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Real Time Eye Blinking Detection and Tracking Using Opencv

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ABSTRACT
Robust and accurate algorithm in real time eye tracking system has been a fundamental and challenging problem for computer vision. This paper proposed a new method to estimate eye-position and direction based on initial centroid analysis technique. The proposed method was validated by tracking eye position within high and low occlusion condition. In this paper, we represent a methodology for detection of eye blinking robustly in real time environment. Here we use the connected component technique and centroid method to track and blinking of eyes on OpenCV platform which is open source and developed by Intel.
***Keywords*-**OpenCv, blink detection, connected component, Eye tracking, DR, FAR, Success Rate

I. INTRODUCTION

Eye tracking as a tool is now more accessible than ever, and is growing in popularity amongst researchers from a whole host of different disciplines and have the potential to become an even more important component in future perceptual user interfaces. The technique is used in cognitive science, psychology, human-computer interaction, advertising, medical research, and other areas. Today, the human eye-gaze, blinking and eye movement can be recorded with relatively high reliability by unobtrusive techniques. Though, there are relatively few techniques proposed for the active scene where the head and the camera move independently and the eye moves freely in all directions independently of the face. Though, care must be taken, that eye-gaze tracking data is used in a sensible way, since the nature of human eye movements is a combination of several voluntary and involuntary cognitive processes.

Normally, eye tracking is performed on two d imensions to measure the horizontal and vertical motions of the eye. Horizontal and vertical eye (2D) positions can be determined from pupil center coordinates, which can be computed using center of mass algorithm [1, 2].

Driver fatigue is a significant factor in a large number of vehicle accidents. Recent statistics estimate that annually 1,200 deaths and 76,000 injuries can be attributed to fatigue related crashes.[3][4] The development of technologies for detecting or preventing drowsiness at the wheel is a major challenge in the field of accident avoidance systems. Because of the hazard that drowsiness presents on the road, methods need to be developed for counteracting its affects. The aim of this paper is to develop a prototype drowsiness detection system. The focus will be placed on designing a system that will accurately monitor the open or closed state of the driver's eyes in real-time. By monitoring the eyes, it is believed that the symptoms of driver fatigue can be detected early enough to avoid a car accident. Detection of fatigue involves a sequence of images of a eyes, and the observation of eye movements and blink patterns. This paper is focused on the localization of the eyes, which involves searching for the entire image of the eyes, and determining the position of the eyes, by a self-developed image-processing algorithm. Once the position of the eyes is located, the system is designed to determine whether the eyes are opened or closed, and detect fatigue.

II. LITERATURE SURVEY

2.1PHYSIOLOGICAL MEASURES

This method has been thought to be accurate, valid, and objective to determine fatigue and sleep. Significant efforts have been made in laboratory to measure it. The popular physiological measures include the electroencephalograph (EEG). EEG is found to be useful in determining the presence of ongoing brain activity, and its measures have been used as the reference point for calibrating other measures of sleep and fatigue [5].

Electroencephalography (EEG) is the recording of electrical activity along the scalp. EEG measures voltage fluctuations resulting from ionic current flows within the neurons of the brain through multiple electrodes placed on the scalp. The frequency of brainwave in EEG is about 1- 30Hz and generally it can be divided into four types in terms of frequency bands, which are delta (0-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), and beta (13-20 Hz). The alpha rhythm is present during a relaxed state and beta activity has been reported to be present during an alert state. Delta waves have been shown to be present during transition to drowsiness and during sleep. Theta rhythm is associated with a variety of psychological states including hypnologic imagery, and low levels of alertness during drowsiness and sleep and as such has been associated with decreased information processing. So alpha, beta and delta rhythm are independent and strongly related to fatigued state, so they three are selected as studying indicators [6].

Electroencephalogram (EEG) [1][2-7] is the most commonly studied signal for vigilance estimation. In most of the EEG-based vigilance research, EEG data of certain people is captured for experimentation and is labeled as per the vigilance states by some observer. Then different machine learning techniques can be applied on such data to find co-relation between EEG signal and observed fatigue state.

