Proceedings of the 17th World Congress
The International Federation of Automatic Control
Seoul, Korea, July 6-11, 2008

Driver vigilance diagnostic based on eyelid movement observation

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Abstract: Driver loss of vigilance is an important cause of road fatalities. The improvement of technologies makes now possible the implementation of in-vehicle driver monitoring systems assessing in real time the evolution of the driver state. Within this paper a Driver Vigilance Monitoring (DVM) system developed by Continental Automotive is described. This system includes a compact CMOS camera for observing the driver eyelid movements and a set of algorithms for analyzing in real time the image provided by the camera, to classify this information and at last to provide drowsiness diagnostic.

Keywords: ADAS, Driver vigilance, diagnostic, image processing, classification

1 INTRODUCTION

Tiredness is one of the major causes of fatal accidents on highways. This risk is particularly great owing to the sudden, extreme tiredness afflicting drivers, who are on the road at night, and who drive uniformly and monotonously. Since the 70' extensive research has been carried out to develop on board systems able to measure and to detect degradation of the driver's vigilance and then to inform him in case of critical situation. In the 70' and 80' researchers were mainly looking to driver behavior i.e. steering wheel and pedal movements. In the mid 90' carried by the strong improvement of vision based technologies a focus has been brought to driver's face analysis and more specifically to on-line analysis of eyelid movements.

Within the EU programs SAVE (SAVE 1996) and AWAKE (AWAKE 2000) Continental Automotive (formerly Siemens VDO Automotive) developed a first real time vision based prototype called EyeLid Sensor (ELS). The ELS prototype used a costly CCD camera to automatically detect and measure the driver's blink parameters and to provide a first ruled based drowsiness diagnosis (Boverie *et al.* 2002). Most recently, Continental Automotive has developed a complete Driver Vigilance Monitoring (DVM) function which uses a compact camera including a low cost CMOS sensor compatible with automotive constraints. A fuzzy based drowsiness diagnostic has been developped so to deal with the variability of the blinking behaviors.

This function has been implemented in a vehicle and tested in real driving conditions.

The aim of this paper is to present the main results of this development. In section 2 a brief system overview is given. Then in section 3 and 4 the image processing, feature extraction and diagnostic algorithms are depicted. At last in section 5 the experimental equipment of the test vehicle as well as some results are presented and commented.

2 System overview

DVM is a monocular vision system which includes a CMOS camera and a set of pulsed Near Infrared (NIR) LEDs (invisible light) integrated in the same packaging. A set of algorithms implemented in a distant processing unit analyze in real time the image flow provided by the camera to extract information about the driver's eyelid and blink patterns and to provide vigilance diagnostic. The system is fully automatic and works by night and day taking into account that drowsiness is not just a night-time phenomenon and is also likely to occur during the morning or the afternoon. It provides multi-level information in relation with the evolution of the driver state. Various warning strategies combining acoustic visual and haptic modalities can then be foreseen.

The general architecture of the DVM is given in *Figure 1*.

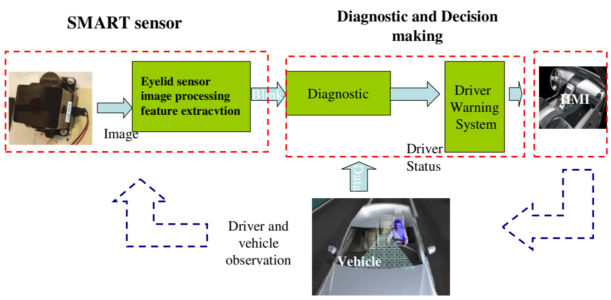


Figure 1: Architecture of the DVM

The camera (see *Figure 2*) is integrated into the instrument cluster. The lens is defined to provide a field of view that covers 95% driver's eyellipse. The lens is equiped with a cut visible light filter to increase the ratio of the light received by the sensor coming from the NIR leds to the received sun light. The main characteristics of the CMOS sensor are the following:

- a low cost compatible with mass car production
- a sampling frequency of about 50Hz full image (SW driven),

- High resolution 750 (H) x 480 (V).
- a low consumption,
- a global shutter for the synchronization of the camera acquisition with the NIR pulsed lights.

