EYE STATE ANALYSIS USING IRIS DETECTION TO EXTRACT DRIVER'S MICRO-SLEEP PERIODS

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Abstract: Eye state analysis is critical step for drowsiness detection. In this paper, we propose a robust algorithm for eye state analysis, which we incorporate into a system for driver's drowsiness detection to extract micro-sleep periods. The proposed system begins by face extraction using Support Vector Machine (SVM) face detector then a new approach for eye state analysis based on Circular Hough Transform (CHT) is applied on eyes extracted regions. Finally, we proceed to drowsy decision. This new system requires no training data at any step or special cameras. The tests performed to evaluate our proposed driver's drowsiness detection system using real video sequences acquired by low cost webcam, show that the algorithm provides good results and can work in real-time.

1 INTRODUCTION

Eye analysis has been used in diverse applications including gaze detection for human-machine interfaces, face alignment for automatic face recognition systems and drowsiness detection for intelligent vehicle systems (Wang and Ji, 2007). The increasing number of traffic accidents due to a diminished driver's vigilance level resulting from sleep deprivation has become a serious problem for society. Statistics show that between 10% and 20% of all the traffic accidents are due to drivers with a diminished vigilance level (Bergasa et al., 2004). Therefore, it is very important to monitor driver's drowsiness level and issue an alarm when he/she is not paying enough attention to the road. Many research projects has been done on facial features detection to identify driver's vigilance level, especially the eyes states (Papanikolopoulos and Eriksson, 2001; Zhang et al., 2008; Parsai and Bajaj, 2007), head motion (Smith et al., 2000), or mouth motion (Wang and Shi, 2005). The eye state is often assumed to give indication of drowsiness level characterized by micro-sleep which is a short period (2-6 s) during which the driver rapidly closes its eyes and sleep. The driver eye detection methods based on computer vision use a camera to obtain facial information, extract the eyes and determine their openness degree. Many researchers use Percent of Eyelid Closure (PERCLOS) as an indicator to detect drowsiness (Papanikolopoulos and Eriksson, 2001; Grace et al., 2001; Roman et al., 2001). Other researchers use the presence of the iris to predict if the eye is open (Tripathi and Rath, 2009; D'Orazio et al., 2004; Parsai and Bajaj, 2007).

Several visual behaviors can be used to characterize the drowsy driver. These visual cues include eyelid movement, mouth movement, and face orientation. The parameters computed from these visual cues can be combined to form a composite drowsiness index that can robustly and consistently characterize driver's drowsiness state.

In this work, we propose an eye state analysis method using iris detection based on Circular Hough Transform (CHT) (Duda and Hart, 1972). This method was incorporate in driver's drowsiness detection system to identify micro-sleep periods. In order to evaluate both method and system, some experiments are done on real video sequences of different subjects in various lighting conditions using statistical measures to expose the results. The proposed method integrated in driver's drowsiness detection system provides good results comparing to some other systems.

The organization of this paper is as follows. Section 2 explains the different steps of the proposed system. In Section 3, experimental results are exposed. Finally, conclusion and discussion are presented.

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2 PROPOSED SYSTEM

The main idea of this work is to develop an eye state analysis algorithm applied to driver's drowsiness detection system. The proposed system performs some steps before determining driver's state. Firstly, the face is extracted from video frames. Secondly, the eyes are localized. Finally, we apply the proposed method based on CHT to detect drowsiness.

2.1 Face Extraction

The face is extracted from video frames to reduce search region and therefore reduce the computational cost required for the subsequent steps. We use an existing face extraction method, based on SVM technique (Burge, 1998), developed by Kienzle (Kienzle et al., 2005).

2.2 Eye Localization

The reduced region where the eyes are situated is obtained for the same purpose as in the previous step. This eye region also eliminates the possibility of confusing other facial features such as the mouth or the nose with the eyes. To do this, we use gradient image to highlight the edge. After that, horizontal projection is computed on gradient image to detect the upper and lower eye boundaries. Finally, we apply vertical projection on resulting image to obtain the right and left face limits and separate the eyes.

