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Real-Time Drowsiness Identification based on Eye State Analysis

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Abstract— **As per the previous year's report concerning to road crashes indicates that the principal cause of such a fatal road accidents is because of negligence behavior as well as drowsiness of driver. This problem reveals the requirement of such a system that can recognize drowsiness state of driver and gives alert signal to the driver before the occurrence of any accidents. Therefore, this proposed work has established drowsy detection as well as accident avoidance system based on the eye blink duration. Here, first the open and close state of eye are detected based on the eye aspect ratio (EAR). Further, the blink duration or count during the changes of eye state from open to close are analyzed. Then, it identifies the state of drowsiness, when blink duration becomes more than a certain limits and sends the alert message to the driver through the alarm. Our developed system has shown the accuracy of 92.5 % approx on yawning dataset (YawDD).**

Keywords— Eye blink detection; Drowsiness Detection; Eye Aspect Ratio (EAR)

1. Introduction

The word "Drowsy" looks very simple but it becomes more crucial in the condition when someone involves in performing jobs where deep concentration is an important factor like working in chemical factory or driving a heavy vehicle etc. In such scenario, once the person is deviated from his/her proper concentration, a great disaster may occur. As observed, most of the road crashes are caused due the negligence behavior driver when he/she is in state of fall asleep or in drowsy condition while driving the vehicle. According to the report 2018 based on the road accidents in India presented by Ministry of Road Transport & Highway, disclose that 4, 67,044 accidents took place in states as well as in Union Territories [1]. Further, the analysis of this report shows that 78% road crashes out of total were caused due driver's inattention. Therefore, there is a need to develop a model that could avoid such a destructive road crashes and save the precious lives of mankind. Here, our proposed work satisfies these requirements.

The various techniques that have been employed till date in order to recognize the drowsy state of driver can be mainly categories into three classes such as physiological, behavioral and vehicle parameter based techniques. Among these technique, physiological as well as vehicle based techniques are intrusive in nature whereas behavioral based technique is non intrusive in nature. Here, the word intrusive means extra equipment that is needed to be attached with the body of driver to fetch the data to identify the state of driver. So, we have considered the 'behavioral' based technique in our proposed work. This technique uses the visual cues for determining the state of drowsiness of driver. In our designed framework, detection of drowsy state of driver is primarily based on blinking characteristics of eye using eye aspect ratio parameter [17, 19, 20].

This complete paper is arranged as follows: Section 2 describes the strengths and weaknesses of existing frameworks in detail through the deep study of literature survey. Section 3 explains the proposed methodology in detail. Further, in Section 4 shows the discussion of result and analysis. In the last i.e. Section 5 contains the idea about the future work and conclusion of proposed work.

2. Literature Survey

Although the number of researches have be done previously in order to distinguish the level of fatigue as well as drowsiness state of driver based on physiological, behavioral and vehicle characteristics. Among these techniques, Forsman et al. [2], designed a framework which employed the various vehicle movement like current position of vehicle on lane, steering wheel movement and movement involve in brake as well as acceleration pedal and so on, in investigation of drowsiness level of driver's. These characteristics are mainly related with vehicle model, driving proficiency as well as intimacy of driver. These procedures are not performing well in case of micro-sleeps (driver fall asleep on wheel for a moment) because it require bulk amount of data as well as time and effort for measuring these parameters. Including this problem, these techniques are sometimes intrusive in nature means external equipments are mounted on the body of driver to capture these parameters which deviates the driver from their normal driving.

Few earlier research works have also evaluated the physiological characteristic such as brain signal, heart rate and nerve impulses etc. in order to recognize the drowsiness state of driver. Simon et al. [3], explore the fact that state of drowsiness in driver identified through the various electric signal such as electromyography (EMG) for muscle tone, electroencephalogram (EEG) [4] for brain activity, electrocardiography (ECG) for heart rate, electrooculogram (EOG) [5] for ocular activity. Here, the analysis involves in deciding the level of drowsiness based on the physiological characteristics is intrusive in nature. Due to this intrusive nature, number of equipments which having the many sensors, have attached on the different portion of driver's body that are capable of learning the brain signals as well nerve impulses and so on. Thus, these equipments produce the extra burden to driver which hindered them from their smooth driving. Therefore, it is necessary that there should not physical attachment between identification system and driver. So, after giving phenomenal result, these techniques are not commercially feasible.

