

Novel Warning System for Detection Driver Drowsiness in Real Time Using Visual Information

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Abstract Traffic accidents due to human errors cause many deaths and injuries around the world. To help in reducing this fatality, in this research, a new module for Advanced Driver Assistance System (ADAS) for automatic driver drowsiness detection based on visual information and Artificial Intelligence is presented. The aim of this system is to locate, to track and to analyze the face and the eyes to compute a drowsiness index, working under varying light conditions and in real time. Examples of different images of drivers taken in a real vehicle are shown to validate the algorithm.

Keywords Driver's drowsiness • Neural networks • Support vector machine • Gabor filter • Artificial intelligence • ADAS • Computer vision

1 Introduction

ADAS is part of the active safety systems that interact much more with drivers to help them avoid traffic accidents, indeed, its goal is to contribute in the reduction of traffic accidents, by using new technologies; that is, incorporating new systems for increasing vehicle security, and at the same time, decreasing the danger situations that may arise during driving, due to human errors. In this scenario, vehicular security research is focused on driver analysis, in this particular case; drowsiness and distraction are studied more intensely [4].

Drowsiness appears in situations of stress and fatigue in an unexpected and inopportune way, and it may be produced by sleep disorders, certain type of medications, and even, boredom situations, for example, driving for a long time. In this sense, sleepiness sensation diminishes the level of vigilance, and it produces danger situations and increases the probability that an accident occurs.

It has been estimated that drowsiness causes between 10% and 20% of traffic accidents with dead [31] and injured drivers [11], whereas the trucking industry shows 57% of fatal truck accidents for this fatality [2, 22]. Fletcher et al. in [12] goes further and has mentioned that 30% of all traffic accidents have been caused by drowsiness and Brandt et al. [4] presents statistics in which 20% of all accidents are caused by fatigue and inattention. In USA drowsiness is responsible for 100,000 traffic accidents whose costs are about \$12,000 million [28]. In Germany, one of four traffic accidents have their origin in drowsiness, in England 20% off all traffic accidents are produced by drowsiness [16] and in Australia 1,500 million dollars has been spent on this fatality [24].

In this context, it is important to use new technologies to design and to build systems that will monitor drivers, and measure their level of attention throughout the

whole driving process. Fortunately, people in a state of drowsiness produce several visual cues that can be detected on the human face, they are:

- Yawn frequency,
- Eye-blinking frequency,
- Eye-gaze movement,
- Head movement and,
- Facial expressions.

Taking advantage of these visual characteristics, computer vision is the feasible and appropriate technology to treat this problem. This article presents the drowsiness detection system of the IVVI (Intelligent Vehicle based Visual on Information) vehicle [1]. The goal of this system is to estimate driver drowsiness automatically and to prevent drivers falling asleep while driving.

The organization of the paper is as follows. Section 2 presents an extended state of the art divided by light conditions. Section 3 introduces the proposed method that consists of face and eye detection, face and eye tracking and the drowsiness index based on support vector machine. Finally, in section 4 results and conclusions are shown.

2 Related Work

To increase the traffic security and to reduce the number of traffic accidents, numerous universities, research centers, automotive companies (Toyota, Daimler Chrysler, Mitsubishi, etc.) and governments (Europe Union, etc.) are contributing in the development of ADAS for driver analysis [2], using different technologies. In this sense, the use of visual information to know the driver's drowsiness state and understand his/her behavior is an active research field.

This problem requires the recognition of human behavior when in a state of sleepiness through the analysis of the eyes and the face (head). This is a difficult task, even for humans because there are many factors involved, for instance, changing illumination conditions and a variety of possible face poses. Taking into account the illumination, the state of the art has been divided in two parts; one is the systems that work with natural daylight; another is the systems which work with the help of illumination systems based on near infrared (NIR) illumination.

