VOL. 13, NO. 4, FEBRUARY 2018 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

ELECTROENCEPHALOGRAPHY (EEG) BASED DROWSINESS DETECTION FOR DRIVERS: A REVIEW

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ABSTRACT

Vehicle accidents are rapidly increasing in many countries. Among many other factors, drowsiness is playing a major role in these accidents and systems which can monitor it are currently being developed. Among them, Electroencephalography (EEG) proved to be very reliable. Indeed, many EEG based drowsiness detection techniques are proposed for drivers. Most of these drowsiness detection techniques are normally subdivided into feature extraction and classification methods. Features obtained from FFT are effective and give higher accuracy; but are limited by the non stationary behavior of EEG signals. This paper reviews some of the most recent work of the EEG based drowsiness detection techniques. It shows a major gap found in all these studies, which is the fact that the channel selection method is not clearly specified. Therefore, research can be undertaken to properly choose suitable channel(s) to realize accurate detection of drowsiness. This survey also highlights the fact that, there is no publicly available data and comparison between techniques is not yet possible, because each technique is tested on its own dataset.

Keywords: drowsiness of drivers, EEG based drowsiness detection, accidents, types of EEG electrodes, drowsiness detection algorithm.

INTRODUCTION

The number of vehicle accidents is rapidly increasing in many countries and because of these accidents many people are losing their lives. According to the World Health Organization (WHO), 1.24 million people were killed in road accidents in 2010 and by 2030 road accidents will become the fifth major cause of death (World Health Organization, 2013). Each year, around 20 to 50 million people suffer non-fatal injuries due to road accidents (Sahayadhas, Sundaraj and Murugappan, 2012). Only in Asian countires, these accidents cause loss of $20 billion per year (Muzammel *et al*., 2017).

There are many factors for these accidents. Among these, drowsiness contributes significantly. According to the US National Highway Traffic Safety Administration (NHTSA), around 100,000 vehicle crashes per year are due to the drowsiness of drivers. These crashes cause 1,550 deaths, 71000 injuries and $12.5 billion financial loss. In the year 2009, the US National Sleep Foundation (NSF) reported that 54% of adult drivers have driven a vehicle while feeling drowsy and 28% of them actually fell asleep (Sahayadhas, Sundaraj and Murugappan, 2012). Similarly, the German road safety council also reports that one out of four fatalities on highways occurs due to the driver drowsiness (Sahayadhas, Sundaraj and Murugappan, 2012). Driver drowsiness can be classified into many different levels: deep sleep, sleep, extremely drowsy, moderately drowsy, drowsy, slightly drowsy and awake (Lee, Lee, and Chung, 2014).

During the drowsiness, changes occurred in head movement, eye movement, brain wave activity, muscle tone and heart rate. Therefore, there are many methods to measure the drowsiness of drivers such as skin conductivity (Bundele and Banerjee, 2009), heart activity (Patel *et al*., 2011) (Tan, Halim and Kok, 2015), facial expressions (Hachisuka *et al*., 2011), eye blink rate (Jemai, Teyeb and Bouchrika, 2013), and brain activity by using electroencephalography (EEG) (Wali, Murugappan, and Badlishah Ahmad, 2013b), etc.

All of the above methods can help to detect drowsy state of the driver and allow him to take a necessary action to avoid a potential accident. Therefore, these methods can be useful to avoid potential accidents and can help in saving many lives. However, among these methods, EEG is one of the most reliable ways to detect the drowsiness of drivers (Kim *et al*., 2009). It is because of its ease of use (which requires simple placement of electrodes upon scalp) and its high temporal resolution.

There are also good review papers online available for driver drowsiness detection (Sahayadhas, Sundaraj and Murugappan, 2012), (Saini and Saini, 2014). These papers cover all types of driver drowsiness detection techniques. However, both papers offer only a little coverage about EEG based methods. Only names of features extraction and classification techniques are mentioned by (Sahayadhas, Sundaraj and Murugappan, 2012). While, our review paper covers in details EEG techniques that can be used for drowsiness detection; such as: types of EEG waves, types of EEG electrodes, artifact removal techniques and feature extraction and classification methods. It also includes the latest EEG based techniques for drivers drowsiness detection.

