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Controlled inducement and measurement of drowsiness in a driving simulator

H. De Rosario[1] *J.S. Solaz*[1] *N. Rodríguez*[2] *L.M. Bergasa*[3]
[1]*Instituto de Biomecánica de Valencia, Universidad Politécnica de Valencia, Edificio 9C. Camino de Vera s/n, E-46022 Valencia, Spain*
[2]*FICOSA International, S.A, Pol. Industrial Can Magarola, Ctra. C-17 km 13. E-08100 Mollet del Vallès, Barcelona, Spain*
[3]*Department of Electronics, Universidad de Alcalá, Campus Universitario s/n. E-28871 Alcalá de Henares, Madrid, Spain*
E-mail: helios.derosario@ibv.upv.es

Abstract: The authors present a study of driver drowsiness, looking for patterns in biomedical and biomechanical variables that allow one to characterise the drowsiness cycle and detect its phases with new technologies. Biomedical signals, eye closure, pressures on the seat, and longitudinal and lateral control of the vehicle were recorded in a driving simulator, during a test in an environment that induced drowsiness, while subjects were motivated to struggle against sleep. Twenty volunteers were measured during the 1 h 45 min tests. A control signal that combined EEG and percent of eye closure (PERCLOS) was defined to classify the different states of the participants during the test. According to that standard, drowsiness was successfully induced in 80% of the subjects. The changes in those states influenced both the performance of the driving task and the biomedical signals, although the former were less sensitive to early fatigue. Heart rate variability and respiration turned out to be promising indicators of the state of the driver, which can be used in future drowsiness detection systems.

1 Introduction

One of the priorities of current approaches in automotive research is helping the driver to avoid accidents. Human error is the primary cause of casualties on the road, due to lack of attention or excess fatigue. Therefore one strategy to address this problem is detecting how the driver feels at each moment, by monitoring his or her activities.

Driver behaviour monitoring and the reliable detection of drowsiness and fatigue is one of the leading objectives in the development of new Advanced Driver Assistance Systems (ADAS). Nowadays, most systems of drowsiness detection in the market are based on the control of driving performance. These techniques assess variables recorded by vehicle standard protocols, like the position of the vehicle on the lane, its speed and steering wheel movements. Some research groups have used techniques based on the movement of eyes and the head [1, 2]; there are also approaches based on biomedical signals, like cerebral, muscular and cardiovascular activity [3–5], although most of them are still far from being effectively introduced in the market, according to recent surveys [6].

Biomedical signals are especially useful to collect detailed information of the body's response during the drowsiness cycle. The information that they provide goes beyond the usual systems that just detect risky situations (degraded driving performance or visual symptoms of lack of attention), and can potentially anticipate the onset of sleepiness. The major drawback of the techniques based on biomedical signals is that they require placing sensors directly on the subject's body, although there are some attempts to record them indirectly, through non-intrusive systems that could be used in real vehicles [7].

Heart activity is an important, easy-to-measure indicator of the driver's state. There are different techniques to measure it, but electrocardiography (ECG) is the most direct and informative one. Heart activity varies depending on the person's activity, and it is possible to identify the lack of attention by analysing heart rate variability (HRV).

A person focused on performing some task usually shows a more regular heart rate, and as the focus on the task decreases, heart rate becomes more irregular and HRV increases [3].

Electroencephalography (EEG) is a standard technique in sleep studies. Brain electric activity shows characteristic wave patterns in some states, and their difference between consciousness and sleep, as well as in the transition from one state to the other, has been widely studied. The power of θ-waves (in the 4–7 Hz range) is commonly regarded as a clear indicator of lack of attention and the onset of sleep [8–10]. The α range (8–12 Hz) plays an important part in the transition from wakefulness to sleep, although the behaviour of α-waves in that phase is less regular. They are not directly related to sleepiness itself, but to 'relaxed wakefulness', which leads to a reduced readiness to react to stimuli [8]. This condition can precede a deeper state of drowsiness, and in fact α-waves have also been regarded as an indicator of early sleep [9]. That interpretation is further supported by the increase of α activity associated with eye closure, which leads to drowsiness in rest conditions. However, this pattern may be misleading in driving conditions.

