# Morphology based Facial Feature Extraction and Facial Expression Recognition for Driver Vigilance

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## ABSTRACT

Driver fatigue is one of the leading causes of traffic accidents. Therefore, the use of assistive systems that monitor a driver's level of vigilance and alert the driver in case of drowsiness and distraction can be significant in the prevention of accidents. This paper presents morphology based operations in extracting various visual cues like eye, eye brows, mouth and head movement. The parameters used for detecting fatigue are: eye closure duration measured through eye state information, head movement through orientation of head ellipse and yawning analyzed through mouth state information. This system was validated with synthetic data under real-life fatigue conditions with human subjects of different ethnic backgrounds, genders, and ages; and under different illumination conditions. It was found to be reasonably robust, reliable, and accurate in fatigue characterization.

## Keywords

Template matching, Top-Hat transformation, Bottom-Hat transformation, Sobel edge, Integration projection, Color Histogram based object Tracker, Ellipse fitting, Support Vector Machine, Gabor filter.

## 1. INTRODUCTION

Driver inattentivity is one of the main causes of traffic accidents. According to the U.S. National Highway Traffic Safety Administration (NHTSA), in the U.S. in 2007, nearly 6100 fatalities occurred as a result of car accidents related to driver inattention, such as distraction, and drowsiness [1, 2, and 3]. Drowsiness involves a driver closing his eyes because of fatigue, and distraction involves a driver not paying sufficient attention to the road despite the presence of obstacles or people. Many inattention-monitoring systems have been developed to prevent highway car accidents. Among many techniques best detection accuracy is achieved with techniques that measure physiological conditions such as brain waves, heart rate, and pulse rate [4], [5]. Requiring physical contact with drivers (e.g., attaching electrodes), these techniques are intrusive, causing annoyance to drivers. Good results have also been reported with techniques that monitor eyelid movement and eye gaze with a head-mounted eye tracker or special contact lens. Results from monitoring head movement [6] with a head-mount device are also encouraging. These techniques, although less intrusive, still are not practically acceptable. A driver's state of vigilance can also be characterized by the behaviors of the vehicle he/she operates. Vehicle behaviors including speed, lateral position, turning angle, and changing course are good indicators of a driver's alertness level. While these techniques may be implemented nonintrusively, they are, nevertheless, subject to several limitations, including the vehicle type, driver experiences, and driving conditions [7].

Driver when inattentive exhibit shows visual behaviors that typically reflect a person's level of fatigue include eyelid movement, gaze, head movement, and facial expression. To make use of these visual cues, another increasingly popular and noninvasive approach for monitoring fatigue is to assess a driver's vigilance level through computer vision. Driver Inattentivity can be divided into two systems: drowsiness detection systems and distraction detection systems. The drowsiness detection system detects drowsiness using features such as eyelid movement, and yawning. The distraction-detection system uses head pose or gaze information to detect if a driver is paying sufficient attention to the road when obstacles or people on the road are detected. Ueno et al. [7] described a system for drowsiness detection by recognizing whether a driver's eyes are open or closed and, if open, computing the degree of eye openness. Boverie et al. [8] described a system for monitoring driving vigilance by studying eyelid movement. Their preliminary evaluations revealed promising results of their system for characterizing a driver's vigilance level using eyelid movement. D'Orazio et al. [9] introduced a system to detect driver fatigue using eyelid movement information, including new drowsiness parameters [frequency of eye closure (FEC) and eye-closure duration (ECD)]. Saradadevi and Bajaj [10] proposed a method for monitoring driver fatigue using yawning information.

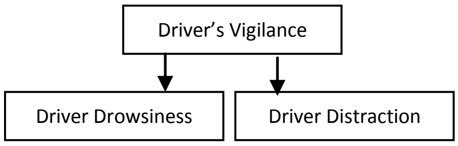
Hattori et al. [11] determines driver distraction when system detects that the driver is not looking straight ahead. Trivedi et al. [12] recognized driver awareness using head pose information obtained by a localized gradient orientation histogram and support vector regressors (SVRs). Kaminski et al. [13] introduced a system to compute both head orientation based on a geometrical model of the human face and eye-gaze detection based on a geometrical model of the human eye. They estimated continuous head orientation and gaze direction.

