Evaluation of a Dry Electrode System for Electroencephalography: Applications for Psychophysiological Cognitive Workload Assessment

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Advances in state-of-the-art dry electrode technology have led to the development of a novel dry electrode system for electroencephalography (QUASAR, Inc.; San Diego, California, USA). While basic systems-level testing and comparison of this dry electrode system to conventional wet electrode systems has proved to be very favorable, very limited data has been collected that demonstrates the ability of QUASAR's dry electrode system to replicate results produced in more applied, dynamic testing environments that may be used for human factors applications. In this study, QUASAR's dry electrode headset was used in combination with traditional wet electrodes to determine the ability of the dry electrode system to accurately differentiate between varying levels of cognitive workload. Results show that the accuracy in cognitive workload assessment obtained with wet electrodes is comparable to that obtained with the dry electrodes.

INTRODUCTION

Numerous studies have reported that psychophysiological data can be used to accurately detect varying cognitive states, with applications in areas such as workload assessment, brain-computer interfaces (BCI), and adaptive automation (Berka, et al., 2004; Birbaumer & Cohen, 2007; Freeman, Mikulka, Prinzel & Scerbo, 1999; Gevins, et al., 1998; Shelley & Backs, 2006; Wilson & Russell, 2003a; 2003b). However, the success of these methods has not led to transitioned systems in operational environments. This result is due, in part, to the invasiveness associated with the process of preparing for psychophysiological data collection, primarily that of electrophysiological measures such as electroencephalography (EEG), electrocardiography (ECG), electrooculography (EOG) and electromyography (EMG). Traditional electrophysiological recording procedures involve preparation of the skin surface at the recording site to reduce contact impedance between the electrode and the skin. This preparation often involves scrubbing the skin surface with an abrasive paste or gel, followed by cleansing with alcohol, and the application of a conductive gel or paste between the electrode and skin surface to facilitate electrical recording. While these methods produce high-quality data, they can lead to skin irritation and discomfort in as little as one recording session. Trained, experienced technicians are also needed for application, and the application itself requires an amount of time dependent on both technician expertise and the number of electrodes involved.

QUASAR, Inc. (San Diego, CA, USA) has developed a prototype dry electrode system for EEG recording that does not require skin preparation or an electrically conductive medium. The prototype can be prepared and applied in very little time and does not require expertise in electrode application (Matthews et al., 2005; 2007). Initial testing of this system shows a very favorable comparison to conventional wet electrodes in time- and frequency-domain analysis of EEG data under varying conditions (Estepp et al., 2009).

The use of QUASAR's dry electrode system in operational or near-operational environments has not, however, been fully determined, nor has its utility to reproduce cognitive state assessment accuracies using wet electrode systems been evaluated. Sellers et al. (2009) showed that a P-300 based BCI using QUASAR's dry electrode system was only 3% less accurate than using a wet electrode system, but the use of QUASAR's system in continuous, real-time EEG recording, and related testing to workload assessment, was not evaluated. Therefore, we have initiated testing of the dry electrode system in other environments where wet electrode EEG recording has previously produced robust, reliable and repeatable classification of cognitive state.

METHODS

Two participants (male, ages 24 and 25), after reviewing and completing comprehensive informed consent, volunteered for participation. The Multi-Attribute Task Battery (MATB; Comstock & Arenegard, 1992) was used as the simulation environment. Previous cognitive state assessment studies using MATB have shown sensitivity in psychophysiological measures (where EEG is the primary concern) to changes in task difficulty (Fournier et al., 1999; Wilson & Russell, 2003). A custom-written version of MATB was implemented in MATLAB (Mathworks, Inc.; Natick, MA). The high and low task conditions described in Wilson and Russell (2003) were recreated to yield varying states of cognitive demand (low and high workload). Each MATB trial consisted of 5 minutes of one of the two workload levels, with 3 trials of each level collected in a single session (for a total of 6 MATB trials). In addition to recording data during the MATB task, a resting baseline (3 minutes of eyes open and 3 minutes of eyes closed) and two different types of voluntarily-induced artifact trials (jaw clenching and walking in place) were recorded.

