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



(Article begins on next page)

# Real-time sleep prediction using a virtual sensor to estimate Heart Rate Variability through Respiratory Rate

Luigi Pugliese
Politecnico di Torino
Dipartimento di Autmatica e Informazione-DAUIN
Turin, Italy
luigi.pugliese@polito.it

Massimo Violante
Politecnico di Torino
Dipartimento di Autmatica e Informazione-DAUIN
Turin, Italy
massimo.violante@polito.it

Sara Groppo
Sleep Advice Technologies Srl
Turin, Italy
sara.groppo@satechnologies.eu

***Abstract*—One of the most important causes of death while driving is sleepiness. To solve this problem, different kinds of technologies are needed. A recent work presented an approach based on Photoplethysmogram (PPG) analysis to predict the sleep onset. As PPG is not always available, especially in the case of commercial of the shelf wearable devices that provide features such as heart beat and respiration rate, in the paper we present a novel approach to predict sleep onset, which leverages a virtual sensor able to provide an estimation of the PPG-related Heart Rate Variability (HRV) through Respiration Rate (RR) analysis. The experimental results show 100% sensitivity and specificity in the collected data.**

***Keywords—Drowsiness onset detection, sleep onset, accident prevention, Photoplethysmogram, Respiration, Respiration Rate, Thoracic band, driver alertness, Heart Rate Variability, wearable devices, Wheels, Safety, Vehicle driving, Road accidents***

## I. INTRODUCTION

As reported by the American National Highway Traffic Safety Administration (NHTSA) sleep while driving is one of the most influential factors in the fatal vehicle crashes, along with excessive vehicle speed and the alcohol consumption [1]. Physiologically speaking, driving for more than two hours in a nocturnal environment, produces a driving impairment like a blood alcohol concentration of 0.05%.

To monitor effectively the driver's status, trying to avoid critical situations such as driving while drowsy, some works have been developed [2], based on different approaches:

- Vehicle-based measurements such as vehicle speed, acceleration, wheel position, etc. These measurements are non-invasive and relatively accurate but strongly depend on the driver's driving skills, road conditions, and vehicle characteristics [3][4].
- Behavioral analysis of the driver's eye state, blinking, yawning, head movement, etc. These measurements have the advantage of being easy to use but are sensitive to camera movement, surrounding environment, lighting conditions [5][6][7].
- Physiological measurements, based on biometric signals such as heart rate, brain activity, respiration [8][9][10].

Several works focused on using the physiological measurements. Some of them are based on the photopletismograph (PPG) signal, from which heart rate variability (HRV) is calculated for sleep classification [11] [12].

These techniques are effective as based on the analysis of the Autonomic Nervous System (ANS) and the action of its subsystems during the transition from awake to drowsy and sleep states:

- Parasympathetic Nervous System (PSNS), also defined as rest and digestion, or inhibitory system, takes control of all the functions of the autonomic body such as respiratory rate, heart rate, etc;
- Sympathetic Nervous System (SNS), also defined as a fight or flight system, which activates during normal activities, in which the variable controlled by the PSNS becomes less regular over time.

Two types of HRV are defined in the literature:

- Peak-to-peak distance, extrapolated from the time domain, of the Electrocardiogram (EKG) or the PPG, as time slice between two consecutive heartbeat peaks;
- $\lambda$ = LF / HF, where the denominator (High Frequency HF) and nominator (Low Frequency LF) are extrapolated from the power spectrum of the PPG (or EKG).

Going into the detail of $\lambda$, it represents the action of the ANS:

- A high $\lambda$ value denotes SNS activity;
- A low $\lambda$ value denotes PSNS activity [13] [14].

Other work has focused on detecting sleep initiation by Electroencephalogram (EEG) or EKG [15].

In this paper we introduce an algorithm capable of predicting the sleep onset, and detecting a certain level of sleepiness, using the Respiratory Rate (RR) calculated from an inductive PPG belt signal.

