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Wireless Dry EEG for Drowsiness Detection

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***Abstract*—Fatigue is a well recognized safety concern for drivers and other industrial workers who must stay alert and attentive for long periods of time. Currently, drowsiness detectors using EEG technology exist but are cumbersome and unreliable. The large number of standard EEG channels requires extensive wiring, while the conventional wet electrodes cause discomfort in long-term monitoring. We propose a simple and cheap one-channel drowsiness detection technology suitable for detecting drowsiness in a variety of environments. Our design incorporates pronged dry-AgCl electrodes in a headband harness, which eliminates the discomfort of gel electrodes while obtaining strong signals from hair covered areas of the scalp. The electrodes send signals to a wireless base unit which then transfers the signal to a computer where it is analyzed using an unique algorithm. With solely this one-channel system, we obtained strong EEG signals from which alpha, beta and theta waves can be observed.**
Keywords - Physiological monitoring, wireless sensors and systems

I. Introduction

Electroencephalography (EEG) provides a non-invasive means of reliably monitoring brain activity spatially and temporally. It is widely used for clinical diagnostics, as well as for neural research. Use of EEG technology, however, is limited to hospitals and laboratories due to its complexity both in signal collection as well as in data interpretation. Extensive wiring and hardware render EEG cumbersome for individual use, and conventional wet electrodes cause discomfort in long-term monitoring. Dry and non-contact electrodes offer a more comfortable, easy-to-use alternative to the traditional gel electrode, but they currently provide limited signal strength [1]. EEG measurement poses an additional challenge of hair which hinders access to a large portion of the scalp.

The development of wireless mobile EEG technology for home use would be a great asset to monitoring medical conditions such as sleep apnea, epilepsy, and traumatic brain injury [1]. The ability to obtain EEG data in everyday environments also has various commercial applications. In this paper, we explore the particular application of wireless EEG for monitoring drowsiness.

Drowsiness and fatigue pose a major risk to workplace and road safety, because they are associated with decreased ability to concentrate, increased reaction time, and increased error rate [2]. Fatigue has been attributed to 1-3% of police reported car crashes and 4% of fatalities [3]. Drowsiness is also a major occupational hazard for people such as industrial workers, pilots and air traffic controllers, for whom a small lapse in judgment could lead to detrimental consequences.

Past research in drowsiness detection have proposed three main categories of monitoring based on eye blink pattern, heart rate variability, and brain activity. The degree of eyelid closure is said to increase with increasing drowsiness. Heart rate variability can also be a drowsiness indicator based on its reflection of the autonomic nerve activity, which is influenced by drowsiness. Both of these methods, however, are indirect and superficial reflections of cognitive activity. EEG provides the most direct measurement of consciousness and, thus is the one we have chosen to pursue in this study. Physiological signals can provide reliable and direct measurement of a driver's mental state, and there is close association of brain activity with human consciousness [4]. EEG technology is fairly standard and its electronic parts are cheap and easy to fabricate, providing an easily implementable design.

In this paper, we present a one-channel wireless EEG system and processing algorithm for detecting drowsiness. Our system uses pronged electrodes as well as a unique detection algorithm, and it is incorporated into a simple to use headband platform.

II. System Design

In our proposed EEG drowsiness detection system, dry Ag/AgCl electrodes are used to measure biopotentials from the scalp. The analog signals from the electrode sensors are sent to a wireless base unit. Here the signal goes through an amplifier, an ADC, and a microprocessor. A Bluetooth module on the base unit then sends the converted digital signal wirelessly to an external computer for signal collection and processing. A general schematic of the system is shown in Fig. 1.

