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Systematic comparison between a wireless EEG system with dry electrodes and a wired EEG system with wet electrodes

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Abstract

Recent advances in dry electrodes technology have facilitated the recording of EEG in situations not previously possible, thanks to the relatively swift electrode preparation and avoidance of applying gel to subject's hair. However, to become a true alternative, these systems should be compared to state-of-the-art wet EEG systems commonly used in clinical or research applications. In our study, we conducted a systematic comparison of electrodes application speed, subject comfort, and most critically electrophysiological signal quality between the conventional and wired Biosemi EEG system using wet active electrodes and the compact and wireless F1 EEG system consisting of dry passive electrodes. All subjects (n = 27) participated in two recording sessions on separate days, one with the wet EEG system and one with the dry EEG system, in which the session order was counterbalanced across subjects. In each session, we recorded their EEG during separate rest periods with eyes open and closed followed by two versions of a serial visual presentation target detection task. Each task component allows for a neural measure reflecting different characteristics of the data, including spectral power in canonical low frequency bands, event-related potential components (specifically, the P3b), and single trial classification based on machine learning. The performance across the two systems was similar in most measures, including the P3b amplitude and topography, as well as low frequency (theta, alpha, and beta) spectral power at rest. Both EEG systems performed well above chance in the classification analysis, with a marginal advantage of the wet system over the dry. Critically, all aforementioned

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Declarations of interest

RTK is a consultant for the Nielsen Consumer Neuroscience division of Nielsen Tele Medical. LYD is a consultant and one of the founders of Innereye, Ltd, which provided the classification algorithm.

Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.neuroimage.2018.09.012.

electrophysiological metrics showed significant positive correlations ($r = 0.54–0.89$) between the two EEG systems. This multitude of measures provides a comprehensive comparison that captures different aspects of EEG data, including temporal precision, frequency domain as well as multivariate patterns of activity. Taken together, our results indicate that the dry EEG system used in this experiment can effectively record electrophysiological measures commonly used across the research and clinical contexts with comparable quality to the conventional wet EEG system.

Keywords

Wet electrodes; Dry electrodes; Electrophysiology; P3b; Resting state EEG; Single trial classification

1. Introduction

Among mainstream neuroimaging methods, electroencephalography (EEG) has the benefits of temporal precision, affordability and ease of maintenance, all of which are crucial factors for both research and clinical purposes. Recent technological advances in EEG recording systems as well as signal processing have opened up opportunities for novel applications. In particular, the development of miniaturized, wireless head-mounted EEG systems has vastly improved the portability of EEG systems (Burton, 2015; Debener et al., 2012). Concurrently, the development of dry electrodes decreased electrode application time by removing the need for conductive gel or paste application, allowing users to record EEG in situations that are impractical for wired and wet electrode systems. Wet EEG systems involve application of a conductive gel or paste to bridge the gap between the scalp and the electrode and to reduce electrode impedance, which requires both time and expertise, as well as means (usually water) for removing gel residues from the subject's head (Teplan, 2002). In contrast, dry electrodes are applied directly to the skin, do not require any gel or paste, are easy to attach to the head, and do not require trained technicians. The benefits of this new technology underscore the importance of establishing whether the performance of these systems is comparable to state-of-the-art EEG systems using wet EEG electrodes, which are commonly used in laboratories. Here, we aim to compare the signal quality of a wireless and dry EEG system consisting of 31 electrodes with a commonly used wired and wet EEG system with 64 electrodes.

Recent developments in EEG technology have focused on wireless systems that still employ wet sensors, requiring conductive gel application (De Vos et al., 2014a, 2014b; Debener et al., 2015, 2012; Lotte et al., 2009; Wang et al., 2011). Some wireless systems consist of electrodes attached to a conventional EEG cap (De Vos et al., 2014a, 2014b; Debener et al., 2012), while others consist of screen-printed electrodes arranged in a C-shaped sticker fitted around the participants' ears for minimal exposure and maximal comfort (Debener et al., 2015). These studies have established the signal quality of wireless wet EEG systems using BCI tasks (Lotte et al., 2009; Wang et al., 2011), as well as in an auditory oddball paradigm while participants were walking or sitting in an indoor and outdoor environment (De Vos et al., 2014b; Debener et al., 2015, 2012). Although the walking condition was associated with reduced classification accuracy than the sitting condition, both conditions were above

chance in differentiating targets from non-targets (De Vos et al., 2014b). This suggests that although movement artifacts reduce signal quality, wireless wet EEG systems still show satisfactory classification performance.

In parallel, the appeal of dry electrodes has initiated considerable development of this technology in recent years. Several of the commercially available dry EEG systems used sensors comprised of metal pins (Guger et al., 2012; Käthner et al., 2017; Lo et al., 2016; Pinho et al., 2017; Toyama et al., 2012). Other materials, including silicon (Taheri et al., 1996; Yu et al., 2014) and foam (Lin et al., 2011) based sensors, have been proposed and are reported in recent reviews of EEG systems using dry electrodes (Liao et al., 2012; Lopez-Gordo et al., 2014). We compared and contrasted several features of the F1 dry EEG system used in our study and previously tested dry EEG systems: the number of electrodes (F1: up to 33), sizes of the headsets (F1: two available sizes), the number of metal pins per electrode (F1: two contact pins per electrode), the wireless feature of the system (F1: wireless), as well as the weight of the amplifier and battery (F1: 165 g). These similarities and differences are outlined in detail in the Supplementary Information. Although variability exists among currently available dry EEG electrodes, they all share the advantage of ease of electrode application by avoiding extensive preparation and cleaning of electrodes, overcoming a major limitation of wet electrodes.

Given these recent advancements in EEG technology, several studies have directly compared the signal quality between wet and dry EEG systems (Fiedler et al., 2015; Käthner et al., 2017; Liao et al., 2012; Lin et al., 2008; Oliveira et al., 2016; Taheri et al., 1994). Three groups reported high comparability in the EEG signal between the two systems (Liao et al., 2012; Lin et al., 2008; Taheri et al., 1994); however, these pioneering studies only recorded from a small number of electrodes placed on the forehead (Liao et al., 2012; Lin et al., 2008) or from one electrode placed on the scalp (Taheri et al., 1994). Similar results were reported for subjects who completed a brain computer interface (BCI) task with eight wet or dry electrodes (Käthner et al., 2017). Other recent studies used a high density dry EEG system covering the entire head (Fiedler et al., 2015; Oliveira et al., 2016). Using a within-subject design, one group compared resting EEG power and visual evoked potentials (VEP) in seated subjects with 128 wet and 97 dry passive electrodes (Fiedler et al., 2015). There were no significant differences between the two systems in power spectral densities across all tested EEG bands during rest, except for the lower frequencies between 4 and 6 Hz, in which the dry system showed higher power relative to the wet system. The global field power time courses of VEP also showed no differences between systems, but minor differences emerged in the topographic maps of two VEP components (Fiedler et al., 2015). Another study reported results from a subset of 12 active electrodes, and compared subjects performing a target detection task while sitting and walking with both EEG systems (Oliveira et al., 2016). Although their wet and dry systems had similar signal-to-noise ratios while subjects were seated, the dry system showed inferior performance in other metrics, including more rejected channels, higher inter-trial variance in the P3 ERP component and a failure to reliably record while subjects were walking (Oliveira et al., 2016). Together, these results suggest that dry electrodes show comparable performance to wet electrodes in stationary environments, but they do not perform well in motion due to the increased impedance level.

The present study provides a systematic comparison in data quality and electrophysiological measures between a state-of-the-art and wired wet EEG system (hereafter referred to as the wet EEG system; ActiveTwo from Biosemi, the Netherlands) with 64 electrodes, and a compact and wireless dry EEG system (hereafter referred to as the dry EEG system; F1 from Nielsen Tele Medical, U.S.A.) with 31 electrodes based on a 10–20 system. For each subject, we recorded the EEG with each system on separate days during rest periods with eyes open and eyes closed, followed by two versions of a rapid serial visual presentation (RSVP) target detection task. Each part of the experiment allows for a neural measure reflecting different characteristics of the data. Specifically, resting EEG data yields spectral power measures without contamination by external task demands. One version of the RSVP task (2 Hz presentation rate) was designed to elicit a clear P3b ERP component. Classification analysis on the other version of the RSVP task (6 Hz presentation rate) examines multivariate patterns in the data to categorize target vs. non-targets during rapid target detection. Taken together, this multitude of measures provides a thorough comparison of the performance of the two systems.

