WakeBand

Wireless Health, Spring 2013

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1. Abstract

Sleep is a mechanism used by the body to revitalize itself and is equally important as nutrition, exercise and stress management. Proper sleep has been proved to be beneficial to learning and memory, and in maintaining body's metabolism and weight. Lack of sufficient sleep makes a person vulnerable to diabetes, cardiovascular disorders and diseases as it alters the immune function of the body. Sleep loss results in irritability, impatience and lack of concentration, thereby causing lapses such as medical errors, air traffic mishaps and traffic accidents [1].

Duration of sleep is as critical as quality of sleep which is affected by the sleep stage in which a person is woken in. Human sleep is characterized by different stages namely REM, NREM1, NREM2 and NREM3 (previously stage 3 and stage 4). Broadly, these stages can be combined into two generic stages, deep sleep (NREM3) and light sleep (REM, NREM1, NREM2). Waking up a user in deep sleep produces greater amount of sleep inertia as opposed to waking a user in light sleep. Sleep inertia is a phenomenon caused due to lack of adequate sleep and is characterized by persistence of physical stages of sleep into waking cycle.

The importance of proper sleep and waking a user in light sleep motivated us to focus our product to handle both the issues and try to make the user as refreshed as possible on waking up.

2. Introduction

As per the data collected by CDC (Centers for Disease Control and Prevention), the percentage of men and women who sleep less than 6 hours a day has increased significantly over the past 20 years. National Sleep Foundation has reported that 1.9 million drivers have fatigue-related car crashes or near misses each year. Research survey results published by 'abc.net.au' indicate that sleep disorders cost Australian economy more than $5 billion a year in health care and indirect costs. The same study has shown that 96% of people wake up tired from sleep. As per the survey conducted by CareerBuilder.com, 19% of the employees are late to work due to lack of sleep. 38% employees admit to falling asleep at work [3]. Oversleeping causes a 50% increase in the risk of diabetes [2].

These figures highlight the importance of sufficient sleep and waking up on time. A lot of interest is being shown in the field of sleep to enhance alarms with sleep staging feature to help wake a person on time and make him or her feel refreshed at the same time. Standard alarms wake up a person without considering the sleep stage the person is at the time of the alarm thereby resulting in the possibility of ringing the alarm in deep sleep, making the person feel groggy. There are some enhanced alarm systems which compute the sleep stages of the user during his sleep and wake him up in light sleep, thereby ensuring that the user feels refreshed on being woken up.

However, these existing systems do not monitor a person's alertness level after waking him up, thus making him vulnerable to fall back to sleep. Hence our new approach is to design a sleep monitoring and waking system, which would wake a user in light sleep and once the user is woken, the system would continue to monitor his alertness levels and blinking activity to make sure that the user does not fall back to sleep. In this paper, we present a complete sleep monitoring and waking system which removes any vulnerability which existing systems possess.

3. Key benefits of the system

3.1 Importance of waking in light sleep stage

3.1.1 Easier to wake up in light sleep stage

Light sleep stages have approximately equal awakening thresholds, which are lesser than those in deep sleep [4]. Hence it is more likely that the user would wake up comparatively quickly from a light sleep stage as opposed to a deeper one.

3.1.2 Lower Sleep Inertia

Sleep inertia is a physiological state characterized by a decline in motor dexterity and a subjective feeling of grogginess immediately following an abrupt awakening, and may interfere with the ability to perform mental or physical tasks. Sleep inertia can also refer to the tendency of a person wanting to return to sleep. [5]

Sleep inertia affects decision making for at least 30 min. Sleep inertia varies with sleep stage at awakening [13]. Subject woken up from light sleep are able to arouse themselves in 3-9 min while those in slow wave sleep take longer time [6]. The effects of sleep inertia may be as bad as being legally drunk [7]. It is important to note, that there is no difference in sleep inertia at awakening between REM, NREM1 and NREM2 [14].

Waking up a user in deep sleep produces greater amount of sleep inertia as opposed to waking a user in light sleep.

3.2 The Snooze Button Problem

'If you hit the snooze button you may go back into deep sleep and you're not supposed to wake from deep sleep — you're supposed to pass to the lighter preparation stage first, then open your eyes. So snoozing creates a huge shock to the body and it makes you feel awful.

If you wake up feeling worse, you'll only be tempted to hit snooze again and then you're in for a vicious cycle.'

- Dr. Neil Stanley, Independent Sleep Expert to The Daily Mail, UK.

The snooze button puts the sleeper back into deep sleep stage and creates a vicious cycle. Although waking up in light sleep reduces sleep inertia, there still is some sleep inertia which may cause the user to fall asleep again, defeating the purpose of waking in a light stage. Hence there is the necessity of a system that prevents the user from falling asleep again during that critical time.

The importance of proper sleep and waking a user in light sleep as well as keeping the user from falling asleep again motivated us to focus our product to handle both the issues and try to make the user as refreshed as possible on waking up.

4. Literature Review

Through the literature review, we identified following research papers and patents to be similar to our study.

- **Title:** Pattern recognition of EEG as a technique for all night sleep stage scoring.
  Authors: W. B. Martin et al

  The authors' purpose of the study of EEG patterns was mainly to compare the performance of computer sleep scoring system with human sleep scorers for all stages of sleep over the entire night.