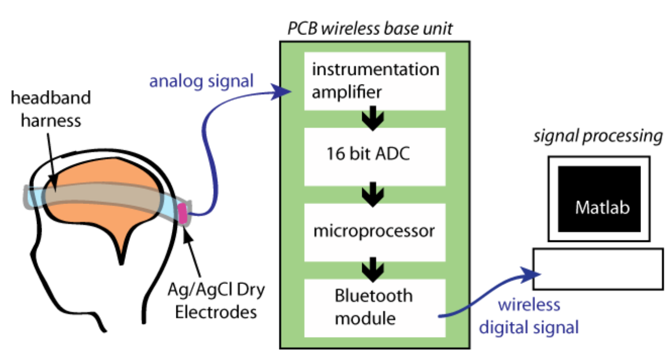

Fig. 1. Schematic of overall EEG drowsiness detection system

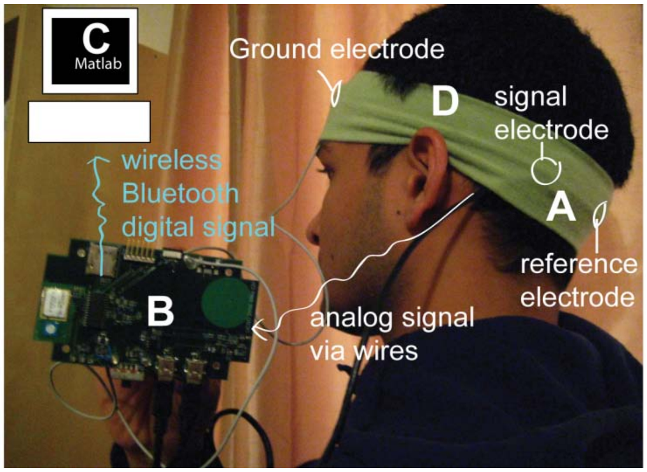

Fig. 2. Overview of the four major components of the EEG drowsiness detection system: A – dry active electrodes; B – wireless base unit; C – signal processing; D – wearable harness.

A. *Ag/AgCl Active Dry Electrodes*

While wet Ag/AgCl electrodes provide the best signal quality and are standard for clinical EEG purposes, the wetness causes discomfort in long term usages such as drowsiness monitoring. Thus, our system uses dry Ag/AgCl electrodes which are reusable and require only skin contact without need for conductive gels. The active electrodes contain an amplifier directly on top of the sensor. Fig. 3. shows a circuit model of the electrode. The electrodes output a unit gain analog signal. Three electrodes (signal, reference and ground) were used in this one-channel system.

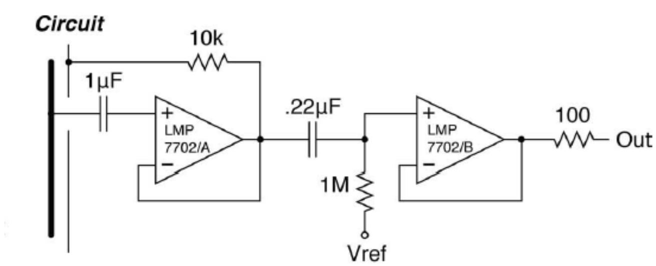

Fig. 3. Circuit diagram of the dry active electrode made from PCB. (1)

The hair with its high resistivity poses a significant hindrance to the conduction of biopotential from the surface of the skull to the electrode. Non-contact electrodes are capable of measuring signal through hair; however they are more susceptible to noise and artifacts [5]. Dry electrodes with 2 mm long contact posts were thus used for the signal and reference electrodes to reach hair-covered areas of the scalp (Fig. 4.). These electrodes, obtained from Biopac Inc, contain 12 posts which provide a total contact area of 10 mm [6]. The signal and reference electrodes were placed 2 inches apart in the mid back region of the head near the occipital lobe where alpha activity originates. A more standard silver plate dry electrode was used for the ground, which was placed on the side of the forehead where there is no hair coverage.

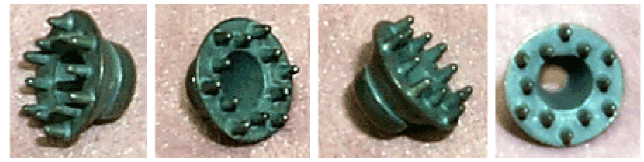
Fig. 4. Dry electrode with contact posts to reach scalp through hair (5)

B. *Wireless Base Unit*

Analog signals from the electrodes were sent via lead wires to a compact battery powered PCB base unit. The base unit contained an instrumentation amplifier, a 16 bit ADC, a microprocessor and a Bluetooth module. The converted digital signal was then sent wirelessly to an external computer for processing.

C. *Signal Processing*

Drowsiness signal detection was performed on an external computer using MATLAB. The power of alpha (8-12Hz), beta (15-20 Hz) and theta (5-7 Hz) waves were examined for indicators of increasing drowsiness, since studies have shown that these are related to driving performance [7]. An average of total power for each band from a reference time period was compared to the power for each other time point to determine changes in the alpha, beta, and theta wave levels.

D. *Wearable Harness*

The electrodes were incorporated into a headband to secure contact with the head, since electrodes are susceptible to motion artifacts. The 1.2 inch wide band is a soft elastic cloth material that fits snuggly on heads of varying diameters (8 to 12 inch).

