Real Time Workload Classification from an Ambulatory Wireless EEG System Using Hybrid EEG Electrodes

R. Matthews, P.J. Turner, N. J. McDonald, K. Ermolaev, T. Mc Manus, R.A. Shelby, & M. Steindorf

***Abstract*—This paper describes a compact, lightweight and ultra-low power ambulatory wireless EEG system based upon QUASAR's innovative noninvasive bioelectric sensor technologies. The sensors operate through hair without skin preparation or conductive gels. Mechanical isolation built into the harness permits the recording of high quality EEG data during ambulation. Advanced algorithms developed for this system permit real time classification of workload during subject motion.**

Measurements made using the EEG system during ambulation are presented, including results for real time classification of subject workload.

I. Introduction

QUASAR is currently developing an integrated Physiological Sensor Suite (PSS) for monitoring the physiological and cognitive states in operational (i.e. non-clinical) settings [1]. This paper describes the EEG module of the PSS system, which has been designed to be wearable and unobtrusive, with an emphasis on the capability of long-term monitoring of EEG signals. These factors are of considerable importance in operational settings where high end-user compliance is required.

The opportunities for measuring physiological variables have been recognized by two recent major programs: the Defense Advanced Research Projects Agency's (DARPA) Augmented Cognition (AugCog) program [2] and the U.S. Army's Warfighter Physiological Status Monitor (WPSM) program [3]. However, those programs were limited in the number of physiological variables they could simultaneously measure and by inadequate development of fully deployable noninvasive sensors and a full complement of integrated sensors.

The PSS is based on a revolutionary noninvasive bioelectric sensor technology pioneered by QUASAR. No modification of the skin's outer layer is required for the operation of this sensor technology, unlike conventional electrode technology that requires the use of conductive pastes or gels, often with abrasive skin preparation of the electrode site.

The EEG system described in this paper is based upon a hybrid (capacitive/resistive) bioelectrode capable of measurements of through-hair electroencephalograms (EEG) [4]. The PSS also uses QUASAR's capacitive bioelectrodes, which are capable of through-clothing measurements of electrocardiograms (ECG) [4], [5], and measurements of electromyograms (EMG) and electrooculograms (EOG).

The EEG module of the PSS has been incorporated into a soldier's Kevlar helmet and successfully tested during combat training. Data is acquired using a miniature, ultra-low power microprocessor-controlled multichannel data acquisition (DAQ) unit that transmits data wirelessly to base station/data logger worn by the subject. The DAQ unit is worn on the body close to the measurement point, reducing the amount of cable clutter, and minimizing the impact on subject mobility without introducing motion artifacts [6], [7].

Military applications of the PSS include monitoring of physiological states for Dismounted Infantrymen, or cognitive state monitoring for Command & Control personnel. Civilian applications include sleep monitoring, outpatient monitoring of patients diagnosed with cardiac or neurological conditions, or computer interfaces for gaming.

II. Hardware

A. QUASAR Hybrid Biosensors

The hybrid biosensor (Fig. 1) uses a combination of high impedance resistive and capacitive contact to the scalp. Electrical contact is made via a set of 'fingers,' each of which is small enough to reach through hair and make electrical contact to the scalp between hair follicles. An integrated impedance measurement confirms that scalp contact has been made. The contact impedance between the scalp and each finger can be as high 10^7 Ω.

Fig. 1. QUASAR hybrid EEG biosensor (with a US 5 cent coin for scale).

These fingers are attached to the electrode, which forms the inner circular section of the sensor in Fig. 1. The inner circular section is sprung to follow the head contour. The amplifier electronics are shielded and mounted immediately behind the electrode in order to limit interference caused by

Manuscript received April 7, 2008. This work was supported in part by the U.S. Department of Defense. All authors are from QUASAR, San Diego, CA 92121 USA.

R. Matthews (President) e-mail: robm@quasarusa.com
P. J. Turner e-mail: peter@quasarusa.com
N. J. McDonald e-mail: neil@quasarusa.com
K. Ermolaev e-mail: konstantine@quasarusa.com
T. McManus e-mail: tobin@quasarusa.com
R.A. Shelby e-mail: rshelby@quasarusa.com
M. A. Steindorf e-mail: msteindorf@quasarusa.com

the pickup of external signals.