Techniques used in [7, 8, 9, and 10] only detect driver drowsiness but cannot prevent car accidents caused by distraction. Also the technique used in [11, 12, and 13] does not deal with the problem of driver drowsiness. In our proposed system, it detects both driver drowsiness and driver distraction. Driver distraction is detected using driver head orientation and gaze direction of driver whereas driver drowsiness is detected using driver eye status (OPEN/CLOSED) and driver's yawning (mouth OPEN/CLOSED). The driver-drowsiness level via eye status is measured through PERCLOS [14], which is the percentage of eye closure time during a certain time interval. Similarly, the distraction level is measured as PERLOOK, which is the percentage of time spent not looking ahead during a certain time interval.

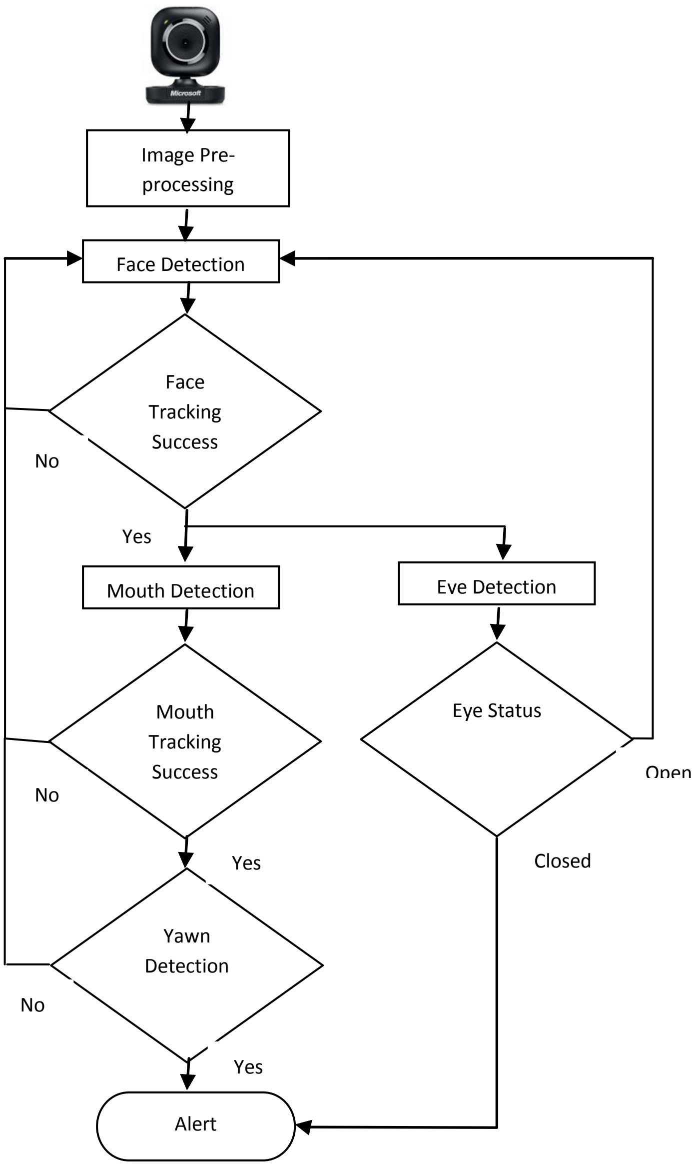
The remainder of this paper is organized as follows. In Section 2, overview of the system is presented, Section 3 describes driver drowsiness, and Section 4 describes driver distraction. In Section 5, we present experimental results and discussion followed by Conclusion and References in Section 5 and 6.