The work in [7] claims that most existing methods have focused on employing supervised learning methods to estimate vigilance states. However, till now, there is no standard criterion for vigilance scale labeling, and the existing vigilance labeling methods are complex, expensive and sometimes unreliable and therefore choose clustering methods to mine the latent distribution of EEG for vigilance estimation. The work extracts features in EEG using spatial filter and further clusters it into 4 clusters as wakefulness (W), middle state 1 (M1), middle state 2 (M2), and sleepiness (S).

The paper [8] proposes a system that combines electroencephalogram (EEG) power spectra estimation, independent component analysis and fuzzy neural network models to estimate subjects' cognitive state in a dynamic virtual-reality-based driving environment. It first uses the independent component analysis (ICA) to remove artifacts and extract possible sources of brain activities from continuous EEG recordings. After calculating power spectrum of each ICA components, it correlates the information between the human alertness and the ICA power spectra. Here human alertness is given by a performance index (driving error expressed as deviation between the center of the vehicle and the center of the lane). They select the alpha-band power in two major ICA components with the maximum correlation coefficients for individual subject as the input features of the estimation models. The correlation between subject's driving performance index (SDPI) and 33-ICA components are calculated to select the most useful representative components. The highest correlated 2-ICA-components power spectra were selected. Then the selected alpha-band features are fed to the self-constructing neural fuzzy inference network (SONFIN) to learn the relationship between the EEG spectra and driving performance.

The paper [9] investigates the use of RF (Random Forest) to select the key EEG features from a broad pool of available features, for the purpose of multilevel mental fatigue EEG classification. The EEG data were labeled to 5-level mental fatigue. EEG data passed through the feature extraction windows, with one window for each EEG channel. The length of each feature extraction window was 2 s (or 334 EEG samples), with half second (or 84 EEG samples) time interval between two adjacent calculations of feature extraction. Four features were chosen to characterize the power spectral density. As a result, in total 304 quantitative EEG features (4 kinds of features, 19 channels, and 4 frequency bands) were extracted. RF is used as Machine Learning Technique for classification / recognition of features.

The work in [10] senses different physiological parameters like galvanic skin resistance (GSR), heart rate variability (HRV), body temperature (THE) and in the context vehicle driving, different mechanical data like steering wheel positioning, brake pedal positioning etc. of driver by sensors put on steering wheel. A fuzzy logic classifier trained with offline statistical results is used to classify the vigilance state of driver. The classifier continuously monitors the data to detect a possible decrease in driver vigilance. If the driver is found to be sleepy, then the system is put on alert to focus on detecting a possible sleep attack and to alert the driver.

2.2BEHAVIORAL MEASURES

Behavioral Measures [5] [1] [11] 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.

In [11], 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 [12] claims that short pauses in performances are more indicative measures of vigilance.

2.3VISUAL MEASURES

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 [13-14] [15].

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) 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 reflects 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. For example, a typical facial expression that indicates the onset of fatigue is yawning. The major benefits of the visual measures are that they can be acquired non-intrusively [5].

Most of the fatigue detection work finds eyes as an interesting and useful visual measure, and fatigue is detected by detecting geometries of eyes, iris. The eyes detection method in [14] uses new circle detection operator and then uses neural network to validate the detected regions as eyes. An appearance based model in [16] uses Support Vector Machine to detect eyes and needs large number of training sets composed of different objects, orientations, light conditions, and eye closure degree. The Hypo-Vigilance Detection based on Eyelid Behavior [17] detects first face in the image and then percentage of eye closure (PERCLOS) and eyelid distance changes (ELDC)are computed for fatigue detection and eye closure rate (CLOSNO) is used for distraction detection. Finally, the computed values are compared with some simple threshold to estimate driver hypo-vigilance. Work in [18] is based on fact the 'Variations in the papillary size which was known controlled by the autonomic nervous system were found to be positively correlated with the level of vigilance in healthy normal subjects'. It computes the size of pupil by finding its minimum closing rectangle and finds variation in pupil size over time to detect fatigue.