In order to resolve the problem shown by physiological a well as vehicle characteristics based drowsiness detection techniques as discussed in above paragraphs, the computer vision techniques came into the existence. In present era, this technique has become more popular due to low cost of execution and easy to configure with the vehicle as well as its non intrusive nature. From the survey of literatures, we found that computer vision technique mostly employed the facial expression in determination of state of drowsiness because it becomes easy to identify the driver is sleepy or alert through the facial expression [16, 18]. According to Bergasa et al. [6], reveal that the frequency, amplitude, duration related to opening and closing of mouth as well as eye play a significant function in identification of driver's drowsiness state. The framework based on this technique, mainly inspect the surrounding area and condition of iris in a particular time slot to compute these variables i.e. frequency, amplitude, duration etc.

3. PRE-PROCESSING TECHNIQUE

The problem with this method was that it was very difficult to capture the eye state in presence of dim lighting condition especially during the bad weather condition. Therefore, in our proposed work, we have adopted the Histogram equalization technique which equally distributes the intensity values throughout the frame as a pre-processing step [7]. Thus, it diminishes the effect of uneven dispersion of light in each frame. Further, we have employed the Gamma Correction method to enhance the contrast through the non-linear transformation among the input as well as output mapped values as a pre-processing step [8].

4. PROPOSED METHODOLOGY

4.1. *Summary of Proposed Work*

In our proposed work, initially we have captured the frontal image of driver from input video stream. Afterward, we have identified the face via drawing the bounding box around the face. Here, for creating bounding box, we have imported the inbuilt face detection library that is available in dlib facial feature tracker based on 68 facial landmarks [9]. Further, we have localized the eye region of interest (ROI) from the coordinates of predefined landmarks present in dlib. Then, we have computed the eye aspect ratio (EAR) to determine the state of eyes i.e. open or close by imposing some threshold value. Thus status of drowsiness i.e. alert or drowsy is detected through the blink duration as well as number of frames involved during the blinking. The stepwise processing of proposed work is shown in flowchart of Figure 1.

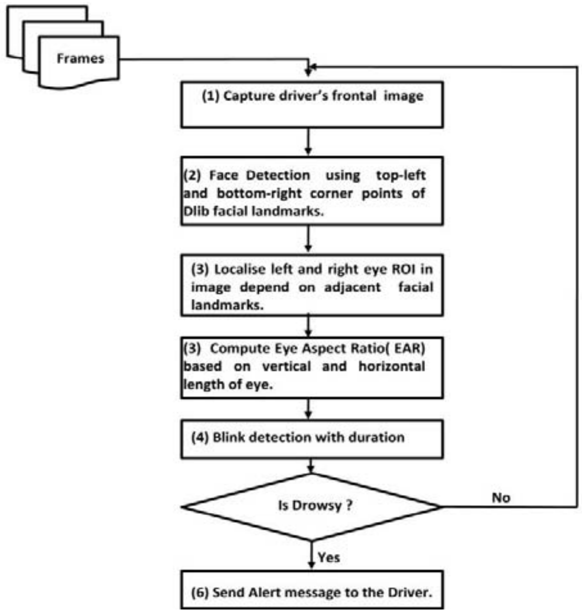

Fig. 1. Summary of proposed work

4.2. *Face Detection*

In our designed framework, we have considered the dlib facial feature tracker library to detect the face from image of driver. Since dlib libraries based on Histogram of Oriented Gradient (HOG) feature descriptor for face detection and Linear Support Vector Machine (SVM) as classifier. Therefore, we will discuss face detection using HOG here [10]. Before start the discussion of HOG, we should know about the gradient. Here, in a simple word, gradient is a sudden change in pixel value when we step from left to right or top to bottom i. e. from black to white or vice-versa. Moving from left to right give the horizontal gradient as well as movement from top to bottom gives the vertical gradient.

There is a block or sliding window in HOG which usually contains 64 pixels. This sliding window consists of matrix of pixel where gradient are comprised for change of magnitude and direction associated intensities of pixel. Since HOG works on the grayscale images. Therefore, image must be converted into grayscale before applying the HOG. Further, horizontal as well as vertical gradient for each pixel available in block are computed as follow with the help of Figure 2 and equation 1&2.

