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Fatigue Detection for Vehicle Monitoring Using Computer Vision

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ABSTRACT

In recent years, the motor vehicles are growing at a faster rate than the economic and population growth. The surge in motorization coupled with expansion of the road-network has brought with it the challenge of addressing adverse factors such as the increase in road accidents. As per the RTI around 60% of total road accidents are caused due to driver's fatigue (drowsiness). This dissertation provides a system using real time face and eye detection techniques further eye blink rates to find out the drowsiness. There are various approaches in computer vision for fatigue detection i.e skin segmentation, template matching, neural networks etc. But one of the fast and most used methods is Viola-Jones object detection algorithm. The performance analyses of viola-jones object detection have been explored taking male and female as subjects. Further, to ensure real-time computation, Haar-cascade samples are used to differentiate between normal eye blink rate to drowsiness. This dissertation attempts to study the drivers drowsiness technique using Viola-Jones detection method on Computer Vision (OpenCV) platform which is open source and developed by Intel.

Keywords: fatigue detection, eye blink opencv, driver drowsiness detection, drowsy detection opencv,

1. INTRODUCTION

Recently many countries have noted the importance of improving driving safety. Developing vision based warning systems for drivers is an increasing area of interest. Computer vision has gained a lot of importance in the area of face detection, face tracking, eye detection [2] for various applications like security, fatigue detection, biometrics. This technique has gained importance due it is non-invasive nature. Proper face detection is one of the most important criteria in a vision based fatigue detection system as the accuracy of the entire method relies on the accuracy of face detection. Various face detection techniques have been developed by different researchers. As per RTI data, around half million accidents occur in a year, in India alone. Further, around 60% of these accidents are caused due to driver fatigue (drowsiness). As per the survey reports of Road Traffic Injuries (RTI) the road accident ranked fourth among the leading causes of death in the world. Nearly 1.3 million people [1] die every year on the world's roads and 20 to 50 million people suffer non-fatal injuries, with many sustaining a disability as a result of their injury. According to forecasting of statistics the number of road accident will increase to 5 million in 2020. A common activity in most people's life is driving; therefore, improving driving (making driving safe) is an important issue in everyday life. Even though the driver's safety is improving in road and vehicle design, the total number of serious crashes is still increasing. Reducing the number of vehicle crashes would benefit to save life of millions people around the world. Most of these crashes result from lack of the driver's attention. There are four major types of reasons that affect driver's reaction, which includes alcohol, aging, distraction and fatigue. Aging results in slower response to hazards. Drivers' distraction is increasing as vehicle technologies such as navigation systems, cell phones and the internet become more advanced. Compared with the above three reason, fatigue is often cited in accidents since drivers tend to adopt risky strategies to drive at night [41]. The incidence of accidental deaths has shown an increasing trend during the period 2003 -2012 with an increase of 51.8% in the year 2012 as compared to 2002, however 0.2% decrease was observed in 2003 over previous year 2002. The population growth during the period 2003-2012 was 13.6% whereas the increase in the rate of accidental deaths during the same period was 34.2%. [25] According to the National Crime Records Bureau or NCRB in 2012 total un-natural death were 3,72,022 out of which 1,39,091 death were due to road accident as shown in table 1

Table 1: India Road Accidents Statistic [27]

S.No	Year	Number of accidental deaths		Percentage share of 'Road accident' deaths in un-natural total deaths
		Road Accidents	Total Un-Natural	
1.	2008	1,18,239	3,18,316	37.1
2.	2009	1,26,896	3,34,766	37.9
3.	2010	1,33,938	3,59,583	37.2
4.	2011	1,36,834	3,59,583	37.3
5.	2012	1,39,091	3,72,022	37.4

2.RELATED WORK

Developing vision based warning systems for drivers is an increasing area of interest. Computer vision has gained a lot of importance in the area of face detection, face tracking, eye detection [2] for various applications like security, fatigue detection, biometrics. This technique has gained importance due it is non-invasive nature. Proper face detection is one of the most important criteria in a vision based fatigue detection system as the accuracy of the entire method relies on the accuracy of face detection. Various face detection techniques have been developed by different researchers.