  Brief explanation of the algorithm

  Input to the system

  While the raw data is live streamed, input of 30 sec epoch data i.e raw data corresponding to 30 sec time interval is analyzed for presence of delta activity.

  Processing by the system

  The first step consists of 1) identifying the peaks as local maximum with no higher local maximum within 0.5 second, 2) identifying valleys as the lowest point between adjacent peaks and 3) connecting peaks and valleys by straight line. The second step consists of computing the number of times cross-correlation between straight line computed in the first step and the raw EEG data is less than 0.75. The third step consists of computing the number of times peak to valley amplitude is less than 75 microvolts.

  Output from the system
  The epoch is classified as deep sleep if the percentage of values observed in the second and the third step is significant.

- **Title:** Systems and Methods for Monitoring Sleep
  Authors: Rubin et al.

Pub No: US 2007/02499552 A1
Pub Date: Oct 25, 2007

This patent describes sleep monitoring and wake up system based on sleep stages.

Brief explanation of their claims

Authors have proposed a system for sleep stage monitoring encompassing primarily two systems. Firstly, a dry electrode for detecting EEG signals a user positioned near the head of the user. Secondly, a sleep stage processor to determine sleep stages of user.

To elaborate the first system, the dry electrode consists of a conductive fabric containing silver, copper, gold or stainless steel. The electrode is proposed to occupy area ranging between 0.25 to 2 square inches. To enable measurement of EEG signals, additional dry electrode is used as an electrical ground.

To elaborate the second system, the sleep stage processor is necessarily a wake up device. The input for the system include exact wake up time for the user as observed daily and more importantly the buffer time before the exact wake up time acting as leveraged time. The significance of this buffer lies in the Neural Network based classification system which wakes up during the transition between REM and non-REM. The output from the system is mainly an alarm capable of emitting at least one of sound, light, vibration or scent. And the output also comprises of sleep stages over the entire night, hypnogram corresponding to sleep stages, sleep debt number, and sleep quality, number of arousals and, time equivalent to going to bed and falling asleep.

The projected limitations

1. Use of training model: Increased memory utilization, necessity to provide training data.

2. Use of overnight monitoring: Increased power utilization.

3. Absence of wake monitoring after alarm: Inability to confirm wakefulness of the user post sleep.

3.a. Absence of blink monitoring: Inability to confirm the absence of regular blinks which might indicate sleep.

3.b Absence of alertness monitoring: Inability to confirm the low level of alertness which necessarily indicates sleep.

4. Absence of feedback about the buffer time before sleep: Inability to adjust buffer time which results in partial reliability on waking during REM transition.

5. Analysis of Approach

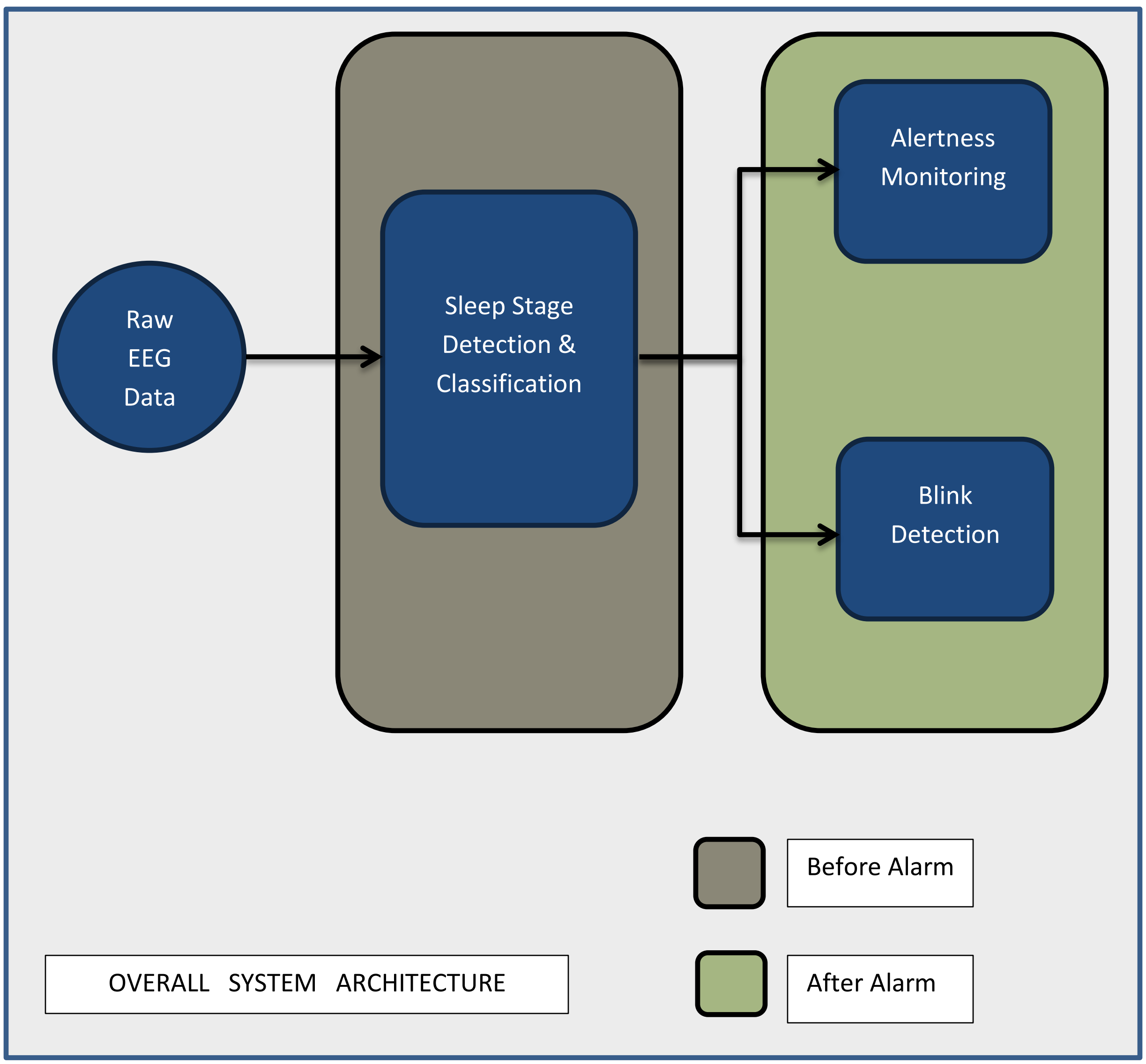
In this section, we give a brief overview of our overall system architecture and its main components.