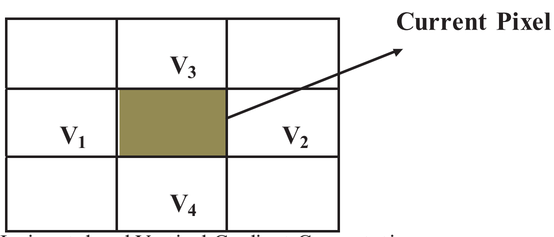

Fig. 2. Horizontal and Vertical Gradient Computation

$$\text{Horizontal Gradient (HG)} = V_2 - V_1 \tag{1}$$

$$\text{Vertical Gradient (VG)} = V_4 - V_3 \tag{2}$$

Where, V_1, V_2, V_3 and V_4 are the pixel values in neighbors of current pixel. After calculating both the gradients, we compute the gradient magnitude and gradient angle from the equation 3 & 4 given below:

$$\text{Gradient Magnitude} = \sqrt{(\mathrm{HG})^2 + (\mathrm{VG})^2} \tag{3}$$

$$\text{Gradient Angle} = \tan^{-1}\left(\frac{\text{Horizontal Gradient}}{\text{Vertical Gradient}}\right) \tag{4}$$

In this way, we have obtained 64 gradient vectors for 64 pixels consecutively and reduce them into 9 vectors. Here, the reduction into 9 vectors is done through a Histogram plot between magnitudes and angles. Thus, we move the sliding window over the whole image space and try to interpret the Histogram results. From the interpretation of Histogram results, we have obtained some HOG features which confirm the face in image. In our experiment, we have created the object of the inbuilt dlib face detector class based on HOG and calling the function detector via passing the grayscale image as argument. Further, draw the bounding box around the face using the coordinate of top-left and bottom-right pixels. Here, Figure 3 represents the image containing the bounding box as a result from our experiment given below.

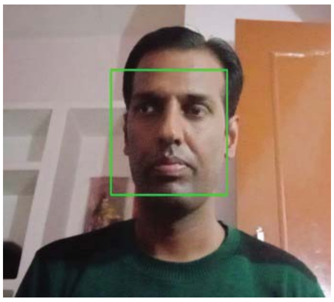

Fig. 3. Bounding box for face detection

4.3 *Eye Detection*

The different feature related to face gives the obvious sign of drowsy state. The eyes give the symptoms of slow as well as fast blinking whereas mouth indicates the drowsiness condition through the yawning. Along with these features, head movement also notice the state of drowsiness once it incline downward or nodding continually. Among these features, blinking of eyes is the prominent one to decide the state of drowsiness as per the various studies discussed above.

Since, in our designed framework, we have imported the Dlib facial shape predictor packages to eliminate the inbuilt landmarks for the both the eyes from the available 68 total landmarks [9]. The sequence numbers of landmark point for both the eyes are from 37 to 48. These are the important data points that capture the feature with respect to our proposed work. Afterward, we have obtained the coordinate values of all these specific selected landmarks i.e. ranges from 37 to 48 for each frame of a video. Thus, acquired coordinates contain the periphery of both the eyes. To show the indication of blinking, this feature has been chosen. The way with which, we extracted this feature is shown below in Figure 4 & 5. Before extracting this feature, we have applied the Histogram equalization and Gamma correction to reduce the effect of light variation in each frame of a video.

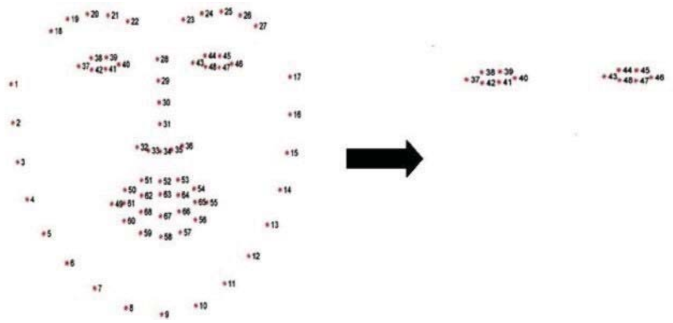

Fig. 4. ROI selection using 68 facial landmarks

Fig. 5. Facial landmarks detection and ROI selection

4.4 *Eye Aspect Ratio (EAR)*

Eye aspect ratio (EAR) was estimated from the spot of the selected landmarks coordinate. The EAR shrinks speedily towards the zero during the state of drowsiness. EAR is the ratio of vertical to the horizontal length of eye. As we can seen in the Figure 4 that 6 contiguous landmarks of dlib package are necessary to localize the each eye i.e. either left or right eye. These landmarks play a key role in the computation of eye aspect ratio.

