

# Drowsiness Detection based on Video Analysis Approach

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**Keywords:** Drowsiness Detection, Multi-scale Analysis, Circular Hough Transform, Haar Features, Wavelet Decomposition, Geometric Features.

**Abstract:** The lack of concentration due to the driver fatigue is a major cause that justifies the high number of accidents. This article describes a new approach to detect reduced alertness automatically from a system based on video analysis, to prevent the driver and also to reduce the number of accidents. Our approach is based on the temporal analysis of the state of opening and closing the eyes. Unlike many other works, our approach is based only on the analysis of geometric features captured from faces video sequence and does not need any elements linked to the human being.

## 1 INTRODUCTION

Many efforts have been made to detect drowsiness of drivers. The drowsiness is the risk of falling asleep for a moment with eyes closed and eyes open at times which is an intermediate state between waking and sleeping. This state is involuntary and is accompanied by reduced alertness. A study of the SNCF (Guy et al., 2008), the characteristic signs of drowsiness are manifested by behavioral signals such as yawning, decreased reflexes, heavy eyelids, itchy eyes, a desire to close eyes for a moment, a need to stretch, a desire to change positions frequently, phases of "micro sleeps" (about 2-5 seconds), a lack of memory of the last stops and trouble keeping head up. In literature, many systems based on video analysis have proposed for drowsiness detecting. Special attention is given to the measures related to the speed of eye closure. Indeed, the analysis of the size of the iris that changes its surface according to its state in the video allows the determination of the eye closure (Rajinda et al., 2011); (Horng et al., 2004) Other work is based on detecting the distance between the upper and the lower eyelids in order to locate eye blinks. This distance decreases if the eyes are closed and increases when they are open (Tnkehiro et al., 2002) (Masayuki et al., 1999) (Hongbiao et al., 2008) (Yong et al., 2008). These so-called single-variable approaches can prevent the driver in case of prolonged eye closure, of its reduced alertness. The duration of eye closure used as an indication varies

from one work to another. Horng (Horng et al., 2004), the driver is considered dozing if he / she close their eyes for 5 consecutive images. Hongbiao (Hongbiao et al., 2008) estimated that the reduced alertness is determined if the distance between the eyelids is less than 60% for a period of 6.66 seconds. Yong (Yong et al., 2008) divides the state of eye opening into three categories (open, half open, closed). This division allows concluding the drowsiness of the driver if the eyes are kept closed more than four consecutive images or eyes move from a state of half open to a closed state for eight successive images. Besides, the percentages of detection of fatigue vary in literature. Yong reached 91.16% of correct average rate for recognition of the condition of the eyes. As for Horng, he explains that the average accuracy rate for detection of fatigue can reach 88.9%. Wenhui (Wenhui et al., 2005) achieved 100% as a correct detection rate. The majorities of this works calculates the results by a study on subjects varying in number from two to ten individuals (four individuals for Horng (Horng et al., 2004) and only two for Yong (Yong et al., 2008). The second type of approach is called multi-variable. In this context, the maximum speed reached by the eyelid when the eye is closed (velocity) and the amplitude of blinking calculated from the beginning of blink until the maximum blinking are two indications that have been studied by Murray (Murray et al., 2005) . The latter shows that the velocity amplitude ratio (A/PCV) is used to prevent the driver one minute in advance. Picot

presents a synthesis of different sizes as the duration to 50%, the PERCLOS 80%, the frequency of blinking and the velocity amplitude ratio. Picot (Picot et al., 2009) shows that its criteria are more relevant to the detection of drowsiness. These variables are calculated every second on a sliding window of the length of 20 seconds. They are fused by fuzzy logic to improve the reliability of the decision. This study shows a percentage of 80% of good detections and 22% of false alarms.

The mono-variable approach enables us to detect the state of drowsiness, but in a very advanced stage. We, hence, focus on studying the characteristics which aim at foretelling the driver, about his fatigue, before she falls asleep, by analyzing the speed of closing his eyes. In the case of multi-variable approaches, we find that some methods are based on the analysis of the EOG signal. This kind of analysis requires technical cooperation between the hardware and the driver. Moreover, these methods need the use of wide range of parameters, which calls for more learning data. Nevertheless, video-based approaches, rest on the segmentation of the iris of the eye so as to extract the features for the subsequent steps. The iris segmentation is calculated from the images difference, in the case of using infrared cameras. Still, the drawback of such a method lies in the noise sensitivity of the luminance. In this context, the Hough Circular transform method is used to localize the iris. This method shows sturdiness in the face of the desired shape, an ability to adapt even to images with poor or noisy quality as well as an identification of all directions due to the use of a polar description. Based on the afore-mentioned remarks, we propose in this paper, an approach that determines the state of drowsiness by analyzing the behavior of the driver's eyes from a video.