5.1 System Architecture

Our proposed system consists of three main components:

- Sleep Stage Detection & Classification
- Alertness Monitoring
- Blink Detection

In the below mentioned system, raw EEG data is fed to the Sleep Stage Detection & Classification module. This module processes the raw EEG data and further triggers two modules namely Alertness Monitoring module and Blink Detection module.



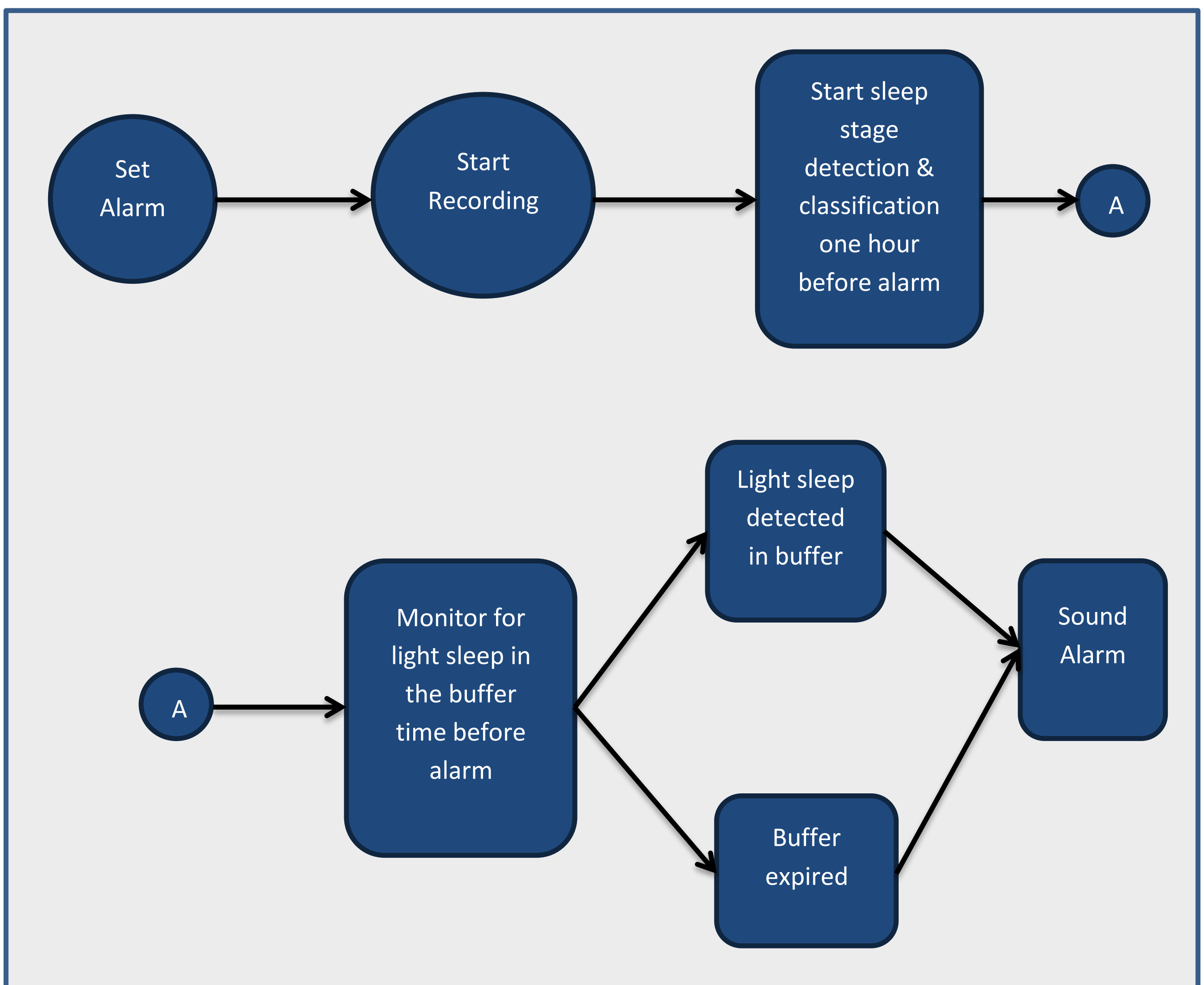
OVERALL SYSTEM ARCHITECTURE

5.2 System Architecture of Sleep Stage Detection & Classification

The system architecture described below consists of following main steps:

- User sets alarm, and enters the buffer time for before and after the alarm (pre-alarm and post-alarm buffer times)
- User starts the recording the brainwave signals
- Sleep Stage Detection & Classification system starts one hour before the scheduled alarm
- In the buffer time before the alarm, the system starts monitoring to detect if the user goes into light sleep
- The system sounds the alarm if:
    - Light sleep gets detected in the buffer time before the alarm

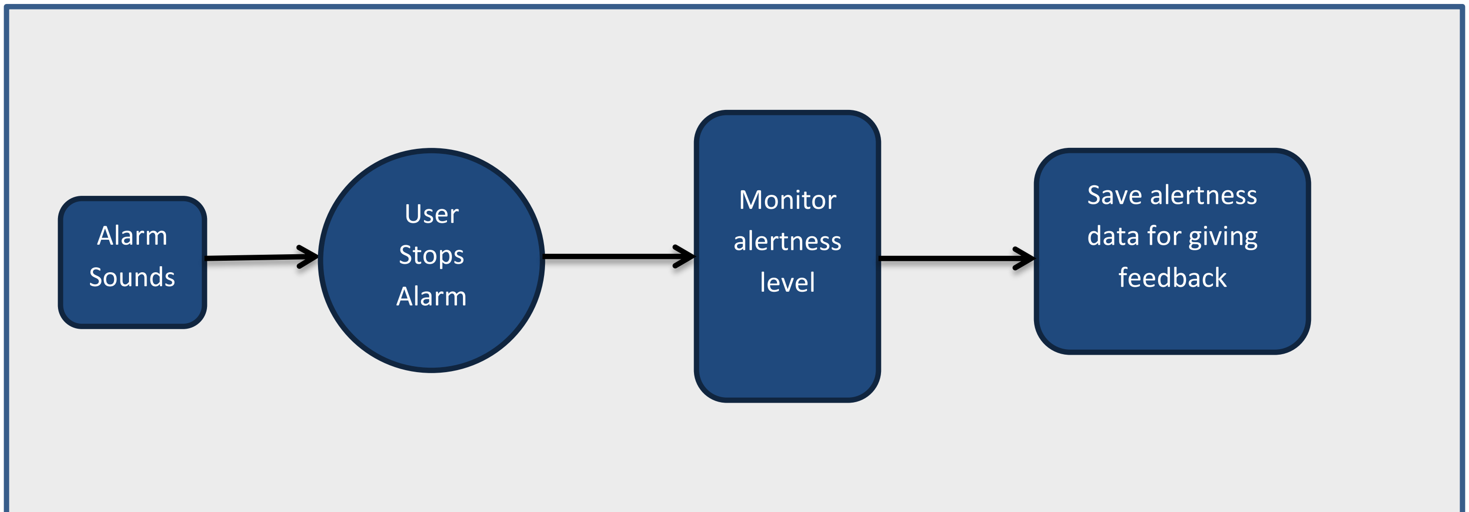
If the buffer time before the alarm expires, then system sounds alarm at the time scheduled by the user



Architecture of Sleep Stage Detection & Classification

5.3 Architecture of Alertness Monitoring

Once the alarm sounds after being triggered by the Sleep Stage Detection & Classification system and user stops the alarm, Alertness monitoring system starts. This system monitors user's alertness level through the buffer period after the alarm. The main purpose of the Alertness monitoring system is to record the alertness level of the user during the buffer time and provide feedback to him about the duration of the buffer time after the alarm.