2. Methods

2.1. Subjects

A total of 30 individuals (9 females and 21 males; M = 19.8 years, S.D. = 13.4) participated in the study. One subject showed noisy data throughout the entire experiment for both wet and dry systems, whereas another subject had noisy data during rest for the dry EEG system. A third subject's blinks could not be completely removed using ICA for both EEG systems. These three subjects were excluded from analysis. The remaining subjects (n = 27) had normal or corrected-to-normal vision and had no neurological problems. They provided written informed consent, and were paid for their participation. The study was approved by the Institutional Review Board at the University of California, Berkeley.

2.2. Task paradigm and stimuli

Subjects performed two versions of a rapid serial visual presentation (RSVP) tasks, adopted from Fuhrman-Alpert and colleagues (2014). In both tasks, stimuli were grayscale images (360 × 360 pixels, 5.9° × 5.9° of visual angle at a distance of 106 cm), consisting of 145 exemplars from each of the following five categories: cars, planes, painted eggs, watches and faces. The images were preprocessed to have the same mean luminance and contrast, and were presented at the center of a CRT monitor. Stimulus presentation was controlled by Eprime 2.0 (Psychology Software Tools, Inc., USA).

Both tasks required subjects to silently count the occurrence of images from the target category, which ensured subjects maintained attention to the presented images without introducing motor confounds associated with target images only. Half the subjects were assigned cars as target images, whereas the other half were assigned planes. In each task, 11.1% of the images were targets that were randomly dispersed throughout the task. The number of images presented within each block ranged between 120 and 180 images, so as to avoid excessive working memory load due to counting increasingly large numbers. At the end of each block, subjects reported the number of targets that appeared, after which they

restarted the count. Subjects rested in between blocks upon request. Since the number of counted targets could be higher or lower than the actual number, target detection accuracy was computed as follows: 1-abs (reported target number - actual target number)/actual target number.

2.2.1. Slow task—In the slow version of the task (i.e. 2 Hz presentation rate), each image was presented for a randomly jittered duration between 450 and 550 ms, with no inter-stimulus interval. Each non-target image was presented twice and each target image was presented once, thereby yielding 11.1% of target images across all presented stimuli. The task consisted of 1305 trials, 420 of which were presented during practice and 885 during the recorded session, and lasted approximately 12 min.

2.2.2. Fast task—In the fast version of the task (i.e. 6 Hz presentation rate), each image was shown for 160 ms, with no inter-trial interval. Each non-target image was presented with 10 repetitions and each target image with 5 repetitions, thereby yielding a target probability of 11.1%. The task consisted of 6525 trials, with 420 presented during practice and 6105 presented during the recorded session, and lasted approximately 30 min.

2.3. Experimental procedure

EEG recording took place over two consecutive days for all subjects except for one, whose testing took place three days apart due to a scheduling conflict. For half of the subjects, the wet electrodes were used on Day 1 of testing and the dry electrodes were used on Day 2 of testing. The order was reversed for the other half of the subjects. On each day, subjects were seated in a dimly lit and sound attenuated room, where we recorded five minutes of rest with eyes open and five minutes with eyes closed, followed by the fast task and the slow task. The recording of rest and the two tasks lasted approximately 50–55 min.

For each session, we recorded the amount of time it took to mount the electrodes on the cap, as well as the cleaning of electrodes. At the end of each session, we asked subjects to rate the comfort level on a Likert scale ranging from 1 (not comfortable at all) to 6 (extremely comfortable) during electrode preparation and throughout recording, as well as agility throughout the entire experiment on a Likert scale ranging from 1 (not able to move at all) to 6 (extremely agile).

2.4. EEG data acquisition and preprocessing

2.4.1. Wet electrodes data acquisition—EEG was recorded continuously from 64 active, pre-amplified Ag/ AgCl electrodes mounted on a cap according to the extended 10–20 layout using the Biosemi ActiveTwo system (Biosemi, Netherland; https://www.biosemi.com/activetwo_full_specs.htm). The amplifier of this system is DC coupled. The electrodes are mounted within plastic holders on the cap, which are filled with electrolyte gel. Vertical and horizontal eye movements were recorded from electrodes above and below the right eye, and two electrodes placed at the right and left outer canthi. Data was amplified and digitized at 512 Hz. An online, low-pass, anti-aliasing filter was applied with a fifth-order sinc response.

2.4.2. Dry electrodes data acquisition—EEG was recorded continuously from 33 passive silver electrodes mounted on a cap according to the extended 10–20 layout using the F1 1.0 EEG system (Nielsen, USA; http://sites.nielsen.com/telemedical/assets/pdfs/spec_sheet_1st_batch.pdf). The amplifier of this system is DC coupled. The electrodes are spring-operated to maximize comfort (as shown in Fig. 1). At the F5 and F6 locations, scalp electrodes were substituted for external electrodes connected via an extension cable placed at the right and left outer canthus to measure horizontal eye movements. Vertical eye movements were recorded from Fp2, an electrode located above the right eye. We lowered electrode impedances to below 10 MOhms prior to onset of the experiment by moving the electrodes in a circular motion and sweeping hair away from underneath the electrodes to facilitate better contact between the scalp and the electrode. EEG data was communicated via wires embedded within the headset from each electrode to a battery-powered module (128 g), which was mounted to the headset above electrode Cz. The module contained the amplifier, wireless transmission board, battery, and hard drive. Data was amplified and digitized at 512 Hz, and subsequently transmitted to a recording computer via an exclusive WiFi connection. An online, low-pass, anti-aliasing filter was applied with a third-order sinc response. The slight disparity in the order of the sinc filter results in minimal differences between systems in the amplitude of the recorded signal mostly at higher frequencies. A detailed description of the different sinc filter responses for the two systems, and their impact on the amplitude of the recorded signal are illustrated in Fig. S3, Table S1 and the Supplementary Information. Fig. 1 presents photos of the dry EEG electrodes and Fig. S1 presents the electrode montage for both the Biosemi wet EEG and F1 dry EEG systems.

2.4.3. EEG data preprocessing—The preprocessing steps were identical for the two systems. For both, EEG data was bandpass filtered between 1 Hz and 50 Hz, and referenced offline to the average of the two mastoid electrodes. Ocular and muscle artifacts were corrected for using independent component analysis. Data decomposition was performed using the fastICA toolbox in EEGLAB, and artifactual components were manually detected based on component time course, topography and power spectral density. Electrodes with excessively noisy signals were interpolated from neighboring electrodes using spherical spline interpolation (Perrin et al., 1989). For both rest recordings, data were segmented into non-overlapping 2000 ms epochs. For the slow task, continuous EEG data were segmented into 1500 ms epochs, beginning at 500 ms prior to stimulus onset. Each trial was visually inspected for remaining artifacts, and was discarded if artifacts were present. Target and non-target trials were then averaged separately for each subject for statistical comparisons. For the fast task, continuous data were marked for artifacts, and then segmented into 1000 ms epochs beginning at 100 ms prior to stimulus onset. Any trials containing these marked artifacts for more than 200 ms within the epoch were discarded. EEG data pre-processing and analysis were performed using EEGLAB (Delorme and Makeig, 2004), FieldTrip (Oostenveld et al., 2011), and custom Matlab scripts (Mathworks, Natick, MA, USA).

2.5. EEG data quantification

2.5.1. Rest—Continuous data were segmented into non-overlapping two second epochs. For each epoch, spectral decomposition was conducted using fast Fourier transforms using a Hanning window for frequencies between 1 and 50 Hz at 1 Hz steps. Subsequently, a log

transform was applied. Each participant's power spectrum was then averaged across all clean epochs for each electrode, and the mean absolute power was computed for each of the following frequency bands: delta (2–4 Hz), theta (4–8 Hz), alpha (8–14 Hz), low beta (14–24 Hz), high beta (24–30 Hz), and gamma (30–50 Hz). In order to compare between systems, we only analyzed the subset of electrodes in the wet system that matched the location of electrodes in the dry system (as highlighted in Fig. S1).

2.5.2. Slow task—For event-related potentials (ERP) analysis, EEG signals were band pass filtered at 1–20 Hz, and target and non-target trials were averaged separately within subjects. All ERPs were quantified by the mean amplitude measure relative to a –200 to 0 ms pre-stimulus baseline. The P2 mean amplitude was measured over frontal sites (F1, Fz, F2) and averaged across a post-stimulus time window of 200–300 ms, whereas the P3b mean amplitude was measured over parietal sites (P1, Pz, P2) and averaged across a post-stimulus time window of 400–600 ms. The average number of trials included in the ERP analyses was similar for the wet (targets:$\overline{X}$ = 82, S.D. = 15; non-targets: $\overline{X}$ = 656, S.D. = 119) and the dry (targets: $\overline{X}$ = 84, S.D. = 11; non-targets: $\overline{X}$ = 675, S.D. = 79) EEG systems.

