

A Review: Driver Drowsiness Detection System

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ABSTRACT

Driver drowsiness is one of the major causes of traffic accidents. It is a serious highway safety problem. If drivers could be warned before they became too drowsy to drive safely, some of these crashes could be prevented. In order to reliably detect the drowsiness, it depends on the presentation of timely warnings of drowsiness. To date, the effectiveness of drowsiness detection methods has been limited by their failure to consider individual differences. Based on the type of data used, drowsiness detection can be conveniently separated into the two categories of intrusive and non-intrusive methods. During the survey, non-intrusive methods detect drowsiness by measuring driving behavior and sometimes eye features, through which camera based detection system is the best method and so are useful for real world driving situations. This paper presents the review of existed drowsiness detection techniques that will be used in this system like Circular Hough Transform, FCM, Lab Color Space etc.

Keywords:- Drowsy Driving; Drowsiness Recognition; Driver Monitoring; Circular Hough Transform; FCM; Lab Color Space; Varying Luminance Conditions.

I. INTRODUCTION

Drowsiness is simply defined as “a state of near sleep due to fatigue”. It is technically distinct from fatigue, which has been defined as a “disinclination to continue performing the task at hand”. The effects of sleepiness and fatigue are very much the same. Fatigue affects mental alertness, decreasing an individual’s ability to operate a vehicle safely and increasing the risk of human error that could lead to fatalities and injuries. Sleepiness slows reaction time, decreases awareness, and impairs judgment. Fatigue and sleep deprivation impact all transportation operators (for example: airline pilots, truck drivers, and railroad engineers). In both conditions, driver can’t focus on primary task of driving which may enhance the likelihood of crash occurrence. With the ever-growing traffic conditions, this problem will further deteriorate. For this reason, it is necessary to develop driver alertness system for accident prevention due to Driver Drowsiness as shown in Fig.1.

Interaction between driver and vehicle such as monitoring and supporting each other is one of the important solutions for keeping ourselves safe in the vehicles. Although active safety systems in vehicles have contributed to the decrease

in the number of deaths occurring in traffic accidents, the number of traffic accidents is still increasing.



Fig. 1 Example of Driver Drowsiness

The National Highway Traffic Safety Administration (NHTSA) estimates that approximately 100,000 crashes each year are caused primarily by driver drowsiness or fatigue in the United States [1]. In Japan, attention lapse, including that due to driving while drowsy, was the primary reason for traffic accidents in 2008. The Ministry of Economy, Trade and Industry in Japan reports that number of such accidents has increased 1.5 times in the 12-year period from 1997 to 2008 [2]. Indian government also passed a law named ‘Motor Bill’ to improve safety on

roads caused by driver drowsiness. The Bill is aimed at bringing down fatalities in road accidents by two lakh in the first five years in a scenario where India reports around 5 lakh road accidents annually [3].

Methods

One solution to this serious problem is the development of an intelligent vehicle that can predict driver drowsiness and prevent drowsy driving. The percentage of eyelid closure over the pupil over time (PERCLOS) is one of the major methods for the detection of the driver's drowsiness. Physiological measurements like electroencephalogram (EEG), electrocardiogram (ECG) [4], capturing eye closure, facial features [5] [6], or driving performance (such as steering characteristics, lane departure, etc.) [7], [8] are used for drowsiness detection. When drowsiness is detected while driving, audible sound [9], [10], vibrations [11], [12], or warning messages on a display [10], [13] are generally used to warn the driver to concentrate on driving or to take a rest. These methods help the drowsy driver to prevent drowsiness-related crashes in a moment, but it is hard to get rid of drowsiness by just being aware of it. As we found in the literature review, most of the methods need lot of equipment which is not possible in real life implementations. Also most of the methods which rely on camera input for detection of opening and closing eyelids are not to be tested like they can be implemented in real time as most of the scholars take image as camera is fixed in front of the driver's road view. As for clear view, it is not possible to put the camera on front mirror. Secondly most of papers have drawbacks when there is high luminance caused by sunlight as well as during dim light conditions like bad weathers. We decided to explore this topic further according to the climate of our country and decided to propose a noble method which can eradicate the above written shortcomings of the literature survey.