In this paper a literature review study is presented for the electroencephalography based drowsiness detection for drivers. Section 2 covers the types of EEG waves that can be used for the drowsiness detection. While section 3 covers the positioning and types of EEG electrodes.

Section 4 covers the artifact removal techniques, features extraction and classification methods. Finally, section 5 concludes the research.

TYPES OF EEG WAVES FOR DROWSINESS DETECTION

In 1912, a Russian physiologist named Vladimir Vladimirovich Pravdich-Neminsky published the first EEG signals recorded from animal (dog). Later, in 1924 a German physiologist and psychiatrist, Hans Berger, recorded EEG signals for the first time from human being and introduced alpha and beta waves. Hangs Berger also introduced the term “electroencephalogram”. In the mid-1930s, Alfred Loomis showed that in humans EEG patterns dramatically changed during a night's sleep (Haas, 2003).

In most of EEG studies, usually, alpha, beta, theta and delta waves are used for sleep studies (Wali, Murugappan, and Badlishah Ahmad, 2013b); and their frequency ranges are given in Table-1. Alpha and beta waves can be used to represent conscious states, while theta and delta waves are mostly used to represent unconscious states (Sharma and Gedeon, 2012).

Table-1. EEG wave band.

EEG Wave	Frequency band (2)
Beta	15-30
Alpha	8-13
Theta	4-8
Delta	0.5-4

Alpha waves significantly increase during closed eyes and eyes blinking in relax and active states (Liao *et al*., 2014), (Wali, Murugappan and Ahmmad, 2013a). While, under a stress/mental work load the alpha wave power decreases and the theta band power increases (Borghini, *et al*., 2014). Hence, alpha, beta, theta and delta band can be used to measure the drowsiness (Brown, Johnson and Milavetz, 2013), (Kaur and Singh, 2013), (Sharma and Gedeon, 2012), (Wali, Murugappan, and Badlishah Ahmad, 2013b).

POSITIONING AND TYPES OF EEG ELECTRODES

Driving is a very complex task, which involves simultaneously many activities from the different brain parts. These brain parts can be identified as brain lobes (Patestas and Gartner, 2013), as given in Table-2. Each brain lobe is related to different functionalities. For example, the frontal lobe (F) is associated with reasoning, planning, movement, problem solving and emotions. The parietal lobe is linked with the movement, perception and recognition of stimuli. Whereas, the temporal lobe is associated with the perception and recognition of auditory stimuli, speech and memory.

Table-2. Different brain lobes.

Electrode name	Brain lobe
F	Frontal
T	Temporal
C	Central
P	Parietal
O	Occipital

It is important to note that there is no such part as a central lobe. However, the letter "C" is used for the identification purpose only for the placement of EEG electrodes. The placement of EEG electrodes is very sensitive (Kar, Bhagat and Routray, 2010). Therefore, the placement and types of EEG electrodes play a major role in detecting the drowsiness of drivers.

Positioning of EEG electrodes

Many researchers utilized the 10-20 international system used for the positioning of EEG electrodes because of its efficiency (Kar, Bhagat and Routray, 2010), (Wali, Murugappan and Ahmmad, 2013a). The 10-20 international System describes the locations of EEG electrodes and is based on the area of the cerebral cortex. The terms "10" and "20" refer to the distance between two adjacent EEG electrodes; which can either be 10% or 20% of the total front–back/right–left skull distance. Each EEG electrode has a letter for the identification of the brain lobe and the number of its hemisphere location.

Types of EEG electrodes

There are two types of electrodes commonly used for EEG signal extraction namely wet electrodes and dry electrodes (Nicolas-Alonso and Gomez-Gil, 2012).