A .Physiological Measure

This method [3] has been thought to be accurate, valid, and objective to determine fatigue and sleep. Significant efforts have been made to measure it in the laboratory. The popular physiological measures include the electroencephalograph (EEG). EEG is found to be useful in determining the presence of on-going brain activity, and its measures have been used as the reference point for calibrating other measures of sleep and fatigue. The spectral analysis of heart rate variability shows that HRV has three frequency bands: high frequency band (0.15-0.4 Hz), low frequency band (0.04-0.15 Hz) and very low frequency band (0.0033-0.04Hz) [13] [14]. Researchers have found out that LF/HF ratio decreases and HF power increases when a person goes from alert state to drowsy state [15]. Power spectrum of EEG brain waves is used as an indicator to detect drowsiness; as drowsiness level increases, EEG power of the alpha and theta bands increases and beta band decreases. EEG-based drowsiness detection methods are not easily implementable because they require the driver to wear an EEG cap during driving the vehicle. Devices being distractive are the main disadvantage of this group of methods.

Table 2: Characteristics of EEG signal.

EEG signal	**Signal Frequency**	**Characteristics**
Delta	*1-3 Hz*	*Deep Sleep, Drowsiness*
Theta	*4-7 Hz*	*Low level of alertness*
Alpha	*8-13 Hz*	*Quite, relax state.*
Beta	*>14 Hz*	*Alert*

B.Behavioral Measure

In order to detect drowsiness, studies on driver's performance use lane tracking, distance between driver's vehicle and the vehicle in front of it; place sensors on components of the vehicle such as steering wheel, gas pedal and analyse the data taken by these sensors. Pilutti and Ulsoy used vehicle lateral position as the input and steering wheel position as the output and they obtained a model which can be useful to detect drowsiness [8] [9]. Behavioral measures are also accurate and objective. This category of devices, most commonly known as acti-graph, is used to measure sleep based on the frequency of body movement. The number of body movement recorded during a specified time period, or epoch, has been found to significantly correlate with the presence of sleep and has a significant correlation with EEG [5]. In jerk profiles for the machine-human interfaces of vehicle are sensed as measures for assessing vigilance of the vehicle driver. Responding to the stimulus was considered as sign of vigilance. The work in claims that short pauses in performances are more indicative measures of vigilance.

C. Visual Measure

An increasing research interest has focused on developing systems that detect the visual facial feature changes associated with fatigue with a video camera. These facial features include eyes, head position, face, or mouth. This approach is non-intrusive and becomes more and more practical with the rapid development of camera and computer vision technology. People in fatigue exhibit certain visual behaviors that are easily observable from changes in facial features like the eyes, head, and face. Visual behaviors that typically reflect a person's level of fatigue include eyelid movement, head movement, gaze, and facial expression. Various studies have shown that eyelid activities are strongly related with level of vigilance, intention, and needs. Percentage of eyelid closure (PERCLOS) [6] has been found to be the most reliable and valid measure of a person's alertness level among many drowsiness detection measures. PERCLOS measures the percentage of eyelid closure over the pupil over time and effects slow eyelid closures (droops). Another potentially good fatigue indicator is the average eye closure and opening speed (AECS). Since eye opening/closing is controlled by the muscle near the eyes, a person in fatigue may open/close eyes slowly due to either tired muscles or slower cognitive processing. Other potentially good fatigue parameters include various parameters that characterize pupil movement, which relates to one's gaze and his/her awareness of the happenings in surroundings. The movement of a person's pupil (gaze) may have the potential to indicate one's intention and mental condition. For example, for a driver, the nominal gaze is frontal. Looking at other directions for an extended period of time may indicate fatigue or inattention. Furthermore, when people are drowsy, their visual awareness cannot cover a wide enough area, concentrating on one direction. Hence, gaze (deliberate fixation) and saccade eye movement may contain information about one's level of alertness. Besides eye activities, head movement like nodding or inclination is a good indicator of a person's fatigue or the onset of a fatigue. It could also indicate one's attention. Head movement parameters such as head orientation, movement speed, frequency, etc. could potentially indicate one's level of vigilance. Finally, facial expression may also provide information about one's vigilance.