Computer vision techniques to detect the changes in driver's facial expressions [14]. Computer vision method to detect driver drowsiness based on detecting eyelid closing and opening using artificial neural networks as classification algorithm. There was no model previously built which is completely automated. Secondly there was no low cost solution existed for driver drowsiness detection. Thirdly there was no model working for varying luminance conditions (caused by sunlight as well as during dim light conditions like bad weathers). So there is an immense need of a low cost, completely automated driver drowsiness detection model working under varying luminance conditions.

FACE TRACKING

Face tracking system as shown in Fig.2, must be robust to head movement, rotation, pose variation and illumination changes. To achieve this goal we propose a method to use face detection and object tracking systems simultaneously. This combination gives us the opportunity to utilize advantages of two programs together.

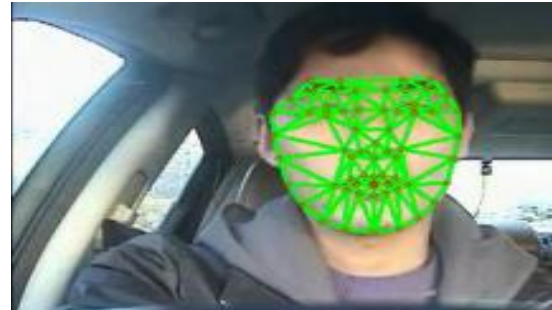


Fig. 2 Example of an Face Tracking

EYE DETECTION

Locating the position of eye is difficult task due to many factors such as lighting condition, expression, facial shadowing, etc. Using eye features, different measures can be calculated with percentage of eyelid closure, maximum closure duration, blink frequency, average opening level of the eyes, opening velocity of the eyes, and closing velocity of the eye and an effective driver drowsiness detection model can be created which can work under varying unconstraint and luminance conditions.

After the position of face has been obtained, locating the eye can be done with better accuracy. We will present the method to detecting eyes using L^*a^*b color space which can easily differentiate the face and non-face areas. As what was said before this method is not robust to pose variation. However we use this disability as an advantage in distraction detection system. If eye could not be detected we can assume that the driver don't look at forward. So this situation can be categorized in distraction state and must alarms the driver.

II. LITERATURE SURVEY

In 2008, Hong Su et. al. [15] described '**A Partial Least Squares Regression-Based Fusion Model for Predicting the Trend in Drowsiness**'. They proposed a new technique of modeling driver drowsiness with multiple eyelid movement features based on an information fusion technique—partial least squares regression (PLSR), with

which to cope with the problem of strong collinear relations among eyelid movement features and, thus, predicting the tendency of the drowsiness. The predictive precision and robustness of the model thus established are validated, which show that it provides a novel way of fusing multi-features together for enhancing our capability of detecting and predicting the state of drowsiness.

In June, 2010, Bin Yang et. al. [16] described '**Camera-based Drowsiness Reference for Driver State Classification under Real Driving Conditions**'. They proposed that measures of the driver's eyes are capable to detect drowsiness under simulator or experiment conditions. The performance of the latest eye tracking based in-vehicle fatigue prediction measures are evaluated. These measures are assessed statistically and by a classification method based on a large dataset of 90 hours of real road drives. The results show that eye-tracking drowsiness detection works well for some drivers as long as the blinks detection works properly. Even with some proposed improvements, however, there are still problems with bad light conditions and for persons wearing glasses. As a summary, the camera based sleepiness measures provide a valuable contribution for a drowsiness reference, but are not reliable enough to be the only reference.

