Journal of Engineering Sciences

Vol 12, Issue 12, DEC /2021

ISSN NO:0377-9254

Supervised Learning Algorithm Driver Drowsiness Detection and Alerting System

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Abstract-- In this paper, we propose an efficient algorithm for driver drowsiness detection and efficient alert system. The existing works mainly follow vehicle-based measures, physiological-based measures, behavioral-based measures. Moreover, the works based on behavioral measures mainly focused on eye movements, yawning, and head position. The proposed method uses more relevant and appropriate behavioral features such as significant variation in aspect ratio of eyes, mouth opening ratio, nose length bending, and the changes that happened in eyebrows, wrinkles, ear due to drowsiness. The binary SVM classifier is used for classification whether the driver is drowsy or not. The inclusion of these features helped in developing more efficient driver drowsiness detection system.

Keywords: Behavior changes, Drowsiness, Wrinkle detection, and Eyebrow variation.

1. INTRODUCTION

Car accidents are one of the major causes for injury or death. Statistics show that car accidents are globally the 9th cause of death: 1.3 million people die in car accidents annually, or 3287 per day. Fatigue at the steering wheel has the following symptoms: frequent yawning, hard to keep the eyes opened and to focus on the road, not remembering what happened in the last few minutes of driving, not keeping the correct distance from the car in front, missing traffic signs and getting too close to the side or center of the road. Statistics have shown that over 10% of accidents are due to fatigue, most of which occur on highways or after driving on a large number of kilometres. The influence of fatigue on accidents has been proven throughout several studies. According to National Highway Traffic Safety Administration (NHTSA), an annually average from 2009 to 2013, there were over 72,000 police-reported crashes involving drowsy drivers, injuring more than 41,000 people, and killing more than 800. In recent years, car manufactures have developed systems which aim to reduce all the factors that may lead to accidents. This is how sensors, over-ride warning sensors, the adaptive auto-pilot which keeps a constant distance from the front vehicle and fatigue detection sensors were born. Car manufacturers have studied the possibilities of detecting driver's fatigue for a long time and, of course, the best solutions for the warning on time. Assistance systems now include different types of equipments that can prevent accidents caused by fatigue: 1. In order to prevent serious accidents due to driving fatigue, the Bosch Group provides drivers with a sleepiness detection system. This system identifies the signs of fatigue, through monitoring the movements of the steering wheel, suggesting drivers to take a break for a time. The necessary information is provided either by the vehicle's steering system or by the steering wheel angle sensor, which is part of the ESP system. This way, the sleepiness detection system helps to increase safety while driving. 2. Volvo currently equips some of it's models with a system called Driver Alerts, which is based on recognizing a tired driver driving style, as opposed to that of a fully awake driver. In order to detect this slightly winding driving pattern, the Swedish system uses a video camera mounted in front of the interior rearview mirror, which constantly transmits the distance between the vehicle and the roadside markings to a computer. When the predetermined limits of the measured oscillations, the driver is warned to take a break, through audio signals, and a coffee break symbol appears on the central display, in order to emphasize the message. 3. "Fatigue assistance" for Mercedes models has the capacity to store data acquired by sensors about the normal reactions of the driver, which can be later compared to eventual unsafe steering actions of the same driver in a state of increased fatigue. The audio and visual warning of the driver can prevent accidents caused by "one second sleep" due to increased fatigue.

II. STATE OF THE ART

Numerous techniques have been implemented in the field of driver drowsiness detection, which includes various machine learning

Journal of Engineering Sciences

Vol 12, Issue 12, DEC /2021

ISSN NO:0377-9254

algorithms. In an attempt to increase the accuracy and accelerate the process of drowsiness detection, many methodologies have come up based on the different arenas of drowsiness detection as described below: Driving Patterns: This approach takes into considerationλ the trajectory or the path followed by a driver on the road. External factors such as the condition of the road, the type of vehicle and the environmental situations greatly influence the model. It calculates the deviation of the vehicle based on the position of the automobile at a specific time. This deviation calculates the driving patterns of the driver based on which the model determines if the driver is drowsy [1]. Thus, the model is not always accurate because of its dependency on various external conditions. Physiological Sensors: This type of drowsiness detectionλ system depends on the Electroencephalogram (EEG), Electrocardiogram (ECG), and Electrocardiographs (EOG) physiological sensors that detect the state of the human brain. It determines if a person is drowsy by sensing the electric currents of the body and the brain [2]. Although the system has an accuracy rate of above 90%, it proves to be unfeasible for drowsiness detection in automobiles due to the number of sensors that have to be attached to the human body, which could cause discomfort to the driver and hinder his/her driving. Computer Vision: These drowsiness detection systemsλ use image processing to detect the facial features, such as the eyes and the mouth of the driver, using different machine learning algorithms. They are deployed on a computer capable of processing the algorithm and is more suitable for drowsiness detection in automobiles.

