Low-Cost EEG-based Sleep Detection

Bryan Van Hal, Samhita Rhodes, Bruce Dunne-*IEEE Member* and Robert Bossemeyer-*IEEE member*

***Abstract*— A real-time stage 1 sleep detection system using a low-cost single dry-sensor EEG headset is described. This device issues an auditory warning at the onset of stage 1 sleep using the "NeuroSky Mindset," an inexpensive commercial entertainment-based headset. The EEG signal is filtered into low/high alpha and low/high beta frequency bands which are analyzed to indicate the onset of sleep. Preliminary results indicate an 81% effective rate of detecting sleep with all failures being false positives of sleep onset. This device was able to predict and respond to the onset of drowsiness preceding stage 1 sleep allowing for earlier warnings with the result of fewer sleep-related accidents.**

I. Introduction

Operator fatigue and drowsiness is a serious safety issue in many forms of transportation [1], [2]. Currently, there are two approaches to drowsiness detection: driving pattern based detection, and eye closure detection. Driving pattern based detection is triggered by sensing driver control errors that occur due to falling asleep at the wheel. The drawback with this approach is that once effects become noticeable, it may already be too late to prevent an accident. Alternatively, the eye closure detection approach utilizes a vision system to track the eyes of a driver to determine if they are closed. This approach allows for earlier detection of driver drowsiness than driving pattern detection, but it is limited by the accuracy of the vision system used to sense eye closure.

Recent new techniques based on changes in body physiology as a function of fatigue are now being used to detect the onset of sleep. One such method is the use of signals recorded from scalp electrodes that measure patterns of changing electrical activity in the brain from a state of complete alertness to fatigue and drowsiness. The process of recording these signals is known as Electroencephalography (EEG). EEG has been used to detect the stages of sleep since the 1930s [3]. It has also been clinically used to monitor driver and pilot drowsiness [4], [5]. However, these medical grade EEG devices are impractical for everyday driver drowsiness detection since they require the use of expensive equipment and complicated skin preparation with conductive gel for effective monitoring. To circumvent this issue, commercially available entertainment-based headsets that detect EEG signals have recently been introduced. These devices use a single dry-electrode to record EEG signal power in select frequency bands (as opposed to medical grade EEG that uses multiple electrodes, attached with conductive gel and adhesive, to record EEG signal power at multiple locations). These simple and cheap systems offer an attractive target for research efforts into effective driver drowsiness detection systems using EEGs. One such low cost EEG headset is the NeuroSky Mindset [6]. This device is shown below in Figure 1.

B. Van Hal is with GE Aviation, Grand Rapids, MI 49512 USA (email: bryanm.vanhal@ge.com).
S. Rhodes is with the School of Engineering, Grand Valley State University, Grand Rapids, MI 49504 USA (phone: 616-331-6267; fax: 616-331-7215; e-mail: rhodesam@gvsu.edu).
B. Dunne is with the School of Engineering, Grand Valley State University, Grand Rapids, MI 49504 USA (e-mail: dunneb@gvsu.edu).
R. Bossemeyer is with the School of Engineering, Grand Valley State University, Grand Rapids, MI 49504 USA (e-mail: bossemer@gvsu.edu).

II. Sleep Detection Method

A. Brain Activity during and preceding Sleep

Traditional methods of frequency domain analysis of EEG activity for studying sleep has centered around four major bands of frequencies as shown in Table I.

TABLE I. EEG Frequency Bands for Sleep Detection

Sleep Stage versus Frequency Band		
Stage	***Band***	***Range***
Adult slow wave	Delta	<4Hz
Drowsiness	Theta	4–7Hz
Resting, relaxed	Alpha	8–16Hz
Alert	Beta	17–30Hz

Sleep is broken into four stages. Stage 1 is the transition from wakefulness to sleep, during which a person can be woken easily, and may not be aware that they were sleeping. Here, EEG signals are low amplitude and low frequency. During stage 2 sleep, body temperature decreases and the heart rate slows. In stage 2, alpha waves are periodically interrupted by alpha spindles which are 12-14Hz bursts of brain activity that last at least half a second [7]. Stages 3 and 4 are progressively deeper stages of sleep. Rapid Eye Movement (REM) sleep follows stage 4. During REM sleep, dreaming occurs and brain activity increases. The sleeper continuously cycles through each of these stages throughout the sleeping period.