Wet electrodes are often used for EEG measurements and are made of silver chloride (AgCl) (Fazli *et al*., 2012), (Koelstra *et al*., 2012), (Soleymani *et al*., 2012). These electrodes and skull tissue interface are resistive and capacitive. Therefore, these electrodes act as a low pass filter and block many EEG signals. To solve this issue, EEG gel is used. This gel creates a conductive path between the electrodes and skin by reducing the impedance to an acceptable value (Nicolas-Alonso and Gomez-Gil, 2012).

However, a continuous maintenance is required for these wet electrodes to achieve good quality EEG signals (Nicolas-Alonso and Gomez-Gil, 2012). The preparation procedure for the use of these electrodes is very uncomfortable and time consuming. The gel leakage can cause a short circuit between different electrodes. Also, the rapid use of gel can cause allergy or any other infection. On the other hand, if the gel gets dry the quality of EEG signals degraded with it (Lin *et al*., 2011b).

In order to address these limitations, many kinds of dry electrodes have been proposed (Grozea, Voinescu and Fazli, 2011), (Kim *et al*., 2009), (Lin *et al*., 2011b), (Liu, Chiang and Hsu, 2013), (Wang, Nie, and Lu, 2014).

These electrodes do not use gel and are made from stainless steel and titanium. Mostly, these dry electrodes are made by the micro-electromechanical system (MEMS) technique.

MEMS dry electrodes acquire the EEG signals in an invasive way and are only limited to the forehead sites (Lin *et al*., 2008). Furthermore, there are many drawbacks of these electrodes. First and foremost, a participant may feel the pain, when these electrodes penetrate into the skin. Secondly, a proper physical strength is required for the penetration of these electrodes. Lastly, these electrodes have high manufacturing costs (Lin *et al*., 2011b).

Other non-contact dry electrodes are also proposed for EEG signal measurements (Chi, Jung and Cauwenberghs, 2010), (Liao *et al*., 2012), (Liao *et al*., 2014), (Lin *et al*., 2011b). These non-contact dry electrodes can be made by using conductive polymer foam (Lin *et al*., 2011b) or spring-loaded sensors (Liao *et al*., 2014). These electrodes work perfectly even on hairy sites (Liao *et al*., 2014), (Lin *et al*., 2011b). For these electrodes, there is no need of gel or any skin penetration. Therefore, these non-contact dry electrodes can be used to get the EEG signals for the drowsiness detection of drivers.

RELATED TECHNIQUES FOR DROWSINESS DETECTION

For the drowsiness detection, the simplest approach is to measure the eye blink rate, eye closed duration and the jaw clenching. It has been observed that the person eyes movement decreases and blink rate increases as he or she enters into a drowsy state (Kim *et al*., 2009). Many techniques have been proposed to measure the drowsiness of the drivers; some of them are given in Table-3.

All of the above techniques used virtual driving simulator for testing due to the safety of the drivers. As, it is unethical and can be dangerous to allow a drowsy driver to drive on the road. Driver drowsiness detection by using EEG signals can be divided into following three phases.

Artifacts removal

Artifacts are usually undesirable signals that affect the EEG signals and are mostly from non-cerebral origin. These artifacts, mostly came from the eye blinking or due to the muscle movement in EEG data recording. These artifacts can affect the accuracy of the drowsiness detection. Mostly, Independent Component Analysis (ICA), Principal Component Analysis (PCA) and linear combination and regression are used to remove the artifacts (Lin *et al*., 2011a), (Nicolas-Alonso and Gomez-Gil, 2012). Independent Component Analysis (ICA) is a very powerful and effective tool for the removal of artifacts in EEG signals (Lin *et al*., 2011a), (Nicolas-Alonso and Gomez-Gil, 2012).

The removal of these artifacts can also corrupt the power spectrum of EEG signals. It's also possible that some important information can be removed with the artifacts.

Feature extraction methods

Many researchers proposed the Fast Fourier Transform (FFT) to find different frequency components in EEG waves (Hashemi, Saba and Resalat, 2014), (Liao *et al*., 2012), (Simon *et al*., 2011), (Yeo *et al*., 2009). It gives accuracy higher than 90% (Hashemi, Saba and Resalat, 2014), (Liao *et al*., 2012), (Simon *et al*., 2011), (Yeo *et al*., 2009). However, for applying FFT, the given EEG signals are considered stationary; whereas they are non-stationary in nature (Nicolas-Alonso and Gomez-Gil, 2012), (Wali, Murugappan and Ahmmad, 2013a).

