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REVIEW ARTICLE

Driver Drowsiness Detection: A Review

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ABSTRACT

Safety of passengers has been a severe issue in all societies of any country in the world. Thousands of people lose their lives daily and many more lose their livelihood because of paralysis caused by accidents. Accidents not only cause physical injuries but also are responsible for high economic losses. According to various studies and investigations it is noticed that one of the major causes behind the road accidents is driver's drowsiness. This drowsiness can be the cause of many reasons. Fatigue or sleep deprivation are the major reasons. Thus, a countermeasure device is currently essential in many fields for sleepiness related accident prevention. Many researchers have been working on different aspects to deal with this drowsiness issue through various aspects like (1) Subjective Measures, (2) Physiological measures, (3) Vehicle-based measures, (4) Behavioural measures This paper proposes a comparative review on different methods used to detect drowsiness of drivers. It looks into the advantages and disadvantages of different methods used for the purpose and creates a detailed comparative analysis for a better future hybrid model to be taken into consideration. This would further help in enhancing the safety measures that should be taken for road safety.

Keywords | Drowsiness Detection, Road Safety, AI Measures, Driver Fatigue

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INTRODUCTION

A survey published by the National Highway Transportation Administration states that 7.277 million traffic accidents occurred in the United States in 2016, causing 37,461 deaths and 3.144 million injuries, of which driver fatigue caused approximately 20–30%. Based on police investigation reports, it is estimated that every year a total of 100,000 vehicle crashes are due to driver drowsiness. These crashes were responsible for approximately 1,550 deaths, 71,000 injuries and $12.5 billion in financial losses. In the year 2009, the US National Sleep Foundation (NSF) reported that 54% of adult drivers has driven a vehicle while feeling sleepy and 28% of them actually fell asleep. The German Road Safety Council (DVR) claims that one in four highway traffic fatalities are a result of momentary driver drowsiness. These statistics suggest that driver drowsiness is one of the main causes of road accidents.

When a driver is under fatigue, the very next moment he would feel drowsy and this would affect the driver's mental faculty to process and respond on the road. As a result, the driver will lose control of the vehicle, leading to accident.

There are many measures that are taken into consideration to monitor drowsiness and to avoid such accidents. Following four measures are used worldwide:-

1. **Subjective Measures:** The level of drowsiness is measured in terms of driver's personal fatigue estimation and using other tools the levels are translated into rating the drowsiness. Mostly theoretical approach.
2. **Vehicle-based Measures:** In some cases, a simulated environment is created where various sensors are placed inside the vehicle and the signals sent by these sensors are then analyzed to detect the level of drowsiness.
3. **Behavioral Measures:** This type of measure focuses on the driver's facial characteristics such as constant yawning, blinking of eyes, jaw drop etc to detect the drowsiness.
4. **Physiological Measures:** They help detect the physiological signals when the driver's head starts nodding. As a result, the vehicle veers off course and causes accidents.

All these measures are repeatedly studied and verified in detail and their advantages and disadvantages have been discussed.

METHOD & MATERIALS

The objective of the study is to verify the extent of the use of these measures to detect driver drowsiness. Some researchers created simulated environments to study drowsiness. Kokonozi et al., conducted an experiment to observe participants who were sleep-deprived prior to observation for 24 hours. Peter et al., took the same participants and studied them for four days at a stretch and concluded that even partially sleep-deprived participants tend to get sleepy after some time. Therefore, sleep quality plays a major role in influencing drowsiness.

According to past studies, the technologies that are used to detect the electrophysiological signals obtained when the driver was driving under fatigue, includes Electroencephalogram (EEG), Electrocardiogram (ECG), etc. In order to detect drowsiness, Khushaba et al., used a wavelet packet transform model to extract the information from EEG, EOG and ECG signals. Li et al., performed wavelet transform on the ECG signals to gain heart rate variability so as to measure the fatigue levels. These were the conventional methods.

Vehicle's turning angle, speed, deviation from centre line etc were measured via facial detection measures that closely focused on the facial characteristics of the driver. Wang et al., studied the relationship between vehicle steering wheel's lateral acceleration, longitudinal acceleration and steering angle with the level of fatigue in periodic time scales. The method has one drawback as it gets easily influenced by external factors such as the vehicle's condition, driving experience, etc.

With the advancement of technologies modern methods have been adapted by researchers to improve their study and get effective results. Facial features analyzing methods such as the PERCLOS (eyelid closure rate exceeds the pupil percentage per unit time), yawning rate, constant jaw dropping etc are acceptable as they do not interfere with the driver's potential to drive. Garcia et al., showed a 3-step method that first detects the traces and eye movements and then under different illumination analyze the performance of eyes. The system later uses PERCLOS measurement.

Another study by Jie et al., yawning detection was introduced in the field that extracted the appearance of eyes and mouth when they close.

