Detection of Driver's Drowsiness by Means of HRV Analysis

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Abstract

It is estimated that 10-30% of road fatalities are related to drowsy driving or driver fatigue. Driver's drowsiness detection based on biological and vehicle signals is being studied in preventive car safety. Autonomous Nervous System (ANS) activity, which can be measured non-invasively from the Heart Rate Variability (HRV) signal obtained from surface ECG, presents alterations during stress, extrem fatigue and drowsiness episodes. Our hypothesis is that these alterations manifest on HRV. In this work we develope an on-line detector of driver's drowsiness based on HRV analysis. Two databases have been analyzed: one of driving simulation in which subjects were sleep deprived, and the other of real situation with no sleep deprivation. An external observer annotated each minute of the recordings as drowsy or awake, and constitutes our reference. The proposed detector classified drowsy minutes with a sensitivity of 0.85 and a predictive positive value of 0.93, using 25 features.

1. Introduction

The number of road fatalities in Spain in 2009 was 1690 [1], and summed 96,445 in the 33 countries members of the International Road Traffic and Accident Database (IRTAD) worldwide [2]. Previous researches estimate that 10-30% of these crashes are related to drowsy driving or driver fatigue [2][3]. That is why the detection of driver's drowsiness is so challenging for preventing car safety.

Electroencephalogram (EEG) is the most used signal to analyze the relaxation level of a subject. However the need of uncomfortable contact electrods on the head of the subject makes this technique not appropriate as part of a safety system for driving daily real life scenarios and other biological or vehicle signals are being studied.

Autonomic Nervous System (ANS) activity presents alterations during stress, extreme fatigue and drowsiness episodes [4]. Wakefulness states are characterized by an increase of sympathetic activity and/or a decrease of parasympathetic activity, while extreme relaxation states are characterized by an increase of parasympathetic activity and/or a decrease of sympathetic activity [4][5]. The ANS activity can be measured non-invasively from the Heart Rate Variability (HRV) signal obtained from surface ECG. Power on low frequency (LF) band (0.04-0.15Hz) is considered as a measure of sympathetic activity mainly, while power on high frequency (HF) band (0.15-0.4 Hz) is considered of parasympathetic origin in classical HRV analysis [6]. Balance between sympathetic and parasympathetic systems is measured by the LF/HF ratio.

The dominance of sympathetic system that characterizes wakefulness states decreases during non-REM sleep, and it increases again up to near wakefulness levels during REM sleep [7]. HRV has been also studied in transitions from wakefulness to extreme relaxation states. It has been observed a decrease in heart rate (HR) and in HRV at the beginning of sleep. The transition period is characterized by a decrease in the oscillation of very low frequency (VLF) of HR that anticipates a change in LF/HF ratio to a parasympathetic predominance [8].

The objective of this work is to develope an on-line detector of driver's drowsiness based on HRV analysis.

2. Materials

Two databases provided by FICO MIRRORS S.A. were used for the development and validation of the detector:

- Simulated Driving Database (SDDB): It consists of 11 records 120 minutes length in a driving simulation environment. The simulator was built in partnership with a provider specialized in trials, following well defined protocols that assure control and repeatability. The subjects that participated in this trials followed a sleep deprivation protocol between 7 and 26 hours before the test. After initial calibration, subjects did a driving simulation test of about 2 hours. During the last 15 minutes the simulator was switched off and signal acquisition kept on, letting most of the subjects rest with lights off. A 2-lead ECG signal was recorded at a sampling frequency of 256 Hz to-

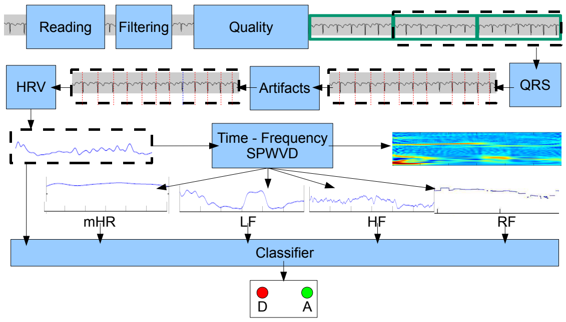

Figure 1. Components of the system

gether with other signals which are not used in this study. The drivers state could be assessed from information of the percentage of eye closure (PERCLOS), derived from video recordings, driving errors reported by the simulator, expert annotations based on EEG recording and external observer annotations. The references used in this study to validate the detector are the external observer annotations, which classify each minute of the recording as drowsy (D), fatigue or awake (A).

