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Driver Alert State and Fatigue Detection by Salient Points Analysis

Javier Jiménez-Pinto, Miguel Torres-Torriti
Dept. of Electrical Engineering
Pontificia Universidad Catolica de Chile
Santiago, Chile
jejimenp@puc.cl, mtorrest@ing.puc.cl

***Abstract*—Assessing a driver's state of awarness and fatigue is especially important to reduce the number of traffic accidents often involving bus and truck drivers, who must work during several hours under monotonous road conditions. Two main challenges arise in resolving the state of alert: first, the system must be capable of detecting the driver's face location; secondly, the driver's facial cues, such as blinking, yawning, and eyebrow rising must be recognized. Our approach combines the well-known Viola-Jones face detector with motion analysis of Shi-Tomasi salient features within the face to determine the driver's state of alert. The location of the eyes and blinking are cues whose detection is also important. To this end, the proposed method takes advantage of the high reflectivity of the retina to near infrared illumination employing a camera with an 850 nm wavelength filter. Motion analysis of the salient points, in particular cluster mass centers and spatial distribution, has proved successful in determining the driver's state of alert.**

***Index Terms*—alert state assessment, fatigue detection, drowsiness detection, driver assistance, IR eye tracking, yawning detection, eyebrow rising detection.**

I. Introduction

Road accidents take a heavy financial and social toll on national economies. The economic cost of traffic incidents is estimated to be 1% of gross national product in low-income countries, 1.5% in middle-income countries and 2% in high-income countries, totaling a global cost of US$518 billion per year [15]. Without appropriate actions to improve education, law enforcement, infrastructure and technology, a global increase of 67% is expected by year 2020. Although global statistics about accidents attributed to fatigue and drowsiness are not available because in many countries such details are not reported or classified, the number of incidents in high-income countries is not negligible. For example, the NHTSA reported as much as 56.000 accidents back in 1996 [1], which increased to 1.35 million in 2002 [19]. The latter is about 0.7% of the reported accidents. These figures are even larger if other accidents related to the driver's state-of-alert, such as distracted driving (3.5%) and cell-phone use accidents (0.1%), are included. Some other alarming accident statistics due to fatigue, stress or distraction can be found in [7], [16]. In this context, developing systems to monitor a driver's state of awareness is fundamental.

Several studies exist about physiological cues that can be used to assess a driver's awareness. Some techniques can be invasive, but fortunately, there are many behavioral changes that provide visual cues, namely, eye-blinking frequency and closure percentage over some window of time (PERCLOS), yawn frequency, head movement, eye-gaze, among other facial expressions. Hence, a variety of systems based on computer vision techniques have been proposed. A summary is presented in Table I, in which the approaches have been grouped according to the technique employed to extract the area of the head. A large number of them, e.g. [3], [10], [17], [18], [22], [24], employ color-based segmentation techniques, while a significant number of other approaches relies on the Viola-Jones detector, e.g. [7], [9], [13], [21], [27], [28], as shown in Table I. The comparison of the approaches is not easy because results are reported in different non-standard ways. Moreover, some approaches only track the eyes, while other focus on particular facial cues, such as yawning [6], [18]. However, it is possible to say that approaches based on color analysis are limited by illumination conditions and often cannot be applied at night. This has motivated some researchers to use near infrared (IR) cameras, exploiting the retinas' high reflectivity to 850 nm wavelength illumination [8], [14]. Some approaches employ neural-networks to extract the head and main features [4], [23], while other rely on a variety of template matching schemes [2], [6], [5], [11], [26].

This paper presents an approach to determine if the driver is becoming drowsy or inattentive by analyzing eye blinking, eyebrow rising and yawning cues. The novelty of the approach is in that in addition to the Viola-Jones face detector, it employs the Lucas-Kanade algorithm to track Shi-Tomasi salient points around the mouth and eyes. Such salient points do not only provide information useful to track the motion of the head, but also to determine if the driver is yawning or rising eyebrows. The group of salient points also provides a reference relative to which the pupil can be located when the camera does not perceive the glare of the retina under IR illumination. The approach is described in greater detail in the next section. The results presented in section III show that the approach yields high detection rates with a low level of false alarms and good tracking rates. The main conclusions are presented in section IV.

