



DRIVER DROWSINESS MONITORING SYSTEM USING MACHINE LEARNING

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ABSTRACT:

In this project by monitoring Visual Behaviour of a driver with webcam and machine learning SVM (support vector machine) algorithm we are detecting Drowsiness in a driver. This application will use inbuilt webcam to read pictures of a driver and then using OPENCV SVM algorithm extract facial features from the picture and then check whether driver in picture is blinking his eyes for consecutive 20 frames or yawning mouth then application will alert driver with Drowsiness messages. We are using SVM pre-trained drowsiness model and then using Euclidean distance function we are continuously checking or predicting EYES and MOUTH distance closer to drowsiness, if distance is closer to drowsiness then application will alert driver.

Key words: *GBM, boosting algorithm, Heart performance.*

I INTRODUCTION

occurring in road accidents. The truck drivers who drive for continuous long hours (especially at night), bus drivers of long distance route or overnight buses are more susceptible to this problem. Driver drowsiness is an overcast nightmare to passengers in every country. Every year, a large number of injuries and deaths occur due to fatigue related road accidents. Hence, detection of driver's fatigue and its indication is an active area of research due to its immense practical applicability. The basic drowsiness detection system has three blocks/modules; acquisition system, processing system and warning system. Here, the video of the driver's frontal face is captured in acquisition system and transferred to the processing block where it is

processed online to detect drowsiness. If drowsiness is detected, a warning or alarm is sent to the driver from the warning system. Generally, the methods to detect drowsy drivers are classified in three types; vehicle based, behavioural based and physiological based. In vehicle based method, a number of metrics like steering wheel movement, accelerator or brake pattern, vehicle speed, lateral acceleration, deviations from lane position etc. are monitored continuously. Detection of any abnormal change in these values is considered as driver drowsiness. This is a non-intrusive measurement as the sensors are not attached on the driver. In behavioural based method [1-7], the visual behavior of the driver i.e., eye blinking, eye closing,



yawn, head bending etc. are analyzed to detect drowsiness.

This is also nonintrusive measurement as simple camera is used to detect these features. In physiological based method [8,9], the physiological signals like Electrocardiogram (ECG), Electrooculogram (EOG), Electroencephalogram (EEG), heartbeat, pulse rate etc. are monitored and from these metrics, drowsiness or fatigue level is detected. This is intrusive measurement as the sensors are attached on the driver which will distract the driver. Depending on the sensors used in the system, system cost as well as size will increase. However, inclusion of more parameters/features will increase the accuracy of the system to a certain extent. These factors motivate us to develop a low-cost, real time driver's drowsiness detection system with acceptable accuracy. Hence, we have proposed a webcam based system to detect driver's fatigue from the face image only using image processing and machine learning techniques to make the system low-cost as well as portable.

II LITERATURE SURVEY

Intelligent Video-Based Drowsy Driver Detection System under Various Illuminations and Embedded Software Implementation

An intelligent video-based drowsy driver detection system, which is unaffected by various illuminations, is developed in this study. Even if a driver wears glasses, the proposed system detects the drowsy conditions effectively. By a near-infrared-ray (NIR) camera, the proposed system is divided into two cascaded computational procedures: the driver eyes detection and the

drowsy driver detection. The average open/closed eyes detection rates without/with glasses are 94% and 78%, respectively, and the accuracy of the drowsy status detection is up to 91%. By implementing on the FPGA-based embedded platform, the processing speed with the 640×480 format video is up to 16 frames per second (fps) after software optimizations

“Driver Fatigue Detection based on Eye Tracking and Dynamic Template Matching”

A vision-based real-time driver fatigue detection system is proposed for driving safely. The driver's face is located, from color images captured in a car, by using the characteristic of skin colors. Then, edge detection is used to locate the regions of eyes. In addition to being used as the dynamic templates for eye tracking in the next frame, the obtained eyes' images are also used for fatigue detection in order to generate some warning alarms for driving safety. The system is tested on a Pentium III 550 CPU with 128 MB RAM. The experiment results seem quite encouraging and promising. The system can reach 20 frames per second for eye tracking, and the average correct rate for eye location and tracking can achieve 99.1% on four test videos. The correct rate for fatigue detection is 100%, but the average precision rate is 88.9% on the test videos.

