2011

A Validation of a Prototype Dry Electrode System for Electroencephalography

Jason Monnin
Wright State University

A VALIDATION OF A PROTOTYPE DRY ELECTRODE SYSTEM FOR ELECTROENCEPHALOGRAPHY

A thesis submitted in partial
fulfillment of the requirements
for the degree of Master of
Science in Engineering

By

Jason William Monnin
B.S., Wright State University, 2008

2011
Wright State University

WRIGHT STATE UNIVERSITY

GRADUATE SCHOOL

27 July 2011

I HEREBY RECOMMEND THAT THE THESIS PREPARED UNDER MY SUPERVISION BY JASON WILLIAM MONNIN ENTITLED A VALIDATION OF A PROTOTYPE DRY ELECTRODE SYSTEM FOR ELECTROENCEPHALOGRAPHY BE ACCEPTED IN PARTIAL FULFILLMENT OF THE REQUIRMENTS FOR THE DEGREE OF MASTER OF SCIENCE IN ENGINEERING.

Ping He, Ph.D., P.E.
Thesis Director

Thomas N. Hangartner, Ph.D.,
Chair
Department of Biomedical, Industrial and Human Factors Engineering
College of Engineering and Computer Science

Committee on
Final Examination

Ping He, Ph.D., P.E.

James Christensen, Ph.D.

Julie Skipper, Ph.D.

Andrew Hsu, Ph.D.
Dean, Graduate School

ABSTRACT

Monnin, Jason William. M.S.Egr., Department of Biomedical, Industrial, and Human Factors Engineering, Wright State University, 2011.
A Validation of a Prototype Dry Electrode System for Electroencephalography.

Current physiologically-driven operator cognitive state assessment technology relies primarily on electroencephalographic (EEG) signals. Traditionally, gel-based electrodes have been used; however, the application of gel-based electrodes on the scalp requires expertise and a considerable amount of preparation time. Additionally, discomfort can occur from the abrasion of the scalp during preparation, and the electrolyte will also begin to dry out over extended periods of time. These drawbacks have hindered the transition of operator state assessment technology into an operational environment. QUASAR, Inc., (San Diego, CA) has developed a prototype dry electrode system for electroencephalography that requires minimal preparation. A comparison of the dry electrode system to traditional wet electrodes was conducted and is presented here. The results show that initially the EEG recorded by the dry electrode system was quite similar to that recorded by the wet electrodes, but the similarity decreased over a testing period of six months. For cognitive state assessment, the dry electrodes were able to achieve classification accuracies within one to two percent of those achieved by the wet electrodes, with no decrease in accuracy over time. The results suggest that the dry electrode system is capable of recording electroencephalographic signals to be used in cognitive state assessment, and aiding in the transition of that technology into an operational environment. Further work should be conducted to improve the reliability of this novel system.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

Page

I. INTRODUCTION

Complex systems for remotely piloted aircraft can place varying levels of cognitive demand on the operators of these systems. If the cognitive demand becomes too great, operator performance will decrease, which could lead to devastating results. Monitoring the cognitive state of an operator is therefore the first step in mitigating potential operator overload. Over the past several years, Wilson *et al.* [1], [2] have been conducting research to design a system capable of monitoring an operator's cognitive state. For example, if cognitive overload is detected, part of the operator's task could be automated to alleviate their mental demand. Electroencephalography (EEG), among other psychophysiological measures, has been successfully used to estimate an operator's cognitive state.

Electroencephalography is the study of the electrical activity of the brain and was first studied in animals by Richard Caton in 1875. The origin of EEG was originally thought to be a summation of action potentials; however, it has been determined that the electrical activity measured at the scalp surface is caused by the superposition of post-synaptic potentials due to volume conduction. EEG can be separated into two categories: spontaneous potentials and evoked potentials (EPs) or event-related potentials (ERPs). Spontaneous EEG occurs without an external stimulus, such as alpha and beta rhythms while EPs and ERPs occur in response to a specific stimulus [3]. Spontaneous EEG has been conventionally classified into five clinical frequency bands: delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-12 Hz), beta (12-31 Hz), and gamma (31-43 Hz). Spontaneous EEG has been widely used as a means to determine a person's cognitive state for use in applications such as workload assessment and adaptive automation, even in the absence of specific events from which ERPs are obtained [1], [2], [4]-[6].

Traditionally, gel-based or wet electrodes have been used to record EEG with excellent quality as in the works cited above; however, there are several major drawbacks of gel-based electrodes that have hindered the widespread adoption of physiologically-driven monitoring and augmentation systems into operational environments. The preparation required for recording EEG involves the abrasion of the outer epidermal layer (stratum corneum) in order to reduce the impedance, and can lead to discomfort. Electrodes must then be held in place on the scalp, either by an adhesive, e.g. collodion, or built directly into a cap which is worn by the user. A conductive electrolyte must then be injected between the electrode and skin for electrical contact between the two, and will dry up after several hours of use. Depending upon the number of electrodes to be applied, preparation can take an hour or more to complete.

Recent advances in dry electrode technology have aimed to develop technology to overcome some of the drawbacks of gel-based electrodes. Chi *et al.* [7] provide an overview of current dry electrode technology, but it spans across all biopotential signals. Only dry electrodes for EEG recordings are discussed here. Dry EEG electrodes may be categorized into three main types: capacitive, invasive, and large contact area. Early work on capacitive dry electrodes for EEG was presented in 1973 [8] and has continued through recent years with different materials and coatings [9]-[11]. Capacitive electrodes do not require direct contact with the scalp – a benefit over dry contact electrodes. However, capacitive electrodes are susceptible to movement and muscle artifact [12].

Grozea also reports that capacitive electrodes have only been successful in steady-state visual evoked potentials applications.

A slightly invasive design is based on micro-fabricated needle electrodes, which penetrate through the high-impedance outer epidermal layer (stratum corneum) and into the conductive stratum germinativum layer [13], [14]. The results from these studies demonstrate high quality EEG can be recorded using this type of dry electrode; however, as discussed in [15], a primary concern with these invasive electrodes is infection. Repeated use of these electrodes, as is typically done with conventional gel-based electrodes, is another major concern with electrodes that break the skin surface. In order to reuse this type of electrode, sterilization [12], [15], is required; however, sterilization may not completely eliminate the transfer of infectious diseases. Therefore, this type of electrode should be disposable, which may not be cost effective.

In 1990, Gevins [16] patented a dry electrode system based on arrays of pins or "fingers" designed to penetrate through the hair to make direct contact with the scalp. Such an approach eliminates the need to penetrate the outer layer of skin, and has been adopted by several groups in the design of their dry electrodes [17], [18]. Fiedler *et al.* [18] proposed a pin-based electrode coated with titanium nitride (TiN). It was reported that this TiN-based dry electrode was appropriate for the acquisition of EEG, but data collection was limited to recording alpha rhythms and eye movements. Further work for this type of electrode includes the design of a cap or headset to house the TiN-based electrodes. Grozea *et al.* [12] reported a passive dry electrode that offers improvement on existing pin-based dry electrodes. This novel dry electrode is constructed from flexible, polymer bristles which reportedly provided better comfort to some subjects over wet electrodes and other pin-based electrodes. These bristle-sensors were tested in several EEG paradigms, such as alpha rhythm recording and various ERP experiments. Results demonstrated that these electrodes were capable of recording EEG signals comparable to recorded signals from gel-based electrodes. These pin-based dry electrodes were all intended for brain-computer interface (BCI) applications and evaluated in that respect; no publication evaluating dry electrodes for operator state assessment has been found.

In attempt to overcome these drawbacks, QUASAR Inc., (San Diego, CA) has developed a novel dry electrode system for EEG recordings which requires no skin preparation or conductive electrolyte and can be easily donned by the user. QUASAR's dry electrode system has been previously tested by Estepp *et al.* [19]. Testing was limited to the comparison between the power spectral densities and correlation of the recorded EEG. The results indicated the correlation between signals decreased from the front to the back of the head. [19] concluded the placement of the reference electrode resulted in the low correlations (less than 0.5), and proposed that changing the location of the reference electrode from a parietal site should improve the results. Due to these findings, QUASAR modified the system, adding a reference electrode over the right mastoid. Initial testing of this modification was reported by Estepp *et. al* [20]. In addition to computing the correlation between the signals recorded by the dry and wet electrodes, classification accuracy of mental workload during a complex task was also used as a metric for comparing the two electrode systems, as this is the intended application of this prototype system. Moving the reference electrode to the mastoid improved the correlations (approximately 0.8), thus [20] concluded that the signals recorded by the dry electrodes were comparable to the signals recorded by the wet electrodes, and that similar classification accuracy could be achieved by both electrode types.

The evaluation of the dry electrode system in [20] was limited to just two participants, and the metric for comparison, correlation, can be "easily influenced by one or more dominating subsignals, be it 50/60 Hz, occipital alpha rhythm, EOG or motion artifact" and "does not capture how accurate the novel signal is as a function of frequency" [12]. Therefore, further testing and analysis needed to be performed to evaluate the novel system, not only for the intended application of cognitive state assessment, but for use in a wide variety of EEG or BCI applications.

An in-depth validation of QUASAR's dry electrode system is presented here, comparing the novel system to traditional gel-based electrode systems. Initially, the electrical properties of each system will be compared. The frequency response of the dry electrode system will be compared to the response of a conventional gel-based electrode system to determine the effectiveness in applications based on the spectral domain of EEG. Similarly, the step response will also be compared, to test the effectiveness in time domain applications, such as ERPs. Additionally, actual EEG, recorded simultaneously from both electrode systems will also be compared. To address concerns about correlation as a comparison metric, the magnitude squared coherence (MSC) will be used to compare the similarity of the spectral content between the simultaneously recorded EEG from each system. Finally, the recorded EEG will also be used to compare the performance of both systems in the intended application of cognitive state assessment. The results reveal that while the electrical properties of the QUASAR system are quite similar to wet electrodes, the MSC between the systems decreased over the six-month testing period. Cognitive state classification accuracies were very comparable throughout. As will be discussed, mechanical fatigue of the QUASAR system may have contributed to the decline in MSC.