In 2011, M.J. Flores et. al. [17] described '**Driver drowsiness detection system under infrared illumination for an intelligent vehicle**'. They proposed that to reduce the amount of such fatalities, a module for an advanced driver assistance system, which caters for automatic driver drowsiness detection and also driver distraction, is presented. Artificial intelligence algorithms are used to process the visual information in order to locate, track and analyze both the driver's face and eyes to compute the drowsiness and distraction indexes. This real-time system works during nocturnal conditions as a result of a near-infrared lighting system. Finally, examples of different driver images taken in a real vehicle at nighttime are shown to validate the proposed algorithms.

In June, 2012, A. Cheng et. al. [18] described '**Driver Drowsiness Recognition Based on Computer Vision Technology**'. They presented a nonintrusive drowsiness recognition method using eye-tracking and image processing. A robust eye detection algorithm is introduced to address the problems caused by changes in illumination and driver posture. Six measures are calculated with percentage of eyelid closure, maximum closure duration, blink frequency, average opening level of the eyes,

opening velocity of the eyes, and closing velocity of the eyes. These measures are combined using Fisher's linear discriminated functions using a stepwise method to reduce the correlations and extract an independent index. Results with six participants in driving simulator experiments demonstrate the feasibility of this video-based drowsiness recognition method that provided 86% accuracy.

In 2013, G. Kong et. al. [19] described '**Visual Analysis of Eye State and Head Pose for Driver Alertness Monitoring**'. They presented visual analysis of eye state and head pose (HP) for continuous monitoring of alertness of a vehicle driver. Most existing approaches to visual detection of non-alert driving patterns rely either on eye closure or head nodding angles to determine the driver drowsiness or distraction level. The proposed scheme uses visual features such as eye index (EI), pupil activity (PA), and HP to extract critical information on non-alertness of a vehicle driver. A support vector machine (SVM) classifies a sequence of video segments into alert or non-alert driving events. Experimental results show that the proposed scheme offers high classification accuracy with acceptably low errors and false alarms for people of various ethnicity and gender in real road driving conditions.

In June, 2014, Eyosiyas et. al. [20] described '**Driver Drowsiness Detection through HMM based Dynamic Modeling**'. They proposed a new method of analyzing the facial expression of the driver through Hidden Markov Model (HMM) based dynamic modeling to detect drowsiness. They have implemented the algorithm using a simulated driving setup. Experimental results verified the effectiveness of the proposed method.

In August 2014, García et. al. [21] described '**Driver Monitoring Based on Low-Cost 3-D Sensors**'. They proposed a solution for driver monitoring and event detection based on 3-D information from a range camera is presented. The system combines 2-D and 3-D techniques to provide head pose estimation and regions-of-interest identification. Based on the captured cloud of 3-D points from the sensor and analyzing the 2-D projection, the points corresponding to the head are determined and extracted for further analysis. Later, head pose estimation with three degrees of freedom (Euler angles) is estimated based on the iterative closest points algorithm. Finally, relevant regions of the face are identified and used for further analysis, e.g., event detection and behavior analysis. The resulting application is a 3-D driver monitoring system based on low-cost sensors. It represents

an interesting tool for human factor research studies, allowing automatic study of specific factors and the detection of special event related to the driver, e.g., driver drowsiness, inattention, or head pose.

III. VARIOUS DETECTION TECHNIQUES

Lab Color Space (LAB): The L*a*b* color space [22] is derived from the CIE XYZ tristimulus values. L* is the luminance or lightness component, which ranges from 0 to 100, and parameters a* (from green to red) and b* (from blue to yellow) are the two chromatic components, which range from -120 to 120). As in the computer, the image is expressed or saved in RGB color model, to use Lab color model [24], the first step is convert the image from RGB to Lab color model in the experiment. To complete the conversion, the fabric image should first be changed to XYZ color model. The conversion method is given as follows:

$$(1) r = R / 255$$

$$(2) \text{if } (r > 0.04045) \quad r = \frac{r + 0.055^{2.4}}{1.055}$$

$$\text{else} \quad r = \frac{r}{12.92}$$

To obtain g, r, the G, B components are be Processed in the same way.

