Real-Time System for Monitoring Driver Vigilance

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***Abstract*— This paper presents a non-intrusive prototype computer vision system for monitoring driver's vigilance in real-time. It is based on a hardware system, for real time acquisition of driver's images using an active IR illuminator, and their software implementation for monitoring some visual behaviors that characterize a driver's level of vigilance. Six parameters are calculated: PERCLOS, eye closure duration, blink frequency, nodding frequency, face position and fixed gaze. These parameters are combined, using a fuzzy classifier, to infer the inattentiveness level of the driver. The use of multiple visual parameters and the fusion of them yield a more robust and accurate inattention characterization than by using a single parameter. The system has been tested with different sequences recorded in night and day driving conditions in a motorway and with different users. Some experimental results and conclusions about the performance of the system are shown.**

***Index Terms*— Driver vigilance, visual fatigue behaviors, PERCLOS, eyelid movement, face position, fuzzy classifier**

I. Introduction

THE increasing number of traffic accidents due to a diminished driver's vigilance level has become a serious problem for society. In Europe, statistics show that between 10% and 20% of all traffic accidents are due to drivers with a diminished vigilance level caused by fatigue. In trucking industry, about 60% of fatal truck accidents are related to driver fatigue. It is the main cause of heavy truck crashes [1].

According to the U.S. National Highway Traffic Safety Administration (NHTSA), falling asleep while driving is responsible for at least 100.000 automobile crashes annually. An annual average of roughly 40,000 nonfatal injuries and 1,550 fatalities results from these crashes [2]. These figures only cover crashes happening midnight and 6 am, involving a single vehicle and a sober driver travelling alone, including the car departing from the roadway without any attempt to avoid the crash. These figures underestimate the true level of the involvement of drowsiness because they do not include crashes at daytime hours involving multiple vehicles, alcohol, passengers or evasive manoeuvres. These statistics do not deal either with crashes caused by driver distraction, which is believed to be a larger problem. As car manufacturers incorporate intelligent vehicle systems in order to satisfy consumer ever increasing demand for a wired, connected world, the level of cognitive stress on drivers is being increased. That is, the more assistant systems for comfort, navigation or communication the more sources of distraction from the most basic task at hand, i.e. driving the vehicle.

With this background, developing systems for monitoring driver's level of vigilance, and alerting the driver when he is not paying adequate attention to the road, is essential to prevent accidents. This paper presents an original system for monitoring driver inattention, focusing in the drowsiness or fatigue category, according to the classification shown in [3].

The rest of the paper is structured as follows. In section II we present a review of the main previous work in this line. Section III describes the general system architecture, explaining its main parts. Experimental results are shown in section IV. Finally, in section V we present the conclusions and future works.

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II. Previous work

In the last few years many researchers have been working on the development of safety systems using different techniques. The most accurate techniques are based on physiological measures like brain waves, heart rate, pulse rate, respiration, etc. These techniques are intrusive, since they need to attach some electrodes on the drivers, causing annoyance to them. A representative project in this line is MIT Smart Car [4], where several sensors (electrocardiogram, electromyogram, respiration and skin conductance) embedded in a car and visual information for sensors confirmation are used. In ASV (Advanced Safety Vehicle) project, held by Toyota [5], the driver must wear a wristband in order to measure his heart rate. Others techniques monitor eyes and gaze movements using a helmet or special contact lens [6]. These techniques, though less intrusive, are still not acceptable in practice.

A driver's state of vigilance can also be characterized by indirect vehicle behaviors like lateral position, steering wheel movements, and time to line crossing. Although these techniques are not intrusive they are subject to several limitations such as vehicle type, driver experience, geometric characteristics, state of the road, etc. On the other hand, these procedures require a considerable amount of time to analyze user behaviors and thereby they do not work with the so-called micro-sleeps: when a drowsy driver falls asleep for some seconds on a very straight road section without changing the lateral position of the vehicle [7]. In this line we can find different experimental prototypes, but at this moment none of them has been commercialized. Among them there is an important

Spanish system called TCD (Tech Co Driver) [8] based on steering wheel and lateral position sensors. Toyota [5] uses steering wheel sensors (steering wheel variability) and pulse sensor to record the heart rate, as explained above. Mitsubishi has reported the use of steering wheel sensors and measures of vehicle behavior (such as lateral position of the car) to detect driver drowsiness in their advanced safety vehicle system [5]. Daimler Chrysler has developed a system based on vehicle speed, steering angle and vehicle position relative to road delimitation (recorded by a camera) to detect if the vehicle is about to leave the road [9].

People in fatigue show some visual behaviors easily observable from changes in their facial features like eyes, head, and face. Typical visual characteristics observable from the images of a person with reduced alertness level include longer blink duration, slow eyelid movement, smaller degree of eye opening (or even closed), frequent nodding, yawning, gaze (narrowness in the line of sight), sluggish facial expression, and drooping posture. Computer vision can be a natural and non-intrusive technique for extracting visual characteristics that typically characterize a driver's vigilance from the images taken by a camera placed in front of the user. Many researches have been reported in the literature on developing image-based driver alertness using computer vision techniques. Some of them are primarily focused on head and eye tracking techniques using two cameras. In [10] the method presented estimates head pose and gaze direction. It relies on 2D template searching and then 3D stereo matching of facial features. A 3D model is then fit and minimized using virtual springs, instead of the least squares fit approach, for determining the head pose. In [11] a method is presented based on a stereo template matching system to determine some specific facial features. A least squares optimization is done to determine the exact pose of the head. Two eye trackers calculate the eye-gaze vector for each eye, these vectors are combined with the head pose to determine gaze direction. In [12] a system called FaceLAB developed by a company called Seeing Machines is presented. This is an evolution of the two previous references. The 3D pose of the head and the eye-gaze direction are calculated in an exact way. FaceLAB also monitors the eyelids, to determine eye opening and blink rates. With this information the system estimates the driver's fatigue level. According to author information, the system operates at day and night but at night the performance of the system decreases. All systems explained above rely on manual initialization of feature points. The systems appear to be robust but the manual initialization is a limitation, although it makes trivial the whole problem of tracking and pose estimation.

In [13] we can find a 2D pupil monocular tracking system based on the differences in color and reflectivity between the pupil and iris. The system monitors driving vigilance by studying the eyelid movement. Another successful head/eye monitoring and tracking of drivers system to detect drowsiness using of one camera, and based on color predicates, is presented in [14]. This system is based on passive vision techniques and its functioning can be problematical in poor or very bright lighting conditions. Moreover, it does not work at night, when the monitoring is more important.

In order to work at nights some researches use active illumination based on infrared LED. In [15] a system using 3D vision techniques to estimate and track the 3D line of sight of a person using multiple cameras is proposed. The method relies on a simplified eye model, and it uses the Purkinje images of an infrared light source to determine eye location. With this information, the gaze direction is estimated. Nothing about monitoring driver vigilance is presented. In [16] a system with active infrared LED illumination and a camera is implemented. Because of the LED illumination, the method can easily find the eyes and based on them, the system locates the rest of the facial features. They propose to analytically estimate the local gaze direction based on pupil location. They calculate eyelid movement and face orientation to estimate driver fatigue. Almost all the active systems reported in the literature have been tested in simulated environments but not in real moving vehicles. A moving vehicle presents new challenges like variable lighting, changing background and vibrations that must be taken into account in real systems. In [17] an industrial prototype called *Copilot* is presented. This system uses infrared LED illumination to find the eyes and it has been tested with truck's drivers in real environments. It uses a simple subtraction process for finding the eyes and it only calculates a validated parameter called PERCLOS (percent eye closure), in order to measure driver's drowsiness. This system currently works under low light conditions.