## 2. SYSTEM OVERVIEW

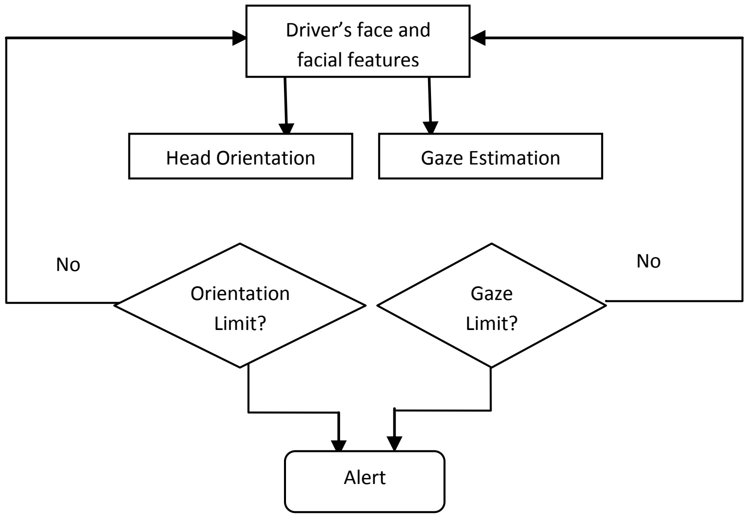
Fig.1 (a), (b) &(c) depict overview of processing scheme. Driver inattentivity is categorized into driver drowsiness and driver distraction. Driver drowsiness detects face, eyes and mouth and analyses eye status and yawning to detect inattentivity. Driver distraction uses driver's face, eyes and mouth features in order to detect driver's head orientation.




**(a)**




**(b)**




**(c)**

**Fig 1: Overview of processing scheme**

## 3. DRIVER DROWSINESS

Detection of driver drowsiness includes detection and tracking of face, eyes and mouth. Eye status (OPEN/CLOSED) is detected with the help of Gabor filter and Mouth status (OPEN/CLOSED/SMILE) is detected with the help of Haar-like feature and linear SVM.

### 3.1 Image Pre-Processing

Before face and facial feature detection, the captured frame is pre-processed to normalize the illumination and reduce image noise. Since Near IR camera focuses mainly on face, face is more illuminated than rest of the objects; uneven illumination is just removed by removing global mean from input IR image

$$M[i,j] = I[i,j] - \bar{I} \tag{1}$$

Where $I[i,j]$ represents IR image, $M[i,j]$ represents mean removed image and $\bar{I} = \frac{1}{N}\sum\sum I(i,j)$. The results of pre-processed image is as shown in Fig.2 below

**(a)** **(b)**

**Fig 2: Image Pre-Processing**

### 3.2 Face Detection

The face detector provides fast and reliable detection on nearly frontal and upright faces. The core function of this detector is based on the Viola-Jones's algorithm [15], which has fairly robust and very fast performance.

## 3.3 Eye Localization

A novel approach has been proposed for the localization of eyes. After detecting the face, only upper part of face ROI is used for localizing the eyes. A morphological top-hat transformation is applied on the upper part of face ROI. Top-hat transformation is given below.

$$T_{hat}(F) = F - (F \circ B) \tag{2}$$

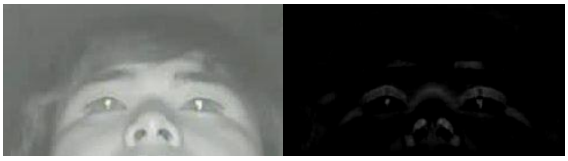
Where $F$ represents gray scale image, $\circ$ represents morphological opening operation, $B$ represents structuring element. In this localization process selecting of structuring element is quite crucial in morphological operations. Here we selected $B_{width} = Half\_Face\_Width\_ROI$, $B_{height} = 1$.

On the morphological top-hat processed image, an Otsu thresholding scheme [16] is applied to obtain binary image. Binary image contains various blobs. In order to eliminate noisy blobs, a histogram is constructed on every blob corresponding to its gray scale ROI. Eye blobs are selected only if the blob has the highest entropy and has a larger width. Entropy is constructed using equation below.

$$Entropy = -\sum_i P(i)\log(P(i)) \tag{3}$$

$$Eye\_Blob = \begin{cases} 1 & Max(Entropy)\ \&\&Width_{\max} \\ 0 & Otherwise \end{cases} \tag{4}$$

The results of morphological top operation, its corresponding binary image and noise filtering output is shown in Fig.3 below.