2.1 Systems with Daylight Illumination

To analyze driver drowsiness several systems have been built in recent years. They usually require simplifying the problem to work partially or under special environments, for example, D'Orazio et al. [10] has proposed an eye detection algorithm that searches for the eyes in the whole image assuming that the iris is always darker than the sclera and based on the Hough transform for circles and geometrical constraints the eyes candidates are located, next, they are passed to a neural network that classify between eyes and non-eyes. This system is able to classify the eyes as being in an open or closed state. The main limitations of this algorithm are: it is applicable only when the eyes are visible in the image, and it is not robust at changing illumination. Horng et al. [17] has shown a system that uses a skin color model over HSI space for face detection, edge information for eye localization and dynamical template

matching for eye tracking. Using eyeball color information, it identifies the eye state and computes the driver's state, i.e., asleep or alert; if the eyes are closed over a five consecutive frames, the driver is dozing. Brandt et al. [4] has shown a system that monitors driver fatigue and inattention. For this task, he uses the Viola & Jones (VJ) method [34] to detect the driver's face. Using the optical flow algorithm over eyes and head this system is able to compute the driver state. Tian and Qin in [31] have built a system for verifying the driver's eye state. Their system uses Cb and Cr components of the YCbCr color space; with vertical projection function this system localizes the face region and with horizontal projection function it localizes the eye region. Once the eyes are localized the system computes eye state using a complexity function. Dong and Wu [11] have presented a system for driver fatigue detection, which uses a skin color model based on bivariate Normal distribution and Cb and Cr components of the YCbCr color space. After localizing the eyes, it computes the fatigue index utilizing the eyelid distance to classify open eyes and closed eyes; if the eyes are closed over five consecutive frames, the driver is regarded as dozing, alike to the Horng's work. Branzan et al. [5] also presents a system for drowsiness monitoring using template matching to analysis the eye state.

2.2 Systems with Infrared Illumination

In this case, due to night-time light conditions, Ji et al. [21] and Ji and Yang [22] has presented a drowsiness detection system based on NIR illumination and stereo vision. This system localizes the eye position by using image differences based on the bright pupil effect. Afterwards, this system computes the blind eyelid frequency and eye gaze to build two drowsiness indices: PERCLOS (percentage of eye closure over time) [28] and AECS (average eye closure speed). Bergasa et al. [2] also has developed a non-intrusive system using infrared light illumination, this system computes driver vigilance level using a finite state automata (FSM) [3] with six eye states that computes several indices, among them, PERCLOS; also, this system is able to detect inattention through face pose analysis. Another work using this type of illumination is presented by Grace [14] for measuring slow eyelid closure. Systems using NIR illumination work well under stable lighting conditions [2, 9]; however, this is a shortcoming for applications in real vehicles, where the light is changing all the time. In this scenario, if the spectral pupils disappear, then it will be difficult to detect the eyes.

3 System Design to Drowsiness Detection

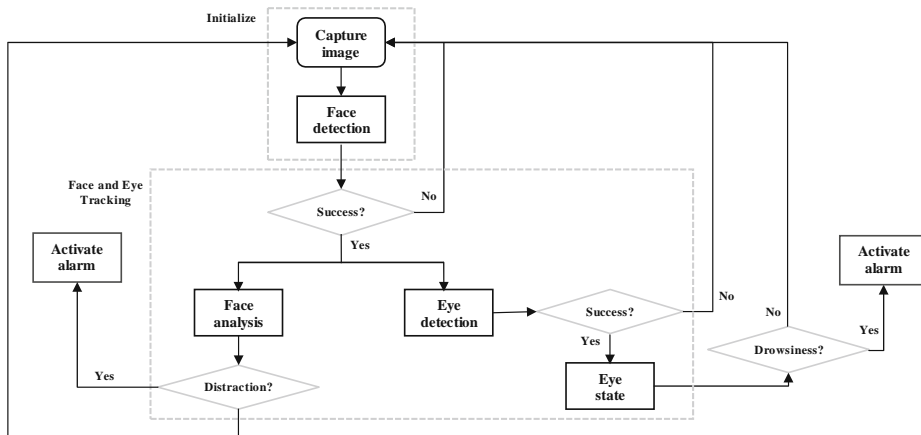
This paper presents a system to detect the driver's drowsiness that works on grayscale images. The scheme of the system is shown in Fig. 1 in which six modules are presented:

- Face detection
- Eye detection
- Face tracking
- Eye tracking
- Drowsiness detection and
- Distraction detection

Each one of these parts will be explained in the following subsections.

