Sleep apnea severity stratification by an FFT-based PPG-derived index

Diego Cajal[1,2,*], Eduardo Gil[1,2], Pablo Laguna[1,2], Carolina Varon[3], Dries Testelmans[4], Bertien Buyse[4], Chris Jensen[5], Rohan Hoare[5], Raquel Bailón[1,2], and Jesús Lázaro[1,2]

***Abstract*— A new index for sleep apnea stratification is proposed. This index is based on the detection of the frequencies at which cyclic variations of the heart rate (CVHR) occur in segments with abnormal breathing. A CVHR detector is also proposed. When this detector is used, the proposed index has a correlation of r = 0.68 with the apnea-hypopnea index. The absence of correlation when the CVHR detector is not used suggests that CVHR detection is necessary for a correct evaluation.**

***Clinical Relevance*—The index is obtained from a photoplethysmography-derived signal. This is a further step in the detection and stratification of sleep disorders with minimally invasive sensors and wearables.**

I. INTRODUCTION

Repetitive episodes of total or partial interruption of the respiratory flow during sleep remains a disorder with high prevalence in the general population. It is estimated that between 6% and 17% of the adult population suffers from obstructive sleep apnea [1]. Their effects can include fragmented sleep, daytime fatigue and impaired cognitive functioning leading to memory loss [2]. The Gold Standard for sleep apnea diagnosis is a polysomnography conducted in a medical center, recording a variety of physiological signals such as electroencephalography, electrooculography and electromyography. Therefore, it is far from being a comfortable test for the patient and has some influence on the regular sleep of the patient.

In [3], a pattern of bradycardia during apnea followed by an abrupt tachycardia at the end, is described in apnea diagnosed patients with an apnea-hypopnea index (AHI) > 5. AHI is the number of apnea and hypopnea events per hour. This pattern is known as Cyclic Variation of Heart Rate (CVHR). The number of CVHR cycles correlates with the number of abnormal breathing events with at least 3% desaturation [3]. This observation has led to the study of this pattern as a basis for sleep apnea detection. In [4], an algorithm for the automatic sleep apnea detection on the pulse-to-pulse interval (PPI) extracted from a PPG signal is presented. A strong correlation (r = 0.81) between the number of CVHRs and AHI was reported.

[1]Biomedical Signal Interpretation and Computational Simulation (BSICoS) Group, Aragón Institute of Engineering Research (I3A), IIS Aragón, University of Zaragoza, 50018 Zaragoza, Spain.

[2]Centro de Investigación Biomédica en Red en Bioingeniería, Biomateriales y Nanomedicina (CIBER-BBN), 28029 Madrid, Spain.

[3]Microgravity Research Center, Universite libre de Bruxelles, Brussels, Belgium.

[4]Department of Pneumology, Leuven University Centre for Sleep and Wake Disorders, UZ Leuven, Belgium.

[5]Brainmatterz, McKinney, TX 75071, USA.

*Correspondence: dcajal@unizar.es

This work presents an alternative to the automatic detection of each CVHR cycle based on the Fourier transform of the PPI extracted from the PPG signal. The proposed approach avoids the need for detecting each single CVHR cycle and its related errors. Since the CVHR pattern does not appear during the entire sleep period, a detector based on Hjörth parameters [5] is presented as a previous segmentation step to the spectral analysis.

II. MATERIALS AND METHODS

15 subjects who underwent polysomnography [6] were analyzed. Five subjects presented AHI$<$15; five 15$<$AHI$<$30; and other five AHI$>$30. Apneic and hypopneic events were labeled by medical experts. A finger PPG signal was recorded at 500 Hz and PPI signal is derived from a pulse detector [7] and resampled to 4 Hz.

A. CVHR detection

A signal segment with CVHR presence is identified with a preprocessing detector previous to the proposed index calculation. The relevance of this preprocessing segmentation and the performance of the detection method itself, is evaluated. A segment with CVHR pattern can last for several minutes with a cycle length ranging from 25 to 130 s [4]. Therefore, the proposed approach is a 180-second segment detection on the PPI signal, with 150 seconds of overlap, *i.e.*, 30-second step. In each segment a binary decision is made, either considered belonging to normal respiration (without CVHR) or to abnormal respiration (with CVHR).