II. Proposed Approach

Define an image frame at sampling instant k as $I_k : p \rightarrow I_k(p)$, $p \in \mathbb{N}^2$, i.e. the assignment of intensity values $I(p)$ to

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TABLE I
SUMMARY OF EXISTING APPROACHES FOR DRIVER STATE OF ALERT DETECTION.

Face Detection Technique	Approach Characteristics	Remarks	Eyes Detection Rate [%]	Blinking Detection / False Alarm Rates [%]	Publication Year
Color Segmentation					
[10]	Eyes location from horizontal projection. Tracking by template matching.	4 test subjects.	99.1	N.A.	2006
[3]	Eyes location from horizontal projection. Tracking by Dynamic Template Matching.	2 test subjects.	98.0	N.A.	2005
[24]	Skin and eye color-based segmentation.	37 test subjects. Requires illumination.	96.9	N.A.	2008
[22]	Eyes location from horizontal projection.	–	95.0	N.A.	1999
[18]	Lips and skin segmented with Fischer classifier and connected component analysis. Mouth is tracked in real-time using a Kalman Filter.	Results obtained from 150 images. Yawning detection rate of 95.3% and true negatives of 100%.	N.A.	N.A.	2004
[17]	Binarization and clustering.	–	96.0	N.A.	2007
Viola-Jones					
[9]	Eyes location from horizontal projection. Dynamic thresholding.	Poor accuracy for tilted faces (detection rate of 60.1%).	88.2	89.3/14.1	2007
[28]	Eyes location from projection. Tracking with Unscented Kalman Filter.	3 test subjects. Few validations samples.	99.5	N.A.	2006
[21]	Eyes location and PERCLOS from horizontal projection.	3 test subjects. Few validations samples.	N.A.	97.8/6.3	2009
[27]	Binarization and histogram of the horizontal projection.	Results obtained from 5646 images.	N.A.	97.1/0.3	2009
[13]	Rectangle and texture features to extract eyes with Adaboost and SVM.	4000 images from FERET database.	96.8	N.A.	2009
[7]	Face poses not detected by Viola-Jones are detected using a neural network.	–	97.3	97.0/–	2008
Neural Networks					
[4]	Iris geometrical information and symmetry.	3 test subjects.	N.A.	90.0/–	2004
[23]	Horizontal projection and 2^{nd} derivative employed to detect eyelids using a SVM.	200 images used for training and validation.	N.A.	96.0/–	2004
IR-based Retina Detection					
[8]	Two different IR wavelengths to detect the retina. Gabor kernels employed to detect facial expressions. Tracking with Kalman Filter.	1 test subject.	99.1	N.A.	2002
[14]	Illumination compensation and SVM to validate the detected eye candidates.	10 test subjects.	98.4	N.A.	2006
Other					
[5]	Local Binary Pattern measure of texture around eyes and Gabor wavelets around mouth combined with Adaboost.	30 test subjects. Yawning detection/misdetection = 90.8/6.9%	N.A.	99.67/0.99	2008
[2]	Curvature and upper eyelid curvature and aperture are employed using fuzzy fusion to detect driver fatigue. Tracking eyes withh Kalman Filter.	–	N.A.	92.1/–	2008
[11]	A *separability filter*, which is a circular template matching approach is used together with the gradient of grayscale values to locate the eyes and detect blinking.	10 test subjects.	N.A.	95.45/–	2002
[26]	A binary eye pair template is used to roughly find eyes and SVM to validate candidates.	Only detects are of the eyes an not directly the pupils.	97.0	N.A.	2006
[6]	Employs a *Gravity-Center* template, together with grayscale projection and Gabor wavelets to detect yawning.	Yawning detection/misdetection = 95.0/6.0%	N.A.	N.A.	2007

