OSAS Detection in Children by using PPG Amplitude Fluctuation Decreases and Pulse Rate Variability

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Abstract

An analysis of the pulse rate variability (PRV) during decreases in the amplitude fluctuations of pulse photoplethysmographic (PPG) signal (DAP) events, and their utility in obstructive sleep apnea syndrome (OSAS) screening is presented as an alternative to heart rate variability (HRV) which will save the need of electrocardiogram (ECG) recording. 21 polysomnographic registers from children whose age was 4.47 ± 2.04 *(mean* $\pm$ *SD) years were manually labeled as OSAS (10 children) or not (11 children) following standard clinical procedures. Then DAP events were automatically detected and classified as apneic or non apneic by a linear discriminant analysis whose features come from the PRV. Subsequently, the apneic DAP event per hour index was used to discriminate OSAS from non-OSAS children. Results show an improvement in accuracy of subject classification with respect to the HRV analysis of* 6.7%*, reaching a* 86.7% *(*100% *for sensitivity and* 71.4% *for specificity). These results suggest that PRV can be used to discriminate apneic and non-apneic DAP events without introducing any additional signal and so a decision from just the PPG with same results as if the ECG were also considered, which takes special relevance in sleep studies.*

1. Introduction

Obstructive sleep apnea syndrome (OSAS) is characterized by an interruption of the airflow to the lungs produced by an upper airways occlusion during sleep. Then arterial oxygen saturation (SaO_2) goes down across time and mechanical respiratory efforts are intensified in order to reopen upper airways. If these efforts are not enough and hypercapnia level is dangerous, an arousal is generated to reactive all the peripheral systems and the respiration is restored. This episode could occur hundreds of times in a single night producing serious health implications [1]. The open-close cycle in the upper airways produces a regular oscillatory state of peripheral systems such as cardiac and vascular. For instance, heart rate decrements during apnea and increases during restore breathing. While vascular system presents vasoconstriction during apnea and vasodilatation after apnea [2].

Polysomnography (PSG) is the gold standard procedure for OSAS diagnosis. It consists of an overnight recording of different electrophysiological signals. PSG is a very expensive procedure because the acquisition and analysis of those signals requires human experience and specialized equipment, and, the number of sleep centers is reduced.

In the last decade, application of different techniques for home sleep apnea monitoring has been extensively developed. Some of the presented alternatives are based on the pulse photoplethysmographic (PPG) signal. The use of PPG signal results particularly interesting since this signal is provided by the pulse oximeter, which is a very simple, cheap, and comfortable sensor. Furthermore, the pulse oximeter is widely adopted as SaO_2 monitor, and this is an essential parameter in the OSAS scrutiny. Obtaining a robust discrimination between normal and pathological subjects from only a pulse oximeter would allow us to consider an ambulatory diagnosis with its both social and economic advantages. The number of decreases in amplitude fluctuations of the PPG signal (DAP) events per hour was proposed as discriminator of OSAS and normal children in [3], and later, a heart rate variability (HRV) analysis during the DAP events was proposed in [2] as discriminator of those DAP events which are related to an apnea from those which are not, improving the accuracy of subject classification and showing that combination of DAP events and HRV could be an alternative for sleep apnea screening.

The principal disadvantage of using HRV is the need of electrocardiogram (ECG) as an additional record, and this takes more relevance in sleep studies context because it is important to minimize the number of sensors over the patient in order not to affect his physiological sleep. In this paper, the study presented in [2] is repeated, this time evaluating the possibility of using the pulse rate variability

(PRV) obtined from the PPG signal instead of the HRV to discriminate apneic from non apneic DAP events, saving the need of ECG recording.

2. Methods

2.1. Data

The same database used in [2] was used in this paper. It includes PSG records of 21 children (11 boys, 10 girls) whose mean age was 4.47 ± 2.04 (mean $\pm$ standard deviation (SD)) years. The registers were acquired at Miguel Servet Children Hospital, Zaragoza, Spain, according to the standard methods defined by American Thoracic Society [4], using a commercial digital polygraph (EGP800, Bitmed). PPG and SaO_2 were recorded by pulse oximetry (COSMO ETCO2/SpO2 Monitor Novametrix, Medical Systems) with a sampling rate of $F_s = 100$ Hz, and air flow was recorded with the same sampling rate by an oronasal thermocouple. The PSG data were scored manually following standard procedures to discriminate OSAS (10 children) from non-OSAS children (11 children).