$$X \quad 0.4124 \quad 0.3576 \quad 0.1805 \quad R$$

$$(3) Y = 0.2106 \quad 0.7125 \quad 0.0722 \cdot g$$

$$Z \quad 0.0193 \quad 0.1192 \quad 0.9505 \quad b$$

After then, the image can be converted to Lab from RGB color space with the help of XYZ color model.

$$(1) \text{if } (X > 0.008856) \quad x = X^{\frac{1}{3}}$$

$$\text{else} \quad x = 7.787 \cdot X + \frac{16}{116}$$

(2) Y, Z components are processed as X component in step 1, and we can get y, z.

$$L = 116 \cdot y - 16$$

$$(3) a = 500 \cdot (x - y)$$

$$b = 200 \cdot (y - z)$$

After the conversion, L, a, b are all belong to [0,128], so we can use cluster method to classify the colors in the yarn-dyed fabric with Lab color space. The results shows of a figure after Lab Color Space operation in Fig.3.

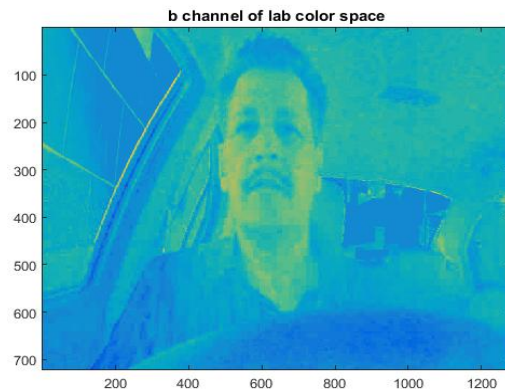


Fig. 3 Example of an LabColor Space

Thresholding: Thresholding is the simplest method of image segmentation. From a grayscale image, thresholding can be used to create binary images. The simplest thresholding methods replace each pixel in an image with a black pixel if the image intensity I_{ij} is less than some fixed constant T (that is, I_{ij} < T), or a white pixel if the image intensity is greater than that constant. In the example image on the right, this results in the dark tree becoming completely black, and the white snow becoming complete white. Fig.4 shows the results of an image after thresholding.



For a thresholding algorithm to be really effective, it should preserve logical and semantic content. There are two types of thresholding algorithms:

1. Global thresholding algorithms
2. Local or adaptive thresholding algorithms

In global thresholding, a single threshold for all the image pixels is used. When the pixel values of the components and that of background are fairly consistent in their respective values over the entire image, global thresholding could be used. In adaptive thresholding, different threshold values for different local areas are used.

Global thresholding :

A simple algorithm:

1. Initial estimate of T
2. Segmentation using T:
 - G1, pixels brighter than T;
 - G2, pixels darker than (or equal to) T.
3. Computation of the average intensities m1 and m2 of G1 and G2.
4. New threshold value:

$$T_{new} = \frac{m1 + m2}{2}$$

5. If $|T - T_{new}| > \epsilon$, back to step 2, otherwise stop.

Local properties based Thresholding:

1. Local properties (e.g., statistics) based criteria can be used for adapting the threshold.
2. For example:

- $T_{xy} = a_{xy} + b_{mxy}$
- $T_{xy} = a_{xy} + b_{mG}$

3. The segmentation is operated using a suitable predicate, Q_{xy} :

$$g(x, y) = \begin{cases} 1, & \text{if } Q_{xy} \\ 0, & \text{otherwise} \end{cases}$$

where Q_{xy} can be, for instance:

- $f(x, y) > T_{xy}$
- $f(x, y) > a_{xy}$ AND $f(x, y) > b_{mxy}$

4. This technique can be easily generalized to multiple thresholds segmentation.

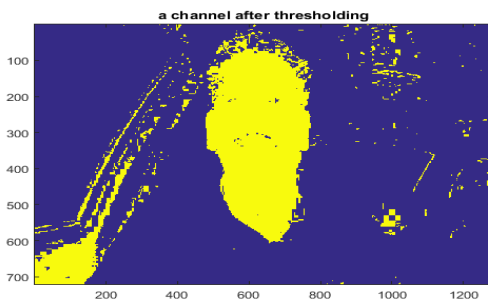


Fig. 4 Example of an image after Thresholding

Connected Components (CC): Connected components [23] labeling scans an image and groups its pixels into components based on pixel_connectivity, i.e. all pixels in a connected component share similar pixel__intensity values and are in some way connected with each other.

Once all groups have been determined, each pixel is labeled with a gray level or a color (color labeling) according to the component it was assigned to. Extracting and labeling of various disjoint and connected components in an image is central to many automated image analysis applications. Connected component labeling works by scanning an image, pixel-by-pixel (from top to bottom and left to right) in order to identify connected pixel regions, i.e. regions of adjacent pixels which share the same set of intensity values V . (For a binary image $V=\{1\}$; however, in a gray level image V will take on a range of values, for example: $V=\{51, 52, 53, \dots, 77, 78, 79, 80\}$.) Connected component labeling works on binary or gray level images and different measures of connectivity are possible.

The connected components labeling operator scans the image by moving along a row until it comes to a point p (where p denotes the pixel to be labeled at any stage in the scanning process) for which $V=\{1\}$. When this is true, it examines the four neighbors of p which have already been encountered in the scan (i.e. the neighbors (i) to the left of p , (ii) above it, and (iii and iv) the two upper diagonal terms). Based on this information, the labeling of p occurs as follows:

- If all four neighbors are 0, assign a new label to p , else
- if only one neighbor has $V=\{1\}$, assign its label to p , else
- if more than one of the neighbors have $V=\{1\}$, assign one of the labels to p and make a note of the equivalences.

After completing the scan, the equivalent label pairs are sorted into equivalence classes and a unique label is assigned to each class. As a final step, a second scan is made through the image, during which each label is replaced by the label assigned to its equivalence classes. For display, the labels might be different gray levels or colors. Fig.5 shows the results after detecting largest region using Connected Analysis.

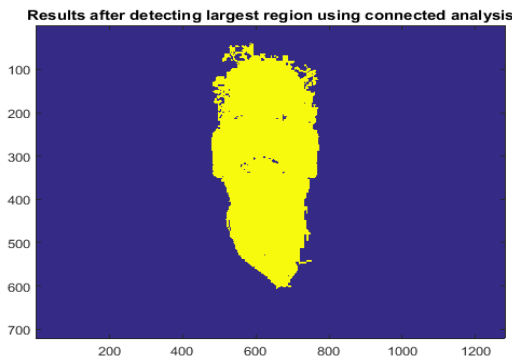


Fig.5 Example of an image using Connected Analysis

Fuzzy C-Means Clustering Method:

In the color segmentation and pattern recognition, cluster is one the most important processes. Among the clusters methods, Fuzzy C-Mean cluster method (FCM) [24] is most famous. FCM algorithm is an unsupervised clustering method. The clustering method attempts to minimize the objective function by organizing the data into clusters. The objective function is as follow:

$$\min J_m(U, V) = \sum_{j=1}^n \sum_{i=1}^c u_{ij}^m d_{ij}^2$$

Fuzzy C mean Algorithm: The **Fuzzy C-Means (FCM) Algorithm** [25] uses fuzzy logic where each data point is specified by a membership grade between 0 and 1. In **fuzzy clustering** (also referred to as **soft clustering**), data elements can belong to more than one cluster, and associated with each element is a set of membership levels. These indicate the strength of the association between that data element and a particular cluster. Fuzzy clustering is a process of assigning these membership levels, and then using them to assign data elements to one or more clusters. One of the most widely used fuzzy clustering algorithms is the Fuzzy C-Means (FCM) Algorithm (Bezdek 1981). The FCM algorithm attempts to partition a finite collection of n elements $X=\{X_1, \dots, X_n\}$ into a collection of c fuzzy clusters with respect to some given criterion. As a result, Fig.6 display the results of face region after Fuzzy Clustering.