III. Testing Using Physiological Data

Physiological testing was performed by using our system to obtain EEG data and analyzing the data using MATLAB. Subjects obtained data in 20 to 60 minute segments, classifying the subject's condition as either drowsy or alert. An algorithm was developed to analyze this data to note increases or decreases in the wave levels and to detect drowsiness according to the criteria described above. In order to optimize our algorithm, various threshold values were tested.

A. *Signal Quality*

The system was able to obtain strong signals with low noise and no filtering was required. The signals collected using our dry-electrode system were comparable to standard EEG data obtained using wet electrodes [1]. Fig. 5 shows an example of the raw data (top) with the corresponding spectrogram over a 0.5-35 Hz bandwidth. Strong alpha wave frequency is clearly detected when eyes are closed.

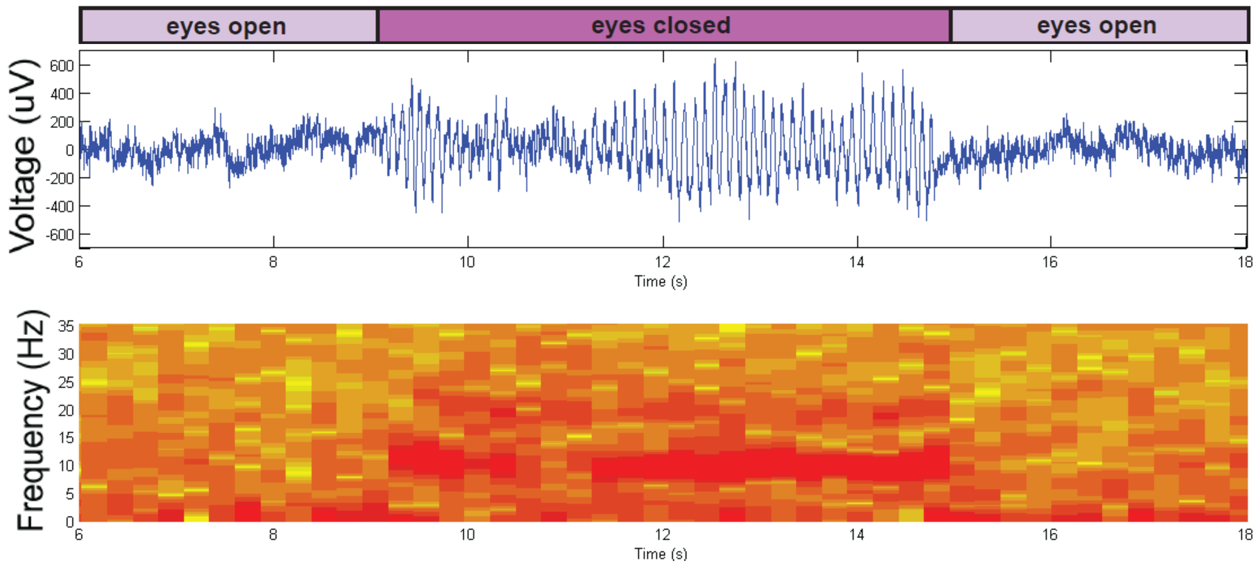

Fig. 5. Raw data (top) and spectrogram (bottom) of eyes open compared with eyes closed. Distinct alpha waves are visible during the eyes closed period both in the raw data as well indicated by the strong band around 10 Hz in the spectrogram

B. Performance Parameters

The following four parameters were used to evaluate the performance of our system.

- **Sensitivity** – algorithm's ability to detect drowsiness when subject is actually drowsy

$$Sensitivity = \frac{true\ positive}{true\ positive + false\ negative} \quad (1)$$

- **Specificity** – algorithm's ability to detect the lack of drowsiness when the subject is not drowsy

$$Specificity = \frac{true\ negative}{true\ negative + false\ positive} \quad (2)$$

- **Positive predictive values** – indicate meaningfulness of the positive result from the algorithm

$$Positive\ \mathrm{Pr}edictive\ Value = \frac{true\ positive}{true\ positive + false\ positive} \quad (3)$$

- **Negative predictive values** – indicate meaningfulness of the negative result from the algorithm

$$Negative\ \mathrm{Pr}edictive\ Value = \frac{true\ negative}{true\ negative + false\ negative} \quad (4)$$

Since the concern is that the algorithm would miss the detection of actual drowsiness, our goal is to have high sensitivity and negative predictive value even at the cost of lower specificity and positive predictive value. However, an overly sensitive algorithm would produce many false positives, which would in turn actually decrease negative predictive value of the algorithm.

