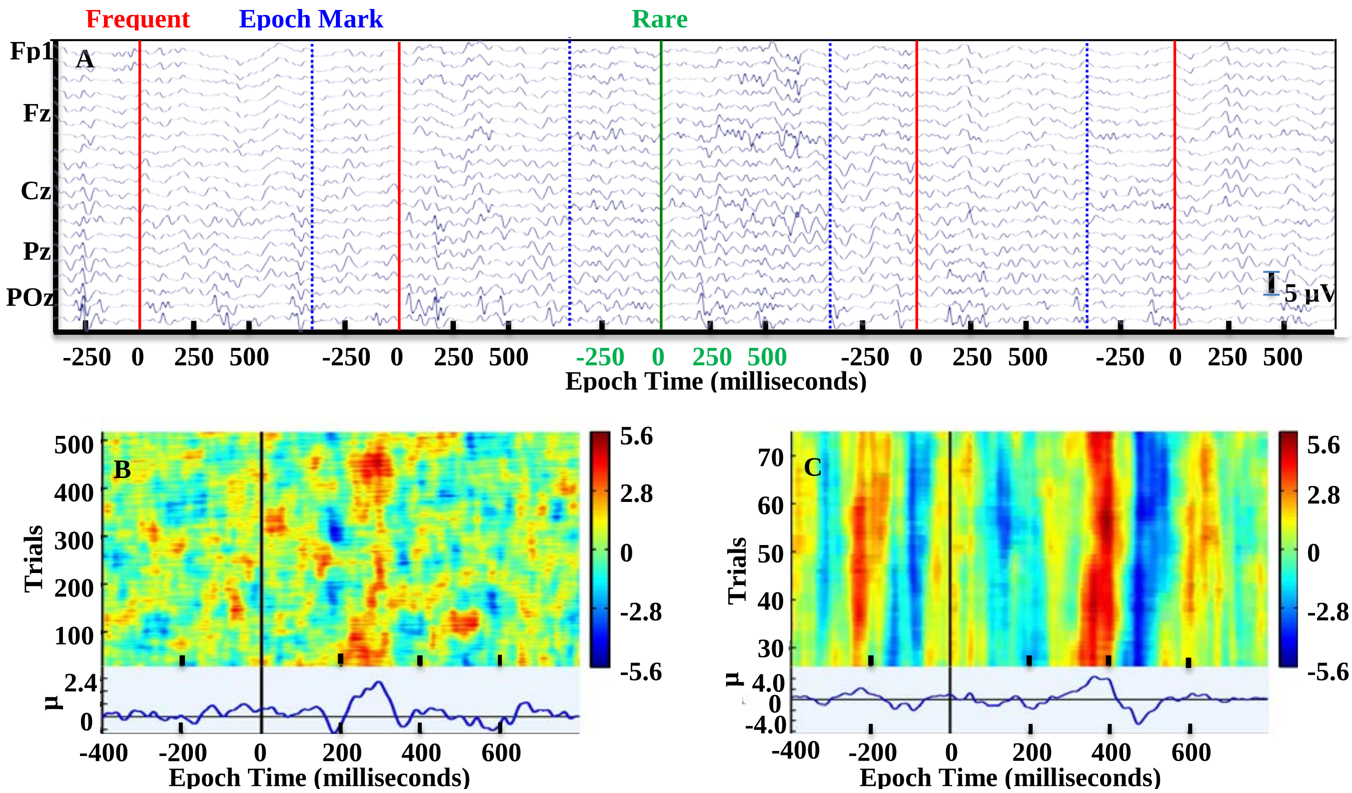


Figure 6. Event-Related Reponses in the Auditory Oddball Task

A. EEG signals were epoched into 1.2-s segments (between blue dashed lines), marking 400 ms before and 800 ms after the onset of sound stimulation (red and green lines). B and C. Spectrogram (top) and averaged auditory responses (bottom) to frequent (B) and rare (C) sounds, respectively, across all trials at sensor F3.

DISCUSSION

Among modern brain imaging techniques, EEG has unequalled temporal resolution for detecting and monitoring brain activity patterns and, therefore, revealing timely and precise neural correlates of behaviors. The emergence of mobile EEG systems in the last two decades has made it possible to take full advantage of EEG technology in iVREs for detecting behaviorally relevant neural markers and establishing cognitive two-way interactions through a brain-machine interface. Challenges, however, remain for achieving these goals. In the current work, we developed a framework for millisecond time synchronization between three mobile EEG systems in an iVRE and successfully detected behaviorally relevant brain activity patterns while subjects performed immersive cognitive tasks.

The three EEG systems tested in this work represent the full technical scope of how EEG signals are acquired, wirelessly transmitted, and time-stamped in the industry. Our approaches for integrating mobile EEG systems, although developed specifically for the PhyCORE, can be easily generalized and adapted by other types of iVREs.