- Real Driving Database (RDDB): It consists of 10 records about 6 hours length from professional drivers in real driving situation: subjects driving a vehicle in highway or road during a working day. The subjects are not sleep deprived, and they have to stop at least every 2 hours. A 2-lead ECG signal was recorded at a sampling frequency of 256 Hz together with other signals which are not used in this study. In this case information of PERCLOS and external observer annotations are available, and, as in the former database, the latter constitute our references.

3. Methods

3.1. System overview

Our system works analyzing running windows of 5 minutes ECG and provides an output every minute, since the running window slides minute by minute.

The system is composed of the following subsystems/steps as shown in Fig.1:

- Data reading block.
- Filtering removes baseline and power line interference using algorithms from BioSigBrowser [9].
- Quality block, explained in more detail in section 3.2, quantifies the quality of each segment, discarding those with very low quality (which may correspond to signal loss or signal saturation) from further analysis.
- QRS detection using [10]. ECG signals were resampled at 500Hz so they fit the delineator requirements.
- Artifact detection identifies ectopic beats and false detections following the algorithm described in [11].
- HRV signal is estimated using the algorithm described in [12] based on the IPFM model.
- Time-Frequency analysis of the HRV signal is done using Smoothed Pseudo Wigner-Ville Distribution (SPWVD), which allows independent time and frequency filtering, as described in [13].
- Feature extraction, described in section 3.3, computes HRV parameters based on the SPWVD.
- Classification block uses a linear discriminant analysis (LDA) to classify each minute as awake (A) or drowsy (D), see section 3.4.

3.2. Signal quality qualification block

The quality qualification of the signal is made in two steps. The firs step characterizes the i-th minute of ECG that enters into the system computing the value defined by function f_i

$$f_i(x_i(n)) = \begin{cases} \sqrt{\frac{1}{L}\sum_{n=0}^{L-1}|x_i(n)-\overline{x_i}|^2} & \text{if} \frac{max(|x_i(n)|)}{|x_i|} \leq T_h \\ 0 & \text{if} \frac{max(|x_i(n)|)}{|x_i|} > T_h \end{cases} \tag{1}$$

where T_h is an experimentally defined threshold, $x_i(n)$ is the one minute i-th ECG segment and $\overline{x_i}$is the mean of $x_i(n)$. In this work T_h = 30.

The second step qualifies the new minute assigning one of the following values to it: Excellent, Good, Poor or Bad. We defined two thresholds C_1= 40 and C_2= 5000 such that if $f_i < C_1$ or $|f_i| \geq C_2$ then new minute is qualified as Bad, otherwise it is qualified using the qualifying function defined in (2), where $g_i = f_i - \sum_{k=1}^{i-1} \frac{f_k}{i-1}$, and E_i are experimentally adjusted thresholds with values E_1= 60, E_2= 125, E_3= 300.

$$q_i(g_i) = \begin{cases} \text{Excellent} & \text{if } g_i < E_1 \\ \text{Good} & \text{if } E_1 \leq g_i < E_2 \\ \text{Poor} & \text{if } E_2 \leq g_i < E_3 \\ \text{Bad} & \text{if } g_i \geq E_3 \end{cases} \tag{2}$$

3.3. Feature extraction

Instantaneous HR obtained prior to the estimation of HRV signal is low-pass filtered with a cut-off frequency of 0.03 Hz and constitutes the time-varying mean HR. Instantaneous power in the LF and HF bands were computed integrating, for each time instant, the SPWVD of the HRV signal in the corresponding bands. The instantaneous LF/HF ratio is also computed. Each component was then normalized by dividing it by the sum of the LF and HF power. Finally, respiratory frequency (RF) is estimated as the frequency at which it is located the maximum peak of the SPWVD in the HF band.

Table 1. # of annotated episodes at each database

Database	Awake	Dowsy
SDDB	60	1153
RDDB	2102	510
Total	2162	1663

Since driver's states annotations are only available for each whole minute, mean, standard deviation (SD), median, median absolute deviation (MAD), minimum and maximum values of the previously defined instantaneous parameters are computed within each minute and constitute the feature set for each minute. The feature mean value of the first three minutes is considered as baseline and it is subtracted from the subsequent minutes feature values. Besides the three minute normalization, the difference of each feature value with respect to the previous minute value was also computed.