3.RELATED ALGORITHM/ WORKING

Object Detection Methods

Face detection can be viewed as a two-class classification problem in which an image region is classified as being either a "face" or a "non-face". In M. Yang et al presented present over 170 reported to face detection, the impact of their research has comprehensive implications on face detection and recognition. The various approaches for face detection can be classified into four categories: Knowledge-based methods, Feature invariant methods, Template matching methods, and Appearance-based methods. These methods are described briefly as follow:

a) Knowledge-Based Method

Knowledge-based methods actually use rule-based methods, which encode human knowledge about what a face is. There are some general rules in the human mind for face detection such as detecting face features include of two symmetric eyes, ears, nose and mouth. These methods which are developed based on the face detection rule in the human brain are part of rule-based methods. The relationships between features are defined by their distance and relative positions. Developing these methods in different situations is difficult because not all states are countable [18] [19].

b) Template Matching Method

Template matching methods compute the correlation between standard patterns of a face and an input image in order to detection. In these methods, several patterns of face are stored in different poses and the correlation of input images with these patterns are used as a criterion for face validation. For a given input image, the correlation with standard templates is computed for face contour, eyes, nose and mouth separately. Multi-scale, multi-resolution and deformable templates and sub-templates have been proposed to cope with deformability and scale invariance [20] [21] [22]. A template method that utilises neural networks to solve the face/non-face classification problem is due to Sung and Poggio [23]. They model the distribution of faces using 6 prototype distributions and also the nearby non-faces using another 6 prototype distributions. The distance of a candidate region from each of these 12 distributions is used to provide a 12 element feature vector. A neural network applied to this feature vector classifies the region as face/non-face.

c) Feature Based Method

Feature invariant approaches are regrouping methods with aim to find robust structural features which are invariant to pose, lighting, etc. This method is one of the most important methods for face detection. In this method, contrasting to the "knowledge-based" methods, researchers have been attempting to find some face features which are invariant in different poses of the face, include ears, hair, eyebrows, mouth and lips. Based on these extracted features, a statistical model is created, which describes their relationship and verify the existence of a face. Papers [24] and [25] have utilized face members as features for face detection. Since the human faces have different texture and color in comparison with other objects, these features can be used to distinct faces images from non-faces [26][27].

d) Skin Color Method

Skin color has proven to be a useful and robust cue for face detection, localization and tracking. Image content filtering, content aware video compression and image color balancing application scan also benefit from automatic detection of skin in images. Numerous techniques for skin color modelling and recognition have been proposed during several past years. A few papers comparing different approaches have been published [Zarit et al. 1999], [Terrillonet al. 2000], [Brand and Mason 2000]. Colorimetry, computer graphics and video signal transmission standards have given birth to many colorspaces with different properties. A wide variety of them have been applied to the problem of skin color modelling.

e) Face Detection

Faces are non-rigid and have a high degree of variability in size, shape, color and texture[49]. In skin segmentation, a set of bounding rules can be taken advantage of for different color spaces (RGB, YCbCr and HSV) in order to improve the detection efficiency. As it is shown in the following algorithm, these bounding rules were applied with "if-AND" way. The RGB color space is used to detect skin color at uniform or lateral daylight illumination and under flashlight illumination:

$(R > 95)AND\ (G > 40)AND\ (B > 20)AND\ (\max\{R,G,B\} - \min\{R,G,B\} > 15)AND$ (|R - G| > 15) AND (R > G) AND (R > B) AND (R > 220) AND (G > 210) AND (B > 170) AND (R > B) AND (G > B) (1)

The Cb-Cr color space is a strong determination of skin color. The following rules apply to this color space:

(Cr <= 1.5862 * Cb + 20) AND (Cr >= 0.3448 * Cb + 76.2069) AND (Cr >= -4.5652 * Cb + 234.5652) AND (Cr <= -1.15 * Cb + 301.75) AND (Cr <= -2.2857 * Cb + 432.85) (2)

The last space to be used is the HSV space. Hue values exhibit the most noticeable separation between skin and non-skin regions. Hue-saturation based colorspaces were introduced when there wasa need for the user to specify color properties numerically. They describe color with intuitive values, based on the artist's idea of tint, saturation and tone. Hue defines the dominant color (such as red, green, purple and yellow) of an area, saturation measures the colorfulness of an area in proportion to its brightness [Poynton 1995].The "intensity", "lightness" or "value" is related to the color luminance.