2.3 Circular Hough Transform

The Hough Transform (Duda and Hart, 1972) can be described as a transformation of a point in Cartesian space to parameter space defined according to the shape of the object of interest. In the case of circular forms, the circle equation $r^2 = (x-a)^2 + (y-b)^2$ is considered for the transformation. Where r represents the radius, a and b refer respectively to the abscissa and the ordinate of the circle center.

The process of finding circles in an image consists to use a modified Hough Transform called Circular Hough Transform. The first step is to find image edges by any edge detector. At each edge point, we draw a circle in the parameter space having center in this point with the desired radius. The radius can be fixed to simplify the parametric representation. At the coordinates which belong to the perimeter of the drawn circle, we increment the value in the accumulator matrix. When every edge point and every desired radius is used, the accumulator will contain numbers corresponding to the number of circles passing through the individual coordinates. Thus the highest numbers correspond to the center of the circles in the image. Figure 1 illustrates the CHT from Cartesian space to parameter space.

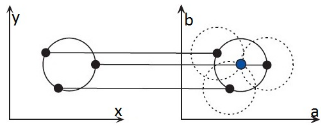

Figure 1: CHT from Cartesian space to parameter space.

2.4 Drowsiness Analysis

The role of this step is crucial in our system since it detects micro-sleep periods in real time and issues immediately an alarm to avert the drowsy driver. To detect micro-sleep periods, we apply CHT on eye region images in order to identify iris. The eye is considered open if an iris is found. As can be seen in previous section, CHT extracts circles from edge images. So, the obtained results depend on applied edge detector. Some classic edge detectors such as Sobel, Prewitt, Roberts, Laplacian of Gaussian (LoG) and Canny was tested for extracting the iris edge on eye region images. Unfortunately, the obtained edges by these detectors did not provide the desired form, i.e. a kind of circular form referring to the iris. In order to solve this problem, we propose a new iris edge detector more suitable to the eye's morphology.

2.4.1 Iris Edge Detector

The proposed iris edge detector respects the eye's morphology. If we observe an open eye we see three main components: the *pupil* which is the little black circle in the center of eye surrounded by the *iris*, the circle distinguished by eye color while the white outer area represents the *sclera*. This structure enables us to extract the iris edge from the significant intensity variations between iris and sclera.

Our iris edge detector considers only pixels x with grayscale intensity lower than an optimal threshold noted th_{edge}, which must be chosen to handle only with pixels appertaining to the iris. For each pixel x, a neighborhood containing n pixels at left and right of x is specified. The difference between x and its n right and left neighbors is then computed.

- Left (Resp. Right) Edge: if n or $n-1$ left (*resp.* right) neighbors of x provide a difference with x higher than a threshold noted th_{high} and also if n or $n-1$ right (*resp.* left) neighbors of x provide a difference with x lower than a threshold th_{low}, we deduct that x is a left (*resp.* right) edge pixel of the iris and we put it at 1. (see Figure 2)

- Interpretation: In the case where x appertains to the left edge, its left (*resp.* right) neighbors pixel's intensity is very higher (*resp.* similar). Inversely, when x appertains to the right edge, the right (*resp.* left) neighbors pixel's intensity is very different (*resp.* similar). The th_{high} should distinguish the large difference between iris and sclera pixel's intensity and the th_{low} should respects the similarity between iris pixels. Figure 2 shows some examples of iris edge detection obtained by the proposed method compared to some classic edge detectors results. As can be seen, the classic edge detectors cannot provide a good iris edge detection. For example, some edge components having circular form are detected in closed eye by classic edge detectors, while the proposed iris edge detector did not identify such component.

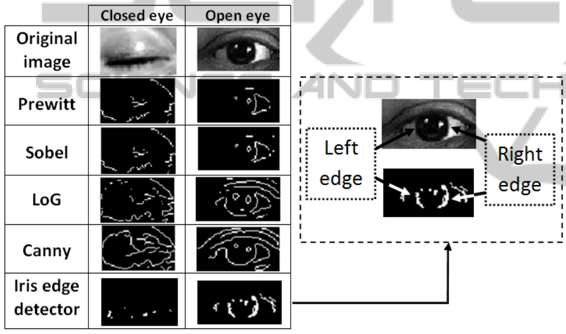

Figure 2: Iris edge detection by proposed method and classic methods.