Microsleeps, which are a critical issue in road safety, are actually characterised by short periods where α-waves vanish and are replaced by θ-waves [10]. An explanation for this phenomenon is that drivers tend to avoid a complete closure of their eyes, even when fatigue seizes them, although they cannot prevent a partial closure and more frequent blinks, which are the cause of α artefacts. Accordingly, it has been stated that combining EEG and eye closure may permit one to detect unsafe situations reliably [10].

Electroencephalography is often combined with electrooculography (EOG), since drivers in fatigue exhibit changes in the way their eyes perform some actions, such as moving or blinking. These actions are known as visual behaviours and are easily observable in drowsy drivers. The percent of eye closure (PERCLOS) has been found to be the most reliable indicator of drowsiness [11]. Computer vision has been the tool chosen by many researchers to monitor visual behaviours, since it is a non-intrusive technique. Most of these systems use one or two cameras to track the subject's head and eyes [12–14]. Mono-camera systems have been a major focus in recent years, because their integration in industrial production is easier and less costly. Commercial products are available for general applications not focused on driving problems. A few companies commercialise systems as accessories for installation in vehicles [15–17], but they are not part of the car manufacturers' developments, since their reliability is still not high enough for car companies to take on the responsibility of their production.

Some camera-based systems also attempt to evaluate the driver's state by recognition of driver facial expressions. Such systems compare the current face of the driver with two calibrated images, one with eyes open and another with the driver in sleepy conditions. This method works Q1
well under ideal circumstances (head straight and face forward) [2], but as in the case of many other camera-based solutions, it is very sensitive to users wearing glasses, head movements and lighting conditions. Regardless of the type of measurement, one of the chief problems of drowsiness detection studies is the difficulty of carrying out experimental tests to validate the techniques. These tests are often conducted in the laboratory with driving simulators, because, for safety reasons, road tests in real vehicles have strong limitations. Laboratory settings allow the use of controlled environments, in which drowsiness can be induced, and it is possible to use many measurement devices that are difficult to integrate in real vehicles. However, the principal limitations of laboratory experiments are their lower realism and the risk of simulator sickness [18]. Another important problem in both road and laboratory studies is the alteration of the spontaneous behaviour of drivers: drowsiness in real driving is caused by a combination of the accumulated fatigue of the driver and the boredom associated with a monotonous task, especially when on familiar roads and in familiar vehicles. The unusual experience of participating in such an experiment, especially when subjects are instrumented, or the 'white coat effect' due to the presence of researchers, may hinder drowsiness; on the contrary, the higher level of stimulation in real road conditions may reduce sleepiness [19]. This limits the efficacy of the experiments, because in order to validate the models of drowsiness detection, it is important to have a balanced and realistic quantity of records of users in both wakeful and drowsy periods.

This paper presents a laboratory experiment conducted with non-intrusive instrumentation in a driving simulator, with a three-fold objective: (a) to gather a database of biomedical signals, plus driving performance parameters, and movements of the eyes and body from drivers in both wakeful and drowsy conditions, which may be successfully used to study measurable changes related to reduced attention and drowsiness; (b) to define a control variable based on EEG and PERCLOS, as recommended in the literature, to classify the drowsiness phases; and (c) to find patterns in the remaining variables that allow one to distinguish the different phases as detected by the control signal in order to define advanced methods of drowsiness detection and prevention.

2 Materials and methods

2.1 Subjects

The number of participants was limited by the hard Q2
conditions of the test, which required different degrees of sleep deprivation, and one also had to pass a test that excluded people with physical problems or the propensity to suffer simulator sickness. Previous studies with similar

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conditions used groups of between 7 and 30 participants to detect driver drowsiness [1, 3, 7, 20–22]. A group of 20 volunteers between 25 and 45 years was selected to participate in this experiment: ten of them performed the test in the afternoon, having slept normally the night before; the other ten performed it in the early morning, deprived of sleep after their workday and having remained awake during the previous 24 h. In each group there were five men and five women. All subjects signed a consent form, were informed of the purpose of the experiment, and were paid for their participation.