H < 25 and H > 230 (3)

(i) RGB Color Space

RGB is a colorspace originated from CRT (or similar) display applications, when it was convenient to describe color as a combination of three colored rays (red, green and blue). It is one of the most widely used colorspaces for processing and storing of digital image data. However, high correlation between channels, significant perceptual non-uniformity (refer equation 6 for perceptual uniformity explanation), mixing of chrominance and luminance data make RGB not a very favourable choice for color analysis and color based recognition algorithms. This colorspace was used in [Brand and Mason 2000], [Jones and Rehg 1999]

(ii) Normalized RGB

Normalized RGB is a representation, that is easily obtained from the RGB values by a simple normalization procedure:

$$r = \frac{R}{R+G+B},\ g = \frac{g}{R+G+B},\ b = \frac{b}{R+G+B} \qquad (4)$$

As the sum of the three normalized components is known (r + g + b = 1), the third component does not hold any significant information and can be omitted, reducing the space dimensionality. The remaining components are often called "pure colors", for the dependence of r and g on the brightness of the source RGB color is diminished by the normalization. A remarkable property of this representation is that for matte surfaces, while ignoring ambient light, normalized RGB is invariant (under certain assumptions) to changes of surface orientation relatively to the light source [Skarbek and Koschan 1994]. This, together with the transformation simplicity helped this colorspace to gain popularity among the researchers [Brown et al. 2001], [Zarit et al. 1999], [Soriano et al. 2000], [Oliver et al. 1997], [Yang et al. 1998]

(iii) HSI, HSV, HSL - Hue Saturation Intensity (Value, Lightness)

Hue-saturation based colorspaces were introduced when there was a need for the user to specify color properties numerically. They describe color with intuitive values, based on the artist's idea of tint, saturation and tone. Hue defines the dominant color (such as red, green, purple and yellow) of an area, saturation measures the colorfulness of an area in proportion to its brightness . The "intensity", "lightness" or "value" is related to the color luminance. The intuitiveness of the colorspace components and explicit discrimination between luminance and chrominance properties made these colorspaces popular in the works on skin color segmentation [Zarit et al. 1999], [McKenna et al. 1998], [Sigal et al.2000], [Birchfield 1998], [Jordao et al. 1999]. Several interesting properties of Hue were noted in [Skarbek and Koschan 1994]: it is invariant to highlights at white light sources, and also, for matte surfaces, to ambient light and surface orientation relative to the light source. However, [Poynton 1995], points out several undesirable features of these colorspaces, including hue discontinuities and the computation of "brightness" (lightness, value), which conflicts badly with the properties of color vision.

$$H = \arccos \frac{\frac{1}{2}((R-G)+(R+B))}{\sqrt{((R-G)^2+(R-B)(G-B))}} \quad (5)$$

$$S = 1 - 3\frac{\min(R,G,B)}{R+G+B} \quad (6)$$

$$V = \frac{1}{3}(R+G+B) \quad (7)$$

Eye Detection

After detecting the face, the location of the eyes will be detected. The main reason behind locating the eyes is to use them as a verification method in order to make sure that the location of the mouth in the face is correctly detected (using the geometrical relation between eyes and mouth in the human face). In order to detect the eyes, the eye maps based on chrominance components are built [42] according to the following equation:

$$Eye_{Map} = \frac{1}{3}\left\{(C_b)^2 + (C_r)^2 + \frac{C_b}{C_r}\right\} \quad (8)$$

Object Detection using Haar feature-based cascade classifiers is effective object detection [7]. It is a machine learning based approach where a cascade function is trained from a lot of positive and negative images. It is then used to detect objects in other images. Initially for face detection, the algorithm needs a lot of positive images (images of faces) and negative images (images without faces) to train the classifier. Then we need to extract features from it. Using haar feature patterns as shown below. They are just like our convolutional kernel. Each feature is a single value obtained by subtracting sum of pixels under white rectangle from sum of pixels under black rectangle.