Systems relying on a single visual cue may encounter difficulties when the required visual features cannot be acquired accurately or reliably, as happens in real conditions. Then, a single visual cue may not always be indicative of the overall mental condition [16]. The use of multiple visual cues reduces the uncertainty and the ambiguity present in the information from a single source. The most recent researches in this line use this hypothesis. Currently, the ambitious European project AWAKE [1] is under development. The Consortium includes two major car manufacturers (Fiat, DaimlerChrysler), four automotive system developers (SIEMENS, ACTIA, NAVTECH and AUTOLIV) and many research institutes and universities. A multi-sensor approach is proposed in this project adapted to the driver, the vehicle, and the environment in an integrated way. This system merges, via an artificial intelligent algorithm, data from on-board driver monitoring sensors (such as an eyelid camera and a steering grip sensor) as well as driver behavior data (i.e. from lane tracking sensor, gas/brake and steering wheel positioning). The system must be personalized for each driver during a learning phase. The system is under exhaustive pilot testing for determining its functional performance and the user acceptance of the application [18]. At the moment only some partial results have been presented.

This paper describes a real-time prototype system based in computer vision for monitoring driver vigilance using active infrared illumination and a single camera placed on the car dashboard. We have employed this technique because our goal is to monitor a driver on real conditions (vehicle moving) and in a very robust and accurate way mainly at nights (when the probability to crash due to drowsiness is the highest). The proposed system does not need manual initialization and monitors several visual behaviors that typically characterize a person's level of alertness while driving. In a different fashion than other previous works, we have fused different visual cues from one camera using a fuzzy classifier instead of different cues from different sensors. We have analyzed the different visual behaviors that characterize a drowsy driver and we have studied the best fusion for optimal detection. Moreover, we have tested our system during several hours in a car moving in a motorway and with different users. Preliminary results of this system were presented in [19].

III. System architecture

The general architecture of our system is shown in figure 1. It consists of four major modules: 1) Image acquisition, 2) Pupil detection and tracking, 3) Visual behaviors and 4) Driver vigilance. Image acquisition is based on a low-cost CCD micro-camera sensitive to near-IR. The pupil detection and tracking stage is responsible for segmentation and image processing. Pupil detection is simplified by the "bright pupil" effect, similar to the red eye effect in photography. Then, we use two Kalman filters in order to track the pupils robustly in real-time. In the visual behaviors stage we calculate some parameters from the images in order to detect some visual behaviors easily observable in people in fatigue: slow eyelid movement, smaller degree of eye opening, frequent nodding, blink frequency, and face pose. Finally, in the driver vigilance evaluation stage we fusion all the individual parameters obtained in the previous stage using a fuzzy system, yielding the driver inattentive level. An alarm is activated if this level is over a certain threshold.

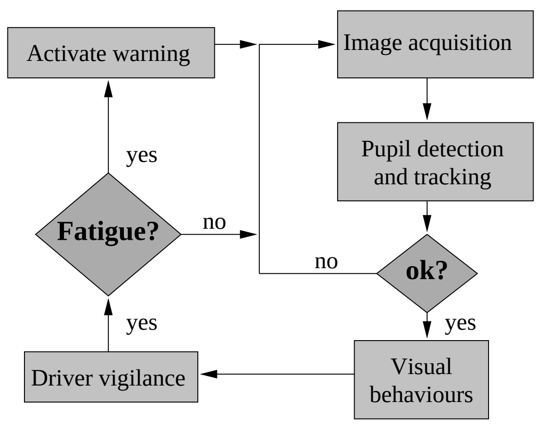

Fig. 1. General architecture

A. Image Acquisition System

The purpose of this stage is to acquire the video images of the driver's face. In this application the acquired images should be relatively invariant to light conditions and should facilitate the eye detection and tracking (good performance is necessary). The use of near-IR illuminator to brighten the driver's face serves these goals [20]. First, it minimizes the impact of changes in the ambient light. Second, the near-IR illumination is not detected by the driver, and then, this does not suppose an interference with the user's driving. Third, it produces the bright pupil effect, which constitutes the foundation of our detection and tracking system. A bright pupil is obtained if the eyes are illuminated with an IR illuminator beaming light along the camera optical axis. At the IR wavelength, the retina reflects almost all the IR light received along the path back to the camera, and a bright pupil effect will be produced in the image. If illuminated off the camera optical axis, the pupils appear dark since the reflected light of the retina will not enter the camera lens. An example of the bright/dark pupil effect can be seen in figure 2. This pupil effect is clear with and without glasses, with contact lenses and it even works to some extent with sunglasses.

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(a) Image obtained with inner IR ring

(b) Image obtained with outer IR ring

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(c) Difference Image

Fig. 2. Fields captured and subtraction

Figure 3 shows the image acquisition system configuration. It is composed by a miniature CCD camera sensitive to near-IR and located on the dashboard of the vehicle. This camera focuses on the driver's head for detecting the multiple visual behaviors. The IR illuminator is composed by two sets of IR LEDs distributed symmetrically along two concentric and circular rings. An embedded PC with a low cost frame- grabber is used for video signal acquisition and signal processing. Image acquiring from the camera and LED excitation is synchronized. The LED rings illuminate the driver's face alternatively, one for each of the image fields, providing different lighting conditions for almost the same image, once the fields are de-interlaced on the next stages.

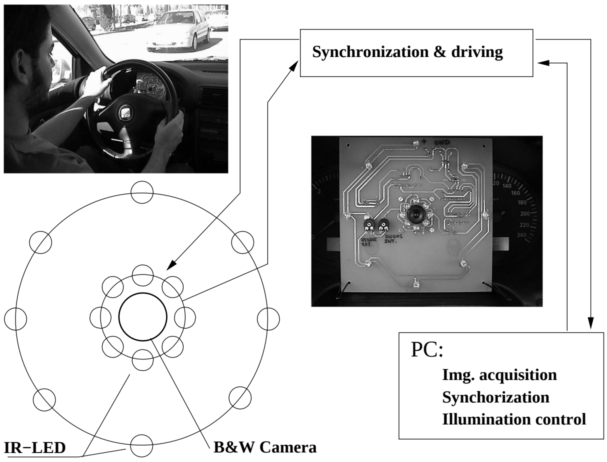


Fig. 3. Block diagram of the prototype

Ring sizes has been empirically calculated in order to obtain a dark pupil image if the outer ring is turned on and a bright pupil image if the inner ring is turned on. LEDs in the inner ring are as close as possible to the camera, in order to maximize the "bright pupil" effect. The value of the outer ring radius is a compromise between the resulting illumination, that improves as it is increased, and the available space in the car's dashboard. The symmetric position of the LEDs in the rings, around the camera optical axis, cancels shadows generated by LEDs. The inner ring configuration obtains the bright pupil effect because the center of the ring coincides with the camera optical axis, actuating as there were only a LED located on the optical axis of the lens. The outer ring provides ambient illumination that is used for contrast enhancing. In spite of those LEDs producing the dark pupil effect, a glint can be observed on each pupil.