**(a)** **(b)**

**(c)** **(d)**

**Fig 3: Eye Localization**

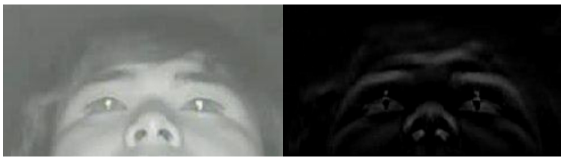
## 3.4 Eye-ROI Detection

In the eye localization process, the white region between eye and eyebrow along with the nose are extracted. But this won’t give eye ROI exactly. In order to get exact Eye-ROI, Eyebrow is used as cue. Since Eyebrow are darker, a morphological bottom-hat operation is used which is given in below equation.

$$B_{hat}(F) = (F \bullet B) - F \tag{5}$$

Where $F$ represents gray scale image, $\bullet$ represents morphological closing operation, $B$ represents structuring element. In this localization process selecting of structuring element is quite crucial in morphological operations. Here we selected $B_{width} = (Face\_Width\_ROI)/4$, $B_{height} = 1$.

On the morphological bottom-hat processed image, an Otsu thresholding scheme [16] is applied to obtain binary image. Thresholded binary image contains various blobs and in order to extract left and right eyebrow blobs, the output of eye-localization process is used as a cue. In the eye-localization process, the white region between eyebrow and eye are extracted, any blobs which are just above the white region are the left and right eyebrows are extracted. The results of eyebrow extraction process using eye-localization output are shown in Fig.4 below.



**(a)** **(b)**

**(c)** **(d)**

**Fig 4: Eye brow Extraction**

Once the left and right eyebrow ROI blobs are extracted, left and right eye-ROI are easily extracted by projecting vertically downwards from eyebrow with blob height and blob width equal to eyebrow width. The results of Eye-ROI extraction using eyebrow and eye-localization process are shown in Fig.5 below.

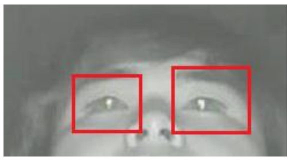


**Fig 5: Eye ROI Extraction**

## 3.5 Mouth Detection

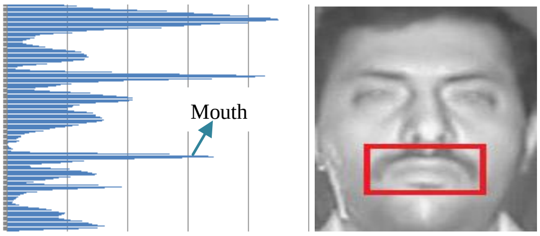
Mouth region in a face ROI has strong horizontal edge. In order to get these strong horizontal lines, a horizontal Haar-like feature mask [17] is used. Here the mask size of 9*9 is used for our experiments. A 2D convolution between horizontal Haar-like feature mask and lower half of the face region to obtain horizontal gradient image as shown in

Fig.6(b). Horizontal profile is constructed on the horizontal gradient image which is the sum of horizontal gradient pixel values perpendicular to the axis and it is represented by the vector of size rows is given below.

$$P_h[j] = \sum_{i=1}^{N} S(i, j) \quad (6)$$

Where $S(i, j)$ represents horizontal gradient image and $N$ represents columns (Image width). A plot of horizontal profile corresponding to horizontal gradient image is shown in Fig.6 below.

**(a)** **(b)**




**(c)** **(d)**

**Fig 6: Mouth Detection Extraction**

From the Fig.6 (c) horizontal edge profile, it is observed that strong horizontal peaks depicts mouth region. On the horizontal gradient image, an Otsu thresholding scheme [16] is applied to obtain binary image. Thresholded binary image contains various blobs and in order to extract only mouth blob, the blobs adjacent to horizontal peak in the horizontal edge profile is extracted. The results of Mouth extraction using horizontal gradient image is shown in Fig.6 (d) above.

## 3.6 Density Confidence based object tracker

Running face detection and mouth detection algorithm for each and every frames of video makes computationally expensive. In order to reduce this complexity, density confidence based object tracker [18] is used.

### *3.6.1 Similarity Measure*

Let $\hat{r}$ and $\hat{c}$ represents $M$ bin histogram of target object and candidate object. Bhattacharya distance [19] is used as a similarity measure between target and candidate object as in the equation below

$$\rho = \sqrt{1 - \sum_{u=1}^{M} r(u)c(u)} \quad (7)$$

Lesser the similarity between the two object, the value of $\rho$ will be closer to one and greater the similarity between two object, the value of $\rho$ will be closer to zero.

