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FEATURED ARTICLE

A Comparison of Electroencephalography Signals Acquired from Conventional and Mobile Systems

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Advances in neurotechnology have made it possible for researchers to investigate brain function beyond the laboratory using mobile electroencephalography (EEG) systems. Mobile EEG systems offer researchers more experimental flexibility and a cheaper alternative to laboratory-based systems; however, it is unclear if their signal quality is comparable. Here we compared signals acquired from two wireless systems, Advanced Brain Monitoring (ABM) X10 and Emotiv EPOC, to signals measured from a conventional, wired BioSemi EEG system using both human participants and a surrogate phantom head. Participants performed a visual oddball task while wearing each of the three systems on different days. Additionally, the phantom provided known-source data that were triggered using the same event-related timing parameters in the oddball task. Results from the participant data, and corroborated from the phantom device, showed that both mobile devices contained an inherent temporal offset with the largest offset seen in Emotiv. Moreover, the Emotiv system required offline processing to properly control for jitter in event synchronization. Data from the Emotiv EPOC system was more susceptible to artifacts, resulting in a higher number of rejected trials with respect to the other systems. However, after proper event alignment we found signal quality was similar between the mobile and laboratory systems on average. Specifically, we found no significant differences between systems in delta, theta, alpha, and beta frequency power in the average-based analysis. Single-trial analysis revealed that data from the ABM system exhibited better classification between standard and oddball stimuli when compared to the Emotiv system. Furthermore, single-trial analysis showed significant differences in classification performance between Emotiv and BioSemi but not between ABM and BioSemi. Our findings suggest signals acquired from the ABM X10 mobile system are comparable to signals obtained from the laboratory-based BioSemi system, and while the Emotiv EPOCH can yield reliable results, data from this system requires significant corrections prior to analysis in event-related paradigms.

KEYWORDS: EEG Comparison, Emotiv, Advanced Brain Monitoring, BioSemi, Translational Neuroscience.

INTRODUCTION

For decades researchers have used electroencephalography (EEG) to track moment by moment fluctuations of neural activity with high temporal precision. As such, EEG has been a productive tool for exploring the neural processes that underlie perception, cognition and action. However, these explorations have, until recently, been limited to the laboratory for two primary reasons. First, EEG investigations (outside of diagnostic applications) were focused on the identification and quantification of fundamental neural processes. In these cases, the controlled laboratory environment was necessary to isolate the specific process (e.g., working memory), control for confounding factors, and minimize the influence of exogenous signals (i.e., artifacts). However, as our understanding of basic brain processes has increased [21], there has been an increasing interest in going beyond these confines and exploring brain function outside of the laboratory [1, 19, 20, 29, 33]. This approach is essential to gain an understanding of the interaction of neural processes and associated cognitive states (e.g., fatigue) within more complex, dynamic situations. Likewise, understanding brain function outside the laboratory is a necessary precursor to the development and transition of neurotechnology for real-world applications [12, 23, 25, 29].

Second, the nature of the EEG technology (sensors, amplifiers, data acquisition devices, etc.) has traditionally required participants to be physically tethered to a system, resulting in limited mobility. Recently, however, advances in the development and commercial availability of low-noise, compact integrated circuits, and amplifiers

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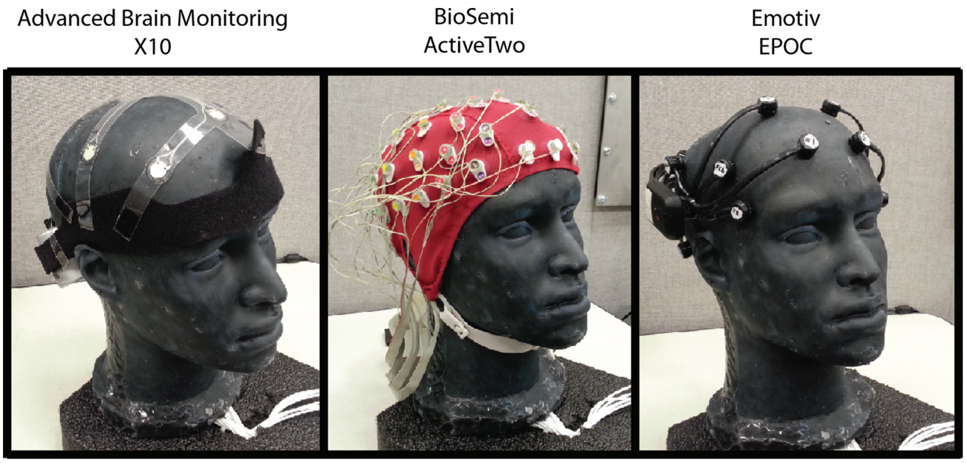

Fig. 1. EEG systems used in the current study. Each system acquired data from human participants, as well as a phantom head device (example shown here).

that operate on high signal input impedance loads have opened the door to a broader commercial market for EEG technology [24, 25]. Several systems now offer the capability of wireless, mobile EEG acquisition, real-time signal processing, and a range of options for electrode contact style (e.g., Ag/AgCl, saline, or even dry) [8, 13, 15]. These cover the gamut of cost from tens of thousands of dollars for laboratory/research-grade equipment to consumer-level systems that can be purchased at a marginal expense.