Figure 1. NeuroSky Mindset Single EEG Headset

The majority of brain activity during the transition from wakefulness to sleep occurs in the frontal and occipital lobes. In the transition from wakefulness to sleep, alpha activity moves from the occipital to the frontal lobe. High occipital lobe activity is associated with relaxed wakefulness. In general, frequencies from 1Hz to 16Hz increase while approaching sleep, while frequencies 17Hz and higher decrease. This pattern continues after the onset of sleep, except that power in the 8–11Hz range begins to increase as well. The change in the 8–11Hz signal is especially noticeable in the occipital region where the signal diminishes and transitions to the frontal lobe [8]. During stages 2-4, delta activity in the frontal lobe increases and theta activity in the occipital lobe increases [9]. A viable approach is to detect sleep onset by observing these changing features in the brain during the transition from wakefulness to sleep.

B. *Comparable Sleep Detection Approaches*

One real-time EEG-based sleep detection system focuses on three critical parameters in EEG recordings: waveform amplitude, waveform frequency, and duration of synchronization of the waveform (time the amplitude exceeds a detection threshold for a particular frequency band) [10]. Settings include a 50μV predefined voltage threshold, focus frequencies of 8–12Hz (Alpha) and 11.5–15Hz (low Beta). Two counters are used to detect the EEG threshold crossing: one to track the number of sequential pattern matches indicative of sleep; a second counter to track the number of sequential non-matches. A frequency, amplitude and duration match increments the first counter; a non-match increments the second counter. A match count of ‘3’ indicates sleep while a non-match count of ‘8’ indicates wakefulness. This method proved highly accurate in detecting alpha-spindle epochs. In addition, the method was able to detect about 12.2% more epochs than visual scoring. While this method may be modifiable to detect stage 1 sleep, the presence of alpha-spindle epochs indicates a deeper stage of sleep. Hence, this approach is not currently applicable to the detection of sleep onset.

In another approach, an algorithm was designed for the detection of drowsiness in drivers, assuming a gradual transition towards sleep [11]. The algorithm classified drowsiness/fatigue EEG signals into transitional (early fatigue phase), transitional–posttransitional (medium fatigue phase), posttransitional (extreme fatigue phase and early stage 1 of sleep), and arousal phases (emergence from drowsiness). The signal was separated into delta, theta, alpha, and beta waves. An EEG baseline was recorded before the subject was drowsy. From this baseline, the mean and standard deviation for each of the frequency bands was computed. The algorithm included coefficients to allow for fine-tuning a threshold for each frequency band. A maximum threshold was also hard coded to remove outliers. Data were analyzed in blocks of thirty seconds and this algorithm demonstrated a 10% error rate in sleep detection.

Both of the above methods utilize a multi-sensor EEG configuration. In one study [12], the frequency domain analysis of EEG collected from the Neurosky dry-sensor EEG device was considered. The frequency content of the signal was divided into clinically relevant frequency bands alpha, beta, and theta waves. It was expected that, as in clinical studies, alpha and beta waves would decrease when drowsy and theta waves would increase in stage 1 sleep. The investigators found that alpha and beta waves did decrease when drowsy, but theta waves remained constant. These results suggest that EEG signals obtained from low-cost EEG devices like the Neurosky Mindset are useable for drowsiness detection schemes.

C. *Our Low-Cost Simplified Sleep Detection System*

We designed a system incorporating the Neurosky Mindset, with a single dry-sensor electrode attached to the forehead at position Fp1 (see Figure 2. [13]) and grounded with three electrodes on the ear (along with supporting portable hardware and software) to detect the onset of stage 1 sleep in real-time. This system records a single EEG signal (at 512Hz) and automatically splits the signal into delta (0.5–2.75Hz), theta (3.5–6.75Hz), low alpha (7.5–9.25Hz), high alpha (10–11.75Hz), low beta (13–16.75Hz), high beta (18–29.75Hz), low gamma (31–39.75Hz), and mid gamma (41–49.75Hz) frequency bands. The Mindset further makes this sampled data available wirelessly through a Bluetooth interface for further processing on an external microprocessor board. As processed on the external board, time-frequency analysis monitors the changes in these bands over time. Stage 1 sleep is indicated when the amplitude of the raw signal is low, and signal power in higher frequencies has been attenuated. The comparable methods previously described are now combined in our algorithm to include the counting approach of [10] (to reduce false positive assertion) combined with the algorithm approach of [11]. Finally, when the EEG transitions resemble that of stage 1 sleep, the device produces an auditory alarm.