2.2 Laboratory

The experiments were conducted in the facilities of the Institute of Biomechanics of Valencia, in a room with controlled light, temperature and background sound. The sessions were programmed at different day hours, but the same night environment was simulated in all cases, with only an artificial dim light and a stable temperature of around 24–26°. A monotonous road sound at low volume was played during the simulation to further induce drowsiness.

The simulator consisted of a bench with a driver's seat, a seatbelt to fasten the subject and driving simulator software (Fig. 1). An infrared camera recorded the face of the driver. Two pads were placed on the seat pan and the backrest to record pressure maps. A thermographic camera and superficial sensors recorded skin temperature. A biomedical monitor was used to record biomedical signals: EEG, EOG, two ECG derivations, abdominal respiration and pulsoximetry. All signals were synchronised by a trigger or by the internal clock of the computers.

All the computers were placed behind the simulator bench, which was surrounded by panels to create a closed environment. To further prevent distraction and the 'white coat effect', the experiment was monitored from a control room out of the participant's sight, so that the subjects did not feel that they were accompanied or observed (Fig. 2).

Figure 1 *Instrumented subject*

2.3 Procedure

Once the subjects were informed and signed the consent forms, they were instrumented and drove for a period between 15 and 30 min until they were familiarised with the driver simulator. Before starting the measurement phase, they were told that they would receive an additional economical compensation if they remained awake through the test, in order to encourage them to struggle against falling asleep, as in a real driving context. Then the simulation was restarted, and the subjects had to drive for

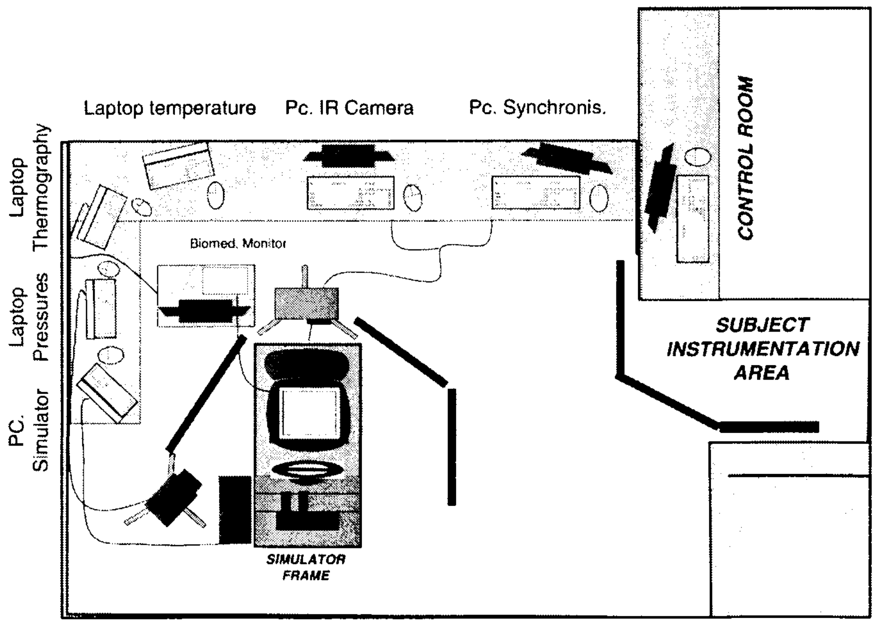

Figure 2 *Laboratory setup*

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1 h 45 min on a highway with low traffic and smooth curves in a night simulation.

During this whole period they were constantly monitored. After finishing the route, the light and sound were turned off and the subjects remained seated with closed eyes, in order to have a baseline measurement of physiological activity in a context similar to drowsiness or sleep without driving.

2.4 Variables and analysis

One group of the recorded variables was used to define a continuous 'control signal', which classified the state of the participants in three phases: 'Phase 0' (wakefulness, attentive behaviour), 'Phase I' (incipient fatigue, moderate fall of attention and decrease of driving performance) and 'Phase II' (risk of falling asleep, symptoms of drowsiness and important degradation of driving performance). Deeper states of drowsiness, such as total lack of attention or sleeps of variable duration, were assumed to fall into Phase II, since they occurred too seldom to be able to define characteristic patterns of the measured variables, and a drowsiness detection system should act before the onset of that phase, so there was no practical advantage in distinguishing it from Phase II.

