

A Survey of Driver Drowsiness Detection System

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Abstract— In this modern era, where technology has influenced the automotive industry deep, almost all four wheels now come with embedded features of mobile communications, wireless communication services, attractive digital displays, etc. This offers user comfort and offers a great user experience, but on the other hand, proves to be the cause of the driver's serious disturbance. Add to this, driver drowsiness causes a high number of road accidents. One of the causes of vehicle accidents is drowsiness of the driver. Many researchers have used many technologies to overcome this problem in recent years

So there are different techniques to detect drowsiness which are 1)Vehicle-based Measures 2)Behavioural Measures 3)Bio-Signal based Measures. A detailed study on these different measures helps to find insight on the present system and problems related to them and improvements we can do so they can perform more accurately and efficiently.

Keywords— Vehicle-based Measurements, Behavioural Measures, Bio-Signal based Measures, hybrid Measures.

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I. Introduction

A person's sleep is a state of flux from a state of function to a state of sleep and fatigue. This can happen for several reasons such as long working hours, medication, insomnia, fatigue, poor health, mental stress/depression. Statistics have identified drowsiness in drivers as a major safety factor for vehicles. Sleep apnea is very bad in terms of the severity of the injury and is most likely in people who do not sleep well. Drowsiness affects mental alertness, reduces a person's ability to drive safely, and increases the likelihood of a person making a mistake that could endanger a person's life. In addition, drowsiness indicates slow response time, decreased awareness, and poor judgment. A drowsy driver cannot predict when to start an uncontrollable sleep. According to a 2016 study, 20% of road accidents in the United States are caused by driver drowsiness. Looking at some quick facts: In India, because of road accidents 1) People die every four minutes 2) 1214 road accidents happen daily 3) 20 children under the age of 14 die every day 4) 377 people die every day 5) According to an article by the Ministry of Road Transport & Highways, Government of India, the country recorded at least 4,80,652 accidents in 2016, resulting in 1,50,785 deaths.

It is therefore very necessary to prevent road accidents caused mainly because the driver gets sleepy, gets the driver drowsy and wakes the driver asleep, and puts him back to work. By doing this, the driver will get to work before any (major) disaster, and we can save lives. The issue of drowsiness needs to be addressed as it is not considered a major cause of injuries in India at least.

Drunk driving is one of the leading causes of death in road accidents. Truck drivers who drive long hours (especially at night), long-distance bus drivers, or night-time buses are the most at risk. Drowsiness for drivers is a nightmare for passengers in all countries. The fact is that this is not the case considered very carefully encourages the need to find solutions to it. The solution to this problem must be provided in a way that reaches out to all of them, users of a four-wheel-drive vehicle or more. Certain steps can be used/implemented to implement the solution to the driver's drowsiness and especially its detection.

The sleepy driver loses control of the vehicle, an action that often leads to a crash of another vehicle or stationary objects. To avoid these destructive dangers, The driver's drowsiness should be monitored closely. The following steps have been used more to monitor sleep:

II. Different Methods To Detect Drowsiness

Over the years many research are done to lower the rate of accidents caused due to drowsiness. Following are some of the standard methods which are used to detect drowsiness.

A. Subjective drowsiness

Subjective indicators of sleepiness level include sleepiness scales, such as Epworth Sleepiness Scale (ESS), Karolinska Sleepiness Scale (KSS), and Stanford Sleepiness Scale.

1) *Epworth Sleepiness Scale (ESS)*: The ESS is a self-contained list of 8 questions. Respondents were asked to estimate, on a 4-point scale (0-3), their normal chances of falling asleep or falling asleep while performing eight different tasks. Most people do those tasks at least occasionally, though not every day. The ESS score (total 8 points for an item, 0-3) can range from 0 to 24. The higher the ESS score, the higher the person's daily sleep rate (ASP), or 'daytime sleep'. The questionnaire does not take more than 2 or 3 minutes to answer. It is available in many different languages.