It uses various detection methods to determine drowsiness, such as eye detection or yawn detection, to recognize if the driver is drowsy. The most feasible method for a Driver Drowsiness Detection System among the three, as seen above, is the Computer Vision method. This is because it neither relies on any external factor that could lead to a false positive nor does it require any physical connections to the driver that could distract the driver. The computer vision domain uses a variety of machine learning algorithms to determine drowsiness, such as the Support Vector Machine (SVM) algorithm that classifies objects by separating data items [3]. It detects the eyes and other facial features using a dataset but gives less accurate results and has a higher error rate, especially in large or noisy datasets. Another such algorithm is the Convolutional Neural Networks (CNN) model, which performs drowsiness detection using neural networks that imitate the working on the human brain on a computer [4, 5]. It proves to be considerably accurate but also requires a high computational cost and a large dataset to train the model due to which it is not the best fit for our drowsiness detection system. The last significant model that we consider for our project uses the Haar Cascades algorithm, which uses the facial features of the driver to detect drowsiness [6]. It is the second most accurate and fastest algorithm after the CNNs, and also works on low computational cost and a smaller training set, which makes the system economical and the most suitable model for our purpose.

3. PROPOSED METHOD

A block diagram of the proposed driver drowsiness monitoring system has been depicted in Fig 1. At first, the video is recorded using a webcam. The camera will be positioned in front of the driver to capture the front face image. From the video, the frames are extracted to obtain 2-D images. Face is detected in the frames using histogram of oriented gradients (HOG) and linear support vector machine (SVM) for object detection [10]. After detecting the face, facial landmarks [11] like positions of eye, nose, and mouth are marked on the images. From the facial landmarks, eye aspect ratio, mouth opening ratio and position of the head are quantified and using these features and machine learning approach, a decision is obtained about the drowsiness of the driver. If drowsiness is detected, an alarm will be sent to the driver to alert him/her. The details of each block are discussed below.

Data Acquisition: The video is recorded using webcam (Sony CMU-BR300) and the frames are extracted and processed in a laptop. After extracting the frames, image processing techniques are applied on these 2D images. Presently, synthetic driver data has been generated. The volunteers are asked to look at the webcam with intermittent eye blinking, eye closing, yawning and head bending. The video is captured for 30 minutes duration.

Face Detection: After extracting the frames, first the human faces are detected. Numerous online face detection algorithms are there. In this study, histogram of oriented gradients (HOG) and linear SVM method [10] is used.

In this method, positive samples of fixed window size are taken from the images and HOG descriptors are computed on them. Subsequently, negative samples (samples that do not contain the required object to be detected i.e., human face here) of same size are taken and HOG descriptors are calculated. Usually the number of negative samples is very greater than number of positive samples. After obtaining the features for both the classes, a linear SVM is trained for the classification task.

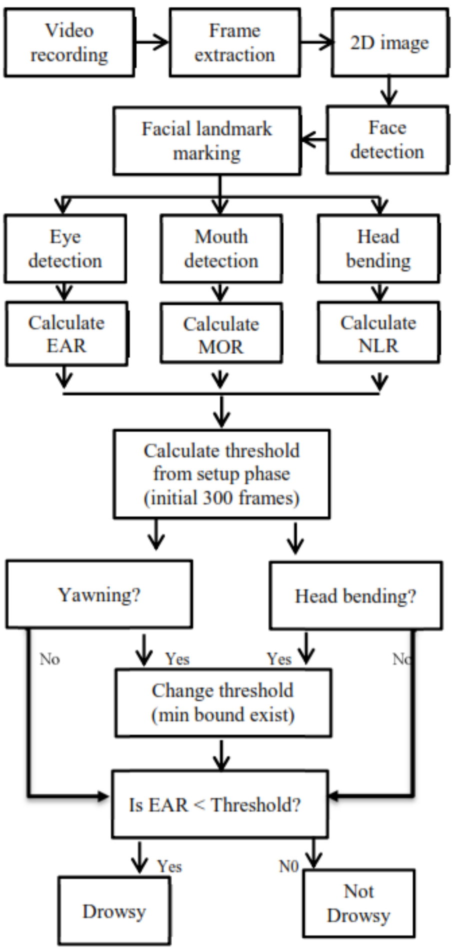

Fig. 1: Block diagram of proposed drowsiness system.