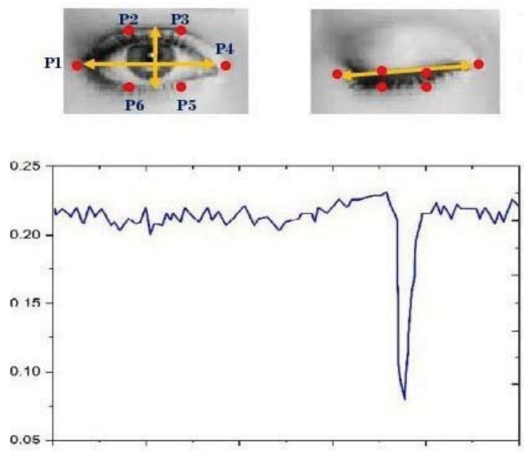

Fig. 6. Eye aspect ratio

As per the convention, here 6 landmark points for a eye are indicated by $P_1, P_2, P_3, P_4, P_5, P_6$ given in Figure 6. First, we have computed vertical Euclidian distance for the pair of points (P_2, P_6) & (P_3, P_5). Further, we have computed the horizontal Euclidian distance for the points (P_1, P_4). These computations are done according to the equation 5 below.

$$
\begin{aligned}
D_{2,6} &= \sqrt{(P_{2x} - P_{6x})^2 + (P_{2y} - P_{6y})^2} \\
D_{3,5} &= \sqrt{(P_{3x} - P_{5x})^2 + (P_{3y} - P_{5y})^2} \\
D_{1,4} &= \sqrt{(P_{1x} - P_{4x})^2 + (P_{1y} - P_{4y})^2}
\end{aligned} \tag{5}
$$

Here, $D_{2,6}$ represents the distance between to landmarks point 2 and 6. Here, (P_{2x}, P_{2y}) and (P_{6x}, P_{6y}) represents the coordinates for the landmarks point 2 as well as for point 6. Similarly, this will hold for rest of landmarks point. Afterward, we have taken the mean of vertical distances as follows from the equation 6.

$$\overline{D} = \frac{D_{2,6}+D_{3,5}}{2} \tag{6}$$

Then, we divide the vertical mean distance by horizontal distance. Thus, we obtained the final value as eye aspect ratio as given in equation 7 below.

$$
\begin{gathered}
\text{EAR} = \frac{\overline{D}}{D_{1,4}} = \frac{D_{2,6} + D_{3,5}}{2.\,D_{1,4}} \\
\text{OR} \\
\text{EAR} = \frac{\|P_2 - P_6\| + \|P_3 - P_5\|}{2\|P_1 - P_4\|}
\end{gathered} \tag{7}
$$

In our consideration, when someone feels drowsiness, their eyes are gets smaller. Depending on this consideration, vertical length of eye goes down quickly but horizontal length of eye in this situation will be same as earlier. Hence, EAR for an individual over contiguous frames lessen rapidly and close to zero.

4.5 *Blink Detection*

The value of EAR varies as per the different state i.e. open or closed of eye as it can be seen from the Figure 7. From the experiment, we have considered a threshold 0.35 for EAR in order to establish the distinction among the open as well as close state of eye. Here, time elapsed during closing state of eye is assumed as T. The different state of driver on the basis of EAR value and elapsed time is emphasized through the Table 1 given below. Since, it is assumed that time elapsed between two consecutive frame is 100ms. Therefore, time elapsed during eye closing can also be consider in terms of number of frames.

Table 1: Driver's state based on different condition

Driver's State	Decision Parameter
Alert	EAR > 0.35
Normal Blink	EAR < 0.35 T<300ms
Drowsy	EAR < 0.35 T >= 300ms & T <900ms
Sleeping	EAR < 0.35 T > 900ms

Fig. 7. a. Eye aspect ratio for open eye, **b.** Eye aspect ratio for closed eye

5. RESULTS AND DISCUSSION

In our proposed work we have developed such a system which can easily be deployable on a machine, robust and reliable to use. This developed method is highly suitable in comparison of physiological method based system such as EEG, EOG etc. because it is intrusive means there is no need to attach any extra equipment with the body of driver to detect the state of drowsiness [3]. Here, mainly two parameter i.e. EAR, time duration (T) is used to make the decision of drowsy state of driver. First, we compare the EAR value with pre initialized threshold value. For a moment when value of EAR is less than the threshold then state of eye changes from open to close. Here, a blink counter is used whose value is increased in this scenario. Actually, this counter keeps the track of time elapsed in the drowsy state. If the value of this counter is rise above the certain limits then an alert message will be generated for the driver to make him to be alert.