The explained acquisition system works very well under controlled light conditions, but real scenarios presents new challenges that must be taken into account. Lighting conditions were one of the most important problems to solve in real tests. As our system is based on the reflection of the light emitted by the IR LEDs, external light sources are the main source of noise. Three main sources can be considered, as are depicted in figure 4: artificial light from elements outside the road (such as light bulbs), vehicle lights, and sun light. The effect of lights from elements outside the road mainly appears in the lower part of the image (figure 4(a)) because they are situated above the height of the car and the beam enters the car with a considerable angle. Then, this noise can be easily filtered. On the other hand, when driving on a double direction road, vehicle lights directly illuminate the driver, increasing the pixels level quickly and causing the pupil effect to disappear (figure 4(b)). Once the car has passed, the light level reduces very fast. Only after few frames, the AGC (Automatic Gain Controller) integrated in the camera compensates the changes, so very light and dark images are obtained, affecting the performance of the inner illumination system.

Regarding the sun light, it only affects at day time but its effect changes as function of the weather (sunny, cloudy, rainy, etc) and the time of the day. With the exception of the sunset, dawn and cloudy days, sun light hides the inner infrared illumination and then the pupil effect disappears (figure 4(c)). For minimizing interference from light sources beyond the IR light emitted by our LEDs, a narrow band-pass filter, centered at the LED wavelength, has been attached between the CCD and the lens. This filter solved the problem of artificial lights and vehicle light almost completely, but it adds a new drawback for it reduces the intensity of the image, and then the noise is considerably amplified by the AGC. The filter does not eliminate the sun light interference, except for cases when the light intensity is very low. This is caused by the fact that the power emitted by the sun in the band of the filter is able to hide the inner illumination. An image of this case, taken by the sun set, is depicted in figure 4(d). A possible solution for this problem could be the integration of IR filters in the car glasses. This option does not have been tested yet.

B. Pupil detection and tracking

This stage starts with pupil detection. As mentioned above, each frame is de-interlaced in even and odd fields, containing the bright and dark pupil images separately. The even image field is then digitally subtracted from the odd image field to produce the difference image. In this image, pupils appear as the brightest parts in the image as can be seen in figure 2. This method minimizes the ambient light influence by subtracting it in the generation of the difference image. This procedure yields high contrast images where the pupils are easily found. It can be observed that the glint produced by the outer ring usually falls close to the pupil, with the same grey level as the bright pupil. The shape of the pupil blob in the difference image is not a perfect ellipse because the glint cuts the blob, affecting the modelling of the pupil blobs and, consequently, the calculation depending on it, as will be explained later. This is the reason why the system only uses subtracted images during initialization, and when light conditions are poor (this initialization time varies depending on the driver and light conditions, but it was below 5 seconds for all test). In other cases, only the field obtained with the inner ring is processed, increasing accuracy and reducing computation time.

Pupils are detected on the resulting image, by searching the entire image to locate two bright blobs that satisfy certain constraints. The image is binarized, using an adaptive threshold, for detecting the brighter blobs in the image.

A standard 8-connected components analysis is then applied to the binaryzed difference image to identify binary

(a) Out-of-the-road lights effect

(b) Vehicle lights effect

(c) Sunlight effect

(d) Sunlight effect with filter

Fig. 4. Effects of external lights in the acquisition system

blobs that satisfy certain size and shape constraints. The blobs that are out of some size constraints are removed, and for the others an ellipse model is fit to each one. Depending on their size, intensity, position and distance, best candidates are selected, and all the possible pairs between them are evaluated. The pair with the highest qualification is chosen as the detected pupils, and its centroids are returned as the pupil positions.

One of the main characteristics of this stage is that it is applicable to any user without any supervised initialization. Nevertheless, the reflection of the IR in the pupils under the same conditions varies from one driver to another. Even on the same driver, the intensity depends on the gaze point, head position and the opening of the eye. Apart from those factors, lightning conditions change with time, which modifies the intensity of the pupils. On other hand, the size of the pupils also depends on the user, and the distance to the camera. To deal with those differences in order to be generic, our system uses an adaptive threshold in the binarization stage. The parameters of the detected pupils are used to update the statistics that set thresholds and margins in the detection process. Those statistics include size, grey level, position and apparent distance and angle between pupils, calculated over a time window of 2 seconds. The thresholds also get their values modified if the pupils are not found, widening the margins to make more candidates available to the system.

Another question related to illumination that is not usually addressed in the literature is the sensitivity of the eye to IR emission. As the exposure time to the IR source increases, its power has to be reduced in order to avoid damaging the internal tissues of the eye. This imposes a limit on the emission of the IR- LEDs. To calculate the power of our system, we have followed the recommendations of [21], based on IEC 825-1 and CENELEC 60825-1 infrared norms. With these limitations, no negative effects have been reported in the drivers that collaborated in the tests.

To continuously monitor the driver it is important to track his pupils from frame to frame after locating the eyes in the initial frames. This can be done efficiently by using two Kalman filters, one for each pupil, in order to predict pupil positions in the image. We have used a pupil tracker based on [16] but we have tested it with images obtained from a car moving in a motorway. Kalman filters presented in [16] works reasonably well under frontal face orientation with open eyes. However, it will fail if the pupils are not bright due to oblique face orientations, eye closures, or external illumination interferences. Kalman filter also fails when a sudden head movement occurs because the assumption of smooth head motion has not been fulfilled. To overcome this limitation we propose a modification consisting on using an adaptive search window, which size is determined automatically, based on pupil position, pupil velocity, and location error. This way, if Kalman filtering tracking fails in a frame, the search window progressively increases its size. With this modification, the robustness of the eye tracker is significantly improved, for the eyes can be successfully found under eye closure or oblique face orientation.

The state vector of the filter is represented as $\mathbf{x}_t = (\mathbf{c}_t, \mathbf{r}_t, \mathbf{u}_t, \mathbf{v}_t)$, where $(\mathbf{c}_t, \mathbf{r}_t)$ indicates the pupil pixel position (its centroid) at time $\mathbf{t}$ and $(\mathbf{u}_t, \mathbf{v}_t)$ be its velocity at time t in $\mathbf{c}$ and $\mathbf{r}$ directions respectively. Figure 5 shows an example of the pupil tracker working in a test sequence. Rectangles on the images indicate the search window of the filter, while crosses indicate the locations of the detected pupils. Figures 5(f) and 5(g) draw the estimation of the pupil positions for the sequence under test. The tracker is found to be rather robust for different users without glasses, lighting conditions, face orientations and distances between the camera and the driver. It automatically finds and tracks the pupils even with closed eyes and partially occluded eyes, and can recover from tracking-failures. The system runs at a frame-rate of 25 frames per second.

Performance of the tracker gets worse when users wear eyeglasses because different bright blobs appear in the image due to IR reflections in the glasses, as can be seen in figure 6. Although the degree of reflection on the glasses depends on its material and the relative position between the user's head and the illuminator, in the real tests carried out, the reflection of the inner ring of LEDs appears as a filled circle on the glasses, of the same size and intensity as the pupil. The reflection of the outer ring appears as a circumference with bright points around it and with similar intensity to the pupil. At the moment we have not applied specific algorithms in order to improve the tracking with glasses, but in the near future we have the intention of detecting the patters generated by the outer and the inner rings and remove them from the images. The system was also tested with people wearing contact lenses. In this case no differences in the tracking were obtained respect to drivers not wearing them.