3.1 Face Detection

To localize the face, this system uses the VJ object detector which is a machine learning approach for visual object detection. It uses three important aspects to make an efficient object detector based on the integral image, AdaBoost technique and



cascade classifier [34]. Each one of these elements is important for processing the

Fig. 1 Algorithm scheme

images efficiently and in near real-time with 90% of correct detection. A further important aspect of this method is its robustness under changing light conditions. However, in spite of the above-mentioned features, its principal disadvantage is that it cannot extrapolate and does not work appropriately when the face is not in front of the camera axis. Such would be the case when the driver moves his/her head; however, this shortcoming will be analyzed later on.

Continuing with the algorithm description, when driver's face is detected, it is enclosed within a rectangle RI (region of interest) which is addressed by left-top corner coordinates $P_0 = (x_0, y_0)$ and right-bottom corner coordinates $P_1 = (x_1, y_1)$, as can be observed in Fig. 2a–c. Indeed, the rectangle size comes from experimental analysis developed on the face database that has been created for this task.

3.2 Eye Detection

Localizing the eye position is a difficult task because different features define the same eye depending, for example, the area of the image where it appears or its iris color, but the main problem during driving is the changing ambient light conditions.

Once the face has been located through the rectangle RI in the previous section, using the face anthropometric properties [13] which come from face database analysis, two rectangles containing the eyes are obtained. Preliminary, this system uses RI_L for the left eye rectangle and RI_R for the right eye rectangle as can be seen in the following four equations and they are shown in the Fig. 3.

3.3 Eye State Detection

To identify drowsiness through eye analysis it is necessary to know its state: open or closed, through the time and develop an analysis over time, i.e., to measure the time that has been spent in each state. Classification of the open and closed state

is complex due to the changing shape of the eye, among other factors, the changing position and the rotating of the face, and variations of twinkling and illumination. All this makes it difficult to analyze eye in a reliable manner. For the problems that have been exposed a supervised classification method has been used for this challenging task, in this case, a support vector machine (SVM). Figure 16 presents the schema proposed for eye state verification.

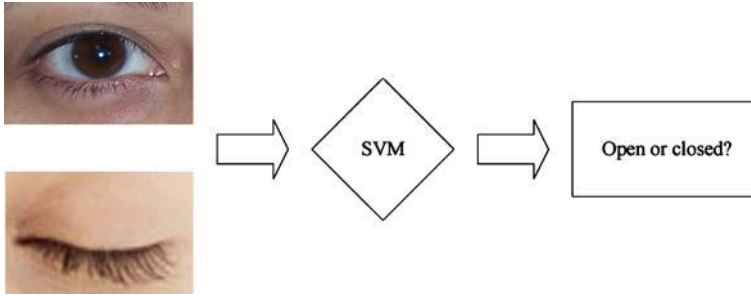


Fig. 2 SVM schema for eye state verification

3.3.1 Support Vector Machine

SVM classification [6, 8, 15] is rooted in statistical learning theory and pattern classifiers, it uses a training set, $S = \{(x_i, y_i) \mid i: 1, \dots, m\}$, where x_i is the characteristic vector in R^n , $y_i \in \{1, 2\}$ represents the class, in this case 1 for open eyes and 2 for closed eyes, and m is the number of elements of S . From a training set a hyperplane is built that allows the classification between two classes and minimizes the empirical risk function [15].

Mathematically, SVM consists of finding the best solution to the following optimization problem:

$$\begin{aligned} \min f(a) &= \frac{1}{2} a^T Q a - e^T a \\ \text{s. t.} \\ 0 &\leq a_i \leq C, \quad i = 1, \dots, m \\ y^T a &= 0 \end{aligned}$$

where e is a m by the 1 vector, C is an upper bound, Q is a m by m matrix with $Q_{ij} = y_i y_j K(x_i, x_j)$ and $K(x_i, x_j)$ is the kernel function. By solving the above quadratic programming problem, SVM tries to maximize the margin between data points in the two classes and minimize the training errors simultaneously; Fig. 17 depicts the mapping of the input space to a high dimensional feature space through a nonlinear transformation and its maximization process.