The control signal was computed with an algorithm that used the values of EEG (filtered by EOG data) and PERCLOS in a 20-s window around every instant, and for which 'fatigue' and 'drowsiness' thresholds were defined according to the personal patterns of the subject's behaviour. The procedure for defining that control signal and its thresholds is represented in the scheme of Fig. 3, and described in detail next.

The EEG parameter used in the analysis was the ratio of θ-waves per minute, in contrast to α patterns. This measurement was adjusted by the judgement of medical experts, who visually interpreted the set of EEG + EOG signals, to discard 'false' waves caused by eye movements or other artefacts. PERCLOS was calculated with a monocular computer vision system. This system was tested in driving simulators and demo-cars driving in real conditions, and it was found to be robust to head turns, partial occlusions and illumination changes in both day and night scenarios.

The PERCLOS measure indicated accumulative eye closure duration over time, excluding the time spent on normal eye blinks. It was calculated by a new method of face and eyes recognition and tracking, developed by the authors, and called R-SMAT (Robust Simultaneous Modelling and Tracking), which was applied over the images in order to robustly detect eye position. A deeper explanation of the method can be found in [23]. The degree of eye opening was characterised by pupil shape. As eyes closed, pupils became occluded by the eyelids and their shapes became more elliptical. Therefore we could use the ratio of the pupil ellipse axes to characterise the degree of eye opening. We considered that eye closure occurred when that ratio was over 80% of its nominal size. Then, the measurement of eye closure duration was calculated as the time that the eyes remained in that state. More details can be found in [24].

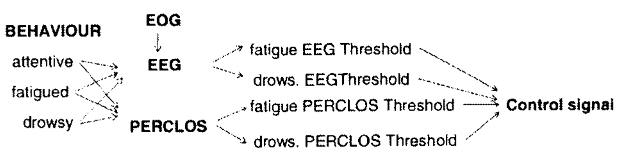

Figure 3 *Definition of the control signal*

The behaviour of users was based on the objective assessment of their driving performance and the subjective assessment of their body and face movements. Driving performance was judged by the lateral deviation of the vehicle and steering delay in curves and overtaking (lateral control) and by speed constancy in relation to posted speed limits (longitudinal controls). Body and face movements were annotated by an observer in the control room every minute during the test, and they were also recorded on video, so that the observer's notes could be contrasted afterwards.

The driver's behaviour was classified as 'attentive', 'fatigued' or 'drowsy', according to the criteria given in Table 1. The levels of EEG and PERCLOS associated with changes from 'attentive' to 'fatigued', and from 'fatigued' to 'drowsy', were determined in each test, and a confidence interval based on the whole set of data was defined for these thresholds, as represented in Table 1.

These thresholds were used to define the control signal, as a combination of the EEG and PERCLOS variables. The algorithm that defined this control signal considered that a high power of EEG θ-waves (and a few α-waves) was a reliable indicator of drowsiness, but that incipient fatigue could appear before this pattern occurred; besides, frequent blinks and high eye closure appeared early, although eyelid movement patterns vary a lot. Thus, the control signal determined that the driver was in 'Phase 0' only if both EEG and PERCLOS were below the lower threshold, and that the driver was in 'Phase II' if EEG was over the upper threshold or one of the signals was over the lower threshold and the other was over the upper one.

One analysis consisted in studying the reliability of a drowsiness detector based on the results of driving reactions alone, which is one of the common methods used for these kinds of devices, in comparison to the described algorithm. This comparison was carried out with the 'Cobweb method' developed by Patel and Markey [25, 26] and a conventional calculation of sensitivity/specificity.

The remaining signals (ECG, pulsoximetry, respiration, pressures and temperature) were used as 'test variables'.