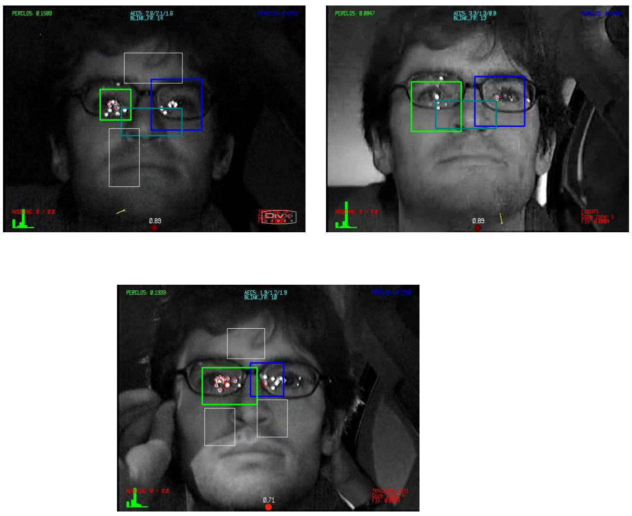


Fig. 6. System working with user wearing glasses

C. Visual behaviors

Eyelid movements and face pose are some of the visual behaviors that reflect a person's level of inattention. There are several ocular measures to characterize eyelid movements such as eye closure duration, blink frequency, fixed gaze, eye closure/opening speed, and the recently developed parameter PERCLOS [22], [23]. This last measure indicates the accumulative eye closure duration over time excluding the time spent on normal eye blinks. It has been found to be the most valid ocular parameter for characterizing driver fatigue [5]. Face pose determination is related to computation of face orientation and position, and detection of head movements. Frequent head tilts indicate the onset of fatigue. Moreover, the nominal face orientation while driving is frontal. If the driver faces in other directions for an extended period of time, it is due to distraction. In this work, we have measured all the explained parameters in order to evaluate its performance for the prediction of driver inattention state focusing on fatigue category.

To obtain the ocular measures we continuously track the subject's pupils and fit two ellipses, to each of them, using a modification of the LIN algorithm [24], as implemented in the OpenCV library [25]. The degree of eye opening is characterized by the pupil shape. As eyes close, the pupils start getting occluded by the eyelids and their shapes get more elliptical. So, we can use the ratio of pupil ellipse axes to characterize the degree of eye opening. To obtain a more robust estimation of the ocular measures and, for example, to distinguish between a blink and an error in the tracking of the pupils, we use a Finite State Machine (FSM) as we depict in figure 7. Apart from the *init_state*, five states have been defined: *tracking_ok*, *closing*, *closed*, *opening* and *tracking_lost*. Transitions between states are achieved from frame to frame as a function of the width-height ratio of the pupils.

The system starts at the *init_state*. When the pupils are detected, the FSM passes to the *tracking_ok* state indicating that the pupil's tracking is working correctly. Being in this state, if the pupils are not detected in a frame, a transition to the *tracking_lost* state is produced. The FSM stays in this state until the pupils are correctly detected again. In this moment, the FSM passes to the *tracking_ok* state. If the width-height ratio of the pupil increases above a threshold (20% of the nominal ratio), a closing eye action is detected and the FSM changes to the *closing_state*. Because the width-height ratio may increase due to other reasons, such as segmentation noise, it is possible to return to the *tracking_ok* state if the ratio does not constantly increase.

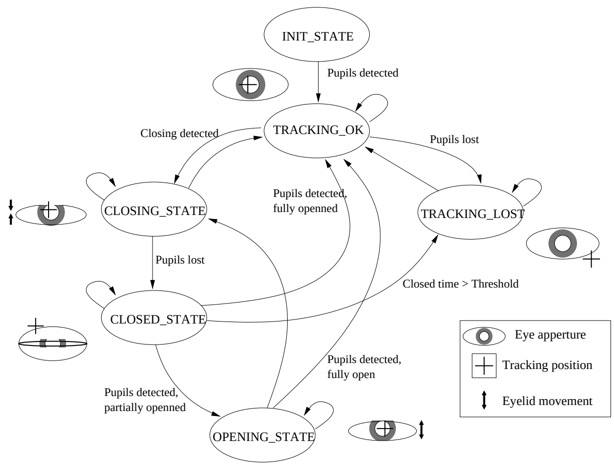
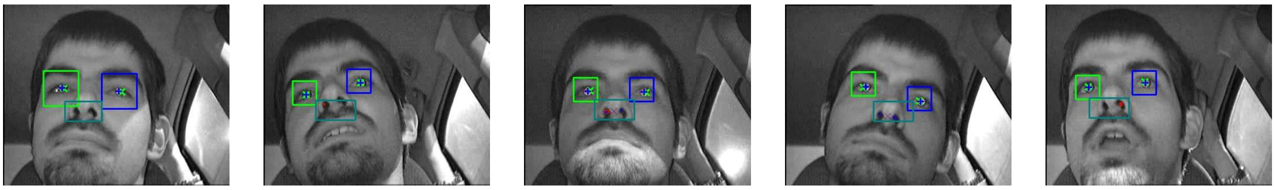


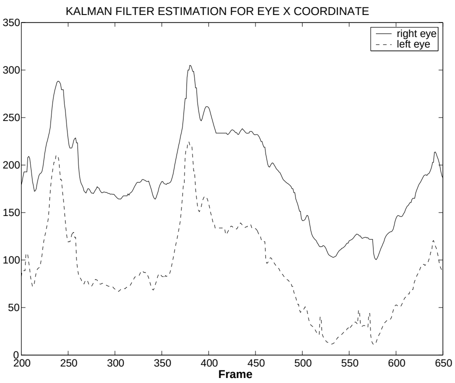
Fig. 7. Finite State Machine for ocular measures

When the pupil ratio is above the 80% of its nominal size or the pupils are lost, being in *closing_state*, a transition of the FSM to *closed_state* is provoked, which means that the eyes are closed. A new detection of the pupils from the *closed_state* produces a change to *opening_state* or *tracking_ok* state, depending on the degree of opening of the eyelid. If the pupil ratio is between the 20% and the 80% a transition to the *opening_state* is produced, if it is below the 20% the system pass to the *tracking_ok* state. Being in *closed_state*, a transition to the *tracking_lost* state is produced if the closed time goes over a threshold. A transition from opening to closing is possible if the width-height ratio increases again. Being in *opening_state*, if the pupil ratio is below the 20% of the nominal ratio a transition to *tracking_ok* state is produced.

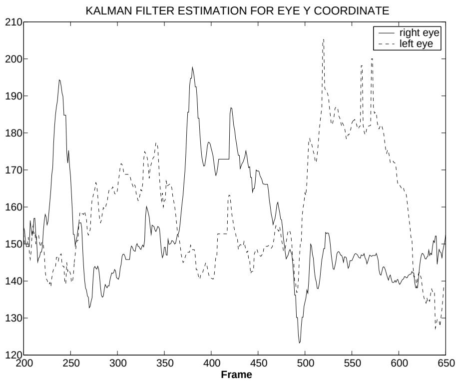
Ocular parameters that characterize eyelid movements have been calculated as a function of the FSM. PERCLOS is calculated from all the states, except from the *tracking_lost* state, analyzing the pupil width-height ratio.