“Monitoring Driver Fatigue using Facial Analysis Techniques”

In this paper, we describe a non-intrusive vision-based system for the detection of driver fatigue. The system uses a color video camera that points directly towards the



driver's face and monitors the driver's eyes in order to detect micro-sleeps (short periods of sleep). The system deals with skin-color information in order to search for the face in the input space. After segmenting the pixels with skin like color, we perform blob processing in order to determine the exact position of the face. We reduce the search space by analyzing the horizontal gradient map of the face, taking into account the knowledge that eye regions in the face present a great change in the horizontal intensity gradient. In order to find and track the location of the pupil, we use gray scale model matching. We also use the same pattern recognition technique to determine whether the eye is open or closed. If the eyes remain closed for an abnormal period of time (5-6 sec), the system draws the conclusion that the person is falling asleep and issues a warning signal.

“The Steps of Proposed Drowsiness Detection System Design based on Image Processing in Simulator Driving “

Drowsiness detection has many implications including reducing roads traffic accidents importance. Using image processing techniques is amongst the new and reliable methods in sleepy face. The present pilot study was done to investigate sleepiness and providing images of drivers' face, employing virtual-reality driving simulator. In order to detecting level of sleepiness according to the signal, information related to 25 drivers was recorded with imaging rate of 10 fps. Moreover, on average 3000 frames was analysed for each driver. The frames were investigated by transforming in grey scale space and based on the Cascade and Viola & Jones techniques and the images

characteristics were extracted using Binary and Histogram methods. The MPL neural network was applied for analysing data. 70% of information related to each driver were inserted to the network of which 15% for test and 15% for validation. In the last stage the accuracy of 93% of the outputs were evaluated. The intelligent detection and usage of various criteria in long-term time frame are of the advantages of the present study, comparing to other researches. This is helpful in early detection of sleepiness and prevents the irrecoverable losses by alarming

III EXISTING SYSTEM

Traffic congestion is one of the major modern-day crisis in every big city in the world. Previously different techniques had been proposed, such as infra-red light sensor, induction loop etc. to acquire traffic data which had their fair share of demerits. In recent years, image processing has shown promising outcomes in acquiring realtime traffic information using CCTV footage installed along the traffic light. Different approaches have been proposed to glean traffic data. Some of them count total number of pixels [3], some of the work calculate number of vehicles [4-6]. These methods have shown promising results in collecting traffic data. However, calculating the number of vehicles may give false results if the intravehicular spacing is very small (two vehicles close to each other may be counted as one) and it may not count rickshaw or auto-rickshaw as vehicles which are the quotidian means of traffic especially in South-Asian countries.

**Drawbacks :**

- Traffic congestion is one of the headache. Here using infra-red light sensor to detect traffic.
- acquire traffic data which had their fair share of demerits image processing has shown promising outcomes in acquiring real time traffic information using CCTV footage installed along the traffic light.

IV PROPOSED SYSTEM

In this paper, a system in which density of traffic is measured by comparing captured image with real time traffic information against the image of the empty road as reference image is proposed. Each lane will have a minimum amount of green signal duration allocated. According to the percentage of matching allocated traffic light duration can be controlled.

Advantages :

minimum amount of green signal duration allocated. According to the percentage of matching allocated traffic light duration can be controlled.

V METHODOLOGY:**A. 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 headbending. The video is captured for 30 minutes duration.

B. 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 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. 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.

