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A review on the measures and techniques adapted for the detection of driver drowsiness

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Abstract. Driver drowsiness is one of the recent reasons behind accidents that can cause serious death, injury, and economic loss. Driving for long hours, sleepiness, medication, sleep disorders, and health conditions can cause drowsiness in a driver. It is of social concern since many lives including the passengers, drivers and wayfarers are at high risk due to drowsy driving. Detection of drowsiness and alarming the drivers can prevent a large number of accidents and thus the precious life can be saved. Input parameters like heart rate, pulse rate, vehicle steering movement, lane change, head movement, yawning, eye-closure can help to detect the drowsiness in advance. In the past, much research has been carried out to design an efficient driver drowsiness detection system using various measures to determine the drowsiness of the driver. In this paper firstly, we have reviewed the measures attempted by many researchers which are grouped under physiological, vehicle-based, and behavioral-based measures. Secondly, a detailed review of the deep learning approaches used is carried out along with the accuracy level achieved by each author. This detailed review will give a better insight for the young researchers to carry out prospective research in the specific field.

1. Introduction
Over the years, several driver safety assistance systems have been proposed to reduce the risk of traffic accidents, and statistics have shown that drowsiness is a major cause of traffic accidents. Conferring to National Sleep Foundation in the United States more than 40% of the adult drivers have admitted having drowsy driving at least once in their careers [1].

According to the estimation made by US National Highway Traffic Safety Administration, every year approximately 100000 road accidents arise due to driver drowsiness and fatigue [2,3]. Drowsiness and driving are a dangerous combination where most people are aware of the dangers of intoxicated driving but do not notice that sleepy driving can be just as deadly. Like alcohol, drowsiness slows down reaction time, reduces the awareness, changes the judgment, and increases the risk of crashing.

As per the survey done by the Ministry of Road and Transport in India [4] approximately 19,73,187 road accident deaths happened between the years 2000 and 2016 which is shown in figure 1. A reasonable count of accidents can be reduced by identifying the drowsiness of drivers and alerting them.

Fig.1 Road Accident Deaths in India[4].

Depriving sleep, working continuously for long hours, use of sedative drugs, working during unusual hours, and untreated sleep disorders are the main cause of driver drowsiness. The identification of drowsiness at the early stage is the much need of the hour to prevent accidents and valuable lives. Even though much research has been carried out on driver drowsiness detection, most of the work falls under three major categories namely, vehicle-based measures, physiological-based measures, and behavioral-based measures [5- 7].

To perform a detailed review keyword such as drowsiness detection, fatigue detection, Vehicle measures, physiological measures, and biological measures were used. The search was carried out in various research paper repositories like IEEE, Elsevier, ACM, ScienceDirect, IET, Google Scholar to get related papers. In the first search level around 450 papers were listed out of which around 150 papers were extracted based on the paper relevance. In the second search level 38 papers were considered to be more relevant to this review process and analyzed in all perspectives.

This paper collectively reviews the various measures to determine the level of driver drowsiness and the methods used for driver drowsiness detection. Section II of this paper discusses about the various measures used to identify the driver drowsiness. Section III will give an elaborate idea about the techniques adopted to determine drowsiness and the level of accuracy they have achieved. It will also give a summary of the work done by the researchers. The survey paper is concluded and a brief research focus is discussed in Section IV.

2. Measures for Driver Drowsiness

Existing driver drowsiness detection techniques can be grouped as Physiological measures, Vehicle-based measures, and Behavioral measures. Various parameters are considered by the different measures to classify the driver drowsiness. This section discusses about the different measures and the parameters used.

1.1. Physiological Measures

In physiological measure the driver's condition can be measured by targeting the heart rate, pulse rate, brain activity, body temperature and [8]. The most frequently used physiological measures uses different signals including electroencephalography (EEG), electro-oculogram (EOG), electromyography (EMG), electrocardiography (ECG) [9-16]. EEG method uses the human brains electrical activity which can measure brainwaves that are used by many applications like epilepsy diagnosis and monitoring sleep disorders [17].