(a) Frame 217 (b) Frame 298 (c) Frame 376 (d) Frame 416 (e) Frame 498



(f)



(g)

Fig. 5. Tracking results for a sequence

We consider that an eye closure occurs when the pupil ratio is above the 80% of its nominal size. Then, the eye closure duration measure is calculated as the time that the system is in the *closed_state*. To obtain a more robust measurement of the PERCLOS, we compute this running average. We compute this parameter by measuring the percentage of eye closure in 30 seconds window. Then, PERCLOS measure represents the time percentage that the system is at the *closed_state* evaluated in 30 seconds and excluding the time spent in normal eye blinks. Eye closure/opening speed measures represent the amount of time needed to fully close the eyes or to fully open the eyes. Then, eye closure/opening speed is calculated as the time period during which pupil ratio passes from 20% to 80% or from 80% to 20% of its nominal size, respectively. In other words, the time that the system is in the *closing_state* or *opening_state* respectively. Blink frequency measure indicates the number of blinks detected in 30 seconds. A blink action will be detected as a consecutive transition among the following states: closing, closed, and opening, given that this action was carried out in less than a predefined value. Many physiology studies have been carried out on the blinking duration. We have used the recommendation value derived in [26] but this could be easily modified to conform to other recommended value. Respecting the eye nominal size used for the ocular parameters calculation, it varies depending on the driver. To calculate its correct value a histogram of the eyes opening degree for the last 2000 frames not exhibiting drowsiness is obtained. The most frequent value on the histogram is considered to be the nominal size. PERCLOS is computed separately in both eyes and the final value is obtained as the mean of both.

Besides, face pose can be used for detecting fatigue or distraction behaviors among the categories defined for inattentive states. The nominal face orientation while driving is frontal. If the driver's face orientation is in other directions for an extended period of time it is due to distractions, and if it occurs frequently (in case of various head tilts), it is a clear symptom of fatigue. In our application, the precise degree of face orientation for detecting this behaviors is not necessary because face pose in both cases are very different to the frontal one. What we are interested in is to detect whether the driver's head deviates too much from its nominal position and orientation for an extended period of time or too frequently (nodding detection).

This paper provides a novel solution to the coarse 3D face pose estimation using a single un-calibrated camera, based on the method proposed in [14]. We use a model-based approach for recovering the face pose by establishing the relationship between 3D face model and its two-dimensional (2D) projections. Weak perspective projection is assumed so that face can be approximated as a planar object with facial features, such as eyes, nose and mouth, located symmetrically on the plane. We have performed a robust 2D face tracking based on the pupils and the nostrils detections on the images. From these positions the 3D face pose is estimated. Nostrils detection has been carried out in a similar way as that used for the pupils' detection. Nostrils appear in the images as dark pixels surrounded by not so dark pixels (skin), then being easily detectable. The effect of dark nostrils benefits from the position of the camera in the car.

Initially, we automatically detect a fronto-parallel face view based on the detected pupils and nostrils, as can be seen in figure 8. Using the distance between the detected eyes (d_{eyes}), the distance between the center of the eyes and the nostrils ($d_{eyes-nostrils}$), eyes and nostrils locations, and some simple anthropometric proportions the scope and the location of the face in the image is estimated. The detected face region is used as the initial 3D planar face pose. This method assumes that the distance from the head to the camera remains constant and that head size is relatively constant for all people. As depicted in figure 8, with the 2D position of the eyes and nostril centers, and estimating the distance to head rotation point (D), we can recover 3D face pose using basic projections. We only calculate vertical and horizontal rotations (α,β) because these are the most important features for our purpose. As a function of the calculated rotation from the model and using the speed data of the pupil movements from the Kalman filters, we classify face direction in nine areas: frontal, left, right, up, down, upper left, upper right, lower left, and lower right. Given the initial face image and its pose in the first frame, the task of finding the face location and the face pose in subsequent frames can be implemented as simultaneous 3D face pose tracking and face detection. This simple technique works fairly well for all the faces we tested, with left and right rotations specially. A more detailed explanation about our method was presented by the authors in [27]. As the goal with this behavior is to detect whether the face pose of the driver is not frontal for an extended period of time, this has been computed using only a parameter that gives the percentage of time that the driver has been looking at the front, over a 30 second temporal window.

Nodding is used to quantitatively characterize one's level of fatigue. Several systems have been reported in the literature to calculate this parameter from a precise estimation of the driver's gaze [16][20]. However, these systems have been tested in laboratories but not in real moving vehicles. The noise introduced in real environments makes these systems, based on exhaustive gaze calculation, not to work properly. In this paper, we present a new technique based on position and speed data from the Kalman filters used to track the pupils and the FSM. This parameter measures the number of head tilts detected on the last 2 minutes. We have experimentally observed that in many occasions nodding follow a pattern along the vertical axis (v) similar to figure 9(a). When a nodding is taking place, the driver closes his or her eyes and the head goes down to touch the chest or the shoulders. If the driver wakes up in that moment, rising his head, the values of the vertical speed of the Kalman filters will describe quite a characteristic curve, as shown in figure 9(b). The speed of the Kalman filters changes its sign, as the head rises. If the FSM is in *closed_state* or in *tracking_lost* and the pupils are detected again, the system saves the speeds of the pupils trackers for 10 frames. After that, the data is analyzed to find if it conforms to that of a nodding. If so, the first stored value is saved and used as an indicator of the "magnitude" of the nodding.

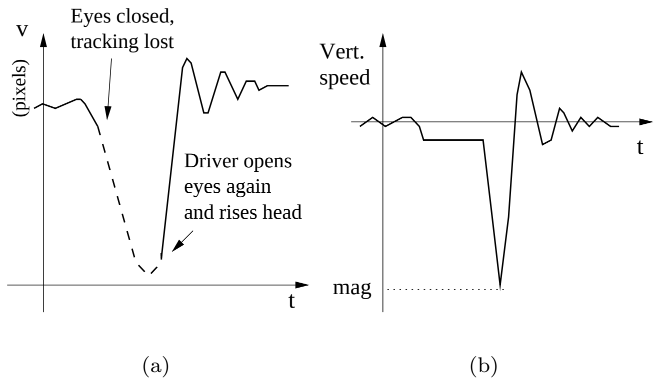


Fig. 9. Nodding curves

Finally, one of the remarkable behaviors that appear on drowsy drivers is fixed gaze. An fatigued driver looses the focus of the gaze, not paying attention to any of the elements of the traffic. This lost of concentration usually takes place before other sleepy behaviors do, such as nodding. As in the parameter explained above, the existing systems calculate this parameter from a precise estimation of the driver's gaze and, consequently, experience the same problems. In order to develop a method to measure this behavior in a simple and robust way, we present a new technique based on the data from the Kalman filters used to track the pupils.

A driver in good condition moves his eyes frequently, focusing to the changing traffic conditions, particularly if the road is busy. This has a clear reflection on the difference between the estimated position from the Kalman filters and the measured ones, as can be seen in figure 10(a), where fixed gaze behavior is present from 150 to 250 seconds.

Besides, the movements of the pupils for a drowsy driver present different characteristics. Our system monitors the position on the x coordinate. Coordinate y is not used, as the difference between drowsy and awake driver is not so clear. The computation of this parameter is based on two temporal windows. On the first one, lasting two seconds, the values in every frame are stored. At the end of it, mean and standard deviation are calculated. If the results for both eyes fall within predefined limits, that window will be computed as '1', and as '0' otherwise, as shown on figure 10(b). The second window computes the average of these values ('0' or '1') during the last 60 seconds figure 10(c), this being the parameter passed to the next stage. This way, the fix gaze parameter is computed locally in a long period of time allowing the leeway of pupil positions over time.