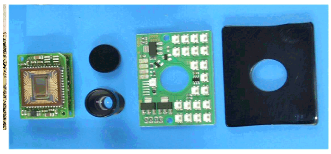


Figure 2: CMOS sensor with integrated Near Infrared light units

3 Eyelid sensing and feature extraction algorithms

The Eyelid sensing algorithms are feature based, meaning that small characteristics regions of the images are used to locate the face and eyes. Such approach allows robust eye detection, in real time, by reducing the image analysis to the feature regions. In counter part it requires an accurate localization of a minimal set of features including the eye corners, the corner of the mouth and the eyebrows The algorithms can be divided into three main modules (see *Figure 3*)

- The initialization detects the face and eyes and initializes the features *Figure 3* shows the image of the driver's face taken by the sensor. The overlaid blue rectangles indicate the position of the selected features by the initialization module
- The face tracker tracks at frame rate the features
- The facial measurements module uses the position of the tracked features to determine the upper and lower eyelid and measure eyelid patterns (blink duration, closing and opening durations, blink amplitude). The "eye opening, blink duration" graphic of *Figure 3* shows a sample signal of left and right eye opening. Blinks are characterized by a "V" or "__/" shape like pattern.

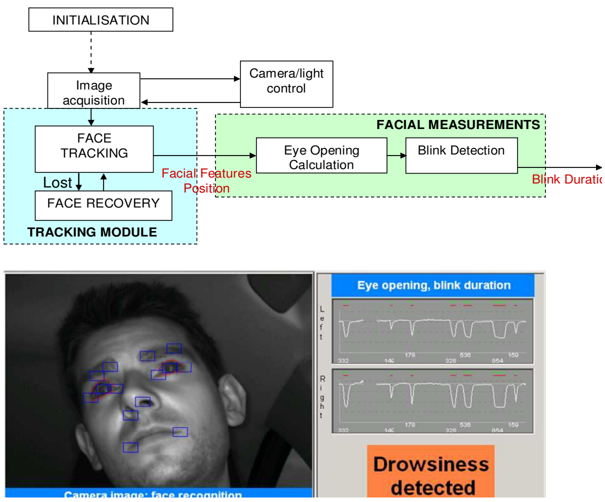


Figure 3: Eyelid sensing algorithm architecture

3.1 The initialization phase

The initialization aims to detect the driver's face and eyes. It scans the overall image till it detects the different features. This includes symbolic features (eye corners, mouth corners) and natural features (small regions on the eyebrows and on other non identified part of the face). The initialization can last some hundred of ms (on a Pentium 4 2 Ghz) depending on the characteristics of the driver's face (head position, contrast, etc.). The accuracy of the feature localization impacts drastically on the performance of the overall application. The initialization is automatically restarted if the global system confidence rate is too low during a given duration.

3.2 The Feature tracking

The tracking is launched once the initialization is completed. Tracking focuses on locating the features in small area around by using geometrically constrained Kalman filter (use of geometric relations between natural features). By that mean real time consraints are achieved. If the tracking process cannot locate the features anymore because of a major head movement or an occlusion a phase of recovery is launched.

3.3 Face recovery

The face recovery aims to locate the features after the tracking was lost. It scans the overall image. During the recovery phase no measurement is available.

3.4 The Eye opening measurement

The eye opening is the height difference between the upper and lower eyelid. The position of the eye corners provides a reduced search area of the eye enabling robust estimation of eyelid position. Upper eyelid is modelled as a 2^{nd} degree curve on the eye edge image. Lower eyelid is modelled as a line on the eye edge image.

3.5 The Blink detection and classification

3.5.1 Blink characteristic parameters

A typical spontaneous blink for an alert person presents 3 phases (see *Figure 4*).

- a **closing phase** (the eyelid goes down),
- a **closed phase** (the eye is shut),
- an **opening phase** (the eyelid goes up).

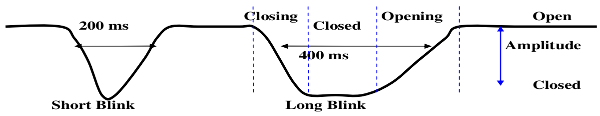


Figure 4: Typical shape of blinks

The closing phase of a normal blink is shorter and faster than the opening phase; it takes about 60 ms with a maximum velocity of approximately 350mm/sec. The opening phase takes about 120 ms with a maximum velocity of 150mm/s. The maximum velocity and durations of eyelid closing and opening do not depend on the starting lid position. A typical blink duration of an alert driver is around 200 ms. Drowsy drivers exhibit long blinks (typically above 300 ms) while driver getting sleepy can exhibit very long blink (typically above 600 ms).