EOG is used for recording the movement of human eye which measures the corneo-retinal level that is a technique for measuring the corneo-retinal standing potential that subsists between the front and the back of the human eye [18]. EMG evaluates and records the electrical activity of the muscles through surface electrodes that are kept in contact with the driver's skin [19]. ECG technique can be used to track and evaluate the cardiac activity which includes the heart rate, rhythm and electrical activity of the driver during driving [20].
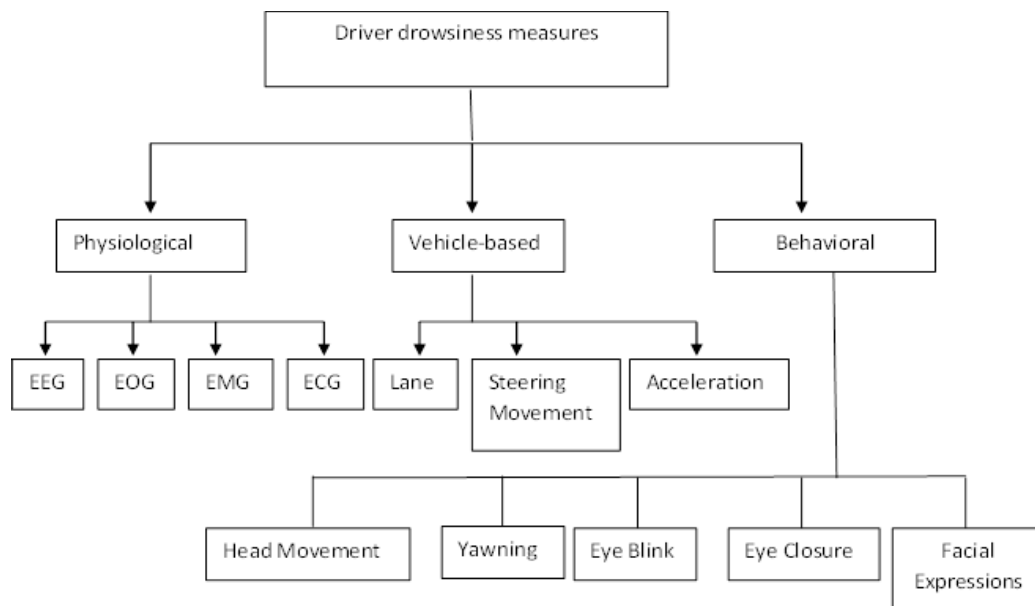
Fig. 2 Classification of Driver Drowsiness Measures

1.2. Vehicle-based Measures
The driving pattern of a drowsy driver can be different from the driving pattern of a normal driver [9]. Monitoring few metrics like deviation from the lane[21, 22], steering movement[23-26, 21-22], sudden changes in acceleration[9b,9bb,9bc], gas pedal and brake pedal[22, 26] can be helpful to predict driver drowsiness. A normal person who drives the car will have a regular driving pattern however, if he slightly changes from his lane or any other vehicle-based measure may generate an unnecessary alert. Very few researchers have used the vehicle-based measure as it may lead to more false positives [10].

1.3. Behavioral Measures
Many researchers have used the behavioral measures based on frequent yawning, eye closure, eye blink and facial expressions [9]. In the recent years many Machine learning algorithms play an important role in identifying driver drowsiness by using the captured images or videos. Researchers have tried to increase the accuracy, reduce the execution time and cost by using various light weight algorithms.

3. Driver Drowsiness Detection Techniques

3.1. Physiological-based Techniques
In this category the drowsiness measurement is done by attaching electronic devices like sensors to the driver's body. The earlier stages of drowsiness can cause physiological changes in human body. Integration of ECG and EEG signals are used to detect drowsiness and improve its performance [12].The authors have induced a monotonous driving environment and extracted the frequency and time feature from the EEG signals and heart rate (HR), heart rate variability(HRV) from the ECG signals. The noteworthy features of ECG and EEG are used to classify the drowsiness using SVM classifier. The combination of ECG and EEG have given better performance than individual signals.

The conventional linear approaches with raw EEG signals are not highly successful [13]. Decomposing raw EEG signals into wavelet sub-bands and extracting nonlinear features from the sub-bands can be helpful for the learning machine to classify the driver status more effectively. Extreme Learning Machine (ELM), ELM with Radial Basis Function (RBF) and SVM classifiers are used and their performance of classification was measured by the recognition accuracy, sensitivity, time consumed and specificity.

A combination of EEG and forehead EOG signals with the help of g discriminative graph regularized extreme learning machine (GELM) is used to predict the driver drowsiness [29].

The root mean square error(RMSE) and prediction correlation coefficient between the estimated drowsiness level and the actual drowsiness level were used to get the performance of single and fusion modality. A comparative study was made between the SVM and GELM using the different modalities.

EEG measurement system together with the analysis of independent component and power-spectrum, correlation evaluations and linear regression model can lead to the classification of driver's cognitive state [30]. The drowsiness detection system was simulated in a Virtual Reality (VR) environment and achieved average accuracy of 88.2%.

EMG signal can identify the level of muscle activation during driving activity[31] . Under non-disturbance situation the EMG and ECG signals are collected using the wireless sensors. EMG and ECG signals are separated by FastICA and using empirical mode decomposition (EMD) they are de-noised.

Reference	Signals	Measurement parameter	Classification algorithm	Accuracy
[12]	ECG EEG	HR, HRV Time and frequency	SVM	80.90%
[13]	EEG	approximate entropy , sample entropy, renyi entropy and recurrence quantification analysis	ELM ELM-RBF SVM classifiers	94.7% 95.6% 94.7%
[29]	EEG Forehead EOG	power spectral density and differential entropy horizon electrooculogram vertical electrooculogram	GELM	prediction correlation coefficient-0.8080 RMSE value -0.0712
[30]	EEG	33-channel EEG data	Linear Regression	88.2%
[31]	ECG EMG	Complexity of EMG, ECG and EMG sample entrophy.	Multiple Regressions	91%

Table.1 Analysis of physiological based techniques

3.2. Vehicle-based Techniques

It is a challenging task to use vehicle measures to predict the driver drowsiness [9]. Changes in lane, steering movement and acceleration are some of the features to be considered for drowsiness detection. In [23] five input parameters like centerline of the road, lateral acceleration, steering wheel angle, yaw rate and steering wheel velocity are considered and classification was done using a combination of CNN and LSTM deep learning algorithms.