Viola-Jones Haar Features:

a) Edge Features.

b) Line Features.

c) FourRectangles Features.

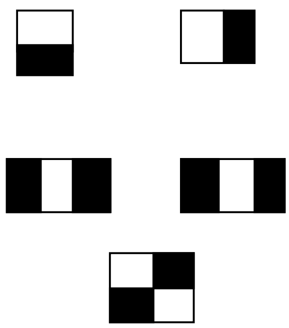


Figure 1: Viola-Jones haar features

Extended Viola-Jones Haar Features

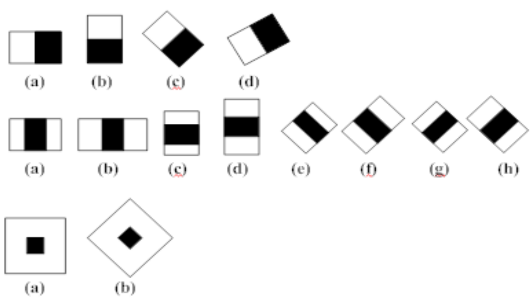


Figure 2: Viola-Jones extended haar features

4.PROPOSED APPROACH

The driver fatigue detection procedure consists of different phases to detect head movement and eye blinking. These steps are categorized as follow and working introduction of each step is given below.

- **1.1** Face Detection
- **1.2** Face Tracking.
- **1.3** Eye Detection.
- **1.4** Eye Tracking.
- **1.5** Eye Blink Detection. (close/open).

The overall system diagram is shown in Figure 1. The details of each step will be further explained in the following subsections.

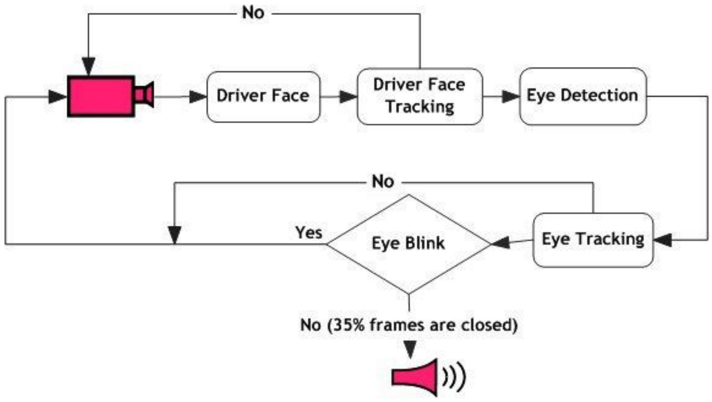


Figure 3: Driver drowsi ness detection flow diagram

System Tools

This system is designed for detecting drowsiness detection for in the real time. The implementation of this approach runs at 25-30 frames per second. The application is implemented in C++ using OpenCV library in Windows environment with a single camera view i.e. iBall Face2Face C8.

STEP 1 - Face Detection

The face of driver is detected using Viola Jones Haar extended features [7]. The system uses trained haar features. We are using haarcascade_frontface_alt.xml for the driver face detection. The XML contains trained sets of positive faces and negative faces (not faces). This is very easy and accurate method to detect real time driver face.

Figure 4: Face detection step

STEP 2 - Eye Detection

The eye of driver is (Region of Interest) ROI detecting fatigue. If eye is blinking normal rates, it means that driver is alert to drive. Whenever the driver feels drowsiness the eye blink rate is decreased (not blinked in 2to 3 seconds). This can cause fatal accidents. The eye detection is also using Viola Jones haar features for eye detection and tracking. We have used haarcascade_lefteye_2splits.xml is used for the left eye and haarcascade_righteye_2splits.xml for the right eye. The two cascade are independent to one another.