3.4. Classification

The classifier is based on LDA using a leave-one out strategy to obtain the coefficients of the discriminant functions and to evaluate its performance. Wilks' lambda minimization criterion has been used for selecting the features in the discriminant function.

Three different scenarios were used for training: training with database SDDB, training with database RDDB and training with both databases merged. Performance was evaluated over the three databases (SDDB, RDDB and SDDB$\bigcup$RDDB) for each scenario. Performance measurements positive predictive value (P+) and sensibility (Se) were computed after balancing the confusion matrix. Our purpose was to identify driver's states non suitable for driving, so reference drowsy and fatigue states were considered as the same state (renamed as drowsy state). Table 1 shows total number of annotated episodes at each database.

4. Results

- Training with database SDDB: subjects of database SDDB had sleep deprivation, thus more drowsy and fatigue minutes than awake are present in the reference. Seven features were selected by the classifier. The five most significant features are: 3 minutes referenced RF minimum (RF3Min), 3 minutes referenced mHR maximum (mHR3Max), 3minutes referenced normalized LF median (LF3nuMed) , normalized LF median (LFnuMed) and mHR maximum (mHRMax). Table 2 shows performance of the classifier.
- Training with database RDDB: subjects of database RDDB did not follow any sleep deprivation protocol and reference is labeled with awake state most of the minutes. This is true except for subject 052, which stopped for sleep after the first driving hour. The reference in this case is labeled as drowsy most of the time. Twelve features were selected by the classifier. The five most significant features are: 3 minutes referenced RF mean (RF3Mean), RF3Min, RF mean (RFMean), RF minimum (RFMin) and normalized LF median(LFnuMed) . Performance is shown in Table 3.
- Resulting database from merging the two databases presented a well balanced drowsy/awake labels in the reference signal. Twenty five features were selected by the classifier. The five most significant features are: RF3Mean, RFMean, 3 minutes referenced RF minimum (RF3Min), RFMin and LFnuMed . Performance is presented in Table 4.

Table 2. Database SDDB trained classifier performance

Database	# features	P+	Se
SDDB	7	0.663	0.4987
RDDB	7	0.3867	0.4196
Merged	7	0.4205	0.4746

Table 3. Database RDDB trained classifier performance

Database	# features	P+	Se
SDDB	12	0.4707	0.7112
RDDB	12	0.8826	0.6941
Merged	12	0.8631	0.7058

Figures 2a and 2b show classification detail of two subjects, one from SDDB and another from RDDB. Bad quality EGC signal segments, plotted in red, are discarded so nor reference nor prediction are shown in their positions. Table 5 presents the mean(μ) and standard deviation(σ) of the most significant features.

Table 4. Merged database trained classifier performance

Database	# features	P+	Se
SDDB	25	0.4943	0.9775
RDDB	25	0.9406	0.4723
Merged	25	0.9313	0.8534

Table 5. Most significant features

Feature	State	$\mu \pm \sigma$
RF3Min	A	-0.0778 $\pm$ 0.1281 Hz
	D	-0.0749 $\pm$ 0.0696 Hz
RF3Mean	A	0.0586 $\pm$ 0.0895 Hz
	D	-0.0232 $\pm$ 0.0664 Hz
RFMean	A	0.3223 $\pm$ 0.1017 Hz
	D	0.2982 $\pm$ 0.0713 Hz
RFMin	A	0.2951 $\pm$ 0.0895 Hz
	D	0.2792 $\pm$ 0.0734 Hz
LFnuMed	A	65.1050 $\pm$ 15.6273 %
	D	64.2910 $\pm$ 18.8805 %

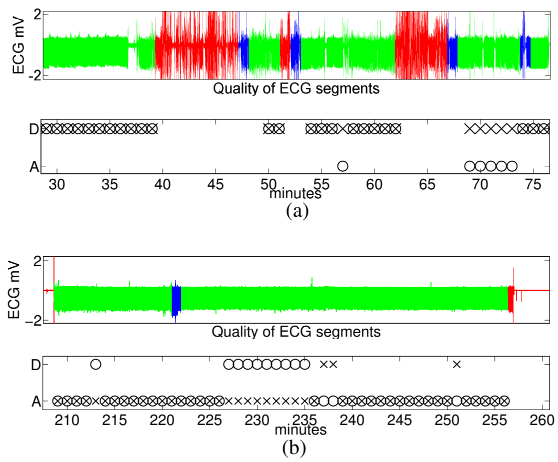

Figure 2. Detail of signal quality and classification of: a) subject 18 from SDDB and b) subject 56 from RDDB. Reference annotation (O), prediction (X). Quality: Bad (red), Low (Blue), Good (Green) or Excellent (Green).