2.2. DAP events and PPG pulses detection

DAP events were detected as in [2], by the algorithm described in [3]. It is based on a preprocessor stage which suppress the mean, an envelope detection using root mean square technique and a decision rule based on an adaptive threshold. The detector also includes an artifact detector stage based on Hjorth parameters.

The pulse detector algorithm is based on the slope sum function (SSF) proposed in [5] to delineate blood pressure signal. The SSF enhances the abrupt upslope of the PPG pulses over the smoother one of the dichrotic pulses:

$$y(n)=\sum_{k=n-w}^{n} u(k),\ u(k)=\begin{cases} x'_{\text{PPG}}(k), & x'_{\text{PPG}}(k)>0 \\ 0, & x'_{\text{PPG}}(k)\leq 0 \end{cases} \quad (1)$$

where $x'_{\text{PPG}}(n)$ is proportional to the first derivative of $x_{\text{PPG}}(n)$:

$$x'_{\text{PPG}}(n) = x_{\text{PPG}}(n) - x_{\text{PPG}}(n-1). \quad (2)$$

The next step is the peak detection, $n^*_{\text{A}_i}$, in $y(n)$. A time varying threshold was proposed in [5] which consists of a percentage of the amplitude reached at previous detection $y(n^*_{\text{A}_{i-1}})$, which keep constant between detections. This percentage should be higher than 50% in order to avoid detections of dichrotic pulses, but that is too high when using the algorithm with PPG signals from PSG records because peaks during DAP events will not be detected due to their fast decrease to low amplitude. For this reason, a new time varying threshold $\gamma(n)$ which decreases between detections was introduced. The threshold keeps the value $\gamma(n) = y(n^*_{\text{A}_{i-1}})$ during a refractory period T_r and after this it begins to decrease linearly. If there is no new detection after a period which consists of an estimation of the interval between peaks $\widehat{m}_{\text{AA}_i}$, the threshold will have decreased to a percentage α of $y(n^*_{\text{A}_{i-1}})$ and then maintains its value until a new detection. T_r was set to $0.15F_s$, and α was set to 30%. At initialization, $\widehat{m}_{\text{AA}_i}$ corresponds to a high heart rate (80 beats per minute). Later it is set to the median of the last three peak-to-peak intervals previously detected.

Finally, the maximum of i^{th} PPG pulse n_{A_i} is searched in a 300 ms-length interval centred around $n^*_{\text{A}_i}$. Figure 1 illustrates the behaviour of this detector.

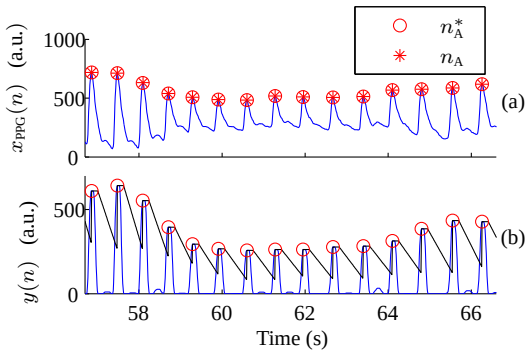

Figure 1. Example of detector behaviour during a DAP event: (a) shows the PPG signal, and (b) shows its SSF (blue) and the resulting time varying threshold (black).

2.3. PRV analysis

The PRV analysis was similar to the HRV one in [2]. Normal sinus beats located at n_{A_i} and determined by the method in [6] are used to generate the inverse interval function:

$$d^u_{\text{IIF}}(n) = \sum_i \frac{1}{n_{\text{A}_i} - n_{\text{A}_{i-1}}} \delta\left(n - n_{\text{A}_i}\right) \quad (3)$$

where the superscript u denotes that the signal is unevenly sampled. A 2 Hz evenly sampled version denoted $d_{\text{IIF}}(n)$ in this paper was obtained by cubic splines interpolation.

The smooth pseudo Wigner-Ville distribution (SPWVD) $S_x(n, f)$ was used to analyse the spectral parameters of the PRV in a time-frequency map. The SPWVD was chosen because of its high time and frequency resolution and its independent smoothing in time and frequency.