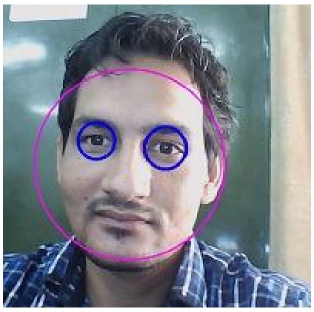


Figure 5: Eye detection step

Eye Blinking

The detection and tracking of real time blink of an eye is very much important in detection of driver drowsiness. Using the above there cascade i.e. Face cascade and Left eye cascade and right eye cascade.

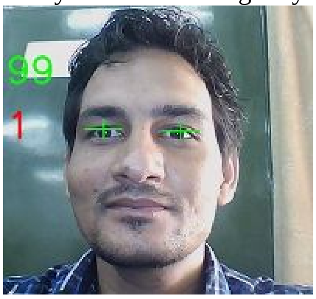


Figure 6: Eye blink detection step

The above figure 3 is real time eye tracking using web camera iBall Face2Face C8.0. Whenever the blink (close eye) frames are greater than 40% to 50% of current frames.

Figure 7: Alert message

The above figure is the state when driver is sleeping, the proposed system will alert the driver with message "Alert – Pull Over!!" to save from road accidents and miss happenings.

5.PROPOSED APPROACH

The performances of this system have been measured under different conditions for 30 days with male and female subjects of age group from 15 years to 50 years. Some subjects were using eyeglasses and some were not.

5.1. Subjects

The subjects are chosen to test the performance of driver drowsiness detection system. The subjects were asked to sit in the driver's seat and fasten their seat belt to make the scenario more realistic. The experiment was conducted for 30 males and 20 female volunteers of different ages and facial characteristics. The statistics about the participants is discussed in section 4.2. A high variety of appearances existed among these 50 volunteers. People participated with and without glasses, men with and without beard, men with and without moustache, women with and without scarf, different hairstyles and different clothing. The experiments were conducted: a) Morning (6 AM to 11 AM). b) Afternoon (11 AM to 5 PM). c) Evening (5 PM to 7 PM) d) Night (7 PM to mid night) and e) Late night (Mid night to 6AM).

Figure 1: Subjects Distribution

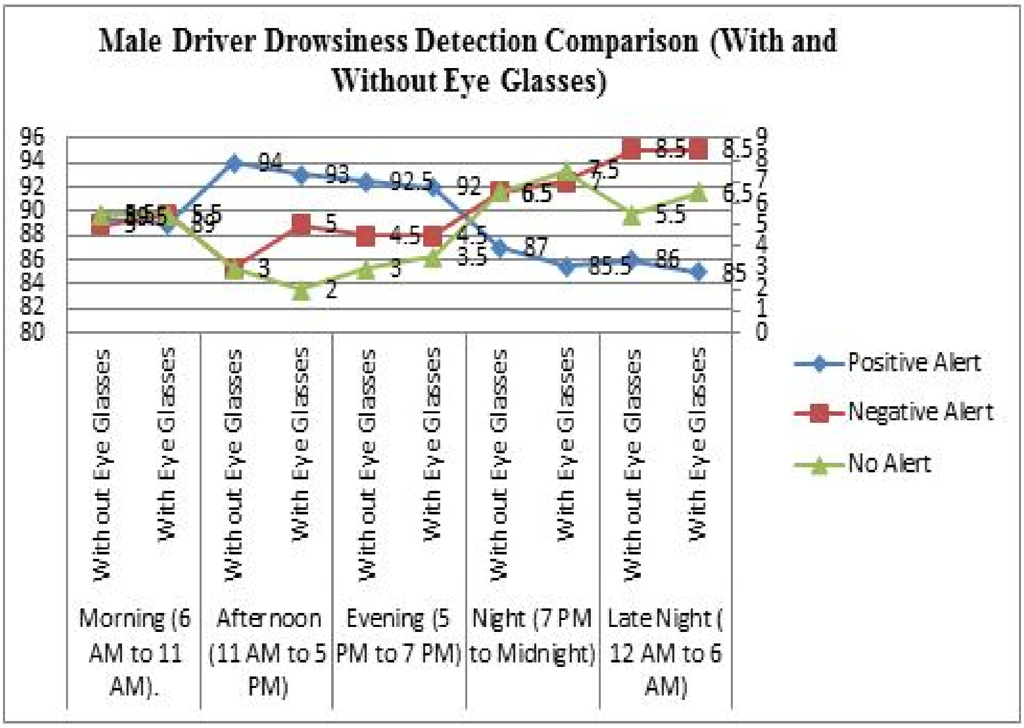
5.1.1. Male Driver Statistics Without and With Eye Glasses