2.5.3. Fast task—We conducted classification analyses to examine whether the algorithm described below can detect whether a given trial is a target or non-target. The input data involved all channels from the dry EEG system and a subset of electrodes from the wet EEG system that matched the location of electrodes in the dry system. EEG signals were first bandpass filtered at 1–20 Hz. The classification analyses were based on the spatially weighted Fisher Linear Discriminant – Principal Component Analysis algorithm developed by Fuhrman-Alpert and colleagues (Fuhrmann Alpert et al., 2014). A random 90% of the trials were used for training and the remaining 10% were used for testing. This procedure was repeated 100 times. We computed several metrics to evaluate the performance of the classification analyses: hit rate (percentage of target trials that were correctly classified as targets), false alarm rate (percentage of non-target trials that were correctly classified as non-targets), and area under the curve (AUC) values associated with the receiver operating characteristic (ROC) curve.

2.6. Statistical analyses

2.6.1. Data quality—The number of electrodes and epochs removed due to poor data quality were compared between the wet and dry systems. We also compared the amount of time dedicated to electrodes preparation and cleaning, as well as the participant's reported comfort and agility level, between the two systems. The electrode cleaning time measurements were recorded for a subset of subjects (n = 14). All comparisons were examined using the Wilcoxon signed ranks test, the non-parametric version of the paired samples t-tests.

2.6.2. Rest

Eyes Open and Eyes Closed.—To examine differences between systems in the magnitude of spectral power, we performed separate Wilcoxon rank-sum tests for each of the six frequency bands, using Bonferroni correction to account for multiple comparisons. We assessed the within-subject reliability of EEG power at rest between the wet and dry

systems by conducting separate Spearman correlations at each frequency band for eyes open and eyes closed. To do this, we identified the five electrodes where activity was maximal per frequency band within each system, and selected electrodes that showed overlap between the two systems. We then correlated the mean power across these electrodes between the two systems across subjects separately for each frequency band.

2.6.3. Slow task—For ERP measures, separate Wilcoxon rank-sum tests were performed to examine differences between systems in the amplitude of the P2 and P3b ERP components, both in terms of the target-evoked activity and the difference between targets and non-targets. In order to assess within-subject reliability, we also ran separate Spearman correlation tests for each ERP component between the wet and dry EEG systems.

2.6.4. Fast task—We compared the classification performance between systems by implementing the Wilcoxon rank sum test for all three metrics (hits, false alarms and AUC). For each metric, we also computed separate Spearman correlations between each subject's classification performance on the wet and dry EEG systems. All statistical analyses were performed using SPSS (IBM, Armonk, NY, USA).

3. Results

3.1. Data quality

To examine the quality of data acquisition, we compared the number of faulty electrodes and bad epochs. The number of faulty electrodes that needed to be interpolated was higher for the dry ($\overline{X}$ = 5.26, SD = 2.16) relative to the wet EEG system ($\overline{X}$ = 2.00, SD = 1.30; Z = 5.25, $p < .001$). Faulty electrodes appear to be driven by muscle tension in the fronto-temporal area over the temporalis muscle, where the headset or cap is securely tightened around the subject's head. A closer examination of the location of the interpolated electrodes confirms this observation, with 42% of the faulty electrodes located in the fronto-temporal area (i.e. F7, F8, T7, T8) in the dry system, and 43% of electrodes in the wet system. Fig. S2 illustrates the spatial distribution of the number of bad electrodes across subjects for each system separately. There was no difference in the proportion of discarded trials (as described in the Methods section) between the dry ($\overline{X}$ = 0.15, SD = 0.08) and wet ($\overline{X}$ = 0.13, SD = 0.07) EEG systems (Z = 0.83, p = .41).

3.2. Subjective experience and duration of electrodes setup and cleanup

Fig. 2 shows measures of subjective experience, electrode preparation and cleaning time for the wet and dry systems. Total electrode preparation time and cleaning times were longer for the wet system relative to the dry system (preparation: Z = 3.59, $p < .001$; cleaning: Z = 2.54, p = .01). Given there were twice as many electrodes in the wet versus dry system, we also divided the two metrics by the number of electrodes to obtain the average time per electrode. Preparation time and cleaning time *per electrode* did not differ between systems (preparation: Z = 1.73, p = .084; cleaning: Z = 1.73, p = .085). Conclusions derived from this comparison need to take the following points into consideration. The experimenters were more experienced with electrode preparation, especially with respect to troubleshooting noisy signals, with the wet EEG system. Moreover, experimenters had to

lower the impedance levels of the dry electrodes, a procedure that was not necessary for the wet EEG system as it employs active (pre-amplified) electrodes that are less sensitive to high impedance.

Subjects rated higher agility with the dry system relative to the wet system ($Z = 3.37$, $p < .001$). The comfort level during electrodes preparation ($Z = 0.58$, $p = .56$) and recording session ($Z = 1.74$, $p = .08$) was comparable between the two systems. A closer look at the comfort level for both EEG systems indicates that the rating was higher during electrode preparation compared to during recording. To further explore this change in comfort level over time, we asked twenty additional subjects to wear either the dry electrodes headset or the wet electrodes cap (n = 10 each) for two hours. At 15 min interval, subjects rated the comfort level on the same Likert scale as the original set of subjects, ranging from 1 (not comfortable at all) to 6 (extremely comfortable). We observed that the average comfort level rating steadily declined over the course of the two-hour session for both systems. Based on the rating during the first and last 15 min of the session, we quantified the decline by computing the slope, which was steeper for the dry system (slope: —0.13) than for the wet system (slope: —0.04). The mean comfort ratings across subjects for both systems at each 15 min interval across the two hours are presented in Fig. 2.

3.3. EEG at rest: eyes open and eyes closed

Fig. 3 illustrates the power spectrum across all electrodes, the topography of each frequency band, as well as the correlation between systems for rest with eyes opened and eyes closed. As observed in Fig. 3a, the power spectrum density averaged across all electrodes was comparable between the systems across the entire frequency range shown. Subsequent statistical analyses focused on a subset of overlapping electrodes that showed maximal power in both the wet and dry EEG systems chosen separately for each band (as described in Methods). The mean power for each system, as well as the Z and p values and Cohen's d comparing the two systems for each frequency band and for both resting state conditions are reported in Table 1. For resting state with eyes open, delta and theta power were higher in the wet system relative to the dry system; however, only the difference in delta power survived Bonferroni correction. No other frequency bands showed differences between systems. For resting state with eyes closed, theta power was higher in the wet compared to the dry system, but this difference did not survive Bonferroni correction. Spectral power in the other frequency bands did not differ between systems. The power differences observed in the lower frequencies cannot be attributed to differences in signal-to-noise ratio (SNR), as the SNR did not differ between systems across any of the frequency ranges ($p = .07–0.74$). A detailed description of SNR calculations and results is reported in the Supplementary Information. For both eyes open and eyes closed, the mean absolute power of theta, alpha, and low beta positively correlated between the wet and dry EEG systems across subjects ($r > 0.54$, $p < .005$), with the strongest correlation in the alpha band. High beta power also significantly correlated across the two systems for rest with eyes closed ($r = 0.62$, $p < .001$).

3.4. Slow target detection task

Mean accuracy of target counting was high for both systems (wet: $\overline{X} = 97.9\%$; dry: $\overline{X} = 97.2\%$), indicating subjects were paying attention to the images and performing the task.

