IJNRD.ORG ISSN : 2456-4184
INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD) | IJNRD.ORG
An International Open Access, Peer-reviewed, Refereed Journal

A REVIEW OF DRIVER DROWSINESS DETECTION METHODS

Deepu Cyriac, Jenet Jose, Harishankar A, Allen K Prince, Dr. Jyothish K John*
Dept. of Computer Science and Engg.,FISAT,
**Professor,Dept. of of Computer Science and Engg.,FISAT*
Angamaly, India

ABSTARCT

Drowsiness detection is one of the essential functions in the advanced driver assistant systems for preventing fatal accidents from the people on a road. Many drivers and pedestrians have lost their lives or are significantly injured by drowsy driving. A sleepy driver is arguably much more dangerous on the road than the one who is speeding as he is a victim of micro sleeps. Automotive researchers and manufacturers are trying tocurb this problem with several technological solutions that will avert such a crisis. Drowsy driver detection is one of the potential applications of intelligent vehicle systems. Therefore, in order to prevent these losses of life and property, it is an important challenge to develop a driver drowsiness detection and prevention method. The current challenges are the increased complexity to produce such a method and also the high cost associated with the development of the method. These challenges can be overcome by using image processing for decreasing the complexity of the systems and using existing hardware like smart phones for drowsiness detection which can in turn decrease the cost associated with the development of the method.

1. INTRODUCTION

Driver drowsiness is a major factor in most driving accidents. Every year, they increase. In recent years the number of automobiles have increased and along with it the accidents which are mostly due to lack of driver alertness. The most common case of lack of driver alertness is due to drowsiness. Most solutions to this problem are either too complicated to implement or too costly. The paper reviews related literature to analyze the methods to find and alert driver drowsiness and gives a comparison of various methods.

II. RELATED WORKS

In this paper [1], a condition adaptive representation framework is proposed which can be used for driver drowsiness detection. The framework is based on a 3D-deep convolution neural network. The above mentioned framework containsfour models. They are spatio-temporal representation learning, scene condition understanding, feature fusion and drowsiness detection. The motion andappearances in the video are described by feature extraction using the spatio-temporal representation framework. The scene conditions related to various conditions about the drivers and driving situations like whether the driver is wearing glasses or not, the illumination inside the car, the motion of the facialelements like head, eye and mouth are classified by the scene condition understanding. A condition-adaptive representation is generated by the feature fusion using two features extracted from the above models. Finally, the drowsiness detection model recognizes driver drowsiness status using the above generated condition-adaptive representation. The future works considered in the paper are optimization of the networkstructure in the proposed framework for use in an embedded board or micro-computing

systems and upgrading the proposed framework to an online update tion method so that the system can be updated online to increase the drowsinessdetection reliability of the model.

In the paper[2], the authors propose a system to detect driver drowsiness is implemented where the onset of N-1 stage of Non-REM sleep is detected using ECG of the driver. The highest peak of the ECG is called the 'R-wave', and the RRI is defined as theinterval between 2 R-waves. The fluctuations in RRI are called HRV. Time domain and frequency domain features are calculated from the RRI. The eight extracted HRV features are then merged into a matrix, which is then pre-processed for model construction, and PCA is applied to the matrix. MSPC algorithm is used to detect abnormalities. The control limits for the T^2 and Q valuesare determined. T^2 value is a measure of the variation in each sample within the PCA model, and Q value indicates how well each sample conforms to the PCA model. The driver status is determined as 'drowsy' only when either the T^2 or Q statisticcontinuously exceeds its control limit for more than the predefined period.

Driver Fatigue is a major reason for many road accidents. Hence driver fatiguedetection is necessary to avoid such fatalities. Even though there are physiological methods and vehicle based methods existing to detect driver drowsiness, in the real world applications these methods are unreliable. In 'Real Time Driver Fatigue Detection System Basedon Multi-Task ConNN' the authors[3] propose a behavioral based method to detect drowsiness of a driver by using multi task Convolution Neural Network(ConNN).They considered eye andmouth characteristics of the driver using Percentage eye closure(PERCLOS) and Frequency Of Mouth(FOM) parameters respectively. Then they classified botheye and mouth into the single Multi task ConNN model. .They used two publicly available datasets to train the model YawDD and NthuDDD video datasets. The YawDDdataset consisted of two video datasets in itself,where the only difference between them was the placement of camera .In the first dataset camera was placed under the front mirror of the car and in the second dataset camera was installed on drivers line of sight. YawDD was mainly used by them to detect yawning ofthe driver. In NthuDDD video dataset each frame was labeled as fatigue or not fatigue, it also consisted of videos from both day and night time.