domain coordinates p. For clarity of exposition it is convenient to define image regions of interest for the head, left eye, right eye and mouth. These regions are specified in terms of bounding boxes $\mathcal{B}_k^s$ defined by three-component vectors $\mathcal{B}_k^s \overset{def}{=} (b_k^s, w_k^s, h_k^s)$, $s = h, l, r, m$, where $b_k^s \in \mathbb{N}^2$ is the upper-left coordinate of the region, w_k^s, h_k^s, are its width and height, respectively, and the labels $s = h, l, r, m$ indicate the head, left eye, right eye and mouth. The subimages corresponding these regions of interest are denoted by I_k^s, $s = h, l, r, m$. It will also be useful to define a list of n_k^s salient points within a given region s at instant k as an ordered list of points $S_k^s \overset{def}{=} \left\{ s_{k,i}^s \in \mathbb{N}^2, i = 1, 2, \ldots, n_k^s \right\}$. With this notation, the proposed approach for drowsiness and state of alert detection is summarized in the following steps:

1) Initial head location and pose estimation using the Viola-Jones detector [25] to compute $\mathcal{B}_k^s$, $s = h, l, r, m$, according to the layout rules shown in fig. 1.
2) Computation of sets S_k^s, $s = h, l, r, m$, of Shi-Tomasi interest points [20] within the bounding boxes $\mathcal{B}_k^s$ and computation of each set's centroid c_k^s.
3) Detection of the eyes' pupils position e_k^l, e_k^r, computation of the eyes's relative location vector $d_k^s \overset{def}{=} e_k^s - c_k^s$, $s = l, r$, (corresponding to the pupils' position relative to the centroid), and update of the relative location vector estimate $\hat{d}_k^s$.
4) Detection of eyebrow rising and yawning by analysing the temporal variation of the spatial distribution of salient points in sets S_k^s, $s = l, r, m$.
5) Detection of eye blinking from intensity averages for image gradients of I_k^s, $s = l, r$.
6) Rule-based classification of state of alert.

The first two steps rely on the well-known computer vision techniques that will not be explained here for the sake of brevity. The remaining steps will be presented in next sub-sections.

A. Eyes Location and Head-Pose Estimation

Because of the retina's high reflectivity to 850 nm wavelengths [8], [14], a simple adaptive threshold filter [12] allows to locate the pupils. The adaptive threshold filter takes the average pixel intensities in a 3×3 block and sets the output on the central pixel p to 1, i.e. $I(p) = 1$ whenever

$$I(p) - \frac{\sum_{i \in \mathcal{N}_{3\times 3}(p)} I(i)}{9} \quad > \quad 0.25 \frac{\sum_{i \in \mathcal{B}_k^s} I(i)}{w_k^s \cdot h_k^s}, \qquad (1)$$

where $\mathcal{N}_{3\times 3}(p)$ is the 3×3 neighborhood of pixel p. The 0.25 coefficient was found experimentally to guarantee an adequate discrimination of the retina from other elements in the image. As a result of the adaptive threshold filtering, binary images for the regions $\mathcal{B}_k^l$ and $\mathcal{B}_k^r$ are generated and convolved with an 11×11 Gaussian mask ($\sigma = 2.15$). This smoothing step is important because it allows to obtain a more accurate location of the pupils than the one that could be computed from the centroid of the non-zero values in the binary images, since filtering spreads out the non-zero values in the binary images,

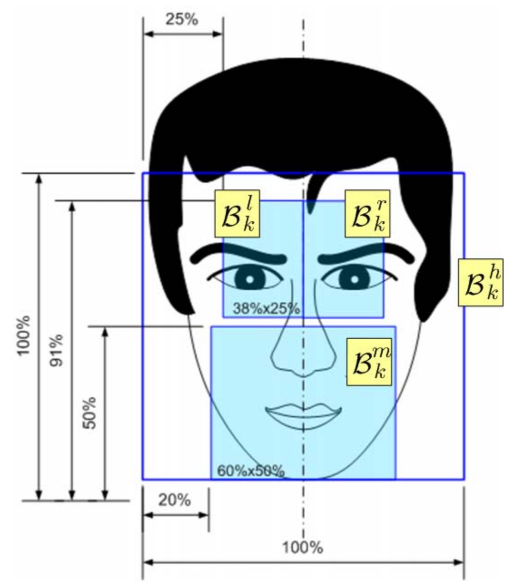

Fig. 1. Head with bounding boxes for the eyes and mouth with sizes proportional to the whole head bounding box.