This is the comparison statistics for the male subject with and without eye glasses.

Table 3: Male Driver Statistics Without and With Eye Glasses

Days.	Male Driver Drowsiness Detection				
	Event Time	*Different Cases*	*Positive Alert*	*Negative Alert*	*No Alert*
10 Days (Average	Morning (6 AM to 11 AM).	Without Eye Glasses	89.5	5.0	5.5
		With Eye Glasses	89.0	5.5	5.5
	Afternoon (11 AM to 5 PM)	Without Eye Glasses	94.0	3.0	3.0
		With Eye Glasses	93.5	2.5	4.0
	Evening (5 PM to 7 PM)	Without Eye Glasses	92.5	4.5	3.0
		With Eye Glasses	92.0	4.0	4.0
	Night (7 PM to Midnight)	Without Eye Glasses	87.0	6.5	6.5
		With Eye Glasses	87.5	7.5	5.0
	Late Night (12 AM to 6 AM)	Without Eye Glasses	86.0	8.5	5.5
		With Eye Glasses	84.0	9.5	6.5

Graph 1: Male Driver Statistics Without and With Eye Glasses

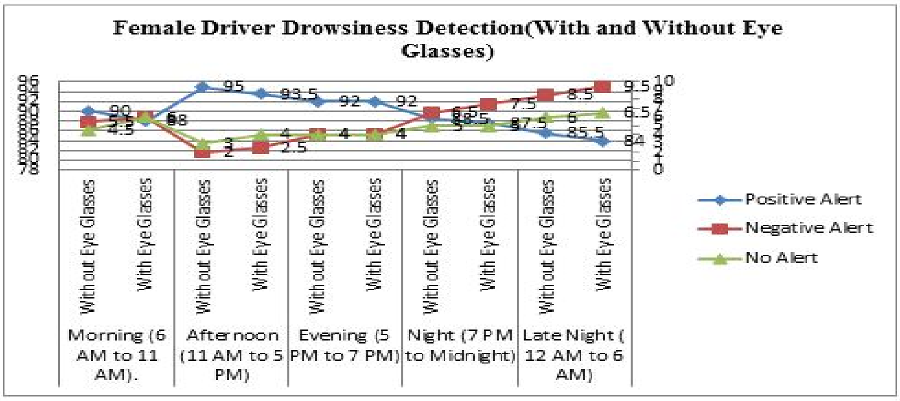


Female Driver Drowsiness Detection				
Event Time	*Different Cases*	*Positive Alert*	*Negative Alert*	*No Alert*
Morning (6 AM to 11 AM).	*Without Eye Glasses*	*90.0*	*5.5*	*4.5*
	With Eye Glasses	*88.0*	*6.0*	*6.0*
Afternoon (11 AM to 5 PM)	*Without Eye Glasses*	*95.0*	*2.0*	*3.0*
	With Eye Glasses	*93.5*	*2.5*	*4.0*
Evening (5 PM to 7 PM)	*Without Eye Glasses*	*92.0*	*4.0*	*4.0*
	With Eye Glasses	*92.0*	*4.0*	*4.0*
Night (7 PM to Midnight)	*Without Eye Glasses*	*88.5*	*6.5*	*5.0*
	With Eye Glasses	*87.5*	*7.5*	*5.0*
Late Night (12 AM to 6 AM)	*Without Eye Glasses*	*85.5*	*8.5*	*6.0*
	With Eye Glasses	*84.0*	*9.5*	*6.5*

5.1.1. Female Driver Statistics Without and With Eye Glasses

This is the comparison statistics for the male subject with and without eye glasses.