The **blink amplitude** of an alert person, with eyes wide open, is characterized by a maximum value of 10 mm. The amplitude can be much lower for some eyes morphology or also during day driving conditions when the driver closes partly his/her eyes to reduce the light input.

3.5.2 *Blink detection*

The objective of the blink detection algorithm is to detect the blinks to measure their durations and of course to reject artifacts as looking at dashboard patterns.

The blink detection process looks for specific patterns within the given eyelid signals. The Opening signal is first processed to determine an open eye reference (base line). A transition from the upper part of the base line to the lower part is then considered as a start of the closing phase of a potential blink. Finally various shape criterias are applied to decide if a potential blink is a blink. The following main criterias are applied:

Steepness of the closing and opening phase: Each phase must last at least 3 samples.

Minimal blink duration: A blink is rejected if its duration is lower a given threshold (in ms).

Maximal blink duration. To take into account as much as possible very long eye closure the maximal duration is set to a max threshold.

A minimal and maximal Amplitude: of respectively 5 pixels and 20 pixels are considered.

Symmetry: The test of Symmetry compares the opening values of the eyelids at the beginning, the end and for the minimum of the blink signal. The blink is rejected if the ratio of the higher edge of the blink and the lower edge is higher than a fixed threshold (typ. value is 20%;

Figure 5).

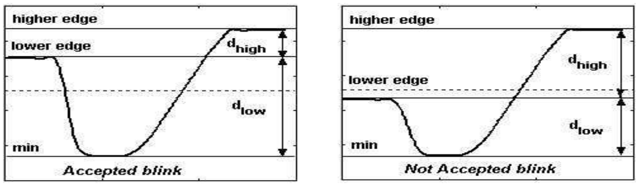


Figure 5: Results for the test of symmetry

3.5.3 *Blink duration measurement*

The usual measure of a blink is done at 90% of the maximal opening. Such a measure is very noise dependant. A more precise measurement is obtained for amplitudes corresponding to the steeper part of the opening and closing.. This corresponds to more or less 40% of the amplitude (

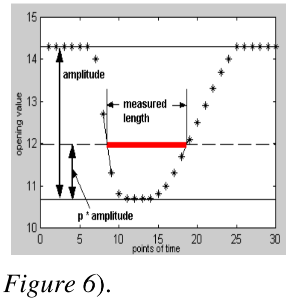


Figure 6).

Figure 6: Measurement of the blink duration

Figure 7 shows left and right eye opening of a drowsy driver. The duration of the detected blinks is indicated in milliseconds below each detected blink. The driver exhibit 3 short blinks (149ms, 159ms and 178ms) 3 long blinks (322ms, 328ms and 536ms) and 1 very long blinks (854 ms).

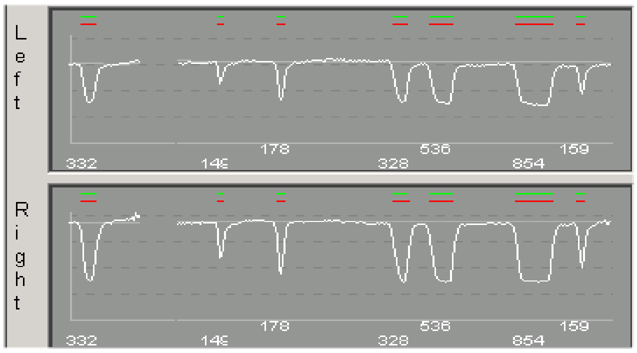


Figure 7: Eyelid opening curve of a drowsy driver

3.5.4 *Blink classification*

The objective of the blink classification is to sort out blinks into several classes. 4 classes have been determined experimentally: Short Blinks, Long Blinks, Very Long Blinks and Sleepy blinks (see

Figure 8). Each class is related with a drowsiness state: short blinks are related with an alert state, long blinks with a slightly drowsy state, very long with a drowsy state while sleepy blinks are related with sleep onset. To take into account uncertainties as well as drivers' inter and intra variability Fuzzy subsets have been used to describe these classes. Then, depending on its duration, a blink can be simultaneously classified in two different and adjacent classes except in the case of the Sleepy blinks.