Discrete Wavelet Transform (DWT) is another linear technique used for the extraction of EEG signal features (Kar, Bhagat and Routray, 2010), (Nicolas-Alonso and Gomez-Gil, 2012), (Wali, Murugappan, and Badlishah Ahmad, 2013b). It can be applied to the non-stationary EEG signals. It divides the EEG signals into different frequency components. Unlike FFT, DWT can achieve higher accuracy even when EEG signals have sharp spikes and discontinuities (Sharma and Gedeon, 2012).

Discrete Cosine Transform (DCT) is normally used for the extraction of feature from the images (Ota, Yoshida and Ikehara, 2013); but it can also be used for the extraction of EEG signal (Birvinskas *et al*., 2012). DCT is basically a transformation method, which converts a time series signal into different frequency components. For EEG signal feature extraction, one dimensional DCT is used (Birvinskas *et al*., 2012).

ICA can be used for the EEG feature extraction. To extract the features, ICA assumes that the input EEG signal is a mixture of several independent signals coming from multiple cognitive activities or artifacts (Nicolas-Alonso and Gomez-Gil, 2012).

Principal Component Analysis (PCA) is normally used to reduce the dimension of features. Another use of PCA is for EEG feature extraction. In order to extract features, PCA uses a linear transformation method to convert a set of observations (possibly correlated) into principal components (uncorrelated variables). Linear transformation, initially generates a set of components from the input EEG data and then sort these components according to their variance. This variance allows PCA to separate the EEG signal into different components (Lin *et al*., 2010), (Nicolas-Alonso and Gomez-Gil, 2012).

Matched Filtering (MF) is another EEG feature extraction method. MF attempts to detect the specific pattern based on its matches with predetermined known EEG signals or any template. It uses a correlation technique between a set of templates and unknown EEG signals. A higher correlation would imply better matching between the template and the unknown EEG signal (Nicolas-Alonso and Gomez-Gil, 2012). The limitation of this technique is that it requires template for the pattern, which the user wants to detect.

Lastly, autoregressive (AR) models can also be used for EEG feature extraction (Lawhern *et al*., 2012). To the extract features, the AR model assumes that the EEG signal can be modeled as a linear combination of the signals at the previous time points.

Table-3. Existing methods for EEG features extraction and classification.

Author/Year	Feature extraction	Classification	Accuracy	EEG waves	Subjects/EEG channels
Birvinskas *et al.* (2012)	Discrete Cosine Transform	Artificial Neural Network	80%	NA	01 / 06
Correa, Orosco and Laciar. (2014)	Wavelet Decomposition	Linear Discriminant Analysis & Artificial Neural Network	83.6%	Alpha, beta, theta, delta, gamma	16 / NA
Hashemi, Saba and Resalat. (2014)	Fast Fourier Transform	Artificial Neural Network	97% for 2 seconds test dataset	NA	05 / NA
Kurt *et al.* (2009)	Discrete Wavelet Transform	Artificial Neural Network	95–96%	Beta, theta, delta	10 / 02
Lawhern *et al.* (2012)	Autoregressive Models	Support Vector Machine	94%	NA	07 / 33
Lin *et al.* (2010)	Fast Fourier Transform, Principal Component Analysis	Threshold level comparison	76.9% and 88.7%	Alpha, theta	10 / 03
Picot, Charbonnier and Caplier. (2012)	Short Time Fourier Transform	Fuzzy Classification	72.6%	Alpha, beta, theta, delta	20 / 04
Wali, Murugappan, and Badlishah Ahmad. (2013b)	Discrete Wavelet Packet Transform, Fast Fourier Transform	Subtractive Fuzzy Clustering, Probabilistic Neural Network, K nearest neighbor	84.41% (Fuzzy Classifier)	Alpha, beta theta, delta	50 / 14
Yeo *et al.* (2009)	Fast Fourier Transform	Support Vector Machine	90%	Alpha, theta, delta	20 / 19

*NA = Not Available

Classification methods

There are many classification techniques for driver drowsiness detection. A few of them are given bellow.