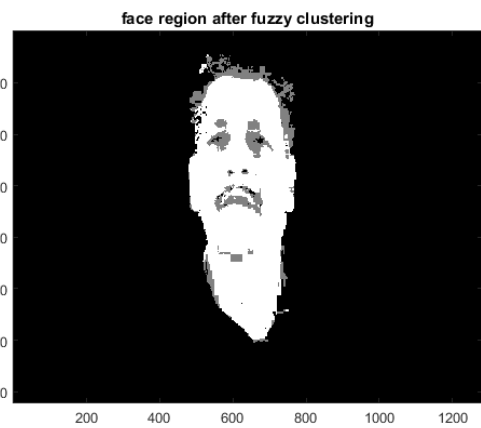


Fig. 6 Face Region After Fuzzy Clustering

Circular Hough Transform (CHT): CHT [26] enables the extraction of circles characterized by a center point $(x_c; y_c)$ and a radius r . The CHT will detect spots with higher brightness in places where centers of round-shaped objects should be found. An ideal laser spot is represented by a white spot in the input image, i.e., a rapid change from a dark background to the local maxima. However, the assumption that the laser spot is represented by an ideal circle holds only when the spot is static and relatively close to the camera. In real-life scenarios, a laser spot can be moving fast, resulting in the deformed image of a laser spot. Further, when a laser spot is at a longer distance from the camera, it only occupies a few pixels of an image and has an irregular shape. While CHT can be used for the detection of round shapes whose outlines are not deformed, to efficiently detect a laser spot, the original CHT should be modified in such a way as to relax the assumption of CHT, which states that the gradient orientation will be uniformly distributed and directed at one point.



Steps:

1. Turn the colored image into grayscale.
2. Create a 3D Hough array (accumulator) with the first two dimensions representing the coordinates of the circle origin and the third dimension represents the radii.

3. Detect edges using the Canny edge detector. For each edge pixel (point), increment the corresponding elements in the Hough array.
4. Collect candidate circles, then delete similar circles.
5. Draw circles around coins.

Here a and b represent the coordinates for the center, and r is the radius of the circle. The parametric representation of this circle is,

$$x = a + r \cdot \cos(\theta)$$
$$y = b + r \cdot \sin(\theta)$$

Unlike the linear HT, the CHT relies on equations for circles. The equation of the a circle is,

