

Real-time sleep prediction using a virtual sensor to estimate Heart Rate Variability (HRV) through Respiratory Rate (RR)

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and the output data sequences are corrupted by additive bounded noise [18].

This paper presents in the chapter II the used dataset, the algorithm that estimates the Respiratory Rate (RR), the methodology used for the calculation of the virtual sensor and the application of this system in a real-time algorithm. The experimental results are discussed in chapter III, where we show that we are able, using only the RR, to predict the sleep onset in a realistic environment within an average of 6 minutes and 54 seconds in advance with respect to the actual sleep, and a minimum of 1 minute and 12 seconds.

## II. METHODOLOGY

### A. Materials

This work has been based on a set of recording acquired in a realistic environment (AVL dynamic car simulator). A certain number of healthy adult subjects (8 subjects, 6 male and 2 female, average age 44.3 yrs., ranging between 18 to 81 years) has been tested. Each subject was instrumented with a state-of-the-art polysomnography device (COMPUMEDICS Somtè PSG4) acquiring the following signals:

- Electroencephalogram (EEG).
- Electrooculogram (EOG).
- Electromyogram (EMG).
- Electrocardiogram (EKG or ECG).
- Nasal cannula.
- Thoracic band.
- Abdominal band.
- Photoplethysmogram (PPG).

Then, the data have been analyzed by sleep expert medical doctors to classify the sleep stages along the timeline. The different sleep stages have been analyzed in compliance with the recommendations of the American Academy of Sleep Medicine (AASM). The following states have been scored:

- Non-REM 1-2-3 and REM sleep stages
- Movements during sleep
- Waking state

Fig. 1. AVL driver simulator, Graz(AT) [19]

In this work:

- The thoracic band signal will be used for estimating the Respiration Rate utilized as input in the algorithm.
- The PPG will be used for calculating the  $\lambda$  value, necessary for the virtual sensor estimation.
- These and all the other signals have been used by the sleep expert medical doctor for the sleep scoring, used as ground truth for validating the results that will be showed in the relative section. The ground truth is provided as sleep onset epoch, that is the time instant when the subject fall asleep while driving.

### B. Respiration Rate estimation

The RR has been calculated utilizing the thoracic band signal, sampled with a frequency of 32 Hz. We developed a MATLAB algorithm performing the following steps:

- Raw signal filtering, using a bandpass filter with cuts off frequencies at 0.1 Hz and 1 Hz;
- Selection of sliding data windows. Each window is composed of 1280 samples, with a partial overlapping among consecutive windows of 32 samples;
- Peaks detection, for each window all the peaks are detected utilizing the standard MATLAB library function “findpeaks”;
- RR(i) is calculated as:

$$RR(i) = \frac{1}{N} \sum_{j=1}^{j=N} \frac{Fs}{Peak(j+1) - Peak(j)} * 60 \quad (1)$$

where N is the number of peaks on which the mean value is calculated, Peak identify the thoracic band signal peak position in the time domain and Fs is the thoracic band sampling frequency.

Fig. 2. Respiration per minute calculated in the time domain in red, calculated in the frequency domain in blue.

### C. Virtual sensor estimation

Van Den Bosch et al. showed that the RRV can be used to detect the phase changing from awake to NREM1. The statistical tools are the standard deviation and the mean value [17]. The analyzed variable is:

$$Cv(x) = \frac{\sqrt{\frac{1}{N} \sum (x - \bar{x})^2}}{\bar{x}} \quad (2)$$

where  $x$  is the RR,  $\bar{x}$  is the RR mean value calculated on  $N$  samples. This variable should drop if the phase transition from awake to NREM1 is taking place.

So, as we know, the same phenomenon happens when looking at  $\lambda$ . The linearity between the differential of  $Cv$  ( $dCv$ ) and the differential of  $\lambda$  ( $d\lambda$ ) was verified and used through the set membership approach. The transfer function we calculated using set membership estimates a value of  $d\lambda$  taking only the  $dCv$  as input.

