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Drowsiness Detection by Thoracic Effort Signal Analysis in Real Driving Environments

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Abstract— **Detection of drowsiness while driving is a leading objective in advanced driver assistance systems. This work presents a new index to assess the alertness state of drivers based on the respiratory dynamics derived from an inductive band.**

More than 100 hours of driving in real environments from 13 healthy subjects were analyzed. The proposed method has a sensitivity of 93.7% and specificity of 86.3% in detecting full awake drivers while it has a sensitivity of 83.1% and specificity of 95.3% in detecting drowsy drivers. The results show that the proposed index may be promising to assess the alertness state of real drivers.

I. INTRODUCTION

DROWSINESS is one of the main causes of vehicle accidents. A recent study showed that 20% of crashes and 12% of near-crashes were caused by drowsy drivers [1]. The morbidity and mortality associated with drowsy-driving crashes are high, perhaps because of the higher speeds involved combined with delayed reaction time [2].

Driver behavior 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). Most systems of drowsiness detection in the market based on measurements of driving performance evaluates variations of the control of velocity, steering wheel angle and other variables recorded by the CAN bus. Some research groups have also advanced methods based on the movement of eyes and head [3]. There are also approaches based on biomedical signals, like cerebral, muscular and cardiovascular activity, although most of them are yet far from being effectively introduced in the market.

Biomedical variables related to the autonomic nervous system provide direct information of the driver physiological state. Therefore, they may be especially useful to collect detailed information of the drowsiness cycle and anticipate risky situations while driving [4]. The systems available nowadays in the market based on the analysis of drowsiness in vehicle with physiological measures use mainly ocular activity, EEG or galvanic response [5].

The aim of this work is to detect drowsiness in drivers by the analysis of the variability of the respiratory signal measured with a thoracic band in real driving conditions.

II. MATERIALS AND METHODS

A. Measurement protocol

The objective of the real vehicle tests [6], is to prove that the behavioral and biomedical parameters that we choose as indicative of somnolence in simulator tests are useful to detect drowsiness in real driver performance using a fleet of professional drivers. The participants in the test were professional drivers (11 male, 2 female) with ages between 26 and 56 years (35.5 ± 8.9 years (mean ± standard deviation)) and no clinical conditions. These tests were designed and performed in IDIADA Technological Center to assure the safety of the drivers. The tests were carried out in two different routes: highway and mountain [7], to analyze the driver behavior with different concentration levels [8].

To perform these tests, a real vehicle was equipped with a biomedical monitor (Bitmed eXim Pro, BitMed) and an infrared high resolution camera. The biomedical signals selected as significant for this test were the external observer (video), Electroencephalography (EEG), Electrooculography (EOG) and thoracic effort. The thoracic effort signal was measured in all cases using an inductive band located at the middle trunk above the diaphragm. The respiratory signal was sampled at 100 Hz and filtered with a 5 Hz low pass filter. EEG signal was measured with a composition of four EEG single electrodes located on the vertex zone of the cranium and attached to the head surface with colloid. The EOG signal was measured with four Electromyography (EMG) single electrodes: two were located in the outer cantus of each eye in the case of the horizontal EOG setup, and two more electrodes located in the upper part and in the lower part of the right eye. Video signal was recorded to

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generate the external observer variable with an infrared high resolution camera.

Once the subjects are seated and connected to the acquisition systems, they were asked to drive for 8 hours on a real highway or a mountain route stopping during at least 10 minutes every two hours of continuous driving or every time they felt drowsy [9]. Figure 1 shows an image of the measurement environment.

Fig. 1. Instrumented subject in vehicle

B. Drowsiness state classification

In order to classify the state of the driver, a reference or Gold Standard signal (GS) was needed. The GS was obtained with an algorithm that combines the partial results by a majority ballot including the analysis of EEG, external observer evaluation of video recording and PERcentage of eye CLOSure (PERCLOS) in a 1 minute window around every instant, and from which 'fatigue' and 'drowsiness' thresholds were defined according to the personal basal signals in awake state. The GS defined three phases: phase 0 or attentive corresponds to a fully awake driver, phase 1 or fatigue to a fatigued driver and phase 2 or drowsy to a drowsy driver [10]. The EEG parameter used in the analysis was the ratio of vertex waves per minute [11]. This measurement was adjusted by the judgement of a team of medical experts (Clinica Dexeus, Barcelona, Spain), 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. 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 [10].