B. *Common-Mode Follower (CMF) Technology*

QUASAR's proprietary common mode follower (CMF) technology [5] is a separate biosensor that is used to reduce the sensitivity of the biosensors to common mode signals on the body. It operates by measuring the potential of the body relative to the ground of the amplifier system. The ultra-high input impedance of the CMF (~10^{12} Ω) ensures that the output of the CMF tracks the body-ground potential with a high degree of accuracy.

The output of the CMF is used as a reference for bioelectric measurements by QUASAR biosensors so that the common-mode signal appearing on the body is dynamically removed from the measurement, typically achieving a common-mode rejection ratio (CMRR) of 50 to 80 dB. A further improvement in CMRR can be achieved by differencing sensor pairs.

C. *Sensor Harness*

The EEG harness shown in Fig. 2 is designed to fit under the Kevlar helmet of a soldier. The array is anchored to a standard helmet harness, and there is mechanical isolation system that isolates the array from helmet motion during strenuous activity.

Sensors are positioned at the nominal C_Z, C_3, C_4, F_Z, F_3, F_4, and P_Z 10-20 array positions. The sensors are referenced to a CMF placed at P_4. The ground reference for the CMF is provided by a conductive cloth incorporated into the forehead part of the headband. A second reference using conductive cloth is incorporated into the chinstrap (to provide some redundancy for subjects with abundant hair across the forehead).

The harness (with Kevlar helmet) has been worn without discomfort for periods up to 3 hours by solders performing combat tasks. Similarly, the harness has been worn in excess of 4 hours without discomfort in the absence of the helmet.

Fig. 2. Hybrid sensor array incorporated into a soldier's Kevlar helmet. Left: The outer aluminium ring and weights load the harness correctly when the helmet is not present. Right: EEG system with helmet attached and ready for use, including wireless module.

D. *Miniature Low Power Data Acquisition (DAQ) Unit*

The DAQ unit was designed to address the general requirements for multichannel EEG, ECG, EOG, and EMG data acquisition. The device shown in Fig. 3 uses 16 bit sigma-delta analog-to digital converters to simultaneously acquire up to 12 channels of EEG data. In environments with high levels of electromagnetic interference, the resulting common-mode signals may not be completely removed by the CMF, so the DAQ was designed to have a high CMRR between channels.

All analog channels are matched to better than -72 dB between 1-50 Hz. The input noise of the DAQ channels has been measured to be 400 nV/√Hz for a sampling rate of 4 kHz. The timing error between ADC channels is less than 1 μs (i.e. a phase error less than -80 dB below 100 Hz).

The DAQ is capable of simultaneously acquiring 12 channels of data at rates up to 1000 samples per second (sps). The EEG module acquires data at a rate of 240 sps. Aliasing of out-of-bandwidth signals is less than -80 dB between 1 Hz and 50 Hz. The total harmonic distortion is less than -75 dB at 35 Hz.

In order to conserve power the microprocessor operates in a low-power "sleep" mode when not acquiring data. Nevertheless, power consumption is dominated by the DAQ section. The run time for the DAQ unit with 8 channels of EEG is in excess of 80 hours from 2 AAA batteries.

The weight of the DAQ unit, including its enclosure, and 8 sensors is 170g.

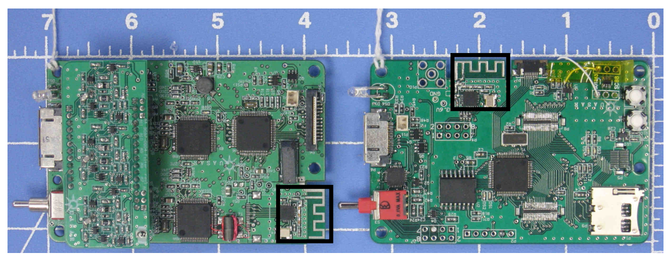

Fig. 3. Left: 12 channel DAQ and wireless EEG system. Analog signal conditioning is confined the left hand third of the board. Right: Base station, with USB connection at the left, and a FLASH RAM card slot at the lower right. The two outlined areas correspond to the wireless electronics (including antenna). For scale, the area of each board is slightly smaller than a standard credit card.