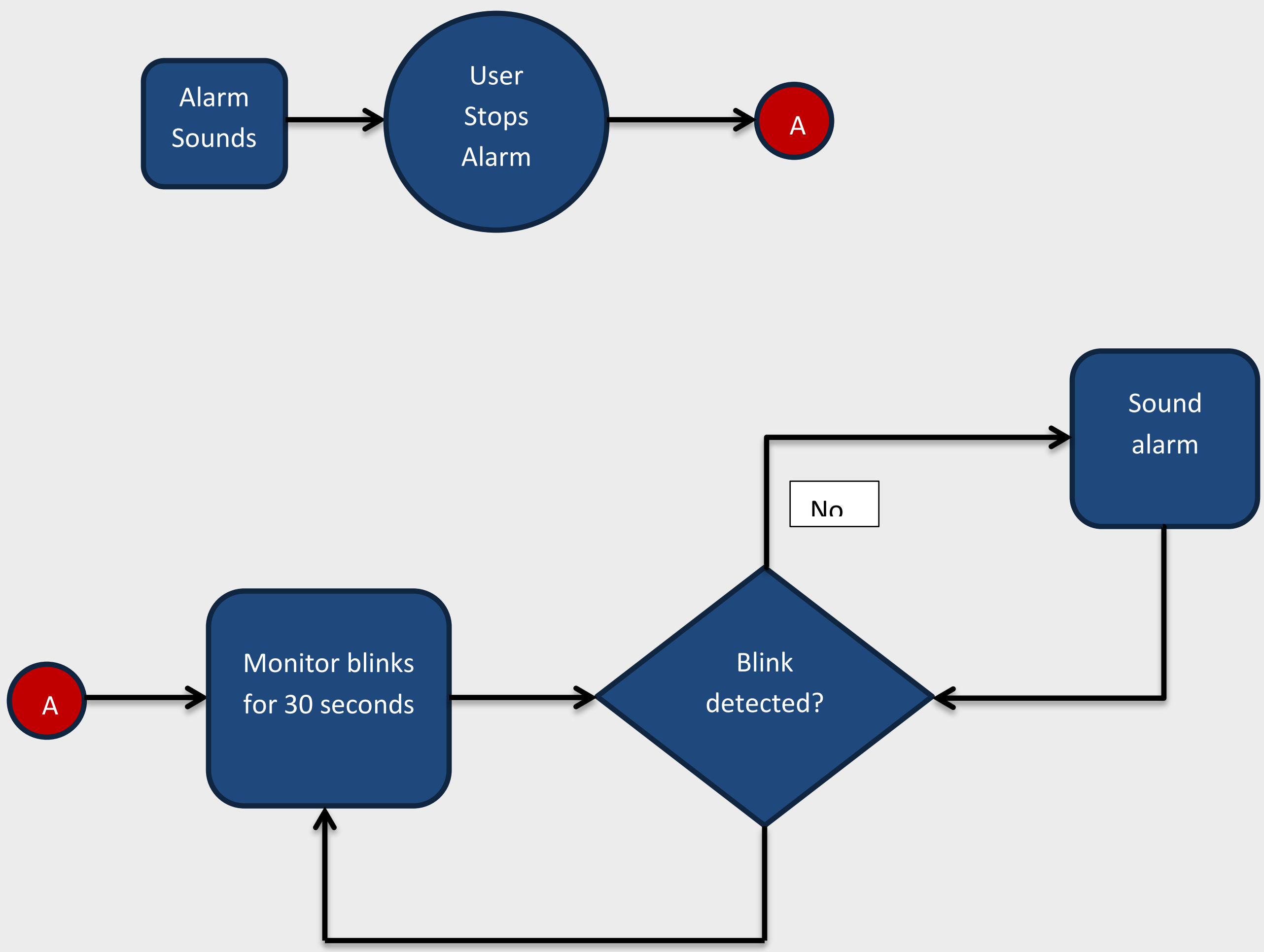
Architecture for Alertness Monitoring

5.4 Architecture for Blink Monitoring System

Once the alarm sounds after being triggered by the Sleep Stage Detection & Classification system and user stops the alarm, the Blink Monitoring system gets initiated.

This system monitors the user's blinks during the buffer period after the alarm. If the system finds that the user is not blinking, then it triggers the alarm and keeps on sounding the alarm until the user starts blinking again.

The main purpose of this system is to prevent the user from falling asleep after being woken up by the scheduled alarm.



Architecture of Blink Monitoring System

5.5 HARDWARE

EEG data was collected using a single channel dry electrode EEG headband from NeuroSky at the forehead. The headband enhances user comfort and dry electrodes give better comfort and convenience. Data is collected at a sampling rate of 512 bps, and transmitted using Bluetooth. Frontal electrodes make blink detection easier since the amplitude of EEG with blinks is much higher compared to that without blinks [8]. Also, frontal electrodes pick up more of slow wave activity [11], which is critical to the detection of deep sleep. More specifically, delta activity is more prominent in anterior regions during NREM3 [12]. As compared to other modalities, EEG gives the highest accuracies in classification [15], [16].

6. UNIQUENESS OF SYSTEM

6.1. Sleep staging without training:

Prior art systems use neural network based algorithms or other machine learning algorithms which might require training data [16], [17]. This would mean identifying the sleep stages and providing sample signals to the software. In order to avoid this training set, we use an algorithm which would not require any training and yet give comparable accuracies.

6.2. Data Cleaning Algorithm to increase accuracy (comparison between w/o dc and w dc results)

The main purpose of the data cleaning algorithm is to process the output of the sleep staging algorithm in order to minimize false positives and preserve true positives of deep sleep. It does this by sliding a window in single steps over the data which checks for the number of positives and thresholds this number. If the number of positives is above the threshold in that window, the entire window is positive, otherwise not. This eliminates noisy false positives. Data Cleaning is performed on an interval of 30s. If the thresholding step does not detect any positives, the threshold continuously adapts to confirm this. If there still aren't any positives, it means deep sleep is absent in that duration. If deep sleep is detected, the point in time where it begins is noted and the threshold is kept higher before that point and lower later on. This adaptive thresholding ensures true positives are retained.

In terms of online processing, the data is updated only every 30s, but in terms of offline processing, time resolution of greater than 30s can be achieved with this method. This gives an added benefit over the sleep scoring as recommended in the R & K manual [18]. Hence an often criticized flaw of the R & K manual with regard to its temporal resolution is overcome [19].