Because ESS item points are based on rational reports, they can be influenced by the same sources of bias and malpractice as other such reports. Convincing evidence of

'excessive daytime sleepiness or increased risk of drowsy road accidents should be sought from other sources.

The ESS does not usually enable accurate predictions of sleep deprivation, and hence the risk of a collision while driving at a certain time. However, there may be a difference in this between people with very high ESS scores (> 15), their ASP is very high under most conditions.

2) *Karolinska Sleepiness Scale (KSS)*: It is the most commonly used drowsiness scale. Unlike ESS its a 9 point scale where after every 5 min ratings were measured and used it as a reference to the EOG signal collected. Some researchers compare the KSS to self-determination, which is recorded every 2 minutes during a driving activity, with a variety of vertical positioning (VLP), and find that these steps were inconsistent. Relationship between the blink of an eye duration and KSS collected every 5 minutes during the driving operation.

Researchers have determined that major lane departures, high eye blink duration, and drowsiness-related physiological signals are prevalent for KSS ratings between 5 and 9. However, the subjective rating does not fully coincide with vehicle-based, bio-signal, and behavioral measures.

3) *Stanford Sleepiness Scale*: It is not that accurate for a drowsiness detection system. Unlike ESS where ratings are calculated over the course of an entire day, Stanford Sleepiness Scale is calculated in a specific moment.,

B. Vehicle-Based Measurements: Another method to detect drowsiness is Vehicle-Based Measurements. In this method, various different types of sensors is used. These sensors are placed into the various part of cars like steering wheels, accelerators, brakes, etc. It is observed that these parameters are drastically changed when the driver is in sleep mode. The Speed of the cars also plays important role in detecting drowsiness. Following are some of the vehicle-Based Measurements.

1) *Using MPU6050, HMC5883L Sensors, and CityCarDriving Simulator*: This is based on a most recent study. The system consists of three main components of 1) system input 2) signal processing 3) application software. System input contains 5 set buttons, an HMC5883L sensor on the steering wheel, two MPU6050 accelerator sensors and brake. Signal processing system input is made by Arduino Promicro, which is used as a visual connector in the middle sensor and application software. The software used here is "CityCarDriving" simulation software. The process that takes place in this system is as follows, whenever there is a changing the steering wheel, or accelerator, or brake, will be read by sensors. The sensor then sends the change data to Arduino Promicro. Arduino Promicro then processes the data and sends it to a computer. Computer, by imitation the software displays data

in the form of almost identical images. This proposed can further be improved using more efficient and accurate sensors.

2) *Steering Wheel Movement*: Steering Wheel Movement (SWM) is a widely used Vehicle-based measurement. In this method, a steering angle sensor is generally used. An angle sensor is used which is fitted in the steering column, the driver behavior is measured. When a driver falls asleep, the number of micro-corrections on the steering wheel is reduced compared to conventional driving. It is obvious that sleepless drivers made fewer steering turns than normal drivers. To eliminate the effect of route changes, researchers look at the movement of small wheels only (between 0.5° and 5°), which is necessary to correct the lateral position within the line. So, based on small SWMs, it is possible to determine the driver's sleeping position. At the mimicry, simple side winds pushed the car to the right of the car the road was added near the curved road to create diversity in the lateral and forced areas drivers to perform SWM corrections. Car companies, such as Nissan and Renault, have adopted it SWMs, however, operate in moderate conditions. This is because they can only work honestly on certain areas and relies heavily on road geometry features as well as here low level in motor kinetic features.

3) *Standard Deviation of Lane Position (SDLP)*: It is another method of vehicle-based Measurements. In a simulated environment, the software is used to get the results while in real-life external camera are used which is placed on the front of a car and the position of the lane is tracked. Some researchers found that KSS rating increases with SDLP rating. SDLP was calculated based on an average of 20 participants; However, with some drivers, the SDLP did not even exceed 0.25 m with a KSS rating of 9. This proposed method can further be improved with the help of steering reversal rate (SRR). After calculating SDLP, the threshold was used to

calculate SRR. Then SDLP and SRR both are compared with the KSS. but there is also one disadvantage associated with this model that Consecutive SDLP analysis focused on only the continuous correlation with fatigue level, but SDLP may not continue to increase at every time interval. To overcome this problem Maximum SDLP method was proposed.