E. *Miniature Low Power Wireless Transceiver and Base Station*

The DAQ unit possesses a short range wireless transceiver that forms a Personal Area Network (PAN) with a custom Base Station (also shown in Fig. 3). Communication is via a Gaussian Frequency Shift Keying (GFSK) protocol that has the ability to use 125 channels of the RF range between 2.400 GHz and 2.525 GHz of the Worldwide ISM band.

To conserve power, the wireless transceiver transmits information in a data "burst" mode, and data rates up to 2.5 ksps have been achieved. The Base Station is a small, low-power, microprocessor-based unit that communicates wirelessly with one or more DAQ unit worn by the subject, enabling consolidation of data collected from multiple sites on the subject (e.g. EEG and ECG measurements in the PSS). The Base Station is worn on the subject's hip or carried in a backpack, and logs data to FLASH RAM for storage. A 2 GB memory card can store up to 4 days of 12-

channel EEG data. The Base Station also communicates with external systems via proprietary, 802.11 or Bluetooth wireless protocols, Ethernet, USB 1.1 or 2.0, or RS-232.

In Fig. 3 the outlined section is the board area required for the wireless components, including the antenna. An external stub antenna can be fitted to the base station to increase the effective range of the wireless communication.

III. Measurements

QUASAR's EEG system has been extensively tested under simulated operational conditions at QUASAR. Additional validation testing has been performed on two subjects at a Future Combat Systems technology demonstration (at the Boeing facility in Huntington Beach CA); on four subjects at a Honeywell facility in Minneapolis, during a NATICK data gathering exercise; and on two solders performing combat tasks in a realistic training environment at the Aberdeen Test Center, MD. Classification accuracy of cognitive workload from subjects at Aberdeen reached 90% or higher for both participants for 10 seconds of temporal smoothing [8].

In all of the following measurements no preparation of the scalp was performed at the hybrid electrode sites. In order to ensure effective contact electrode to the scalp some initial rotational agitation is applied to the sensors to work them through the hair until the integrated impedance measurement confirms that scalp contact has been made. EEG data collected at Aberdeen over continuous periods of up to 3 hours demonstrated that no further adjustment of the system is required.

Preparation of the scalp for the wet electrodes included abrasion with Nu-Prep, followed by cleaning with alcohol and then application of Grass EC2 electrode paste.

The results presented in this Section were obtained during trials conducted under simulated operational conditions.

A. EEG Measurements Using Hybrid and Wet Electrodes

The measurements described in this section were performed on a single subject while the subject was seated, with eyes closed, and demonstrates the equivalence of the EEG signals detected by the QUASAR hybrid electrodes and conventional wet EEG electrodes. Simultaneous measurements were made using hybrid/wet electrode pairs positioned at the nominal C_Z and F_Z positions. Less than 5 mm separated the hybrid and wet electrodes placed at each position, and care was taken to prevent the electrode paste forming an electrical short between the two electrodes.

Fig. 4 presents a comparison between EEG data recorded using QUASAR's hybrid sensor technology and conventional wet electrodes. Data for C_Z and F_Z are shown separately, with hybrid and wet electrode data overlaid to illustrate the similarity in the signals measured. Alpha activity is observed in each electrode, and the correlations between hybrid and wet electrodes are in excess of 90% at both electrode sites.

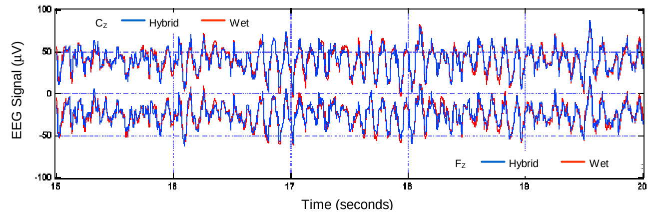

Fig. 4. Comparison of EEG data (eyes closed) recorded using hybrid and wet electrodes. The data are high pass filtered at 1 Hz and low pass filtered at 30 Hz with 8th order Bessel filters.