Guede Fernandez et al., proposed to use the RR to predict sleep, proposing an algorithm capable of reaching the specificity of 96.6%, and a sensitivity of 90.3% [16]. Our work, as well as previous approaches, leverage on the concept that Respiration Rate Variability RRV decreases during the stages of NREM sleep [17]. On the basis of this observation, we propose a virtual sensor capable to estimate the HRV based on RR analysis. The utilized methodology for virtual sensor estimation is the Set Membership approach for Single Input Single Output Linear Time Invariant (LTI) model. To gurantee the robustness of the virtual sensor, both the input 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 λ 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.

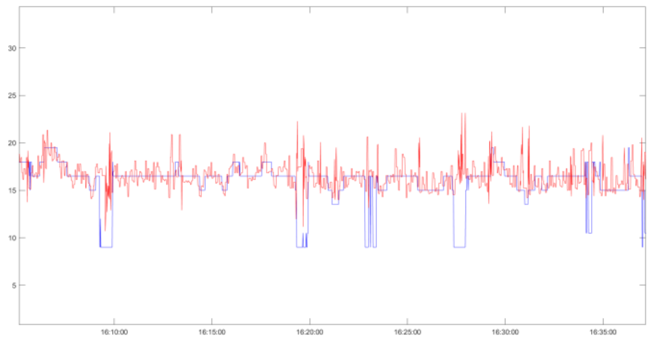


Fig. 2. Respiration per minute calculated in the time domain in red, calculated in the frequncy domain in blue.

### 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:

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

where x is the $RR_i$, $\bar{x}$ is the $RR_i$ 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 λ. The linearity between the differential of Cv (dCv) and the differential of λ (d λ) was verified and used through the set membership approach. The transfer function we calculated using set membership estimates a value of dλ 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 Δε and Δη are assumed to be equal to 1.

For the calculation of the transfer function G(z) dCv has been considered as input and dλ 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 dλ and dCv. Based on the work developed in [20], the same algorithm was used, but instead of using dλ as input, it uses the dCv.

**Algorithm 1** DrowsyLess

```
ComputeState(PPGsample):
i = 0;
while i < N do
    s=&(PPGsample[i * 2048]);
    x=computeFastFourierTransform(s);
    psd=computePowerSpectralDensity(x);
    if artifactsAreDetected(psd) then
        return (Awake);
    end if
    LF = FindPeak(psd,0.04-0.15 Hz)
    LF = FindPeak(psd,0.15-0.4 Hz)
    λ[i] = LF/HF;
    i++;
end while
j=0;
while j < N − 1 do
    δλ[j] = λ[j] − λ[j + 1]
end while
DrowsinessOnSetIndex = Σ_{i=0}^{N−1} |δλ_i| > δλ_T
if DrowsinessOnSetIndex < N/2 then
    return (Awake);
end if
if DrowsinessOnSetIndex ≥ N/2 then
    return (Drowsy);
end if=0
```

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

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

$$\begin{cases} \dot{x} = Ax + B\,dCv \\ d\lambda = Cx + D\,dCv \end{cases} \tag{3}$$

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 dλ 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 export 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.


## ACKNOWLEDGMENT

This work has been carried out in cooperation with Sleep Advice Technologies Srl (https://www.satechnology.eu/) as well as with Jmedical Srl (https://jmedical.eu/) who made available sleep expert medical doctors for the duration of the activity. The application experiment on the dynamic vehicle simulator in Graz (AT) has been accomplished in cooperation with AVL (www.avl.com) in the framework of the PRESLEEP project, funded by the European Commission through the grant agreement No 761708.


## REFERENCES


[1] Jin L, Niu Q, Jiang Y, Xian H, Qin Y, Xu M. Driver Sleepiness Detection System Based on Eye Movements Variables. Advances in Mechanical Engineering. January 2013. doi:10.1155/2013/648431

[2] LEE, Hyeonjeong; LEE, Jaewon; SHIN, Miyoung. Using wearable ECG/PPG sensors for driver drowsiness detection based on distinguishable pattern of recurrence plots. Electronics, 2019, 8.2: 192.

[3] W. Wierwille and L. A. Ellsworth, “Evaluation of driver drowsiness by trained raters,” Accident Analysis amp; Prevention, vol. 26, no. 5, pp. 571–581, 1994.

