A Novel Dry Electrode for Brain-Computer Interface

Eric W. Sellers[1], Peter Turner[2], William A. Sarnacki[3], Tobin McManus[2], Theresa M. Vaughan[3], Robert Matthews[2]

[1] East Tennessee State University, PO Box 70649, Johnson City, TN 37614; sellers@etsu.edu
[2] QUASAR, 5764 Pacific Center Blvd. Suite 107, San Diego, CA 92121; peter@quasarusa.com; tobin@quasarusa.com; robm@quasarusa.com
[3] Wadsworth Center, NY State Dept. of Health, E1001 Empire State Plaza, Albany, NY 12201; Sarnacki@wadsworth.org; vaugan@wadsworth.org

Abstract. A brain-computer interface is a device that uses signals recorded from the brain to directly control a computer. In the last few years, P300-based brain-computer interfaces (BCIs) have proven an effective and reliable means of communication for people with severe motor disabilities such as amyotrophic lateral sclerosis (ALS). Despite this fact, relatively few individuals have benefited from currently available BCI technology. Independent BCI use requires easily acquired, good-quality electroencephalographic (EEG) signals maintained over long periods in less-than-ideal electrical environments. Conventional, wet-sensor, electrodes require careful application. Faulty or inadequate preparation, noisy environments, or gel evaporation can result in poor signal quality. Poor signal quality produces poor user performance, system downtime, and user and caregiver frustration. This study demonstrates that a hybrid dry electrode sensor array (HESA) performs as well as traditional wet electrodes and may help propel BCI technology to a widely accepted alternative mode of communication.

Keywords: Brain-computer interface, P300 event-related potential, dry electrode, amyotrophic lateral sclerosis.

1 Introduction

Severe motor disabilities such as amyotrophic lateral sclerosis can reduce or eliminate neuromuscular control and deprive affected people of communication that is vital to their mental and physical health. Recent advances in noninvasive EEG-based brain-computer interfaces (BCIs) have given these patients new hope for communication and control of their environment [1], [2], [3], [4], [5], [6], [7]. BCIs can succeed where other devices fail because they use a control technology that depends directly on neuronal signals without any requirement for neuromuscular control [8]. In the last few years, the P300-based BCI has proven to be an effective and reliable means of communication for severely disabled individuals. However, limitations in the duration of each use, the need for extensive caregiver support and training, and technical support from trained researchers have made providing the technology to more than a few individuals impractical. An obvious impediment to widespread acceptance of BCI technology is the need for an improved wet electrolyte-based EEG sensor [9], or a dry sensor. The current study provides data showing that a hybrid dry electrode array (HESA) can perform as well as a standard wet electrode array (WEA) in a P300-based BCI paradigm. HESA sensors have been tested in a variety of contexts and have been shown to record EEG signals with high fidelity [10], [11]. The hybrid sensors can be applied with light, comfortable pressure of approximately 2 psi and record EEG for practically unlimited times without the need for electrolytes or skin treatments of any kind.

The P300 component of the event-related potential (ERP) is a large, vertex-positive component with a latency of about 300 ms after a triggering event. It was discovered more than 40 years ago [12], and after intensive research the robust nature of the component has been well established [13], [14], [15]. A P300 is generated when a human observer detects a rare or meaningful event, especially among a series of other, more frequent events [16]. A stimulus presentation typically used to elicit a P300 is called the oddball paradigm. To qualify as an oddball paradigm the presentation must meet three requirements. First, the stimuli must be presented in a random order. Second, the subject must attend to the presentation sequence. Third, one category must be presented infrequently. The P300 Speller meets these criteria because the rows and columns of the matrix flash randomly, the subject attends to one specific matrix character, and the attended character flashes one out of every six flashes.

