Changes in Heart Rate Variability Indexes due to Drowsiness in Professional Drivers Measured in a Real Environment

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Abstract

The study aims to assess the changes in Heart Rate Variability (HRV) indexes in healthy subjects while driving in a real environment in order to detect drowsiness. The ECG of ten professional drivers was acquired while driving on routes familiar to the subjects. RR time series were quantified using a sliding window of 300 beats. Mean (mRR), standard deviation (SDNN), standard deviation of the differentiated time series (rmsDD), power of the low (PLF) and high (PHF) frequency bands as well as the ratio LF/HF were computed. In addition, the median frequency of the power spectrum (MEDF), the bandwidth that contains the 50% of the power (BW50) and a measure of the asymmetry of the spectrum (AFS) were obtained. Moreover, the Hurst exponent estimated by fractional differintegration (HFDI) and the short scaling exponent obtained by detrended fluctuation analysis (α_1) were computed. Two observers classified the state of the drivers minute by minute by inspection of video recordings as alert or drowsy driver. Five subjects were alert for the whole recording while the others presented one or more periods of drowsiness in seven recordings between resting stops. There are not significant differences between groups for all indexes but BW50 ($p<0.05$). Nevertheless paired tests comparing drowsy and alert periods show significant differences ($p<0.05$) for SDNN, HFDI, mRR, BW50, AFS, α_1, LF/HF and MEDF.

1. Introduction

Driver 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. The morbidity and mortality associated with drowsy-driving crashes are high, perhaps because of the higher speeds involved combined with delayed reaction time [1]. One approach for preventing traffic accidents is to develop technological countermeasures for detecting driver drowsiness, so that drivers can be warned before a crash occurs.

In the last decade diverse drowsiness detection systems have been developed that can be categorized in three classes. In the first there are the systems based on driving performance measurements, which evaluate variations of velocity, steering wheel angle, and other variables recorded by the Controlled Area Network (CAN) bus. Although some of these systems have entered the commercial market, they are subject to limitations of different kinds and do not work with micro-sleeps. The second class includes methods based on driver visual analysis using image processing techniques [2]. Notwithstanding that some of them are commercial products, they require hard calibration processes, and are limited to well controlled environments.

Heart rate variability (HRV) provides direct information of the driver physiological state, and may be especially useful to collect detailed information of the drowsiness cycle and anticipate risky situations while driving. The aim of the work is to study if HRV indexes can be used as a means to detect drowsiness while real driving. The measurements are intended to monitor drivers in normal conditions (not sleep deprived) and in a real environment.

2. Materials and methods

The standard lead I of ten male professional drivers (mean age: 41 years, standard deviation: 9 years) was acquired using a Bitmed eXea Ultra system at 500 Hz. During the measurement, the subjects were driving a known route mostly in highway roads. Mean measured time for each subject was 223 minutes (with a standard deviation of 106 minutes) and the mean time between stops was 93 minutes (with a standard deviation of 28 minutes). Total time of analyzed ECG was 2230 minutes.

Video recordings of the subjects were performed and two independent observers classified the state of drivers each minute as alert or drowsy. Criteria for the classification as drowsy were the reduction or absence of saccadic movements, eyes closed or nearly closed for periods longer than three seconds, eye rolling, inexpressive or angry expression, loss of body movement and/or uncontrolled head movements.

RR time series were detected between car stops. Missing beats, ectopic beats and false detections were manually corrected after visual inspection of the tachograms. A window of 300 beats was considered to track the changes in indexes that quantify the RR time series. The window was shifted along the RR time series in increments of one beat.

Eleven indexes were considered to explore changes due to drowsiness. Analyzed time domain indexes were the mean RR (mRR), the standard deviation of the time series (SDNN) and the standard deviation of the differentiated time series (RMSDD) [3]. Three classical frequency domain indexes were also computed: the power of the low frequency band (PLF), the power of the high frequency band (PHF) and the ratio of powers between both bands (LF/HF). Low frequency band is defined between 0.04 Hz and 0.15 Hz while high frequency band between 0.15 Hz and 0.4 Hz. For the estimation of the power spectrum, the RR time series have been resampled at 4 Hz using cubic splines, detrended using a Hodrick-Prescott filter [4] with cut-off frequency at 0.02 Hz and finally estimating the periodogram by applying a Hanning window. Three novel frequency domain indexes were also computed that do not require band definition: the median frequency (MEDF), the bandwidth that contains 50% of the power (BW50) and a measure of how the frequency limits of this bandwidth is symmetric with respect to MEDF (AFS). More details on the computation of these indexes can be found in [5]. Finally two indexes that estimate the scaling properties of the time series were computed: the short-scaling exponent estimated by detrended fluctuation analysis (α_1) between scales 4 and 16 [6] and a novel index that in the case of monofractal self-similar time series provides the Hurst exponent (H_{FDI}). To estimate H_{FDI}, the RR time series is fractional differentiated to a certain order [7] and its standard deviation is computed. A minimum search algorithm finds the order of the fractional differentiator that provides the minimum standard deviation (α_c). Then