$$r^2 = (x - a)^2 + (y - b)^2$$

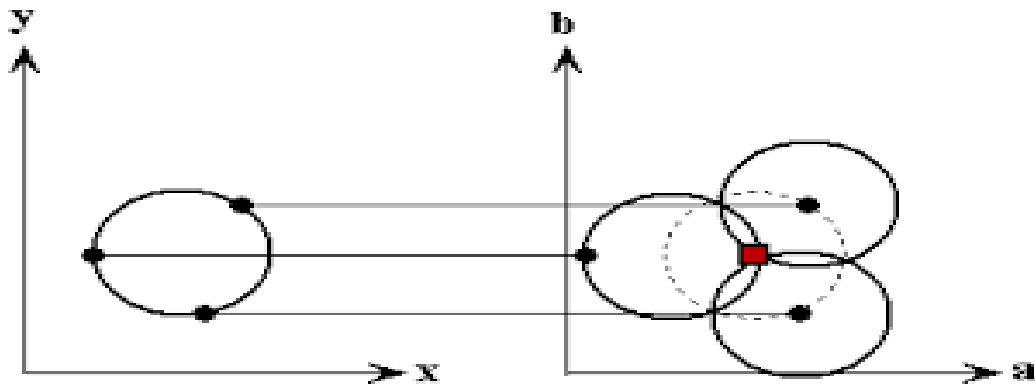
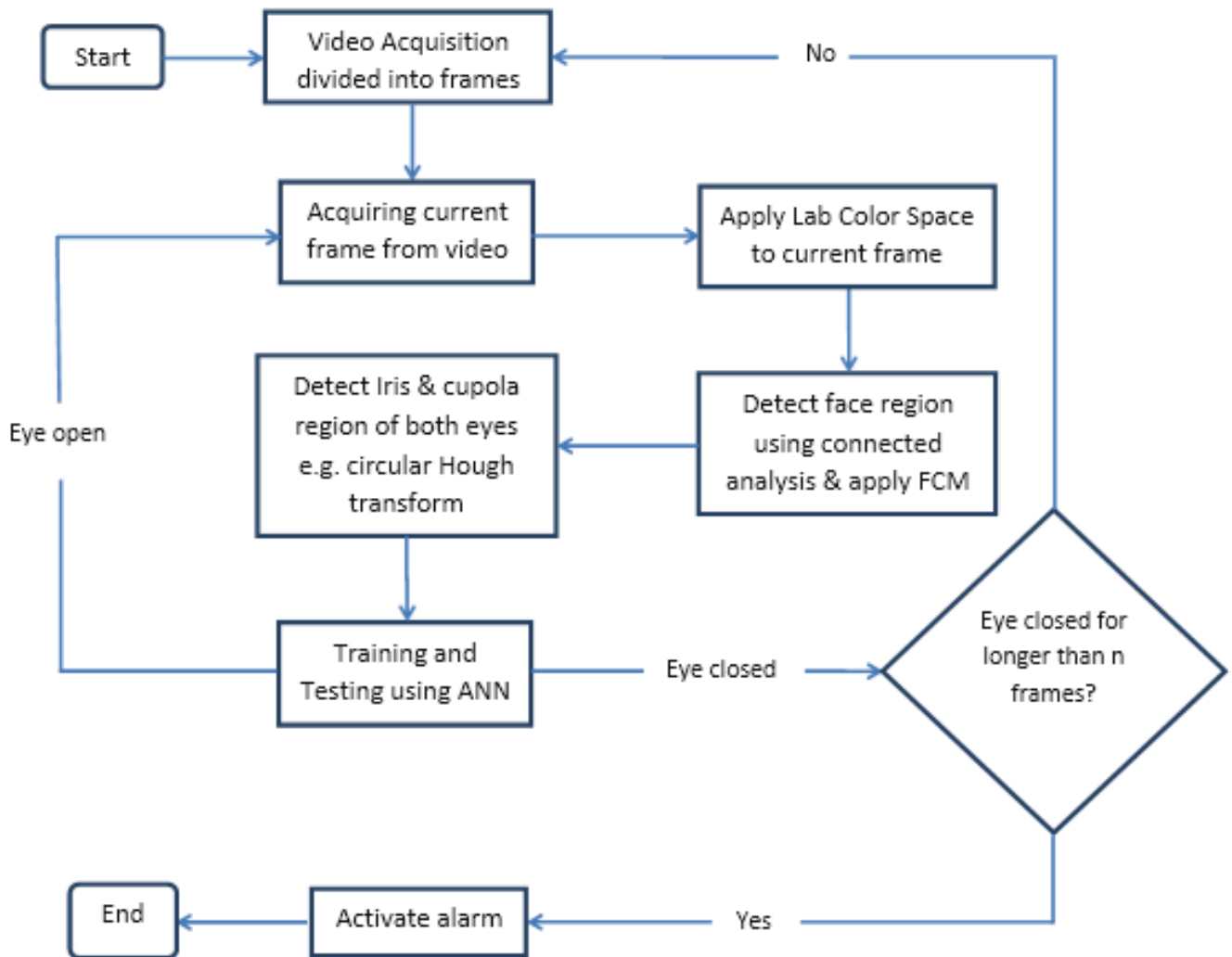


Fig. 7 Circular Hough Transform

Flowchart: The given flowchart represents the all process of various techniques which are to be used in Driver Drowsiness Detection System step by step.