The External Observer signal was based on the subjective assessment of the behaviour (body and face movements) of the driver. Body and face movements were annotated by three external observers that analyze the video in real time and classify every minute of the test. The final External Observer signal was also computed with a majority ballot.

The driver's behaviour was classified as 'attentive', 'fatigued' or 'drowsy', according to the criteria given in Table I. These criteria are derived of the investigations reported in reference [10]. 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 I. These thresholds were used to define the GS, as a combination of the EEG, external observer and PERCLOS variables. The algorithm that defined this control signal considered that a high power of EEG vertex waves (and a few alpha 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. Both signals were combined with the external observer evaluation of the state.

TABLE I
CLASSIFICATION CRITERIA TO OBTAIN CONTROL SIGNAL

Variable	Phase 0 (attentive)	Phase I (fatigued)	Phase II (drowsy)
Behavior	High level of activity. Fast reactions to road events. Good lateral and longitudinal control.	Slower reactions. Yawns and large body movements.	Fall of attention to the road. Driving errors. Loss of facial expressivity.
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 pattern. 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)

C. Thoracic effort derived drowsiness index

In order to classify the state of the driver from the thoracic band, we have used a new index based in the comparison between the characteristics of the respiratory signal when a subject is awake (it is supposed that in this state the respiration is stable and more or less periodic), with the characteristics of the signal along the driving period. The Thoracic Effort Derived Drowsiness index (*TEDD*) is computed as follows:

The thoracic effort signal (*Resp*) is first filtered using a second order Butterworth lowpass filter with a cutoff frequency of 1 Hz.

The first three minutes of acquisition are devoted to the search of a 40 second reference window where the respiratory signal is maximally stable. In order to identify so, a sliding window with a delay of one sample is displaced along the first three minutes and the following estimator is computed for each sample:

$$RCX_{Wi} = \frac{1}{M}\sum_{n=1}^{M}\left|\left[\frac{\sum_{i=1}^{n}\left(Resp(i)\right)^2}{\sum_{i=1}^{M}\left(Resp(i)\right)^2}\right] - \frac{n}{M}\right| \qquad (1)$$

M is the number of samples inside the window. The estimator quantifies the stability of the variance [12] so the maximum of stability corresponds to the window that has the minimum value. Once the interval with maximum stability is set, the 70% percentile of *Resp* inside the interval (*Th*) is obtained. The respiratory period is determined breath by breath by identifying the crossings of *Th* with positive slope across the whole recording, and computing the time interval between consecutive crossings. The BB time series is defined by these time intervals. Next, the smoothed BB time series (sBB) is obtained by applying a moving average filter of 4 respiratory periods. The breathing variability signal is obtained as

$$VBB(n) = \left|sBB(n) - sBB(n-1)\right| \qquad (2)$$

This variability is smoothed again with another moving average filter of 10 respiratory periods obtaining the sVBB time series and finally, the TEDD index for the respiratory period *n* is defined as:

$$TEDD(n) = \frac{sVBB(n)}{VBB_{ref}} \qquad (3)$$

being VBB_{ref} the mean value of *VBB* inside the reference window.

TEDD is, then, an index of the stability of the breathing frequency. To classify the state of the driver and compare with the GS, two empirical thresholds have been obtained from previous studies in driving simulators [10]. The mean of *TEDD* (*mTEDD*) has been computed for each minute of the recording. For each minute, if *mTEDD*

- is below 3, a phase 0 is decided.
- is between 3 and 6, a phase 1 is decided.
- is above 6, a phase 2 is decided.

D. Statistical analysis

For each minute of recording, the phases obtained by the thoracic effort signal and the GS were compared in order to estimate the sensitivity and specificity of *TEDD*. Table II shows a symbolic assignment to interpret equations (4) to (9). In the equations, BC should be interpreted as the number of times in all recordings that *TEDD* classified the minute as a phase 1 while GS classified it as phase 2.