II. METHODS

A) Hardware

QUASAR's prototype dry electrode system for EEG recordings is comprised of a headset and a wired analog amplifier/filter module, illustrated in Fig. 1. Built into the headset are six hybrid and three capacitive electrodes [21]. The hybrid electrode relies on a combination of high impedance and capacitive contact with the scalp. A set of fingers on each hybrid electrode are designed to penetrate through hair in order to make contact with the scalp [22]. Of the six hybrid electrodes, five are active scalp sites located at Fz, F4, Cz, Pz, and T5, according to the International 10-20 Standard [23]. The sixth hybrid electrode is the system's common-mode follower (CMF) located at P4. The CMF "measures the potential of the body relative to the ground of the amplifier system" and is used to remove common-mode signals on the body [22]. Two of the capacitive electrodes are built into a forehead strap and are used as a sixth active site (Fp1) and system ground (Fp2). The third capacitive electrode is built into the earpiece located behind the right ear and contacts the right mastoid process. During data acquisition, all EEG channels will be referenced to the capacitive electrode on the right mastoid. The wired amplifier/filter module provides: unity gain, a fourth order Butterworth low-pass filter with a corner frequency at 340 Hz, and a single-pole high pass filter with a corner frequency at 0.2 Hz. The output impedance of the module is approximately 5 kΩ for use with current physiological data acquisition systems. The amplifier/filter module allows for both AC- and DC-coupled operation. Dipswitches allow each channel to be switched between each mode of operation. Materials used in the construction of the electrodes are proprietary to QUASAR, Inc., and are therefore not discussed.

Fig. 1 Prototype dry electrode headset with wired amplifier/filter module.

For comparison, a conventional gel-based electrode system was used. The wet electrode system consisted of single-lead tin electrodes and a conductive electrolyte (Electro-gel, ECI Inc., Eaton, OH). For electrical testing, the output from neither the dry nor the wet electrode systems was filtered or digitized by a data acquisition system, although filtering is done within the dry electrode system prior to the signal output. For the human EEG recordings, filtering (in addition to the filtering performed within the dry electrode system) and digitization for both electrode systems was performed via the same data acquisition system (Vitaport 2, Temec Instruments, Netherlands).

B) Electrical Testing

To measure the electrical properties of each system, an anatomical head model with a conductive cloth draped over it was used. Ground and V^- were connected to the conductive cloth on the head model. V^+ was connected to a small conductive plate and placed under the active electrode. The dry electrode headset was placed directly on the conductive cloth so that each electrode, except the active site, was in contact with the cloth. Measurements were performed on the hybrid and capacitive electrodes during both AC- and DC-coupled operation. A similar setup was used to test the wet electrodes, with the addition of a conductive gel injected between each wet electrode and the conductive surface.

The frequency response was measured for each system. An Agilent 33120A function generator was used to produce a 100 mV sinusoidal input signal. Both input and output signals were displayed and measured using an Agilent 54622A oscilloscope. The magnitude of the input and output was measured and the ratio of the output and input signals was calculated to determine the magnitude response. The phase response was determined by measuring the phase difference between input and output signals. Both metrics were measured over a bandwidth of 0.01 – 1000 Hz. Step responses were measured for each system as well. To approximate a unit step function, a 100 mV square wave with a period at least ten times greater than the expected time constant of the system was used.

C) Human EEG Testing

The human EEG signals recorded by each system were compared. The primary goal was to compare the EEG recording capability of the novel system to traditional wet electrodes when used for cognitive state classification. The Multi-Attribute Task Battery, or MATB, [24] is a complex multitask that was used to manipulate the operator's cognitive state. A custom version of the task [25] written in MATLAB (MathWorks, R2010a), was used. Additionally, data were recorded during a variety of artifact-induction trials, such as jaw clenching and head movement, in order to determine the susceptibility of the dry electrode system to such artifacts as compared to wet electrodes.

Twelve participants (8 male, 4 female), age range of 20 to 27 (mean of 23 years) volunteered for the experiment. Hair length of the participants ranged from less than an inch to over twelve inches. Hair thickness of each participant also varied from thick to thin. Following comprehensive written informed consent, participants were trained to asymptotic performance on MATB. Asymptotic performance was defined as consistent performance across trials with the same level of difficulty, and was attained after approximately ten hours of training, spread out over several days. Once asymptotic performance was achieved, participants were titrated on MATB to determine their specific high-workload level. An estimated titration level was chosen based on the participant's performance on a difficult task during training. Five consecutive levels of the task surrounding the estimated titration level were used to determine the final titration level. These five levels were randomized within a block and each block was repeated three times. The performance curves obtained from these three blocks were used to confirm that a participant had been correctly titrated to approximately 80% correct on the systems task. The same low-workload level, which consisted of the minimum event rate, was used for all participants.

Data collection was separated into two sessions with a one hour break between sessions. Five of the six dry electrode sites were chosen for data collection. The dry electrodes were located at the 10-20 standard sites: Fp1, Fz, F4, Pz, and T5. Two wet electrodes were placed approximately 2.5 cm (center-to-center distance) from each dry electrode and each other to create an equilateral triangle. This parallel configuration [20], [26] allowed for a spatially-separated but time-synchronized comparison between the recorded EEG from the dry and wet electrode systems. These offset wet electrodes are labeled as ‘Wet A’ and ‘Wet B’. A diagram of the electrode placement is shown in Fig. 2. A desired center-to-center distance between electrodes of 2.5 cm was selected to minimize the potential for shorting between electrodes. 2.5 cm is also the approximate 3dB point of the point spread function of brain potentials [27]. The sixth active dry electrode was not used due to a structural housing for the headset surrounding the electrode that did not allow for the desired distance between dry and wet electrodes.

To measure the center-to-center distance between electrodes at the scalp surface, the location of each electrode was first recorded using a 3D positioning system (3Space; Polhemus; Burlington, Vermont, USA). Electrode locations were then projected to the scalp by subtracting the electrode thickness prior to all distance calculations. The precision of the positioning system is approximately 1 mm as reported by [28].

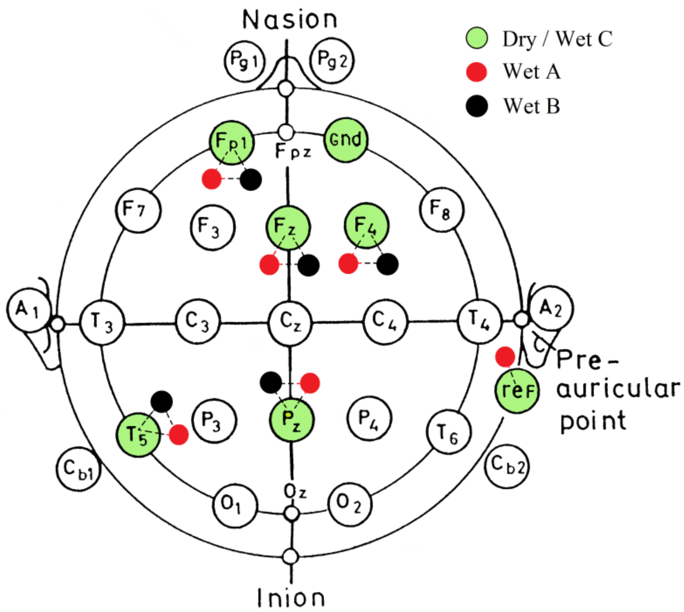

Fig. 2 Diagram of the electrode placement. Green indicates the location of the dry electrodes, while red (Wet A) and black (Wet B) indicate the offset wet electrode placement. During session two, the dry electrodes (green) were replaced with additional wet electrodes (Wet C). This diagram has been adapted from [29].

The offset wet electrodes were affixed to the scalp with collodion. After each scalp site was lightly abraded to remove the outer epidermal layer, conductive gel was injected into each electrode. The impedance for all wet electrodes was verified at less than 5 kΩ. Dry electrode impedance was not recorded, as it was not possible to measure with this particular system. Signal quality from the dry electrodes was assessed via visual inspection by a trained EEG technician prior to data collection to ensure proper contact with the scalp. The common reference for the dry electrode system is located on the right mastoid. The reference for the wet electrodes was placed slightly offset to the dry reference at the desired 2.5 cm. Amplifier ground for both systems was from the dry electrode system ground located in the forehead strap.

During the second session, the dry electrode headset was removed and replaced with additional wet electrodes, hereafter known as 'Wet C' electrodes. This serial configuration [20], [26] allowed for a comparison of the dry and wet electrode systems at the same scalp site, but recorded at different times. The original offset wet electrodes were not removed between sessions, to allow for a parallel comparison between the primary and offset wet electrodes. A second wet reference for the Wet C electrodes replaced the dry reference and an additional wet electrode replaced the dry electrode system ground on the forehead. Preparation for the replacement wet electrodes was as previously described.

Each session consisted of eleven randomized tasks: eyes open, eyes closed, jaw clench, head movement, brow raise, and six MATB trials (three low-workload and three high-workload). For a detailed description of each task, see Appendix A. Each participant began each artifact trial (jaw clench, brow raise, and head movement) with a twenty second resting period. Following the resting period, the participant was instructed to perform the artifact of interest for ten seconds, and rest for another twenty seconds. This procedure was repeated four times, lasting approximately two and a half minutes. The eyes open and eyes closed trials were both five minutes in length.