Du et al., proposed an MFRNN model that measures the degree of mouth and eyes opening along with heart rate and comparing it with the driver's fatigue level.

Sun et al., proposed a two-level method which was based on MCSVM. Deng et al., explained a 3-level criteria that show the blinking frequency, closed time and yawning time of the driver's sleepiness.

Parkd et al., used IAA and FFA that accurately detects the level of driver's drowsiness.

Various studies have shown the use of these measures as successful methods to detect drowsiness by calculating the geometrical facial features and using those algorithms to improve the accuracy of the detectors. Many facial recognition models have come in handy for the purpose and gave precise results as and when needed.

Methods for Measuring Drowsiness

The section reviews the four most used drowsiness measuring methods, from which the first one is purely questionnaire-survey based and the other three uses sensors or detectors for the study.

Subjective Measures

Subjective measures estimate the driver's level of sleepiness using some external tools (to create simulated tests). Karolinska Sleepiness Scale (KSS) is a nine-point scale that is mostly used to measure drowsiness. Hu et al., used KSS scale to measure the sleepiness of drivers at an interval of 5 minutes and collected EOG signals. Portouli et al., collected the EEG data of the drivers and verified the interpreted results through questionnaires and a medical practitioner. Ingre et al. established the relationship between the blinking of eyes and KSS data collected every 5 minutes during the driving.

Researchers concluded that lane-changing, blinking rate and drowsiness-related physiological signals give KSS rating between 5 and 9. Therefore, subjective measures output does not give conclusive results as compared to vehicle-based, behavioral and physiological measures.

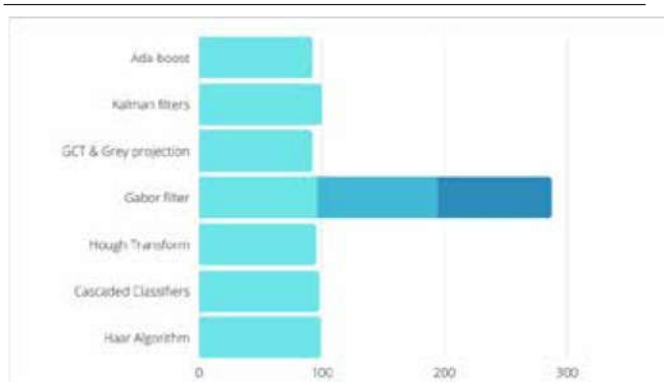
As the level of sleepiness changes even in time duration of as small as 5 minutes, subjective measures cannot detect that change. Also the subjective ratings perform poorly during self-introspection alerts that reduces the drowsiness of the driver in question. Therefore, subjective measures are only good when taken in a simulated environment and not in real conditions.

Vehicle-based Measures

Vehicle-based measurements include placing sensors in various parts of the vehicle including the steering wheel and the acceleration pedal. These sensors will send signals that will be analyzed and alert will be sent to the driver. Researchers found that sleep-deprivation can lead to large variation in driving speed. Given below are the two most commonly used vehicle based measures

Steering Wheel Movements: (SWMs) This method is widely used by the manufacturer like Renault and Nissan for detecting driver drowsiness. An angle sensor is placed on top of the steering column, when the driver is drowsy the micro-correction on the steering wheel reduces as compared to normal circumstances. Sleep deprivation leads the driver to make lesser steering wheel movements than in normal conditions (this characteristic was noted by Fairclough and Graham). Lane change is an important factor that is SWM, so to eliminate this effect, researchers considered only minimum steering wheel movements therefore between 0.5° and 5° which is needed to change lateral position within the lane. Although many companies have adopted SWMs but it comes with certain limitation and works only in very limited situations. This is because they are too dependent on the geometric characters of the road and very less dependent on the kinetic

SNO	DETECTION TECHNIQUES	EXTRACTED FEATURE	CLASSIFICATION	DETECTION RATE
1	Ada- boost	Texture detection and Red Eye Effect	Ratio of height and width of eye	92%
2	Kalman filters for pupil detection	Modified algebraic distance algorithm	Fuzzy classifier	Nearly 100%
3	Gravity center template and grey projection	Gabor wavelets	LDA	92%
4	Gabor filters	Wavelet decomposition	SVM	pp96%
5	Hough transform	Discrete wavelet transform	Neutral classifier	95%
6	Gabor filters	Local binary/condensation algorithm	Ada-boost/SVM	98.3%/93%
7	Cascaded Classifiers Algorithm detects face and Diamond searching algorithm to trace the face	Duration of eyelid closure, number of blinks, and its frequency	Region mark algorithm	98%
8	Haar algorithm to detect face	Unscented Kalman filter algorithm	SVM	99%



characteristic of the vehicle.

