International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 07 Issue: 05 | May 2020 www.irjet.net p-ISSN: 2395-0072

Drowsy Driving Detection via Hybrid Deep Learning

Najla[1], Reshma V K[2]

[1]MTech Scholar, Department of Computer Science and Engineering, Jawaharlal College of Engineering and Technology, Kerala, India

[2]Assistant Professor, Department of Computer Science and Engineering, Jawaharlal College of Engineering and Technology, Kerala, India

---

Abstract - *Automotive industry plays a vital role in the country's economic and industrial development. The rapid growth brought great convenience in day to day life as well as increase in the number of traffic accidents. Every year many people lose their lives due to fatal road accidents around the world and drowsy driving is one of the primary causes of road accidents and death. Fatigue driving and drowsiness are the major reasons for fatal accidents. The capability of the transportation system to detect the alertness of drivers is very essential to ensure road safety. Most of the traditional methods to detect drowsiness are based on behavioural aspects while some are intrusive and may distract drivers, while some require expensive sensors. The hybrid deep learning approach is used to detect driver drowsiness. The real time application of drowsiness detection is based on facial expression recognition in video sequences. Facial and eye behaviours such as yawning and eye-blink patterns are analyzed based on the live facial video focused on the driver's face. Since the facial expression recognition is challenging, deep temporal convolutional neural network are employed on video segments. Both the spatial and temporal convolutional neural networks features are retrieved and integrated to form a deep belief network. The system records the videos and detects the driver's face in every frame by employing deep learning techniques. Facial landmarks on the observed segments are pointed and the eye aspect ratios are computed and drowsiness is detected based on the adaptive thresholding ratio.*

***Key Words*:** Drowsiness detection, deep learning, Computer vision, Convolutional neural network, facial landmark detector.

1. INTRODUCTION

Human faces reflect the inner feelings or emotions and hence facial expressions are susceptible to changes in the environment. Emotion is the conscious and subjective experience characterized by mental states, biological reactions and psychological or physiologic expressions otherwise known as facial expressions. A facial expression is a gesture executed with the facial muscles and conveys the emotional state of the observer. Facial expressions are the carrier of non-verbal information, which conveys the mental state of human beings as well as the outward manifestation of psychological activity [3].

Expressions play a vital role in the daily communications, and recent years have witnessed a great amount of work being done to develop accurate and reliable facial expressions recognition (FER) systems. FER systems can be employed in many applications, such as in daily communications, personality and child development, neuroscience and psychology, access control and surveillance, and human behaviour studies in telemedicine and e-health environments. In FER phases are identified as feature extraction and classification phases. In feature extraction phase certain features of an image is extracted based on classifier and in classification phase, classifies image to one of the label of domain [2]. Techniques such as ANN, SVM, HMM, KNN, Spherical Classifiers and compressive sensing based sparse classifiers were used for recognizing facial expressions [5].

According to the WHO statistics, more than 1.2 million people worldwide have died in traffic accidents every year and millions of people are injured. Among many accident causes, drowsy driving is one of the main causes of accidents and the proportion of traffic accidents caused by drowsy driving is about 25% to 30%. If drivers can be warned in the early stage of driver drowsiness, the possibility of traffic accidents can be greatly reduced. The advancement in the field of computer technology has provided the means for building the intelligent drowsiness and fatigue detection system. Driver drowsiness detection system is one of the best application of intelligent vehicle system. For the study of drowsy driving, there are mainly the following methods: to detect the physiological parameters of the driver, such as EMG, EEG, ECG, EOG, etc., blood flow and respiratory changes; to detect the characteristics of the driver's movement, such as driver's head displacement, hand characteristics, steering wheel motion characteristics; to detect vehicle driving behavior, such as driving speed and lane departure detection; based on machine vision, by studying visual characteristics such as eye movements and facial expressions perform drowsiness testing [4].

