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A Comparative Study of Driver Fatigue Detection Systems

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ABSTRACT

Driver fatigue also known as driver drowsiness is caused by various factors, which can impair and hinder safe driving, including biological, physical, psychological, and other various factors. Accidents through driver fatigue are observed especially in the case where journeys are long-distance, and sleep-deprivation also plays the role of a prominent determining parameter.

There is an extensive number of accidents caused by driver fatigue and these are of major safety concern; hence it is of critical importance to come up with some mechanism that can combat and prevent such road accidents to save precious lives. Thanks to technological advancements we can deploy systems that can detect driver fatigue and drowsiness. In this paper, we would be reviewing the various techniques that can be used to implement a system for the detection of driver fatigue.

KEYWORDS: *driver fatigue, driver drowsiness, detection, fatigue, drowsiness*

I. INTRODUCTION

Fatal situations all over the world arise due to traffic accidents [1]. According to a global report produced by the World Health Organization in 2018, 1.35 million people die annually from road traffic accidents. The same report also highlights the fact that road traffic fatalities and injuries are the primary cause of death of children and young aged people, age group 5 – 29 years. Fatigue and drowsiness are a factor in almost one-third of a single-vehicle crash in rural areas [2]. Driver fatigue is a significant issue bringing about a huge number of road mishaps every year.There are various reasons for this condition of drowsiness to arise; a few of these are enlisted below:

- Shift employees and people operating extended hours: Shift employees area unit half dozen times a lot of possibilities to be in an exceedingly fatigue-related crash, whether that be at work (operating machinery or vehicles) or traveling.
- On long journeys on monotonous roads, like motorways
- Your level of mental and physical activity at the time
- The amount and quality of your last amount of sleep

It is not possible to compute the specific number of fatigue-related mishaps however research shows that driver drowsiness might be a contributory factor in up to 20% of road mishaps and up to one-fourth of lethal and serious mishaps and accidents. A reliable and effective technique for the measurement of neurophysiological fatigue known as PERCLOS (percentage of closure) is used to determine driver drowsiness. PERCLOS indicates the percentage amount of time for which a driver's eyes are closed within a certain specified period of time.

The project can facilitate vastly in reducing accidents that happen on roads due to driver fatigue. The ensuing harms of drowsy/fatigued driving may be even higher among commercial vehicles. Drowsy driving crashes are sometimes of high severity because of the drivers' vital loss of management, usually resulting in unexpected vehicle flight and no braking response. Accidents through driver somnolence do not seem to be uncommon particularly on highways once covering larger distances. So, it is most urgent to come up with a reliable and relevant automotive safety technology, which is what the project aims at delivering and being contributive of.

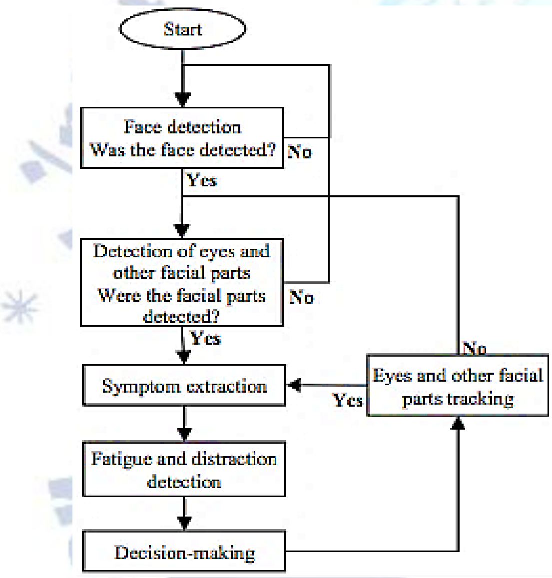

Figure 1: Data Flow Diagram

A driver will not even recognize once he or she is washed-out as a result of signs of fatigue square measure arduous to spot. Some people may experience micro-sleep — short, involuntary periods of the basiccognitive process. Within the four or five, seconds a driver experiences micro-sleep, at highway speed, the vehicle can travel the length of a football field [3].

In this particular review paper, we would be comparing two different implementations for the system of drowsiness detection.