B. EEG Measurement During Subject Motion

The measurements described in this section demonstrate the fidelity of EEG data recorded using the wireless EEG system during subject motion. The subject's EEG was measured with the subject seated, and another measurement was made while the subject was walking on a treadmill at 2 mph.

Fig. 5 presents a comparison between EEG data recorded with subject sitting (upper trace) and with subject walking on a treadmill at 2 mph (lower trace) measured with QUASAR's wireless EEG system. Both sets of data show similar levels of brain activity.

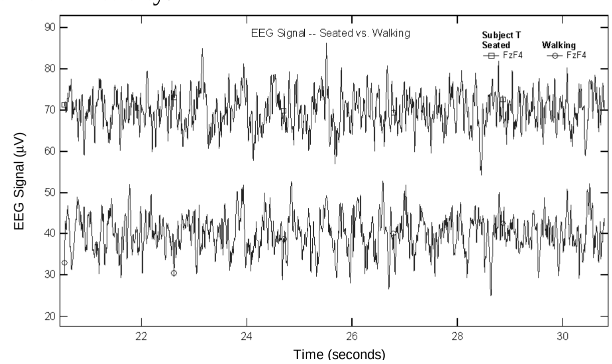

Fig. 5. Representative difference data for the F_ZF_4 electrode sites when the subject is sitting (upper trace) or walking on a treadmill at 2 mph (lower trace). The data are high pass filtered at 1 Hz and low pass filtered at 30 Hz with 7th order Bessel filters.

C. Cognitive State Classification Methodology

The EEG data is processed in two stages: A preprocessing stage for artifact removal, and generation of the classifier feature vector. Feature vectors from training data sets are used, following the general methods described by Abdi [9], to generate a proprietary real time classifier developed by QUASAR, which is subsequently used for classification of EEG data in real time. This classifier is robust with respect to motion artifact, and has been stabilized against daily variations in the physiological state of the subject.

D. Real Time Classification of Workload

Fig. 6 shows the result for real time classification for a subject walking at 2 mph on a treadmill and performing N0 (low) and N3 (high) workload tasks. Two trial data sets were first collected to train a workload classifier: a passive trial, during which the subject listened to music, and a trial in which the subject performed a divide-by-seven task. The classifier was then used to obtain the real time classification results in Fig. 6.

The vertical axis is the probability that the subject is undergoing a high workload task. The N0 task shows a low probability (always less than 30%); the N3 task shows a significantly higher probability, reaching 100% on numerous occasions.

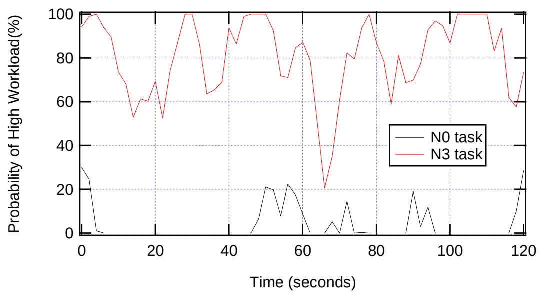

Fig. 6. Real time classification while subject was walking at 2 mph on a treadmill and performing an N0 task and an N3 task. Two trial data sets were collected to train the classifier at different workload levels: a passive trial, during which the subject listened to music, and a trial in which the subject performed a divide-by-seven task.

Fig. 7 is an illustration of QUASAR's EEG system being used for real time classification of cognitive workload and engagement while subjects play a first-person shooter video game. The methodology used at QUASAR includes a split screen video-recording system that logs the game progress and an image of the player so that during post processing it will be possible to independently evaluate the engagement and workload of the player, and later correlate this assessment with the real time classification results.

Fig. 7. A test system for assessing workload and engagement of computer gamers.

During these measurements the base station was connected to a laptop computer and the physiological data and classification were displayed in real time. Classifiers were constructed for each subject using three training data sets: data collected during passive viewing of the game, while fighting two enemies in the game, and while fighting 25 enemies in the game. The classifier for a given subject was then used to perform real time classification of workload while the subject was playing the game.