Power in the very low frequency (VLF) (0.0033-0.04 Hz) ($\mathcal{P}_{\text{VLF}}(n)$), low frequency (LF) (0.04-0.15 Hz) ($\mathcal{P}_{\text{LF}}(n)$), high frequency (HF) (0.15-0.5 Hz) ($\mathcal{P}_{\text{HF}}(n)$) bands, and low to high frequency ratio ($\mathcal{R}_{\text{LF/HF}}(n)$) were computed. Their normalized versions with respect to the total power were also computed, and they follow the same

nomenclature with an additional n as subscript, for example, $\mathcal{P}_{\text{HF}_n}(n)$ is the normalized version of $\mathcal{P}_{\text{HF}}(n)$.

Features set. In order to discriminate whether a DAP event is associated or not to an apnea, the same four windows defined in [2] related to DAP events onset (n_{DO_j}) were used. Three of the four windows have a length of 5 s.: The reference window (w_{r_j}) which begins 15 s. before n_{DO_j}, the DAP window (w_{d_j}) which begins 2 s. before the DAP, and the post-DAP window (w_{p_j}) which begins 15 s. after n_{DO_j}. The fourth window is called global window. It begins 20 s. before n_{DO_j} and its length is 40 s. Fig 2 illustrates w_{r_j}, w_{d_j}, and w_{p_j} over the mean of $d_{\text{IIF}}(n)$ during related and non related to apnea DAP events.

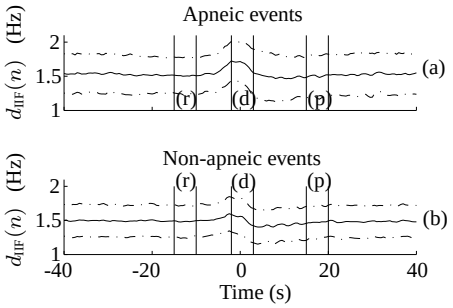

Figure 2. $d_{\text{IIF}}(n)$ mean $\pm$ SD for apneic (a) and non-apneic (b) DAP events. Reference (r), DAP episode (d), and post-DAP episode (p) windows, with DAP onset at time 0 s.

The set of features is composed of the same 34 features used in [2] but using the PRV instead of HRV. These features come from the computation within the four defined windows of the mean of $\mathcal{P}_{\text{VLF}_n}(n)$, $\mathcal{P}_{\text{LF}_n}(n)$, $\mathcal{P}_{\text{HF}_n}(n)$, $\mathcal{R}_{\text{LF/HF}}(n)$, and the mean and the variance of $d_{\text{IIF}}(n)$. These last two indexes are computed after a normalization by subtracting the mean value and dividing by the variance of the 5 min.-length segment centred at n_{DO_j}. In addition, for each index the differences w_{r_j}–w_{d_j}, and w_{r_j}–w_{p_j} was computed.

Classifier and feature selection. A linear discriminant analysis was used to separate between DAP events related and not related to apnea episodes, as described in [2]. The classifier was trained by using the same 268 DAP events used in [2], which were clustered in two groups: apneic DAPs (Ga) and non apneic DAPs (Gn) based on physiological characteristics. DAP events were classified into Ga when SaO_2 decreases at least 3% or airflow decreases at least 50% respect to the baseline for a minimum duration of 5 seconds and into Gn otherwise. A summary of the clustering is presented in Table 1.

Feature selection was addressed using wrap method as in [2], i. e., by adding gradually one more feature and selecting the one which provides the highest accuracy.

Table 1. Clustering of DAP events

Clinical diagnosis	DAP group		Total
	Ga	Gn	
Normal	41	107	148
Pathological	98	22	120
Total	139	129	268

2.4. Clinical study

In order to evaluate the proposed techniques, the same clinical study described in [2] was performed. It consists of the separation of the PSG registers into 1-hour length fragments and the labeling of them as control, doubt or pathological based on SaO_2 desaturation. To establish this separation, it was considered a baseline level β corresponding to the SaO_2 signal mode of the entire night recording, and $t_{\beta-3}$ is the total time with SaO_2 signal below $\beta - 3\%$. The fragment is clustered as pathological if $t_{\beta-3}$ is more than 3 min. This implies a minimum of 5% of the time with evident oxygen desaturation which corresponds to a severe OSAS criteria in children [7] of 18 apneas/hour having a mean duration of 10 seconds. If $t_{\beta-3}$ is less than 0.9 min., which corresponds to to 5 apneas/hour, the fragment is clustered as normal. Fragments which are not clustered as normal or pathological are clustered as doubt. Table 2 shows this classification.