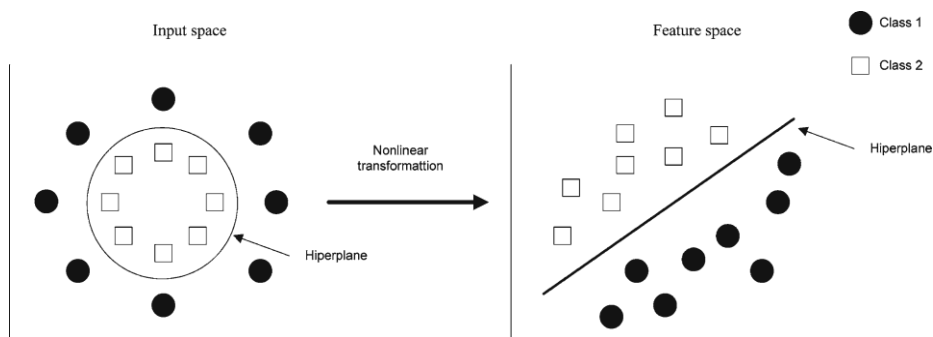


Fig.3 SVM representaion

3.3.2 Eye Characteristic Extraction Using Gabor Filter

The Gabor filter was used by Daugman for image analysis, changing the orientation and scale [9, 23]. Indeed, they are multi-scale and multi-orientation kernels. They can be defined by Eq. 19 that is a complex function.

$$g(x, y, \theta, \varphi) = \exp\left(-\frac{x^2 + y^2}{\sigma^2}\right) \exp(i2\pi\theta(x \cos(\varphi) + y \sin(\varphi))) \quad (19)$$

where θ and φ are the scale and orientation parameters, σ is the standard deviation of the Gaussian kernel that depends upon the spatial frequency to measured, i.e. θ . The response of the Gabor filter to an image is obtained by a 2D convolution operation. Let $I(x, y)$ denote the image and $G(x, y, \theta, \varphi)$ denote the response of a Gabor filter with scale θ and orientation φ to an image at point (x, y) on the image plane. $G(\cdot)$ is obtained by (20).

$$G(x, y, \theta, \varphi) = \iint I(p, q) g(x-p, y-q, \theta, \varphi) dpdq \quad (20)$$

Some combinations of scales and orientations are more robust for the classification between open eye and closed eye. Indeed, three scales, four orientations have been used to generate Fig. 18, they are $\{1, 2, 3\}$ and $\{0, \pi/4, \pi/2, 3\pi/4\}$ that were obtained experimentally over an image of size 30 by 20.

Once the response of a Gabor filter is obtained, the eye characteristic vector is extracted by a sub-window procedure described by Chen and Kubo [7] and denoted

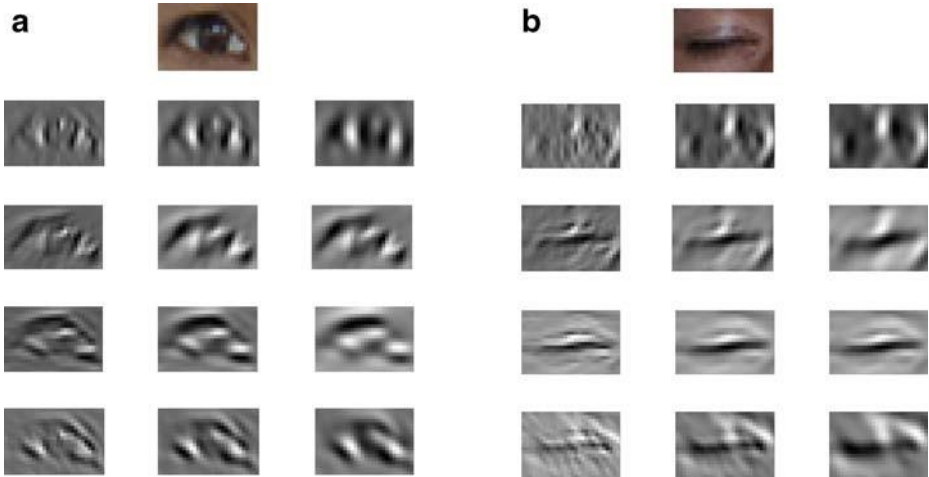
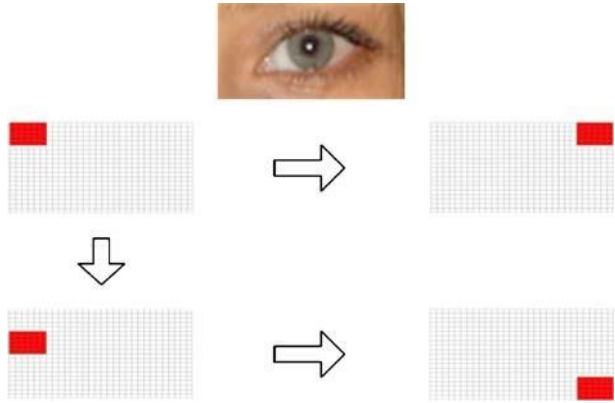