## 2 PROPOSED APPROACH

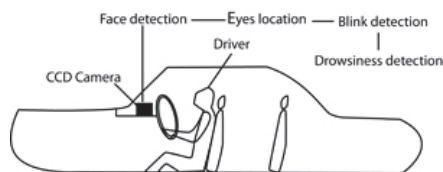


Figure 1: Detection scheme of drowsiness.

This paper presents an approach for detecting drowsiness of a driver by studying the behavior of conductor eyes in real time by an RGB camera (Figure 1). This approach requires a critical step

presumed through the automatic face detection, first, and the detection of the box that encompasses both eyes, in the step that follows.

### 2.1 Face and Eyes Location

In order to come to delight the face and the eyes, our approach exploits the object detector of Viola and Jones that is about a learning technique based on Haar features. This method (Viola and Jones, 2001) uses three concepts: the rapid extraction of features using an integral image, a classifier based on Adaboost and the implementation of a cascade structure.

### 2.2 Iris and Both Eyelids Detection

With reference to the observation of the eye, we note that human eyes are characterized by horizontal contours representing the eyelids and the wrinkles or vertical contours as the ones of the iris. The application of two-scale Haar wavelet allows extracting the vertical, horizontal and diagonal contours. The vertical contours are used in the localization of the iris of the eye following application of the Circular Hough Transform. The use of the wavelet allows us to highlight the contours that we want to spot more and more. In our case, the scale of the second rate improves the contours of the iris and the two lids which are going to be detected.

#### 2.2.1 Edge Extraction based on 2D Haar Wavelet

The application of the Haar wavelet allows us to split the image to find the vertical and horizontal details for the detection of the iris and both eyelids. The wavelet transform is characterized by its multi-resolution analysis. It is a very effective tool for noise reduction in digital image. We can also ignore certain contours and keep only the most representative ones. This type of analysis is allowed by the multi-resolution.

#### 2.2.2 Iris and the Two Eyelids Detection based on Circular Hough Transform

In general, the Hough transform (Cauchie et al., 2008) has two spaces, the space XY and parameter space which varied according to the detected object. Our approach involves the detection of the iris by applying the Hough transform on the vertical details of the eye. Both eyelids are located using the

Circular Hough Transform on the image of horizontal details of the Haar wavelet decomposition.

### 2.3 Geometric Features Extraction

With reference to the detection of the iris, the upper eyelid and lower one, we can extract geometric features able to characterize the state of drowsiness of a driver.

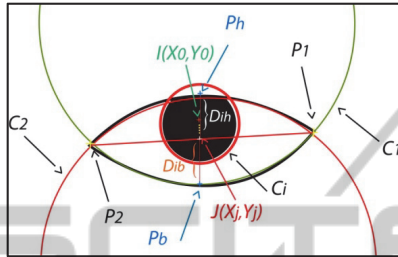


Figure 2: Representation of features from the figure of the eye.

We propose two geometric features  $D_{ih}$  and  $D_{ib}$  (Figure 2). These features represent the distance between the point  $J$  and respectively the point  $P_h$  and  $P_b$ , (Equation 1).

$$D_{ih} = \sqrt{(x_j - x_1)^2 + (y_j - y_1)^2}$$

and

$$D_{ib} = \sqrt{(x_j - x_2)^2 + (y_j - y_2)^2}$$
(1)

The use of the point  $J$  as a reference calculation, not the point  $I$  of the center of the iris, allows us to avoid the uncertainties of calculation. These uncertainties are due to the positioning of the point  $I$  above the upper eyelid of the eye, resulting in miscalculations of the feature  $D_{ih}$ .