2.4.2 Eye State Analysis using Iris Detection

Once the appropriate iris edge detector is found, we can apply the CHT on this edge to obtain the iris radius from which we decide if the eye is open or close. In the following, we present the CHT algorithm steps. At each iteration, three edge pixels are randomly chosen. If these pixels are not collinear and if the distance between each two pixels coordinates is higher than a fixed threshold th_{dist_px}, we compute the radius and center coordinates of the candidate circle defined by these three pixels. If these parameters are between two specific thresholds for each parameter, they are assigned to the accumulator. After that, we compute the distances between the center and all edge pixels. If a distance is lower than a threshold th_{dist_ctr}, we increment the counter of pixels in the candidate circle. If this counter is higher than a threshold $th_{counter}$, we consider that the candidate circle can represents the iris and we keep the other pixels as a new edge and we repeat the previous steps. The algorithm stops when the edge contains few pixels or when the maximum number of iterations is reached. Since we need to detect the circle representing the iris, we select the circle having the highest radius after the end of the algorithm.

2.4.3 Drowsiness Detection

Drowsiness is characterized by micro-sleep periods. So, we need to find the sleep intervals of at least 2 seconds. We analyze firstly the left eye state then the right eye: if one of them is open, we pass to the next frame. If the left eye is closed, we analyze the right one, if it is also closed, we increment the consecutive closed eye counter. We issue an alarm to avert the drowsy driver if the eyes remain closed for a certain period of time related to the counter.

Figure 3 summarises and depicts our proposed system for driver's drowsiness detection.

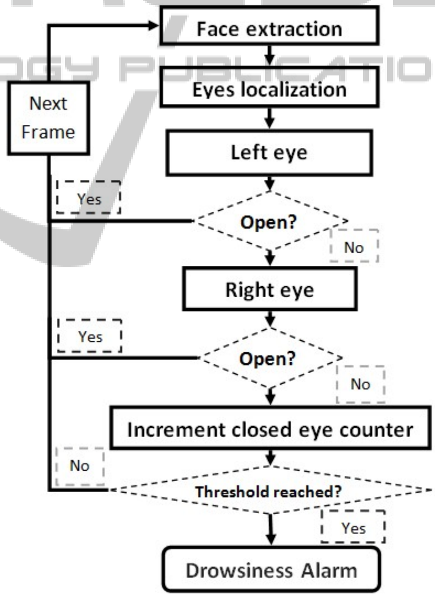

Figure 3: Driver's drowsiness detection schema.

3 EXPERIMENTAL RESULTS

In this section, we discuss the experimental results obtained by testing the proposed method to detect iris. These results will be presented as statistical measures such Confusion Matrix, Correct Classification Rate and kappa Statistic. In the first subsection, we define briefly these statistical measures. After that, we present the obtained results for real test video sequences.

3.1 Statistical Measures

3.1.1 Confusion Matrix

Confusion Matrix is a tool to measure the quality of a classification system. Each column of the matrix represents the number of occurrences of an estimated class, while each row represents the number of occurrences of a real class. Table 1 shows the confusion matrix of a system that allows to classify two classes *a* and *b*.

Table 1: Confusion Matrix.

Real class / Estimated class	**a**	**b**	Total
a	TP	FN	p
b	FP	TN	n
Total	P	N	T

- TP (*resp.* TN) represents the number of instances of class **a** (*resp.* class **b**) well classified by the system.
- FN (*resp.* FP) represents the number of occurrences of class **a** (*resp.* class **b)** that have been classified by the system as instances of class **b** (*resp.* class **a**).
- $P = TP + FP$ (*resp.* $N = FN + TN$) represents the total of real occurrences of class **a** (*resp.* class **b**).
- $p = TP + FN$ (*resp.* $n = FP + TN$) represents the total of estimated occurrences of class **a** (*resp.* class **b**).
- T is the sum of occurrences of both classes.