Fig. 4 presents the ERP waveforms at all channels, selected channels relevant for the ERPs, as well as the correlation in ERP amplitudes between the two systems. ERP data analyses focused on the P2 and P3b mean amplitude measures. We statistically compared the difference values (i.e. targets minus non-targets) between the two systems, as well as the target condition itself. Both P2 and P3b amplitudes were larger for targets compared with non-targets for both the wet system (P2: $Z = 4.32$, $p < .001$, Cohen's $d = 1.38$; P3: $Z = 4.16$, $p < .001$, Cohen's $d = 1.53$) and the dry system (P2: $Z = 4.49$, $p < .001$, Cohen's $d = 1.07$; P3: $Z = 4.54$, $p < .001$, Cohen's $d = 1.80$). For the P2, the target – nontarget difference score was higher in the wet system relative to the dry system (wet: 3.34 μV, dry: 2.26 μV; $Z = 2.45$, $p = .01$, Cohen's $d = 0.47$). This was driven by a larger response to the targets, as shown in the higher mean amplitude in the wet system compared with the dry system (wet: 4.84 μV, dry: 3.51 μV; $Z = 3.10$, $p = .002$, Cohen's $d = 0.46$). In contrast, the P3b amplitude was similar across the two systems in the difference scores (wet: 2.03 μV, dry: 1.79 μV; $Z = 0.91$, $p = .36$, Cohen's $d = 0.17$) and in the target condition (wet: 1.50 μV, dry: 1.46 μV; $Z = 0.29$, $p = .77$, Cohen's $d = 0.02$). For both P2 and P3 mean amplitudes, there was a positive correlation across subjects between the wet and dry EEG systems as plotted in Fig. 4 ($r > 0.64$, $p < .001$).

3.5. Fast target detection task

Mean accuracy was high for both systems (wet: $\overline{X} = 96.6\%$; dry: $\overline{X} = 98.9\%$), indicating subjects were paying attention to the images and could detect the targets well despite the fast presentation. Classification analyses yielded three metrics of performance, including AUC, hit rate, and false alarm rate. Fig. 5 shows the ROC curves for each individual subject, and the mean values of the three performance metrics for each system, as well as the correlation between the two systems across subjects in each of the metrics. Both EEG systems performed well above chance. There was a trend for the wet system to perform slightly better across all performance metrics ($Z = 1.42–1.90$, p = .06–0.16), but only the false alarm rate differed significantly ($Z = 2.02$, $p = .04$). Importantly, performance of the wet and dry EEG systems correlated well for all metrics ($r > 0.57$, $p < .005$).

4. Discussion

In the current study, we present a comprehensive comparison of the signal quality between a compact and wireless dry EEG system (F1, Nielsen) and a conventional laboratory-based wet EEG system (Active-Two, Biosemi). The performance correlated well between the two systems for all metrics, including P2 and P3b amplitude, spectral power at rest (with the exception of delta and gamma bands), as well as single trial classification results. This combination of measures captures different aspects of EEG data, including event-related potentials, low frequency power, and multivariate patterns of activity. Taken together, the results indicate that the F1 dry EEG system effectively detects electrophysiological measures commonly used across research and clinical contexts.

Low frequency power from 4 to 50 Hz at rest was similar across the two systems, with the exception that delta power was marginally reduced in the dry EEG system. Moreover, EEG power for each frequency band correlated within subjects between the two systems for theta,

alpha and low and high beta. For these frequency bands, scalp topographies were similar across the two EEG systems, with a slightly more posterior distribution for the dry system. EEG recorded during rest reflects ongoing processes in the absence of an external task. In applied contexts, resting EEG power has reliably differentiated healthy individuals from clinical and neurological populations, such as Alzheimer's disease (Babiloni et al., 2013) and depression (Thibodeau et al., 2006). Our results established the robustness of low frequency spectral power measures (i.e. theta, alpha and beta) during rest in the dry EEG system, and given the utility of these measures support its potential applications in a variety of research and clinical contexts.

The P2 and P3b amplitudes correlated within subjects between the two systems, indicating high test-retest reliability on different EEG systems tested on two separate days. These correlations are comparable to the test-retest reliability of the target P3b in previous studies that tested subjects within one experimental session on the same system in different environments ($r = 0.85$, Debener et al., 2012; $r > 0.70$, Oliveira et al., 2016) and different systems in the same environment ($r > 0.77$, De Vos et al., 2014b). Our results expand on these findings and indicate that test-retest reliability in the target P3b response is maintained even when testing on separate days using two different systems. Within the research realm, the P3b has been shown to reflect attentional resource allocation, working memory, target detection, as well as processing capacity (for reviews, see Kok, 2001; Linden, 2005; Polich, 2007). In clinical and medical environments, the P3b has been employed as an endophenotype of psychiatric disorders including schizophrenia (Turetsky et al., 2007) and alcoholism (Porjesz et al., 2005), as well as an early marker of neurological disorders, including Alzheimer's disease (Polich, 1990). Given the widespread applications of the P3b, and the potential benefits of using dry electrodes, the dry EEG system can facilitate testing of large numbers of research subjects in more natural environments, as well as testing of patients in their homes or the doctor's offices as long as they remain stationary.

Performance of the classification analyses was satisfactory in both the wet and dry EEG systems, suggesting the dry system can be used for examining not only univariate but also multivariate electrophysiological measures. Both systems performed well above chance in categorizing the data into targets and non-targets. This is especially remarkable given that the categorization was very demanding, both in terms of the cognitive effort required by subjects to perform well in the RSVP task (with six images presented per second), as well as the signal processing requirements to classify data from a fast RSVP task with highly overlapping responses. This type of multivariate single trial analyses nicely complements the advantages of the wireless dry EEG system, and can be applied to address a diverse range of questions. For instance, mind wandering is a ubiquitous phenomenon in which one's attention is internally oriented while performing another externally oriented task (Smallwood and Schooler, 2006), and a state that occupies up to half of our waking hours (Killingsworth and Gilbert, 2010). While numerous EEG studies have examined mind wandering in the laboratory (Baird et al., 2012; Bra-boszcz and Delorme, 2011; Kam and Handy, 2013), none have been able to study participants in their natural environment due to the constraints of the wired wet EEG system. Using the wireless dry EEG system opens the way for classification of the subjects' state (i.e. mind wandering or not) in more natural situations, although the sensitivity of dry systems to head movements, which was not

addressed here, limits the range of situations that can be studied. In addition to addressing basic scientific questions, the dry EEG system also has important implications in applied contexts. For instance, many professionals, such as pilots and power plant operators, are required to monitor their environment for sustained periods of time (Gouraud et al., 2017). While it is human nature to slip into an attentional lapse from time to time, the consequences can be grave in these positions. Real time classification of these professionals' electrophysiological signals using the dry EEG system in their workplace may allow them to detect when their attention is lapsing, and to subsequently initiate efforts to reorient their attention back to their job. Taken together, the wireless dry EEG system combined with single trial classification analyses has the potential to address research questions in both the laboratory and applied contexts.

Although most of the EEG metrics we considered in our comparisons showed similar results across the two systems, there are some exceptions that deserve consideration. For example, delta and gamma power at rest did not correlate well between the systems. In the delta band, not only was there a lack of correlation, but delta power was higher in the wet system. Importantly, the signal-to-noise ratio (SNR) was comparable between the two systems across all frequency ranges, therefore, SNR cannot account for power differences between systems. Given that movement artifacts usually appear in the low frequencies, and dry systems are generally more sensitive to movement artifacts, we would have expected to see higher delta power in the low frequencies. However, we observed higher delta power in the wet system instead. The reason for this difference between systems is unclear. Although the P2 response was larger over the frontal region in the wet compared to the dry system, the target P3b response was similar across systems. Single trial classification performance in the fast target detection task was marginally better with the wet EEG system, but classification was well above chance for both systems. These results converge on slightly better performance in the wet EEG system, which may be attributable to this system's use of wet and actively amplified electrodes.

Differences in hardware and user experience between the two systems are also noteworthy. Although electrode placement of both systems are in accordance to the 10–20 or 10–10 system, rendering them applicable for clinical contexts, the number of channels for the dry EEG system (n = 31) is half of that for the wet EEG system (n = 64). Aside from hardware differences, the user and researcher experience are also important factors to consider. The average preparation time per electrode was slightly higher for the dry system in this study. This may be surprising considering that no gel had to be applied in the case of the dry system. The combination of two factors likely prolonged the electrodes preparation with the dry system. First, experimenters were relatively inexperienced with the dry electrodes compared to the wet electrodes, especially with respect to troubleshooting noisy signals. Moreover, experimenters had to lower the impedance levels of the dry electrodes; in comparison, the active, pre-amplified, electrodes of the Biosemi wet system do not require this care in reducing impedances across electrodes. Having worked with wet and dry EEG systems, both experimenters preferred to work with the dry EEG system due to the ease of electrode preparation and clean up. The user's reported agility was superior for the dry EEG system, but the comfort level during set up and recording did not differ between the two systems. Notably, comfort level steadily declined over the course of two hours, with a

steeper decline in the dry electrodes. Future studies are needed to determine whether this observed pattern in comfort level applies to recording sessions beyond two hours as in the current experiment.