### 2.4 Experimental Study, Analysis of Eye Closure and Result of Blink Detection

In this section, we describe the experimental studies we conducted to validate the two features  $D_{ih}$  and  $D_{ib}$  previously proposed. In order to produce realistic data, a human subject is placed in front of our system to simulate different possible movements of the head, the eyelids and the positions of the iris, probably related to different states of fatigue. This experiment consists of studying the temporal variation of both features and normalized the initial state of the eye (Equation 2).

$$f(x_t) = \frac{D_{ih}^t + D_{ib}^t}{V_i} \quad (2)$$

The initial value  $V_i$  is calculated at the beginning of the algorithm when the eyes were open by 75%. The first analysis consists of determining the change of state positions, whether the beginning of closure of the eyes or the beginning of opening. The first derivative of the function  $f'(x_t)$  allows finding these variations which are characterized by a negative abrupt change for early closing of the eyes, and by a positive sudden change for early opening of the eye. Experimentally and after analyzing the video recordings, we found that the derivative of the signal requires a low pass filter to eliminate noise. The selecting of a period considered as blink, is located in the case where  $f'(x_t)$  falls below (closure) and above (opening) of a well-defined threshold. Sharabaty (Sharabaty et al., 2008) showed that the maximum duration of a normal blink is 0.5 seconds whereas above this value is considered prolonged closure. In our case the normal or long blink is validated if it satisfies the two previous conditions and its period must exceed 0.15 seconds. Figure 3 shows blink validated with interrupted lines and not validated (between frames 479 and 490) for the signal of  $f'(x_t)$ .

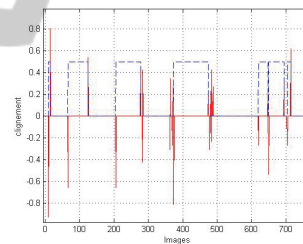


Figure 3: Figure shows the blinking validated.

The purpose of the second experiment is to study the difference in closing speed of a person's eyes in a normal state and in another drowsy one. Figure 9 shows the average time of closing of the eyes of a normal person and of a sleepy one. Generally, for a tired individual, the eye closure is slower than that of a vigilant person. This measure can be used as a factor to determinate the level of fatigue. The cumulative change (Equation 3) allows calculation from the period when the individual has their eyes closed.

$$C(x_t) = \sum_{t=1}^n f'(x_t) \quad (3)$$

Fatigue states are characterized by a continuous segment because the evolution of  $f'(x_t)$  is too low.

This time is lower than 0.5 second (Sharabaty et al., 2008) for a normal blink and it is greater than two seconds (Dinges et al., 1998) for a blink of an individual in a state of drowsiness. In brief, the three conducted experiments show the difference between an alert individual and a sleepy one by analyzing the variation of the features  $D_{ih}$  and  $D_{ib}$ . Generally, the detection of states of drowsiness is processed by the location of blinking first, then by studying the speed of blinking and finally by calculating the duration of eye closure. The driver is considered in a state of drowsiness if the speed of eye closure exceeds 1 second or the duration of eye closure is greater than 2 second.

Table 1: Result of drowsiness detection.

Videos	1	2	3	4
Real drowsiness	9	7	4	8
Generated alarm	8	7	4	8
False negative	1	0	0	0
False positive	0	0	0	0
Correct alarm	8	7	4	7
Correct rate of fatigue	88%	100%	100%	87%
Accuracy rate of fatigue	100%	100%	100%	100%

Table 1 shows an example of drowsiness detection result conducted on the four test videos. The opinion of an expert in this step is essential to determine the actual driver drowsiness. Our approach does not generate false alarms for the detection of fatigue in all videos. On the other hand, there are alarm errors of states of fatigue due to false detections of the iris that influences the detection of both eyelids and subsequently the values of features.

### 3 CONCLUSIONS

This paper presents an approach to the detection of reduced alertness, based on video analysis. Our system uses a study of the eyes by analyzing the video of several topics. The steps of detecting drowsiness consist firstly of locating a driver face and eyes by applying Haar features. The circular Hough transform allows the detection of the center of the iris and the intersection points of both eyelids (Figure 2) in order to capture two geometric features. The blink detection, the frequency and the period of eye closure are major factors in determining the fatigue of an individual. The guidance, other facial feature as yawning, the monitoring and the 3D pose estimation of the face are also indicators of the state of vigilance of an individual. These data are the subject of our future work in order to improve the obtained results.

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