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Table 1 Description of the parameters used to define the control signal in the different phases

Variable	Phase 0 (attentive)	Phase I (fatigued)	Phase II (drowsy)
Behaviour	High level of activity. Fast reactions to road events. Good lateral and longitudinal control	Slower reactions. Yawns and large body movements. Driving errors. Loss of facial expressivity	Fall of attention to the road. Departures off the lane
EEG	Lack of θ-waves. Regular patterns of α-waves with closed eyes. Threshold for θ ratio: <1.92 (s.d. = 0.88)	Small ratio of θ-waves. Regular patterns of α-waves with closed eyes. Thresholds for θ ratio: >1.92 (s.d. = 0.88), <8.22 (s.d. = 3.0)	High ratio of θ-waves. Loss of α regular patterns. Threshold: >8.22 (s.d. = 3.0)
PERCLOS	Small PERCLOS. Low and fast blinking. Threshold: <0.24 (s.d. = 0.19)	PERCLOS increase. More frequent and slower blinks. Thresholds: >0.24 (s.d. = 0.19), <0.45 (s.d. = 0.24)	High PERCLOS and slow blinks. Threshold: >0.45 (s.d. = 0.24)

They were analysed using a moving 20-s window, splitting them into the different phases, in order to look for parameters and patterns that characterise the drowsiness cycle. The resulting values of amplitude, frequency and correlation with predefined patterns were statistically compared with an ANOVA test, with the following factors:

- The phase of drowsiness (Phase 0, I or II), as a within-subjects factor, to find the differences due to the stage of the test.

- The group of subjects (sleep-deprived or non-deprived), as a between-subjects factor, to find the differences due to the initial state of the driver.

3 Results

The control signal indicated that 80% of users in both groups (normal and sleep-deprived) entered Phase I at least once during the trial. Phase II was detected in 20% of the subjects on average, but three more times in persons deprived of sleep (30%) than in normal subjects (10%). All
Q3 the subjects who entered Phase I experimented alternate periods of alertness and drowsiness, with an average of seven cycles during the test. Drowsiness periods (Phases I and II) were 80 s long on average for normal subjects and 110 s long for subjects deprived of sleep. The accumulated time of these periods over the whole test was 11 min for normal users and 15 min for subjects deprived of sleep (10 and 13% of the total time, respectively).

These results contrast with the longer and more frequent periods of drowsiness and sleep detected in other studies, which are several minutes long and account for more than 90% of time [20], or are associated with an increasing degradation of vigilance [21]. However, this experiment was designed to reproduce the frequent and dangerous situation in which drivers are not inclined to fall asleep, but are motivated to keep awake regardless of their level of fatigue. The relatively short spans of drowsy phases may be because of a difference in the drowsiness scales, but probably was also due to the active struggle of the subjects to keep awake. Thus, these results may be comparable to the microsleeps that occur in real driving.

The classification of driving performance measurements was compared with the control signal (Table 2 and Fig. 4). The Cobweb plots show that the classification based on driving performance alone coincided with the control signal for Phases 0 and II in more than 75% of the cases. The sensitivity to Phase I was lower, because an important amount of Phase I cases (47%) were classified as Phase 0.

Therefore driving performance is a good discriminator of Phases 0 and II (completely awake and drowsy), with a sensitivity (ability to detect true positives) of 83% and a specificity (ability to detect true negatives) of 89%. However, the intermediate Phase I (incipient fatigue, without risk of falling asleep yet) is difficult to predict with driving performance alone.

The test variables were compared as a function of the group and the state of the participants, in order to find to what extent these measurements may be effective detectors of the symptoms of drowsiness in comparison to the most usual methods. Significant differences were found in the ECG and respiration parameters.

Table 2 Confusion matrix of the classification according to driving as compared to control signal

	Control signal		
	P0	PI	PII
Classification			
P0	0.96	0.47	0.13
PI	0.05	0.39	0.04
PII	0.00	0.10	0.78