3.1.2 Correct Classification Rate

Correct Classification Rate noted CCR is the sum of good detections represented by TP and TN divided by the total number of samples T.

$$CCR = \frac{TP + TN}{T} \quad (1)$$

3.1.3 Kappa Statistic

Kappa Statistic (Fleissa et al., 1969) (κ) is a measure of the degree of non-random agreement between observers or measurements of the same categorical variable given by following equation.

$$\kappa = \frac{P_0 - P_e}{1 - P_e} \quad (2)$$

Where P_0 is observed agreement proportion corresponding to CCR and P_e represents random agreement proportion given by:

$$P_e = \frac{1}{T^2}[(P \times p) + (N \times n)] \quad (3)$$

We specify that $-1 \leq \kappa \leq 1$. Table 2 is used to interpret kappa statistic.

Table 2: Kappa statistic interpretation.

Kappa Statistic	**Interpretation**
> 0.81	Almost perfect agreement
> 0.61 and < 0.8	Strong agreement
> 0.2 and < 0.6	Moderate agreement
> 0.0 and < 0.2	Poor agreement
< 0	Disagreement

3.2 Experiments

The aim of this paper is to present a method for eye state analysis based on iris detection using CHT applied to detect micro-sleep period, which is a powerful drowsiness indicator. To validate this method, we conduct several tests on real video sequences of different subjects and various lighting conditions. These subjects have different face dimensions, skin colors and eye shapes. In this work we assumed that the distance between the camera and the subject cannot greatly change while no constraints have been imposed on the background. All sequences are taken with the same low cost webcam at 30 frames per second (fps) providing images of resolution 640 x 480. First, we evaluate our iris detection method. For this purpose, we analyze all frames of the sequences to identify the presence of irises on cropped eye images. The second experiment is done to evaluate the method when it is introduced in the driver's drowsiness detection system which led us to reduce the considered number of fps from 30 to 3 frames to meet the real-time constraints. In this experiment, automatic detection of face and eyes has also been integrated but not evaluated in this work. The main purpose of these integrations is to take them into account in assessing the runtime system. The final experiment provides a comparison between our driver's drowsiness detection system and other existing systems. All experiments are done on PC having Intel Core 2 Duo Processor.

3.2.1 Evaluation of Eye State Analysis using Iris Detection

The experiment was made on seven real video sequences of different subjects in various lighting conditions where eyes are manually cropped. Figure 4

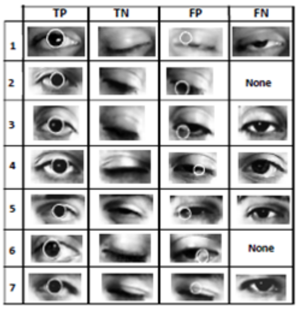

Figure 4: Results of iris detection.

shows examples of TP, FP, TN and FN for each sequence of this experiment. Table 3 presents the statistical measures for all videos. V. refers to video number and Avr. represents the average. We observe, from Table 3, that the average of CCR is 99% and the average of kappa statistic is 88%. According to Table 2, our eye state analysis method using iris detection provides an almost perfect agreement between observers. In other words, the real class of the samples usually matches the estimated class proposed by the method. So, we deduct that our eye state analysis method is very strong.

Table 3: Statistical measures of iris detection.

V.	**TP**	**TN**	**FP**	**FN**	**T**	**CCR**	κ
1	3336	233	17	14	3600	0.99	0.93
2	1760	36	4	0	1800	0.99	0.94
3	1772	18	2	8	1800	0.99	0.79
4	1482	273	9	38	1802	0.97	0.90
5	1762	24	2	14	1802	0.99	0.74
6	380	237	1	0	618	0.99	0.99
7	1636	135	14	17	1802	0.98	0.89
					Avr.	0.99	0.88

3.2.2 Evaluation of Proposed Method in Drowsiness Detection System

This experiment is important since it permits evaluation of eye state analysis using iris detection when it is integrated in driver's drowsiness detection system. We use the same statistical measures defined above in addition of two parameters representing time in seconds. The first one $vid.D$ refers to video duration and the second one $exec.T$ refers to execution time of the whole system (see Table 4).