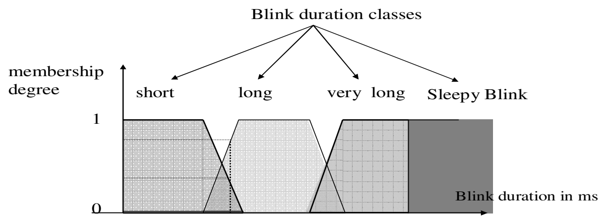


Figure 8: Blink duration classification

The degree of membership [0, 1] is describing how much a blink belongs to a class. Then each detected and validated blink is associated to a dim (4, 1) vector, which components are representing its degree of membership to each of the class:

$$Blink\ Classification\ vector = \begin{bmatrix} \mu_S \\ \mu_L \\ \mu_{VL} \\ \mu_{SB} \end{bmatrix}$$

It should also be noticed that when $\mu_{SB} = 1\ then\ \mu_S = \mu_L = \mu_{VL} = 0$ or $\mu_S or \mu_L or \mu_{VL} \neq 0\ then\ \mu_{SB} = 0$

3.5.4.1 Estimation of the blink confidence rate

For each detected blink a measurement confidence is estimated. It depends on the quality factor of the eyelid opening assessed in real time for each new image delivered by the sensor. The following criteria are considered to determine a

- o Contour quality (mainly based on the contrasts of the contours)
- o Confidence level in the eye corner tracking
- o Geometrical data (for example the matching between an eyelid edge and a parabola shape).

Each of these criteria provides a score. and all the scores are aggregated thanks to a weighted average. The weights are related to the importance of the criterion. The Blink Confidence rate is the average of the opening quality factor for all measurements during a given blink.

$$\text{Blink Confidence rate} = \frac{\sum_{i=1}^{N} \text{Opening quality factor}_i}{N}$$

$$N = \text{number of measurements during the blink}$$

$$\text{Blink Confidence rate} \in [0,1]$$

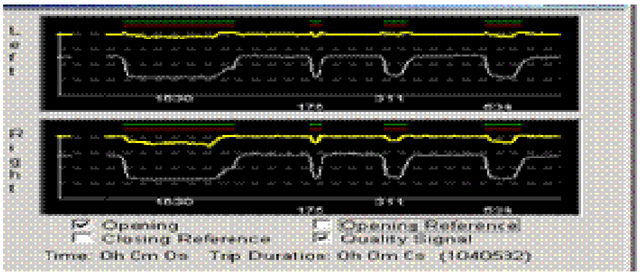


Figure 9: Opening signal

Figure 9 gives an example of the opening quality signal. This picture displays for left eye (top) and right eye (bottom) the eyelid opening signal (in white), the opening quality of the signal (in yellow). The red bar indicates that a blink has been detected and the green bar indicates that the blink has been validated according to the blink confidence rate. In addition the duration of each blink is written in white below the blink signals.

4 Diagnostic.

4.1 State of the art

The PERCLOS diagnostic has been developed a few years ago by Wierville (1999). It is the most popular measure of drowsiness. PERCLOS measures the proportion of time over 1 or 3 minutes where the eyes are 70 or 80 % closed. However the reliability of PERCLOS in real driving conditions is questionable. In fact PERCLOS is a function of two parameters: blink duration and blink frequency. Blink rate differs a lot from one driver to another. Tests performed within SAVE project (1996) have shown an important disparity. One of the drivers blinked 54 times in a minute, while another only 3 times. Besides, blink frequency is modified by some external conditions, like heat, brightness, humidity.

N. Galley *et al.* (2002) performed a wide study on different oculomotor parameters. He concluded that besides blink duration other parameters, like delay of reopening, speed of eyelid opening and closure and blink interval are at some degree indicator of drowsiness.

(Johns W.*et al.*, 2005) focused their work on lid closure and opening velocities and more specifically the peak velocities They conclude that sleepiness is associated with reduced lid closing and opening speed). The main drawback of these parameters is the inter-subject variability.