To improve the accuracy of SVM, hard negative mining is used. In this method, after training, the classifier is tested on the labeled data and the false positive sample feature values are used again for training purpose. For the test image, the fixed size window is translated over the image and the classifier computes the output for each window location. Finally, the maximum value output is considered as the detected face and a bounding box is drawn around the face. This non-maximum suppression step removes the redundant and overlapping bounding boxes.

Feature Extraction

After detecting the facial landmarks, the features are computed as described below.

Eye aspect ratio (EAR): From the eye corner points, the eye aspect ratio is calculated as the ratio of height and width of the eye as given by

$$EAR = \frac{(p_2 - p_6) + (p_3 - p_5)}{2(p_4 - p_1)}$$

Where$p_i$represents point marked as i in facial landmark and$\left(p_i - p_j\right)$ is the distance between points marked as i and j. Therefore, when the eyes are fully open, EAR is high value and as the eyes are closed, EAR value goes towards zero. Thus, monotonically decreasing EAR values indicate gradually closing eyes and it's almost zero for completely closed eyes (eye blink). Consequently, EAR values indicate the drowsiness of the driver as eye blinks occur due to drowsiness.

Mouth opening ratio (MOR): Mouth opening ratio is a parameter to detect yawning during drowsiness. Similar to EAR, it is calculated as

$$MOR = \frac{(p_{15} - p_{23}) + (p_{16} - p_{22}) + (p_{17} - p_{21})}{3(p_{19} - p_{13})}$$

As defined, it increases rapidly when mouth opens due to yawning and remains at that high value for a while due to yawn (indicating that the mouth is open) and again decreases rapidly towards zero. As yawn is one of the characteristics of drowsiness, MOR gives a measure regarding driver drowsiness.

Classification

After computing all the three features, the next task is to detect drowsiness in the extracted frames. In the beginning, adaptive thresholding is considered for classification.

JES Journal of Engineering Sciences
Vol 12, Issue 12, DEC /2021
ISSN NO:0377-9254

Later, machine learning algorithms are used to classify the data.

For computing the threshold values for each feature, it is assumed that initially the driver is in complete awake state. This is called setup phase. In the setup phase, the EAR values for first three hundred (for 10s at 30 fps) frames are recorded. Out of these three hundred initial frames containing face, average of 150 maximum values is considered as the hard threshold for EAR. The higher values are considered so that no eye closing instances will be present. If the test value is less than this threshold, then eye closing (i.e., drowsiness) is detected. As the size of eye can vary from person to person, this initial setup for each person will reduce this effect. Similarly, for calculating threshold of MOR, since the mouth may not be open to its maximum in initial frames (setup phase) so the threshold is taken experimentally from the observations. If the test value is greater than this threshold then yawn (i.e., drowsiness) is detected.

After computing the threshold values, the system is used for testing. The system detects the drowsiness if in a test frame drowsiness is detected for at least one feature. To make this thresholding more realistic, the decision for each frame depends on the last 75 frames. If at least 70 frames (out of those 75) satisfy drowsiness conditions for at least one feature, then the system gives drowsiness detection indication and the alarm.

To make this thresholding adaptive, another single threshold value is computed which initially depends on EARthreshold value. The average of EAR values is computed as the average of 150 maximum values out of 300 frames in the setup phase. Then offset is determined heuristically and the threshold is obtained as offset subtracted from the average value. Driver safety is at risk when EAR is below this threshold. This EAR threshold value increases slightly with each yawning up to a certain limit. As each yawning and head bending is distributed over multiple frames, so yawning and head bending of consecutive frames are considered as single yawn and added once in the adaptive threshold. In a test frame, if EAR value is less than this adaptive threshold value, then drowsiness is detected, and an alarm is given to the driver.