C. Facial Landmark marking

After detecting the face, the next task is to find the locations of different facial features like the corners of the eyes and mouth, the tip of the nose and so on. Prior to that, the face images should be normalized in order to reduce the effect of distance from the camera, non-uniform illumination and varying image resolution. Therefore, the face image is



resized to a width of 500 pixels and converted to grayscale image. After image normalization, ensemble of regression trees [11] is used to estimate the landmark positions on face from a sparse subset of pixel intensities. In this method, the sum of square error loss is optimized using gradient boosting learning. Different priors are used to find different structures. Using this method, the boundary points of eyes, mouth and the central line of the nose are marked and the number of points for eye, mouth and nose are given in Table I. The facial landmarks are shown in Fig 2. The red points are the detected landmarks for further processing.

D. 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

E. 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. 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. Head bending feature is used to find the angle made by head with respect to vertical axis in terms of ratio of projected nose lengths. Normally, NLR has values from 0.9 to 1.1 for normal upright position of head and it increases or decreases when head bends down or up in the state of drowsiness. The average nose length is computed as the average of the nose lengths in the setup phase assuming that no head bending is there. 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.

VI SYSTEM ARCHITECTURE

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.

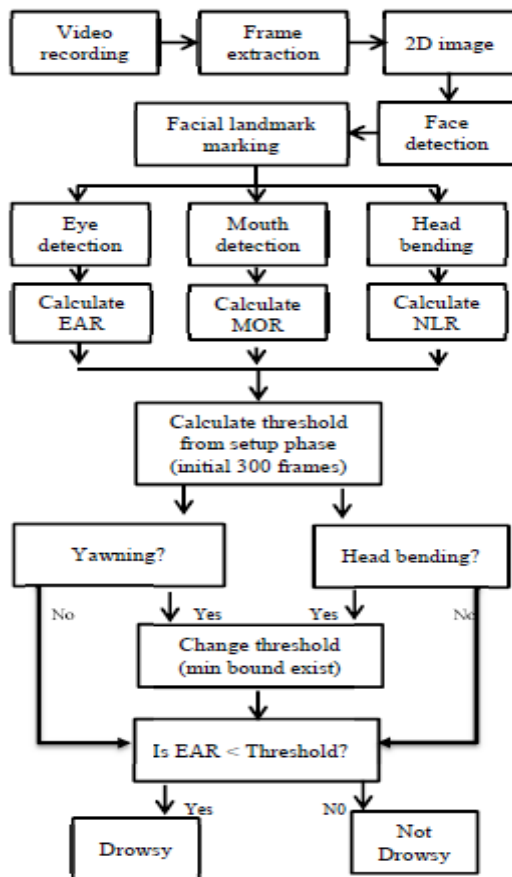


Fig. 1 The block diagram of the proposed drowsiness detection system

VII RESULT DESCRIPTION

User

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threshold 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 and head bending upto 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 head bending 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. Sometimes it may happen that when the head is too low due to bending, the system is unable to detect the face. In such situation, previous three frames are considered and if head bending was detected in those three frames, drowsiness alarm will be shown

In this project by monitoring Visual Behaviour of a driver with webcam and machine learning SVM (support vector machine) algorithm we are detecting Drowsiness in a driver. This application will use inbuilt webcam to read pictures of a driver and then using OPENCV SVM algorithm extract facial features from the picture and then check whether driver in picture is blinking his eyes for consecutive 20 frames or yawning mouth then application will alert driver with Drowsiness messages. We are using SVM pre-trained drowsiness model and then using Euclidean distance function we are continuously checking or predicting EYES and MOUTH distance closer to drowsiness, if distance is closer to drowsiness then application will alert driver.

To implement above concept we are using following modules

Video Recording: Using this module we will connect application to webcam using OPENCV built-in function called VideoCapture.

Frame Extraction: Using this module we will grab frames from webcam and then extract each picture frame by frame and convert image into 2 dimensional array.

Face Detection & Facial Landmark Detection: Using SVM algorithm we will detect faces from images and then extract facial expression from the frames.

Detection: Using this module we will detect eyes and mouth from the face

Calculate: Using this module we will calculate distance with Euclidean Distance formula to check whether given face distance closer to eye blinks or yawning, if eyes blink for 20 frames continuously and mouth open as yawn then it will alert driver.