Mobile EEG technology allows users to interact with their environment outside the controlled confines of the laboratory. This freedom enables researchers to investigate cognitive and neural functions as they occur in natural situations, thereby increasing ecological validity of research findings. For instance, the B-Alert X10 mobile EEG device, developed by Advanced Brain Monitoring (ABM), has been used in studies examining cognitive performance in applied settings, such as marksmanship training and team interaction, or where traditional tethered systems would either impede operator performance or not allow for dynamic participant interaction [3, 35]. Similarly, a recent study employing a modified version of the EPOC from Emotiv Systems enabled users to complete an auditory oddball task while walking through a college campus [10]. The researchers performed single-trial classification on the auditory events and found the neural signals induced by standard and oddball auditory stimuli were discriminated equally well between stationary and ambulatory conditions.

While many developers and vendors of mobile EEG systems have reported the similarity between neural signals acquired with their system and those from a laboratory-based system, there have been few investigations performed by independent researchers. A recent report compared auditory evoked ERPs acquired from a modified Emotiv EPOC system and a laboratory-based (Neuroscan) system [2]. They found similar amplitudes and latencies in the ERPs gathered between the two systems, suggesting the technology underlying the Emotiv EPOC system can provide a valid alternative to laboratory based systems. However, the approach taken within this study required sacrificing two of the EEG data channels to serve as a direct input for event timing; therefore, it is not known how reliable this system performs without making significant hardware modifications. Likewise, this study mainly focused on data averaged over multiple trials, leaving unresolved the questions of how well this system may work for event-based BCI-based technologies that rely on single-trial classification. Moreover, no comparison was made between the measured power in traditional frequency bands (delta, theta, alpha, and beta); therefore, it remains unclear if differences exist between the mobile and laboratory-based system's ability to capture oscillatory processes.

The current study compared the performance of three EEG systems of differing cost and target application spaces, when used as delivered by the manufacturer. Our goal was to assess their signal quality within a standard event-related paradigm, as would be performed in a typical laboratory setup. Specifically, we evaluated data acquired with two mobile EEG systems, Advance Brain Monitoring (ABM) X10, and Emotiv EPOC, and compared them to data recorded from a standard 64-channel (BioSemi ActiveTwo) system. We evaluated signal quality using RMS of the average amplitude, power in the delta, theta, alpha, and beta frequency bands as well as discrimiatability of neural features using single-trial classification. Additional analyses were performed on surrogate data generated using a phantom head device to examine intrinsic characteristics of each EEG recording system (Fig. 1).

METHODS

Participants and Tasks

Sixteen right-handed participants (7 females) aged 19 to 45 years volunteered for the study. The voluntary, fully

informed consent of the persons used in this research was obtained as required by 32 CFR 219 and AR 70–25, and also in compliance with the Declaration of Helsinki.

The current analysis focuses on data obtained from the ABM B-Alert X10, BioSemi ActiveTwo, and Emotiv EPOC systems during a two-stimulus visual oddball task. For this task, participants were seated in a sound-attenuated recording chamber and viewed a series of centrally presented images using E-prime software (Psychology Software Tools; Sharpsburg, PA) on a Dell P2410 monitor at a distance of approximately 70 cm. Images (152×375 pixels) contained either a picture of an American Soldier (standard) or a picture of a man wearing a headscarf and holding a weapon (oddball). Standard and oddball images appeared with a 0.88 and 0.12 probability respectively. Each image was presented for 150 ms with a 1650–2150 inter-stimulus interval. Participants were encouraged to maintain fixation on the center of the screen and to respond as fast and as accurately as possible by pressing button 1 on a keypad for standard stimuli and button 2 for oddball stimuli. Each participant completed three blocks of 89 trials per block. EEG system order was counterbalanced with at least one but no more than 14 days between systems.

Recording and Analysis

EEG recordings for each system were acquired on a Windows XP PC, separate from the E-prime computer, using the native software provided by the system manufacturer (B-Alert for ABM X10, ActiView for BioSemi, and TestBench for Emotiv) without any modifications. Table I shows the electrode locations, sampling rate, signal bandwidth, and reference used for each system. Both the BioSemi and ABM system use conductive gel to facilitate conductivity between the electrodes and the scalp, while the Emotiv system uses saline soaked felt pads. EEG data obtained from ABM and Emotiv were compared to data acquired from the BioSemi system by creating a montage and reference scheme that matched that of the ABM or Emotiv system. Therefore, there were four datasets from each participant used in the comparative analysis: native ABM data, BioSemi data matched to the ABM montage, native Emotiv data, and BioSemi data matched to the Emotiv montage. EEG data were processed using EEGLAB and ERPLAB [11, 28]. Data from the BioSemi system were decimated to match the respective sample rate of the other two systems. Prior to analysis continuous EEG data from each file were digitally filtered 0.2–40 Hz offline. Gross artifacts from electromyography (EMG) and amplifier blocking were removed from the continuous data. ICA was subsequently performed separately for each dataset to identify and remove eye-blinks [18]. Following these conventional preprocessing steps, the EEG data were processed with four additional steps to enable comparisons between the two mobile systems and their data matched BioSemi equivalents.

Step 1: *Mitigating Temporal Jitter*: Unlike most EEG systems designed for research purposes, the Emotiv EPOC does not provide a hardware-based provision for integrating event trigger data into the EEG data stream. Instead, the native TestBench software relies on input through the PC serial port, which can lead to substantial temporal imprecision and jitter relative to true event onset [16]. Some efforts have addressed this challenge using hardware modifications to the units to provide a direct signal, such as sacrificing EEG channels for use as an event channel [2], but these modifications have required wire-tethering the user and modifying the unit. As an alternative, we used a software-based post-hoc event realignment procedure based on data from a third-party log file, described previously [16, 37]. Briefly, during data collection, a series of synchronizing pulses at the beginning of each data run, as well as the onset of each event in the experiment was recorded by the stimulus presentation software and the EEG acquisition software. During analysis, the event times from these two sources were compared to calculate the offset and drift rate between system clocks (stimulus and acquisition units). Offset and drift were calculated and the timing of the events in the EEG data were corrected by these factors [37]. The same procedure was applied to all three systems in order to ensure consistency across platforms.