Work in [13] detects eyes and tracts pupils. It also associates state with every eye status as CLOSED, CLOSING etc. and changes state based on certain observation in eyes. For example when the pupil ratio is above 80% of its nominal size or the pupils are lost, being in the CLOSING_STATE, an FSM transition to the CLOSED_STATE is provoked, which means that the eyes are closed. A new detection of the pupils from the CLOSED_STATE produces a change to the OPENING_STATE.

In [5] probabilistic model (Bayesian model) of fatigue is presented. Fatigue is modeled as the target hypothesis variable that we intend to infer while other contextual factors, which could cause fatigue (e.g. sleep quality, circadian, work condition, work environment, and physical condition), and visual cues, which are symptoms of fatigue, are information variables. On the other hand, when a person is fatigued, he/she tends to exhibit various visual behaviors that deviate from the nominal behaviors. The behaviors that typically capture the cognitive state of a person include eye movement, head movement, and facial expression. The Conditional Probability Tables (CCPTs) required for Bayesian Mode is constructed using several series of large-scale subjective surveys.

If H is hypothesis variable, o is observed evidence and s are hidden variables, H can be inferred with following probability.

$$\mathrm{P.H.O} = \alpha \sum_{S} \mathrm{PH, o, s} \qquad \ldots\ldots\ldots..(1)$$

Since fatigue is developed over period of time, in [5], it is actually modeled as Dynamic Bayesian Network (DBN). If T is a time boundary, hidden variables S= { $s0$, ..., $sT-1$} ,observations O= {$o0$, ... , $oT-1$} and hypothesis H= {$h0$, ... ,$hT-1$} , the probability distribution of DBN expressed as following:

$$PH,S,O = PH_0 * \prod_{t=1}^{T-1} PH_t\, H_{t-1} * \prod_{t=1}^{T-1} PS_t\, H_t * \prod_{t=1}^{T-1} PS_t\, S_{t-1} * \prod_{t=1}^{T-1} PO_t\, S_t \qquad ..(2)$$

As H and S at each point in time depends also on H and S at previous point in time respectively.

Different eye features are proposed in [15] like blink duration, eye closure, blinking rate, head nodding frequency etc. Finally drowsiness classification is defined as to combine these different features to a single continuous-valued drowsiness measure or the discrete classes awake, questionable and drowsy. An artificial neural network (ANN) was used for classification.

Yawning is used as fatigue measure in [19] and it detect yawing by detecting first mouth in an image and then its size and shape as increasing or decreasing. In [20], the face and features of the face like eyes, mouth, and facing direction are identified and tracked which can be used for driver's fatigue detection.

III. SYSTEM FLOWCHART

A flowchart of the major functions of the DrowsyDriver Detection System is shown in fig.