Apart from using thresholding, the machine learning algorithms are used to detect drowsiness as well. The EAR, and MOR values are stored for the synthetic test data along with actual drowsiness annotation. Prior to classification, statistical analysis of the features has been done. At first, the feature space is transformed into an independent one. After transforming the feature values, student's t test is used to test whether the features are statistically significant for the two classes. As all the three features are statistically significant at 5% level of significance, all the three features are used for classification using Support vector Machine [12].

SVM is one of the most popular Supervised Learning algorithms, which is used for Classification as well as Regression problems. However, primarily, it is used for Classification problems in Machine Learning.

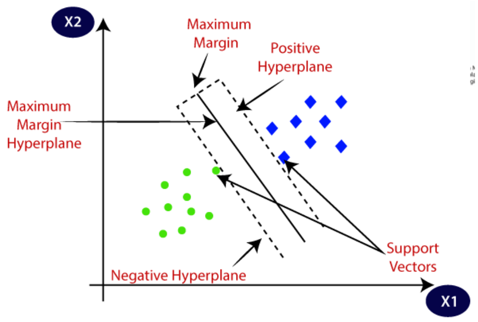

Figure 2: SVM classification

The goal of the SVM algorithm is to create the best line or decision boundary that can segregate n-dimensional space into classes so that we can easily put the new data point in the correct category in the future. This best decision boundary is called a hyperplane. SVM chooses the extreme points/vectors that help in creating the hyperplane. These extreme cases are called as support vectors, and hence algorithm is termed as Support Vector Machine. Consider the below diagram in which there are two different categories that are classified using a decision boundary or hyperplane:

4. Simulation Results

In above screen click on 'Start Behaviour Monitoring Using Webcam' button to connect application with webcam, after clicking button will get below screen with webcam streaming

Journal of Engineering Sciences
Vol 12, Issue 12, DEC /2021
ISSN NO:0377-9254

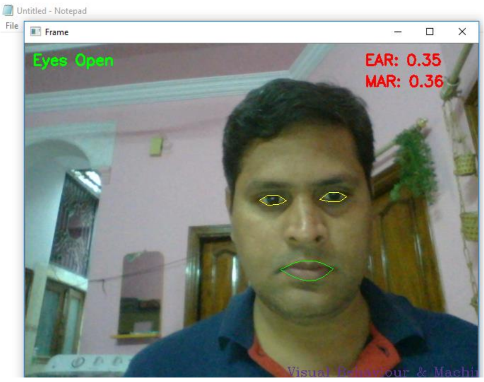

Figure 3: Eyes open

In above screen we can see web cam stream then application monitor all frames to see person eyes are open or not, if closed then will get below message.

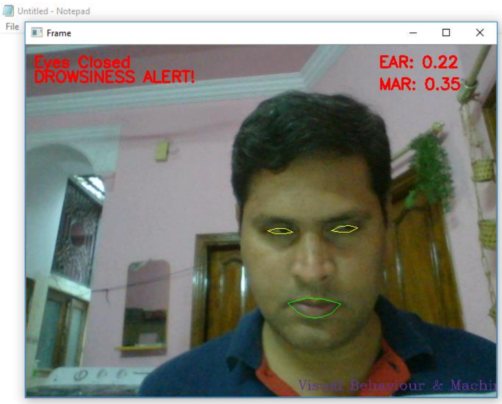

Figure 4: Eyes close

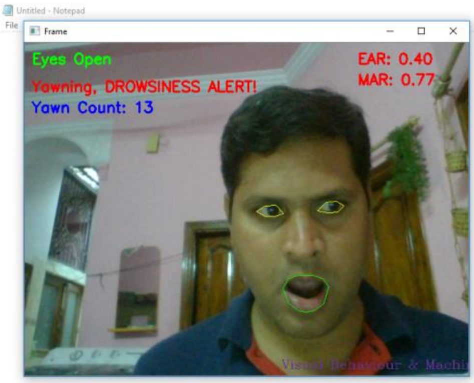

Figure 5: Mouth open

5. Conclusion

In this paper, a low-cost, real-time driver drowsiness monitoring system has been proposed based on visual behavior and machine learning. Here, visual behavior features like eye aspect ratio, mouth opening ratio and nose length ratio are computed from the streaming video, captured by a webcam. An adaptive thresholding technique has been developed to detect driver drowsiness in real time. The developed system works accurately with the generated synthetic data. Subsequently, the feature values are stored, and SVM have been used for classification.

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