1. A real-time system through OpenCV based on eye aspect ratio property.
2. Physiological signals such as an electrocardiogram (ECG) and electroencephalogram (EEG) for detection of fatigue.

The flow of developing a system for detection of drowsiness and fatigue can be represented through the following figure:

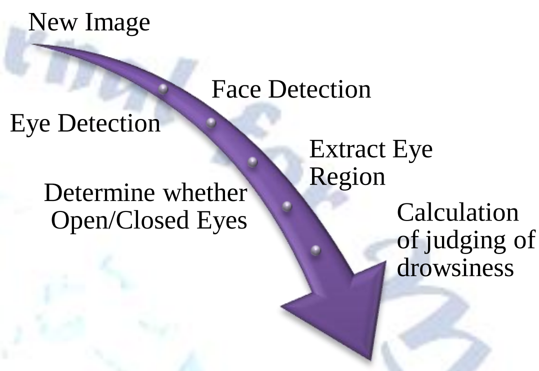

Figure 2: Flow Chart: Driver Drowsiness Detection System

II. RELATED WORK

Driver drowsiness can be broadly divided into three major categories:

- Vehicle-based
- Behavioural-based
- Physiological based[4]

Vehicle-based measures: a variety of metrics, including deviations from lane position, movement of the steering wheel, pressure on the acceleration pedal, etc., square measure perpetually monitored and any modification in these that crosses a nominal threshold indicates a considerably multiplied probability that the motive force is drowsy.

Activity-based measures: The behaviour of the motive force, including yawning, eye closure, eye blinking, head pose, and others are monitored through a camera and also the driver is alerted if any of those sleepiness symptoms square measures detected.

Physiological based measures: The correlation between physiological signals cardiogram (Electrocardiogram) and EOG (Electrooculogram). Sleepiness is detected through pulse rate, heartbeat, and brain data.

In 2010, Bin Yang et. al. [5] described 'Camera-based Drowsiness Reference for Driver State Classification under Real Driving Conditions' given that measures of the driver's eyes area unit capable to discover a temporary state below machine or experiment conditions. The performance of the most recent eye following based mostly on in-vehicle fatigue prediction measures the area unit evaluated. This measure is assessed statistically and by a classification methodology supported by a large dataset of ninety hours of real road drives. The results show that eye-tracking temporary state detection works well for a few drivers if the blink detection works properly. Even with some proposed enhancements, however, the area unit still issues with improper light conditions and for persons who need to wear glasses. As an outline, the camera-based drowsiness measures offer a valuable contribution for a temporary state reference however do not seem to be reliable enough to be the sole and only reference.

In 2014, 'A Review on Driver Face Monitoring Systems for Fatigue and Distraction Detection' given by Mohamad-Hoseyn Sigari, Muhammad-Reza Pourshahabi, Mohsen Soryani, and Mahmood Fathy [6] highlighted the main challenges that are faced while developing a face monitoring system for the detection of drowsiness as well as fatigue. The questions being (1) "how to measure fatigue?" and (2) "how to measure concentration?" Despite the advancements of science and technology, we find that a formal definition for the word fatigue is missing in the fields of psychology and physiology [7]. The result of this is that there exists no criterion for the measurement. However, we see that there are relations between fatigue and body temperature, eye movement, breathing rate, skin resistance, heart rate as well as brain activity. The most essential signs for drowsiness are seen in the eyes first.

The second challenge, to measure the attention of the driver while driving on the road. It can be estimated through gaze, head movement. However, a barrier is encountered here, which is, even if the driver is looking straight ahead at the road it necessarily does not mean that he is paying attention. Besides the mentioned main challenges of the driver face monitoring systems for detection of fatigue, developing a real-time system on conventional hardware platforms, reducing the error of the system in the detection of the face and its components, reducing the error of face tracking, and increasing system accuracy in detection of fatigue and distraction are considered as other problems of such systems.