In order to show the typical blink of driver, we have illustrated this through the Figure 8. Here, it can be easily identify start and end points of the blink. Further, we can calculate the time duration for a blink via taking the difference between start and end point of blink. A simple formula for this is shown in the equation 8 below.

$$\text{Duration}_i = \text{end}_i - \text{start}_i + 1 \tag{8}$$

Where, Duration_i is the time elapsed in ith blink and start_i as well as end_i is the starting and ending time of ith blink.

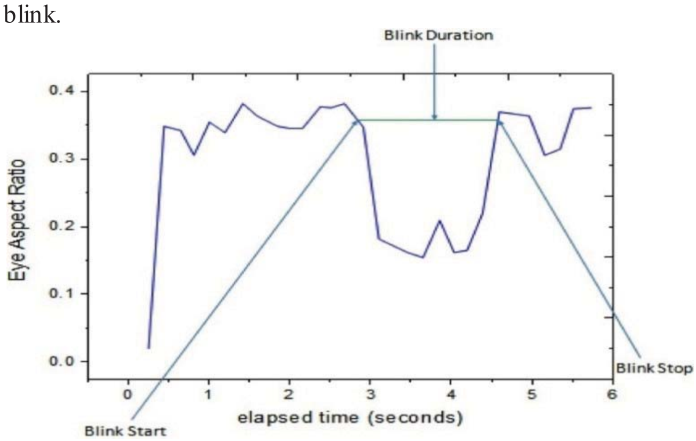

Fig. 8. Visualization of a typical blink

Our whole work is tested on YawDD video dataset that contains the clip of driver's with diverse facial cues [11]. Here, in YawDD dataset, the videos are taken in two ways based on the position of camera i.e. one below the front mirror as well as another over the driver's dash. For our proposed work, we have considered the videos which were taken from the camera present in the position of driver's dash. It consists of approximately 29 videos concerning to male and female drivers with glasses as well as without glasses. In our experiment, we have observed that blinking of eye can be detected accurately or not. In this observation, we have gotten the accuracy of approx 92.5% with YawDD. This observation result has been shown in the Table 2 below. From this experiment, we have reached on this conclusion that our designed system was working well in eye blink detection along with the blink duration. But sometime it was not giving the reliable result when driver wear the glasses. Here, we are showing some frames through the Figure 9 which have utilized in our research work. In order to establish the comparison between our proposed work and previous work, we have used the Table 3 for this purpose.

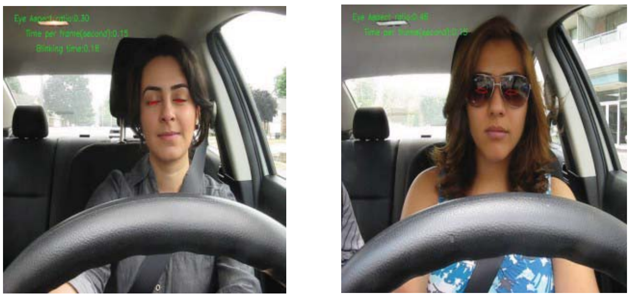

Figure 9: Processed frames from YawDD dataset

Table 2: The acquired result on YawDD

Video categories	Total tested videos	Accurately Identified videos
Female without glasses	07	07
Female with glasses	04	03
Male without glasses	04	04
Male with glasses	08	07

Table 3: Comparison of Earlier and Proposed work

Previous Work	Features Used	Accuracy
[12]	ECG	90%
[13]	EEG	84%
[14]	Pupil	92%
[15]	Yawning	91.90%
Proposed Work	Eye blink pattern	92.5%

6. CONCLUSION AND FUTURE WORKS

Although, our developed framework gives the better result in recognizing driver's state of drowsiness. Yet, some issues still remain which badly affect the performance of our designed system like our system will not give the prominence result under the low visibility condition or during night hour. Likewise, our system is not capable to identify the driver's eyes due severe movement of head or movement of head extremely in any direction. This developed system is also not capable to detect the driver's eyes when he/she wears sun glasses. Besides these limitations, our system has clearly identified the eye blinks as well as drowsiness under the sufficient lighting. The developed system can detect eye blink even driver wears the power glass.

In future, we would like to use some robust software like CNN-face detector which could identify the face clearly when head movement is extremely in any direction but we will have to keep attention to settle the time elapsed in recognition of drowsiness. Since, we have faced the problem to set threshold value of EAR due to the different dimension of eye of participant. Therefore, one can normalize the data at this stage to suite this problem in future and enhance the accuracy of overall system. Further, we would like to test some other features mouth, hand or leg movement and head movement etc. along with eye blinking in order to enhance the accuracy as well as performance of our system.

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