4) *Limitation of Subject Vehicle-Based Measurement:* In simulator lateral position, and thus all performance indicators based on this rating, are very accurate when found. As soon as a car is used or in real life, it becomes very difficult to get into this scale. For automatic detection, either line has to be painted and the adjacent area has to be present, just as for lane departure warning systems. If not, a custom solution should be found, which may be automatic based on visual recognition, or manually, based on video taken from the handling car, in the next car, or on sidewalk cameras. Personal data reduction is time-consuming has errors, which makes its use impossible

C. *Behavioral Measures:* Human face shows various signs when a person is in a drowsy state such as continuous blinking of eye, head movements and yawning, etc. So Behavioral Measures consist of tracking such an expression with the help of various ML techniques. So for this, there are requirements for robust, accurate, and fast ML techniques. A wide range of algorithms has been used in the past to detect drowsiness. But with development in the technological field, rise in the neural network it is important to revisit and evaluate their accuracy. Most of the that had done on behavior measures are based on blinking, PERCLOS (Percentage of eyelid closure over the pupil over time). Some studies were also done on various other facial actions like brow rise, jaw drop, lip stretch, and an eye blink, to detect drowsiness.

Following are some of the research done on Behaviour Measurements.

1) *Driver Drowsiness Detection using Eye-Closeness Detection:* This paper introduces a process for detecting drowsiness on the basis of blinking of the eye and head tilting. For this there are several methods that are applied in this research paper 1) Using Haar Cascade Classifier to classify the faces 2) ROI (Region of Interest) which is used to mark the regions on the face and to extract the dimension of the eye 3) After extracting the dimension detect eyes on the basis of frequency of a blinking of an eye.

Limitation: This model will work only in constant light. Haar cascade classifier will not detect the face if the person wears sunglasses. Also model will not detect one having a very dark skin tone.

2) *Histograms of Oriented Gradient:* As the above model is only worked in constant light and also it fails to detect the face of dark skin persons to overcome this problem another model which is based on Histogram of Oriented gradient is introduced. Histograms of Oriented Gradient (HOG) are basically used in computer vision and optimization problems as well. It is more effective in detecting faces. Following are the steps of HOG: 1) Using a regular grid extract HOG descriptors. 2) Vector quantization of each descriptor into different codewords 3) Classify face as face and non-face using Support Vector Machine (SVM)

Limitations: It is the most commonly used technique but its computational speed is relatively low as its used sliding window technique. Detecting face and processing fastly should be the main goal in Driver Drowsiness Detection System.

3) *Using PERCLOS and Grey Scale Image Processing:* This study developed a system for finding real-time drowsiness based on gray image processing and PERCLOS to determine if the driver is sleepy or not. The proposed system consists of three parts: first, calculate the proximity of the driver's face to the gray images, and then use a small template to analyze eye positions; second, it uses data from the previous step and PERCLOS to establish a fatigue model; and finally, based on the driver's personal fatigue model, the system constantly monitors the driver's condition. Once the driver has shown signs of fatigue, the system tells the driver to stop driving and rest.

Following are the behavioral-based technique:

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

A deep drowsiness discovery (DDD) network is developed to read and see drowsiness. The network captures RGB camera input video that can be used for reading face movements and head gestures using three deep networks. Third output layers and a softmax separator help detect drowsiness. Both physical and behavioral measures are applied to the custom database taken using the Logitech C920 HD Pro Webcam. Multi-task Cascaded Convolutional Networks (MTCNN) is used for fast and accurate face detection. Driver Sleep Discovery.