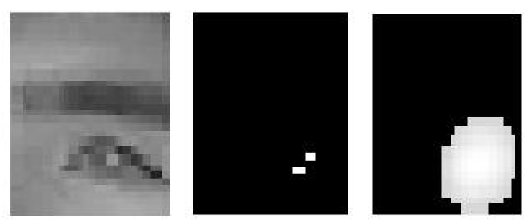

Fig. 2. Original image, adaptive threshold binarization image and Gaussian filtered image.

thus eliminating noise and generating peaks from which the position of the pupils can easily be obtained as:

$$e_k^s = \arg\max_{p \in \mathcal{B}_k^s} \breve{I}_k^s(p), \;\; s = l, r, \qquad (2)$$

where $\breve{I}_k^s$ represents the smoothed version of the binary image for region s. The results of the process of binarization by adaptive thresholding and posterior Gaussian smoothing of the area around an eye is illustrated in fig. 2.

When daylight illumination is strong, pupils are smaller making the previous approach difficult to apply. To cope with this limitation, a second method based on the computation of the so-called horizontal and vertical projections in $\mathcal{B}_k^s$, $s = l, r$ is employed. The horizontal projection is a one-dimensional vector computed here from column-wise summation of elements in I_k^s, $s = l, r$ as:

$$h_k^s(j) \quad \overset{def}{=} \quad \sum_i I_k^s(i, j), \qquad (3)$$

Since the pupil appears smaller under daylight and the eyelids, as well as iris, are darker than the rest of the average intensity of image I_k^s, the minimun of h_k^s provides a good reference for the pupil's horizontal position (horizontal component of e_k^s).

To find the vertical component of e_k^s, the vertical projection of I_k^s cannot be used directly since often dark eyebrows may produce a wrong position measurement. To avoid this problem, a variant of the Laplacian kernel in the horizontal direction defined as:

$$\nabla_x^2 \stackrel{def}{=} \begin{bmatrix} 1 & -2 & 1 \\ 2 & -4 & 2 \\ 1 & -2 & 1 \end{bmatrix}, \tag{4}$$

is applied to I_k^s, $s = l, r$. Noting that the vertical projection of $\nabla_x^2 * I_k^s$, given by the row-wise summation

$$v_k^s(i) \stackrel{def}{=} \sum_j \left[\nabla_x^2 * I_k^s\right](i,j), \tag{5}$$

presents strong components for the eye, while weaker ones for the eyebrow, a good reference of the pupils' vertical position can be obtained from the point at which v_k^s is largest. More precisely, the horizontal and vertical position of the pupils $e_{x,k}^s$ and $e_{y,k}^s$, $s = l, r$ are calculated as:

$$e_{x,k}^s = \arg\min_{j\in\mathbb{N}} h_k^s(j) \tag{6}$$

$$e_{y,k}^s = \arg\max_{i\in\mathbb{N}} v_k^s(i) \tag{7}$$

To validate that pupils have been correctly located, the following geometrical constraints must be checked:

$$(e_{x,k}^l - b_{x,k}^l) - (b_{x,k}^r + w_k^r - e_{x,k}^r) < \delta_x \tag{8}$$

$$\left|e_{y,k}^l - e_{y,k}^r\right| < \delta_y \tag{9}$$

with thresholds δ_x, δ_y defining the maximum horizontal and vertical distances.

To make the estimation of the pupils' location more robust to head movements and possible illumination variations, salient points set S_k^s for $s = l, r$ in the corresponding regions $\mathcal{B}_k^s$ are obtained with the Shi-Tomasi detector [20], which selects prominent points that are good for tracking. The centroid of points $s_{k,i}^s \in S_k^s$, $i = 1, 2, \ldots, n_k^s$, given by

$$c_k^s = \frac{1}{w_k^s \cdot h_k^s} \sum_{i=1}^{n_k^s} s_{i,k}^s, \tag{10}$$

provides a reference position from which it is possible to locate the center of the pupil, even when it may not be possible to detect the pupil directly in some frames due to the driver's motion or illumination changes. The pupil's estimated position can in this case be found as