Table 2. PSG fragments classification

Clinical diagnosis	subjects	fragments	PSG fragments classification		
			normal	doubt	pathological
Normal	10	46	42	4	0
Pathological	11	59	28	20	11
Total	21	105	70	24	11

These one hour fragments were then automatically classified in normal or pathological based on the DAP per hour ratio using the DAP coming from the DAP detector in Section 2.2, r_{DAP}, or alternatively considering only those classified as apneic DAP events with the methodology presented in 2.3, r^a_{DAP}. ROC curves were calculated for both indexes and the optimum thresholds in terms of maximizing accuracy were established. In addition, Wilcoxon non parametric statistical analysis was carried out for both indexes in order to evaluate their discriminant power between groups. Then, the percentage of time under pathological fragments based on r_{DAP} and r^a_{DAP} was analysed as a rule to consider a subject as pathological or not. The threshold for this percentage was selected for maximizing accuracy. Only 15 subjects (8 OSAS and 7 non-OSAS) were included in this study since subjects with less than 4 hours of acceptable quality signal were excluded.

3. Results

The best features for classification obtained by the wrap method were: the mean of $d_{\text{IIF}}(n)$ signal within the

DAP event, and post-DAP episode windows, the mean of $\mathcal{P}_{\text{VLF}_n}(n)$ within the post-DAP episode window, the mean of $\mathcal{P}_{\text{LF}_n}(n)$ within the DAP window, the variance of the $d_{\text{IIF}}(n)$ signal within the DAP window, and the mean of $\mathcal{P}_{\text{VLF}_n}(n)$ within the reference episode window. Results about PSG fragments are shown in Table 3. The inclusion of PRV information improves the PSG fragments classification accuracy (Acc) in 2.5%, reaching a 70.4%. The Wilcoxon test shows a similar discriminant power between pathological and normal for r^a_{DAP} ($p = 0.0062$) and r_{DAP} ($p = 0.0060$). ROC curves in Figure 3, varying thresholds in r_{DAP} and r^a_{DAP} demonstrate the advantage of including PRV information. In subjects classification, the Acc is improved by a 6.7% obtaining a 86.7%.

Table 3. PSG fragments and subjects classification

	PSG fragments classification			Subjects classification		
	Acc (%)	Se (%)	Sp (%)	Acc (%)	Se (%)	Sp (%)
r_{DAP}	67.9	90.9	64.3	80.0	87.5	71.4
r^a_{DAP}	70.4	81.8	68.6	86.7	100.0	71.4

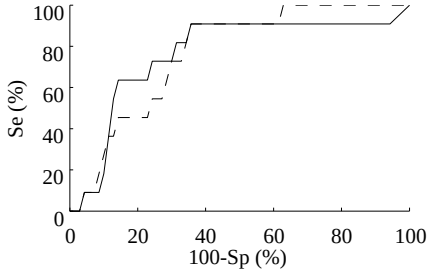

Figure 3. ROC curves for r_{DAP} (dashed line) and r^a_{DAP} (solid line)

4. Discussion and conclusions

The PPG signal carries information related to the cardiovascular function as well as blood gasses concentration. This signal presents interesting characteristics that can be used to detect apneic episodes. In [2], a diagnosis based HRV analysis during DAP events was proposed, but that requires the recording of ECG in addition to PPG signal. The minimization of signal recordings takes special relevance in sleep studies because the use of many sensors could disturb the physiological sleep affecting its analysis, so the use of PRV obtained from PPG signal instead of HRV obtained from ECG signal is proposed in this paper avoiding the need of ECG recording.

Before introducing the PRV information, the fragment and subject classification obtained an Acc of 67.9% and 80.0%, respectively. The introduction of PRV information increased the classifier performance obtaining an Acc of 70.4% for fragment classification and 86.7% for subject classification. In terms of Acc, both r_{DAP} and r^a_{DAP} have obtained better subject classification results than the ones obtained with HRV in [2] (73.3% for r_{DAP} and 80.0% for r^a_{DAP}). This improvement could be explained by the DAP exclusion criteria, which in [2] is related to the quality of ECG but in this paper it is related to the quality of PPG signal where also DAP events are detected, and this could improve the DAP event detection by excluding DAP events which are related to an artifact and not related to an apnea.

Results obtained with PRV are comparable to those extracted from HRV in [2] and suggest that PRV can be used to discriminate apneic and non-apneic DAP events without introducing any additional (ECG) signal, which takes special relevance in sleep studies.

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