EEG from both the dry and wet systems was recorded using the Vitaport 2 data acquisition system. Data were sampled at 256 Hz, and band-passed from 0.482 – 100 Hz. In addition to each EEG channel, a channel with the difference between the dry electrode's reference and the wet electrode's reference was recorded during session one. During session two, the Wet C electrode's reference was referenced to the original wet electrode's reference for the additional channel.

1) Magnitude Squared Coherence: The magnitude squared coherence (MSC), also referred to as coherence in some of the literature, was calculated to determine the similarity between raw EEG recorded from the wet and dry electrodes simultaneously at each frequency. The MSC function illustrates the spectral similarity of recorded EEG signals [12], [30] beyond other comparisons as previously reported in [19], [26]. The MSC has been used previously to measure the performance of other dry electrodes [12] and is given by

$$C_{xy}(f) = \frac{\left|P_{xy}(f)\right|^2}{P_{xx}(f)P_{yy}(f)}$$

where P_{xy} is the cross spectral density between two signals $x(t)$ and $y(t)$, and P_{xx} and P_{yy} are the power spectral densities of each signal.

The MSC was computed using MATLAB's *mscohere* function. To match parameters used to create the features for the application of cognitive workload assessment, a five-second window with no overlap and 1024-point FFT were used. The MSC was calculated between the dry electrode and each offset wet electrode, as well as between the two offset wet electrodes within each electrode triangle. The same analyses were also performed on data recorded during the second session.

2) Classification of Cognitive Workload: A 3-layer, feed-forward artificial neural network (ANN) with back-propagation training was implemented as described in Wilson & Russell [31] to classify the two levels of workload from the MATB task. The first and last fifteen seconds of each MATB trial were removed before processing to remove starting and ending effects. For each channel of data, spectral log power in each of the five clinical frequency bands over a sliding five-second Hanning window with no overlap was computed. These log power values for each band and site formed the feature set. Features from each electrode set were combined to create six datasets (Dry, Wet A, Wet B from session one, and Wet C, Wet A, Wet B from session two). Each electrode set consisted of the five similar electrodes, i.e., the five Wet A electrodes from session one are an electrode set. Each feature set contained 25 X N features: five frequency bands times five electrodes, with N being the total number of values per feature set. These datasets were used to train separate ANNs for each electrode set. A ten-fold cross-validation scheme [32] was used for ANN training, wherein a randomly-assigned ninety percent of each dataset was used to train and validate each ANN, and the remaining ten percent was used for testing the trained ANN.

III. RESULTS

A) Electrical Testing

Measured magnitude and phase responses of the dry electrode system are shown in Fig. 3 and Fig. 4, for DC- and AC-coupled operation, respectively. Responses for both hybrid and capacitive electrodes are overlaid on each plot. The measured DC-coupled pass-band is 0.01 – 360 Hz. The measured AC-coupled pass-band is 0.2 – 360 Hz. A gain of 1.04 instead of unity was measured for both DC- and AC-coupling. The magnitude and phase responses from both the hybrid and capacitive electrodes are nearly identical, with any variance likely attributable to noise. Regardless of coupling, the dry electrode system exhibits constant gain with approximately zero phase within a 1 to 100 Hz range. Responses for the wet electrodes are shown in Fig. 5. Unity gain and zero phase were measured over the bandwidth 0.01 – 1000 Hz.

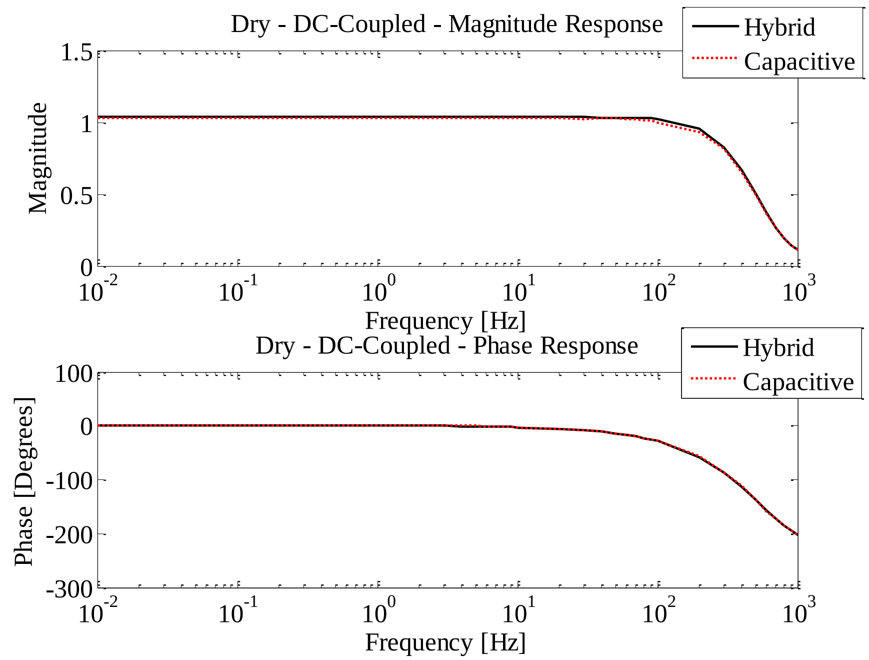

Fig. 3 Magnitude and phase responses of the DC-coupled dry electrode system.

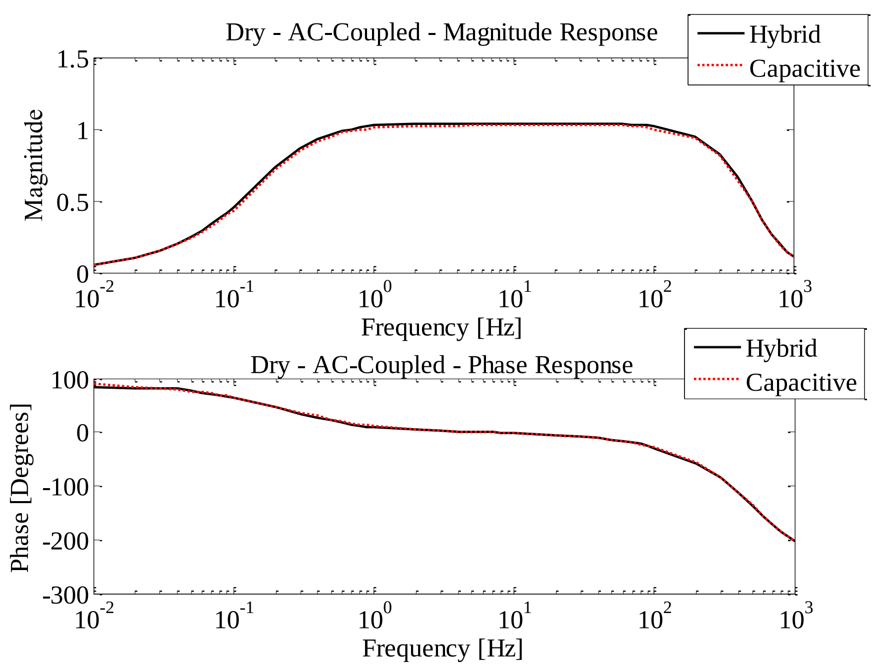

Fig. 4 Magnitude and phase responses of the AC-coupled dry electrode system.

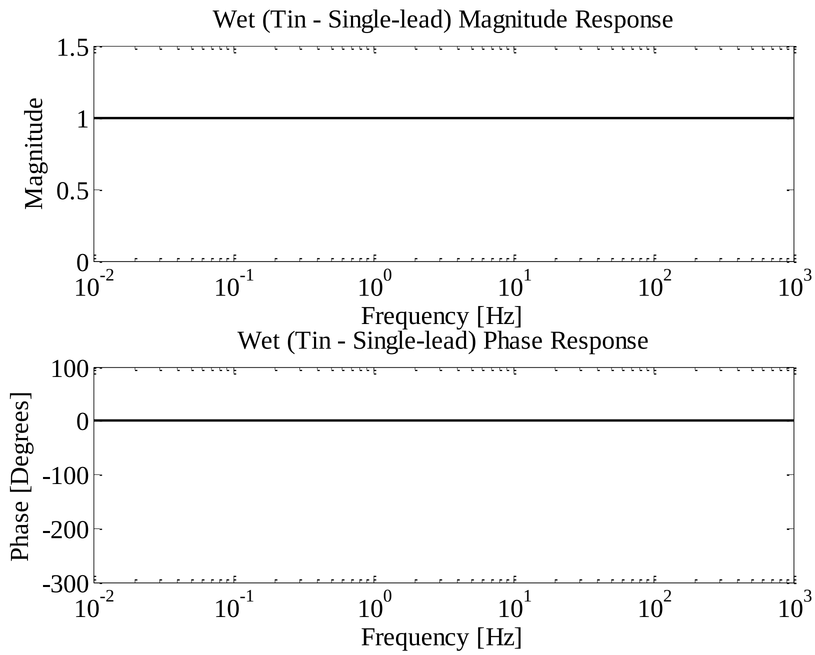

Fig. 5 Magnitude and phase responses of single-lead tin electrodes.

The step responses of the dry electrode system (DC- and AC-coupled) and the wet electrode system are shown in Fig. 6. The first subplot illustrates the approximated unit step function used as the input into each system. The responses are plotted together and on a time scale of a typical ERP to illustrate the relative timing of major ERP components and the response of the electrodes. A few early auditory response ERPs peak at 10 ms [33], so a vertical, dotted line is shown on each plot in Fig. 6 at 10 ms to illustrate these earliest ERP components. Only the step responses of the hybrid electrodes are shown, as the step responses of the capacitive electrodes are nearly identical.