$$\hat{e}^s = c_k^s + \hat{d}_k^s \tag{11}$$

where $\hat{d}_k^s$ is an estimate of the pupil's location vector relative to the centroid. An estimation of the relative position vector d_k^s is found by means of a simple first-order IIR running average filter of the form

$$\hat{d}_k^s = (1-\alpha)\hat{d}_{k-1}^s + \alpha d_k^s, \tag{12}$$

with $d_k^s = e_k^s - c_k^s$, $\hat{d}_0^s = d_0^s$, $s = l, r$, where α is the update rate, normally set at 0.05.

Finding the head-pose, in terms of standard pitch, roll and yaw angles, can be solved by computing the deviation of the driver's nose from a reference point corresponding to the position of the nose when the person is looking forward. Finding the reference position is simple, because it corresponds to the position for which the distance between the eyes, as observed in the image, is the largest. The roll angle ϕ is found by calculating the angle of the segment joining the eyes and a horizontal line, while the pitch ψ and yaw θ angles are computed as $k_1\Delta p_\psi$, $k_2\Delta p_\theta$, where k_1 and k_2 are scaling factors and Δp_ψ and Δp_θ are vertical and horizontal deviations (in pixels) with respect to the reference point. This approximation is valid since $\sin(\alpha) \approx \alpha$ for small angles α. On the other hand, true values of the pose angles are not necessary to determine if the person is distracted and looking away from the road ahead for too long periods of time.

B. Detection of Eyebrow Rising, Yawning and Blinking

Analyzing the temporal variation of the spatial distribution of salient points $x_{i,k}^s$, $s = l, r, m$, with respect to the centroid c_k^s provides a good measure of eyebrow rising and yawning. To this end, the spatial distribution of salient points is first characterized in terms of their standard deviation at sampling instant k:

$$\sigma_k^s = \sqrt{\frac{1}{n_k^s}\sum_{i=1}^{n_k^s}\left(s_{i,k}^s - c_k^s\right)^2} \tag{13}$$

A reference value for the spatial distribution of salient points is defined simply as the running average of the salient points' standard deviation:

$$\hat{\sigma}_k^s = (1-\alpha)\hat{\sigma}_{k-1}^s + \alpha\sigma_k^s \tag{14}$$

with an update rate α set to 0.05. Yawns or eyebrow risings are said to occurr in frame k, if $\|\hat{\sigma}_{k,y}^s - \sigma_{k,y}^s\| > \lambda^s$,where $\hat{\sigma}_{k,y}^s$ and $\sigma_{k,y}^s$ are the vertical components of the distributions, and λ^s is a threshold that must be found experimentally for the eyes ($s = l, r$) and mouth ($s = m$) regions.

Since the number of lines with vertical directions, i.e. lines with stronger horizontal gradients, increases when the eyes and mouth are open, the average intensities in the horizontal gradient image, given by

$$\bar{G}_{x,k}^s = \frac{1}{|\mathcal{B}_k^s|}\sum_{(i,j)\in\mathcal{B}_k^s}[\nabla_x * I_k^s](i,j),\ s = l, r, \tag{15}$$

provides a measure to determine if the person is blinking or yawining. An analogous filter to (14) provides a reference value $\hat{G}_{x,k}^s$ against which $\bar{G}_{x,k}^s$ must be compared to according to $\|\hat{G}_{x,k}^s - \bar{G}_{x,k}^s\| > \eta^s$, in order to establish if a blinking or yawning has occurred. Here η^s is a threshold determined in such a way as to maximize the rate of detection, while minimizing the rate of false alarms. Figure 3 illustrates a closed eye (upper-left), an open eye (lower-left) and the corresponding responses obtained from the application of the horizontal

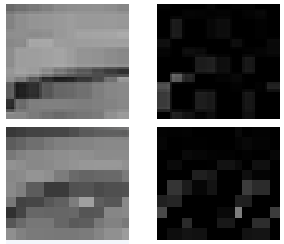

Fig. 3. Horizontal Laplacian filter responses for a closed and an open eye.