This fixed gaze parameter may suffer from the influence of vehicle vibrations or bumpy roads. Modern cars have

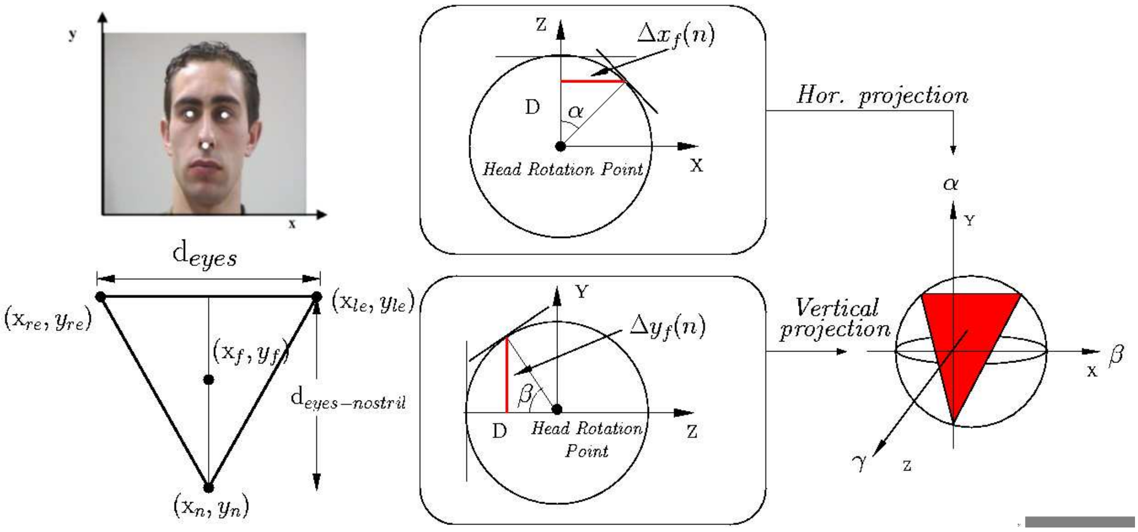


Fig. 8. Recovering the 3D face pose from 2D projections

reduced vibrations to a point that the effect is legible on the measure. The influence of bumpy roads depends on their particular characteristics. If bumps are occasional, it will only affect few values, these will not represent an important quantity in the overall measure. On the other hand, if bumps are frequent and their magnitude is high enough, the system will probably fail to detect this behavior. Fortunately, the probability for a driver to fall asleep is significantly lower in very bumpy roads. The results obtained for all the test sequences with this parameter are encouraging. In spite of using the same a priori threshold for different drivers and situations, the detection was always correct. Even more remarkable was the absence of false positives.

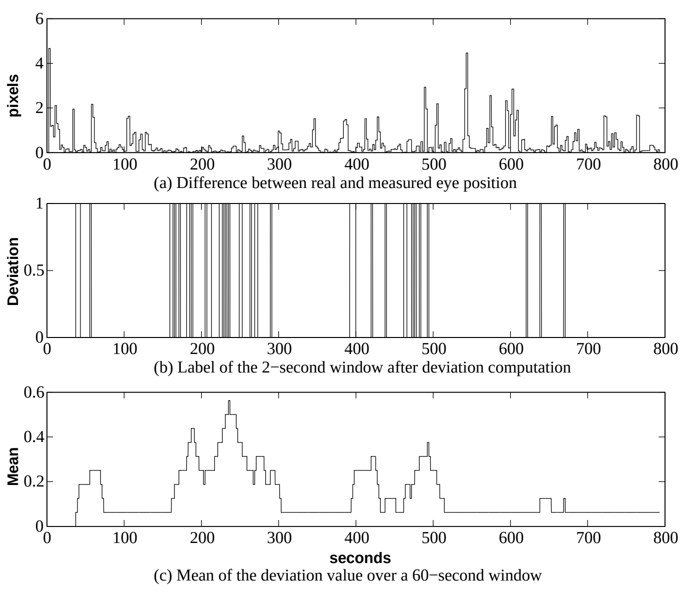


Fig. 10. Measures for the "fixed gaze" parameter

D. Driver vigilance computation

This section describes the method to determine the driver's visual inattention level from the parameters obtained in the previous section. This process is very complicated because several uncertainties may be present on it. First, fatigue is not observable and it can only be inferred from the available information. In fact, this behavior can be regarded as the result of many contextual variables such as environment, health, and sleep history. To effectively monitor it, a system that integrates evidences from multiple sensors is needed. In the present work, several fatigue visual behaviors are subsequently combined to form an inattentive parameter that can robustly and accurately characterize one's vigilance level. The fusion of the parameters has been obtained using a fuzzy system. We have chosen this technique for its well known linguistic concept modelling ability. The fuzzy rule expression is close to expert natural language. Then, a fuzzy system manages uncertain knowledge and infers high level behaviors from the observed data. On the other hand, as it is a universal approximator, fuzzy inference system can be used for knowledge induction processes. The objective of our fuzzy system is to provide a driver's inattentive level (DIL) from the fusion of several ocular and face pose measures, along with the use of expert and induced knowledge. This knowledge has been extracted from the visual observation and the data analysis of the parameters in some simulated fatigue behavior carried out in real conditions (driving a car) with different users. The simulated behaviors have been done according to the physiology study of the US Department of Transportation, presented in [5]. This paper does not delve into the psychology of driver visual attention, rather it merely demonstrates that with the proposed system, it is possible to collect driver information data and infer whether the driver is attentive or not.

The first step in the expert knowledge extraction process is to define the number and nature of the variables involved in the diagnosis process according to the domain expert experience. The next variables are proposed after appropriate study of our system: PERCLOS, eye closure duration, blink frequency, nodding frequency, fixed gaze and frontal face pose. Eye closing and opening variables are not being used in our input fuzzy set because they mainly depend on factors such as segmentation, correct detection of the eyes and take place in such a period of time comparable in length with that of the image acquisition. As a consequence, they are very noisy variables. As our system is adaptive to the user, the ranges of the fuzzy selected inputs are approximately the same for all users. The fuzzy inputs are normalized and different linguistic terms and its corresponding fuzzy sets are distributed in each of them using induced knowledge based on the hierarchical fuzzy partitioning (HFP) method [28]. Its originality lays in not yielding a single partition, but a hierarchy including partitions with various resolution levels based on automatic clustering data. Analyzing the fuzzy partitions obtained by HFP, we determined that the best suited fuzzy sets and the corresponding linguistic terms for each input variable are those shown in table I. For the output variable (DIL), the fuzzy set and the linguistic terms were manually chosen. The inattentiveness level range is between 0 and 1, with a normal value up to 0.5. When its value is between 0.5 and 0.75, driver's fatigue is medium, but it the DIL is over 0.75 the driver is considered to be fatigued, and an alarm is activated. Fuzzy sets of triangular shape were chosen, except at the domain edges, where they were semi-trapezoidal.

Based on the above selected variables, experts state different pieces of knowledge (rules) to describe certain situations connecting some symptoms with a certain diagnosis. These rules are of form *"If condition, Then conclusion"*, where both premise and conclusion use the linguistic terms previously defined, as in the following example:

1) **IF** *PERCLOS* is *large* **AND** *Eye Closure Duration* is *large*, **THEN** *DIL* is *large*

In order to improve accuracy and system design, automatic rule generation and its integration in the expert knowledge base were considered. To ease such an integration the generated rules use the readable fuzzy partitions already designed. The process of generating rules from data is called induction. It aims at producing general statements, expressed as fuzzy rules in our case, valid for the whole set, from partial observations obtained from some real experiments. As the data are likely to give a good image of interactions, induced rules may yield complementary pieces of knowledge. A lot of methods are available in the fuzzy literature [29]. We restrict our interest to the ones which generate rules that share the same fuzzy sets (Wang and Mendel (WM)[30], Fast Prototyping Algorithm (FPA)[31] and Fuzzy Decision Trees (FDT)[32]). Among them we chose the FDT with pruned method (FDT+P) because it produces the best quality, the more interpretable and accurate knowledge base.