Step 2: *Selecting Datasets and Evaluating Single Trial Classification*: We established a general index of data quality to ensure all datasets from each subject contained a minimum signal to noise metric. This was achieved by using a linear classifier to discriminate neural signals between frequent targets and infrequent oddball stimuli

Table I. EEG systems and specifications.

Manufacturer and system	Sampling rate (Hz)	Bandwidth (Hz)	Reference	# of electrodes and locations	Wireless transmission	Conductive mechanism
BioSemi Active Two	512	0.01–256	Averaged Mastoids	64-10/10 montage	None	Gel
Advanced Brain Monitoring X10	256	0.1–100	Linked Mastoids	9-Fz, F3, F4, Cz, C3, C4, POz, P3, P4	Bluetooth	Gel
Emotiv EPOC	128	0.16–43	Averaged Mastoids	14-AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4	Proprietary	Saline

using a leave-one-out cross validation of xDAWN spatial filtering [34] followed by Bayesian linear discriminant analysis (collectively referred to as XD+BLDA) [17]. The XD+BLDA algorithm is well suited to discriminate neural activity between images in oddball-style tasks [7]. The algorithm used the 0–1000 ms post-stimulus window from each of the 16 subjects. The Az value (area under the receiver operating characteristic) from XB+BLDA was used as an objective measure of data quality. Participants having an Az value above 0.6 in all files were included in all analyses, resulting in three participants being excluded, as at least one of the four Az values failed to meet the objective criterion. We set the Az criterion low in order to identify subjects/sessions with near zero signal to noise and not to exclude subjects who naturally have a small P300. Of the three participants who were not included in the analysis, two had data from ABM and one from Emotiv that failed to meet the objective criterion. Therefore, 13 of the 16 subjects were included in the final analysis (all right-handed, average age 28.5 years, 5 female). Detailed results of the classifier scores are presented below.

Step 3: *Computing Metrics of Epoched Data*: For the 13 subjects who met the objective criteria in Step 2, their artifact-free data were epoched based on a -1.5 to 1.5 s window surrounding onset of the standard stimuli for correct trials when a button response occurred 200–1000 ms post stimulus onset. Epochs containing peak to peak amplitudes greater than ± 75 μv using a 200 ms window with a 100 ms window step were rejected prior to averaging (see Fig. 2). For each subject, the data file containing the fewest number of epochs (out of the 3 systems) was identified and this number of epochs was randomly selected from the other files, so that data averages for each subject contained the same number of events. The average number of trials included in the averaged waveforms was 148 (SD = 43; range = 51–212). Event-related potentials (ERPs), root of the mean squared amplitude (RMS), and power in theta, alpha, and beta frequency bands were calculated on the epoched data (-1000 to 1000 ms) for each channel. Frequency power was calculated using the *spectopo* function (256 point FFT, 128 point window) in EEGLAB. Results from each channel were averaged for

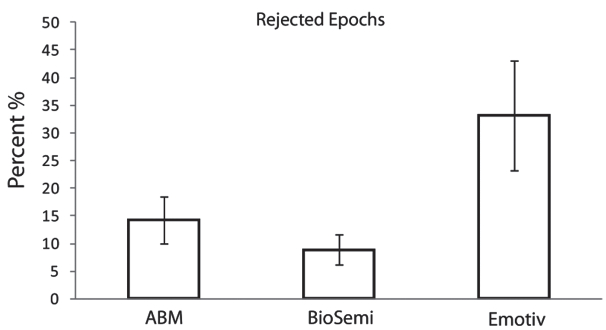

Fig. 2. Percent of epochs rejected prior to analysis for each EEG system. Error bars depict +/− standard error.

RMS and frequency power calculations, which resulted in an overall system measure for pre and post stimulus. Comparisons were made by computing the post/pre stimulus RMS and frequency power ratios.

Step 4: *Generating Simulated Data via Head Phantom*: We employed a "phantom head" device to evaluate the origin of variability in ERP event latency observed among the systems. A Thor Labs PDA36A amplified photodetector connected to a Sony AFG320 function generator was placed on the monitor while the same stimulus paradigm used by the human participants was re-played, such that the onset of a bright portion (white outline) of the visual stimulus (standard or oddball image) triggered a single 10 Hz sine wave with a latency of < 1 ms. The sine wave was fed into a conductive head-shaped phantom model possessing an external shape and surface conductance roughly analogous to that of human skin, described previously [22], with a dipole elicited between scalp CPz and CP3 at an amplitude typical of scalp EEG and detectable by all systems. Thus, the simulated data matched the experimental paradigm for each system, where the event timing was known and then pre-processed using the same 3rd party log file realignment pipeline as the experimental data (Step 1). The resulting waveforms illustrate the encoding latency of each system, as well as any distortion from on-board signal processing, in the absence of inherent variance associated with neural responses. Latencies relative to stimulus onset were quantified by computing the difference between the actual time of the initial waveform peak (25 ms) and the observed time of the peak relative to stimulus onset.