Laplacian filter ∇_x^2. When the eyes are open, the value of $\hat{G}_{x,k}^s$ and $\bar{G}_{x,k}^s$ are similar. However, when the eyes are closed there is only a horizontal line, thus the average brightness is weaker, resulting $\bar{G}_{x,k}^s < \hat{G}_{x,k}^s$ instead of $\bar{G}_{x,k}^s \approx \hat{G}_{x,k}^s$ as when eyes are open.

III. Results

The proposed approach was implemented using a standard security camera with integrated IR leds. An IR 850 nm wavelength filter was added to the camera to block other sources of illumination and glare from the sun. The algorithms were developed using the OpenCV computer vision library and executed on a laptop with a 2.2 GHz CPU and 3 GB of available RAM, delivering a frame rate of 16.5 fps for 384x288 pixel frames.

Threshold values λ^s for eyebrow-rising ($s = l, r$), yawning ($s = m$) and η^s ($s = l, r$) for eye blinking, were chosen so as to yield the highest detection rates with lowest possible false alarm rate, i.e. the threshold values correspond to the points in the ROC curves of figs. 4-5 closest to the $(0, 1)$ point in the ROC chart. A sequence of snapshots of one of the test drivers waiting at a traffic light and being tracked by the system is shown in fig. 6. The fourth frame of the sequence does not show the two bright dots on the eyes, which means the driver is blinking, while the circle around the mouth in this same frame indicates that the subject is yawning. Eye blinking was effectively detected 98.37% of the time on average with a rate of false alarm of 0.98%, as shown in table III. In three out of five subjects, blinking was detected every time it occurred. However, the blinking of the other two subjects was harder to detect on every occurrence because they tended to move more. The time duration of blinks was measured on each occasion they were detected, thus providing a good estimate for PERCLOS.

Eyebrow rising results are presented in table III, which shows an average detection rate of 82.00% with a very low false alarm rate of 1.56%. Similarly, yawn detection results are reported in table III, with a high rate of successful detections (86.96%) and a moderate false alarm rate of 5.29%. The difficulty in detecting eyebrow rising and yawning is mainly due to occlusions occurring when some drivers moved their hands close to their faces. Also some false yawns were detected when people would laugh or talk with some exaggerated lip movements.

TABLE II
Blink detection results.

Subject	Events	Detection Rate [%]	False Alarm Rate [%]
1	24	100.00	1.05
2	20	100.00	1.61
3	24	96.00	0.4
4	40	97.56	0.88
5	13	100.00	0.85
Mean		98.37	0.98

TABLE III
Eyebrow rising detection results.

Subject	Events	Detection Rate [%]	False Alarm Rate [%]
1	7	77.78	2.17
2	8	80.00	0.49
3	9	81.82	1.15
4	8	72.73	2.68
5	9	100.00	1.71
Mean		82.00	1.56

TABLE IV
Yawn detection results.

Subject	Events	Detection Rate [%]	False Alarm Rate [%]
1	5	71.43	4.34
2	10	100.00	2.94
3	8	90.00	13.80
4	8	66.67	3.76
5	10	100.00	1.71
Mean		86.96	5.29

TABLE V
Eye tracking results.

Subject	Frames	Tracking Rate [%]
1	2768	93.39
2	6122	99.46
3	5219	98.58
4	3310	94.46
5	5253	98.50
Mean		97.10

Tracking of the eyes was very good for most subjects, except for the two subjects that would move more while driving. In spite of driver motion and changes in the external illumination, a tracking rate of 97.1% was achieved, i.e. 97.1% of the time the tracking system would know where the head was and its pose.