6.3. Blink detection:

The blink detection algorithm used in our system detects blinks from raw EEG data derived from a forehead electrode. Blink detection based on raw data makes the system hardware independent. It uses fixed thresholds in time as well as frequency domains to differentiate blinks. These thresholds are based on baseline parameters derived from raw data and the following relationships between baseline and blink parameters [8]:

i. In frontal electrodes, EEG amplitudes are 3 to 5 times higher with blinks compared to without blinks
ii. Averaged EEG power spectrum for frequencies below 3Hz is more than 100 times higher with blinks as opposed to without.

6.4. Alertness monitoring:

Alertness monitoring algorithm is intended to give a feedback to the user regarding the post alarm buffer time. If a low alertness level is detected even at the end of the post alarm buffer, it means a longer buffer might be needed next time to monitor eye closure and prevent falling asleep again. Alertness is detected by taking several samples of raw data from a baseline alert state and the current state to be measured for alertness. These samples are fast Fourier transformed and the magnitude of each frequency component across these samples is compared between baseline and current data using left and right tailed paired t-tests. If frequencies lower than 10Hz show a significant increase compared to baseline and those greater than 15Hz show a significant decrease, alertness is determined to be low [9]. The alpha level is set to a lower value to find which changes are more significant than others if a significant change in the same direction is found in lower as well as higher frequencies. Based on how many frequency bins show these changes as expected in low alertness levels, the alertness level is determined.

6.5. Feedback regarding buffer times:

Based on the alertness level as explained above, the user is given feedback regarding the set post alarm buffer time and whether it needs to be changed.

7. Algorithm

In this section, we describe the algorithm used for each of three components of our system.

7.1. Algorithm for Sleep Stage Detection & Classification

- Start reading the file containing raw EEG data (this file is updated on the fly while reading continues)
- Read the data in parts of 30 seconds at a time
- Filter the data by applying 5th order low pass Butterworth filter
- Find peaks in the digitized data and store their positions
- Find secondary peaks and valleys such that the interval between them is less than 2Hz
- Maintain amplitude and correlation counters
    - Find percentage of peaks and valleys with amplitude greater than 75 µV
- Calculate the cross correlation between the original signal and peak-valley signal
    - Find percentage of points having correlation greater than 0.75

- If points having ‘percentage of peaks and valleys with amplitude greater than 75 µV’ > 80% and points having ‘percentage of points having correlation greater than 0.75’ > 30, then classify the portion of sleep data as deep sleep
- Following steps cover the data cleaning part:
    - Keep a sliding window over data (single data point steps), if minimum number of positive points in the window are greater than the set threshold, then set the whole window as 1
    - If positives found, then reduce threshold
        - If minimum possible threshold is reached and there is still no point in the window classified under deep sleep, then set the whole window as ‘no deep sleep’
        - Else set highest threshold for data up to the first instance found by highest threshold that did give some positives, and lowest threshold after that

7.2. Algorithm for Alertness measurement:

- Read files(first file containing the data after waking the user and second file containing data of user when he was awake)
- Extract ‘n’ samples of ‘m’ second data from each file
- Apply FFT to each sample from both the data
- Apply paired t-test on FFT outputs of both the data
- Low alertness is present if there is more significant increase in lower frequencies than higher & more significant decrease in higher frequencies than lower

7.3. Algorithm for Blink detection:

- Read the data file
- Read 5 seconds data at a time
- Filter the data
- Take a temporary signal of 1 second
- Apply FFT to the signal
- Apply threshold on 0.5-3Hz and mean value of mod(signal)
- Interval that crosses threshold contains blinks
- If blink stops then ring the alarm

Keep checking for blinks every 30 seconds

8. Experimental Analysis

8.1 Sleep Stage Detection & Classification system:

This algorithm was tested using sleep EEG data downloaded from the Physionet Sleep EDF Database [a][a]. These recordings are from eight Caucasian males and females (21-35 years old). The primary reason behind using data from an online database was that these datasets were already scored and had a hypnogram. This enabled us to reliably verify our algorithm against the provided hypnograms.

The two different accuracies described in the table below are,
the overall accuracy – determined by the percent agreement in the entire hypnograms given by judges and by our system,
and the deep sleep overlap accuracy – which is the percent overlap only between the deep sleep intervals.

Overall Accuracy in %	Overlap of Deep Sleep between Given Hypnogram and Computed one in %
93.5300	73.2673
92.4086	94.0476
98.9700	47.6200
95.0330	77.0000
82.7400	31.8500
97.1800	89.7600
92.7800	71.4300
85.5500	98.0600
Avg : 92.27	Avg: 72.88