From the perspective of convenient installation and driving comfort, the method of detecting drowsy driving based on machine vision has become the main research direction. However, artificially extracting drowsiness features by visual features such as template matching and edge detection to identify the closed state of the human eye and the degree of opening of the mouth, to judge the drowsy state; training SVM classification to discriminate the state of the eye opening and closing and combines the change of the vertical position of the head to make a comprehensive judgment; training strong classifiers, the drowsiness characteristics are trained and studied to detect the drowsy state. Due to individual differences such as the state of the eyes, mouth and the amplitude of the head movement, the traditional method is likely to have misdetection and the detection result is not very satisfactory. When the vehicle is driving under different road conditions, the head posture will change. In the driving process, the change of the light intensity in the driving room will also interfere with the recognition of the driver's facial state, which has high requirements for the accuracy and real-time of the drowsiness detection [4].

In recent years, with the rapid development of deep learning methods, especially in the field of image classification and recognition, the use of Convolutional Neural Network (CNN) to train the extraction of image features has attracted widespread attention. The CNN can automatically learn the most effective deep features of images. Compared with other vision-based methods, CNN can learn image features and avoid the poor robustness of traditional artificial feature extraction. At present, the application of CNN in drowsiness detection is mainly about the detection of human face and eye state. Hence, using computer vision technology, combined with video processing and CNN, the facial drowsy expression features are trained and learned to realize the driver's drowsy expression [4].

Based on the image acquisition of video from the camera which is placed ahead of the driver's face, perform real time processing of video stream so as to urge frames from which the driver's face is detected for the further detection of drowsiness. By continuously monitoring the eyes, yawn, fatigue etc. the symptoms of driver's drowsy behaviour is detected early enough to prevent the crashes. The video of driver is captured and is converted to frames and every frame is processed separately. The optical flow images and cropped facial images are fed into temporal CNNs.

2. LITERATURE SURVEY

The methods to detect drowsy driving includes vehicle based, behavioural based and physiological based techniques. In vehicle based detection several metrics such as steering wheel movement, accelerator or break pattern, vehicle speed, deviations from lane position etc. are monitored continuously. Detection of any abnormal change in the values of the metrics is considered as driver drowsiness. In behavioural based method, the visual behavior of the driver such as eye blinking, eye closing, yawn, head bending etc. are analyzed to detect drowsiness. Both vehicle based and behavioural based are non-intrusive measurements as the former doesn't requires any sensors attached on the drivers and the latter requires only simple camera to detect the features. In physiological based method, the physiological signals like ECG, EOG, EEG, heartbeat, pulse rate etc. are monitored and from these metrics, drowsiness or fatigue level is detected. The physiological based detection is intrusive measurement as the sensors are attached on the driver which will distract the driver [2].

In image processing based techniques, drivers face images are used for processing so that one can find the states. Using same images, drowsiness of driver can be found because if driver is sleeping or dozing then the eyes are closed in image. In template matching technique, if driver closes eye for some particular time then system will generate the alarm as the system has both close and open eyes template of driver. In eye blinking based technique, eye blinking rate and eye closure duration is measured to detect driver's drowsiness. When driver felt sleepy the eye blinking and gaze between eyelids are different from normal situations so drowsiness can be easily detected. The position of irises and eye states are monitored through time to estimate eye blinking frequency and eye closure duration [6].

The Electroencephalogram (EEG) sensor system monitors the human cognitive state and provides a biofeedback to the driver while the driver is drowsy. The fluctuations in drivers performance is detected with respect to brain activity and modulates the EEG recordings [7]. In artificial neural network (ANN) based technique, neurons are used to detect driver's drowsiness. People in fatigue exhibit certain visual behaviours that are easily observable from changes in facial features such as the eyes, head, and face. Visual behaviours that typically reflect a person's level of fatigue include eyelid movement, gaze, head movement, and facial expression [8].

3. METHADOLOGY

To construct a real-time drowsiness classification model, the driver's visual behaviour has to be monitored. Unlike traditional image processing methods for computing eye blinks, involving combination of eye localization, thresholding to find the whites of the eyes and determining if the white region of the eyes disappears for a period (indicating a blink), CNN is used to determine eye opening and closure. The eye detection is performed with facial landmarks.