RESULTS

Artifact Rejection

We evaluated the number of epochs rejected based on the amplitude threshold criterion during preprocessing (± 75 μv using a 200 ms window with a 100 ms window) for each system from the 13 subjects included in the final analysis. We used an ANOVA with system as the main factor (ABM, BioSemi, Emotiv). Across all of the native channels for each system (64 for BioSemi, 9 for ABM, and 14 for Emotiv), the number of epochs rejected was significantly different between systems, $F(1.33, 15.92) = 12.35$, $p = 0.002$; Greenhouse-Geisser corrected (Fig. 2). Specifically, significantly more epochs were rejected from the Emotiv data when compared to BioSemi and ABM ($t(12) = 5.7$, $p < 0.001$, $t(12) = 2.81$, $p = 0.016$ respectively), while there was no difference in the number of epochs rejected between ABM and BioSemi ($t(12) = -1.37$, $p = 0.197$).

Averaged ERPs: Event Timing

The second striking difference among the systems occurred when evaluating the effect of temporal variability in the event triggers used to temporally-align stimulus

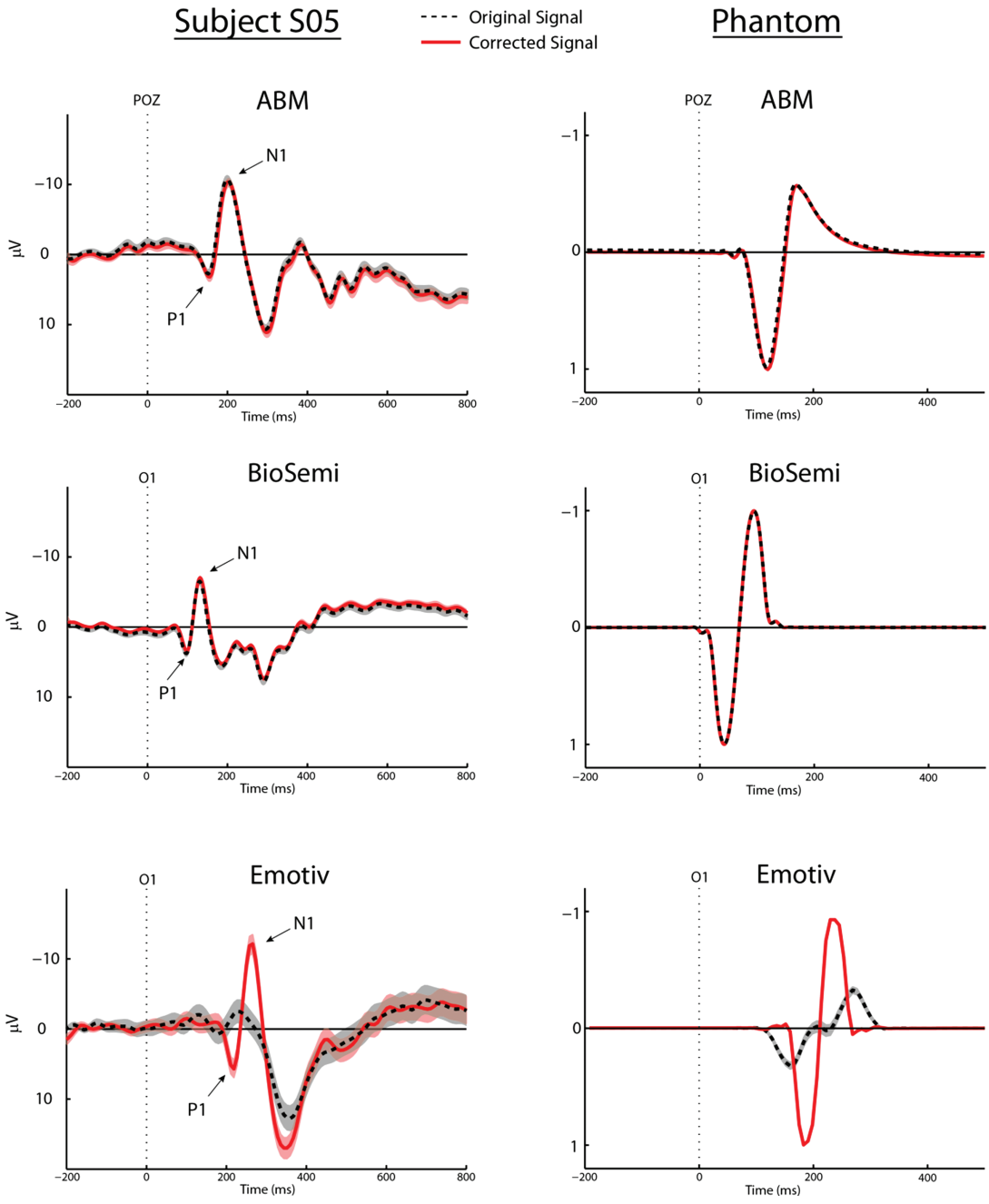

Fig. 3. Average waveforms from subject S05 (left) and phantom (right) before and after timing correction. Shaded areas indicate standard error.

onset across trials. Individual subject ERPs were calculated using two methods: (1) using the original stimulus event onset time data that were natively encoded on-line by each system at the time of acquisition, and (2) using a corrected onset time that was derived from a 3rd party log file to mitigate jitter in the event trigger signals (see Step 1). In addition, these ERPs were compared to surrogate data generated by a phantom device and recorded by each system to quantify the inherent system lag and signal distortion (see Step 4). Results for both ERP methods (original dashed line; corrected—solid line) are plotted for an example subject in Figure 3, with the experimental data shown in the left column and phantom head data plotted in the right.