The use of the P300 response for BCI control has been well documented [2], [17], [18], [19], [20], [21], [22]. The matrix speller version of the P300-based BCI flashes rows and columns of letters and numbers in rapid succession. Each flash of a row or a column is one stimulus. For a 6 x 6 alphanumeric matrix (Figure 1), each character flashes in only one of six rows, and in only one of six columns. The user is instructed to attend to only one character while it flashes in the matrix. This is the target character. Thus, two of 12 stimuli are targets and 10 of 12 stimuli are non-targets. A P300 response is produced when either the row or column containing the target item flashes. This sequence of flashing rows and columns is repeated a number of times. The BCI system recognizes the user’s selection by detecting and averaging the P300 responses. Averaging is required as the P300 signal is smaller than the other components of the typical brain signal. Thus, improvements in signal recording and/or signal processing methods should increase the overall speed and accuracy of the P300-based BCI.

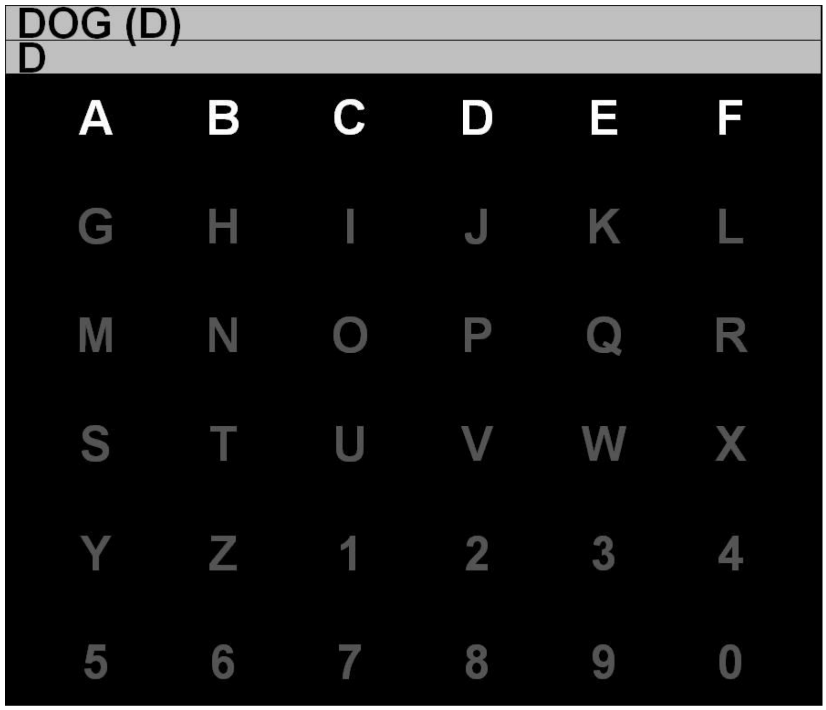

Fig. 1. An example of a 6x6 speller matrix configured for copy-spelling. At the top, the word DOG is presented. The letter in parentheses (D) is the current target letter. As rows and columns flash successively, the user is asked to count how many times the letter D (the target) flashes. This twelve-flash series is repeated a predetermined number of times. The responses for each row and column are averaged, and a classifier is applied. The intersection of the row and column with the highest classification values is selected. In this case, the target letter D flashing in either a column or a row elicits a P300 response and the a D is presented as feedback to the user on the line below the presented word DOG at the top of the matrix.

2 Methods

2.1 Hybrid EEG Sensor Technology

Measurement of the EEG for everyday use of a BCI requires the application of sensors through thicknesses of hair. To meet this requirement, QUASAR has developed a novel *hybrid biosensor* (Figure 2). This sensor measures EEG through hair and without any skin preparation. To accomplish this, the sensor uses a set of 'fingers' that are small enough to reach through the hair without trapping hair beneath the finger. Figure 3 shows the hybrid electrodes mounted in a headpiece along with the conventional wet electrodes.

In contrast to conventional EEG electrode technology, which relies on a low impedance contact to the scalp, these hybrid biosensors use a combination of high impedance resistive and capacitive contact to the scalp, and innovative processing electronics to reduce pickup and susceptibility to common-mode signals on the body. The hybrid biosensor consists of an electrode, an ultra-high input impedance amplifier circuit, a common-mode follower (CMF; a proprietary technology for reducing common mode signals), and a wireless node that contains a gain/filter module and a data acquisition/communications module. As the contact impedance between the scalp and each finger can be as high $10^7 \Omega$, the amplifier electronics are shielded and integrated with the electrode in order to limit interference caused by the pickup of external signals. The hybrid sensors and wireless node data acquisition channels are closely phase and gain matched and can provide individual EEG signals or high common-mode rejection ratio difference signals (CMRR > 70dB between 1Hz – 50Hz) between biosensors.