It is important to note our comparisons are specific to the F1 dry EEG system used in this study. While several studies have directly compared other wet and dry EEG systems, they typically involve fewer electrodes (Guger et al., 2012; Käthner et al., 2017; Liao et al., 2012; Lin et al., 2008; Lo et al., 2016), with the exception of two studies that recorded from high density EEG electrodes (Fiedler et al., 2015; Oliveira et al., 2016). The F1 dry EEG system records from 31 electrodes placed in accordance to the 10–20 system. In addition, previous studies primarily reported ERP measures (Fiedler et al., 2015; Liao et al., 2012; Lin et al., 2008), and low frequency power (Fiedler et al., 2015; Oliveira et al., 2016). In addition to these measures, we also showed the dry system performed well in classification analyses, which is one of the main measures used in the brain-computer interface context, for example, for locked-in patients. To what extent these classification results apply to other dry EEG systems remain to be tested.

Taken together, the F1 dry EEG system shows comparable user experience and data quality in most metrics in a laboratory environment in which subjects are seated. In general, dry electrode systems share the advantage of ease of electrode application by avoiding extensive preparation and cleaning of electrodes. This advantage has important potential applications. In the clinical context, this benefit is especially crucial for testing certain populations, such as psychiatric and neurological patients as well as children, who are generally less tolerant of gel application. For instance, severely aphasic or locked-in patients benefit from brain computer interfaces (BCIs) to communicate with others (Birbaumer et al., 1999). BCIs that use the wired EEG systems typically restrict patients to locations such as hospitals or clinics, where the system needs to be set up. The minimal technique required for electrodes preparation is particularly beneficial in these situations in which patients require chronic EEG monitoring, as it allows their family members to apply the electrodes in the patients' home without the need of a trained EEG technician (Käthner et al., 2017). This finding underscores the potential application of the dry electrodes technology in other clinical populations in a less controlled environment. One population to potentially benefit from this technology involves individuals at risk for epilepsy. The current practice often requires these patients' electrophysiological activity to be monitored for 24 h using an EEG system in the hospital to identify the epileptic source prior to surgical treatment. The similar signal quality between dry and wet EEG systems in stationary environments highlight the prospect of using the dry electrodes technology for presurgical monitoring for seizures in a patient's home as long as patients stay in a stationary position.

In conclusion, we demonstrated that the signal quality of a wireless dry EEG system is comparable with that of a conventional wet EEG system in a controlled laboratory environment. These results provide support for dry EEG systems as a technology with novel research and clinical applications.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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References

Babiloni C, Carducci F, Lizio R, Vecchio F, Baglieri A, Bernardini S, Cavedo E, Bozzao A, Buttinelli C, Esposito F, Giubilei F, Guizzaro A, Marino S, Montella P, Quattrocchi CC, Redolfi A, Soricelli A, Tedeschi G, Ferri R, Rossi-Fedele G, Ursini F, Scrascia F, Vernieri F, Pedersen TJ, Hardemark H-G, Rossini PM, Frisoni GB, 2013 Resting state cortical electroencephalographic rhythms are related to gray matter volume in subjects with mild cognitive impairment and Alzheimer's disease. Hum. Brain Mapp. 34, 1427–1446. 10.1002/hbm.22005. [PubMed: 22331654]

Baird B, Smallwood J, Mrazek MD, Kam JWY, Franklin MS, Schooler JW, 2012 Inspired by distraction. Psychol. Sci. 23, 1117–1122. 10.1177/0956797612446024. [PubMed: 22941876]

Birbaumer N, Ghanayim N, Hinterberger T, Iversen I, Kotchoubey B, Kubler A, Perelmouter J, Taub E, Flor H, 1999 A spelling device for the paralyzed. Nature 398, 297–298. [PubMed: 10192330]

Braboszcz C, Delorme A, 2011 Lost in thoughts: neural markers of low alertness during mind wandering. Neuroimage 54, 3040–3047. 10.1016/j.neuroimage.2010.10.008. [PubMed: 20946963]

Burton A, 2015 Brainwaves from Bhutan. Lancet Neurol. 14, 1154–1155. 10.1016/S1474-4422(15)00311-7. [PubMed: 26581967]

De Vos M, Gandras K, Debener S, 2014a Towards a truly mobile auditory brain-computer interface: exploring the P300 to take away. Int. J. Psychophysiol. 91, 46–53. 10.1016/j.ijpsycho.2013.08.010. [PubMed: 23994208]

De Vos M, Kroesen M, Emkes R, Debener S, 2014b P300 speller BCI with a mobile EEG system: comparison to a traditional amplifier. J. Neural. Eng. 11 10.1088/1741-2560/11/3/036008.

Debener S, Emkes R, De Vos M, Bleichner M, 2015 Unobtrusive ambulatory EEG using a smartphone and flexible printed electrodes around the ear. Sci. Rep. 5, 1–11. 10.1038/srep16743.

Debener S, Minow F, Emkes R, Gandras K, de Vos M, 2012 How about taking a low-cost, small, and wireless EEG for a walk? Psychophysiology 49, 1617–1621. 10.1111/j.1469-8986.2012.01471.x. [PubMed: 23013047]

Delorme A, Makeig S, 2004 EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. J. Neurosci. Meth. 134, 9–21. 10.1016/j.jneumeth.2003.10.009.

Fiedler P, Pedrosa P, Griebel S, Fonseca C, Vaz F, Supriyanto E, Zanow F, Haueisen J, 2015 Novel multipin electrode cap system for dry electroencephalography. Brain Topogr. 28, 647–656. 10.1007/s10548-015-0435-5. [PubMed: 25998854]

Alpert Fuhrmann G., Manor R, Spanier AB, Deouell LY, Geva AB, 2014 Spatiotemporal representations of rapid visual target detection: a single-trial EEG classification algorithm. IEEE Trans. Biomed. Eng. 61, 2290–2303. 10.1109/TBME.2013.2289898. [PubMed: 24216627]

Gouraud J, Delorme A, Berberian B, 2017 Autopilot, mind wandering, and the out of the loop performance problem. Front. Neurosci. 11, 1–13. 10.3389/fnins.2017.00541. [PubMed: 28154520]

Guger C, Krausz G, Allison BZ, Edlinger G, 2012 Comparison of dry and gel based electrodes for P300 brain-computer interfaces. Front. Neurosci. 6, 1–7. 10.3389/fnins.2012.00060. [PubMed: 22294978]

Kam JWY, Handy TC, 2013 The neurocognitive consequences of the wandering mind: a mechanistic account of sensory-motor decoupling. Front. Psychol. 4, 725 10.3389/fpsyg.2013.00725. [PubMed: 24133472]

Käthner I, Halder S, Hintermüller C, Espinosa A, Guger C, Miralles F, Vargiu E, Dauwalder S, Rafael-Palou X, Sola M, Daly JM, Armstrong E, Martin S, Kübler A, 2017 A multifunctional brain-computer interface intended for home use: an evaluation with healthy participants and potential end users with dry and gel-based electrodes. Front. Neurosci. 11, 1–21. 10.3389/fnins.2017.00286. [PubMed: 28154520]

Killingsworth MA, Gilbert DT, 2010 A wandering mind Is an unhappy mind. Science 80, 932.

Kok A, 2001 On the utility of P3 amplitude as a measure of processing capacity. Psychophysiology 38, 557–577. [PubMed: 11352145]

Liao L De, Chen CY, Wang IJ, Chen SF, Li SY, Chen BW, Chang JY, Lin CT, 2012 Gaming control using a wearable and wireless EEG-based brain-computer interface device with novel dry foam-based sensors. J. NeuroEng. Rehabil. 9 10.1186/1743-0003-9-5.

Lin C. Teng, Ko L. Wei, Chiou J. Chern, Duann J. Ren, Jung T. Ping, Huang R. Song, Liang S. Fu, Chiu T. Wen, Chiu T. Wen, 2008 Noninvasive neural prostheses using mobile and wireless EEG. Proc. IEEE 96, 1167–1183. In: 10.1109/JPROC.2008.922561.

Lin CT, Liao L De, Liu YH, Wang IJ, Lin BS, Chang JY, 2011 Novel dry polymer foam electrodes for long-term EEG measurement. IEEE Trans. Biomed. Eng. 58, 1200–1207. 10.1109/TBME.2010.2102353. [PubMed: 21193371]

Linden DEJ, 2005 The p300: where in the brain is it produced and what does it tell us? Neuroscientist 11, 563–576. 10.1177/1073858405280524. [PubMed: 16282597]

Lo CC, Chien TY, Chen YC, Tsai SH, Fang WC, Lin BS, 2016 A wearable channel selection-based brain-computer interface for motor imagery detection. Sensors 16, 1–14. 10.3390/s16020213.