IV. Conclusion

A robust and computationally effective approach for estimating the drivers state of drowsiness and alert was presented. The approach relies on the motion analysis of salient points, which are selected using the Shi-Tomasi approach and tracked with the Lucas-Kanade tracker. Changes in the spatial distribution of the salient points around the eyes and mouth indicate that the person may be yawning or blinking. Tracking of the centroids of the groups of selected points

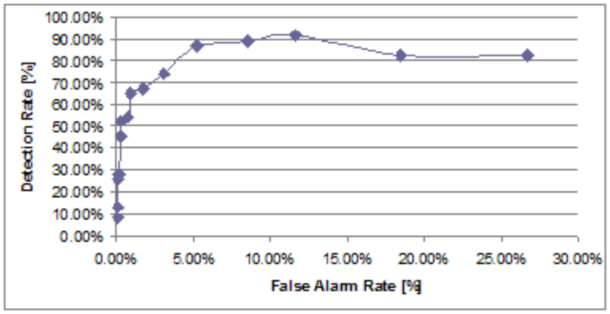

Fig. 4. Yawning ROC curve.

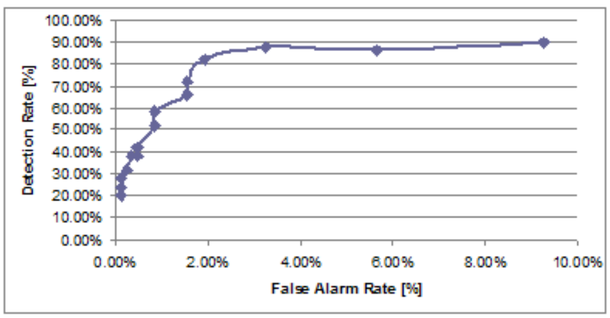

Fig. 5. Eyebrow rising ROC curve.

within regions of interest around the eyes and mouth allow to keep track of the driver's pupils at all times without requiring a computationally expensive face detection process on every frame. The Viola-Jones approach applied to face detection is used only to obtain an initial estimate of the eyes and mouth location, and every certain frames, when a large movement of the head is detected. The approach performs under day or night illumination conditions because it uses a standard camera together with a circular array of infrared leds integrated to the camera and an 850 nm infrared passband filter that blocks illumination variations during the day due to external sources.

Results showed that blinking can be detected 98.37% of the time with a false alarm rate of 0.98% on average. Detection of yawning and eyebrow rising is more difficult, but also can be achieved on average in 82%–87% of the events with a low false alarm rate in the interval 1.5%–5.5%. Detection of yawning or eye-brow rising is more difficult because head motion and illumination changes can influence the selection of some of the salient points. On the other hand, higher detection rates are possible, but at higher false alarm rates because changes in facial gesture or talking may be confused with yawning when decision thresholds are lowered. Finally, it is to be noted that the approach performs in real-time comparing favourably with respect to other approaches reported in the literature. Moreover, the proposed approach can be easily implemented with currently available low-cost security cameras that include IR leds.

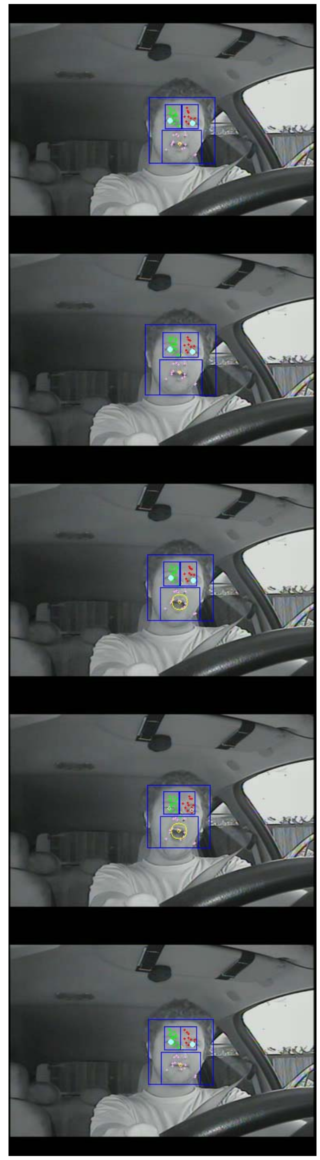

Fig. 6. Snapshots sequence of driver activity showing eye tracking and yawning.

Ongoing research is concerned with the development of algorithms to detect occlusions, in order to handle situations in which salient points are affected by driver actions that make it harder to detect yawning and eyebrow rising, such as moving a hand close to the face.

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