Along with this, there are various techniques like 1) Ada-boost which is used to detect Pupil having the accuracy of 92% and which comes under the classification of Red eye effect, Texture detection method.

2) Hough Transform which is used to detect Eye Closure Duration & Freq of eye closure and which comes under Neural Classifier having an accuracy of 95%.

3) Gabor filter which is used to Eye State and which comes under SVM having an accuracy 93%.

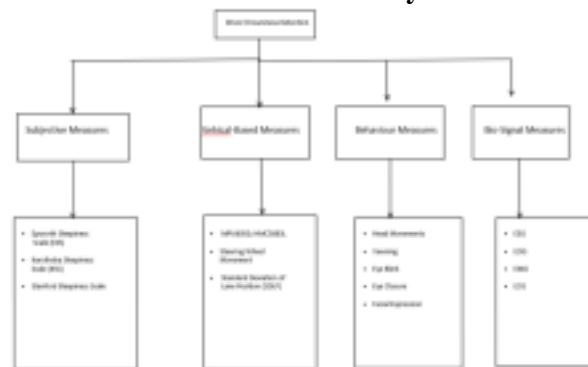
D) *Bio-Signal / Physiological-based Techniques*: At this stage measurement of drowsiness is done by attaching electrical components sensors in the driver's body. The early stages of drowsiness can cause physical changes in the human body. The combination of ECG and EEG signals is used to detect drowsiness once and for all improve its performance. The authors have created a key driving environment and extracted the frequency and time factor from the EEG signal, heart rate variability (HRV), and heart rate (HR), from ECG signals. Significant features of ECG and EEG are used to separate drowsiness using an SVM separator. The combination of ECG and EEG has given a better performance than individual features. Conventional linear methods with immature EEG symptoms are less effective.

Rotting raw EEG signals into sub-band wavets and removing indirect features from sub-bands can be useful in the reading machine to differentiate the driver status more successfully. Extreme Learning Machine (ELM), ELM with Radial Basis (RBF) function, and SVM separators are used and their partition performance is measured by accuracy of awareness, empathy, time spent, and clarity.

The reliability and accuracy of the driver's

drowsiness by using live signals is very high compared to other methods. However, the disruptive nature of measuring life signals it is still a matter for discussion. To address this, researchers have used wireless devices for measurement physiological symptoms in an unusual way by placing electrodes in the body and finding signals using wireless technologies such as Zigbee, Bluetooth. Some researchers have already further measured life signals in a non-disruptive way; by placing the electrode on the steering wheel or driver's seat. The signals received are then processed internally smartphone devices based on android and driver notified in time. The accuracy of a non-disruptive system is relatively small due to movement materials and errors that occur due to incompetence.

III. Summary



IV. Conclusion

In this way, we saw the different measures of detecting drowsiness which is Subjective, Vehicle-Based, Behaviour, and Bio-signal Measures. In subjective Measurements, every person's behavior is different so it's hard to calculate the accuracy and efficiency on the basis of subjective measures. To improve these subjective measures with the help of another approach like vehicle-based and behavior to get the accuracy. If talking about Vehicle-based Measurements, In a simulated environment it gives the most accurate results but in real life where a road is not marked with lines properly, there are no proper edges of the road, condition of the road is not so good so in this scenario, this measures will fail badly. Now come to Behaviour Measures, It is the most explored measure of the drowsiness detection system. With the rising in

technology, one can assume that this type of problem can be solved more effectively and accurately using these measures. As HAAR CASCADE is fast but will not work in certain condition and HOG based approaches show great results in most of the extreme condition but is slow as compared to HAAR Cascade. One

can improve the speed of this HOG-based approach further to get beautiful results. Researches should be done in order to find more fast algorithms as speed is everything in the detection of drowsiness.. Now the last one which Bio-Signal/Physiological Measures is a most accurate than above all but its quite expensive and also not a driver-friendly idea to have sensors all over the body. This can further be improved by decreasing the number of sensors and obtaining signals using wireless technologies like Bluetooth.

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