The system is assumed to be an LTI system of order  $n = 2$  with an Errors-In-Variables (EIV) structure. The noise limits  $\Delta\varepsilon$  and  $\Delta\eta$  are assumed to be equal to 1.

For the calculation of the transfer function  $G(z)$   $dCv$  has been considered as input and  $d\lambda$  as output. Both the input and the output were calculated by examining 40 seconds of signal.

For this work, the SparsePOP Matlab package was used to find an overall optimal POP solution. The solver used to approximate the global optimal solution was SeDuMi.

#### D. Virtual sensor implementation

The aim of this work is to develop an algorithm capable of predicting the sleep onset using the mathematical relationship between  $d\lambda$  and  $dCv$ . Based on the work developed in [20], the same algorithm was used, but instead of using  $d\lambda$  as input, it uses the  $dCv$ .

Fig. 3. Drowsiness detection algorithm developed in [20]

The differences between the Algorithm shown in the Fig. 3, instead of calculating  $d\lambda$  by the PPG power spectrum, it is calculated as:

$$\begin{cases} \dot{x} = Ax + B dCv \\ d\lambda = Cx + D dCv \end{cases} \quad (3)$$

Where  $A$ ,  $B$ ,  $C$  and  $D$  are the state space equation calculated by the transfer function. The other two variables  $x$  and  $\dot{x}$  are initialized as vectors of zero.

### III. RESULTS

As previously discussed this work was developed and tested on using data collected during the experimental activity carried out in Graz, on the driving simulator of the AVL. The transfer function used for the  $d\lambda$  estimation was calculated by observing a subset of those data. Once the transfer function was implemented in the algorithm, as presented in section II.C, it was tested on the collected dataset, reaching the results shown in Tab. 1.

TABLE I. COMPARISON ABOVE GROUND TRUTH, DROWSINESS DETECTION WITH THE PPG METHOD AND THE ONE WITH THE RR

	Realistic environment experimental activity		
	Sleep onset epoch	Drowsiness onset PPG	Drowsiness onset RR
1	17:13:31	17:04:23	17:07:30
2	13:56:54	13:42:26	13:40:32
3	18:00:13	17:54:07	17:53:14
4	15:15:43	15:06:08	15:07:15
5	11:49:57	11:48:19	11:47:26
6	No sleep	TN	TN
7	10:56:02	10:48:11	10:54:50
8	No sleep	none	none

The sleep onset epoch is the time instant when the subject falls asleep while driving, as defined by the sleep medicine expert through the analysis of the full PSG4 data set. The drowsiness onset PPG is the epoch when the PPG-based algorithm we presented in [20] provides an indication that the subject is about to fall asleep. Drowsiness onset RR is the epoch the algorithm presented in this paper provides the indication the subject is about to fall asleep.

As the reader can observe, both algorithms are able to predict the subject is about to fall asleep, while recognizing properly the case in which the driver does not fall asleep. The main advantage of using the RR-based approach over the PPG-based one is that, provided a sensor is available to measure the RR in a contactless fashion (e.g., through a radar), we can perform drowsiness onset computation effectively and accurately. This paves the way for innovative contactless drowsiness monitoring system, which are not possible to implement as contactless PPG measurement is today not as effective as contactless RR measurements.

This work improves over similar approaches, such as [14], in terms of both sensitivity and specificity, which are both 100%. Although only healthy subjects were involved in this study, and the number of participants involved is limited, these preliminary findings are significant since neither a false positive nor a false negative was found, and the data were collected in a realistic environment, with subject actually falling asleep while driving.

### IV. CONCLUSION

In this work we proposed an approach to predict the sleep onset using RR. The algorithm was tested on 8 different healthy subjects, showing sensitivity and specificity of 100%. A possible future application of this algorithm is drowsiness monitoring through contactless RR monitoring, which is not possible when using the PPG signal. This methodology reflected a set of good results, but in a little cluster of recordings, in an optimal condition, with a set of medical

devices. An important step would be to test and adapt it with a no-contact commercial device.

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