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A REVIEW ON SLEEP DETECTION USING EEG SIGNAL

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ABSTRACT

Sleepiness of drivers is a dangerous situation with hazardous consequences. Prolong and constant driving results in transient state of brain that resonates between awake and sleep. The brain signal pulses are studied to detect the state of sleepiness and alarm the driver about his condition. This paper reviews, the system for sleepiness detection using Electroencephalogram (EEG) signal.

INTRODUCTION

Sleep is a behavioural state that contrasts from attentiveness by a promptly reversible loss of reactivity to occasions in one's surroundings. This reversibility separates sleep from different manifestations of conditions of modified awareness, for example, coma or a condition of anaesthesia, which are portrayed by insensitivity.

In spite of the fact that people show comparable sleep practices, their sleep propensities vary: Humans go to sleep at distinctive times, they have inclination for diverse sleep situations and they require distinctive measures of sleep to be rested in the morning. Anyhow sleep propensities don't just change between persons, they additionally change inside an individual's lifetime. New-borns sleep 80% of the time. A normal adolescent grown-up guy on the other hand, sleeps somewhere around 7 and 9 hours a day and as he or she gets older, this time is further diminished.

The road accidents due to micro-sleep are one in four. This state of single person affects two vehicular units and all the passengers accommodated. To prevent micro-sleep state, many remedies such as: chewing gum, listening radio, opening window are used yet a study [2] states that: "Drowsiness is persistent and eventually sooner or later will beat us". Numerous studies on this subject led the same conclusion. The condition is generally is not concerned with type of vehicle, but is related with state of mind. The primary factors responsible for sleepiness are: physical and mental activities, prolonged awaken state, anxiety, some sort of disease etc. This state is sometimes also termed as grade of vigilance [3]. Electroencephalography is the division of human study that deals with brain signals. The signals are recorded through a series of sensors that captures the fluctuations in electric pulses inside brain.This study signifies the behaviour of brain for various situations such as: stressed,disturbed, quiet, disease, irritation, sleepiness etc. The behaviour of brain is reviewed in this research for purpose of sleep detection. Drowsiness is a general term commonly termed for the transient state of mind among awake and sleep. The brain at sleep state cuts of all the signals of physical world and gets engaged in some irrelevant signal activities. This state is a lateral stage of transient. The transient stage allows the brain to partially cut the physical signals for relaxing. The subjects in transient stage respond to the quality for first few minutes. After 10 minutes the response time gradually increases [1]. The subjects are generally unaware of this condition and keeps on driving. To minimize the risk of accidents in such cases, the brain signals are analysed for state of brain.

The research for drowsiness detection has enriched history of favourable works. In this segment, only specific amount of works are considered that holds significant importance and are described in accordance as stated by authors. Ueno and his team [10] made a system that uses image processing technology and drowsiness is detected on the basis of the degree to which the driver's eyes are open or closed. Drowsiness detection on the basis of analysis of eyelid movement was introduced by Boverie et al., [2] in 1998. Wavelet method was used by Abdulhamit Subasi [3] in 2005, in which he extracted some statistical features from wavelet sub bands and for classification he used artificial neural networks. Another paper based on decomposing EEG signal to sub bands by wavelet transform and then extracted Shannon entropy of each sub bands. Dynamic clustering method was introduced in 2008, based on EEG to estimate vigilance states and used temporal series information to supervise EEG data clustering [4]. Wavelet transform for decomposition of EEG signal to its sub bands was used by Kurt et al. [5] and for increasing the accuracy of diagnosing the transition

IJESMR

International Journal OF Engineering Sciences & Management Research

from wakefulness to sleep, they applied EEG sub bands and chine EMG and also left and right EOG to artificial neural network. Electrooculogram (EOG), to measure electrical muscles activity of the eye, has been widely used in the literature to estimate drowsiness ([2], [6]). EOG is the most reliable technique to detect and characterize blinks due to its high sample rate (from 250Hz to 500Hz) and is used as a reference to evaluate drowsiness by expert doctors ([7], [8]). EOG signal can be replaced by a high frame rate video (200fps) for the extraction of several blink features with the same accuracy as shown in a study by Picot et al. [9]. The database is first used to select the most relevant blinking features. A drowsiness detection method based on extraction of IMF's from EEG signal using EMD and using Artificial Neural network to characterize its features is then proposed and validated on the database.