Among many other techniques, Artificial Neural Network (ANN) is one of the famous non-linear techniques that is used for the classification of EEG parameters for the drivers drowsiness detection (Correa, Orosco and Laciar, 2014), (Hashemi, Saba and Resalat, 2014), (Kaur and Singh, 2013), (Kurt *et al.*, 2009), (Tan and Halim, 2015). One of the main advantages of using ANN is that, it can classify the EEG data without prior information about it. It can extract the patterns from EEG signals even if there is no relation between input and output. This is a very important characteristic, as in many realistic cases the input and output relation is very difficult to establish. But, the accuracy of the ANN is very low as compared to the other techniques (Kaur and Singh, 2013).

Fuzzy clustering (also known as fuzzy classification) is another non-linear technique used for EEG feature classification (Picot, Charbonnier and Caplier, 2012), (Wali, Murugappan, and Badlishah Ahmad, 2013b). It is famous due to its linguistic concept modeling ability. Fuzzy classification is very close to a natural language. The fuzzy classification can manage the uncertain data and can classify the EEG data based on its behavior (Dong *et al.*, 2011). .

Support Vector Machine (SVM) is basically a statistical learning technique and can be used for EEG features classification (Dong *et al.*, 2011), (Kurt *et al.*, 2009). There are many applications of SVM, such as detection/recognition of objects, faces, hand written text/digits and the retrieval of other information from the images. The learning ability of SVM also makes it suitable to detect different cognitive states of humans. SVM can generate and compute both linear and non-linear models efficiently. This technique initially transforms the input EEG data by using a kernel and then separate the data into different classes based on hyper-plane (Nicolas-Alonso and Gomez-Gil, 2012).

Lastly, Linear Discriminant Analysis (LDA) can also used for the classification of EEG signals. LDA is a simple classifier and it provides reliable accuracy. For LDA, there is no need for high computation performance.

Therefore, it can be a good option for online Brain Computer Interface (BCI) systems; as many of these systems required a rapid response and have limited computational recourses. But the limitation of LDA is its relatively acceptable accuracy. Therefore, it cannot be used in such systems where we need high accuracy (Nicolas-Alonso and Gomez-Gil, 2012).

Although there are many techniques available for drowsiness detection of drivers based on EEG, however there is still a gap for improvement. Mostly these techniques are applied to insufficient number of subjects; therefore their accuracy is not reliable. Another major issue is that in all techniques no concrete reasons are given for the corresponding EEG channel selections and their positions. In some techniques, limited information is provided about EEG waves being utilized. The comparison of the above techniques is not yet possible due to the non availability of online datasets.

CONCLUSIONS

From this research it can be concluded that although there are effective algorithms available for the drowsiness detection of drivers by using EEG. These algorithms can help us to alert the drivers, when they felt drowsy. For feature extraction, FFT based features are effective and give higher accuracy; but limited by the non stationary behavior of EEG signals. Similarly, the ANN can classify the EEG data without prior information about it; but limited by the low accuracy. The major gap found in these studies is the channel selection method. In all techniques no justifications are given in the selection of the corresponding EEG channels and their positions. Therefore, a further research can be performed on the suitable channels to be selected. There is also a lack of publicly available data and comparison between techniques is not yet possible, because each technique is tested on its own dataset.

ACKNOWLEDGEMENT

We express gratitude to and acknowledge the Department of Electrical & Electronic Engineering, Universiti Teknologi Petronas, Malaysia. This research is partially supported by Ministry of Education Malaysia under Higher Institution Centre of Excellence (HICoE) Scheme, Centre for Graduate Studies (CGS) and University Research Internal Fund (URIF-015AA-B78) by Universiti Teknologi Petronas, Malaysia.

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