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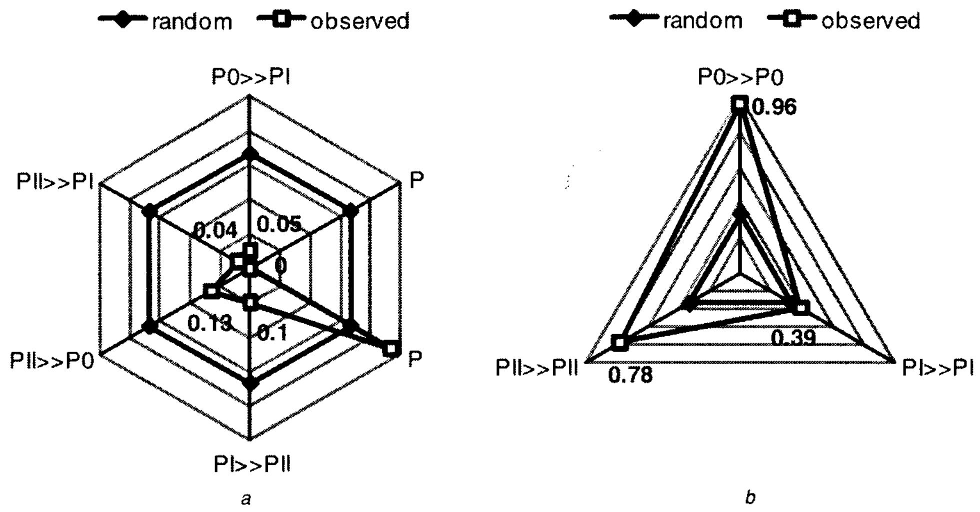

Figure 4 *Cobweb plots of*

a Wrong classification
b Correct classification

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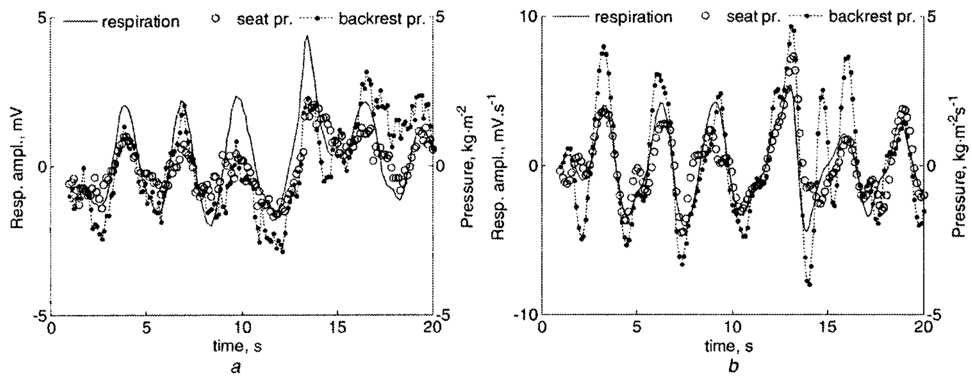

Figure 5 *Example of the correlation between respiration and mean pressures on seat pan and backrest*

a Raw data
b Derivatives

Heart rate variability (HRV) was parameterised as the RMS of differences between consecutive beats (rMSSD), and it differed significantly for one of the derivations, depending on the initial condition of the subject ($F(1, 12) = 7.773$, $p = 0.016$). rMSSD was 51 ms on average for sleep-deprived subjects, and 39 ms for non-deprived subjects. This coincided with the usual increment of HRV associated with fall of attention [3].

The phase indicated by the control signal had a marginally significant effect on the respiration amplitude ($F(1, 12) = 3.201$, $p = 0.099$): during Phase I or II (fatigue or drowsiness), its amplitude was 5% greater than during Phase 0 (alertness).

The parameters measured with the pressure sensors did not show significant differences depending on the factors of the analysis, but in static conditions a correlation was observed between the dynamics of respiration and the mean pressure on the backrest. From each subject, ten samples of 20 s of the respiration and pressure signals were randomly chosen, five of them corresponding to Phase 0 intervals and the other five to Phase I or II. In 14.3% of those cases, the derivative of the average seat pressure was significantly correlated with the derivative of the respiration signal (Pearson's rho >0.5, p corrected by Sidak's criterion <0.05). This ratio increased for backrest average pressure, to 20% of cases. These significant cases were concentrated in 50% of subjects. Fig. 5 shows one of these cases where the correlation can be clearly observed.

4 Conclusions

The experiments that have been described allowed one to study how drivers reacted in strenuous conditions, in which they tended to become fatigued and drowsy but struggled

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against falling asleep. This setting yielded periods of inattention shorter than previous, similar research; however, this result might actually reflect a more realistic situation, since a driver cannot remain asleep for more than a few seconds without having an accident [22], and the typical risk of accident owing to fatigue is not a deep, sustained state of drowsiness but 'microsleeps' or a transitory fall of attention in critical manoeuvres.