They used Dlib library to detect the facial landmarks of the driver. It was used to determine face, mouth and eye regions from the video datasets. Now Percentage Eye Closure(PERCLOS) parameter was used to determine whetherthe eyes were open or closed. If 80% of eyes were opened ,then eyes were givena label value of '1',and was considered as open.

Else the eyes were given label '0'and were considered as closed. Similarly, Frequency Of Mouth(FOM) was usedto detect whether the mouth was open or closed.FOM was given a label value '1' if 80% of the mouth was open else it was given a label value '0'.

The paper [4] focuses on the most recent deep learning based systems, algo rithms and techniques for the detection of Human Driver Inattentive and Aaggressive Driving Behavior (HIADB). Here human Inattentive driving behavior (HIDB) is classified into two major categories, Distraction and Fatigue/Drowsiness. Distraction of a driver refers to loosing concentration behind the wheels while doing another event or activity and when an object, or person outside or insideof the vehicle takes away the driver's attention from the driving task. Drivers' visual behavior and Vehicle related features are collected in order to predict driver distraction.

Fatigue of a human driver refers to a state when he/she is too tired to remain alert. Human Driver's Fatigue results due to his physical or mental exertion, prolonged driving, inadequate, fragmented or interrupted sleep etc... This is predicted by categorizing human driver fatigue or drowsiness into two major measures (i) Driver based measures and (ii) Vehicle based measures. Driver based measure , derived from driver includes physiological features(Intrusive) and Visual features(Non-Intrusive). Vehicle based features include those which are derived from the vehicle including Lateral displacement, Speed, Acceleration. Deep learning model like discriminative model which include CNN(Convolutional Neural Network) , RNN(Recurrent Neural Network) and LSTM(Long Short Term Memory) are the most common methodologies used for the process of feature extraction and HIADB detection.

The paper [5] is focused on using convolutional neural networks techniques forthe detection of drowsiness in drivers. The accuracy of the model proposedwas much more increased by utilizing facial landmarks which are detected bythe smart phone camera and passed to the CNN. This data can be used to classify the drowsiness. The model proposed here is able to provide a lightweight alternative to heavier classification models. The accuracy for the category with- out glasses is 88 percent and for night without glasses id 85 percent. Overall,the system was able to achieve an accuracy of 83 percent.

One of the important parts of the proposed system is the android device used to capture the image data and send it to the CNN for processing. The native mobile application developed for android is capable of taking pictures of the driver. This image is passed to the Dlib C++ library for processing and return the facial landmarkcoordinates. These facial landmark data is send to the CNN which passes thedata through the neural networks to determine whether the data belongs to the drowsiness set of values or the non-drowsiness set of values based on its pre- trained network. If the values given as input is found to belong to the drowsi- ness category, it will produce the true value for output indicating drowsiness. The android application on receiving this will take preventive measures suchas notifications via visual and audio messages to remove the drowsiness. If the driver is not found to be drowsy then, no measure is taken. The real-time results of the input image data is displayed on the android application.

One of the important features of intelligent vehicle system is drowsiness detection. In the paper[6] a machine learning based method was deployed to identify human behavior during situations of actual drowsiness. Automatic classifiers are used here. These classifiers correspond to 30 facial actions which are from the facial action coding system. The facial actions include blinking and yawn motions. The motion of the head was collected using an eye-trackingmechanism and an accelerometer. The classification of the data is done using learning-based classifiers such as adaboost and multinomial ridge regression.The proposed system showed 98 percent accuracy in predicting sleep and crash episodes on a simulator. The analysis in this paper also revealed new information corresponding to human facial behavior for drowsy drivers.

In the paper[7]a smart phone based driver drowsiness detection was proposed. They considered using smart phones instead of purchasing additional hardwareas it is readily available for all the drivers. Another reason for using smart phonesis that most middle class people will not consider buying equipments like acamera just for this single purpose. Even though there are some car manufacturers who was able to implement driver drowsiness detection in their cars, allsuch cars are luxury cars. They implemented an algorithm which takes into consideration the Voice, Vision and Touch response of the driver based on smart phone.