A screen capture for the subject engaging 25 enemies is shown in Fig. 8. An estimation of the cognitive state of the subject is calculated in real time and is given by the workload indicator on the right of the screen, which is a combination of two separate classifiers: a Workload classifier (High/Low) and an Engagement classifier (Engaged/Disengaged). The workload indicator in Fig. 8 shows the subject's workload as High, which is an accurate reflection of the workload at this level of difficulty in the video game.

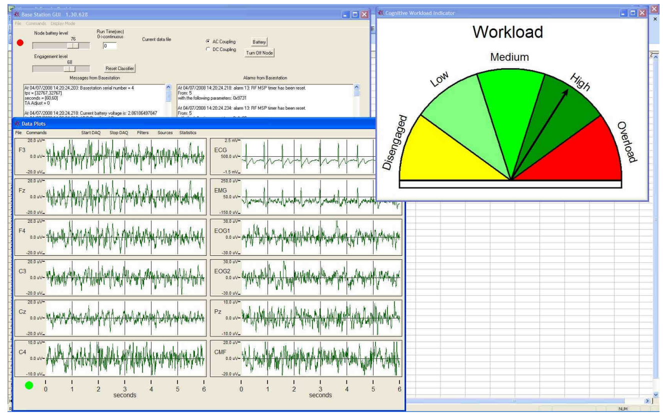

Fig. 8. Laptop screenshot showing data collection and engagement classifier running on the gaming subject of Fig. 7. The six traces on the left are EEG signals at F_3, F_Z, F_4, C_3, C_Z, and C_4 respectively. The right hand six traces show ECG, EMG at the back of the neck, EOG sensors at the left and right of the eyes, EEG at Pz and the CMF output (not used for classification, but useful to monitor system performance). The Workload indicator shows the real time output of the classifier.

Table I presents the classification accuracies for each classifier for a series of tests conducted on 4 separate days (over a period of 10 days). Intrasession cross validation for each day was performed using 60% of the data for training, and 40% for classification, and repeating this process 8 times. Real time classification accuracies are also presented for data in which the training data sets are from one day, and classification was performed during testing on a subsequent day. The 4 days of testing have been paired as shown in the Table because the protocol was altered to 32 enemies for 5th and 6th April due to an increased proficiency of the subject at playing the video game.

TABLE I
CLASSIFICATION ACCURACY

Training Data Set/ Classification Data Set	Workload Classifier	Engagement Classifier
Cross Validation 28th March	83.6%	89.1%
Cross Validation 1st April	86.1%	88.2%
Cross Validation 5th April	83.4%	84.9%
Cross Validation 6th April	73.8%	84.3%
28th March / 1st April	81.4%	81.1%
5th April / 6th April	74.8%	78.8%

The results in Table I demonstrate that the Workload and Engagement classifiers routinely achieve greater than 80% classification 8 seconds of temporal smoothing. Similar classification accuracies are also found when the training data sets are taken from a different day, demonstrating the classifiers' robustness to daily variations in physiological state.

IV. CONCLUSION

Measurements have been presented to demonstrate that QUASAR's hybrid EEG electrodes provide data of quality similar to that of conventional wet electrodes. Additional measurements using wireless EEG hardware developed at QUASAR have demonstrated that there is no loss in EEG signal fidelity during subject motion. QUASAR's hardware has been integrated with robust classifiers developed at QUASAR that enable real time determination of cognitive workload.

QUASAR has developed a modular, compact, lightweight and ultra-low power wireless ambulatory EEG system that uses hybrid EEG electrodes. The noninvasive nature of QUASAR's EEG system (i.e. zero skin preparation, minimal wiring) permits greater subject freedom of motion and considerably improves user compliance for such systems. The system is readily expandable to include additional sensor technologies, thereby forming a comprehensive body-worn sensing system capable of real time monitoring of a subjects cognitive and physiological status.

Applications of the EEG system extend beyond cognitive state determination to medical applications, such as the monitoring of patients with epilepsy or other neurological conditions, and to computer interfaces for the disabled.

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