### *3.6.2 Tracking Algorithm*

This tracker algorithm creates a confidence map in new image based on the density histogram of the object in the previous image, and finds the peak in the confidence map near the objects old position.

Input: The target model $\hat{q}$ and is location $y_0$ in the previous frame.

a) Initialize the iteration number $k \leftarrow 0$

b) In the current frame, calculate the histogram of the target candidate model $\hat{p}(y_0)$

c) Calculate the confidence weights $w_i, i = 1,2,..n_h$ of each pixel contributing towards foreground object using

$$w_i = \sum_{u=1}^{64} \sqrt{\frac{\hat{q}_u}{\hat{p}_u(y_0)}} \quad (8)$$

d) Calculate the new location $y_1$ of the target candidate using

$$y_1 = \frac{\sum_{i=}^{n_h} x_i w_i}{\sum_{i=}^{n_h} w_i} \quad (9)$$

e) Let $k \leftarrow k+1, d \leftarrow \|y_1 - y_0\|, y_0 \leftarrow y_1$. Set the threshold $\varepsilon$ and maximum iteration number $N$.

If $d < \varepsilon$ or $k \geq N$

Stop and go to step (f)

Else

Go to step (b)

f) Load the next frame as the current frame with initial location $y_0$ and go to step (a).

## 3.7 Eye Status Detection

From the Eye-ROI detection process, we need to detect the status of eye (OPEN/CLOSED). In order to detect eye status, we use phase information using Gabor filter as a cue. Gabor filter works as band pass filter for the local spatial frequency distribution, achieving an optimal resolution in both spatial and frequency domain. The real component of 2D Gabor filter is given in the below

$$g(x, y; \lambda, \theta, \psi, \sigma, \gamma) = \exp\left(-\frac{x'^2 + \gamma * y'^2}{2\sigma^2}\right)\cos\left(2\Pi\frac{x'}{\lambda} + \psi\right) \quad (10)$$

$$x' = x\cos(\theta) + y\sin(\theta)$$
$$y' = -x\sin(\theta) + y\cos(\theta)$$
$$\lambda => wavelength \cong 0.5$$
$$\theta => Orientation \cong 0^0$$
$$\psi => Phase\_Offset = 90^0$$
$$\sigma => sigma\_gaussian\_envelope = 5$$
$$\gamma => Spatial\_Aspect\_Ratio = 1$$

When eyes are opened, pupils are present in Eye-ROI and when eyes are closed, pupils are absent. Since pupils are present at $0^0$ phase, we tune our Gabor filter orientation angle $\theta = 0^0$ in order to detect the presence/absence of pupils. The results of Eye OPEN/CLOSE using Gabor filter on Eye-ROI detected image is as shown in Fig.7 below.


**(a)** **(b)** **(c)**


**(d)** **(e)** **(f)**

**Fig 7: Eye State Detection**

## 3.8 Drowsiness Detection

After detecting the eye status (OPEN/CLOSED), driver drowsiness level is measured using PERCLOS. It is defined as the portion of time that the driver eyes are closed over a certain period of time [20-23].

$$PERCLOS[k] = \sum_{i=k-n+1}^{k} \frac{Blink[i]}{n} * 100(\%) \qquad (11)$$

Where $PERCLOS[k]$ means $PERCLOS$ in the $k^{th}$ frame and $n$ is a period measuring $PERCLOS$. $Blink[i]=1$ represents eye is closed at the $i^{th}$ frame and $Blink[i]=0$ represents eye is open at the $i^{th}$ frame. Higher the $PERCLOS$ means higher the degree of driver drowsiness. When $PERCLOS$ exceeds predetermined threshold, system generates warning. From the experimental results the predetermined threshold was found to be approximately 0.35.

## 3.9 Yawning Detection

After detecting and tracking mouth templates, mouth status (OPEN/CLOSED) is detected by collecting Haar-Like features and classifying it with Linear SVM.

### 3.9.1 *Haar-Like features*

Haar-Like features technique was proposed by Viola and Jones [24]. The Haar-like features were applied on mouth templates. We have used specific Haar-like features as shown Fig.8 which contributed towards better classification accuracy.