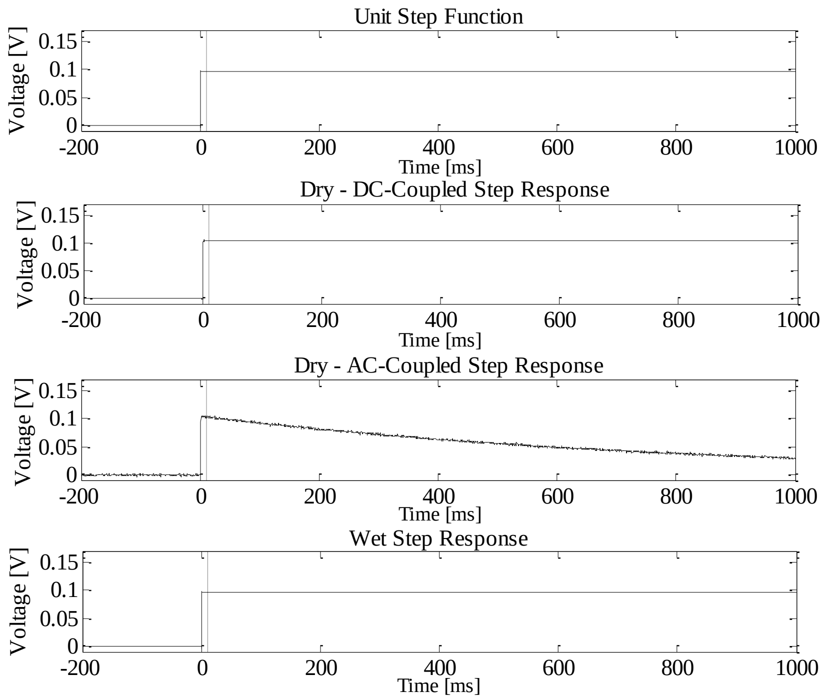

Fig. 6 Step responses plotted on a typical ERP time scale.

In Fig. 7 and Fig. 8, step responses from both hybrid and capacitive dry electrodes are overlaid and shown in greater detail. The time constant of the rising edge of the step response for the dry electrode system (DC- and AC-coupled) is 900 µs. Although the AC-coupled response (Fig. 8) does not illustrate the rising phase in detail due to the time-scale, the rising phase does match that of the DC-coupled response shown in Fig. 7. The AC-coupled response was plotted on the larger time-scale to illustrate the full step response. Since the wet electrode system signals were not filtered for this testing, a time constant was not determined; because the system behaves as a zero-order system, the time constant of the wet electrode system would be dependent on the filters implemented.

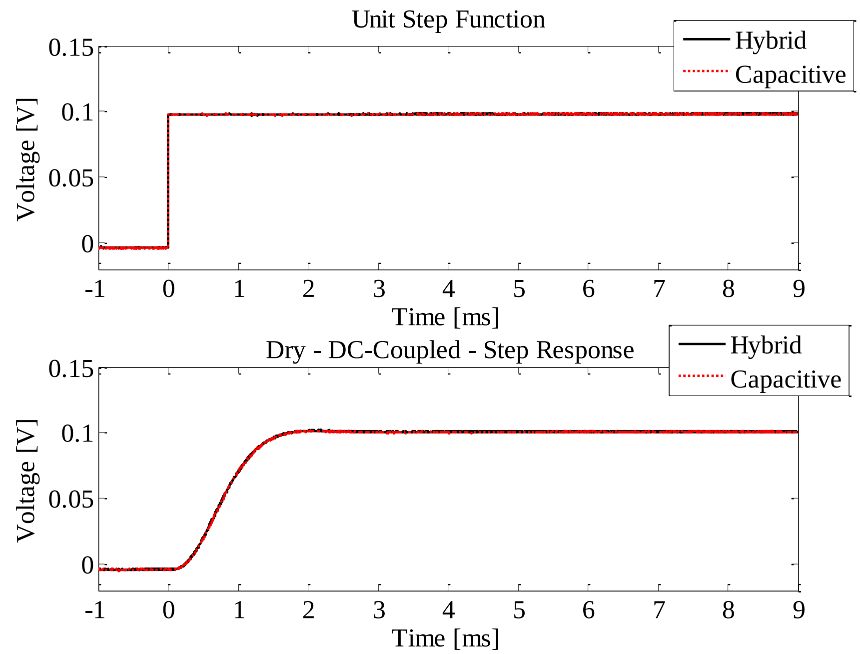

Fig. 7 Step responses of the DC-coupled hybrid and capacitive dry electrodes.

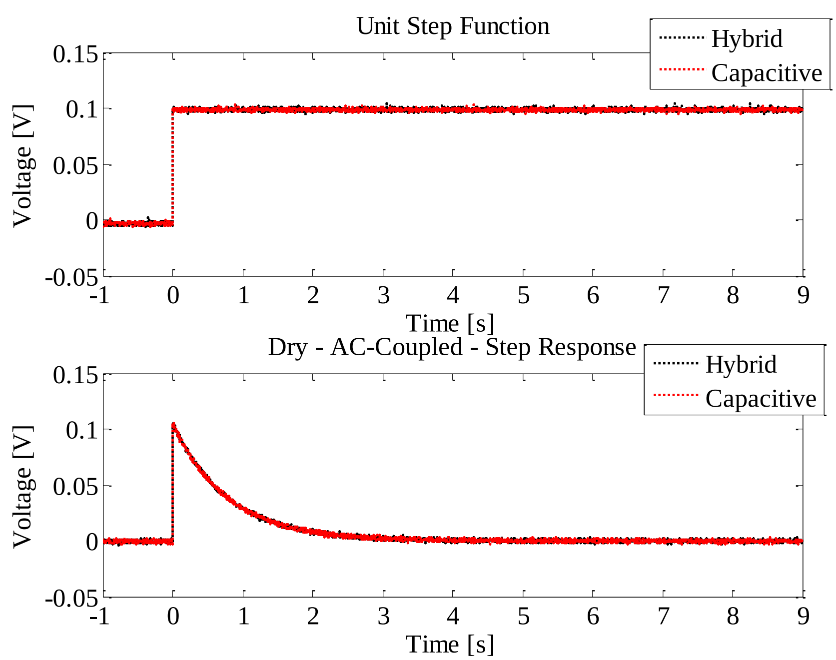

Fig. 8 Step responses of the AC-coupled hybrid and capacitive dry electrodes.

B) Human EEG Testing

Average distances between electrodes for each session are shown in Table I. The average distance between dry and offset wet electrodes was 2.56 cm, the average distance between the offset wet electrodes in session one was 2.45 cm, and the average distance between the Wet C and offset wet electrodes was 2.36 cm. Since the offset wet electrodes were not removed between sessions, the distance between them did not change.

TABLE I

Average distance between electrodes.

	Session 1 [cm]	Session 2 [cm]
Dry (Wet C) - Wet	2.56	2.36
Wet - Wet	2.45	2.45

Analysis of the performance data on the MATB system's task showed a significant difference in performance between the low- and high-workload levels, $p << 0.01$ (Fig. 9). This significant difference demonstrates that the two levels of workload are distinct and the task as run provided two separate levels of cognitive workload for classification. Error bars shown are standard error of the mean.

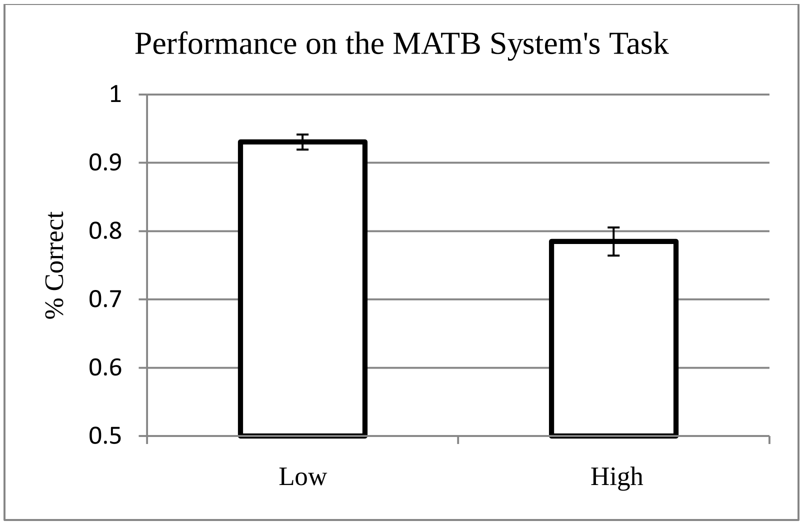

Fig. 9 Average performance across participants in the MATB system's task.

1) Magnitude Squared Coherence: The MSC functions computed for session one are shown in Fig. 10. Data shown are averaged across all subjects, trials, and scalp sites. The MSC values presented throughout the rest this paper were averaged over the bandwidth of 0.5 – 43 Hz, which is the range from which typical EEG features are derived for operator state assessment. This bandwidth is shaded on each MSC plot. Plots are shown up to the Nyquist frequency for illustration of the MSC function at higher frequencies. The average MSC values for the dry – wet pairs were 0.42 and 0.43 (session one) and the average MSC value for the wet – wet pair (session one) was 0.89. The wet – wet pair provides a baseline for a typical MSC function for two electrodes separated by a distance of 2.5 cm on the scalp. The MSC function is larger in value at low frequencies (below 20 Hz) and can be attributed to the highly correlated alpha rhythms and EOG artifact. This trend is consistent across all MSC functions.