Lopez-Gordo MA, Morillo Sanchez D., Pelayo Valle F, 2014 Dry EEG electrodes. Sensors 14, 12847–12870. 10.3390/s140712847. [PubMed: 25046013]

Lotte F, Fujisawa J, Touyama H, 2009 Towards ambulatory brain-computer interfaces: a pilot study with P300 signals. Int. Conf. Adv. Comput. Enterntainment Technol 336–339. 10.1145/1690388.1690452.

Oliveira AS, Schlink BR, Hairston WD, König P, Ferris DP, 2016 Proposing metrics for benchmarking novel EEG technologies towards real-world measurements. Front. Hum. Neurosci. 10, 1–15. 10.3389/fnhum.2016.00188. [PubMed: 26858619]

Oostenveld R, Fries P, Maris E, Schoffelen JM, 2011 FieldTrip: open source software for advanced analysis of MEG, EEG, and invasive electrophysiological data. Comput. Intell. Neurosci. 2011, 156869, 9 pages. 10.1155/2011/156869.

Perrin P, Pernier J, Bertrand O, Echallier JF, 1989 Spherical splines for scalp potential and current density mapping. Electroencephalogr. Clin. Neurophysiol. 72, 184–187. [PubMed: 2464490]

Pinho F, Cerqueira J, Correia J, Sousa N, Dias N, 2017 myBrain: a novel EEG embedded system for epilepsy monitoring. J. Med. Eng. Technol. 41, 564–585. [PubMed: 28994627]

Polich, 1990 P300, probability, and inter-stimulus interval. Psychophysiology 27, 396–403. [PubMed: 2236442]

Polich J, 2007 Updating P300: an integrative theory of P3a and P3b. Clin. Neurophysiol. 118, 2128–2148. 10.1016/j.clinph.2007.04.019. [PubMed: 17573239]

Porjesz B, Rangaswamy M, Kamarajan C, Jones KA, Padmanabhapillai A, Begleiter H, 2005 The utility of neurophysiological markers in the study of alcoholism. Clin. Neurophysiol. 116, 993–1018. 10.1016/j.clinph.2004.12.016. [PubMed: 15826840]

Smallwood J, Schooler JW, 2006 The restless mind. Psychol. Bull. 132, 946–958. 10.1037/0033-2909.132.6.946. [PubMed: 17073528]

Taheri BA, Knight RT, Smith RL, 1994 A dry electrode for EEG recording. Electroencephalogr. Clin. Neurophysiol. 90, 376–383. [PubMed: 7514984]

Taheri BA, Smith RL, Knight RT, 1996 An active, microfabricated, scalp electrode array for EEG recording. Sensor. Actuator. 54, 606–611.

Teplan M, 2002 Fundamentals of EEG measurement. Meas. Sci. Rev. 2, 1–11. 10.1021/pr0703501.

Thibodeau R, Jorgensen RS, Kim S, 2006 Depression, anxiety, and resting frontal EEG asymmetry: a meta-analytic review. J. Abnorm. Psychol. 115, 715–729. 10.1037/0021-843X.115.4.715. [PubMed: 17100529]

Toyama S, Takano K, Kansaku K, 2012 A non-adhesive solid-gel electrode for a non-invasive brain-machine interface. Front. Neurol. 1–8. 7 10.3389/fneur.2012.00114. [PubMed: 22279441]

Turetsky BI, Calkins ME, Light GA, Olincy A, Radant AD, Swerdlow NR, 2007 Neurophysiological endophenotypes of schizophrenia: the viability of selected candidate measures. Schizophr. Bull. 33, 69–94. 10.1093/schbul/sbl060. [PubMed: 17135482]

Wang Y Te, Wang Y, Jung TP, 2011 A cell-phone-based brain-computer interface for communication in daily life. J. Neural. Eng. 8 10.1088/1741-2560/8/2/025018.

Yu YH, Lu SW, Liao L, De Lin CT, 2014 Design, fabrication, and experimental validation of novel flexible silicon-based dry sensors for electroencephalography signal measurements. IEEE J. Transl. Eng. Heal. Med. 2 10.1109/JTEHM.2014.2367518.

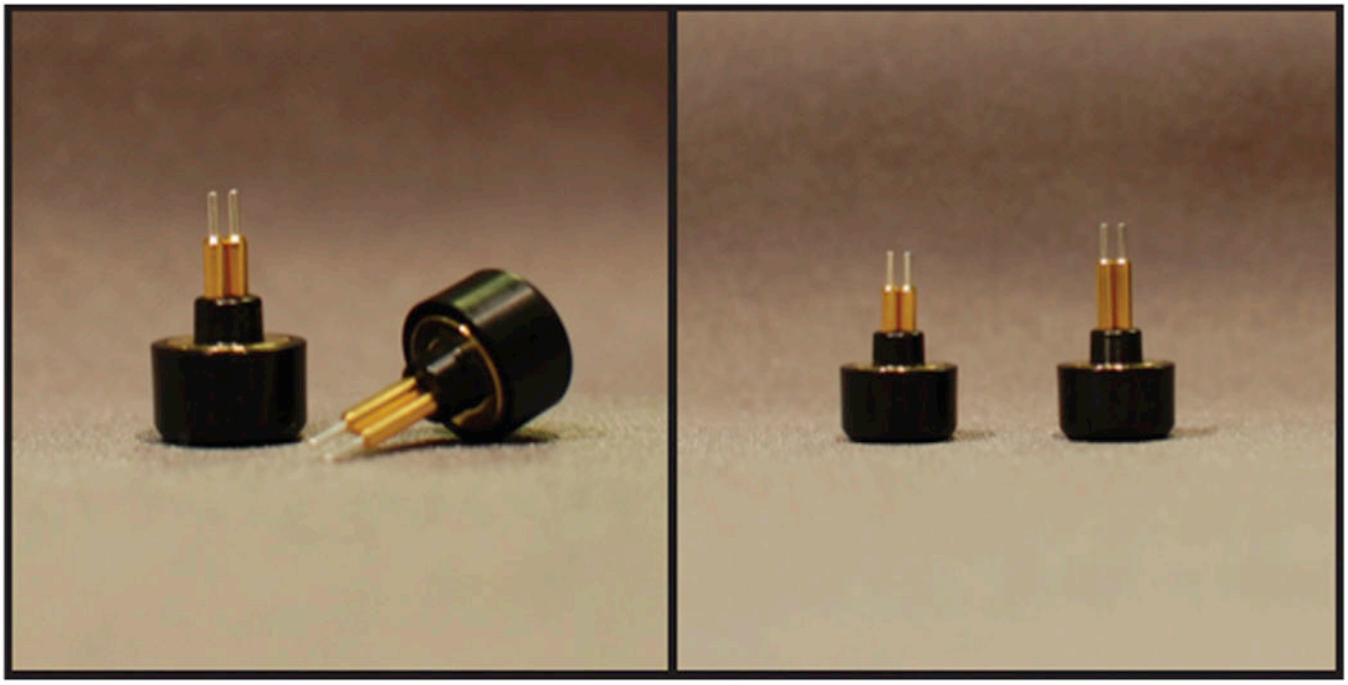

Fig. 1.

Dry electrodes of the F1 system. There are two versions of the electrodes in which the metal pins vary in length, in order to accommodate different hair types. The electrodes are spring loaded such that the two pins are adjustable in length as they push through the subject's hair and come into contact with the scalp. The black casing of the electrodes magnetically attaches to the headset.