Initially, and for the first 30 seconds, baseline “wake” data is collected to calculate threshold levels. The power in each of the frequency sub-bands alpha low (A_L), alpha high (A_H), beta low (B_L) and beta high (B_H) is calculated, and the mean and standard deviation of these power measurements are computed. From the mean and standard deviation results, thresholds are determined to be used to increment or decrement a sleep-indication counter. Six such thresholds are calculated for the following frequency bands for both sleep and wake states: low alpha sleep (A_{LST}) and wake (A_{LWT}), high alpha sleep (A_{HST}) and wake (A_{HWT}), low beta sleep (B_{LST}) and wake (B_{LWT}) and high beta sleep (B_{HST}) and wake (B_{HWT}).

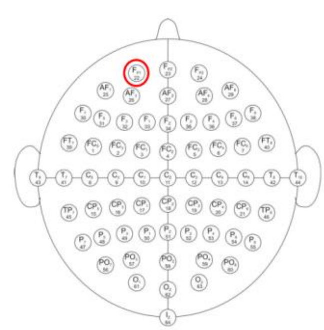

Figure 2. Placement of Single Electrode at Fp1

The computation of each of the thresholds is similar as

$$X_{bmT} = x_{bm1} X_{bM} + x_{bm2} X_{bSD} \,, \tag{1}$$

where 'X' indicates the frequency band (restricted to *A-alpha* and *B-beta* bands), with 'b' indicating L-low or H-high sub-band and 'm' mode (S-sleep or W-wake). X_{bM} and X_{bSD} are the particular frequency band X mean and standard deviation, respectively, and x_{bm1} and x_{bm2} are heuristically derived proportionality constants associated with this X frequency band, b sub-band and m mode. These proportionality constants are determined by relating the mean and standard deviation of the wake baseline signal to the signal amplitude when sleep is indicated. They are then fine-tuned during debugging to improve response time while limiting false positives. Once determined, these constants are used for each subject without modification. In other words, these values need to be fine-tuned for the specific hardware and software configuration but are not altered once set.

Additionally, using the unfiltered EEG data (denoted as signal 'R'), overall "raw" sleep mean (R_{STM}) and raw wake (R_{WT}) thresholds are computed as

$$R_{STM} = r_{s1} R \,, \tag{2}$$

$$R_{WT} = r_{w1} R_M + r_{w2} R_{SD} \,. \tag{3}$$

Above, R_M and R_{SD} are the mean and standard deviation of the baseline R signal, respectively, and r_{s1}, r_{w1} and r_{w2} are similarly derived heuristic proportionality constants.

Once the baseline is complete and the thresholds computed, the EEG raw data and sub-band data are compared to their respective thresholds in order to update a sleep detection counter at a rate of once per second. The rule for the A_L signal is summarized as

$$A_L \overset{1}{<} A_{LST} \,,\; A_L \underset{1}{>} A_{LWT} \,, \tag{4}$$

which is interpreted as: if A_L is less than A_{LST}, increment the sleep counter by one; conversely, if A_L is greater than A_{LWT}, decrement the sleep counter by one. Similar rules based on the other signals and thresholds to affect the sleep counter are given in the equations below:

$$A_H \overset{1}{<} A_{HST} \,,\; A_H \underset{1}{>} A_{HWT} \,, \tag{5}$$

$$B_L \overset{2}{<} B_{LST} \,,\; B_L \underset{2}{>} B_{LWT} \,, \tag{6}$$

$$B_H \overset{2}{<} B_{HST} \,,\; B_H \underset{2}{>} B_{HWT} \,, \tag{7}$$

$$R \overset{7}{<} R_{STM} \,,\; R \underset{7}{>} R_{WT} \,. \tag{8}$$

When the sleep counter *CNT* reaches and exceeds a predetermined threshold (in our current configuration this counter threshold is 35), sleep is declared and the alarm asserts. Additionally, the Neurosky Mindset has a feature that identifies and flags noisy data. This notification was used to validate the baseline computations insuring that only low-noise signals were used to create the baseline. Lastly, (and in keeping with [11]), a maximum signal threshold "*max*" was used to discard any data with a value inappropriately large to help reject artifacts. The constants used for this configuration are shown in Table II.

III. Testing

A. Implementation

For hardware, the commercially available Arduino Uno board serves as the main processor for the data retrieval and sleep algorithm analysis [14]. The similarly available BlueSMiRF module is the interface between the Neurosky Mindset and the Arduino board. Fig. 3 gives the wiring diagram showing each hardware component.

The algorithm was implemented in the C programming language on the Arduino. A piezoelectric buzzer sounds to indicate that sleep has been detected, producing a 4000Hz sound at 70dBA measured at 12 inches from the device enclosure. LEDs indicate the establishment of a connection to the Neurosky Mindset. The LEDs also indicate the progression toward sleep by displaying the current sleep counter value. Finally, if a poor connection to the headset or poor contact with the scalp is sensed after the baseline has been recorded, the alarm is activated to alert the user that the device is no longer functional.