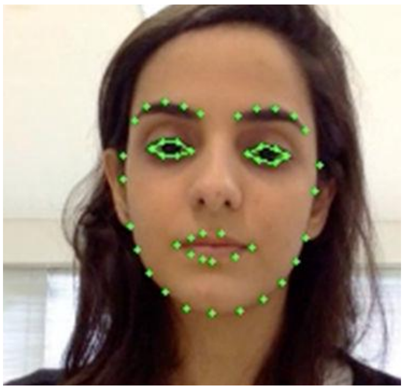

Fig 1: Landmarks on face

The goal is to detect important facial structures on the face using shape prediction methods. The dlib library is used for facial landmark detection, which uses Haar Caascade in the procedure. The library provides landmarks for the entire face, displayed as light green dots in Fig.1. The landmarks are adaptive to recognize the shape of distinct human faces.

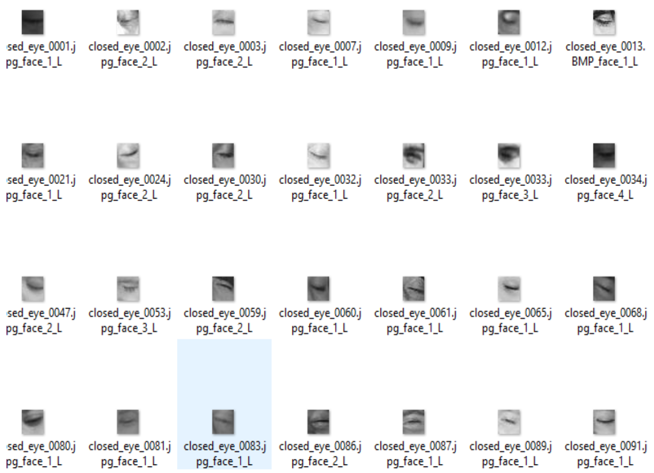

Fig 2: CEW Dataset

To investigate the performance of eye closeness detection in these conditions, we collected a dataset for eye closeness detection in the Wild. Eye patches are collected based on the coarse face region and eye position automatically and respectively estimated by the face detector and eye localization. We first resize the cropped coarse faces to the size 100×100 (pixels) and then extract eye patches of 24×24 centered at the localized eye position as shown in fig 2.

The model used is built with Keras using CNN. The hybrid deep learning model exploits three distinct deep models consisting of two deep CNNs namely spatial convolutional neural network and temporal convolutional neural network, and one deep fusion network built with a deep belief network (DBN) fig.3. The deep learning models utilize multiple layers to extract higher level features from raw input. A deep CNN is comprised of one or more convolutional layers and pooling layers [1]. The CNN is a special type of deep neural network which performs extremely well for image classification purposes.

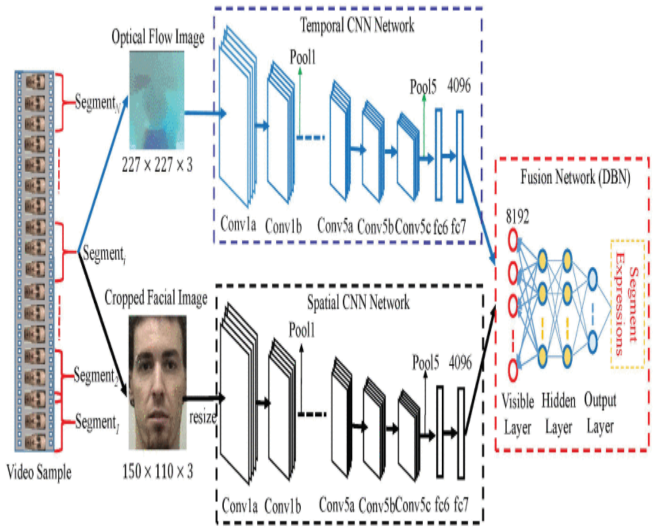

Fig 3. The hybrid deep learning network in video sequence

Image acquisition mainly involves obtaining the image of the automobile driver. The video of the driver is captured using a webcam. A video segment with length 16 cm can generate 15 frames as input, ensuring that the input frames of both spatial CNN and temporal CNN are equal in a video segment. By utilizing the features of OpenCV frames are extracted from the video. The RGB image captured is converted to grayscale image. From the grayscale image captured using haar cascade features of OpenCV the face is detected. Dlib landmark detector is utilized in order to provide the facial landmarks. After the application of facial landmark, feature extraction is performed. Here the input for feature extraction is the eyes.