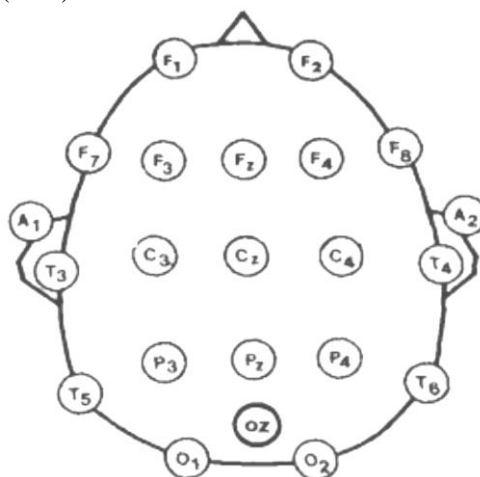I.   ELECTROENCEPHALOGRAM (EEG) SIGNAL

Figure 1: 10-20 system of montage of electrodes. Notation: F - frontal, C - central, P - parietal, T - temporal, O - occipital and A - earlobe reference. Modified from Reilly, 1993 [11]

Human Brain could be scaled as the most intricate systems existing. Brain supports enormous activities that co-operate with surroundings to produce best possible efforts. Certain brain diseases like Alzheimer's a neuro-degenerative disease that could be identified only by brain signal processing [12]. The study of brain in terms of mathematical model is a complex approach. Many methods of brain activity recognition are available such as Gabor Transform, Wavelet Transform, Deterministic Chaos, Wavelet Entropy etc [13].

The electrodes of impedance < 5000 are placed at different ends over scalp for measurement of EEG values. The electric potential is the difference among the active pair of electrodes (bipolar recordings) or passive electrodes (monopolar recordings) also known as base values. Figure 1 illustrates the rough architecture of EEG recordings.

Electroencephalography allows the processing of brain signals to investigate the internal functionality and look for abnormalities based on pre-defined protocols (methods) [14]. The measure of brain activities are the potential difference of two fixed points in scalp. Electroencephalogram or EEG is the non-invasive measure of the electrical signals (Figure 2) in brain [15]. For the research and medical purposes brain activity signals are differentiated on basis of signal's frequency [16]. These frequency bands exist only for the purpose of nomenclature and are sourced by rhythmic activity in brain. The free available EEGLAB can extract the frequency by employing spectral methods (For ex. Welch). A tabular form of EEG signal's frequency to compare is shown in Table 1 [17].

IJESMR

International Journal OF Engineering Sciences & Management Research

Table 1: Rhythmic Activity Signals Frequency Band Comparison [17]

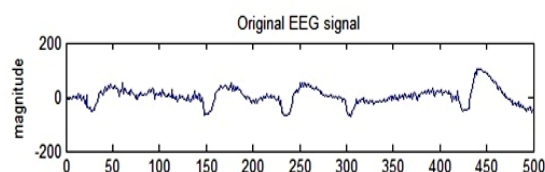| Band	Frequency (Hz)	Location
Delta	2-4	Adults
Theta	4-8	Hand Tasks
Alpha	8-13	Posterior Regions
Beta	13-35	Low-Amplitude Waves
Gamma	35+	Somatosensory cortex
Mu	8-12	Sensorimotor cortex