Fig. 4 Gabor filter for $\theta = \{0,1,2\}$ and $\varphi = \{0, \pi /4, \pi /2, 3\pi /4\}$

Fig. 5 Sub-window images from the Gabor filter



by $d \in R^{360}$. This vector is computed by Eq. 21 over each sub-window of size 5 by 6. Figure 19 shows the sub-window diagram.

$$d_i^{\theta, \varphi} = \frac{1}{30} \sum_{y=1:5, x=1:6} G(x, y, \theta, \varphi) \quad i = 1, \dots, 20 \quad (21)$$

To do this work a training set has been built that consists of open eyes and closed eyes. The images come from diverse sources, under several illumination conditions and are of different races. A further important aspect of this eye database is that it contains images of different eye colors, i.e., blue, black, green see Fig. 20.

Previous to SVM training, it is indispensable to process each image that consists of histogram equalization, filter with the median filter, followed by the sharpen filter. The median filter is used to reduce the image noise, whereas the sharpen filter is used to enhance the borders.

The main objective of training SVM is to find the best parameters and the best kernel that minimizes Eq. 11, so, after several training experiments of the SVM, it was decided to use the RBF kernel, i.e., $K(x_i, x_j)$ is $\exp -\gamma \|x_i - x_j\|^2$, $C = 30$ and $\gamma = 0.0128$; these parameters reach a high training classification rate that is about 93%.



Fig. 6 Examples of eye database

Table 3 Result of eye state analysis

Driver	Total frames	Eyes open	Eyes closed	Correct rate (%)
D1	960	690/700	258/260	98.90
D2	900	520/560	339/340	96.27
D3	500	388/400	99/100	98.00
D4	330	150/170	152/160	91.61
D5	1,400	891/980	401/420	93.19

Table 3 presents several results of this method computed over a several sequences of drivers. It shows that a high correct rate of classifications.

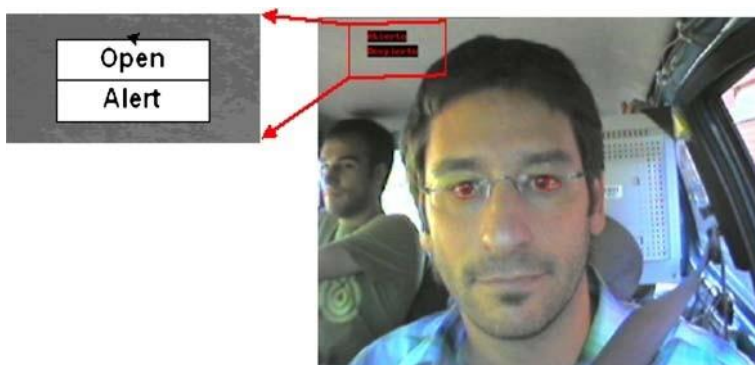
3.4 Drowsiness Index

The eye-blinking frequency is an indicator that allows a driver's drowsiness (fatigue) level to be measured. As in the works of Horng et al. [17] and Dong and Wu [11], if five consecutive frames or during 0.25 s are identified as eye-closed the system is able to issue an alarm cue; PERCLOS [28] also is implemented in this system.

Figure 21 presents an instantaneous result of this system over a driver's image, whereas Fig. 22 pictures the evolution drowsiness index graph for a driver's drowsiness sequence.

3.5 Distraction

Distraction may also cause traffic accidents, it is estimated that it is the cause of about 20% of them [4]. To detect distraction the driver's face should be studied because the pose of the face contains information about one's attention, gaze and level of fatigue [22]. To verify the driver's distraction, this contribution has implemented the following procedure.