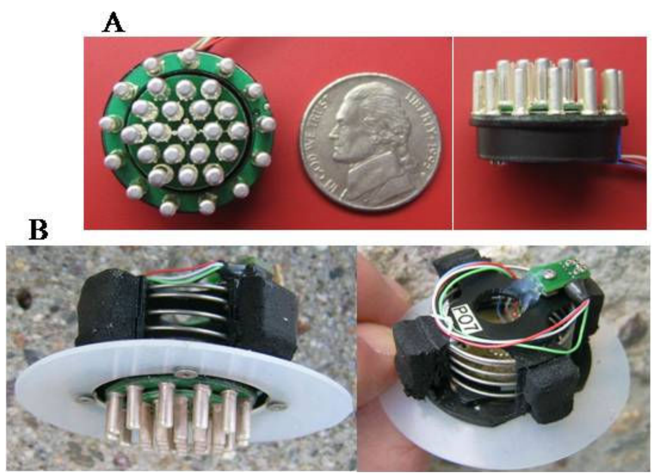

Fig. 2. A) QUASAR hybrid EEG biosensor used in the current study. B) The sensor and housing with padding to fit the sensor into the headpiece.

The CMF is used to reduce the sensitivity of the hybrid biosensor to common mode signals on the body. The CMF is a separate hybrid biosensor on or near the scalp that measures the potential of the body relative to the ground of the amplifier system. Ultra-high input impedance for the CMF ($\sim 10^{12}\ \Omega$) ensures that the output of the CMF tracks the body-ground potential with a high degree of accuracy. The CMF output is used in the wireless node as a reference for the EEG measurement by the electrodes. In this way, the common-mode signal appearing on the body is dynamically removed from the EEG measurement. This typically achieves a CMRR of 50 to 70 dB.

2.2 Data Acquisition and Processing

The HESA and WEA sensors were mounted in the headpiece shown in Figure 3. Each array had four sensors or electrodes (Cz, Pz, PO7, PO8) and one reference sensor or electrode located on the right mastoid. The WEA had a ground electrode located on the left mastoid. The HESA had a biosensor reference on the right mastoid and common-mode follower on the left mastoid. The EEG signals were acquired, digitized at a rate of 256 Hz, digitally bandpass filtered 0.5–30, and stored using a g.USBamp. The HESA samples were buffered at the sensor by a trans-conductance amplifier with ultra high impedance, calibrated to provide data samples for the software in the same voltage range as those of the WEA, then digitized by the g.USBamp. Thus, four WEA channels and four HESA channels were simultaneously recorded. All aspects of data collection and experimental control will be performed by the BCI2000 system [23].

Fig. 3. Headpiece used to make simultaneous HESA and WEA electrode comparison measurements. Spring loaded clamps on the elastic pieces made for quick and convenient adjustment for head size and sensor loading. The smaller electrodes on the left (right panel) are the WEA electrodes, and the larger disk to the right is the HESA electrode.

2.3 Task, Procedure, Design, and Analysis

Participants sat in a reclining chair approximately 1.5 m from a CRT video monitor that presented the P300 spelling matrix (Figure 1), all were able-bodied. In each experimental session, the participant was asked to focus on each letter in the words “Wadsworth brain computer interface” between each word of the phrase a 1-min break was given. As Figure 1 illustrates, each word in the phrase appeared in sequence on the top line above the matrix. The participant was instructed to attend to the letter indicated with parenthesis while it flashed in the matrix and to silently count the number of times it flashed. Each row and column was flashed 15 times. Thus, the selected letter flashed 30 times out of 180 total flashes. The data collected during the first two words was used to train the SWLDA classifier (described in [20] and [24]). That classifier was then applied to the second two words. Thus, the training data set included 14 character presentations and the test data set included 17 character presentations.