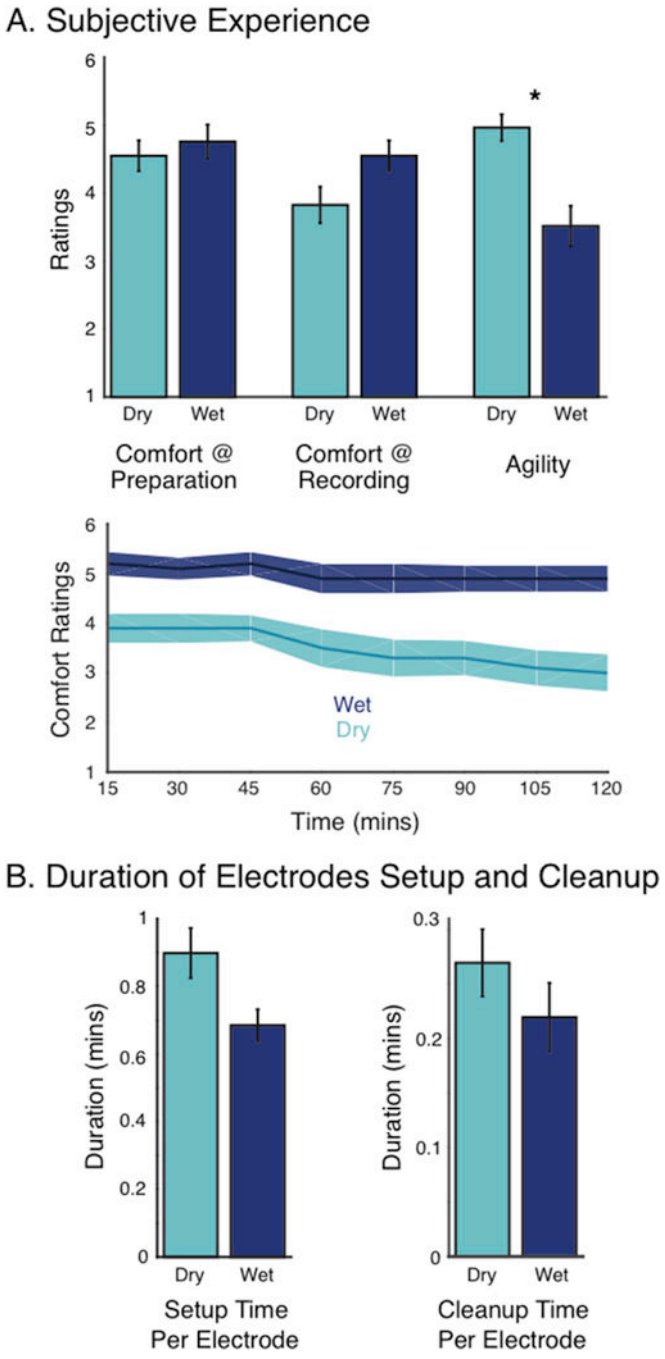

Fig. 2.

Comparison of qualitative metrics between systems. A) In the top panel, participants' reported level of comfort during preparation and during recording (on a Likert scale ranging from 1 = not comfortable at all to 6 = extremely comfortable) are illustrated separately for the dry and wet EEG systems. Agility was also rated on a Likert scale (ranging from 1 = not agile at all to 6 = very agile) for each system. In the bottom panel, the mean comfort ratings across a new set of subjects for each system are illustrated across the two hours of testing, during which subjects were seated at a desk and allowed to do whatever they choose to focus

their attention on. Shaded area reflects standard errors. At each 15 min interval, subjects (n = 10 per system) rated how comfortable they felt with the head set on. B) The average setup and cleanup time per electrode are reported for the two systems separately.

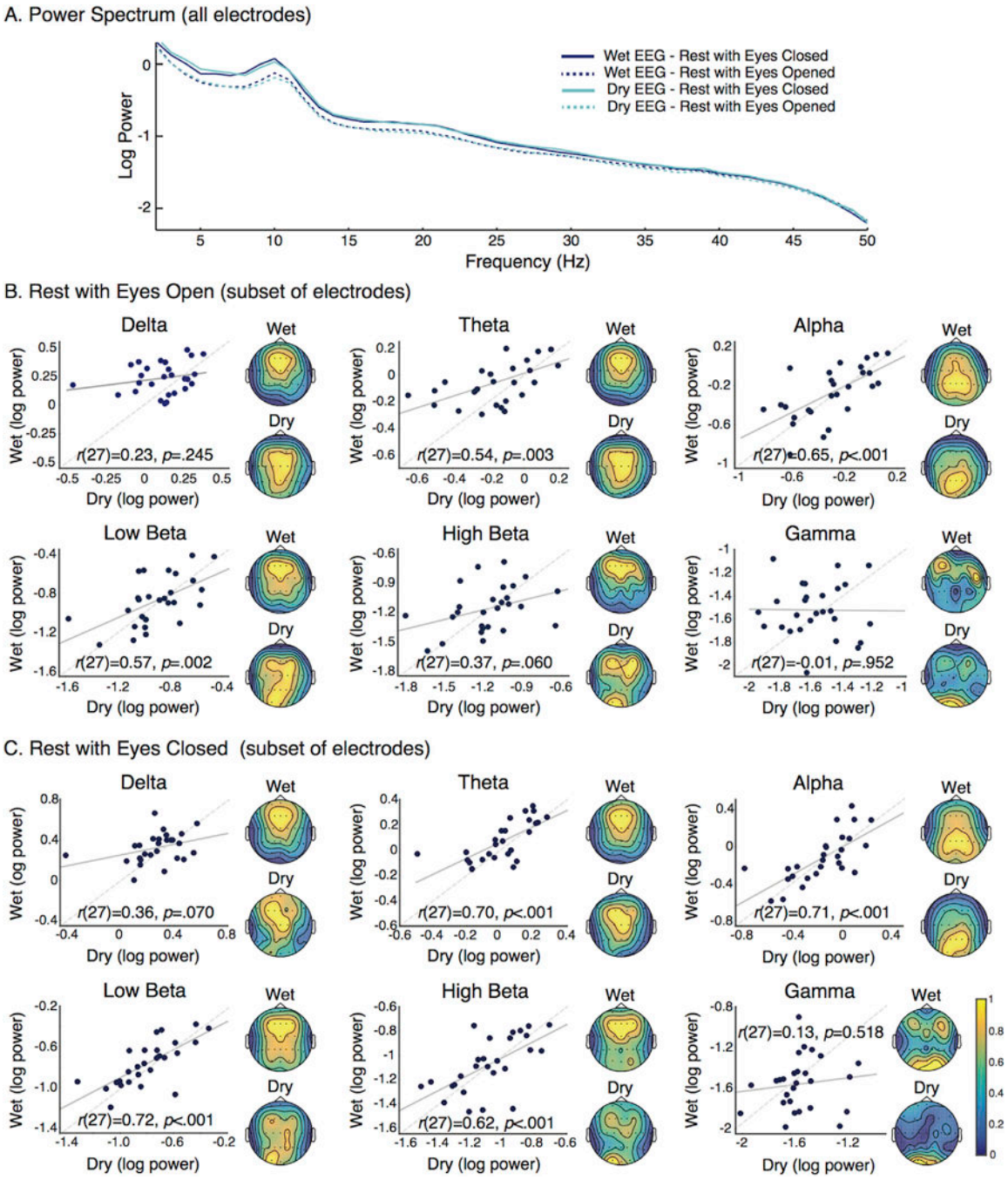

Fig. 3.

Resting EEG power spectrum and topography. A) The power spectrum density averaged across all electrodes for the dry EEG system and the corresponding electrodes for the wet EEG system are shown separately for rest with eyes open and closed. B) For rest with eyes open, separate scatterplots of individual subjects' mean absolute log power for delta, theta, alpha, low beta, high beta, and gamma for the wet and dry EEG systems are plotted. Spearman correlations are reported for each scatterplot (gray solid line = regression line; gray dotted line = identity line). Topographic plots are also plotted separately for each

frequency band and EEG system. C) The same scatterplot and scalp topography are plotted for rest with eyes closed. Topographic plots were normalized within system.