**Fig. 6** System instantaneous result

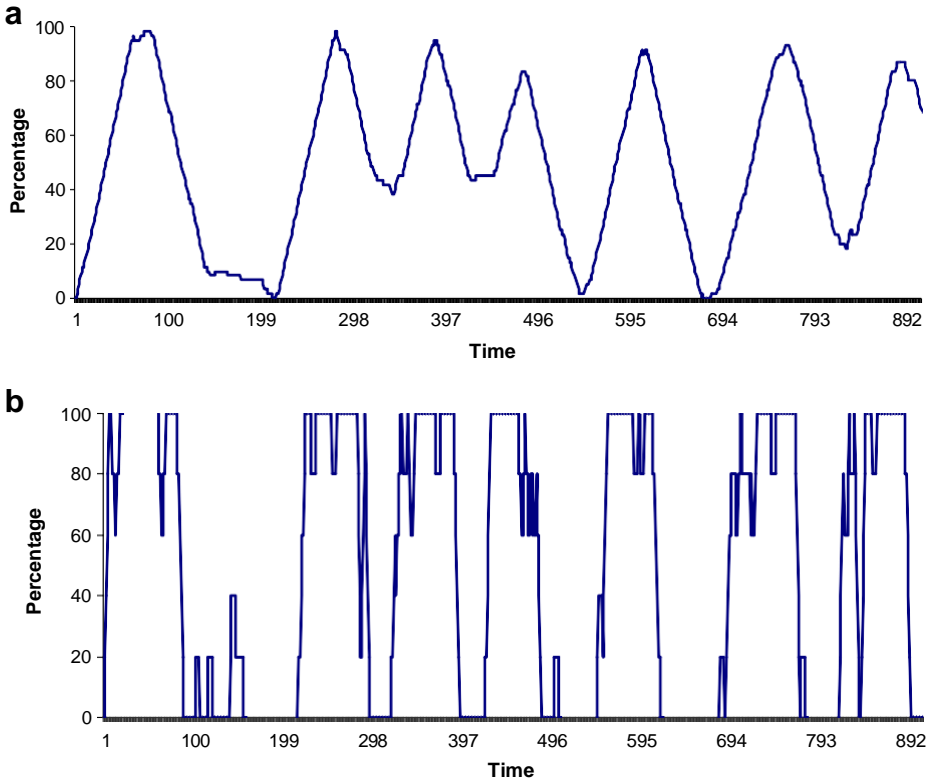
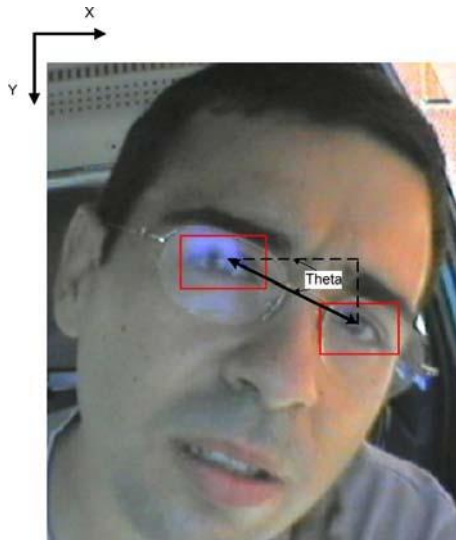


Fig. 7 Drowsiness index graph in a 900-frame sequence of a drowsy driver, **a** Perclos, **b** Horng-Dong and Wu index

Fig. 8 Face orientation



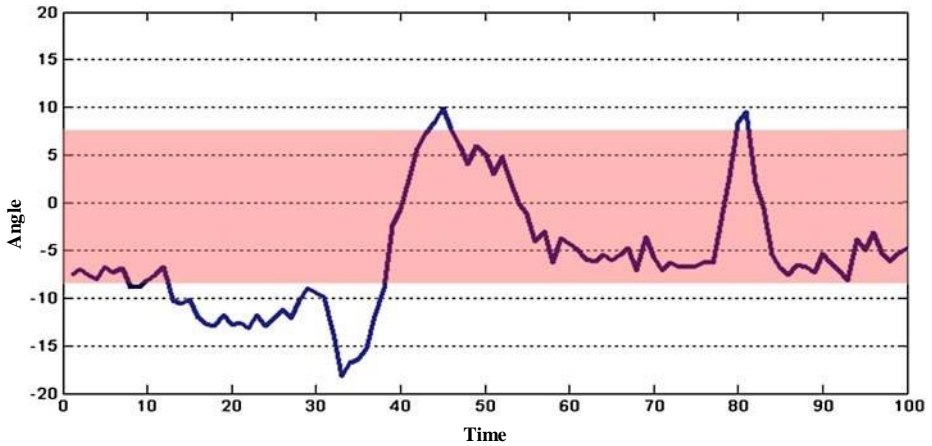


Fig. 9 Head-orientation monitoring over time in a 100-frame sequence

3.5.1 Face Orientation

Driver's face orientation is estimated using the eye position, through Eq. 22.