3.1SYSTEM PROCESS

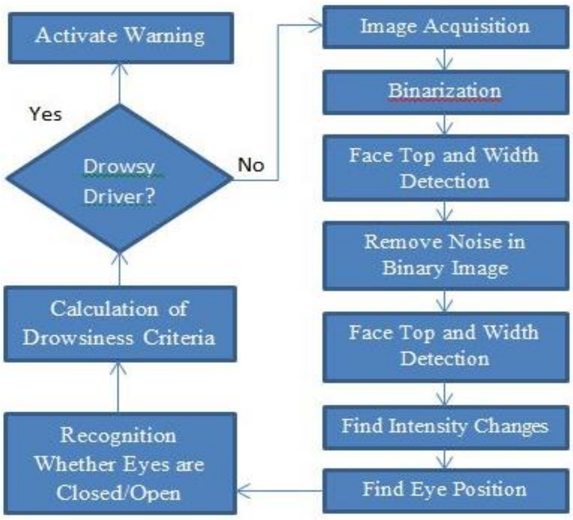


Fig.1. System Flowchart of Drowsiness Detection System

3.1.1 Eye Detection Function

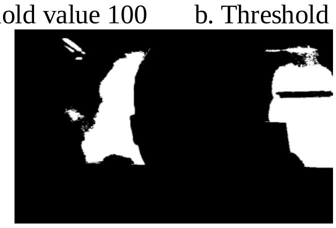
An explanation is given here of the eye detection procedure. After inputting a facial image, preprocessing is first performed by binarizing the image. The top and sides of the face are detected to narrow down the area of where the eyes exist. Using the sides of the face, the center of the face is found, which will be used as a reference when comparing the left and right eyes. Moving down from the top of the face, horizontal averages (average intensity value for each y coordinate) of the face area are calculated. Large changes in the averages are used to define the eye area. The following explains the eye detection procedure in the order of the processing operations.

3.1.2 Binarization

The first step to localize the eyes is binarizing the picture. Binarization is converting the image to a binary image. Examples of binarized image is shown in Figure 2

a. Threshold value 100

b. Threshold value 150



c. Threshold value 200

Fig.2 Different Threshold Values for Binarization

A binary image is an image in which each pixel assumes the value of only two discrete values. In this case the values are 0 and 1, 0 representing black and 1 representing white. With the binary image it is easy to distinguish objects from the background. The grayscale image is converting to a binary image via thresholding. The output binary image has values of 0 (black) for all pixels in the original image with luminance less than level and 1 (white) for all other pixels. Thresholds are often determined based on surrounding lighting conditions, and the complexion of the driver. After observing many images of different faces under various lighting conditions a threshold value of 150 was found to be effective. The criteria used in choosing the correct threshold was based on the idea that the binary image of the driver's face should be majority white, allowing a few black blobs from the eyes, nose and/or lips. Figure 2 demonstrates the effectiveness of varying threshold values. Figure 2a, 2b, and 2c use the threshold values 100, 150 and 200, respectively. Figure 2b is an example of an optimum binary image for the eye detection algorithm in that the background is uniformly black, and the face is primary white. This will allow finding the edges of the face, as described in the next section.

3.1.3 Face Top and Width Detection

The next step in the eye detection function is determining the top and side of the driver's face. This is important since finding the outline of the face narrows down the region in which the eyes are, which makes it easier (computationally) to localize the position of thee yes. The first step is to find the top of the face. The first step is to find a starting point on the face, followed by decrementing the y-coordinates until the top of the face is detected. Assuming that the person's face is approximately in the center of the image, the initial starting point used is (100,240). The starting x-coordinate of 100 was chosen, to insure that the starting point is a black pixel (no on the face). The following algorithm describes how to find the actual starting point on the face, which will be used to find the top of the face.

1. Starting at (100,240), increment the x-coordinate until a white pixel is found. This is considered the left side of the face.
2. If the initial white pixel is followed by 25 more white pixels, keep incrementing x until a black pixel is found.
3. Count the number of black pixels followed by the pixel found in step2, if a series of25 black pixels are found, this is the right side.
4. The new starting x-coordinate value (x1) is the middle point of the left side and right side.

3.1.4Removal of Noise

The removal of noise in the binary image is very straightforward. Starting at the top, (x2,y2),move left on pixel by decrementing x2, and set each y value to white (for 200 y values).Repeat the same for the right side of the face. The key to this is to stop at left and right edge of the face; otherwise the information of where the edges of the face are will be lost. Fig3, shows the binary image after this process

Fig.3. Binary Picture after noise removal

3.1.5 Finding Intensity Changes on the Face

The next step in locating the eyes is finding the intensity changes on the face. This is done using the original image, *not* the binary image. The first step is to calculate the average intensity for each y-coordinate. This is called the horizontal average, since the averages are taken among the horizontal values. The valleys (dips) in the plot of the horizontal values indicate intensity changes. When the horizontal values were initially plotted, it was found that there were many small valleys, which do not represent intensity changes, but result from small differences in the averages. To correct this, a smoothing algorithm was implemented. The smoothing algorithm eliminated and small changes, resulting in a smoother, clean graph.