Graph 2: Female Driver Statistics Without and With Eye Glasses



The performance of the system is calculated by using experiment data i.e positive alert, negative alert and no alert. The data set for male and female subjects were recorded daily (Please see APPENDIX II) for 10 days and the average of positive alert, negative alert and no alert. The performance is based on the time the event is conducted for with and without eye glasses.

Alert Performance

a) Alert Performance for Male Drivers

Table 5: Alert Performance for Male Drivers

Days	*Event Time*	*Different Cases*	*Positive Alert*	$PA_{Performanc}$
10 Days (Average)	*Morning (6 AM to 11 AM).*	*Without Eye Glasses*	*89.5*	*8.50*
		With Eye Glasses	*89.0*	*8.12*
	Afternoon (11 AM to 5 PM)	*Without Eye Glasses*	*94.0*	*14.89*
		With Eye Glasses	*93.0*	*12.76*
	Evening (5 PM to 7 PM)	*Without Eye Glasses*	*92.5*	*11.91*
		With Eye Glasses	*92.0*	*11.16*
	Night (7 PM to Midnight)	*Without Eye Glasses*	*87.0*	*6.88*
		With Eye Glasses	*85.5*	*6.17*
	Late Night (12 AM to 6 AM)	*Without Eye Glasses*	*86.0*	*6.38*
		With Eye Glasses	*85.0*	*5.95*
Total			*893.5*	
$PA_{all\_average}$			*89.35*	

According to the inferences obtained from the experimental statistics, the positive alert for male drivers without eye glasses was best recorded in afternoon (11 AM to 5 PM). The worst performance of the system was recorded in late night (12 AM to 6 AM) for the drivers who were prescribed eye glasses. The average performance for the positive alert for all the 30 male subjects with and without eye glasses was 89.35%.

b)Alert Performance for Female Drivers

Table 6: Alert Performance for Female Drivers

Days	*Event Time*	*Different Cases*	*Positive Alert*
10 Days (Average)	*Morning (6 AM to 11 AM).*	*Without Eye Glasses*	*90.0*
		With Eye Glasses	*88.0*
	Afternoon (11 AM to 5 PM)	*Without Eye Glasses*	*95.0*
		With Eye Glasses	*93.5*
	Evening (5 PM to 7 PM)	*Without Eye Glasses*	*92.0*
		With Eye Glasses	*92.0*
	Night (7 PM to Midnight)	*Without Eye Glasses*	*88.5*
		With Eye Glasses	*87.5*
	Late Night (12 AM to 6 AM)	*Without Eye Glasses*	*85.5*
		With Eye Glasses	*84.0*
Total			*896*
$PA_{all\_average}$			*89.6*

For the female subjects the inferences obtained from the experimental statistics, the positive alert for female drivers without eye glasses was best recorded in afternoon (11 AM to 5 PM). The worst performance of the system was recorded in late night (12 AM to 6 AM) for the drivers who were prescribed eye glasses. The average performance for the positive alert for all the 30 female subjects with and without eye glasses was 89.60%.

6. CONCLUSION

The system detect real time eye blink using Viola Jones object detection technique. The performance of this method was measured in different light conditions. The experiment was implemented on female and male participants; some were prescribed with eye glasses.This system easily detects the face and eye of a driver. The blinking of eye has been detected at a very high rate because independent haar classifiers are used for the left and right eyes. Most recent 100 frames of left and right eye are analysed and the average positive and negative alert were determined. The experiment was conducted for 10 days. The whole day was divided into 5 section (morning, afternoon, evening, night and late night). The female participants were given the same setups, webcams and programs for night and late night experiments.The eyes blinks were detected more accurate for the driver without eye glasses. The positive alert without eye glasses was best recorded in after noon condition (95%) for female driver and the negative alarm or error was more for the with eye glasses in late night (12AM to 6AM). It was recorded 16% same for male and female drivers. The average performance of drowsiness detection system for male was recorded 89.35% and for the female drivers it was recorded to be 89.60%.

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