The original, averaged waveforms (Fig. 3, dashed lines) revealed that the ABM and BioSemi systems showed fairly typical ERPs, including the visual-evoked P1/N1 responses, but these same components are virtually non-existent in the Emotiv average waveform; likewise, the phantom input waveform is highly distorted when recorded with the Emotiv system (bottom right, dashed line). The event timing variability, which caused these

distortions, was quantified using the standard deviation of the response onset peaks across trials: Emotiv was +/− 32.65 ms compared to only +/− 3.3 ms for ABM and +/− 1.7 ms for BioSemi.

The temporally corrected average (Fig. 3, solid lines) revealed almost no change in the ABM and BioSemi ERP as expected, given the minimal inherent variance in these systems; however, a strong, positive change occurred for the Emotiv system. The corrected Emotiv waveforms now resemble the expected waveform, including a similar, strong P1/N1 profile (bottom left, solid line) and a clear single sinusoid from the phantom input waveform (bottom right, solid line). This improvement suggests that the source of the poor average signal is a result of the data logging method, rather than an intrinsic property of the signal encoding hardware.

Figure 3 also shows a systematic difference in the mean response latency for ERPs across the three systems. Although this variability is seen in the experimental data (left column), the data from the phantom head (right column) highlights the system dependence for the ERP latency. By using the phantom configuration, we ensured identical waveforms, with minimal latency, were consistently delivered to each EEG system. The only difference among the waveform plots is the system used to record the surrogate EEG signal. The mean latencies relative to stimulus onset after correction were 95.71 ms (ABM), 17.34 ms (BioSemi), and 155.75 ms (Emotiv). It is important to note that a contributing factor to this latency is the time it takes the frame buffer to be drawn, via the raster refresh processes, onto the LCD monitor (about 10 ms). Additional distortion observed in phantom data for all systems is likely an effect of on-board and pre-processing filters.

Averaged ERPs: Matched Electrode Montages

Using the datasets with corrected event timing, the wireless EEG data were compared to those acquired from the conventional, wired BioSemi system. Specifically, ABM and Emotiv were separately compared to a BioSemi montage and reference scheme matched to the corresponding wireless system. This evaluation highlights the particular effects of each wireless system design and configuration on the measured ERP. Results for both systems are plotted for all channels in Figure 4 with ABM shown in the top half of the figure and Emotiv shown in the bottom half. Overall, ERP waveforms from the mobile systems were similar to the matched BioSemi data across participants (ABM/BioSemi correlation, $r = 0.596$, SD 0.230; Emotiv/BioSemi correlation, $r = 0.48$, SD 0.230), but the latency of the event related peaks were markedly different. The latency difference was 78.38 ms between ABM and BioSemi matched channels, and it was 138.41 between Emotiv and BioSemi. This corroborates the finding from the phantom data above showing an inherent lag in the EEG record relative to the event markers when using the mobile wireless systems.

Averaged RMS: Matched Electrode Montages

The root-mean-squared (RMS) of the ERP was computed for the 1000 ms pre- and post-stimulus epoch periods for each wireless system and its BioSemi matched channel montage (Fig. 5). The ratio of these RMS values (post/pre) provided an overall measure of signal-to-noise that did not emphasize the number, timing, and direction of peaks in the waveform.

RMS ratio was evaluated using a 2×2 repeated measures ANOVA (Greenhouse-Geisser corrected) using System (ABM, Emotiv) and Data (Native, BioSemi Matched) as factors. The analysis resulted in a main effect for Data, $F(1, 12) = 5.92$, $p = 0.032$, as the RMS ratio for BioSemi Matched (2.92) was greater than Native (2.21). There was no main effect for System $F(1, 12) = 0.18$, $p = 0.683$ or a System by Data interaction $F(1, 12) = 0.85$, $p = 0.375$.

Averaged Frequency Bands: Matched Electrode Montages

Using the same pre- and post-stimulus timeframes as the RMS analysis, power in the delta, theta, alpha, and beta frequency bands was computed for each wireless system and its BioSemi matched equivalent (Fig. 6). Variability in frequency power was evaluated using a 2×2 repeated measures ANOVA (Greenhouse-Geisser corrected) using System (ABM, Emotiv) and Data (Native, BioSemi Matched) as factors. No main effects or interactions were statistically significant in any frequency band, all $p > 0.05$.

Single Trial Classification: Standard versus Oddball Trials

Using an established classification algorithm (see Methods, Step 2), an Az value that represents the area under the receiver operating characteristic was computed for each wireless system and its BioSemi matched montage. This value is related to how well the neural signals between frequent targets and infrequent oddball stimuli can be discriminated. Classification results for all systems are shown in Figure 7.

A 2×2 ANOVA (Greenhouse-Geisser corrected) was performed on the Az scores with System (ABM and Emotiv) and Data (Native and BioSemi Matched) as factors. There was a main effect of System $F(1, 12) = 4.74$, $p = 0.050$ with ABM (0.90) having higher Az scores on average compared to Emotiv (0.88). There was no main effect of Data $F(1, 12) = 1.98$, $p = 0.185$, and a significant System by Data interaction $F(1, 12) = 6.25$, $p = 0.028$ showing a larger difference in Az between Emotiv and its matched BioSemi data compared to ABM and its matched BioSemi-derived data.