TABLE II. Sleep Detection Algorithm Constants

Constant Name and Value					
Name	***Value***	***Name***	***Value***	***Name***	***Value***
a_{LS1}	0.7	a_{HW1}	0.7	b_{HS1}	1.0
a_{LS2}	0.0	a_{HW2}	0.0	b_{HS2}	−0.53
a_{LW1}	0.8	b_{LS1}	1.0	b_{HW1}	0.9
a_{LW2}	0.0	b_{LS2}	−0.57	b_{HW2}	0.0
a_{HS1}	0.6	b_{LW1}	0.9	r_{W1}	3.0
a_{HS2}	0.0	b_{LW2}	0.0	r_{W2}	0.0
CNT	35	*max*	300.0	r_{S1}	0.6

B. Test Protocol

Three subjects were tested in two different sleep positions, lying down and seated. Only tests which concluded in a false positive or actual sleep were recorded; those tests for which the subject remained awake and the alarm did not activate were discarded. The subjects were informed that they needed to stay awake for a few minutes to record baseline values. Once the baseline was recorded, they were encouraged to fall asleep. Subjects were given the option of trying to immediately fall asleep or wait until they felt drowsy.

IV. Results

A. Sleep Detection Effectiveness

A total of 16 tests were run using the three test subjects. For these 16 tests, drowsiness was correctly detected in 13 or 81% of the cases. In 10 cases, the sleep algorithm indicated sleep an average of about 8.4 seconds after stage 1 sleep was

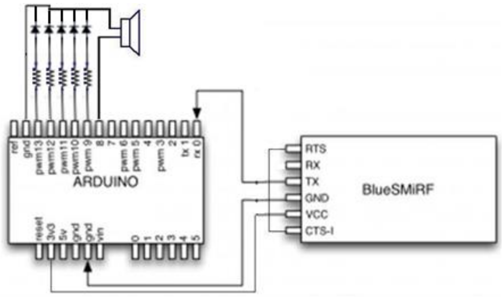

Figure 3. Hardware Configuration of Sleep Detection System

inferred by manually observing the EEG data and monitoring the test subject's appearance. In two cases, the sleep algorithm indicated sleep an average of about 38 seconds before stage 1 sleep was visually inferred. In another case, the sleep algorithm indicated sleep about 13 minutes into a 33 minute session in which stage 1 sleep was never clearly identifiable from visually observing the EEG data.

In three cases, the sleep algorithm indicated sleep before the subject had begun to attempt to sleep; these cases were considered false positives. These false alarms tended to occur almost immediately after the baseline was recorded. Here, the signals registered fairly high levels following the baseline period but dropped suddenly while the subject was awake but attempting to sleep. Finally, it was found that the baseline values in all cases of false positive were higher than other, correctly functioning tests.

B. Validation

To validate the algorithm, three EEG datasets (for which sleep occurred) from an electrode at position Fp0 from physionet.org were used [15]. This data includes defined sleep assertion time points. Following filtering to separate into low alpha, high alpha, low beta, and high beta frequency bands, the data was processed by our detection algorithm. The results from processing this control data closely mirrored the results from real-time live testing.

For all of the control datasets, sleep was detected, but arguably too early. On average, the algorithm indicated sleep approximately 120 seconds before clinical results indicated sleep. A comparison between the clinical reference time point and the algorithm performance is given below in Table III.

TABLE III. COMPARISON OF CONTROL SLEEP DETECTION TIME AND DERIVED DETECTION TIME

Stage 1 Sleep Detection Time Point			
Dataset	***Derived (s)***	***Control (s)***	***Error (s)***
one	968	1226	258
two	1046	1106	60
three	724	766	42

C. Conclusion

The stage 1 sleep detection algorithm herein presented shows potential for use as a simple, low-cost drowsiness detection system. The major deficiency of the algorithm is the false positive assertion of stage 1 sleep for about 20% of the test cases. Examination of these problematic cases has identified that the critical baseline data used in creating the thresholds tends to larger values with higher variance. These differences may be due to variability of the subject's alertness at the start of test (drowsy versus alert) and other arrangements such as test subject position. The variability of the baseline data suggests that improvement in obtaining the baseline thresholds will directly translate into reduction of the false positive rate. Furthermore, the possibility of offline, long-term calibration of each subject's baseline thresholds stored and accessed on an as-needed basis is promising. Lastly, further use of the control data [15] will provide a highly reliable source for improved algorithm development.

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