According to table II, sensitivity (*Sens*) and specificity (*Spec*) for each phase is defined as:

$$Sens_0 = \frac{AA}{AA+BA+CA} \qquad (4)$$

$$Spec_0 = \frac{BB+BC+CB+CC}{BB+BC+CB+CC+AB+AC} \qquad (5)$$

$$Sens_1 = \frac{BB}{BB+AB+CB} \qquad (6)$$

$$Spec_1 = \frac{AA+CC+AC+CA}{AA+CC+AC+CA+BA+BC} \qquad (7)$$

$$Sens_2 = \frac{CC}{CC+AC+BC} \qquad (8)$$

$$Spec_2 = \frac{AA+BB+AB+BA}{AA+BB+AB+BA+CA+CB} \qquad (9)$$

TABLE II

SYMBOLIC ASSIGNMENT FOR SENSITIVITY AND SPECIFICITY DEFINITION

GS		**PHASE 0**	**PHASE 1**	**PHASE 2**
TEDD	**PH0**	*AA*	*AB*	*AC*
	PH1	*BA*	*BB*	*BC*
	PH2	*CA*	*CB*	*CC*

III. RESULTS

Figure 2 shows an example of the performance of *TEDD* for a subject that it's always alert and a subject with occasional drowsiness. The driver's stops along his/her route are easily recognizable because the thoracic effort signal is zero (denoting disconnection of the inductive band). The drowsy subject is specially fatigued at the start of the recording and improves the performance after the first stop.

The second driver performed pretty well during the whole recording being always alert.

Table III shows the results of sensitivity and specificity for all subjects.

TABLE II

SENSITIVITY AND SPECIFICITY OF PROPOSED INDEX WHILE REAL DRIVING

	Sensitivity	Specificity
Phase 0 (fully awake)	93.7%	86.3%
Phase 1 (fatigue)	49.3%	88.7%
Phase 2 (drowsiness)	83.1%	95.3%

IV. DISCUSSION AND CONCLUSIONS

The results confirmed the viability of drowsiness detection while driving using the thoracic effort signal. The

Phase 1 state shows a lower sensitivity because it is a transition zone.

Some misdetections of the algorithm may be due to the inter-subject variability of the thoracic effort signal. In order to check so, future work will test if the thresholds on *mTEDD* can be adapted with the body mass index of the subject under measurement.

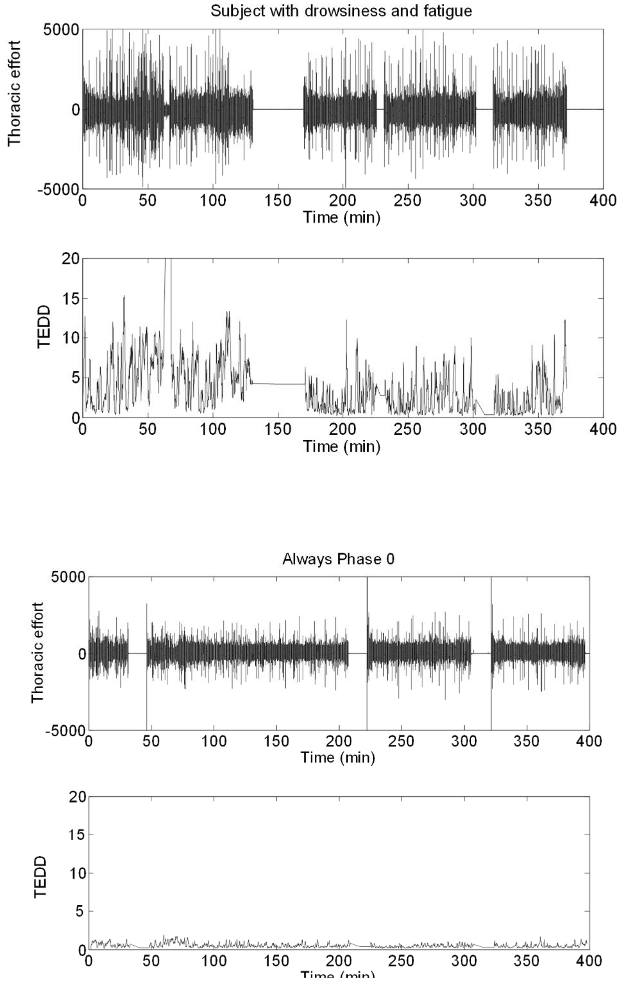

Fig. 2 Results for a drowsy driver (above) and alert driver (below)

TEDD avoids many pitfalls of PERCLOS that is highly influenced by sunlight or the wearing of sunglasses. The recordings in real vehicles analyzed in this paper did not show any adverse effect in the results due to vibrations and movement due to driving.

The thoracic band is a robust sensor that is sensitive to changes in the entire thoracic contour, while other sensors that measure displacement of the thoracic wall (ie. radar) will be more sensitive to vibrations and body motion. Further work will focus on unobtrusive measurement of the respiratory signal using bioimpedance techniques in order to avoid the use of the inductive band.

The results show that *TEDD* may be a promising index to assess the alertness state of real drivers.

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