In the paper [8], the authors not only developed a driver drowsiness detection algorithm but also considered the individual driver differences. To detect the face region they used DCCNN (Deep Cascaded Convolution Neural Network. Compared to CNN in DCCNN sub-network has less numbers of filters but more discrimination ofthem, which effectively improved the speed of the algorithm. In DCCNN, they also build an image pyramid such that face can be detected, even if it has verylarge proportion. Then to determine facial landmarks they used DLib toolkit. They also developed a new parameter called an Eye Aspect Ratio (EAR),whichwas used to determine whether the eyes were in open state or closed state. The paper[ ]proposes a method for driver drowsiness detection at an early stageby computing the heart rate variations using advanced logistic regression based machine learning algorithm. The attributes taken into consideration are Lowering detection time, Increasing accuracy and Detection of drowsiness probability .ECG is an electrical signal derived from automatic heart chemical recombination, generating different electrical potential voltages. An intrusive device which is attached to driver's chest is used to collect ECG, But it is important that the driver to maintain his or her freedom of mobility and not to have any attached sensors. In that case ECG sensors can either be placed on the back of the seat or on the seat belt , the data collected from theECG sensors have unwanted noise signals which must be eliminated. The out-put from the non-contact sensors is a low voltage (mV) signal, which shouldbe amplified in order to extract information. In the next step, a combination of micro-controllers and A/D convertors generates a discrete ECG signal and pre- pares the data for the software stage. The primary focus of software development is to calculate the time series between every two consecutive R complex peaks and thenstore this data. There may be a chance for environmental noise having same frequency of HRV signal exist , which may lead to a wrong peak in the R complex or there is a chance of showing S wave instead of R wave. In order to cleanthe ECG signal least means square (LMS) adaptive filter method with an LMS algorithm is used. This method removes the noise within the same frequency range which is mixed with the ECG signal.

In the paper[9] a low-cost and easy to implement system for detecting driver drowsiness has been implemented here where the video feed from a device like a smart phone is passed to the processing algorithm, where it detects facial features and after performing calculations it determines whether the driver isin a drowsy state or not. If the driver is determined to be drowsy, an alarm is issued to alert the driver.

Video feed of 30 minutes with intermittent blinking, yawning etc is collected, which is passed on to a

laptop for processing, where face detection is done us-ing HOG method using SVM classifier. If face is detected, then marking of faciallandmark points are done. There are 28 such pointss. After these points are marked, the following parameters are calculated.

III. COMPARISON OF DROWSINESS DETECTION METHODS

Reference Paper	Methodology	Advantage	Disadvantage
Driver Drowsi-ness Detection Using Condition- Adaptive Repre- sentation Learning Framework	It implements a condition-adaptive representation learning framework based ona 3D CNN which candetect drowsiness in different situations by classifying them with the help of pre-traineddata.	Experimental results show that the proposed framework out-performs the existing drowsi- ness detection methods based onvisual analysis	It is an offline method so, if a situation notin the training data arises the model won't be able to classify it.%
Heart Rate Variability-based Driver Drowsiness Detection and its Validation with EEG	HRV features are ex-tracted, preprocessed and PCA is applied. Anomalies are detected using MSPC algorithm and drowsiness is de- tected, when T^2 and Q values exceed controllimits.	Method classifies sleep condition into awake, REM, and NREM and the accuracy of their method was 72% -88%	Current im-plementation uses electrodesinserted into skin , causes -discomfort
Real Time Driver Fatigue Detection System Based on Multi-Task ConNN	Multi task CNN was used to detect and clas- sify driver drwosniessinto 3 categories using PERCLOS and FOM pa- rameters	The proposed model achieved 98.81% fatigue de-tection on YawDD and NthuDDDdataset	Performance of Mutli task CNN might be lim- ited by the use- less information about the facial landmarks

Reference Paper	Methodology	Advantage	Disadvantage
Detecting Human Driver Inattentive and Aggressive Driving Behaviour Using Deep Learning: Recent Advances , Re-quirements and Open Challenges	The proposed method detects driver drowsi-ness by categorising HIADB into two and using CNN , RNN andLSTM to predict the driver fatigue level	They proposed a novel method to detect driver drowsiness using CNN,RNN andDBN	Classification of HIADB into two categiries may not solve the issue as there may be a chance of new category which can lead to driver drowsi- ness can come into existence inthe future

Driver Drowsi-ness Detection Model Using Convolutional Neural NetworksTechniques forAndroid Applica-tion	The system consists of drowsiness detection method based on the data obtained from a smartphone device using an android appli- cation.	Model that is presented here has achieved an average of 83.33% of accuracy for all categories where the maximum size of the model did not exceed 75KB	If the facial features are obstructed in any way thenthis leads to decrease in accuracy of the system.
Machine Learn- ing Systems for Detecting DriverDrowsiness	In this paper, a machine learning based method was deployed to iden-tify human behaviour during situations of ac- tual drowsiness using automatic classifiers.	Given a 30-s video segment the system can dis-criminate sleepy versus non sleepy segments with 0.99 accuracy across subjects	If the facial data is obstructed in any way thenthe system will not provide ex-pected results.