The duration of each experimental session was approximately 30 minutes. Eight participants completed one session that concurrently recorded HESA and WEA data. Classification accuracy was the dependent variable used to examine system performance. We also compared the event-related potential data for the participants.

3 Results

The event-related potentials were similar for the HESA and WEA sensors. Figure 4 shows averaged waveforms for data collected concurrently from the HESA and WEA electrodes. It is reasonable to expect slight variability in the waveforms because the HESA and WEA sensors were located approximately 1.5 cm away from each other, center-to-center distance. The average signal strength for each sensor and each subject was also calculated. To calculate this quantity, the data from each electrode are plotted on a histogram (x-axis Signal, y-axis Number of Events at each voltage). Mean amplitude Vrms is then read to include 90% of the points. This gives a quantity that represents the amplitude that captures 90% of all the signals recorded. The mean rms amplitude for all subject’s EEG was 9.10μV for the HESA sensor and 9.17μV for the WEA sensor. Thus, the wet and dry sensors variability is near identical, to be expected of sensors of equal fidelity measuring a common EEG signal.

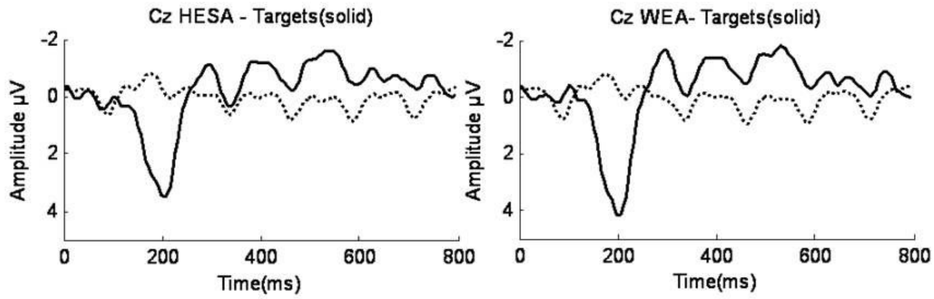

Fig. 4. Averaged ERP waveforms for target items (solid line) and non-target items (all other rows and columns) are graphed as a function of time after the flash, with positive voltage downward. The periodic signal in the non-target waveform corresponds to the frequency the flashes. These data are averaged across all trials in a session in which HESA and wet data was recorded concurrently for one representative participant.

Mean percent correct classification accuracy for each of the eight participants is shown in Table 1. Overall, the classification accuracy was similar for the HESA and the WEA arrays when the EEG was collected in side-by-side concurrent recordings (paired t-test; $p=.50$). These initial results demonstrate the efficacy of the HESA system and provide confirmation that a HESA-based BCI system can perform as well as a wet electrode-based BCI system, when proper care is taken to ensure signal quality.

Table 1. Mean classification accuracy for each participant.

Participant	HESA % correct	WEA % correct
A	29	29
B	76	94
C	82	76
D	12	18
E	65	47
F	94	100
G	82	100
H	100	100
Mean	67.5	70.5

4 Discussion and Conclusions

These data show that the HESA and WEA sensors provide equivalent BCI classification accuracy while participants perform a copy spelling task, in a preliminary data set. In addition, the signal fidelity of the two EEG recording methods is very similar (as measured by root mean square and the event-related potentials). This initial success suggests that dry sensor technology may provide a more user friendly and more acceptable implementation of a P300-based BCI.

One common complaint among able-bodied and disabled BCI users is the necessity of the electrolyte based gel that needs to be washed out of the hair after each session. Obviously, the need to wash the hair is eliminated with HESA sensors and this can substantially reduce the burden associated with BCI use for the BCI user and also for the person assisting the BCI user. It is also not necessary to abrade the scalp when using the HESA sensors which makes them more comfortable to wear. Future work will focus on testing the HESA with a larger group of subjects who will participate in multiple experimental sessions and on developing a mounting system that can be comfortable to wear for severely disabled individuals who may be limited to a prone position.

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