The effect of electrode montage on classification performance was also examined, as the scalp coverage differed between the two wireless systems. Moreover, the wireless systems have substantially fewer electrodes than typically used in conventional EEG laboratory

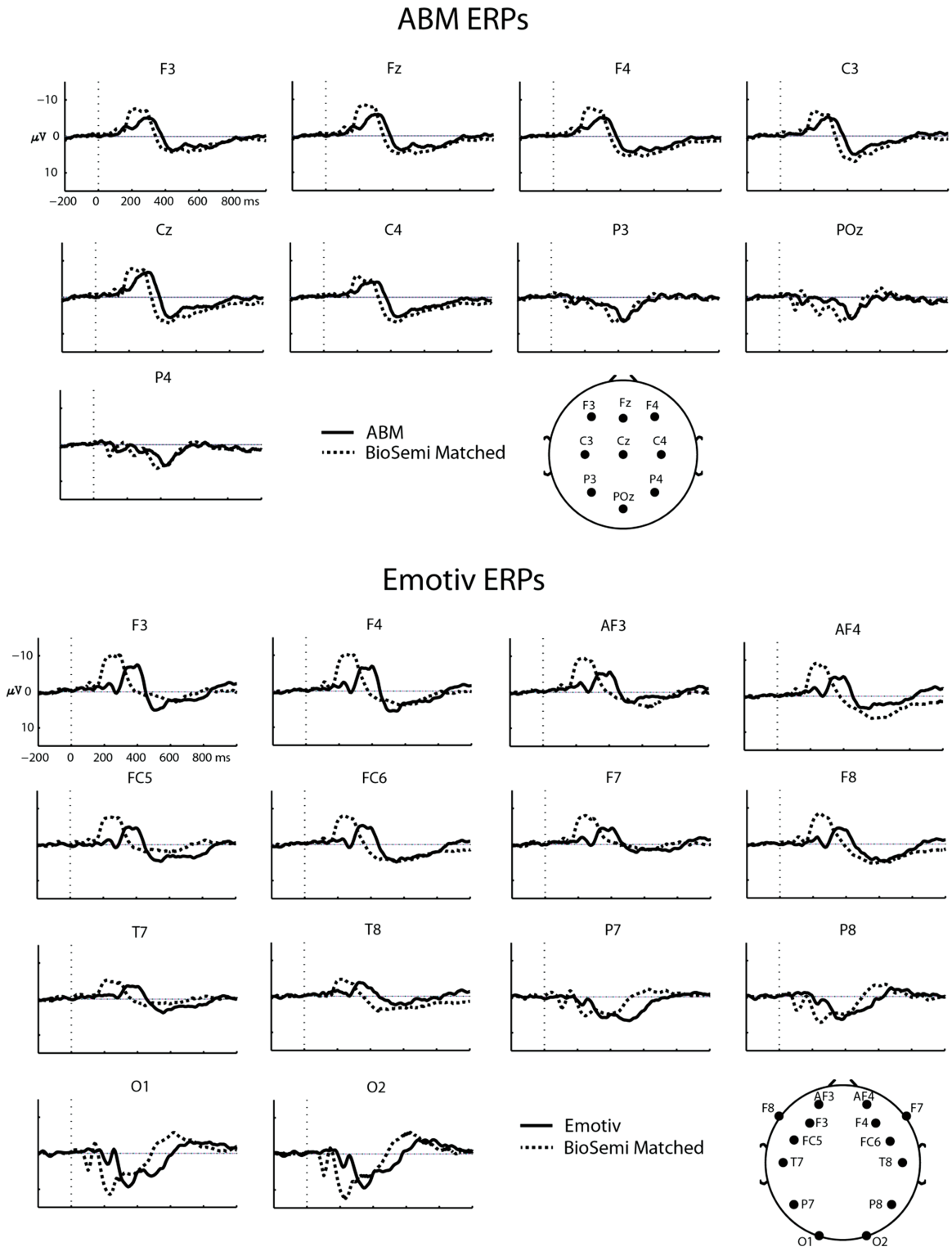

Fig. 4. Grand-average ERPs at each electrode location from the ABM system and BioSemi matched to ABM (top) and Emotiv with matched BioSemi data (bottom).

experiments. To evaluate the effect of electrode location and number of electrodes we compared three BioSemi channel montages: 9 channel ABM-matched montage, 14 channel Emotive-matched montage, and the full 64 channel BioSemi montage. We found a significant effect (Greenhouse-Geisser corrected) of electrode montage ($F(1.86, 22.3) = 16.21$, $p < 0.001$), and follow up paired comparisons showed that Az scores were not significantly different between the 9 channel ABM matched and 14 channel Emotiv matched electrode configurations

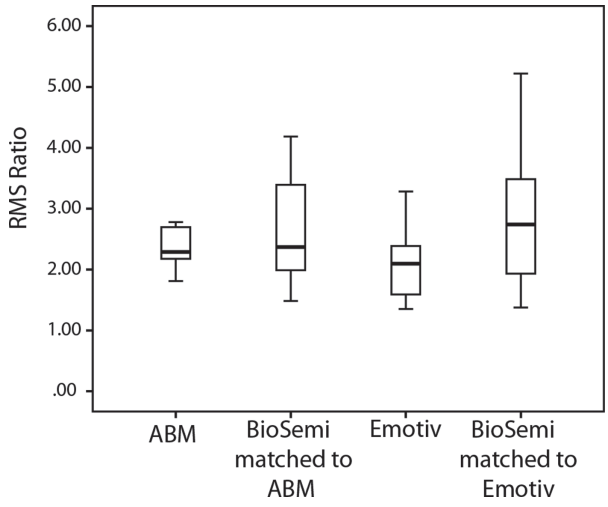

Fig. 5. Box and Whisker plot of the RMS ratio (post/pre stimulus) for each system.

($t(12) = -0.23$, $p = 0.821$). However, there were significant differences between Az scores for the 9 channel ABM matched and 64 channel BioSemi positions ($t(12) = -5.19$, $p < 0.001$) and 14 channel Emotiv matched and 64 BioSemi positions ($t(12) = -5.4$, $p < 0.001$).