IV. CONCLUSION

Previous studies have proposed a number of methods to detect drowsiness. After doing literature survey, different techniques has been found for detecting driver drowsiness and they use different types of data as input for their algorithm. After the survey of different types of methods, it is found that using camera is the best method which can be easily applied and appropriate in all conditions. We decide to explore this method of computer vision and proposed a noble method to detect driver drowsiness based on detecting eyelid closing and opening using artificial neural networks as classification algorithm. In this paper, First of all, the video frames are acquired from the camera which could be fixed in such a way that it should not obstruct the road-view of the driver.

Secondly, the Lab Color Space technique is applied to each frame then thresholding is to be done in an image. After thresholding, the largest region is to be detected using Connected Analysis. The face of the driver will be found in the video in such a way that it should not affect the performance of accurate face detection in terms of varying lightning conditions. The Fuzzy Clustering (FCM) technique is to be applied on the face region. Then the eye region of the driver along with the boundary of iris region in the frame will be detected using Circular Hough Transform. The Morphological Operations are applied to the eye region. After that features will be fed to the network as input and classified using artificial neural networks. The buzzer sound generating function will be build which will alarm the driver in case drowsiness is detected. Finally False and true positive rates will be calculated to measure the precision ratio of the algorithm.

- [19] Ralph Oyini Mbouna, Seong G. Kong, *Senior Member, IEEE*, and Myung-Geun Chun, "Visual Analysis of Eye State and Head Pose for Driver Alertness Monitoring." *IEEE TRANSACTIONS ON INTELLIGENT TRANSPORTATION SYSTEMS*, VOL. 14, NO. 3, SEPTEMBER 2013.
- [20] Eyosiyas Tadesse, Weihua Sheng, Meiqin Liu, "Driver Drowsiness Detection through HMM based Dynamic Modeling." 2014 IEEE International Conference on Robotics & Automation (ICRA) Hong Kong Convention and Exhibition Center May 31 - June 7, 2014. Hong Kong, China.
- [21] Gustavo A. Peláez C., Fernando García, Arturo de la Escalera, and José María Armingol, "Driver Monitoring Based on Low-Cost 3-D Sensors." *IEEE TRANSACTIONS ON INTELLIGENT TRANSPORTATION SYSTEMS*, VOL. 15, NO. 4, Page(s): 1855 - 1860 AUGUST 2014.
- [22] Zhi-Kai Huang, Ling-Ying Hou, Zhi-Hong Li, "Image Clustering Using Graph Cuts in LAB Color Space", *International Journal of Digital Content Technology and its Applications (JDCTA)* Volume 7, Number 12, August 2013.
- [23] Jongho Kim and YongYun Cho, "Efficient Character Segmentation using Adaptive Binarization and Connected Components Analysis in Ubiquitous Computing Environments", *International Journal of Multimedia and Ubiquitous Engineering* Vol. 8, No. 2, March, 2013.
- [24] Zhang Ronghua, et al., "Unsupervised Color Classification for Yarn-dyed Fabric Based on FCM Algorithm", 2010 International Conference on Artificial Intelligence and Computational Intelligence.
- [25] Chih-Cheng Hung, *Member, IEEE*, Sameer Kulkarni, and Bor-Chen Kuo, *Member, IEEE*, "A New Weighted Fuzzy C-Means Clustering Algorithm for Remotely Sensed Image Classification", *IEEE JOURNAL OF SELECTED TOPICS IN SIGNAL PROCESSING*, VOL. 5, NO. 3, JUNE 2011.
- [26] Damir Krstinić, Ana Kuzmanić Skelin * and Ivan Milatić, "Laser Spot Tracking Based on Modified Circular Hough Transform and Motion Pattern Analysis", *Sensors* 2014.