IV. ALGORITHM

An explanation is given here for drowsiness detection procedure. For that we capture the video from camera. OpenCV supports capturing images from a camera or a video file (AVI) First we initialize the capture from a camera by setting zero which grab the frame from default camera. After getting the frame we converted into Gray scale. Using OpenCV conversion we can convert color image into Gray scale image. This Gray scale frame will give us the binary image. Then we locate the eye using centroid method by which we can locate the eye center in the face for tracking purpose. To find the centroid of an image, the image first has to be binarized. The centroid program will then calculate the centroid based on where the majority of black pixels are located. For example if you have a complete black 20 x 20 BMP, then the centroid would be located in the exact center of that square. After getting this centroid we mark the eye with rectangle with connected component technique by which we can easily figure out how many components of pixels are connected each other. If eyes are found during tracking then its X and Y coordinates are detected by finding centroid of contours. This gives the center coordinates of the eye pupil. This method is for detection of eye blinking. Based on blink detection we can decide by connecting loop that whether driver is drowsy or active.

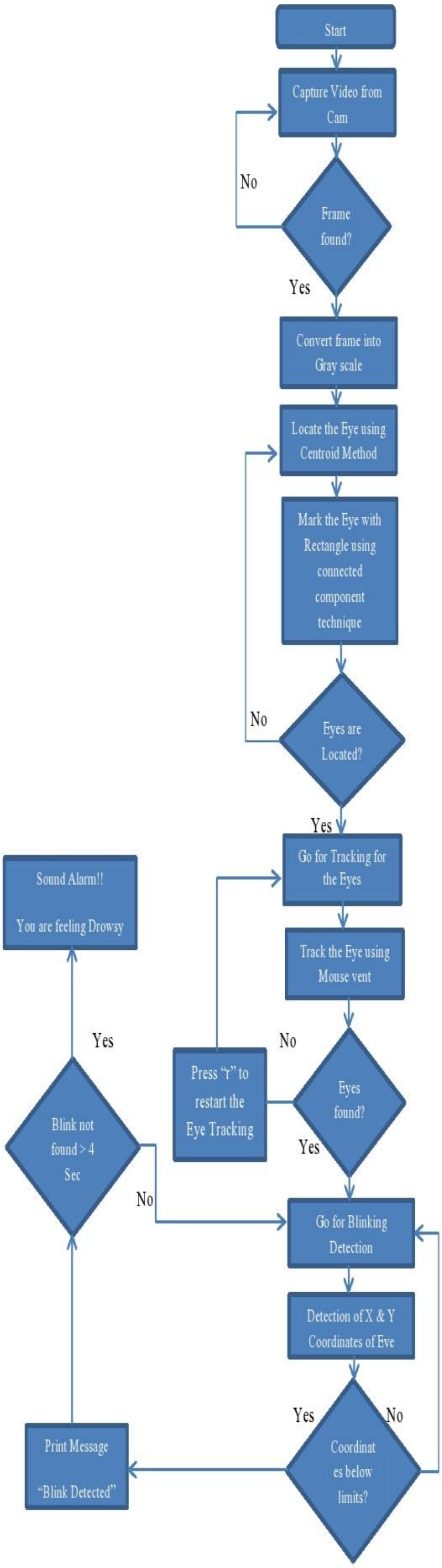


Fig.4. Drowsiness Detection Algorithm

4.1Connected Component Labeling

One common problem encountered in image analysis is to figure out which parts of an object are "connected", physically. That is, irrespective of the color. Here's an example:

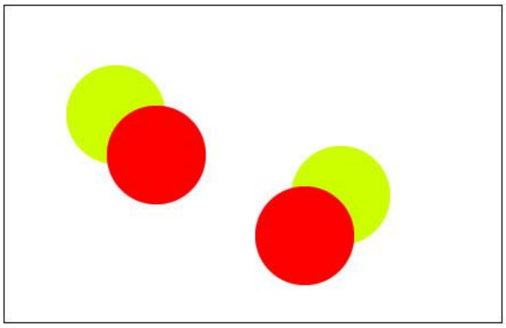


Fig.5. Distinct circles

In the above image, the red and green circles are distinct. But the goal is not to detect circles you can do that using the Circle Hough Transform. The goal is to identify the two "blobs". Each blob consisting of two circles, one red and one green. So, the desired output is something like this:

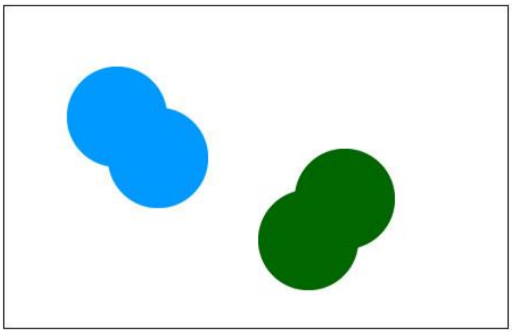


Fig.6. Two blobs in the circles

With this type of output, you can easily figure out how many components the image has, and which pixels are connected. The blue pixels are all connected and form one component, similarly the green one.

4.2Labeling

In the current context, labeling is just giving a pixel a particular value. For example, in the previous picture, all pixels in the blue region have the label '1'. Pixels in the green region have the label '2'. The white region, or the background, has the label '0'. This, the problem is to 'label' connected regions in an image. [19]

V. RESULTS

5.1 Qualitative Analysis

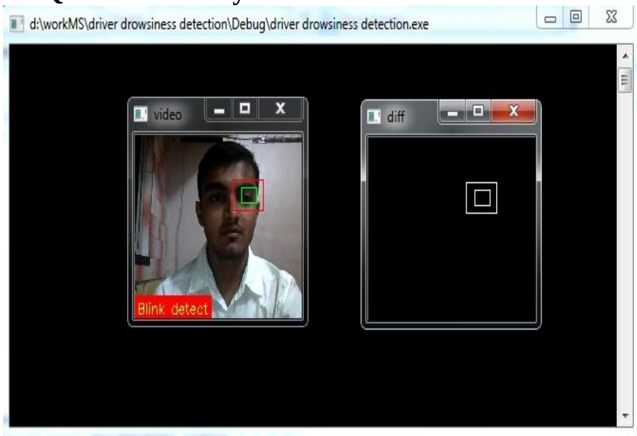


Fig.7. Blinking Detection with Right Eye

Fig.8. Blinking Detection with Left Eye

In the above figures the blinking is detected with Right eye and left eye respectively. Here system is such a designed that it will detect only one eye for blink detection because nature of the eyes. So memory consumption for detection of both the eyes will be less.

5.2Quantitative Analysis

Quantitative analysis is done using two metrics viz. Detection Rate (DR) and False Alarm Rate (FAR). These metrics are calculated based on following parameters:

A. TP (*true positive*): Detected regions that correspond to suspicious bag detection.
B. FP (*false positive*): Detected regions that do not correspond to suspicious bag detection. (Also known as false alarms).
C. FN (*false negative*): suspicious bag not detected (also known as misses).

These scalars are combined to define the following metrics:

$$DR = TP/(TP + FN) \quad \ldots\ldots\ldots\ldots\ldots (3)$$
$$FAR = FP/(TP + FP) \quad \ldots\ldots\ldots\ldots\ldots (4)$$
$$Success\ Rate\ (\%) = DR/(DR + FAR) \ldots\ldots (5)$$

Table.1: DR, FAR, Success Rate

Test / Parameter	1	2	3	4	5
TP	43	62	35	51	60
TN	10	16	4	7	5
FP	0	2	4	1	2
FN	0	0	2	1	1
DR	100	100	94.59	98.07	98.36
FAR	0	3.125	10.25	1.92	3.22
Success Rate	100	96.97	96.49	98.07	96.83

CONCLUSION

In this paper we presented the self - developed algorithm for drowsiness detection. The proposed method easily detects the blinks and the drowsiness as success rate is high because centroid and connected component methods are used instead of haar classifier.

Our 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. The methods we presented for video surveillance system shows promising results under good lighting conditions.

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