Figure 2: The EEG signal

Review of Existing Research

Brain during Sleep

Sleep is typically broken into four sleep stages proceeded by Rapid Eye Movement (REM) sleep. Stage 1 sleep is the transition from wakefulness to sleep. At this stage, a person can be woken easily, and may not be aware that they were sleeping. During stage 1 sleep, EEG signals are low amplitude and low frequency. An example of these signals can be seen in Figure 3.
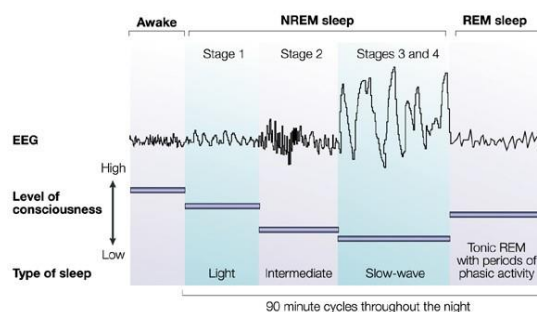

Figure 3: Stages of Sleep in Humans [19]

During stage 2 sleep, body temperature decreases and the heart rate slows. In stage 2 sleep, alpha waves are periodically interrupted by alpha spindles or sleep spindles. Alpha spindles are 12-14 Hz bursts of brain activity that last at least half a second [18]. These periods of alpha spindle activity are sometimes called alpha spindle epochs. Stages 3 and 4 are deeper sleep, with stage 4 being deeper than stage 3. REM sleep follows stage 4 sleep. REM sleep is most readily identified by rapid eye movement. During REM sleep, dreaming occurs and brain activity increases. Each of these stages continue to cycle from stage 1 through REM sleep throughout the sleeping period.

EEG Drowsiness and Sleep Detection

Morrow et al. [20] outlined a method for the real-time detection of sleep by focusing on three critical parameters in EEG recordings: waveform amplitude, waveform frequency, and duration of synchronization of the waveform. This last parameter is critical in that the waveform amplitude may meet a predefined voltage threshold for a frequency band for short periods of time, but this does not necessarily indicate sleep unless it meets the threshold for a given duration. Morrow et al. used a 50 µV predefined voltage threshold. The frequencies of focus were 8-12 Hz (Alpha) and 11.5-15 Hz (low Beta). Two counters were used to detect EEG threshold crossing with one counter for the number of sequential pattern matches indicative of sleep, and the other counter for the number of sequential non-matches. When a frequency and amplitude matched the focus frequencies and thresholds the matching counter was incremented.

When it did not match, a non-matching counter was incremented. When the match counter reached 3, sleep was indicated. When the non-matching counter reached 8, wakefulness was indicated. Morrow et al. was able to reach a reliability of 97.9% for 48 of 49 alpha-spindle epochs. In addition, the detector was able to detect about 12.2% more epochs than visual scoring. This methodology may be applicable to Stage 1 sleep detection, but the presence of alpha-spindle epochs indicates a deep stage of sleep.

Merica et al. [21] found that the transition between sleep and wakefulness was a gradual transition. When comparing both delta waves and beta waves to the overall power of the EEG signal, a gradual increase in delta waves was seen along with a gradual increase of beta waves. Merica commented that sleep was, "more one of withdrawal from the waking state rather than of invasion of the sleeping state." In this way, it may be easier to detect the progression toward sleep rather than its onset. In general, frequencies from 1 Hz to 16 Hz increase while approaching sleep, while frequencies 17 Hz and higher decrease. This pattern continues after the onset of sleep, except that power in the 8-11 Hz range begins to increase as well. The change in the 8-11 Hz signal is especially noticeable in the occipital region where the signal diminishes and transitions to the frontal lobe.

With this gradual transition toward sleep in mind, Lal et al. [22] documented the creation of an algorithm for detection of drowsiness in drivers. The algorithm classified drowsiness/fatigue EEG signals into transitional (early fatigue phase), transitional– post transitional (medium fatigue phase), post transitional (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 analysed in blocks of thirty seconds and this algorithm demonstrated a 10% error rate in sleep detection.