OpenCV is an artificial intelligence API available in python to perform various operation on images such as image recognition, face detection, and convert images to gray or coloured images etc. This API written in C++ languages and then make C++ functions available to call from python using native language programming. Steps involved in face detection using OpenCV.

Face Detection Using OpenCV

This seems complex at first but it is very easy. Let me walk you through the entire process and you will feel the same.



Step 1: Considering our prerequisites, we will require an image, to begin with. Later we need to create a cascade classifier which will eventually give us the features of the face.

Step 2: This step involves making use of OpenCV which will read the image and the features file. So at this point, there are NumPy arrays at the primary data points.

All we need to do is to search for the row and column values of the face NumPyN dimensional array. This is the array with the face rectangle coordinates.

Step 3: This final step involves displaying the image with the rectangular face box.

SVM Description

Machine learning involves predicting and classifying data and to do so we employ various machine learning algorithms according to the dataset. SVM or Support Vector Machine is a linear model for classification and regression problems. It can solve linear and non-linear problems and work well for many practical problems. The idea of SVM is simple: The algorithm creates a line or a hyperplane which separates the data into classes. In machine learning, the radial basis function kernel, or RBF kernel, is a popular kernel function used in various kernelized learning algorithms. In particular, it is commonly used in support vector machine classification. As a simple example, for a classification task with only two features (like the image above), you can think of a

hyperplane as a line that linearly separates and classifies a set of data.

Intuitively, the further from the hyperplane our data points lie, the more confident we are that they have been correctly classified. We therefore want our data points to be as far away from the hyperplane as possible, while still being on the correct side of it.

So when new testing data is added, whatever side of the hyperplane it lands will decide the class that we assign to it.

How do we find the right hyperplane?

Or, in other words, how do we best segregate the two classes within the data?

The distance between the hyperplane and the nearest data point from either set is known as the margin. The goal is to choose a hyperplane with the greatest possible margin between the hyperplane and any point within the training set, giving a greater chance of new data being classified correctly.

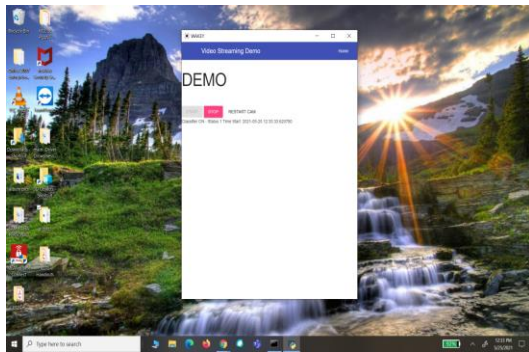
Project Description

Drowsy driving is one of the major causes of road accidents and death. Hence, detection of driver's fatigue and its indication is an active research area. Most of the conventional methods are either vehicle based, or behavioural based or physiological based. Few methods are intrusive and distract the driver, some require expensive sensors and data handling. Therefore, in this study, a low cost, real time driver's drowsiness detection system is developed with acceptable accuracy. In the developed

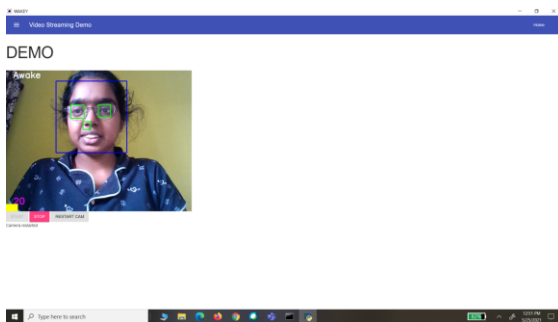
system, a webcam records the video and driver's face is detected in each frame employing image processing techniques. Facial landmarks on the detected face are pointed and subsequently the eye aspect ratio, mouth opening ratio and nose length ratio are computed and depending on their values, drowsiness is detected based on developed adaptive thresholding.