To extract the significant features of CNN for feature extraction we adapted a dataset CEW which includes both opened and closed eyes. CNN algorithm is used to train the dataset and a model is prepared. Each element in the dataset is allowed to pass through the multiple layers of the CNN. The temporal convolutional neural network processes optical flow images which are the displacement change of corresponding positions between consecutive frames in a video sequence. Both the temporal CNN and spatial CNN consists of convolutional layers, pooling layers and fully connected layers. After training with both spatial and temporal CNNs, the outputs are concatenated and are fed as the input to the fusion network built with a deep belief network. The DBN is composed of multi layered neural network structure having a visible layer and a hidden layer. The DBN captures the nonlinear relationships among spatial and temporal networks. The existing dataset is retrained when a new image comes using tensor flow and the state of the eye is predicted. Multiple frames are observed and a threshold value is set for the eye closing. Once the threshold value is reached the alarm arises indicating that the driver is drowsy.

4. CONCLUSION

The development of technologies for detecting or preventing drowsiness at the wheel is a major challenge in the field of accident avoidance systems. Because of the hazard that drowsiness presents on the road, methods need to be developed for counteracting the affects. By monitoring the eyes, the symptoms of driver fatigue can be detected early enough to avoid an accident. Detection of drowsiness involves a sequence of images of a face, and the observation of eye movements and blink patterns. The proposed hybrid deep learning method makes use of convolutional neural network and deep belief network in order to detect drowsiness. The pre trained temporal and spatial neural networks are fed into deep belief networks which captures the relationship among the networks. Drowsiness is detected based on the threshold value set.

REFERENCES

1. Shiqing Zhang, Xianzhang Pan, Yueli Cui, Xioming Zhao and Limei Liu (2019), Learning Affective Video Features for Facial Expression Recognition via Hybrid Deep Learning, *IEEE Acess,* Vol. 7, 32297 – 32304
2. Ashish kumar and Rusha Patra (2018), Driver Drowsiness Monitoring System using Visual Behaviour and Machine Learning, *IEEE*, 339-344
3. Kejun Wang, Jing Chen, Xinyi Zhang and Liying Sun (2018), Facial expression recognition based on deep convolutional neural network, *IEEE 8th Annual International Conference on CYBER Technology in Automation Control and Intelligent Systems.*
4. Mengtao Huang and Yi Wang (2018), Driver Fatigue Expression Recognition Research Based on Convolutional Neural Network, *IEEE International Symposium on Computer, Consumer and Control (IS3C).*
5. Aysegul Ucar (2017), Deep Convolutional Neural Networks for Facial Expression Recognition, *IEEE International Conference on Innovations in Intelligent SysTems and Applications (INISTA).*
6. Jay D. Fuletra and Dulari Bosamiya (2014), A Survey on Driver's Drowsiness Detection Techniques, *International Journal on Recent and Innovation Trends in Computing and Communication*, Vol.1, 816-819
7. Umit Budak, Varun Bajaj, Yaman Akbulut, Orhan Atilla and Abdulkadir Sengur (2019), An Effective Hybrid Model for EEG Based Drowsiness Detection, *IEEE Sensors Journal*, Vol.19, 7624 – 7631
8. Jay D. Fuletra and Dulari Bosamiya (2014), A Survey on Driver's Drowsiness Detection Techniques, *International Journal on Recent and Innovation Trends in Computing and Communication*, Vol.1, 816-819