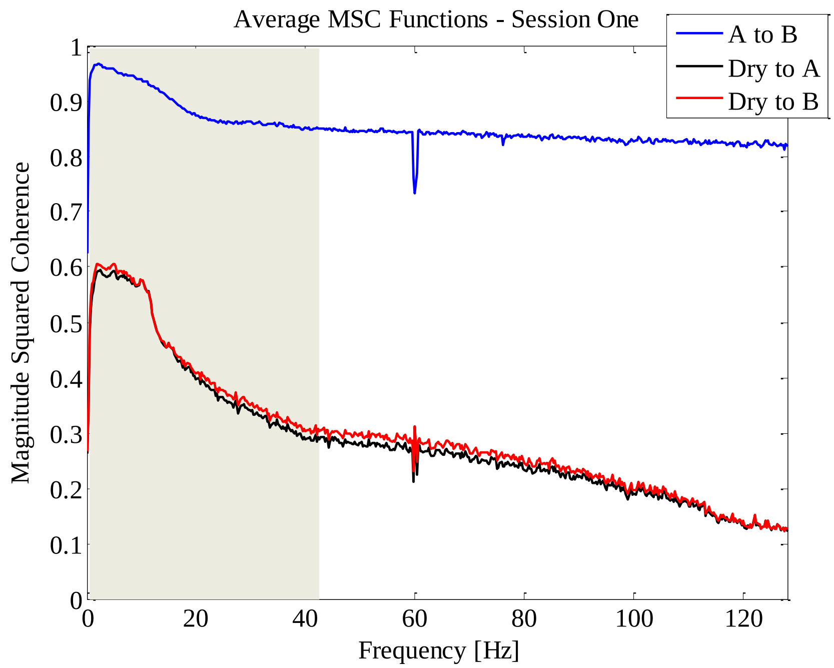

Fig. 10 Average MSC functions for session one. Functions are averaged across participants, trials, and electrodes from session one.

The overall MSC functions for the dry – wet pairs were substantially lower than the wet – wet MSC function, therefore the average MSC value (over the frequency range of 0.5 – 43 Hz) were plotted for each participant (Fig. 11). The initial participant shows higher similarity between electrodes (average MSC value of .71) versus the final participant (average MSC value of 0.22). A large drop in the average MSC value between the first six and last six participants is shown in Fig. 11. However, a similar trend does not occur in the Wet A – Wet B pair. The average MSC values from each participant and session are tabulated in Appendix C.

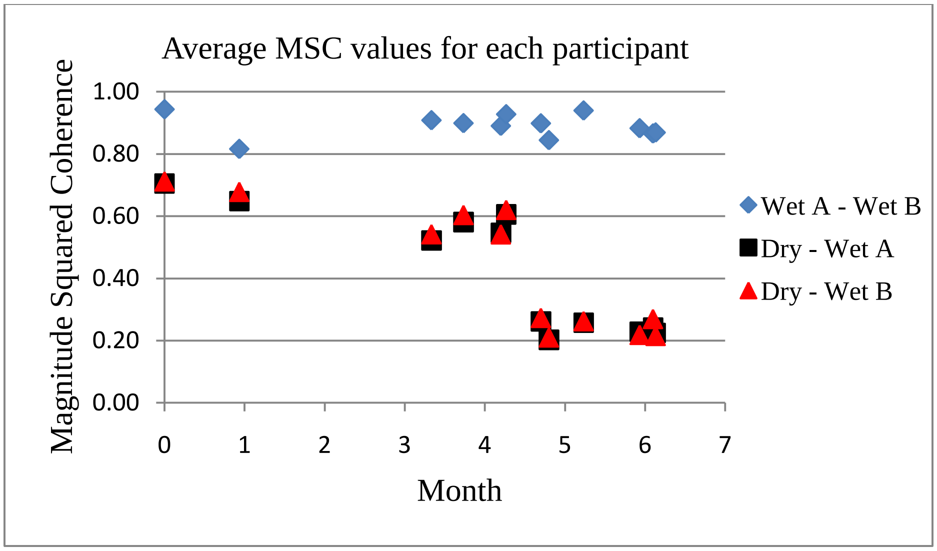

Fig. 11 Average MSC values for each participant.

To determine if the decrease in the dry – wet MSC functions over time was the result of mechanical wear on the headset, or coincidental to the order in which the participants completed in the study, the second participant agreed to run through session one of data collection a second time. Fig. 12 illustrates the MSC functions for the dry – wet and wet – wet pairs for the first participant's initial data collection. The average MSC values were 0.82 (Wet A – Wet B), 0.65 (Dry – Wet A), and 0.68 (Dry – Wet B). Data from the second data collection, which was completed after the original twelve participants (approximately six months later), are shown in Fig. 13. The average MSC values calculated for each of the electrode pairs for the second data collection were 0.84 (Wet A – Wet B), 0.22 (Dry – Wet A), and 0.24 (Dry – Wet B). This suggests that the drop was not due to differences between participants.

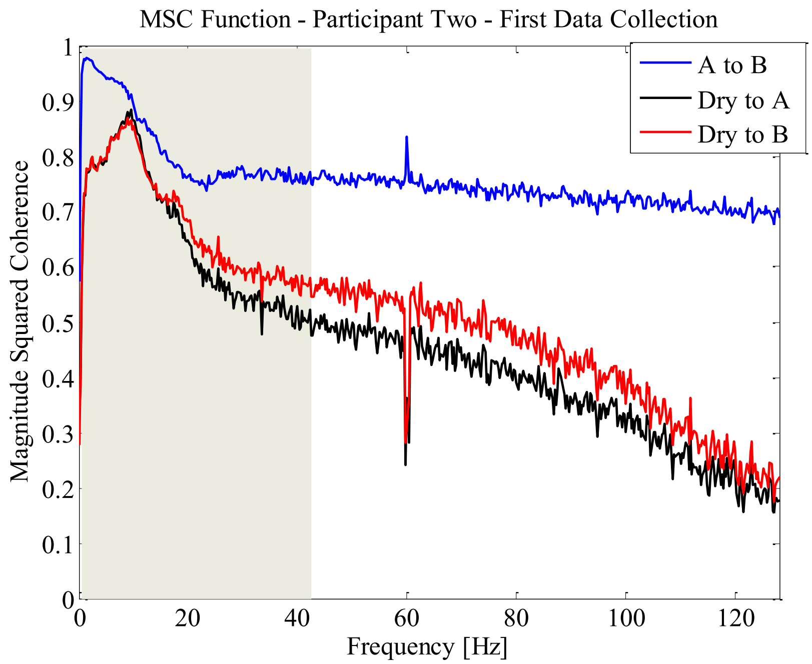

Fig. 12 Average MSC functions from the second participant’s first data collection.

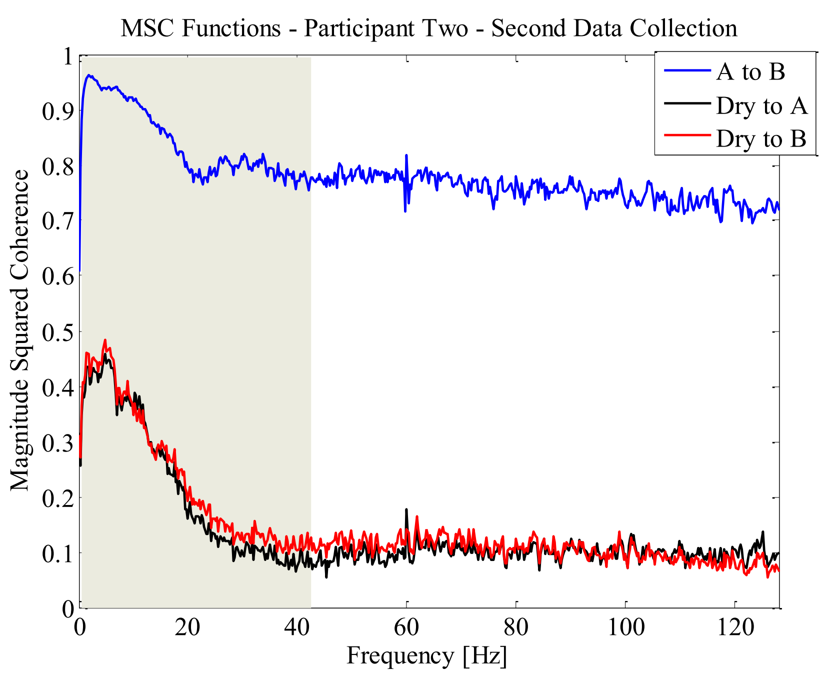

Fig. 13 Average MSC functions from participant two's second data collection.

The MSC functions for the wet electrode pairs from session two are shown in Fig. 14. The average MSC values for the Wet C – Wet A and Wet C – Wet B pairs were 0.65 and 0.67. The average MSC value for the Wet A – Wet B pair was 0.88. The average MSC values calculated for the Wet C pairs in session two are quite lower than expected when compared to the Wet A – Wet B pair. This is caused, at least in part, by the separate reference used for the Wet C electrodes. A separate reference was used to mimic the separate dry electrode reference in session one. Re-referencing the Wet C electrode data to the original Wet A and Wet B reference electrode increases the MSC values to similar values as those obtained with the Wet A – Wet B pair (Fig. 15). However, due to the separate dry reference, the initial lower MSC values obtained for the Wet C pairs are the appropriate comparison for MSC values derived from dry – wet pairs.