$$H_{FDI} = \alpha_c + 0.5 \qquad (1)$$

The fractional differintegration is performed by applying an IIR filter [7]:

$$D^{\alpha} RR(k) \cong \sum_{j=0}^{k} c_j^{\alpha} \cdot RR(k-j) \qquad (2)$$

where the coefficients are recursively computed as:

$$c_0^{\alpha} = 1, \qquad c_j^{\alpha} = \left(1 - \frac{1+\alpha}{j}\right) \cdot c_{j-1}^{\alpha} \qquad (3)$$

Explored orders (α) to find α_c were considered between 3 (third order differentiation) and -3 (third order integration) and the search algorithm was configured to a resolution of 0.001

Once all the indexes were computed for each window, the mean, 95% and 5% percentiles of each index were computed for each time series between car stops. Comparisons were made between time series that presented at least a drowsy episode (D group) and those without drowsy episodes (A group). Moreover, in the case of time series including episodes of drowsiness according to the experts, the mean of the indexes were computed during the episode including ten minutes before and after the episode (drowsiness period). For comparison purposes, the mean of the indexes for the rest of time series not included in the drowsiness period were also evaluated (alert period).

3. Results and discussion

Table 1 shows the mean ± standard deviation of the mean indexes grouped by time series that presented (N=7) or did not present any drowsiness period (N=17). A t-Student test shows that there were no significant differences when comparing D and A groups except for BW50 ($p<0.05$) due to inter-subject variability of the indexes. Table 2 shows the mean ± standard deviation of the range of indexes between the 5% and 95% percentiles for time series in groups D and A. Once again, only BW50 shows significant differences ($p<0.05$) hinting a greater variability of the index during the recordings showing drowsy episodes.

Table 1. Results of the mean indexes computed along the time series.

Index	Mean ± SD A	Mean ± SD D
mRR (ms)	870 ± 95	907 ± 133
SDNN (ms)	55.8 ± 15.4	68.1 ± 22.4
RMSDD (ms)	31.8 ± 15.1	43.7 ± 19.8
PLF (ms^2)	1111 ± 614	1527 ± 1040
PHF (ms^2)	366.2 ± 418.7	584.5 ± 476.7
LF/HF	5.21 ± 2.64	3.62 ± 1.77
MEDF (Hz)	0.101 ± 0.019	0.109 ± 0.016
BW50 (Hz)	0.088 ± 0.039	0.132 ± 0.048
AFS	-29.11 ± 19.08	-40.18 ± 10.88
α_1	1.23 ± 0.17	1.15 ± 0.12
H_{FDI}	1.37 ± 0.19	1.24 ± 0.16

Table 2. Results of the range between the 5% and 95% percentiles for the indexes

Index	Mean ± SD A	Mean ± SD D
mRR (ms)	86.9 ± 35.4	93.3 ± 28.7
SDNN (ms)	93.3 ± 28.7	35.7 ± 10.6
RMSDD (ms)	13.9 ± 6.2	20.3 ± 8.5
PLF (ms^2)	1290 ± 820	1943 ± 1571
PHF (ms^2)	355 ± 266	636 ± 450
LF/HF	6.14 ± 3.34	4.63 ± 2.91
MEDF (Hz)	0.045 ± 0.018	0.059 ± 0.023
BW50 (Hz)	0.10 ± 0.047	0.15 ± 0.06
AFS	78.0 ± 20.6	72.7 ± 13.0
α_1	0.309 ± 0.062	0.315 ± 0.071
H_{FDI}	0.396 ± 0.104	0.397 ± 0.097

Results show that studying the evolution of indexes in the whole time series, the only index that show significant differences when comparing time series on group D or A is BW50. In those recordings that show drowsy states, the power spreads in a higher bandwidth and the spreading changes more than in time series where the subject is alert.

Focusing on the recordings of D group, Table 3 shows the mean and standard deviation of indexes during the alert and drowsiness periods.