First, event-based labels from the annotation dataset, *i.e.*, the beginning and end of each apnea/hypopnea, are transformed into segment-based labels, whether the segment contains normal or abnormal breathing. The number of apneic events within each segment is evaluated. If it presents at least 3 events, at a maximum distance of 90 s between events, the segment is considered as abnormal breathing. Once the segment-based labels were obtained, a bagged-trees classifier was used, using Hjörth parameters as inputs. The hypothesis is that segments with CVHR have a lower complexity index than segments without CVHR, since oscillations in a more narrow band are expected compared to the wider band spectrum of heart rate in segments of normal breathing. A leave-one-out strategy is used for validation.

B. Proposed Cyclic Variation of Heart Rate Index (CVHRI) for apnea quantification

For each segment, the FFT of the PPI signal is calculated and the frequency at which the maximum is found between 0

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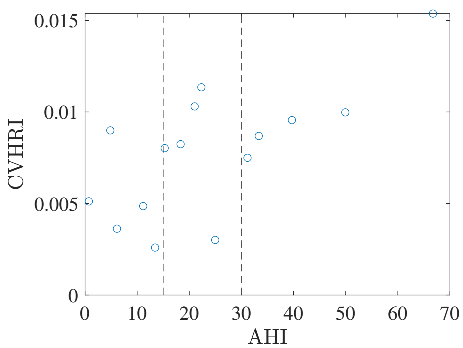
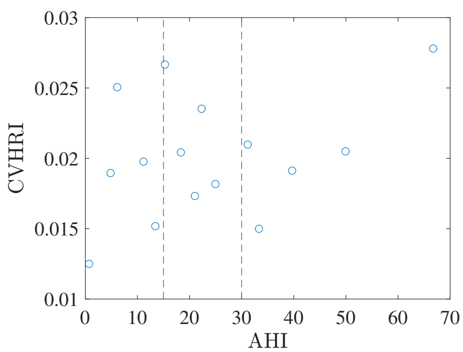


(a) With CVHR detection



(b) Without CVHR detection

Fig. 1: CVHRI vs AHI. Vertical lines separate AHI<15, 15<AHI<30 and AHI>30 groups.

and 0.1 Hz is obtained. Cyclic Variation of Heart Rate Index (CVHRI) is computed as the sum of the frequencies of the spectrum peaks divided by the total number of segments. In the case of pre-detection of CVHR, only the frequency values of the segments detected as abnormal breathing are taken into account in the sum, while still dividing by the total number of segments. Once the values for all subjects have been obtained, the pairwise correlation with the AHI is tested using Pearson's test. This correlation is also computed for subjects with AHI<15 (absence or mild apnea) and AHI>15 (moderate-to-severe sleep apnea) separately.

III. RESULTS

CVHR segment detection obtained 50.43% precision, 40.29% recall and 61.43% accuracy. Correlation between AHI and the proposed CVHRI with prior CVHR detection reaches r = 0.68 ($p < 0.05$), while no correlation is obtained without prior detection. No correlation is obtained for AHI<15 with CVHR detection nor without CVHR detection. The group with AHI>15 obtained r = 0.61 (p = 0.06) with CVHR detection and no correlation without CVHR detection. Fig. 1 shows CVHRI vs AHI.

IV. DISCUSSION

Results indicate a moderate correlation of the newly proposed CVHRI, with prior CVHR segment identification, with AHI. No correlation is obtained in the case with prior CVHR segment identification for AHI<15. This suggests that the method may be effective only for moderate and severe cases. No correlation was observed in any case when no prior CVHR segment identification is performed, regardless of the apnea severity groups. These results suggest that the role of the CVHR detector is very relevant. Further studies should be carried out in order to improve the CVHR pattern detection.

The detector's performance for CVHR segment identification, in its actual structure, is low. It remains as future work to improve the detector, and to include more subjects and eventually oxygen saturation information. The latter is greatly affected by the total or partial interruption of respiratory flow during apneas so it can provide additional valuable information, as suggested by the work in [3], which shows that CVHR pattern is closely related to oxygen desaturation, as this pattern is blunted when patients are supplied with oxygen during sleep.

V. CONCLUSION

An apnea-severity related index based on Cycle variation in Heart rate, CVHRI, has been proposed, obtaining a correlation of r = 0.68 ($p < 0.05$) with AHI when calculated in segments where the presence of a CVHR pattern was automatically identified. A method based on Hjörth parameters of PPI has been proposed for the detection of these patterns. Prior detection of these patterns has been proved necessary, to restrict the index calculation to those segments. Only the PPI signal derived from PPG has been used in this work, implying a step ahead in the challenge to evaluate sleep apnea with minimally invasive and wearable methods.

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