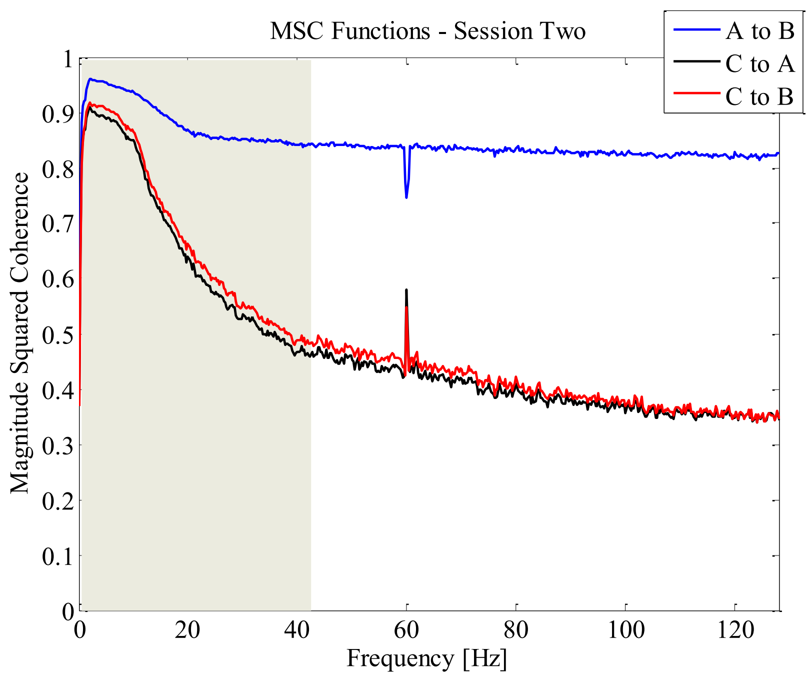

Fig. 14 Average MSC functions for session two. Functions are averaged across all participants, trials, and electrodes for session two.

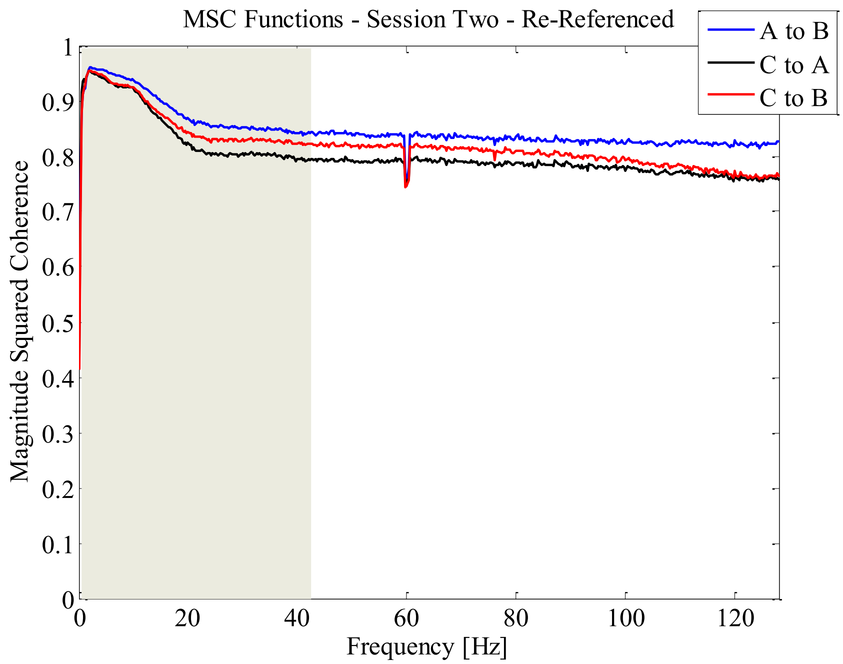

Fig. 15 MSC functions after re-referencing Wet C data from session two.

Although a dry reference to wet reference channel was recorded, re-referencing the dry EEG data to the original wet reference was not possible because of large magnitude noise present in this channel, likely due to electrode mismatch. Therefore, to determine the amount of variance caused by the use of separate references, the original and offset wet reference electrodes were separately referenced to each of the five Wet A electrodes on the scalp for data recorded during the second session. The MSC function was then computed between the reference electrodes for each Wet A site, and is illustrated in Fig. 16. This figure suggests that the use of a separate reference introduces variance which is not representative of the true coherence function between spatially-separated electrodes on the scalp.

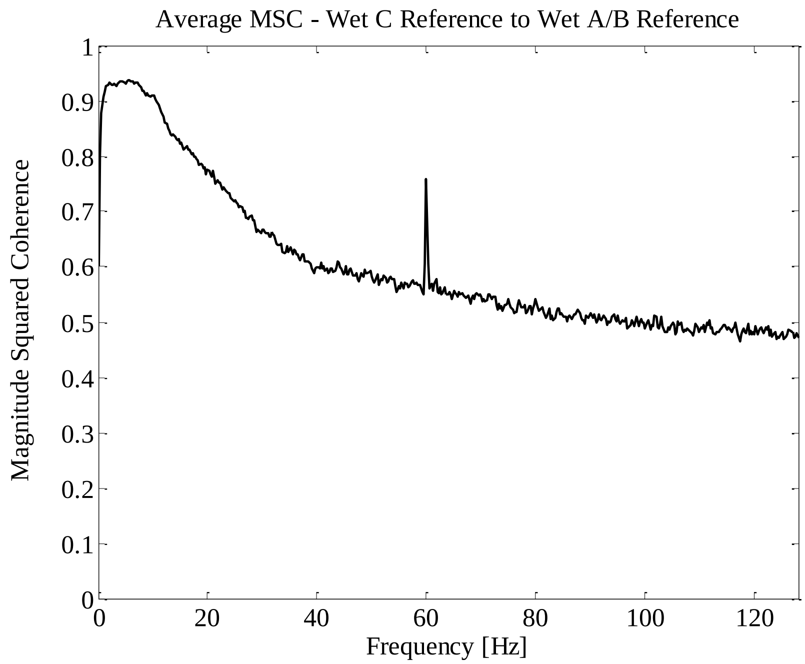

Fig. 16 MSC function between the two reference electrodes from session two.

2) Classification of Cognitive Workload: Classification accuracies are shown in Table II. Overall classification accuracies for session one were 78% (Dry), 79% (Wet A), and 79% (Wet B). The classification accuracies for session two were 82% (Wet C), 79% (Wet A), and 79% (Wet B). The accuracies presented are averaged across the ten-fold cross-validation and twelve participants for each electrode set. All accuracies are above the expected value of chance (50%) for a two-class problem. Results for each participant can be found in Appendix B. Classification accuracies are consistent across dry and wet electrodes within a session, in addition to across sessions. Training and validation accuracies are also presented in Table II, and are consistent across electrode type and session as well. Values presented in Table II are the percent of epochs classified as the correct level of workload.

TABLE II

Classification accuracies of workload state.

Session 1	Dry		A		B	
	Low	High	Low	High	Low	High
Train	89	89	89	90	89	88
Validation	80	76	78	79	78	77
Test	79	78	79	79	79	79

Session 2	C		A		B	
	Low	High	Low	High	Low	High
Train	91	93	90	89	88	88
Validation	83	81	79	77	79	77
Test	81	82	80	78	80	78

Unlike the decreasing trend found in the coherence analysis, classification accuracy does not decrease across participants. This is illustrated in Fig. 17, showing overall test accuracies for the dry electrode feature set across each participant. Overall test accuracies are the average of both low- and high-workload classification accuracies.

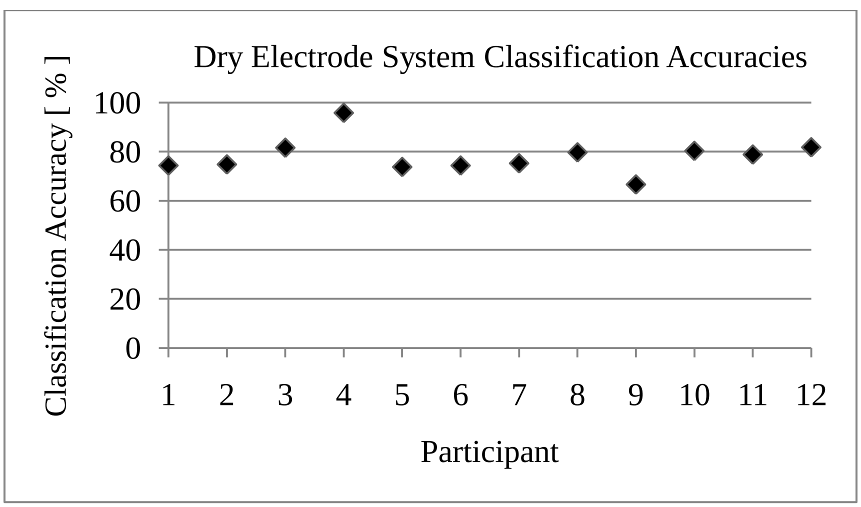

Fig. 17 Overall classification accuracies for the dry electrode dataset. Participants are listed in order of completion.

In addition to overall accuracies, the Ruck saliency [34] of each trained ANN was also compared to determine if the features of each electrode set were ranked similarly. The percentages of the top ten features that overlap between electrode sets are shown in Table III for each participant. The average percentage of overlap for the Dry – Wet A and Dry – Wet B datasets is 62% and 65%, respectively. The average percent overlap between wet electrode datasets is 78%. Chance overlap is 40%. The average percentage of overlap of salient features was higher for the wet datasets, but was not consistently higher across all participants. For example, the overlap was consistent across all electrode datasets for subjects two and twelve, but it varied greatly for participants four and eleven. Additionally, there does not seem to be a decreasing trend as found with the coherence analysis; this is consistent with the results from the workload classification, where no decreasing trend across participants was found as well.

TABLE III

The percentage of overlap between top ranked salient features.