Screen shots

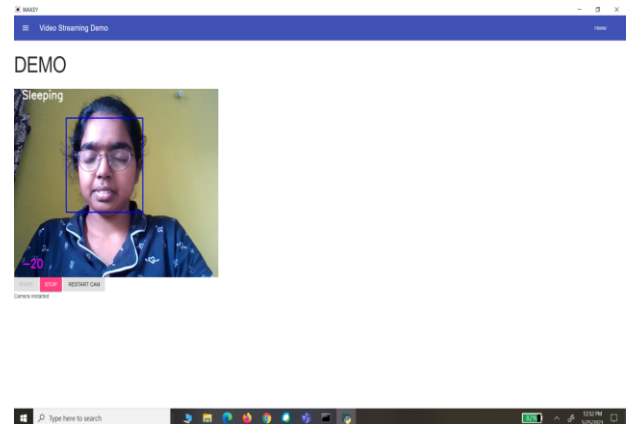
To run this project double click on 'run.bat' file to get below screen



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



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



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 machine learning algorithms have been used for classification. Bayesian classifier, FLDA and SVM have been explored here. It has been observed that FLDA and SVM outperform Bayesian classifier. The sensitivity of FLDA and SVM is 0.896 and 0.956 respectively whereas the specificity is 1 for both. As FLDA and SVM give better accuracy, work will be carried out to implement them in the developed system



to do the classification (i.e., drowsiness detection) online. Also, the system will be implemented in hardware to make it portable for car system and pilot study on drivers will be carried out to validate the developed system.

REFERENCES

- [1] W. L. Ou, M. H. Shih, C. W. Chang, X. H. Yu, C. P. Fan, "Intelligent Video-Based Drowsy Driver Detection System under Various Illuminations and Embedded Software Implementation", 2015 international Conf. on Consumer Electronics - Taiwan, 2015.
- [2] W. B. Horng, C. Y. Chen, Y. Chang, C. H. Fan, "Driver Fatigue Detection based on Eye Tracking and Dynamic Template Matching", IEEE International Conference on Networking, Sensing and Control, Taipei, Taiwan, March 21-23, 2004.
- [3] S. Singh, N. P. papanikolopoulos, "Monitoring Driver Fatigue using Facial Analysis Techniques", IEEE Conference on Intelligent Transportation System, pp 314-318.
- [4] B. Alshaqaqi, A. S. Baquhaizel, M. E. A. Ouis, M. Bouumehed, A. Ouamri, M. Keche, "Driver Drowsiness Detection System", IEEE International Workshop on Systems, Signal Processing and their Applications, 2013.
- [5] M. Karchani, A. Mazloui, G. N. Saraji, A. Nahvi, K. S. Haghighi, B. M. Abadi, A. R. Foroshani, A. Niknezhad, "The Steps of Proposed Drowsiness Detection System Design based on Image Processing in Simulator Driving", International Research Journal of Applied and Basic Sciences, vol. 9(6), pp 878-887, 2015.
- [6] R. Ahmad, and J. N. Borole, "Drowsy Driver Identification Using Eye Blink Detection," IJSET - International Journal of Computer Science and Information Technologies, vol. 6, no. 1, pp. 270-274, Jan. 2015.
- [7] A. Abas, J. Mellor, and X. Chen, "Non-intrusive drowsiness detection by employing Support Vector Machine," 2014 20th International Conference on Automation and Computing (ICAC), Bedfordshire, UK, 2014, pp. 188- 193.
- [8] A. Sengupta, A. Dasgupta, A. Chaudhuri, A. George, A. Routray, R. Guha; "A Multimodal System for Assessing Alertness Levels Due to Cognitive Loading", IEEE Trans. on Neural Systems and Rehabilitation Engg., vol. 25 (7), pp 1037-1046, 2017.
- [9] K. T. Chui, K. F. Tsang, H. R. Chi, B. W. K. Ling, and C. K. Wu, "An accurate ECG based transportation safety drowsiness detection scheme," .