5. Discussion and conclusions

Before implementing the classifier, features from all subjects where analyzed searching patterns like those described in previous works as [4, 5]. We focused on one minute characterization instead of timed events. No significant patterns were found prior to state changes.

The best performance is achieved using both databases for training, so including subjects with no sleep deprivation is important to obtain reliable classifiers.

Most significant features in Table 5 show lower and more stable RF in D states, which can reflect a predominance of parasympathetic activity, and higher and more stable LF, which can be associated with wakefulness, during A states.

Fig. 2 shows that the classifier overestimates drowsy states in subjects with sleep deprivation. Fig. 3 presents drowsy states underestimation by the classifier in subjects with no sleep deprivation. These results suggest that classifier identifies the global state of the subject to drive or not. Although the beginning and end of isolated drowsy episodes within a non sleep deprived subject, are not identified precisely, in general the detector is able to identify some minutes of the isolated (drowsy or awake) episodes.

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References

[1] Ministerio del Interior. Accidentes mortales en carretera 2009. In Dirección General de Tráfico. Spain, 2010; .

[2] Wegman F. Annual report. In IRTAD Road safety 2010. International Traffic Safety Data and Analysis Group, 2010; 278.

[3] Ministerio del Interior. La fatiga causa el 30% de los accidentes de tráfico en España. In Nota de Prensa. Dirección General de Tráfico, Spain, 2008; 1–2.

[4] Michail E, Kokonozi A, Chouvarda I, Maglaveras N. EEG and HRV markers of sleepiness and loss of control during car driving. In Engineering in Medicine and Biology Society, 2008. EMBS 2008. 30th Annual International Conference of the IEEE. aug. 2008; 2566 –2569.

[5] Furman G, Baharav A, Cahan C, Akselrod S. Early detection of falling asleep at the wheel: A heart rate variability approach. In Computers in Cardiology, 2008. sept. 2008; 1109 –1112.

[6] TASK FORCE OF ESC AND NASPE. Heart rate variability : Standards of measurement, physiological interpretation, and clinical use. Circulation 1996;93(5):1043–1065.

[7] Baharav A, Kotagal S, Gibbons V, Rubin BK, Pratt G, Karin J, Akselrod S. Fluctuations in autonomic nervous activity during sleep displayed by power spectrum analysis of heart rate variability. Neurology 1995;45(6):1183–1187.

[8] Shinar Z, Akselrod S, Dagan Y, Baharav A. Autonomic changes during wake-sleep transition: a heart rate variability based approach. Auton Neurosci 2006;130:17–27.

[9] Bolea J, Almeida R, Laguna P, Sörnmo L, Martínez J. Biosigbrowser, biosignal processing interface. In Information Technology and Applications in Biomedicine, 2009. ITAB 2009. 9th International Conference on. nov. 2009; 1 –4.

[10] Martínez J, Almeida R, Olmos S, Rocha A, Laguna P. A wavelet-based ecg delineator: evaluation on standard databases. Biomedical Engineering IEEE Transactions on april 2004;51(4):570 –581.

[11] Mateo J, Laguna P. Analysis of heart rate variability in the presence of ectopic beats using the heart timing signal. Biomedical Engineering IEEE Transactions on march 2003; 50(3):334 –343.

[12] Mateo J, Laguna P. Improved heart rate variability signal analysis from the beat occurrence times according to the ipfm model. Biomedical Engineering IEEE Transactions on aug. 2000;47(8):985 –996.

[13] Bailón R, Laouini G, Grao C, Orini M, Laguna P, Meste O. The integral pulse frequency modulation model with time-varying threshold: Application to heart rate variability analysis during exercise stress testing. IEEE transaction On Biomedical Engineering 2011;58(3):642–652.

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