Driver Fatigue Detection

There are many commercial systems that can detect changing driving patterns of fatigued drivers, such as the Ford Driver Alert, the Mercedes Attention Assist, the Volkswagen Driver Alert System, or Volvo Driver Alert Control and Lane Departure Warning [23], [24], [25] and [26]. Each of these systems monitor changes in driving displayed by drowsy drivers like jerky steering movements or drifting out of lanes. When this occurs, an audible and visual warning is produced. Ford's Driver Alert system even includes scenarios in which if the warning is ignored for too long, it can only be discontinued by stopping and exiting the car. The Danish "Anti Sleep Pilot" not only monitors driving patterns, but it requires that the driver push a button on the device as quickly as possible when indicated to verify that the driver's response time is adequate [27].

Other systems like the Fraunhofer's Eyetracker or the Toyota Driver Monitoring System monitor the driver's eyes to confirm that they are watching the road [28], [29]. The driver can be warned if they are not watching the road when an obstacle is ahead. The driver is also warned if their eyes close for a period of time.

Each of these systems has its pros and cons. The erratic driving detection systems can monitor all forms of erratic driving, which includes distracted driving. Their disadvantage is a slow response time so that by the time driving has become erratic; it may be too late to stop an accident from occurring. The driver monitoring systems have the potential to detect driver drowsiness before an accident occurs, but they rely on being able to monitor a driver's eyes to

IJESMR

International Journal OF Engineering Sciences & Management Research

determine if they are open. According to Barr et al. [30], "For real-world, in-vehicle applications, sunlight can interfere with IR illumination, reflections from eyeglasses can create confounding bright spots near the eyes, and sunglasses tend to disturb the IR light and make the pupils appear very weak." An EEG based device may be able to detect the onset of sleep before erratic driving has begun, and it has the added benefit of not requiring an unhindered view of the driver's eyes.

Low-Cost EEG devices
Low cost EEG devices have not been on the market for long and relatively little research has been done on them. Most of the limited literature involves detecting the attentiveness of the user. In most cases, these low cost EEG devices proved to be adequate substitutes for medical grade EEG devices for certain low-level signal analysis. Since they usually have fewer sensors than medical grade equipment, they do not do a good job of locating specific signals within the brain.

In one test with a low cost EEG device, Crowley et al. [31] conducted two psychological tests [32] and [33], to induce stress and correlate the results to the measured attention and meditation signals recorded from the Neurosky Mindset. By relying on signal trends, they were able to detect when a subject's emotions changed. In another test, Haapalainen et al. [34], collected data from multiple bio-sensors, including a Neurosky Mindset, and compared their ability to assess cognitive load. The attention signal from the device was then given a ranking of third best predictor of high cognitive load after heat flux and electrocardiogram (ECG) across the cognitive experiments conducted.

Tan [35] used a Neurosky Mindset to record EEG signals for adults and children reading easy or difficult sections of text to determine whether a user was having difficulty reading the text. They were able to distinguish easy/hard text pairings with an accuracy of 70% for adults and 64% for children. The thesis commented that the Neurosky Mindset was shown to be "capable of collecting quality information".

Choi et al. [36] wrote a short article about several low cost EEG devices, including a few Neurosky dry-sensor EEG devices, and their ability to detect drowsiness. They found that these devices made "suitable candidates for further research in the detection of vigilance states." They did not perform real-time analysis of the data or produce a warning when drowsiness was detected.

In the study by Choi et al. [36], the main area of focus was the frequency domain analysis of EEG collected from the Neurosky dry-sensor EEG device. The frequency content of the signals were divided into clinically relevant frequency bands Alpha (8-13 Hz), Beta (14-30 Hz), and Theta (4-7 Hz) 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. In the study using EEG signals obtained from the Neurosky device, 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 may prove a useful target for drowsiness detection schemes.

Conclusion
Carrying out literature is very significant in any research project as it clearly establishes the need of the work and the background development. It generates related queries regarding improvements in the study already done and allows unsolved problems to emerge and thus clearly define all boundaries regarding the development of the research project. Plenty of literature has been reviewed in this paper in connection with sleepiness detection using Electroencephalogram (EEG) signal.

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