Data collection was separated into two parts: a dry vs. wet (DW) validation and a wet vs. wet (WW) validation. Both the DW and WW validations provide a parallel configuration as described by Gargiulo et al (2010). This parallel configuration is used since the recording electrode, either wet or dry, takes up some amount of surface area on the skin surface, making it impossible to co-locate (or even co-center) two electrodes at the exact same location. Previous testing of this dry electrode system (Estepp et al., 2009) used an offset wet electrode that was approximately 1 [cm] linearly separated from the dry electrode location at the standard 10-20 scalp electrode site. This allowed the two electrodes to be temporally synchronized (data could be collected from each dry/wet electrode pair simultaneously) but not spatially synchronized. This dry/wet electrode pair configuration was modified in this data collection with the addition of a second wet electrode for each dry/wet electrode pair. Since the dry/wet pair cannot be spatially co-located, the additional wet electrode provided an estimate of anticipated variability between two offset (wet) electrodes that were temporally synchronized, but not spatially synchronized.

Six standard 10-20 electrode sites were used (Fp1, F4, Fz, Cz, Pz and T5) with two offset wet electrodes for each dry electrode at the 10-20 site (Figure 1). A common reference for the dry electrode system is located at the right mastoid (also a dry electrode). A separate wet reference was used at the right mastoid, slightly offset from the dry electrode reference location, for comparison of identical electrode types used as common references to their respective active sites. A common ground is located in the forehead strap of the dry electrode system, approximately in the location of Fp2.

The WW validation was designed to provide a sense of spatial comparability between the wet and dry electrodes (referred to as serial testing in Gargiulo et al. (2010)). In the WW validation, dry electrodes located at the 10-20 sites were replaced with wet electrodes centered at the same location (Figure 1), and all data trials (resting baseline, MATB and artifact trials) were repeated. The dry common reference was replaced by a second wet reference at the location of the original dry electrode on the right mastoid. A wet ground electrode was added to the forehead in the original location of the dry electrode system ground (approximately Fp2). As with the DW validation, the WW validation used the parallel configuration, where each electrode at a 10-20 site had two offset wet electrodes.

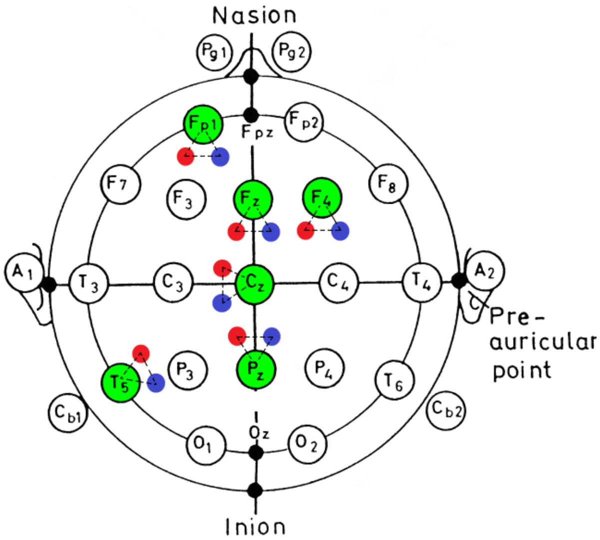

Figure 1. Location of the dry electrodes (at 10-20 sites, in green), and the two offset electrodes (in red and blue) for each electrode site. The naming convention for each of the electrodes, for example, is Fz (dry electrode), FzA (offset wet electrode, in red), FzB (offset wet electrode, in blue), and FzC (replicated wet electrode at the 10-20 site for the WW validation).

All wet electrodes were standard tin disc electrodes, approximately 1 [cm] in diameter, with impedances below 5k [ohms]. Each of the tri-electrode combinations formed an approximate equilateral triangle, with approximately 3 [cm] (average of 3.28 [cm], standard error of 0.4 [mm]) between each electrode center (shown in Figure 2).