Accuracy of the Sleep Stage Detection & Classification system

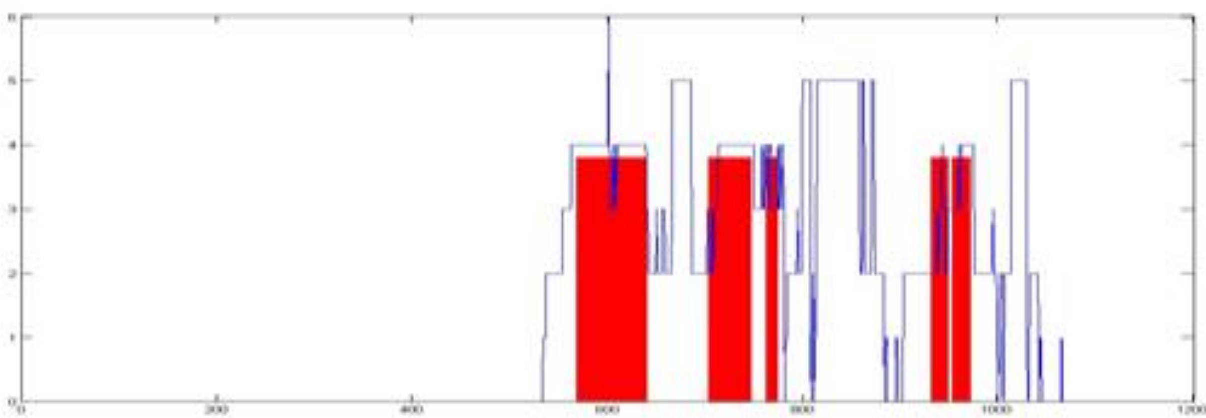


Figure depicting the overlap of the deep sleep detected by our Sleep Stage Detection & Classification system and the deep sleep detected by PhysioNet dataset's hypnogram

The accuracy table for the same data is shown below, without the use of the data cleaning algorithm.

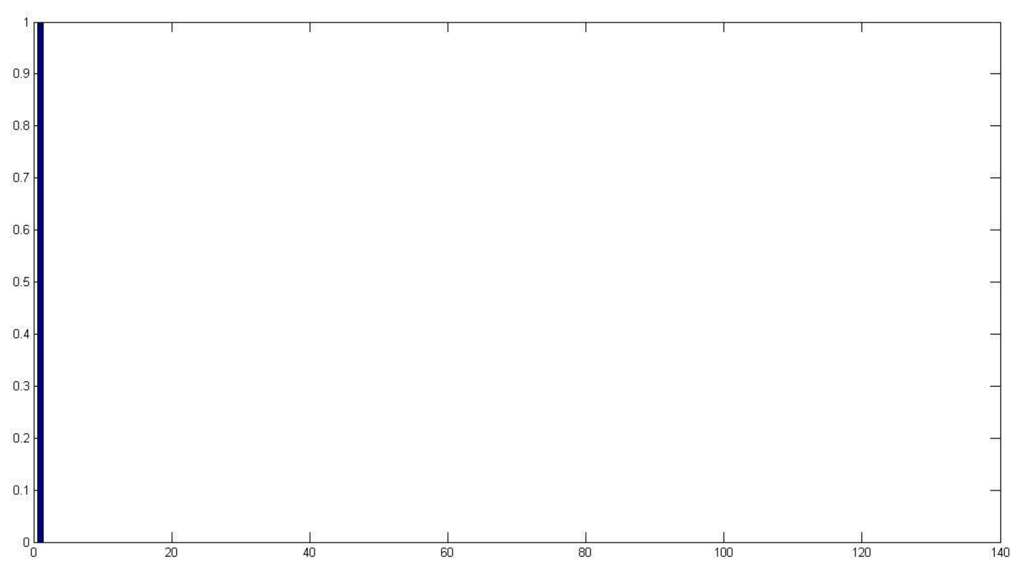
Overall Accuracy in %	**Overlap of Deep Sleep between Given Hypnogram and Computed one in %**
89.4096	44.0594
89.9719	48.8095
97.9381	28.5714
93.7207	39.0000
80.5816	23.3333
92.4015	51.2048
87.9925	36.9458
93.9024	93.2039
Avg : 90.7398	Avg: 45.6410

As seen above, there is a sharp decrease in deep sleep detection accuracy from 72.88% to 45.6410%. Thus, the data cleaning algorithm is an important incremental improvement to the previous code since in our alarm system, deep sleep should not be missed even if the overall accuracy is high.

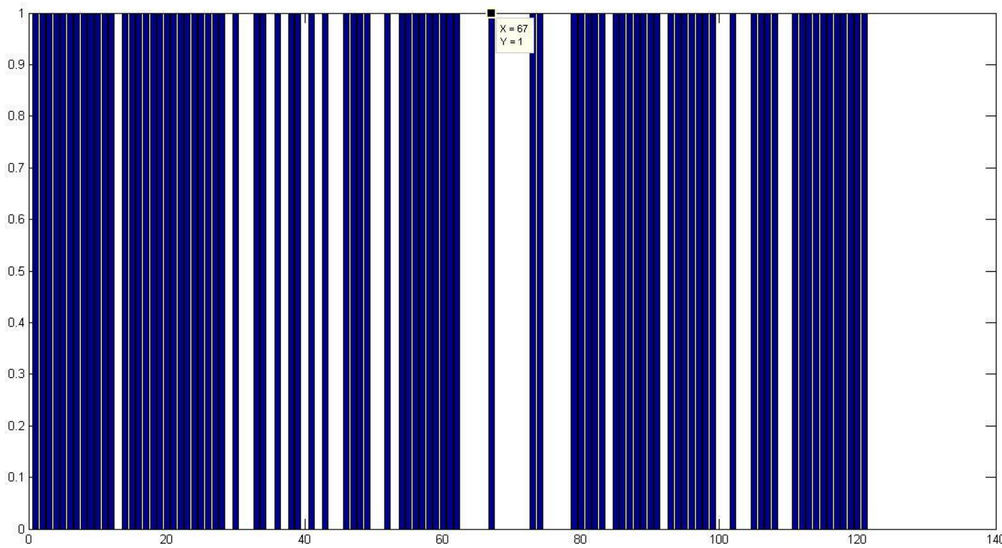
8.2 Analysis of results obtained by Blink Detection

In each of the following tests, the blink data was collected for 2 minutes.