Table 3. Results of the indexes in the D group separated by alert or drowsy periods

Index	Mean ± SD Alert period	Mean ± SD Drowsiness period
mRR (ms)	889 ± 122	927 ± 132
SDNN (ms)	63.6 ± 21.1	73.7 ± 24.3
RMSDD (ms)	43.2 ± 21.8	43.2 ± 18.9
PLF (ms^2)	1216 ± 686	1789 ± 1248
PHF (ms^2)	572 ± 488	576 ± 520
LF/HF	3.18 ± 1.58	4.33 ± 2.27
MEDF (Hz)	0.116 ± 0.020	0.100 ± 0.012
BW50 (Hz)	0.149 ± 0.062	0.110 ± 0.047
AFS	-43.9 ± 11.4	-34.6 ± 12.1
α_1	1.13 ± 0.14	1.20 ± 0.12
H_{FDI}	1.19 ± 0.18	1.30 ± 0.16

Paired student t-tests show that the differences when comparing the drowsy and alert periods are significant for several indexes. mRR is lower when the subject is alert ($p<0.05$) as well as SDNN ($p<0.005$), LF/HF ($p<0.05$), α_1 ($p<0.05$) and H_{FDI} ($p<0.01$). On the other hand, MEDF is higher when the subject is alert ($p<0.05$) as well as BW50 ($p<0.05$) and ASF ($p<0.05$). No significant differences were found for RMSDD, PLF and PHF. Those results indicate that during a drowsy period, the heart rate changes to a state with lower heart rate, higher variability, narrower spectrum (all these indicating a relaxing state) but with predominance of lower frequencies. On the other hand, BW50 in the alert period is much higher than in recordings of A group. This result may reflect the fighting of the driver to stay awake.

Figure 1 shows the evolution of some of the studied indexes in a recording of the D group. As seen, during the drowsiness periods, BW50 is lower and HFDI higher than in the alert periods. Nevertheless, an alarm of drowsiness based in only one index is not sufficient effective to classify correctly all the drowsiness periods. Further studies will focus in a multivariate alarm based on some of the studied (and maybe others) indexes based on heart rate variability.

On the other hand and because in order to reproduce their normal routine the drivers were not sleep deprived, the number of recordings with drowsiness periods is small (only seven). Then, the presented results must be regarded as preliminary although they hint the potentiality of some indexes.

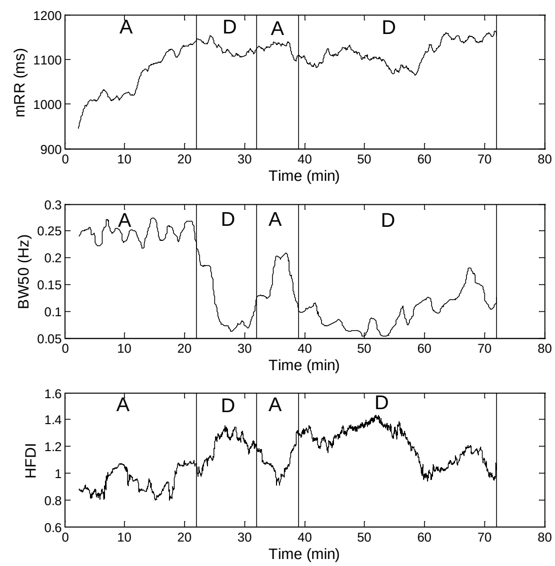

Figure 1. Example of evolution of mRR, BW50 and HFDI in a recording with drowsy periods.

The sleep onset induces physiological changes in the sympathetic-vagal system traduced in a drop of hearth beat frequency and a higher variability of the RR interval. The use of a physiological variable as HRV to estimate drowsiness detection in real environments may improve the current systems in the market avoiding misdetections due to variation of by sunlight or the wearing of sunglasses in the case of PERCLOS based systems and the attitude of the driver in the case of Driving behavior based algorithms.

BW50 may be a promising index to evaluate the drowsiness state of real drivers with “fighting not to sleep” patterns related to sleep onset while doing complex activities.

4. Conclusions

There are not significant differences between alert and drowsy subjects for all indexes but BW50 ($p<0.05$). Paired tests comparing drowsy and alert periods show significant differences ($p<0.05$) for SDNN, HFDI, mRR, BW50, AFS, α_1, LF/HF and MEDF. Results suggest that a drowsiness alarm based on HRV indexes is feasible but cannot rely in only one index.

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