DISCUSSION

The current study compared the EEG signal quality from two commercially available mobile EEG systems, ABM X10 and Emotiv EPOCH, to a conventional, laboratory-grade system, BioSemi ActiveTwo. In separate sessions, each system was used to (1) record experimental EEG data from a visual event-related paradigm and (2) record phantom surrogate data where the precise shape and timing of the simulated EEG signal was known. The EEG data were equated across session and system. A channel montage of the BioSemi data was created to match the

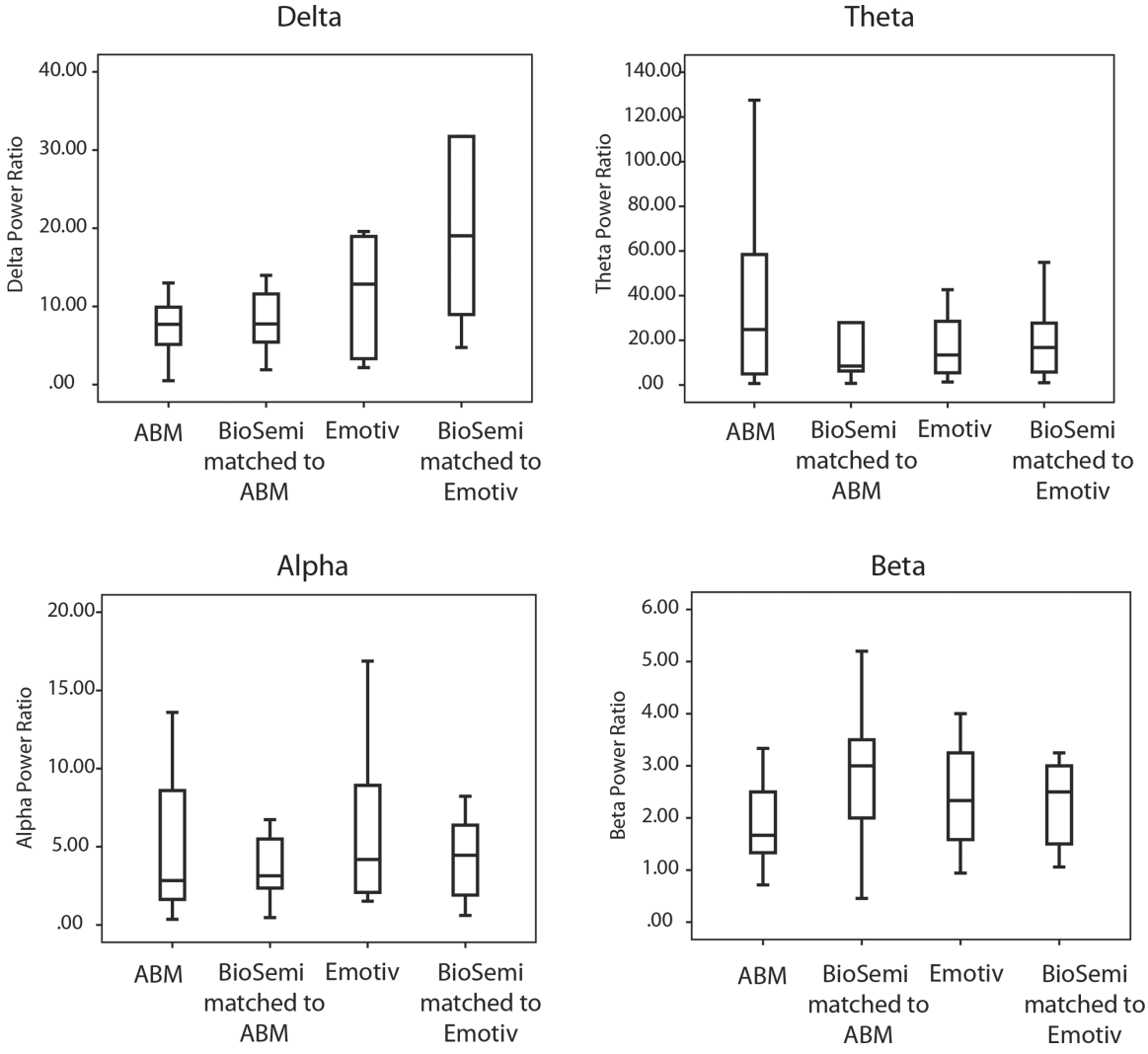

Fig. 6. Box and Whisker plots of power ratios (post/pre) at delta (0.1–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), and beta (13–30 Hz) frequencies for each system.

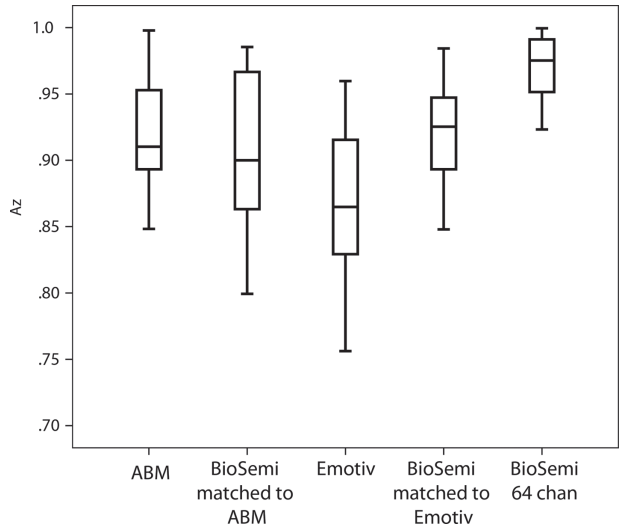

Fig. 7. Single-trial classification results.

locations of each of the two wireless systems. The EEG signal quality of each system was then evaluated using metrics applied to the raw data (artifact rejection statistic), averaged data (RMS and Frequency Band power), and single trial classification performance (standard versus oddball discrimination). Overall, both wireless systems performed similarly for the averaged, time-locked event-related potential analysis metrics. After a synchronization procedure to correct for inherent temporal jitter for event triggers, both systems captured the expected waveform peak and frequency band power profiles. In contrast, the two wireless systems differed in the quality of their single trial data, with the gel-based ABM outperforming the saline-based Emotiv system. The Emotiv showed a higher number of amplitude artifacts in trial epochs, and led to poorer discrimination performance in classifying the standard versus oddball experimental trials.