The AVRBs proposed by Johns W (2002) estimates the amplitude/peak closure velocity ratio of blinks. (Hargutt *et al* 2000) found that the blink velocity and the blink amplitude are strongly and linearly correlated for alert subjects. They stated that there is a control process that strives to maintain constant this ratio. Furthermore it has been observed that the AVRBs ratio is changing from alert subjects to drowsy subjects.

Most of these parameters require a high sampling rate and resolution. Thus they cannot be measured by the Eyelid sensor. The Blink rate and Blink interval are affected by other factors depending on the driving situation, environmental conditions (sun light) on the emotional state and stress

For these reasons the DVM diagnosis is based on blink duration. This parameter is a strong drowsiness indicator, robust to driver inter variability and measurable with a low frequency camera.

4.2 Fuzzy based diagnostic

Based on these conclusions, a specific diagnostic algorithm has been developed (Boverie *et al.*2005) Four different classes are used to describe the driver vigilance level: **Alert (A), Slightly Drowsy (SD), Drowsy (D), Sleepy (S).** They have been selected in accordance with physiologist expertise but also with the agreement of ergonomic engineers in order to take care about the Driver understanding and acceptance. Obviously the transition from one class to another is not crisp. Then the different classes can be described by fuzzy subsets. The vigilance diagnostic is calculated on a time sliding window ΔT and is updated when a new blink occurs.

Basically this diagnostic depends on the number of blinks of each category (*Short, Long, Very Long, Sleepy Blin*k) that can be observed on this time window. For example for the *Drowsy* state it depends on the number of *Long* and/or *Very Long* blinks, while for the Sleepy state it only depends on the number of *Sleepy* blinks. It should be noticed that the *Short* blinks are not used for the diagnostic because their number is highly variable from one driver to another. *Short* blinks are only used for the calculation of the confidence level.

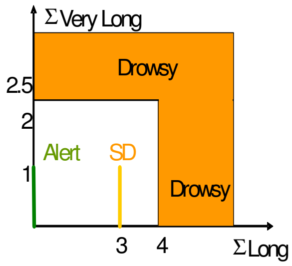
Nevertheless, instead of directly using the number of blinks, the sum of the membership degrees to each blink class of all blinks detected over the time windows is used as inputs of the vigilance diagnostic. In that way it is possible to preserve the progressiveness of the fuzzy information and also to cope with incertitude and inter and intra drivers' variability all along the process. For example if 4 *Long* blinks are detected on the window ΔT, with each of one a membership degree equal to 1, the vigilance state will be *Drowsy* with a membership degree of 1. The results will be the same with 5 *Long* blinks with for each a membership degree equal to 0.8.

The values of the sum of the membership degrees of the *Long* blinks, *ΣLong*, are fuzzified in 3 fuzzy subsets: *Small, Medium, and Large.*

Those of the *Very Long* blinks, *ΣVeryLong*, are fuzzified in 2 fuzzy subsets *Small* and *Large*.

The reasoning rules are directly deduced from the physiologist expertise. Only a few rules are used:

$Rule0:\ \ If\ Sleepy\ Blink\ \det ected$
$Then\ State\ is\ Sleepy$
$\quad if\ \ not\ \det ected$
$Rule1:\ \ If\ \Sigma Long\ is\ Small\ and\ \Sigma VeryLong\ \ is\ Small$
$Then\ State\ is\ Alert$
$Rule2:\ \ If\ \Sigma Long\ is\ Medium\ and\ \Sigma VeryLong\ \ is\ Small$
$Then\ State\ is\ Slightly\ Drowsy$
$Rule3:\ \ If\ \Sigma Long\ is\ L\arg e\ or\ \Sigma VeryLong\ \ is\ L\arg e$
$Then\ State\ is\ \ Drowsy$



A representation of the core of the vigilance subsets is given in *Figure 10*. It is assumed that there are a minimum number of blinks (N) on the window; otherwise, the current diagnostic is not validated. In that case, no diagnostic is delivered.