Reference Paper	Methodology	Advantage	Disadvantage
A Smartphone- Based Drowsiness Detection and Warning System for AutomotiveDrivers	Voice,Vision and Touch response based classi-fication methods was used to predict the driver is drowsy or not	The framework pro- vides 93.33% drowsi- ness state classifica- tion as compared toa single stage whichgives 86.66%	The acquired speech data may be noisy, Illumination sensitivity ofa smartphone camera is too high,
A Real-time Driv- ing Drowsiness De- tection Algorithm With Individual Differences Consid-eration	DCCNN was used to detect face and Dlib was used for facial pa-rameters.EAR was cal-culated .Finally SVM algorithm was used to evaluate the drowsi- ness state of the driver	Detects the drowsy state of driver quickly from 640 × 480 reso- lution images at over 20fps and 94.80% accuracy	Can't detect driver drowsi-ness during night,
Real Time Driver Drowsiness Detection Using a Logistic-Regression	Driver drowsiness is detected using the HRV signal which is collected using a non-intrusive device and using Naive bayes and Logistic regression algorithm in conjuc-tion	Developed technique has been tested with human subjects and it can detect drowsiness in a minimum amount of time, with an accu-racy above 90%	As the method suggests to place the sensor either back seat or on seat belt , certain seatingpositions of the driver may cause the ECG sensor fail to do its task
Driver Drowsiness Monitoring Sys-tem using Visual Behaviour and Machine Learning	Calculate NLR, EAR, MOR values from video stream and alert driver if all these val- ues are beyond theirthresholds	The sensitivity of FLDA and SVM is 0.896 and 0.956 re-spectively and the specificity is 1 for both	Detection accu- racy is lesser in darker condi-tions.

IV. CONCUSION

Driver drowsiness detection and prevention is one of the important features of the driver assistance system of the automobiles.The technology behind this is analysed in the paper. The requirement of current situation is to select the driver drowsiness detection system in terms of ease of implementation, cost-effectiveness and better accuracy. The paper focuses on the varous techniques such systems employ and their probable merits and demerits

V. REFERENCES

1. Jongmin Yu, Sangwoo Park, Sangwook Lee, and Moongu Jeon. Driver drowsiness detection using condition-adaptive representation learning framework. IEEE transactions on intelligent transportation systems, 20(11):4206–4218, 2018.

2. Koichi Fujiwara, Erika Abe, Keisuke Kamata, Chikao Nakayama Yoko Suzuki, Toshitaka Yamakawa,

3. Toshihiro Hiraoka, Manabu Kano, Yukiyoshi Sumi, Fumi Masuda, et al. Heart rate variability-based driverdrowsiness detection and its validation with eeg. IEEE transactions on biomedical engineering, 66(6):1769–1778, 2018.

4. Burcu Kir Sava and Ya ̧sar Becerikli. Real time driver fatigue detection system based on multi-task connn. IEEE Access, 8:12491–12498, 2020.

5. Monagi H Alkinani, Wazir Zada Khan, and Quratulain Arshad. Detect- ing human driver inattentive and aggressive driving behavior using deeplearning: Recent advances, requirements and open challenges. IEEE Ac- cess, 8:105008–105030, 2020.

6. Rateb Jabbar, Mohammed Shinoy, Mohamed Kharbeche, Khalifa Al- Khalifa, Moez Krichen, and Kamel Barkaoui. Driver drowsiness detection model using convolutional neural networks techniques for android appli- cation. In 2020 IEEE International Conference on Informatics, IoT, and EnablingTechnologies (ICIoT), pages 237–242. IEEE, 2020.

7. Esra Vural, Müjdat Çetin, Aytül Erçil, Gwen Littlewort, Marian Bartlett, and Javier Movellan. Machine learning systems for detecting driver drowsiness. In In-vehicle corpus and signal processing for driver behavior, pages 97–110. Springer, 2009.

8. Anirban Dasgupta, Daleef Rahman, and Aurobinda Routray. A smartphone-based drowsiness detection and warning system for automo- tive drivers. IEEE transactions on intelligent transportation systems, 20(11):4045–4054, 2018.

9. Feng You, Xiaolong Li, Yunbo Gong, Hailwei Wang, and Hongyi Li. A real-time driving drowsiness detection algorithm with individual differences consideration. IEEE Access, 7:179396–179408, 2019.

10. Mohsen Babaeian, Nitish Bhardwaj, Bianca Esquivel, and Mohammad Mozumdar. Real time driver drowsiness detection using a logistic- regression-based machine learning algorithm. In 2016 IEEE Green Energyand Systems Conference (IGSEC), pages 1–6. IEEE, 2016.