The EEG devices evaluated in our study acquired brain activity signals through wet (B-Alert X24 and eegoSports 64) and dry (DSI-24) sensors. Our results demonstrate that both types of sensors can detect high quality brain electrical activity as needed to establish neural correlates of cognitive behaviors under both sitting and walking conditions (Figures 4-7). The 60 Hz power line noise level picked up by the wet and dry sensors was acceptable; however, there were significant differences among the three systems (Figure 4B). Furthermore, although the percentage of recording channels considered bad was compatible between the wet and dry sensor systems in the sitting condition, the dry sensor system exhibited more bad recording channels compared with the other systems in the 20-minute walking condition (Figure 4C). The lower yield of good recording channels in the dry sensor system can be attributed to multiple factors. The most likely factor was the relative movement of these sensors against the scalp while subjects were in motion, as supported by the highly significant difference between sitting and walking conditions (7% vs. 16%). It is interesting that the percentage of bad channels in the wet systems was lower in the walking than in the sitting condition for both wet sensor systems. This difference may be explained by the observation that the conductive gels between the sensors and the scalp had settled in after the 10-minute sitting sessions; if this observation is accurate, then we would recommend waiting for this period of time before conducting experiments when using a wet sensor system. In contrast, a waiting period for the dry system would likely be unnecessary, which further supports the relative set-up time advantage of dry sensor systems over their wet system counterparts.

In the current study, the EEG signals were transmitted to the data acquisition computer wirelessly either through Bluetooth (B-Alert X24 and DSI-24) or WiFi (eegoSports 64). We did not detect any differences in signal quality between these two transmission methods; however, whether the EEG signals were time-stamped before being wirelessly transmitted made a difference in the degree of precision with which the EEG signals were event time-stamped. As shown in Figures 1 and 2, even after off-line calibration, the time delay and jittering (T_{blue}) caused by Bluetooth transmission prior to event time-stamping in the B-Alert X24 could not be calibrated accurately by users. In the DSI-24 and eegoSports 64, the delays and jittering associated with wireless transmission could be accurately measured, as the EEG signals for these devices were already time-stamped before wireless transmission. However, because subjects wearing the DSI-24 and eegoSports systems were tethered to their devices by event-carrying cables, these systems were deemed “less mobile” than the B-Alert X24. Therefore, when choosing a preferred mobile EEG system for integrating into an iVRE, we strongly recommend that consideration be given to potential sources of interference brought on by other Bluetooth or WiFi signals within or adjacent to the iVRE system, as well as the multitude of factors which could affect the security and timing of the EEG data transmission.

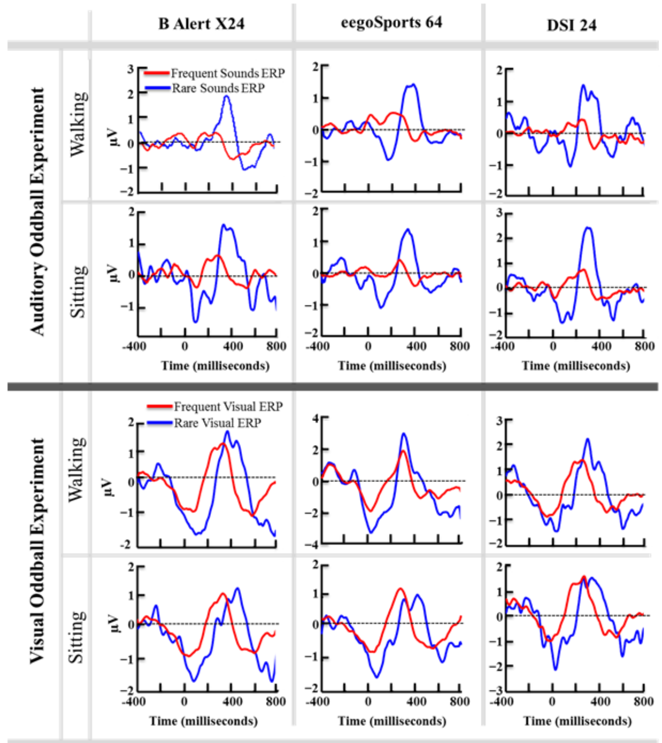


Figure 7. Comparisons of the Grand Average ERPs

Despite a number of technical challenges, we were able to obtain adequate quality and behaviorally relevant EEG signals from all three mobile EEG systems that we integrated into the PhyCORE. Although detailed analyses of the EEG data revealed differences in signal quality across the three EEG systems (data not shown due to the scope of this paper), the high quality of the two neural activities of interest, alpha oscillations and ERP, demonstrate that all three EEG systems were capable of supporting the goals of this work. Specifically, we successfully acquired behaviorally relevant neural markers in an iVRE with mobile EEG systems. This work represents a critical step forward on the path to establishing cognitive two-way interactions as needed to maximize the capability of iVREs for training and rehabilitative purposes.

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