Induced rules with FDT+P were integrated into the expert knowledge base. As a result the rule base consists of 94 rules, 8 expert rules and 86 induced ones. During this last step, the fundamental properties of the rule base have to be guaranteed: consistency, lack of redundancy and interpretability. Both kinds of rules use the same linguistic labels thanks to the previously defined common universe. Therefore rule comparison is made at linguistic level only.

First of all, a consistency analysis [33] of the knowledge base is made in order to detect conflicts at linguistic level. Afterwards a simplification process is applied with the goal of achieving a more compact knowledge base, with a smaller size to improve interpretability, mantaining the accuracy of the original knowledge base. The simplification process is described in detail in [34].

This paper only describes the simplification process results in the real problem under consideration. Please refer to the cited literature for a complete description. The final knowledge base is more compact, with a smaller number of rules which are incomplete and more general, and a smaller number of labels. We have obtained a rule base with 32 rules, which are easily interpretable. According to these rules, three variables (fixed gaze, PERCLOS and eye closure duration) are crucial for determining driver's fatigue. Two induced rules are shown below:

1) **IF** *PERCLOS* is *small* **AND** *Eye Closure Duration* is *small* **AND** *Face Position* is *medium* **AND** *Nodding Frequency* is *small* **AND** *Blink Frequency* is *medium***AND** *Fixed Gaze* is *small*, **THEN** *DIL* is *small*
2) **IF** *PERCLOS* is *medium large* **AND** *Eye Closure Duration* is *medium* **AND** *Blink Frequency* is *medium* **AND** *Fixed Gaze* is *large*, **THEN** *DIL* is *large*

The fuzzy system implementation was done using the licence-free tool KBCT (Knowledge Base Configuration Tool) [35] developed by the intelligent systems group of the Technical University of Madrid (UPM). In the next section we present experimental results obtained with this tool with the following basic fuzzy options: minimum operator as connective AND, maximum as aggregation method and centre of area as defuzzification method. All induced rules have the same weight.

IV. Experimental results

The goal of this section is to experimentally demonstrate the validity of our system in order to obtain fatigue behaviors in drivers. Firstly, we show some details about the recorded video sequences used for testing, then, we analyze the parameters measured for one of the sequences. Finally, we present the performance of the detection of each one of the parameters, and the overall performance of the system.

A. Test Sequences

Ten sequences were recorded in real driving situations over a highway and a both-senses road. Each sequence was obtained for a different user. The images were obtained using the system explained in section III-A. The

TABLE I
Fuzzy variables

Variable	Type	Range	Labels	Linguistic terms
PERCLOS	In	[0.0, 1.0]	5	small, medium small, medium, medium large, large
Eye closure duration	In	[1.0 - 30.0]	3	small, medium, large
Blink freq.	In	[1.0 - 30.0]	3	small, medium, large
Nodding freq.	In	[0.0 - 8.0]	3	small, medium, large
Face position	In	[0.0 - 1.0]	5	small, medium small, medium, medium large, large
Fixed gaze	In	[0.0 - 0.5]	5	small, medium small, medium, medium large, large
DIL	Out	[0.0 - 1.0]	5	small, medium small, medium, medium large, large

drivers simulated some drowsy behaviors according to the physiology study of the US Department of Transportation presented in [5]. Each user drove normally except in one or two intervals where the driver simulated fatigue. The length of the sequences and the fatigue simulation intervals is shown in table II. All the sequences were recorded at night except for sequence number 7 that was recorded at day, and sequence number 5 that was recorded at sunset. Sequences were obtained with different drivers not wearing glasses, with the exception of sequence 6, that was recorded for testing the influence of the glasses in real driving conditions.

B. Parameter measurement for one of the test sequences

The system is currently running on a PC Pentium4 (1,8 Ghz) with Linux kernel 2.4.24 in real time (25 frames/s) with a resolution of 640x480 pixels. Average processing time per frame (both even and odd fields) is 11.43ms. Figure 11 depicts the parameters measured for sequence number 9. This is a representative test example with a duration of 465 seconds where the user simulates two fatigue behaviors separated by an alertness period. As can be seen, until second 90, and between the seconds 195 and 360, the DIL parameter is below 0.5 indicating an alertness state. In these intervals the PERCLOS is low (below 0.15), eye closure duration is low (below the 200 ms), blink frequency is low (below 2 blinks per 30-second window) and nodding frequency is zero. These ocular parameters indicate a clear alert behavior. The frontal face position parameter is not 1.0, indicating that the predominant position of the head is frontal, but that there are some deviations near the frontal position, typical of a driver with a high vigilance level. The fixed gaze parameter is low because the eyes of the driver are moving caused by a good alert condition. The DIL parameter increases over the alert threshold during two intervals (from 90 to 190 and from 360 to 565 seconds) indicating two fatigue behaviors. In both intervals the PERCLOS increases from 0.15 to 0.4, the eye closure duration goes up until 1000 ms, and the blink frequency parameter increases from 2 to 5 blinks. The frontal face position is very close to 1.0 because the head position is fix and frontal. The fixed gaze parameter increases its value up to 0.4 due to the narrow gaze in the line of sight of the driver. This last variation indicates a typical lost of concentration and it takes place before the other sleepy measurements, as can be observed. The nodding is the last fatigue effect to appear. In the two fatigue intervals a nodding occurs after the increasing of the other parameters, indicating a low vigilance level. We must remark that this last parameter is calculated over a temporal window of 2 minutes, this is the reason why its value remains stable during this time.

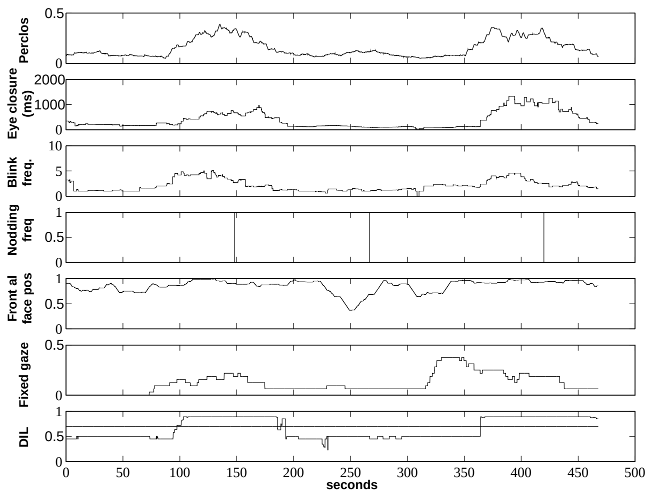


Fig. 11. Parameters measured for the test sequence number 9

This section described an example of parameters evolution for two fatigue behaviors and one driver. Then, we analyzed the behaviors of other drivers in different circumstances, according to the video tests explained above. The results obtained are very similar to those shown for sequence number 9. Overall results of the system are explained in what follows.