One of the most salient differences among the systems was the inherent temporal delay of an event-locked response. Our results indicate two sources for the system-dependent latency. The first source was evidenced in the highly distorted, averaged event-related potentials using the native, uncorrected system data (Fig. 2, left column), particularly in the Emotiv system. These distortions arise from considerable jitter, as well as drift between the system ADC clock and stimulus paradigm PC that has been both noted here and previously documented in this system [16]. However, it has been previously shown that these distortion effects can be ameliorated by performing on offline timing correction procedure [16, 37]. This approach allowed us to analyze data from all EEG channels without having to sacrifice an electrode as a designated event channel. While this approach worked well in the present study, there may be situations where it is not possible or desirable to perform offline timing correction procedures, and following a procedure with a dedicated event channel could be used to ensure proper event alignment (see Ref. [10]). Unlike the first source, a mitigation strategy was not employed for the second source of event-locked temporal delay. This source was strongly evidenced in the phantom head results where the precise timing of the simulated EEG input signal to each system was known and delays relative to stimulus onset were still observed. Even after the temporal correction for event timing, all systems showed some amount of delay with the smallest latency in the BioSemi system (17 ms) and larger delays in the ABM (96 ms) and Emotiv systems (156 ms).

The interest in recording EEG applications in mobile environments is not limited to event or trial-based neural response. There is a growing interest in mobile EEG recording extending from the traditional clinical and experimental domains [14] to lifestyle, entertainment, and consumer research applications [6]. One class of research focuses on state-based neural signatures that capture task-relevant mental states which can vary slowly over time and are not dependent on time-locking to specific events [39, 40]. This domain of mobile EEG uses variable time windows to investigate task-dependent mental states, such as task difficulty [4, 5, 31], cognitive workload [4, 9, 38], alertness [4], and driving performance [26, 27, 36]. In fact, the Emotiv system was designed primarily to record and process continuous data to track general cognitive states over time, on the order of seconds; therefore, it is not surprising that the Emotiv system lacked the inherent temporal precision needed for accurate event-based analysis.

The Emotiv system produced a greater number of trial epochs that exceeded the amplitude threshold indicating the data may be inherently noisy. It is unclear whether this decrement in signal quality arises from the hardware or from the use of saline as the conductive medium. Both the BioSemi and ABM systems use conductive gel. The gel may provide better conductivity between the electrodes and the scalp and/or the gel may just prevent less movement of the sensors on the scalp. Second, the single-trial analysis revealed the ABM montage produced better classification accuracy between standard and oddball stimuli when compared to the Emotiv system. This difference does not appear to arise from the different montage used between the systems, as the only effect of montage found was dependent on a substantial increase in both number and spatial coverage of the electrodes; that is, the 64 channel BioSemi montage outperformed the smaller subsets of the BioSemi montage that were matched to the ABM and Emotiv montage designs. However, the single trial analysis (Az) was better for Emotiv matched BioSemi montage data when compared to native Emotiv data. These results suggest that Emotiv may be more applicable in situations where multiple trials can be averaged or when continuous measures incorporate data over multiple time windows.

The EEG systems compared here are suited for a range of application spaces. The BioSemi system, while the

most expensive of the three, is capable of producing the highest resolution in terms of sampling rate. It also is designed with multiple configurations for various electrode densities and allows for source localization. Both wireless systems hold promise for targeted EEG recording applications in mobile environments. The ABM system was the most expensive of the mobile systems tested; however, its recording quality is on par with the BioSemi system showing a stable SNR profile in all averaged time windows, and high discrimination of single trial responses between standard and oddball stimuli. The ABM system is available in 10 and 24 channel configurations and allows extended wear and data acquisition. The ABM system, as of this evaluation, still relies on a conductive gel which may be less conducive to future applications where subjects are not sitting in a laboratory environment. The Emotiv system was the most cost effective of the three tested. It is capable of producing quality signals when a sufficient number of trials are available for averaging or in paradigms that require non-time-locked analysis. It uses saline as the conductive medium between the electrode and the scalp, thus limiting the wear and record time relative to BioSemi and ABM. However, the use of saline also allows for easy application, removal and clean-up of the system.

Overall our results indicate the promise of using existing wireless EEG systems for mobile EEG recording. Our findings suggest signals acquired from both the ABM and Emotiv systems are comparable to signals obtained from the laboratory-based BioSemi system, but the Emotiv system requires significant corrections prior to analysis in event-related paradigms. We provide insight for targeted applications best suited to the existing system design as well as a framework to evaluate the signal quality of future advancements in wireless technology. Our evaluation was based on data acquired from an established laboratory task. Future work should expand the evaluation to tasks commonly encountered in real-world interactions (e.g., driving, visual search, human-computer interaction).

Conflict of Interest

The authors have no conflict of interest.

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