In 2019, 'A Machine Learning Approach for Driver Drowsiness Detection Based on Eye State' written by Venkata Rami Reddy Chirra, Srinivasulu Reddy Uyyala, and Venkata Krishna Kishore Kolli [8] suggests the very fact that a stacked deep convolutional neural network can be trained to offer a solution for the detection of drowsiness and fatigue. The infamous algorithm of 'Viola Jones' is implemented for face recognition. The stacked deep convolutional neural network is developed so that it can extract features eye regions from the face images. This is done by using dynamically identifies keyframes from the cameras and implement those in the learning phase. Finally, a softmax layer will classify the image of a person who is drowsy or not drowsy. This proposed idea gave out results with 96% accuracy.

In 2019, 'An Effective Hybrid Model for EEG-Based Drowsiness Detection' written by Umit Budak, Varun Bajaj [9] suggests that early detection of driver drowsiness and therefore the development of a functioning driver alertness system may support the prevention of various vehicular accidents worldwide. Wearable sensors and camera-based systems are generally employed within the driver drowsiness detection. Electroencephalogram (or EEG) is considered as another effective option for the motive force drowsiness detection. Various EEG-based drowsiness detection systems are proposed up to now. During this paper, EEG signals are used for the detection of drowsiness, with the proposed method being composed of three main building blocks. Both raw EEG signals and their corresponding spectrograms are utilized in the proposed building blocks. Within the first building block, while energy distribution and zero-crossing distribution features are calculated from the raw EEG signals, spectral entropy and instantaneous frequency features are extracted from the EEG spectrogram images. Within the second building block, deep feature extraction is utilized directly on the EEG spectrogram images using pre-trained AlexNet and VGGNet. Within the third building block, the tuneable Q-factor wavelet transform (TQWT) is employed to decompose the EEG signals into related sub-bands. The spectrogram images of the obtained sub-bands and statistical features, like mean and variance of the sub-bands' instantaneous frequencies, are then calculated. Each feature group from each building block is fed to a long-short term memory (LSTM) network for the needs of classification. The obtained results from the LSTM networks are then fused with a majority voting layer. The MIT-BIH Polysomnographic database was utilized in the experimental works. The evaluation of the proposed method was allotted with a ten-fold cross-validation test and the average accuracy represented accordingly. The obtained average accuracy score was 94.31%. The obtained result was also compared with other results to be found within the literature. The comparison shows that the proposed method's achievement was found to be better than the compared results.

Given in, 'Detection of driving fatigue by using noncontact EMG and ECG signals measurement system' by Rongrong Fu and Hong Wang. Building a discriminant mode utilizing can recognize driver exhaustion a few highlights got from physiological signs. There exist two significant difficulties of this sort of strategy. One is how to gather physiological signs from subjects while they are driving with no interference. The other is to discover highlights of physiological signs that are of comparing change with the loss of consideration brought about by driver weakness. Driving exhaustion is recognized as dependent on the investigation of surface electromyography (EMG) and electrocardiograph (ECG) during the driving time frame. The noncontact information obtaining framework was utilized to gather physiological signs from the biceps femoris of each subject to handle the main test. Quick autonomous segment investigation (FastICA) and advanced channel were used to handle the first signals. In light of the factual investigation results given by the Kolmogorov–Smirnov Z test, the pinnacle factor of EMG ($p < 0.001$) and the limit of the cross-connection bend of EMG and ECG ($p < 0.001$) were chosen as the joined trademark to recognize the weakness of drivers. The discriminant measure of exhaustion was acquired from the preparation tests by utilizing Mahalanobis separation, and afterward, the normal grouping exactness was given by 10-crease cross-approval. The outcomes demonstrated that the technique proposed in this paper could give well execution in recognizing the ordinary state and weakness state. The noncontact, locally available vehicle drivers' weakness location framework was created to decrease exhaustion related dangers.

III. METHOD

Driver fatigue detection systems use a variety of images and sensors through image acquisition equipment. This equipment helps to collect driver behaviour parameters and physiological parameters and other kinds of parameters. The parameters hence collected are used as input for the analytical model to comprehend the drowsy/fatigue level of the driver. Hence, called the objective fatigue detection methods. These methods are more reliable than subjective detection methods.

Therefore, objective fatigue detection methods have been mentioned as the focus of research in the field of engineering application and scientific research. This review paper focuses on objective detection methods. The objective detection method is divided into two major categories: driver facial features-based detection method and the driver physiological parameters-based detection method.