C. Parameter performance

The general performance of the measured parameters for a variety of environments with different drivers, according to the test sequences, is presented in table III. Performance was measured by comparing system performance to results obtained by manually analyzing the recorded sequences, on a frame-by-frame basis. For each parameter, the correct percentage per sequence is depicted. This includes correct detection and false positives. The last column depicts the total correct percentage for all sequences excluding sequence number 6 (driver wearing glasses) and sequence number 7 (recorded by day). Then, this column shows the parameter detection performance of the system for optimal situations (driver without glasses driving at night). As can

TABLE II
LENGTH OF SIMULATED DROWSINESS SEQUENCES

Seq. Num.	Drowsiness Behavior time(sec)	Alertness Behavior time(sec)	Total time(sec)
1	394 (2 intervals:180+214)	516	910
2	90 (1 interval)	210	300
3	0	240	240
4	155 (1 interval)	175	330
5	160 (1 interval)	393	553
6	180 (1 interval)	370	550
7	310 (2 intervals:150+160)	631	941
8	842 (2 intervals:390+452)	765	1607
9	210 (2 intervals:75+135)	255	465
10	673 (2 intervals:310+363)	612	1285

be seen, the performance gets considerable worse by day and it dramatically decreases when drivers wear glasses.

PERCLOS results are quite good, obtaining a total correct percentage of 93.12%. It has been found to be a robust ocular parameter for characterizing driver fatigue. However, it may fail sometimes, for example, when a driver falls asleep without closing her eyes. Eye closure duration performance is a little worse than that of the PERCLOS(84.37%), because the correct estimation of the duration is more critical. The variation on the intensity when the eye is partially closed with regard to the intensity when it is open complicates the segmentation and detection. This causes the frame count for this parameter to be usually less than the real one. These frames are considered as closed time. Measured time is slightly over the real time, as a result of delayed detection. Performance of blink frequency parameter is about 80% because some quick blinks are no detected with a frame rate of 25 frames per second. Then, the three explained parameters are clearly correlated almost linearly, being PERCLOS the most robust and accurate one.

Nodding frequency results are the worst (72.5%), as the system is not sensible to noddings in which the driver rises her head and then opens her eyes. To reduce false positives, the magnitude of the nodding (i.e., the absolute value of the Kalman filter speed), must be over a threshold. In most of the non-detected noddings, the first situation took place, while the second limitation did not have any influence on any of them. The ground truth for this parameter was obtained manually by localizing the noddings on the recorded video sequences. It is not correlated with the three previous parameters and it is not robust enough for fatigue detection. Consequently, it can be used as a complementary parameter to confirm the diagnosis established based on other more robust methods.

The evaluation of the face direction provides a measure of alertness related to drowsiness and distractions. This parameter is useful for both detecting the pose of the head out of the front direction and the duration of the displacement. The results can be considered fairly good (87.5%) for a simple model that requires very little computation and not manual initialization. The ground truth in this case was obtained by manually looking for periods in which the driver is not clearly looking at front in the video sequences, and comparing their length to that of the ones detected by the system. There is not a clear correlation between this parameter and the ocular ones for fatigue detection. This is the most important cue in case of distraction detection. Performance of the fixed gaze monitoring is the best of the measured parameters (95.62%). The maximum values reached by this parameter depend on users' movements and gestures while driving, but a level above 0.05 is always considered to be an indicator of drowsiness. Values greater than 0.15 represent high inattentiveness probability. This parameter did not have false positives and is largely correlated to the frontal face direction one. On the contrary, it is not clearly correlated to the rest of the ocular measurements. The ground truth for this parameter was manually obtained by analyzing eye movements frame by frame for the intervals where a fixed gaze behavior was being simulated. Fixed gaze and PERCLOS have been found to be the best detectable parameters for characterizing driver fatigue.

All parameters presented above are fused in the fuzzy system to obtain the DIL for final evaluation of drowsiness. There is some delay between the moment when the driver starts his fatigue behavior simulation and when the fuzzy system detects it. This is a consequence of the windows span used in parameter evaluation. Correct percentage for this output parameter is very high (98%). It is higher than the obtained using only the PERCLOS, for which the correct percentage is about the 90% for our testbench. This is due to the fact that fatigue behaviors are not the same for different drivers. Then, parameters evolution and absolute values from the visual cues differ from user to user. Another important fact is the delay between the appearance of fatigue and its detection. Each parameter responds to a different stage in the fatigue behavior. For example, fixed gaze behavior appears before PERCLOS starts to increase, thus rising the DIL to a value where a noticiable increment of PERCLOS would rise an alarm in few seconds. This is extensible to the other parameters. Using only the PERCLOS would require much more time to rise an alarm (tens of seconds), specially in drivers for which the PERCLOS increases more slowly. Our system provides an accurate characterization of a standard driver's level of fatigue, using multiple visual parameters to resolve the ambiguity present in the information from a single parameter. Additionally, the system performance

TABLE III

Parameter detection performance

Parameters	Correct percentage per sequence										Total correct percentage
	1	2	3	4	5	6	7	8	9	10	
PERCLOS	90	90	95	95	95	25	50	95	95	90	93.12%
Eye closure duration	90	80	85	90	85	20	50	80	85	80	84.37%
Blink freq.	75	75	85	80	85	0	30	85	80	75	80%
Nodding freq.	70	60	80	80	60	0	20	70	100	60	72.5%
Face position	100	70	85	95	90	0	50	85	90	85	87.5%
Fixed gaze	100	90	95	95	95	20	60	95	95	100	95.62%

is very high in spite of the partial errors associated to each input parameter. This was achieved using redundant information. The system performance was evaluated by comparing the intervals where the DIL parameter was above 0.75 to the intervals, manually analyzed over the video sequences, in which the driver simulates fatigue behaviors. This analysis consisted in a subjective estimation of drowsiness by human observers, based on the Wierwille test [23].

V. Conclusions and future works

We developed a non-intrusive prototype computer vision system for real-time monitoring of driver's vigilance. It is based on a hardware system, for real time acquisition of driver's images using an active IR illuminator, and the implementation of software algorithms for real-time monitoring of the six parameters that better characterize the fatigue level of a driver. These visual parameters are PERCLOS, eye closure duration, blink frequency, nodding frequency, face position and fixed gaze. In an attempt to effectively monitor fatigue, a fuzzy classifier was implemented to merge all these parameters into a single Driver Inattentive Level. Monitoring of other inattention categories would be possible using this method. The system is fully autonomous, it can initialize automatically, and reinitialize when necessary. It was tested with different sequences recorded in real driving condition with different users during several hours. In each of them, several fatigue behaviors were simulated during the test. The system works robustly at night, for users not wearing glasses, yielding and accuracy percentage close to 100%. Performance of the system decreases at day, especially in bright days, and at the moment it does not work with drivers wearing glasses.

The results and conclusions obtained are an approach to the drowsiness detection problem and they will be completed in the future with actual drowsiness data. In the next future, we have the intention of testing the system with more users for long periods of time, to obtain real fatigue behaviors. With this information we will generalize our fuzzy knowledge base. Then, we would like to improve our vision system in order to solve the problems of daytime operation, and to improve the solution for drivers wearing glasses. On the other hand, we plan to add two new sensors (a steering wheel and a lateral position sensor) for fusion with the visual information to achieve correct detection, specially at daytime. Finally, this system could be easily extended to other kind of vehicles, such as aircrafts, trains, subways, etc, helping to improve safety in transportation systems.

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