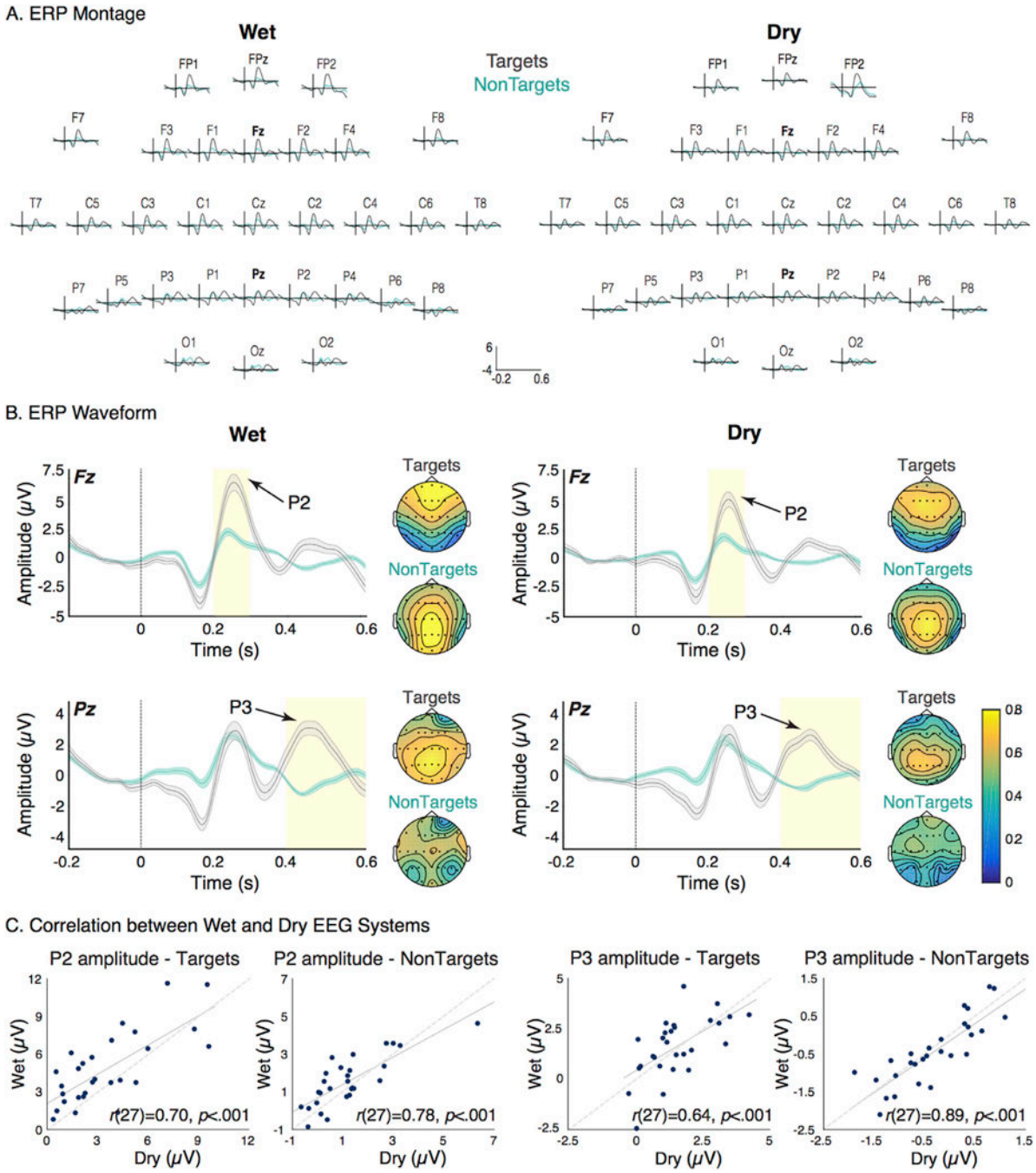

Fig. 4.

ERP waveform and topography. A) ERP waveforms time locked to targets and non-targets at all channels. B) P2 shown at Fz and P3b shown at Pz are presented separately for the wet and dry EEG systems, along with their corresponding scalp topography. Topographic plots were normalized within systems and conditions. C) The scatterplot of each subject's P3b mean amplitude for the wet and dry EEG systems are presented (gray solid line = regression line; gray dotted line = identity line), with their associated Spearman correlation values.

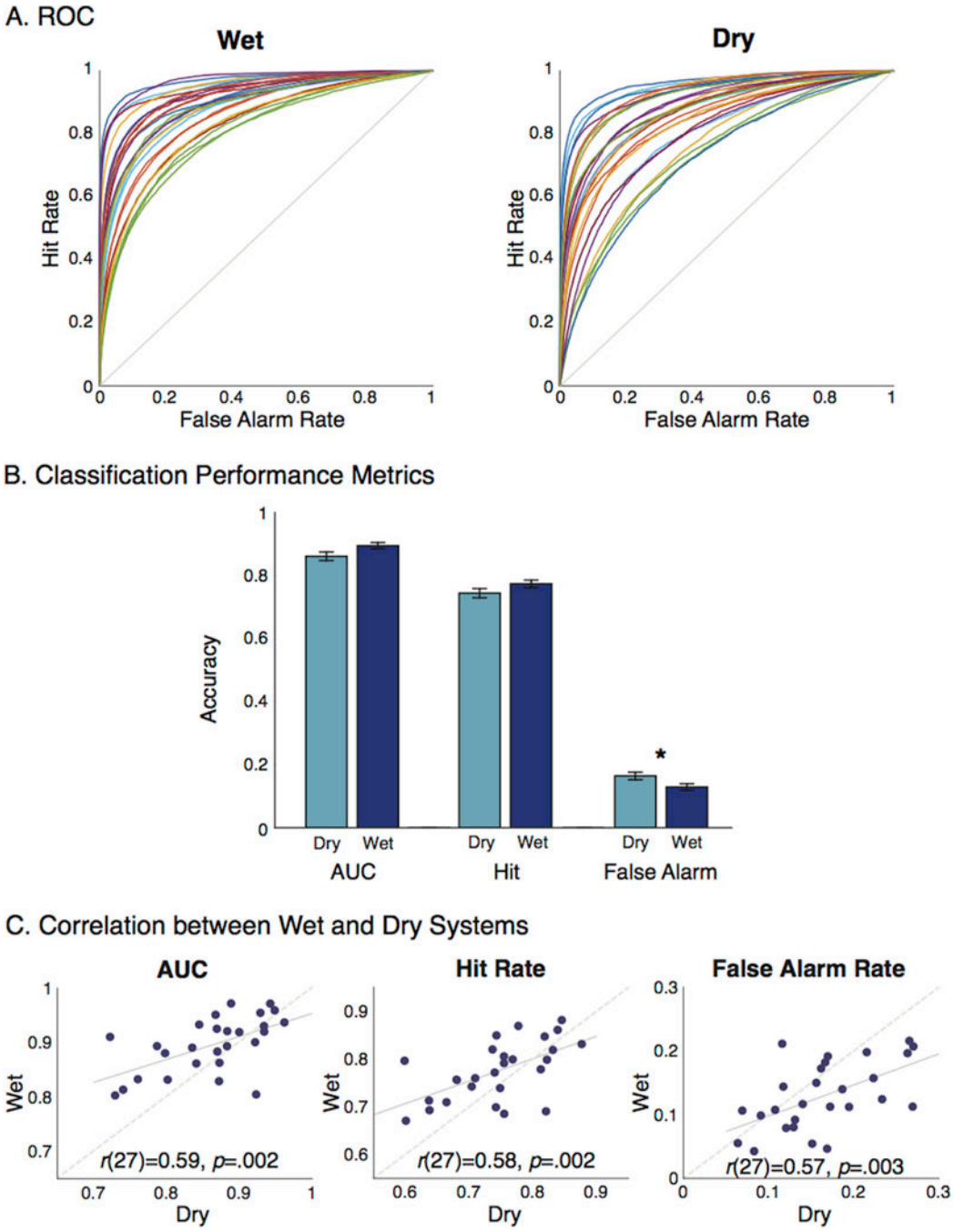

Fig. 5.

Classification performance. A) The ROC curve for each individual subject is shown separately for the wet and dry EEG systems. B) Bar plots of the mean performance on area under the curve (AUC), hit rate, and false alarm rate are shown separately for the dry (light blue) and wet (dark blue) EEG systems. C) The scatterplots of each subject's performance on each of the three metrics for the two EEG systems and their corresponding Spearman correlations are presented (gray solid line = regression line; gray dotted line = identity line).

Table 1

Descriptive and statistical values for resting state EEG power. The mean log power for the wet and dry system, as well as the *Z* and *p* values and Cohen's *d* for each frequency band comparing the two systems are reported for resting state with eyes open and closed.

	Wet	Dry	*Z*	*P*	Cohen's *d*
Eyes Open Delta	0.233	0.114	2.79	.005*	0.70
Theta	−0.056	−0.158	2.50	.012	0.51
Alpha	−0.275	−0.312	1.01	.313	0.13
Low Beta	−0.877	−0.906	0.41	.683	0.11
High Beta	−1.164	−1.159	0.31	.755	0.02
Gamma	−1.524	−1.575	1.11	.269	0.22
Eyes Closed Delta	0.320	0.267	1.59	.113	0.29
Theta	0.069	0.013	2.21	.027	0.32
Alpha	−0.126	−0.153	0.51	.614	0.10
Low Beta	−0.764	−0.797	1.27	.203	0.14
High Beta	−1.078	−1.088	0.60	.548	0.04
Gamma	−1.559	−1.567	0.34	.737	0.03

**Note:* indicates significance after Bonferroni correction.