Figure 10: Representation of the core of the vigilance subsets

In addition, a "Diagnostic Confidence Level" is calculated for each vigilance class. This confidence level is achieved by aggregating the Confidence rates of the blinks that contribute the more to the corresponding state (respectively *Short* blinks for *Awake* state, *Long* and *Very Long* for *Drowsy* and *Slightly Drowsy*, *Sleepy blinks* for *Sleepy*). C_A, C_{SD}, C_D, C_S are the Confidence level for each vigilance class.

$$C_A = C_S;\ C_{SD} = C_D = (C_L + C_{VL})/2;\ C_S = C_{SB}$$

With

$$C_S = \frac{\sum_{i=1,N} \mu_{Si} C_i}{\sum_{i=1,N} \mu_{Si}} \quad C_L = \frac{\sum_{i=1,N} \mu_{Li} C_i}{\sum_{i=1,N} \mu_{Li}}$$

$$C_{VL} = \frac{\sum_{i=1,N} \mu_{VLi} C_i}{\sum_{i=1,N} \mu_{VLi}} \quad C_{SB} = \frac{\sum_{i=1,N} \mu_{SBi} C_i}{\sum_{i=1,N} \mu_{SBi}}$$

With C_S, C_L, C_{VL}, C_{SB} the confidence rate of each class of blink on ΔT and N the number of blinks on ΔT.
The diagnostic output is a (4, 2) vector which components are the degrees of membership of each of the predefined vigilance state classes with their associated confidence level.

$$State\ Vigilance\ Level = \begin{bmatrix} \mu_A,\ CL_A \\ \mu_{SD}, CL_{SD} \\ \mu_D,\ CL_D \\ \mu_S,\ CL_S \end{bmatrix}$$

5 Experimentation

The objectives of these experiments were to compare the performances of the DVM diagnostic with the expert references provided by a medical team.
The processing algorithms have been developed in a C++ environment and implemented in a Lap top. The camera and NIR units have been integrated into the instrumet cluster of the test vehicle. During the experimentations several information are recorded in real time:
Output of the system: Eyelid closure time, diagnostic.
Supervision data: During the experiments a technical supervisor and a medical team (a doctor) accompanied the drivers. Drivers are instrumented with physiological sensors to record their Electroencephalogram (EEG) and ElectroOculogram (EOG). Drivers are also asked to self rate the evolution of their state. In addition the technical supervisor annotations are recorded. At last videos of the driver head and upper part of the body as well as, front and back videos of the road are recorded. The images provided by these cameras, plus the images of the driver face from the DVM sensing device are mixed into a QUAD and then recorded by a VCR.
In addition some vehicle parameters are stored: Vehicle speed; Steering wheel angle; In-vehicle temperature; Yaw . . .
Experimentations have been performed on motorway, in real driving conditions, with 11 drivers following a strict experimental protocol. Each driver drove about 360 km for each experiment. The driver is not allowed to talk, listen to the radio or open the window. The driver is asked to stay as much as possible in the right lane and drive smoothly so to enhance the occurrence of drowsy situations.

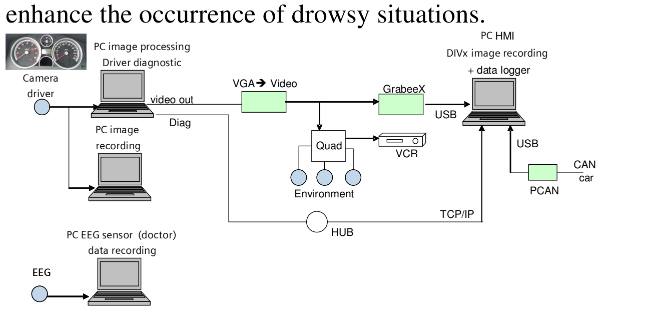
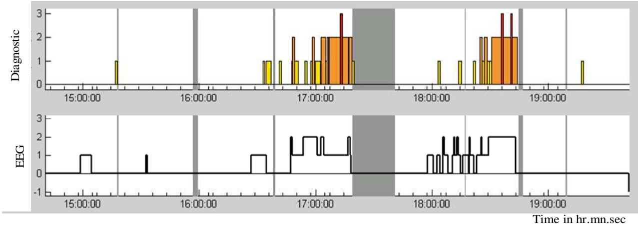