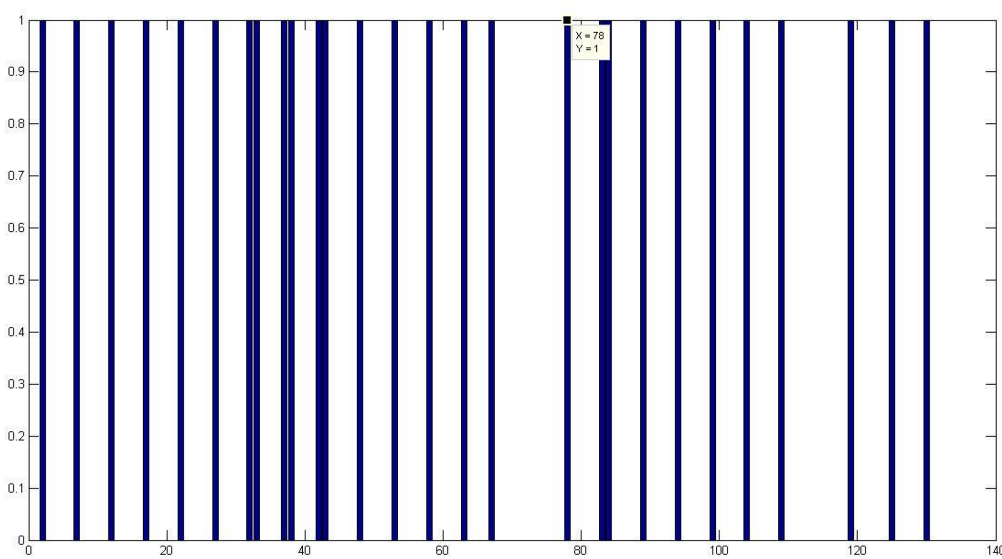
a. In the below test, the subject was asked to close his eyes during the entire duration.



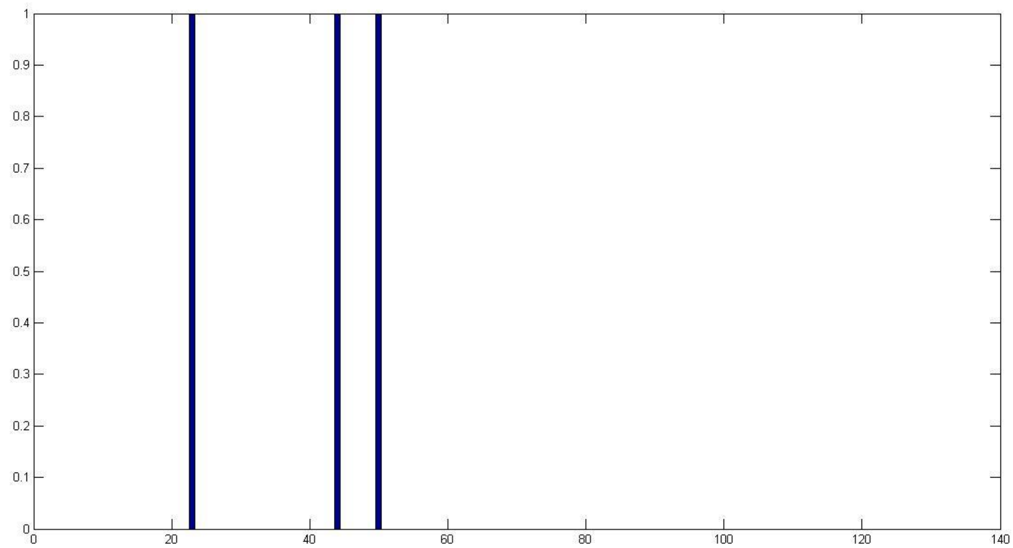
b. In the below test, the subject was to blink every 1 second.



c. In the below test, the user was asked to blink every 5 seconds.



d. In the below test, the user was asked to blink normally for 1 minute and for the remaining one minute, the user was asked to close his eyes.



9. Conclusion and Future Work

We have developed a sleep detection and classification system which wakes up the user in light stages and also monitors the blink activity of the user after waking him to ensure that the user does not go back to sleep.

We were able to perform sleep detection and classification with accuracy which was in par with the existing systems and better than some of existing systems. We also succeeded in providing an additional feature to the existing sleep monitoring alarm systems by monitoring the blink activity of the user after waking him.

Currently, we are using the alertness monitoring system to provide feedback to the user in respect to the buffer period after the alarm. In the future, the alertness monitoring algorithm can be made faster and more sensitive to change in order to use it not just as a feedback tool, but to actively perform sleep prevention.

We firmly believe that with the amount of attention being given to the field of sleep monitoring, our system would be beneficial to a broad set of users.

10. References

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