1. DRIVER PHYSIOLOGICAL PARAMETERS BASED DETECTION METHOD

Studies show that [10], when a driver gets to the drowsy/fatigued state, his physiological response becomes slow, his physiological indicators will deviate a bit from the normal state, his body's response to a stimulation appears to show some delay. Therefore, a driver's physiological parameters collected by the sensors can be used to comprehend whether the driver is in the drowsy/fatigue state or not. Currently, there are many detection methods. Methods based on the detection of ECG (electrocardiogram), EMG (electromyography), EEG (electroencephalogram), respiratory frequency, and pulse beat [11-13].

1.1 ECG DETECTION

The electrocardiogram or the ECG is constructed in the process of cardiac excitation by the weak current. When the driver is drowsy or tired, the electrocardiogram signal will show a remarkable decline in regularity [14]. The heart rate variability index and heart rate index become the important indexes to judge the degree of fatigue.

Sangeetha et al. [15] developed a vehicle-mounted driver fatigue detection system. The system gathered the driver's electrocardiogram signal and compared it with the stored drowsy/fatigue driving electrocardiogram signal. The system fired the driver an alarm when the similarity between the two signals reached a certain threshold value.

ECG detection method is easy to carry and easy to operate. However, the sensitivity is poor. Also because of the individual differences in drivers, their heart rate change is different, which results in a high false-positive rate of this method.

1.2 EMG DETECTION

Electromyography or the EMG is the superposition of action potential of the motor unit in space and time. SEMG is a comprehensive effect of the electrical activity and the superficial muscle electrical signals on the skin surface, which can reflect the neuromuscular activity to some extent [16]. When the driver's drowsy/fatigue degree increases, the frequency of the electromyography signal will continue to drop, the amplitude gradually rises [17]. Therefore, the analysis of electromyography signals can achieve the purpose of the driver's drowsy/fatigue level. In general, the potential method is used to measure the electromyography signal, it uses an electrode which is fixed on the muscle surface of the driver to collect the signals.

HONG et al. [16] judged the driver's drowsy/fatigue based on the driver's electromyography signals. They used sensors to collect the electromyography signal of the driver, processed the original signals with the FastICA algorithm program, and then the digital filter. The processed results were then classified using the classification results and Mahalanobis distance and then used to judge the degree of driver fatigue.

This detection method is true and objective, but it attacks the driver's skin, which is not beneficial to the driver's safe driving.

1.3 EEG DETECTION

The fluctuations in the potential of synchronous changes in nerve cells in the human brain are called Brain waves. The change of the electroencephalogram or EEG reflects the change in the human brain. There are four kinds of waves in the human brain namely, alpha wave, beta wave, theta wave, and a delta wave. The beta wave and alpha wave decrease while the theta wave and delta wave increase when the driver changes from a state of consciousness to a state of fatigue [18].

Based on the relationship between the change of brain signal and the degree of driver drowsy/fatigue, the detection algorithm and program can use the real-time EEG signals to make accurate sense of the degree of driver fatigue. Electroencephalogram signals are the most reliable and important index for fatigue detection [18].

Mohammedabubasim developed a driving system based on the Electroencephalogram signals [19]. The system first collected the real-time EEG signals using the sensors. Then the signals were processed by the linear SVM classifier and the Gobar filter to get the analysis result. At last, alarms are fired to the drivers falling into a drowsy/fatigued state.

EEG signal detection has high sensitivity, reliability, and strong anti-interference ability. But its cost is high because of the structure and complexity of the sophisticated instrument. Also, it might affect the driver's operation because the sensors are in direct contact with the driver.

2. DRIVER FACIAL FEATURES BASED DETECTION METHOD

When the driver is in a state of drowsy/fatigued, the facial features of the driver will be quite different from that of the conscious state. Therefore, it is a much effective method to detect fatigue driving in real-time by continuously collecting and analyzing the driver's facial features data using some equipment [20]. The changes in the facial and head features are more obvious and most easily detectable. The methods of detection include gaze direction detection, head position detection, PERCLOS, mouth state detection, and blink frequency detection [21-23].