[4] P. M. Forsman, B. J. Vila, R. A. Short, C. G. Mott, and H. P. A. Van Dongen, “Efficient driver drowsiness detection at moderate levels of drowsiness,” Accident Analysis amp; Prevention, vol. 50, pp. 341–350, 2013.

[5] H. Ueno, M. Kaneda and M. Tsukino, "Development of drowsiness detection system," Proceedings of VNIS’94 - 1994 Vehicle Navigation and Information Systems Conference, 1994, pp. 15-20, doi: 10.1109/VNIS.1994.396873.

[6] S. Hu and G. Zheng, “Driver drowsiness detection with eyelid related parameters by support vector machine,” Expert Systems with Applications, vol. 36, no. 4, pp. 7651–7658, 2009.

[7] C. Schwarz, J. Gaspar, T. Miller, and R. Yousefian, “The detection of drowsiness using a driver monitoring system,” Traffic Injury Prevention, vol. 20, no. sup1, 2019.

[8] K. Fujiwara et al., "Heart Rate Variability-Based Driver Drowsiness Detection and Its Validation With EEG," IEEE Transactions on Biomedical Engineering, vol. 66, no. 6, pp. 1769-1778, 2019. Available: 10.1109/tbme.2018.2879346.

[9] G. Li and W.-Y. Chung, “Detection of driver drowsiness using wavelet analysis of heart rate variability and a support vector machine classifier,” Sensors, vol. 13, no. 12, pp. 16494–16511, 2013.

[10] Kannan, Aadharsh, et al. "Drowsiness onset detection." U.S. Patent No. 9,955,925. 1 May 2018.

[11] P. Boudreau, W.-H. Yeh, G. A. Dumont, and D. B. Boivin, “Circadian variation of heart rate variability across sleep stages,” Sleep, vol. 36, no. 12, pp. 1919–1928, 2013.

[12] G. Li and W.-Y. Chung, “Detection of driver drowsiness using wavelet analysis of heart rate variability and a support vector machine classifier,” Sensors, vol. 13, no. 12, pp. 16494–16511, 2013.

[13] F. Chouchou and M. Desseilles, “Heart rate variability: A tool to explore the sleeping brain?,” Frontiers in Neuroscience, vol. 8, 2014.

[14] P. Boudreau, W.-H. Yeh, G. A. Dumont, and D. B. Boivin, “Circadianvariation of heart rate variability across sleep stages,” Sleep, vol. 36, no.12, pp. 1919–1928, 2013.

[15] M. Awais, N. Badruddin, and M. Drieberg, “A hybrid approach to detect driver drowsiness utilizing physiological signals to improve system performance and wearability,” Sensors, vol. 17, no. 9, p. 1991, 2017.

[16] Guede-Fernandez, Federico, et al. Driver drowsiness detection based on respiratory signal analysis. IEEE access, 2019, 7: 81826-81838.

[17] Van Den Bosch, Oscar FC, et al. Breathing variability—implications for anaesthesiology and intensive care. Critical Care, 2021, 25.1: 1-13.VAN DEN BOSCH, Oscar FC, et al. Breathing variability—implications for anaesthesiology and intensive care. Critical Care, 2021, 25.1: 1-13.

[18] V. Cerone, D. Piga and D. Regruto, "Set-Membership Error-in-Variables Identification Through Convex Relaxation Techniques," in IEEE Transactions on Automatic Control, vol. 57, no. 2, pp. 517-522, Feb. 2012, doi: 10.1109/TAC.2011.2168073.

[19] L. Pugliese, M. Violante and S. Groppo, "A Novel Algorithm for Detecting the Drowsiness Onset in Real-Time," in IEEE Access, vol. 10, pp. 42601-42606, 2022, doi: 10.1109/ACCESS.2022.3167708.

[20] S. Groppo, E. Armengaud, L. Pugliese, M. Violante, and L. Garramone, “Automatic detection and prediction of the transition between the behavioural states of a subject through a wearable CPS,” Lecture Notes in Mobility, pp. 177–185, 2020.