Standard deviation of lane position (SDLP)- this is also a useful technique to detect driver drowsiness. In case of a field experiment the position of lane is tracked using a field camera whereas in stimulated environment the software itself gives SDLP. In an experiment it was found that if the KSS rating increases, SDLP also increases. SDLP has a limitations; it is purely dependent on external factors like road markings, lighting conditions and climate. Moreover SDLP can be caused by impaired driving and driving under influence, when the driver is under drugs or alcohol.

Behavioural Measures

A lot of facial movement such as nodding of head, yawning and constant blinking is observed. These behavioural changes can be used to detect driver drowsiness. Following are the detection techniques using behavioural methods:

Physiological Measures

The measures discussed above have a limitation even though they are very precise and accurate. Behavioral measures are very accurate, but it can detect drowsiness of the driver only after the driver's head sways when they start getting sleepy. Same is the case of Vehicle based measures. Preventing accidents in this scenario becomes very difficult. But when we are talking about Physiological measures, they are very efficient in detecting drowsiness in the early stages and hence preventing accidents with these measures is an appropriate option. Physiological measures alert the driver timely and hence prevent any upcoming accidents.

The most common sensors that are being used to develop the physiological measures are:

1) Electrocardiogram (ECG)

2) Electromyogram (EMG)

3) Electroencephalogram (EEG)

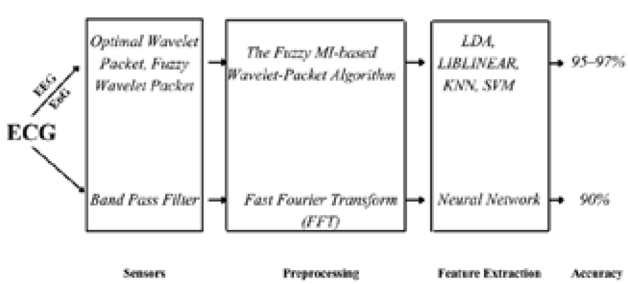
4)Electro-oculogram (EoG)

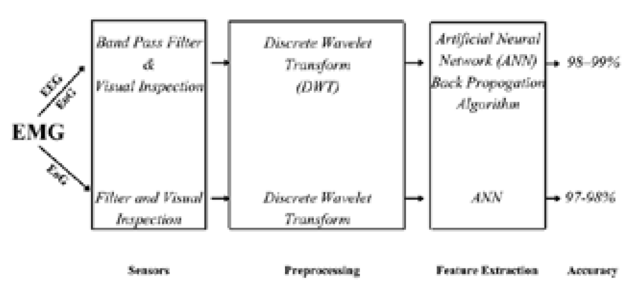
Electrocardiogram (ECG)

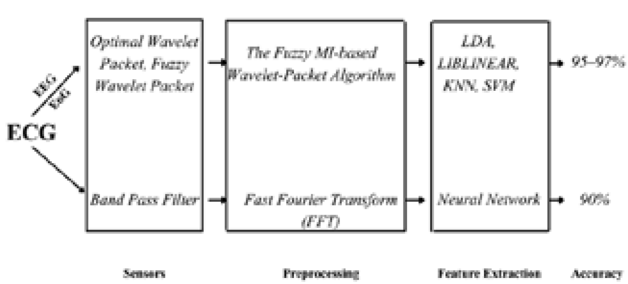
As the name suggests, ECG's role is to monitor cardiac activity. When a driver is drowsy, the heart rate is seen to be slower thcaan normal when the driver is sleepy. The heart rate drops from the driver being awake to being sleepy. ECG combinations for detection is shown below:

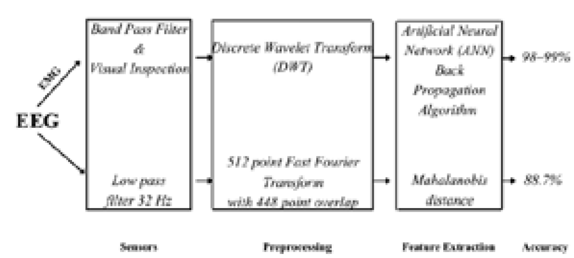
Electroencephalogram (EEG)

EEG's role is to monitor brain activity. Electroencephalography is an electrophysiological monitoring method to record electrical activity on the scalp that has been shown to represent the macroscopic activity of the surface layer of the brain underneath. It is typically non-invasive, with the electrodes placed on the scalp. EEG combinations for detection is shown below.









Electro-oculogram (EoG)

Electro-oculogram (EoG) is used to detect eye movement of drivers such as Rapid Eye Movement (REM) and Slow Eye Movement (SEM). The REM and SEM is explained with a picture below. Electrooculography is a technique for measuring the corneo-retinal standing potential that exists between the front and the back of the human eye. The resulting signal is called the electrooculogram. EoG combinations for detection is shown below:

REM and SEM in sleep cycle:

Stage 1(SEM) It is the stage in which the person goes off to sleep slowly.