$$\theta = \tan^{-1} \frac{O_x}{O_y} \quad (22)$$

where $O_x = x_2 - x_1$, $O_y = y_2 - y_1$, (x_1, y_1) and (x_2, y_2) correspond to the left and right eye positions. Equation 23 presents the classification limits. Figure 23 depicts an example of face orientation, whereas, Fig. 24 also shows an extended example of driver's face orientation from eyes through a sequence of images.

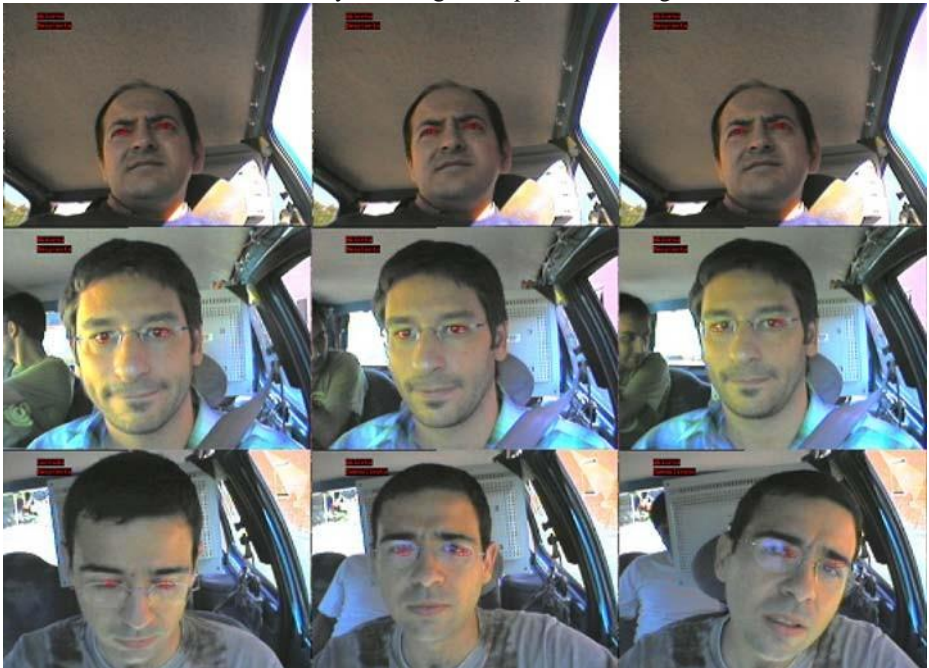


Fig. 10 Different stages of the proposed algorithm on several instants of time, driving conditions

and different drivers

3.5.2 Head Tilt

The above method has a problem when using a monocular camera, so, to correct this drawback, this contribution implements a head-tilt based on neural networks. Let us remember that the driver's face database is made up of examples of faces in five orientations, so, the face is passed to neural networks to know its orientation, especially for the up and down cases. If the system detect that the face position is not frontal, an alarm cue is issued to alert the driver of a danger situation.

4 Conclusions

In this paper, a research project to develop a non-intrusive driver's drowsiness system based on Computer Vision and Artificial Intelligence has been presented. This system uses advanced technologies for analyzing and monitoring drivers eye state in real-time and in real driving conditions. Based on the results presented on Tables 1, 2 and 3, the proposed algorithm for face tracking, eye detection and eye tracking is robust and accurate under varying light, external illuminations interference, vibrations, changing background and facial orientations.

To acquire data to use while developing and testing the algorithms, several drivers were recruited; they were exposed to a variety of difficult situations commonly encountered on the roadway. This guarantees and confirms that these experiments have proven robustness and efficiency in real traffic scenes. The images were taken with the camera inside the IVVI vehicle. For future work, the objective will be to reduce the percentage error, i.e., to reduce the false alarms; for this, extra experiments will be developed, using additional drivers and incorporating new modules.

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