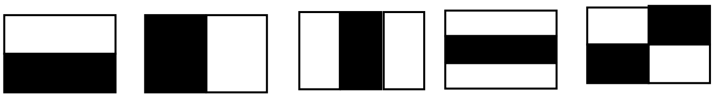


**Fig 8: Haar-like features**

The advantage of Haar-like features over a lot of competitive features is the rapid processing time due to integral images. The integral image [24] has to be calculated just once and enables a fast computation of all Haar-like features.

### 3.9.2 *Support Vector Machine*

Support Vector Machines (SVM) has been considered as one of the powerful classifiers for character and numeral recognition. SVM is defined for two-class problem and it finds the optimal hyper-plane which maximizes the distance, the margin, between the nearest examples of both classes, named support vectors [26]. Given a training database of $M$ data: $\{x_m \mid m = 0,1,...M\}$, the linear SVM classifier is then defined as: $F(x) = \sum \alpha_j x_j . x + b$ where $\{x_j\}$ are the set of support vectors and the parameters $\alpha_j$ and $b$ have been determined by solving a quadratic problem.

$$Mouth\_Status = \begin{cases} Open & if \quad Sign(\sum \alpha_j x_j x + b) > 0 \\ Closed & if \quad Sign(\sum \alpha_j x_j x + b) < 0 \end{cases} \qquad (12)$$

## 4. DRIVER DROWSINESS

In order to detect driver distraction, we need to have driver facial features like eyebrows and lips. These facial features are used in order estimate head orientation.

## 4.1 Driver Head Orientation Detection

A novel approach has been proposed for head orientation estimation using facial features. Upper boundary curves obtained from Eye-Localization process and mouth contour facial features constitute an ellipse. The orientation of an ellipse constitutes head orientation. For this purpose, we use the least square ellipse fitting algorithm proposed by M. Pilu [25]. The algorithm considers only one ellipse that fits all the points. Thus, it is robust to noise and quite fast. Fig.9 shows an example of ellipse fitting.

**(a)** **(b)**


**(c)** **(d)**

**Fig.9 Driver Head Orientation Detection**

## 4.2 Distraction Detection

After detecting the driver head orientation, driver distraction level is measured using PERLOOK. It is defined as the portion of time that the driver head is rotated and the driver does not look at the road ahead.

$$PERLOOK[k] = \sum_{i=k-n+1}^{k} \frac{NonFront[i]}{n} * 100(\%) \quad (13)$$

Where $PERLOOK[k]$ means $PERCLOS$ in the $k^{th}$ frame and $n$ is a period measuring $PERLOOK$. $NonFront[i]=1$ represents eye is closed at the $i^{th}$ frame and $Blink[i]=0$ represents eye is open at the $i^{th}$ frame. Higher the $PERLOOK$ means higher the degree of driver distraction. When $PERLOOK$ exceeds predetermined threshold, system generates warning. From the experimental results the predetermined threshold was found to be approximately 0.4.

## 5. RESULTS AND DISCUSSION

The proposed method has been implemented on Intel Dual Core processor with 1.6GHZ, CPU 256 MB RAM running on windows vista operating system. The program was developed using C language and OpenCV2.0. Near IR videos of resolution 352*288 are captured using CCD mini vehicle camera (878TAHM02A). The processing time for each frame by our proposed method is around 90-110ms which satisfies real-time requirements. In order to evaluate the performance of the system, we have taken videos from 8 different subjects (male and Female) under night time conditions with and without moustache. Results and discussion phase consists of three parts Eye Detection and Mouth Detection, Eye Status and Mouth status detection followed by vigilance level of driver.

## 5.1 Eye and Mouth Detection results

In order to evaluate the performance of Eye and Mouth detection, the system has been tested with 20 Male/Female videos, with/without spectacles and with/without moustache during night time conditions. It has been observed that the system is unable to detect eyes if $Roll\_Angle > \pm 45^0$ while the detection of mouth is robust and less sensitive to rotation.