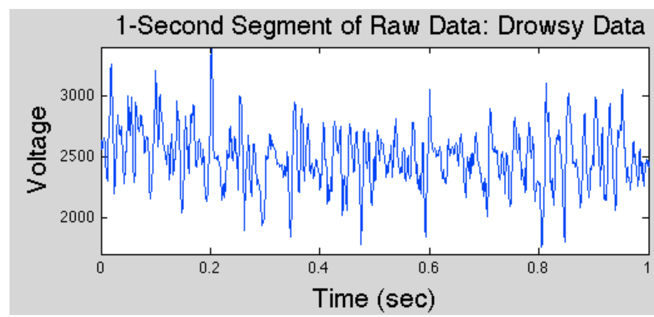

Fig. 6. a. one-second samples of raw drowsy signal

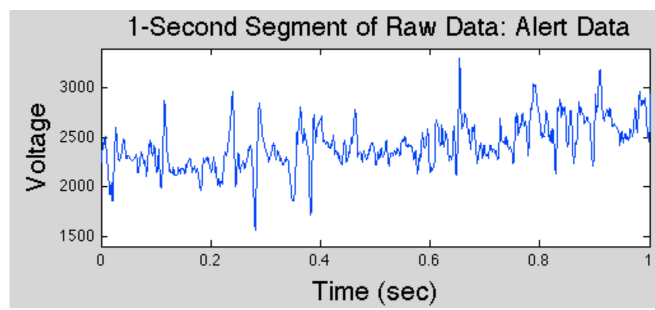

Fig. 6. b. one-second sample of raw alert signal

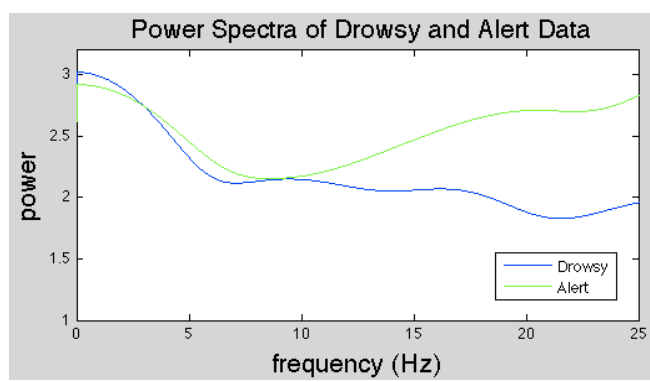

Fig. 6. c. A comparison of the power spectra of drowsy and alert data.

C. Results

The data acquired were divided into 1-minute segments, resulting in a sample size of n=239. The highest sensitivity level achieved was 0.863, at a threshold level of 0.1%. The highest negative predictive value achieved was 0.604, at a threshold level of 1%. This was as expected, because at low threshold values, the algorithm will be the most sensitive in detecting changes in the activities of the three waves, thus producing more true positives as well as false positives. The highest positive predictive value achieved was 0.813, at 5%. This was expected as well, because at higher threshold values, the algorithm will pick up fewer false positives.

The raw plots of representative alert and drowsy data is shown in Fig. 6.a. and Fig. 6.b. A difference in the two data is observable. Also, a power spectrum of each data was plotted, showing the difference in the level of alpha, beta, and theta waves (Fig. 6.c.). The drowsy data shows lower levels of alpha and beta waves than the alert data, as expected.

IV. Discussion

Our one channel wireless EEG system was able to provide simple drowsiness detection. The pronged dry electrodes allowed for contact with scalp through hair without need for uncomfortable gels. The overall design was comfortable for hours of wear and required a quick setup time of less than 15 minutes. This is a proof of concept, and additional testing is needed to reveal information about the repeatability and variations of the system. A higher sensitivity and positive predictive value would also be more desirable. One possible way to improve these two parameters is to modify the algorithm so that drowsiness is detected via multiple segments of smaller time frames of data. While signal processing and analysis were performed on collected data sets, these can be easily programmed onto a microprocessor and run in real time. Additionally, further engineering can reduce the size of the PCB wireless base unit as well as its power consumption. In this paper, we focused on using wireless EEG for commercial use in drowsiness detection, however, a similar system can be used for health monitoring in the home.

Acknowledgment

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