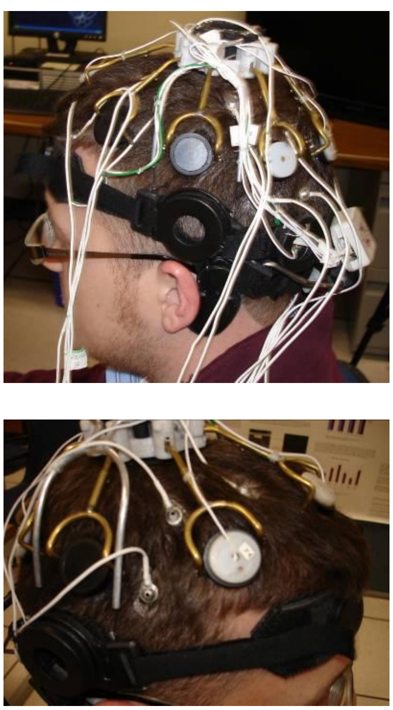

Figure 2. QUASAR's dry electrode system, with two offset wet electrodes corresponding to each dry electrode location at the 10-20 site.

To determine the spatial location of, and linear distance between, each electrode, a 3-D electromagnetic tracking system (3SPACE; Polhemus; Burlington, Vermont, USA; for reference, see He et al., 2007) with custom MATLAB software was used. Electrode locations were projected to the scalp surface (correcting for electrode thickness) for all distance calculations. As reported by He et al (2007), standard deviation in electrode position is approximately 1 [mm].

Classification of the MATB task (low workload vs. high workload) was accomplished via an Artificial Neural Network (ANN) classifier (3-layer, feed-forward with back-propagation training, allowing for an independent validation set; see Wilson & Russell (2003) for a review). A total of 30 features (frequency band log power in the five standard clinical bands for each of the 6 electrode sites) from each of the electrode sets (active 10-20 site and 2 offset electrodes, in both the DW and WW validations) were used to train 6 different ANN classifiers (one each for the electrode set combinations). The ANN features were combined using a 10 [second] window with a 9 [second] overlap. From the 6 MATB trials, two-thirds of this dataset (for each electrode combination) was used to train the ANN, after which the trained ANN acted as a pattern classifier on the remaining one-third of the dataset. Classification accuracies reported here are combined accuracies for both the low and high workload conditions.

As in Estepp et al. (2009) and Gargiulo et al (2010), Pearson correlation coefficients were calculated within both parallel configurations (DW and WW) to provide an estimate of comparability between the spatially-separated (parallel) electrode sets. All correlations are reported as r-values.

RESULTS

Figure 3 shows the classification accuracy for the MATB task (where 3 random permutations of training and testing data were taken from the combined dataset to achieve a composite classification accuracy). Each of the three electrode sets in the DW validation and the three electrode sets in the WW validation were used to train independent ANNs.

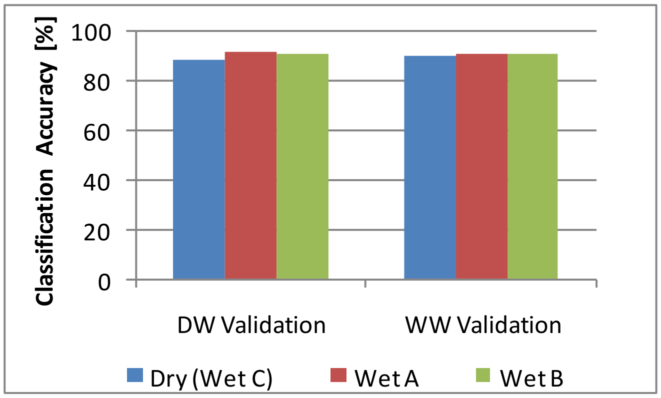

Figure 3. Classification accuracies provided by the ANN for the MATB task (low workload vs. high workload). Reading from left (Dry/DW validation) to right (Wet B/WW validation), the accuracies were 88.81%, 92.34%, 91.54%, 90.21%, 90.96% and 91.18%.

Correlation values (r-values) for each of the individual tasks are presented for the DW validation (Table 1) and WW validation (Table 2). Correlation values were collapsed across all electrodes, where the correlation pairs included the 10-20 site to both offset electrodes (in both the DW and WW validation data sets).