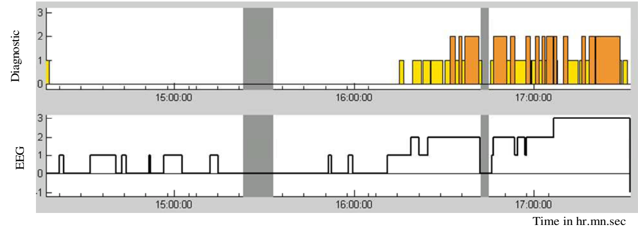
Figure 11: In vehicle experimental architecture

Figure 12 shows the comparison between the diagnostic automatically provided by the DVM system and the expertise deduced from the electrophysiological data by the medical team. Each experiment lasts about 3 hours. In the following pictures, only results for Drivers 05 and 11 are reported. For the first driver two Drowsy phases have been detected by the medical team and have been confirmed by the diagnostic. For the second driver drowsy and then sleepy situations occur by the end of the drive test. The diagnostic is able to detect this evolution quite well but under evaluates the state by the end of the test. It should also be noticed that some isolated slightly drowsy situations are detected by the expert and not confirmed by the diagnostic but this is not critical at all. For each experiment, a table of correlation between diagnostic and expertise is built up (see *Table 1*).The t_{ij} variables are calculated by analyzing the experimental results. The t_{ij} are representing the duration where expertise is rated as "state i" and diagnostic is rated as "state j". For example t_{11} represents the data points where the expertise is rated as sleepy and diagnostic as sleepy.
From this set of variables some statistics can be calculated. The HIT corresponds to the case when the expertise detects a degradation of the driver state and this degradation is well

detected by the diagnostic. The PASS corresponds to the case when the expertise does not detect any degradation and that is confirmed by the diagnostic. The MISS corresponds to the case when the diagnostic under evaluates the expertise. And the FA corresponds to the case when diagnostic over evaluates the expertise.



Driver D05



Driver D11

Figure 12: Comparison between physiological expertises issued from EEG and EOG and the diagnostic provided by the DVM system for drivers D04 and D11. Red bar indicates Sleepy state Orange for Drowsy and yellow for Slightly Drowsy

	Expertise				
		Sleepy	Drowsy	Slight. Drowsy	Alert
Diagnostic	Sleepy	Hit t_{11}	FA t_{12}	FA t_{13}	FA t_{14}
	Drowsy	Miss t_{21}	Hit t_{22}	FA t_{23}	FA t_{24}
	Sligh.Drowsy	Miss t_{31}	Miss t_{32}	Hit t_{33}	FA t_{34}
	Alert	Miss t_{41}	Miss t_{42}	Hit t_{43}	Pass t_{44}

Table 1: Table of correlation

Then two statistics can be derived from these data:
The Sensitivity refers to the proportion of people with state degradation who have a positive test result.

$$Sensitivity_{driver\ N} = \frac{HIT_{driver\ N}}{HIT_{Driver\ N} + MISS_{Driver\ N}}$$

The Specificity refers to the proportion of people without state degradation who have a negative test result.

$$Specificity_{driver\ N} = \frac{PASS_{driver\ N}}{PASS_{Driver\ N} + MISS_{Driver\ N}}$$

The final results are reported in *Table 2*. This table shows that the Sensitivity is good for all the subjects (greater then 80% for most of the subjects) with an average value of 86%. The Specificity is above 96% for 7 drivers. The average value is nearby 89% (92% without driver D04).

Drivers	01	02	04	05	06
Sensitivity	0.58	0.85	0.92	1.00	1.00
Specificity	1.00	0.75	0.49	1.00	1.00
Drivers	07	08	09	10	11
Sensitivity	0.81	0.95	0.75	0.89	0.87
Specificity	0.96	0.99	0.70	0.97	1.00

Table 2 Diagnostic performances for the set of experimented drivers

6 Conclusion

A robust vision based system for monitoring driver's vigilance has been designed, able to work autonomously in various conditions by night or day with critical sun illuminations. This system has been implemented in an experimental vehicle. The camera has been fully integrated in the vehicle instrument cluster leading to a good driver acceptance. At last the system has been tested in real driving conditions with different drivers. The results achieved are very promising with a very high detection rate and an extremely low false alarm rate for most of the drivers. The future steps will be mainly concerned by the test and evaluation on a wider Driver sample but also of the complete process including HMI in regard with Driver acceptance.

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