The steering wheel angular velocity is considered and time series analysis is done on it to identify the fatigue condition [32]. The common driving pattern is that the driver frequently adjusts the steering wheel to a trifling degree which can be increased or decreased due to drowsiness.

Smart steering wheels [33] can used to increase the driver's safeness. Sensors are attached to the steering wheel which can indicate the presence or absence of driver's hand. Another research on steering angular movement was done by mounting sensors to it [34]. The system linearizes the approximate entropy through an adaptive piecewise linear fitting by considering the given deviation. The wrapping distance between the linear feature series is used to determine the drowsiness state.

Although many research has been carried in the vehicle-based measure it is still challenging to be considered as a detection system. It can be more effective while it is integrated with physiological and behavioral measures.

Reference	Input parameters	Data collection method	Classification algorithm	Accuracy
[23]	1. road centerline 2. lateral acceleration 3. yaw rate 4. steering wheel angle 5. steering wheel velocity	44 sessions in a fixed-base driving simulator simulating monotonous night-time highway drives.	CNN, LSTM	96.0%
[32]	Steering wheel data	bus driving simulator (BI301Semi) 39 bus drivers with different driving professions	feature selection using neuro-fuzzy systems SVM classifier	98.5%
[33]	Steering wheel	Sensors	Threshold of comparator	100% reliability
[34]	Steering wheel angle	Sensors	Binary decision classifier	78.01%

Table.2 Analysis of vehicle-based techniques

3.3. Behavioral-based Techniques
With a great demand in driver drowsiness detection techniques many researchers have done effective work with the help of various measures used for driver drowsiness detection. The authors in [19] have used the physiological, behavioral and vehicle-based measures to test the different combinations of data. In both detection and prediction behavioral measure has proved its strength with a detection mean square of 0.22 and prediction mean square error of 4.18 min.

Author	Materials	Method/Algorithm used	Dataset	Accuracy
[22]	SCANeR Studio, faceLAB, pulse plethysmography	Aritificial Neural Networks	21 participants simulated car for 110mins	95%
[35]	RGB input video	Deep networks	NTHU-drowsy driver detection benchmark dataset	73.06%
[5]	Sensors, Logitech C920 HD Pro Webcam	Deep Neural Networks	Custom Dataset	89.5%
[36]	web-cam of the laptop	Image processing, Decision making algorithm	55 min of video, in which 130 drowsiness events have occurred	90%
[37]	Camera	Artificial Neural Networks	200 image dataset	100%
[38]	HD Camera	Deep Belief Network	videos of 30 subjects (with ages ranging from 20 to 55 years)	96.7%

Table.3 Analysis of behavioral-based techniques

A deep drowsiness detection(DDD) network [35] is developed to learn and detect drowsiness. The network takes a RGB input video of a driver which can be used to learn the facial movements and head gestures using the three deep networks. The output of the three layers along with the softmax classifier helps drowsiness detection.

Both the physiological and behavioral measures were applied on the custom dataset which was captured using Logitech C920 HD Pro Webcam [5]. Multi-task Cascaded Convolutional Networks (MTCNN) is used for fast and accurate face detection. Driver Drowsiness Detection Network (DDDN) is used for detecting driver drowsiness.

Images are processed by human visual system to detect driver drowsiness [36]. The energy levels in the image frames are changed to improve the robustness of the drowsiness detection system and predicted using better decision making algorithm. Extracting the facial feature is an important task which can be done using the Viola-Jones algorithm.

The state of eye whether it is opened, half-closed and closed can be analyzed by processing the images collected [37]. An artificial neural network with a hidden layer network and an auto-encoder network can be used for this purpose. 200 images of a driver during the regular driving task was taken as data set.

A Deep Belief Network (DBN) [38] is used to classify driver drowsiness expressions for which the high-definition camera is used to extract the landmarks and textures of the facial regions. The behavioral measures are the recent trend among the researchers. A complete and accurate is still a challenge in the recent time.

4. Conclusion
Drowsiness detection model is necessary to be implemented to avoid accidents. This paper has surveyed the various measures and techniques used to detect the driver drowsiness by various researchers in the recent years. The physiological, vehicle and behavioral measures are discussed in the paper in which the behavioral measures have reached the highest accuracy. A quick response time is expected by the algorithms used in the detection model as it can save numerous human lives. Integrated measures such as combining physiological and behavioral based or vehicle based and behavioral based can provide more accuracy than individual measures. More experimental results are required for different countries as the research is also based on the road conditions, light effect and traffic scenario.

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