2.1. PERCLOS

Carnegie Mellon University Driving Research Center developed a system called the PERCLOS system [24] in 1998. The system was based on the theory that the ability of the retina to reflect the infrared light of different wavelengths is different in the same illumination. The retina was located according to the difference of image formed by different wavelengths, analyzed the size and position of the eyes, and then finally determined the closed eyes according to the image of the eye region.

The experiment shows that there is a close relationship between the degree of fatigue and the length of the eyes closed. The longer the eyes remain closed, the more serious is the degree of fatigue. This method is used to evaluate the driver's drowsy/fatigue degree by comparing the percentage of eye closure time per unit time.

The method has advantages like high accuracy, real-time, and non-contact. It is one of the most widely used detection methods in the market currently. However, this method gets affected by light easily, like, driver's glasses, occlusion, and other factors. There is still some room for improvement.

2.2. BLINK FREQUENCY DETECTION

Blink frequency refers to the total number of eye blinks per unit of time. When a driver is tired, the eye blink frequency rises from the normal value. Sigari et al. [25] used computer vision (CV) technology to extract the driver's eye information and calculated its blink frequency. The so calculated blink frequency was then used to analyze the driver's fatigue.

Blink frequency detection method has advantages like real-time and high accuracy. Its robustness is poor because it can get affected by occlusion, driver's glasses, and other factors easily. With the development of computer vision (CV) technology, this problem can be overcome [26]. Hence, eye blink frequency is an important fatigue evaluation index.

2.3. YAWNING DETECTION

Yawning is one of the most obvious and important facial features of fatigue driving. Many researchers have detected the drowsy/fatigue degree by extracting the characteristics of the driver's mouth and around the region [27-28]. Using image recognition technology, researchers have extracted and analyzed the mouth features of a driver to judge whether the driver was yawning or not. They evaluated the driver's fatigue degree based on the number of times the driver yawns per unit time and the mouth opening degree when the driver yawns.

This method is easy to go wrong when the driver is talking rather than yawning. The researchers [29] used the hidden Markov model to successfully separate the two characteristics of talking and yawning. The method of yawning detection in real-time and has high accuracy, which is suitable to be used as an auxiliary method for fatigue detection.

III. SUMMARY

Driver facial features-based detection method and driver physiological parameters-based detection method have their own disadvantages and advantages. As shown in Table 1, both fatigue detection methods are compared in terms of accuracy, sensitivity, contact, and cost. Overall, the fatigue detection method based on the driver facial features is a more promising method.

The advantage of the driver facial features-based method is obvious and intuitive. It can more precisely determine the degree of driver fatigue. Apart from that, it realizes the feature of non-contact, which does not even affect the normal driving of the driver. The disadvantages comprise of recognition algorithm complexity, difficulty in feature extraction, and the detection results can be easily affected by illumination and occlusion factors. But in recent years, machine learning and image recognition techniques have made great advancement. Especially the deep learning technology has made remarkable headway in the field of computer vision (CV).

Table 1: Method Comparison

Detection Method	Contact	Sensitivity	Accuracy	Cost
Driverfacial features-based detection method	No	Med	High	Med
Driver physiological parameters-based detection method	Yes	High	High	High

The advantages of the driver physiological parameters are that it can accurately and objectively reflect the degree of driver fatigue. The disadvantages are that data acquisition equipment are expensive and complex; also, that the equipment needs to be in contact with the driver's body directly, which affects the traffic safety and the normal operation of the driver. Hence, application of this method to driver fatigue detection system is limited.

IV. CONCLUSION

The rise in the number of cars can further lead to an increase in the number of traffic accidents. Drowsy/fatigued driving is one of the most important reason for traffic accidents. Hence, it is of great importance to study fatigue detection methods which are real-time, have high accuracy, and strong anti-interference. One single parameter is not accurate enough to determine the drowsy/fatigue state of the driver. Drowsy/Fatigue detection methods based on data fusion technology judge fatigue driving by the fusion data of parameters related to driver and the vehicle. This is a significant research direction; Besides, these fatigue detection methods analyzing fatigued state by deep learning can get more strong result. The strong analytical capabilities and data transmission will make a great contribution to the real-time performance and accuracy of fatigue driving detection.

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