We used a control signal that classified the state of the driver during the test, defined by a combination of EEG patterns and PERCLOS, as recommended in the literature, and thresholds were defined from the observation of the driver's behaviour in terms of gestures and driving control. A comparison of this signal with a classification of the state of the user according to driving performance alone showed that the latter successfully identified the fully awake and drowsy states, although it was less sensitive to incipient fatigue. This might be because the driving scenario was a monotonous highway with low traffic, and some experienced drivers can maintain good control of the vehicle in such a context, despite increasing fatigue and fall of attention.

These results mean that the drowsiness detectors based on driver performance parameters such as lane crossings, speed and steering wheel movements are a good solution to detect risky situations, and could be used to prompt some emergency 'wake-up' system to give the user some time to get off the road and rest. Nevertheless, they should be complemented with more direct measurements of the physical state of the driver in order to anticipate those situations.

EEG cannot still be applied to real vehicles, but PERCLOS can be measured with non-intrusive in-vehicle cameras. The system that was used in the reported experiments has been tested in real driving conditions; it worked robustly during day and night and for users not wearing glasses, and yielded an accuracy ratio of over 95%. Unlike other systems, our proposal was robust to head turns, partial occlusions and illumination changes, although its performance decreased with drivers wearing glasses and it did not work with drivers wearing sunglasses. The results obtained in the simulator showed a high correlation between PERCLOS and EEG patterns; therefore PERCLOS can be a good candidate as non-intrusive ground-truth for the development of other sensors.

These experiments were also used to study the patterns of other biomedical and biomechanical signals as a function of the state of the driver, in order to check their potential as an input for future drowsiness detectors. Consistent with previous research, HRV showed higher rates in fatigued participants, but the factor that dominated the differences was the initial state of the driver, and this obscured the differences along the test; that is participants who were sleep-deprived generally showed higher rates of HRV than 'rested' participants, but we did not find a significant increase of HRV as the test progressed. On the other hand, respiration did increase in amplitude during Phase I and Phase II periods, when compared to Phase 0. This effect may be associated with a change in the sympathetic-vagal activity owing to the fall of conscience.

Another interesting finding is the correlation between respiration and average pressure on the seat, and especially on the backrest, which was found in some periods, although pressure was not found to be affected by the state of the user. The lack of significance in the results of the pressure measurements might be due to the artefacts introduced by the voluntary, large movements of the drivers.

The results of this study provide a promising background for the development of reliable advanced drowsiness detectors, based on sensor fusion. In addition to the information provided by driving performance (to detect critical situations) and PERCLOS (as a more sensitive indicator of early sleepiness), heart rate measurements can work as a general indicator of the driver's state on different days, which might be used to weigh the other signals. We analysed it through invasive ECG, but there are systems that claim to be able to measure heart rate through the steering wheel, although they are still under development [7, 27, 28].

A further concern related to ECG measures is that heart rate can vary for reasons not related to drowsiness. Nevertheless, we analysed heart activity on the basis of its instantaneous variability, or to put it another way, the regularity of heartbeats, rather than their rate. This indicator has been found to be more sensitive and diagnostic of alertness than heart rate [3]. In any case, all individual indicators must be taken with caution, since all systems are subject to noise and artefacts (intentional manoeuvres, glares, body movements and reactions etc.), so it is important to have redundant data to achieve robust measurements.

On the other hand, respiration amplitude changed as the test progressed. That is an understudied parameter that we are researching in more depth, in order to find more detailed patterns that can provide valuable information of the state of the driver, to be combined with the other variables.

In these experiments, respiration was measured by intrusive plethysmography, but we also found a high correlation with average pressures on the seat and the backrest in some drivers, although artefacts obscured them when drivers were moving. This problem hinders the application of pressures to evaluate the respiration, although it has a great technical potential, since it is an absolutely non-intrusive measurement. A possibility to overcome the problem of artefacts is to define an algorithm to filter the contribution of large movements, which could be complementarily recorded by visual recognition or by other techniques.

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