	Participant											
	1	2	3	4	5	6	7	8	9	10	11	12
Dry - Wet A	70	60	70	50	50	70	60	60	70	50	60	70
Dry - Wet B	70	60	70	50	50	60	70	70	60	80	70	70
Wet A - Wet B	80	60	60	90	90	70	70	80	90	80	100	70

IV. DISCUSSION

The dry electrode headset and amplifier/filter module are integrated into a single system, therefore responses of the individual electrodes cannot be determined; the responses shown are for the entire system. The dry electrode system's bandwidth is sufficient for typical EEG and ERP studies [2], [5], [33] and based on the results of the electrical testing will cause little to no distortion to the spectral content of the EEG data. The observed responses are primarily the result of the system's filter bank. Although the dry electrode system produces a gain of 1.04, this is constant over the useful bandwidth for EEG studies. This slight amplification is likely to be caused by tolerances in electrical components of the system. Since the gain is quantified, post-processing can correct for the slight amplification if needed.

The results from the step response testing illustrates the dry electrode system is also suitable for time-domain applications. The rising phase of the step response reaches steady-state after approximately 2 ms, much before the earliest components of any ERP waveform; several auditory responses peak at 10 ms. Therefore, no distortion to any ERP component should occur. Evaluation of the novel system in a time-domain based application was not extended beyond the analysis of the step response, primarily because the dry electrode system is intended for use in a frequency-domain application; however, Sellers *et al*. [35] reported only a 3% drop in classification accuracy during a P300-based BCI using the dry electrode system as compared to traditional wet electrodes, demonstrating the usability of the novel system in an ERP-based application.

The wet electrode system produced a flat response over the useful frequency range of EEG studies. Using high- and low-pass filters that are similar to those implemented in the dry electrode system would yield comparable responses to those of the dry electrode system. Similarly, the rising phase of the wet electrode step response is dependent upon the filter bank as well.

The average MSC values for the first two participants were 0.71 and 0.66, which are comparable to MSC values presented in the literature [12] (approximately 0.70) for EEG recorded simultaneously from dry and wet electrodes. The average MSC values are also consistent with the average MSC values for the Wet C to Wet A/Wet B pairs (0.66). The general shape of the MSC functions are also consistent with those reported [12]. The coherence analysis demonstrated a decreasing trend in the spectral similarity between the two systems over time. The experimenters noted the visual similarity of the simultaneously recorded EEG during data collection decreased over the span of the study as well. In an attempt to determine the cause for the decrease in similarity, electrical testing of the dry electrode system was repeated after the completion of the study. However, no change in the electrical properties of the system was found. The magnitude and phase response as well as the step response were identical to the original responses shown previously. This suggests the decrease in signal similarity was not caused by changes in the electrical properties of the system.

The lower MSC values of the dry electrode system compared to the wet electrode system, as well as the lower MSC values for the Wet C electrodes, are partially the result of the use of separate references for each system. Although the reference electrodes were separated at the same distance (2.5 cm) as the electrodes on the scalp, the coherence between the reference electrodes was much lower. While the underlying anatomy on the scalp is primarily homogenous at 2.5 cm, the underlying anatomy at the placement of the reference electrodes is much more varied. The dry and Wet C reference electrodes were placed directly on the right mastoid process, while the Wet A/Wet B reference electrode was placed slightly offset to the mastoid process at the desired distance of 2.5 cm, potentially placing the second reference over a more electrically active site rather than directly on bone [3]. This, of course, does not explain the decrease in MSC over the span of the study, but it is one explanation for some of the variance found in the MSC between the dry and wet electrodes.

The classification accuracies presented are consistent across electrode sets and sessions. The accuracies are also comparable to results reported in the literature [1], [20], [31], ranging from 82 – 92%. On average, there was a substantial overlap in the top ten ranked features between the three electrode sets, although not for all participants. This suggests that each system was recording similar spectral information that was crucial for classifying two distinct levels of workload. Even though the coherence analysis demonstrated a decrease in the similarity between EEG signals recorded by the dry and wet electrodes, the dry electrode system was still capable of recording salient EEG signals that could be used to discriminate varying levels of workload with similar accuracy to the wet electrodes. It may be possible that small differences in spectral power and an increase of uncorrelated noise over time in the simultaneously recorded EEG are negligible in discriminating two distinct levels of cognitive workload; therefore, classification accuracy did not decrease over time. However, the MSC function, which is highly sensitive to additive uncorrelated noise [36], was more affected by these differences in the recorded signal.

A second viable explanation for the signal decrement is a change at the electrode-scalp interface. It is important to mention that the dry electrode system is a first generation prototype, especially the headset housing electrodes. Extensive use of this particular system has been ongoing for approximately two years. Over this time, the experimenters noticed that the headset itself was beginning to wear. The springs that hold the electrode in contact with the scalp began to lose tension over time, thus decreasing the contact pressure of the electrode onto the scalp. As reported by Yamamoto *et al.* [37] contact pressure between a dry electrode and the scalp largely influences the skin admittance. Therefore, a decrease in contact pressure may have led to an overall increase in the impedance at the electrode – skin interface. However, this cannot be verified since the impedance of the dry electrodes cannot be measured.

Mechanical wear of the headset may therefore be a possible explanation for the decrease in the MSC function over time. Presumably, such wear should occur over time, instead of a near instantaneous change as shown by the drastic drop in the MSC function between participants six and seven. However, participant six had the largest head circumference of all participants at 60 cm, potentially stretching the headset beyond the normal range of use, and thereby causing the subsequent decrease in signal quality from the remaining participants.

The results presented here indicate, at least initially, that the dry electrodes are able to record EEG signals comparable to those from traditional wet electrodes.

Classification accuracies achieved from EEG recorded from the dry electrode system was within one to two percent of those achieved by the wet electrode system. The electrical properties of the dry electrode system are similar to those found in traditional wet electrode systems as well. The dry electrode system recorded signals that could be used to accurately classify two different levels of cognitive workload with results consistent with conventional gel-based electrodes. Thus, this novel system should aid in the transition of cognitive state assessment technology into an operational environment. However, further work should be conducted to improve the reliability of such a system to maintain the ability to record high-quality signals over time.

REFERENCES

[1] G. F. Wilson and C. A. Russell, "Operator functional state classification using multiple psychophysiological features in an air traffic control task," *Human Factors*, vol. 45, no. 3, pp. 381-389, 2003.

[2] G. F. Wilson and C. A. Russell, "Performance enhancement in an uninhabited air vehicle task using psychophysiologically determined adaptive aiding," *Human Factors*, vol. 49, no. 6, pp. 1005 - 1018, 2007.

[3] P. L. Nunez and R. Srinivasan, *Electric fields of the brain*, 2nd ed. New York, United States: Oxford University Press, 2006.

[4] C. Berka, D. J. Levendowski, M. N. Lumicao, A. Yau, G. Davis, V. T. Zivkovic, R. E. Olmstead, P. D. Tremoulet, and P. L. Craven, "EEG correlates of task engagement and mental workload in vigilance, learning, and memory tasks," *Aviation, Space, and Environmental Medicine*, vol. 78, no. 5, pp. B231 -B244, 2007.

[5] F. G. Freeman, P. J. Mikulka, L. J. Prinzel, and M. W. Scerbo, "Evaluation of an adaptive automation system using three EEG indices with a visual tracking task," *Biological Psychology*, vol. 50, pp. 61 - 76, 1999.

[6] A. Gevins, M. E. Smith, H. Leong, L. McEvoy, S. Whitfield, R. Du, and G. Rush, "Monitoring working memory load during computer-based tasks with EEG pattern recognition methods," *Human Factors*, vol. 40, no. 1, pp. 79-91, 1998.

[7] Y. M. Chi, T.-P. Jung, and G. Cauwenberghs, "Dry-contact and noncontact biopotential electrodes: methodological review," *IEEE Reviews in Biomed. Eng.*, vol. 3, pp. 106-119, 2010.

[8] T. Matsuo, K. Iinuma, and M. Esashi, "A barium-titanate-ceremic capacitive-type EEG electrode," *IEEE Trans. Biomed. Eng.*, vol. 20, pp. 299-300, 1973.

[9] B. A. Taheri, R. T. Knight, and R. L. Smith, "A dry electrode for EEG recording," *Electroencephalography and Clin. Neurophysiol.*, vol. 90, no. 5, pp. 376 - 383, 1994.

[10] A. Searle and L. Kirkup, "A direct comparison of wet, dry and insulating bioelectric recording electrodes," *Physiological Measure*, vol. 21, pp. 271 - 283, 2000.

[11] C. Fonseca, J. P. Silva Cunha, R. E. Martins, V. M. Ferreira, J. P. Marques de Sá, M. A. Barbosa, and A. Martins da Silva, "A novel dry active electrode for EEG

recording," *IEEE Trans. on Biomed. Eng.*, vol. 54, no. 1, pp. 162 - 165, 2007.

[12] C. Grozea, C. D. Voinescu, and S. Fazli, "Bristle-sensors - low-cost flexible passive dry EEG electrodes for neurofeedback and BCI applications," *J. Neural Eng.*, vol. 8, no. 2, 2011.

[13] M. Matteucci, R. Carabalona, M. Casella, E. Di Fabrizio, G. Gramatica, M. Di Rienzo, E. Snidero, L. Gavioli, and M. Sancrotti, "Micropatterned dry electrodes for brain-computer interface," *Microelectronic Eng.*, vol. 84, pp. 1737 - 1740, 2007.