In this stage the heart rate, breathing and brain activity slows down. It lasts for several minutes

Stage 2 (SEM) In this stage the heart rate and breathing decreases more and the muscles starts relaxing. There is a drop in body temperature and eye movement stops.

Stage 3 (SEM) More decrease in heart rate and breathing. Muscles completely relax. Slow brain waves are observed.

Stage 4 (REM) Most dreams occur in this stage. It occurs 90 minutes after stage 1. The eye moves faster from one side to another and heart rate and blood pressure increases.

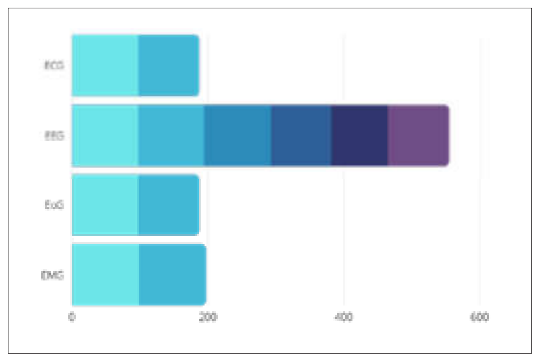
Below is a comparative chart of all physiological measures:

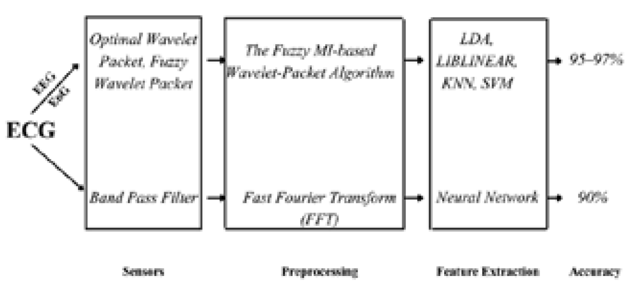
DISCUSSION

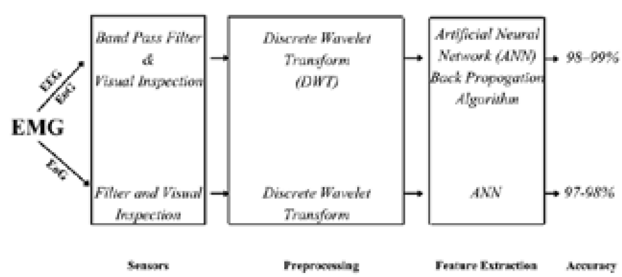
The review paper focused on various aspects of how drowsiness can be detected and measures can be improved to attain precise results in order to avoid devastating road accidents.

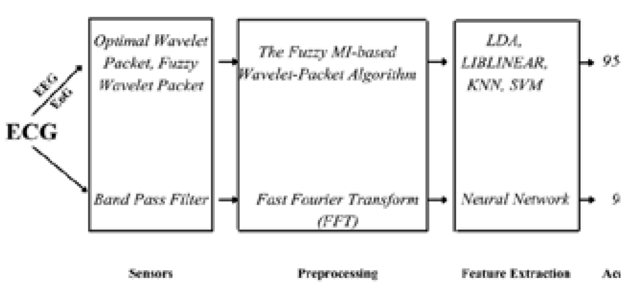
The detection of drowsiness depends on various factors for which four main types of measures came into existence.

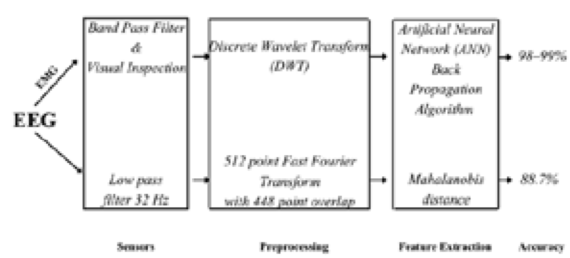
According to various researchers, experiments were conducted to draw a comparison between the simulated and real driving conditions and gave clear cut results that the simulated measures gave ratings that are not reliable when it comes to real driving experiences as the real conditions provide











more challenges that a controlled environment can not. And these significant differences prompted the researchers to search for better and reliable technologies that are advanced and can detect various aspects of drowsiness.

CONCLUSION

In this paper, we focused on a different approach to detect drowsiness in drivers and how these measures can be improved to get better results. The study focused on four measures: Subjective, vehicle-based, behavioral and physiological, to detect drowsiness. And their advantages and disadvantages were also mentioned. Out of all the measures, physiological measures showed the most accurate results but some more work needs to be done. Incorporating the vehicle-based approach along with the behavioral measures into the physiological measures can boost the precision to higher levels. Hence the detection can be implemented in real driving conditions. Fusing ECG results with other technologies can also help in providing optimal outcomes. IJFMP

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