Table 1. Correlations (r-values) for the DW validation. Correlations are presented (across all 6 electrode sites) for each individual task.

	Eyes Open	Eyes Closed	MATB	Jaw Clench	Walk In Place
Dry v Wet	0.84	0.85	0.78	0.82	0.62
Wet v Wet	0.96	0.96	0.96	0.95	0.95

Table 2. Correlations (r-values) for the WW validation. Correlations are presented (across all 6 electrode sites) for each individual task.

	Eyes Open	Eyes Closed	MATB	Jaw Clench	Walk In Place
Wet C v Wet	0.90	0.88	0.88	0.89	0.83
Wet v Wet	0.95	0.96	0.95	0.94	0.95

DISCUSSION

Overall, results from the dry electrodes were very favorable in comparison to those found with the wet electrodes. Classification accuracies were all near 90%, which is comparable to results presented in Wilson and Russell (2003a). This demonstrates that the dry electrodes are capable of producing acceptable levels of cognitive workload assessment in dynamic task environments, which has not been previously demonstrated for QUASAR's dry electrode system.

The correlation values between the two offset wet electrodes, in both the DW validation and WW validation, are all above 0.94, which is comparable to an average correlation coefficient of 0.90 presented for signals recorded by the same acquisition system (Gargiulo et al., 2010). These values provide a baseline measure of the anticipated variability between two offset electrodes from the same system.

Correlation values for the WW validation in Table 2 were at or above 0.83. The lower correlations for "Wet C vs. Wet", in comparison to the correlation between the offset wet electrodes ("Wet v Wet", Table 2), could be attributed, in part, to the separate reference used for the wet electrodes at the 10-20 site (which was used to replicate the separate dry reference on QUASAR's headset). It is anticipated that re-referencing all of the electrodes in both the DW and WW validations to a common reference would improve correlation, as the only independent variable in all of the electrode sites would be reduced to spatial separation of the monopolar electrodes that are offset from the active 10-20 location.

In Table 1, correlation values for the DW validation for eyes open, eyes closed, and jaw clench are all above 0.82 and are comparable to like values in the WW validation. These correlation values are similar to those reported by Gargiulo et al. (2010), where they obtained correlation values of 0.83 for their dry electrode to the surrounding, offset wet electrodes (in the parallel testing condition, after artifact removal). It should be noted that, in this study, no attempt was made to remove large artifacts from the data, as part of the design was to assess the performance of the dry electrode system under artifact conditions (jaw clenching and walking in place).

The reported correlation value for the walk in place task was 0.62, which is lower than the other dry-to-wet correlation values. This could be due to a difference in time-constant and filter properties in the dry electrode system as the amplifiers recover from large signal deviations due to movement artifact. In addition, as the dry electrodes are not fixed to the head (where the wet electrodes were fixed to the scalp surface with collodion, and both the wet and dry electrodes in Gargiulo et al. (2010) were affixed with collodion), some movement artifact due to electrode shearing at the recording site may be present.

These correlation values are improved over those presented in Estepp et al. (2009) due to a re-design in the dry electrode system (accomplished by QUASAR). In previous work, the dry electrode common reference was located at P3. Estepp et al. (2009) speculated that low correlation values at electrode sites near P3 were due to the use of an active reference at this site. As anticipated, moving the common reference from P3 to the right mastoid (a relatively inactive recording location) improved correlation in the DW validation.

Given these very promising results, and the improvements being made to the QUASAR prototype system, it can be stated that the very high quality data produced by the dry electrode system is comparable in system properties, time- and frequency-domain properties (Estepp et al., 2009), and, as demonstrated by this work, utility in a cognitive workload classification system. Further inclusion of this system into other validation studies should help to expand the number of domains in which its utility can be verified. In addition, the no-prep, non-invasive, ease-of-use qualities of the system makes it perfect for use in human factors applications without compromising data quality.

CONFLICT OF INTEREST STATEMENT

The authors of this paper state that they have no financial interest in QUASAR, Inc., and derive no personal profit or gain from the success or failure of this dry electrode system.

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