**Table 1. Video Database**

| | | |
|---|---|---|
| Night Time | No of subjects | 5 Male, 3 Female, 2 glasses, 6 without glasses, 2 Moustache, 6 without moustache |
| | No of Images | 4000 |

**Table 2. Eye Detection Rate**

| | No of Images | Eye Detection |
|---|---|---|
| With Glass | 1000 | 907 |
| Without Glasses | 3000 | 2486 |
| % Detection rate | 86.75% | |

**Table 3. Mouth Detection and Tracking Rate**

| | No of Images | Mouth Detection & Tracking |
|---|---|---|
| With Moustache | 1000 | 967 |
| Without Moustache | 3000 | 2801 |
| % Detection rate | 95.15% | |

From the above table it is observed that eye detection rate is 87% whereas the detection rate of mouth is 95%. Detection rate with moustache and Detection rate with spectacles were quite better compared to without moustache and without glasses. As glasses and moustache gives more gradient image so that edge features are more reliable.

## 5.2 Eye status and Mouth status Detection results

In order to evaluate the performance of Eye and Mouth status detection, the system has been tested with Gabor filter and linear SVM using Haar-like features. Eye status detection is invariant to head rotation since the algorithm uses Gabor filter with phase angle as cue in identifying the pupil. Since pupil always located at $0^0$ phase angle, it is robust under head rotation. The performance of eye status detection is around 72%. Eye status detection results vary a lot if driver wears spectacles which lead to glints (because of reflections) which contribute to $0^0$ phase component, hence false alarms.

Moreover the results also give false alarms when eyes are partially CLOSED/OPEN which also contributes to $0^0$ phase of pupil. Apart from that system gives more satisfactory results when eyes are fully CLOSED/OPEN.

**Table 4. Eye Status Detection Rate**

| | No of Images | Eye Detection |
|---|---|---|
| With Glass | 1000 | 592 |
| Without Glasses | 3000 | 2562 |
| % Detection rate | 72.4% | |

In order to verify mouth status detection system was analyzed with 1200 samples from 8 different persons and used in Linear SVM training. The training set for the SVM classifier in the Mouth (OPEN/CLOSE) process contains 800 positive samples (Mouth Open) and 400 negative samples (Mouth Close). Mouth status detection rate is around 82%. The system gives false alarms if the mouth is partially OPEN/CLOSED.

**Table 5. Mouth status Detection and Tracking Rate**

| | No of Images | Mouth Detection & Tracking |
|---|---|---|
| With Moustache | 1000 | 728 |
| Without Moustache | 3000 | 2760 |
| % Detection rate | 82.4% | |

It is observed from the Table 4 & 5, the eye status and mouth status detection results are degraded for With Moustache and Spectacles compared to Without Moustache and Spectacles. The results of Eye and Mouth detection results With/Without Moustache and EyeGlasses are shown in Fig 10 below

**(a)** **(b)**

**(c)** **(d)**

**(e)** **(f)**

**(g)** **(h)**

**Fig.10 Eye and Mouth detection results**

## 5.3 Driver Vigilance level

In order to measure the driver vigilance level we have used Eyes (OPEN/CLOSED) and Head Orientation is used as a cue. PERCLOS and PERLOOK are the two measures are used to detect driver drowsiness and driver distraction level. Continuous sequences of 100 frames are used to estimate driver vigilance level. From the experimental results we have observed that if $PERCLOS \geq 0.35$ and $PERLOOK \geq 0.4$ then driver is inattentive and suitable alarm needs to be given in order to alert driver.

## 6. CONCLUSION

In this paper we proposed a non-intrusive approach for driver vigilance. Driver vigilance is measured using Driver drowsiness and Driver Distraction. In order to detect driver drowsiness, we need to detect face, eyes, eye-brow and mouth. Morphological top-hat and bottom-hat transformations are used to extract and eyes and eyebrow part. To detect eye status (OPEN/CLOSED), Gabor filter is used. To measure the amount of driver drowsiness level, PERCLOS is estimated with a predetermined threshold of 0.35. Driver's mouth is detected using Haar-like edge feature and integral projection technique. In order to determine mouth status (OPEN/CLOSED), haar-like features of specific type are extracted and classified using Linear SVM. Driver distraction module extracts facial features obtained eye-localization module and chin region just below mouth detection module which together constitutes an ellipse. Direct least square ellipse fitting is used to determine the orientation of an ellipse face. The system performance evaluation results has been shown with an accuracy of 92% for eye detection, 86% for mouth detection, 72% for eye status detection and 86% for mouth status detection. This system is currently ready to be implemented for automotive applications and in future we try to address the situation with a person wearing glasses and in real-time car environment.

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