[14] C.-T. Lin, L.-W. Ko, J.-C. Chiou, J.-R. Duann, R.-S. Huang, S.-F. Liang, T.-W. Chiu, and T.-P. Jung, "Noninvasive neural prostheses using mobile and wireless EEG," *Proc. IEEE*, vol. 96, no. 7, pp. 1167 - 1183, 2008.

[15] T. C. Ferree, P. Luu, G. S. Russell, and D. M. Tucker, "Scalp electrode impedance, infection risk, and EEG data quality," *Clin. Neurophysiol.*, vol. 112, pp. 536 - 544, 2001.

[16] A. S. Gevins, D. Durousseau, and J. Libove, "Dry electrode brain wave recording system," Patent U.S. 4 967 038, Oct. 30, 1990.

[17] R. Matthews, N. J. McDonald, P. Hervieux, P. J. Turner, and M. A. Steindorf, "A wearable physiological sensor suite for unobtrusive monitoring of physiological and cognitive state," in *Proc. IEEE Annu. Int. Conf. Eng. Med. Biol. Soc.*, 2007, pp. 5276-5281.

[18] P. Fiedler, S. Brodkorb, C. Fonseca, F. Vaz, F. Zanow, and J. Haueisen, "Novel TiN-based dry EEG electrodes: influence of electrode shape and number on contact impedance and signal quality," *IFMBE Proc.*, vol. 29, pp. 418 - 421, 2010.

[19] J. R. Estepp, J. C. Christensen, J. W. Monnin, I. M. Davis, and G. F. Wilson, "Validation of a dry electrode system for EEG," *Proc. of the Human Factors and Ergonomics Society 53rd Annual Meeting*, vol. 53, no. 18, pp. 1171-1175, 2009.

[20] J. R. Estepp, J. W. Monnin, J. C. Christensen, and G. F. Wilson, "Evaluation of a dry electrode system for electroencephalography: applications for psychophysiological cognitive workload assessment.," *Proc. of the Human Factors and Ergonomics Society 54th Annual Meeting*, vol. 54, no. 3, pp. 210-214, 2010.

[21] R. Matthews, N. J. McDonald, P. Hervieux, P. J. Turner, and M. A. Steindorf, "A Wearable Physiological Sensor Suite for Unobtrusive Monitoring of Physiological and Cognitive State," in *Proc. IEEE Annu. Int. Conf. Engineering Medicine Biology*

Soc., 2007, pp. 5276-5281.

[22] R. Matthews, N. J. McDonald, H. Anumula, and L. J. Trejo, "Novel hybrid sensors for unobtrusive recording of human biopotentials," in *Foundations of Augmented Cognition*, San Ramon, 2006, pp. 91-101.

[23] H. Jasper, "The ten-twenty electrode system of the International Federation," *Electroencephalography and Clin. Neurophysiol.*, vol. 10, pp. 371 - 375, 1958.

[24] J. R. Comstock and R. J. Arnegard, "The multi-attribute task battery for human operator workload and strategic behavior research.," NASA Technical Memorandum No. 104174, 1992.

[25] W. D. Miller, "The U.S. Air Force-developed adaptation of the multi-attribute task battery for the assessment of human operator workload and strategic behavior.," Tech. Rep. No. AFRL-RH-WP-TR-2010-0133, 2010.

[26] G. Gargiulo, R. A. Calvo, P. Bifulco, M. Cesarelli, C. Jin, A. Mohamed, and A. van Schaik, "A new EEG recording system for passive dry electrodes," *Clin. Neurophysiol.*, vol. 121, pp. 686 - 693, 2010.

[27] A. Gevins, J. Le, N. K. Martin, P. Brickett, J. Desmond, and B. Reutter, "High resolution EEG: 124-channel recording, spatial deblurring and MRI integration methods," *Electroencephalography and Clin. Neurophysiol.*, vol. 90, pp. 337-358, 1994.

[28] P. He, B. Yang, S. Hubbard, J. Estepp, and G. Wilson, "A sensor positioning system for functional near-infrared neuroimaging," in *Proc. of the 12th Int. Conf. on Human Computer Interaction (HCII)*, Beijing, China, 2007.

[29] R. Cooper, J. W. Osselton, and J. C. Shaw, *EEG technology*, 3rd ed. London, United Kingdom: Butterworths & Co (Publishers) Ltd, 1980.

[30] G. Nolte, O. Bai, L. Wheaton, Z. Mari, S. Vorbach, and M. Hallett, "Identifying true brain interaction from EEG data using the imaginary part of coherency," *Clin. Neurophysiol.*, vol. 115, pp. 2292-2307, 2004.

[31] G. F. Wilson and C. A. Russell, "Real-time assessment of mental workload using psychophysiological measures and artificial neural networks," *Human Factors*, vol. 45, no. 4, pp. 635-643, 2003.

[32] S. Lemm, B. Blankertz, T. Dickhaus, and K. Müller, "Introduction to machine learning for brain imaging," *NeuroImage*, vol. 56, no. 2, pp. 387-399, 2011.

[33] S. J. Luck, *An introduction to the event-related potential technique*. Massachusetts: The MIT Press, 2005.

[34] D. Ruck, S. Rogers, and M. Kabrisky, "Feature selection using a multilayer perceptron.," *Journal of Neural Network Computing.*, vol. 2, pp. 40-48, 1990.

[35] E. W. Sellers, P. Turner, W. A. Sarnacki, T. McManus, T. M. Vaughan, R. Matthews, "A novel dry electrode for brain-computer interface," in *Proc. 13th Int. Conf. on Human-Computer Interaction*, San Diego, CA, 2009, pp. 623-631.

[36] K. M. Ropella, A. V. Sahakian, J. M. Baerman, and S. Swiryn, "The coherence spectrum. A quantitative discriminator of fibrillatory and nonfibrillatory cardiac rhythms," *Circulation*, vol. 80, pp. 112-119, 1989.

[37] Y. Yamamoto, T. Yamamoto, and T. Ozawa, "Characteristics of skin admittance for dry electrodes and the measurement of skin moistuisation.," *Med. Bio. Eng. Comput.*, vol. 24, pp. 71-77, 1986.

APPENDIX A

Description of tasks used during data collection.

Eyes Open:	The participant, while sitting, stares straight ahead without movement. Blinks are allowed. This task is five minutes.
Eyes Closed:	The participant, while sitting, closes his/her eyes while keeping his/her head up, and not moving. This task is five minutes.
Low Workload:	The participant performs a low workload condition using the MATB software. This task is five minutes. In total, there are three trials of this task.
High Workload:	The participant performs a high workload condition using the MATB software. This task is five minutes. In total, there are three trials of this task.
Jaw Clench:	The participant begins this task in a sitting relaxed state for ten seconds, the participant will then be asked to clench his/her jaw and holds for twenty seconds. This pattern repeats four times, with a final ten second relaxed period at the end. A relaxed state consists of no movement or active muscle tension, with eyes open.
Head Movement:	The participant begins in a sitting relaxed state (see Jaw Clench) for ten seconds, then turn his/her head ninety degrees to the left and holds for twenty seconds. The participant returns his/her head to center for a relaxed state for ten seconds, turns his/her head to the right for twenty seconds and returns his/her head back to center at a relaxed state for ten seconds. The participant then tilts his/her head up and holds for ten seconds and returns his/her head back to center for ten seconds. The participant then tilts his/her head down for twenty seconds and then returns back to center for a relaxed state for ten seconds.
Brow Raise:	The participant will begin in a sitting relaxed state (see Jaw Clench) for ten seconds, then raises his/her brow (corrugator muscles) and holds for twenty seconds. This pattern repeats four times with the relaxed sate of ten seconds at the end.

APPENDIX B

TABLE IV

Classification accuracy of cognitive workload presented as percentages for each participant.

Session	Condition	Workload	Participant 1	2	3	4	5	6	7	8	9	10	11	12
Session 1	Dry	Low	75	75	83	96	82	74	73	79	60	82	82	82
		High	74	75	80	96	66	75	78	80	73	79	76	82
	Wet A	Low	74	80	76	98	55	79	80	85	82	80	80	82
		High	71	78	82	92	70	75	82	83	74	80	81	84
	Wet B	Low	70	84	82	96	52	73	81	83	82	77	83	82
		High	73	71	79	94	75	74	80	80	73	86	80	82
Session 2	Wet C	Low	75	92	76	90	81	73	81	79	68	83	86	90
		High	79	88	84	90	85	68	82	72	82	84	80	93
	Wet A	Low	72	95	74	93	72	75	77	75	77	88	87	79
		High	67	90	70	92	70	72	77	81	67	86	83	83
	Wet B	Low	72	95	78	88	77	71	73	79	76	81	82	83
		High	68	93	69	86	71	64	81	79	74	80	87	88

APPENDIX C

TABLE V

Average MSC values calculated from 0.5 to 43 Hz for each participant.

		Participant											
		1	2	3	4	5	6	7	8	9	10	11	12
Session 1	Wet A - Wet B	0.95	0.82	0.91	0.90	0.89	0.93	0.90	0.84	0.94	0.88	0.87	0.87
	Dry - Wet A	0.71	0.65	0.52	0.58	0.54	0.60	0.26	0.20	0.25	0.22	0.23	0.22
	Dry - Wet B	0.71	0.68	0.54	0.60	0.54	0.61	0.27	0.20	0.25	0.21	0.26	0.21
Session 2	Wet A - Wet B	0.94	0.81	0.91	0.87	0.88	0.94	0.89	0.81	0.94	0.88	0.84	0.88
	Wet C - Wet A	0.83	0.72	0.64	0.66	0.59	0.66	0.55	0.57	0.70	0.56	0.61	0.71
	Wet C - Wet B	0.84	0.77	0.67	0.68	0.58	0.67	0.58	0.61	0.71	0.58	0.64	0.73