Figure 5 depicts some examples of iris detection of TP, FP, TN and FN for the seven test video sequences different from the ones presented in the previous experiment. Note that the face and the eyes are detected automatically.

According to Table 4, the average of CCR is 98% and the average of kappa statistic is 95%. From Table 2 and this average, we deduct that the integration of the proposed eye state analysis method in driver's drowsiness detection system procures also an almost perfect agreement between the observers. This means that driver's drowsiness detection system permits assignation of the correct classes in the most cases. After comparing the two lasts columns, we deduce that the system respect the real time constraints because execution time and video duration are almost the same. Thus we deduct that the proposed system can be used to have an excellent and real-time estimation of driver's state.

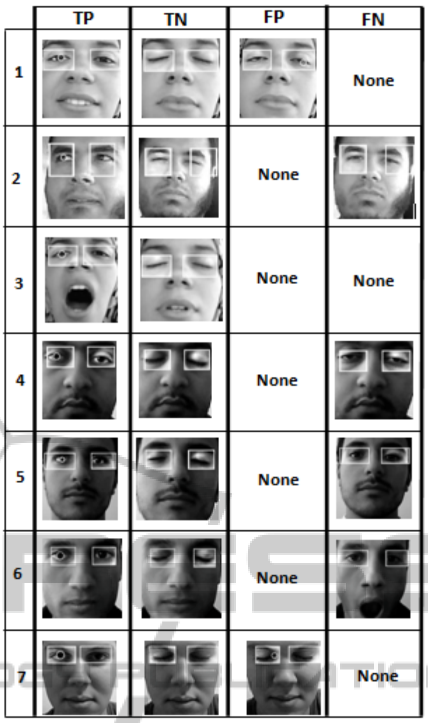

Figure 5: Results of iris detection in driver's drowsiness detection system.

The last experiment exposes a comparison between our system and other existing systems of drive's drowsiness detection. The system depicted in (Tripathi and Rath, 2009) is also based on CHT and uses 173 images of ORL database for experiments, this system provides success accuracy rate of 90.3%. The second system presented in (Hrishikesh et al., 2009) uses 70 images taken with an infra-red camera for tests and obtains a success rate of 90%. While the third system (Zhang et al., 2008), which is based on adaptive learning method to detect driver's eyes, uses 13000 real frames for tests and find an accuracy of about 95%.

We deduct that our proposed system for driver's drowsiness detection provides a very high success rate comparing to the mentioned existing systems.

Table 4: Statistical measures of iris detection in driver's drowsiness detection system.

V.	**TP**	**TN**	**FP**	**FN**	**T**	**CCR**	κ	**vid.D**	**exec.T**
1	154	31	1	0	186	0.99	0.98	62	66
2	143	12	0	1	156	0.99	0.95	52	55
3	165	52	0	0	217	1	1	73	75
4	103	20	0	1	124	0.99	0.97	42	47
5	122	19	0	2	143	0.98	0.94	48	50
6	98	17	0	4	119	0.96	0.88	41	44
7	69	9	1	0	79	0.98	0.94	27	30
					Avr.	0.98	0.95		

4 CONCLUSIONS

This paper presents an eye state analysis method using iris detection based on CHT and applied on driver's drowsiness detection system in order to find micro-sleep periods. The whole system uses three steps: face extraction method using the SVM face detector, eyes region localization applied on gradient image and eye state analysis method to identify the drowsy driver. In the last step, we apply the CHT on our proposed edge detectors in order to find irises. With 98% accuracy of CCR and rate of 95% of kappa statistic, it is obvious that our driver's drowsiness detection system is robust compared to some existing systems. Note that, the iris detection method provides a detection rate of 99% and kappa statistic value attaining 88%. As future works, we plan to generalize the system to detect driver's inattention. We are studying some other indicators such yawning frequency to detect fatigue, and head pose and gaze orientation to determine the focus of attention of the driver. We also plan to use multiple cameras in order to detect irises in various head orientations.

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