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Detection of Obstructive Sleep Apnea in children using decreases in the amplitude fluctuations of PPG signal and HRV.

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Abstract— **An analysis of the HRV during decreases in the amplitude fluctuations of PPG (DAP) events, and their utility in OSAS screening is presented. The overall data set used in the study includes the polysomnographic records of 21 children. DAP events were automatically detected by an algorithm based on the envelope attenuations of the PPG. DAP events were classified as apneic or non apneic by a linear discriminant analysis. The features used by the linear discriminant come from the temporal and spectral parameters of the heart rate obtained by Smooth Pseudo Wigner Ville Distribution. Two indexes were defined: the number of DAP events per hour ratio r_{DAP} and the number of apneic DAP events per hour ratio r^a_{DAP}. Results show a 12% increase in accuracy for r^a_{DAP} with respect to r_{DAP} in classifying 1 hour polysomnographic segments, reaching values of 72.7% and 80% for sensitivity and specificity, respectively. As for subject classification, the improvement in accuracy is 6.7% obtaining values of 87.5% and 71.4% for sensitivity and specificity respectively. These results suggest that the combination of DAP and HRV could be an alternative for sleep apnea screening with the added benefit of low cost and simplicity.**

I. INTRODUCTION

Obstructive Sleep Apnea Syndrome (OSAS) is one of the most common sleep pathologies with high prevalence in the general population, as high as 4% in men, 2% in women and 3% in children. Generally, sleep apnea is undiagnosed since pain symptoms do not appear and patients not attain for medical aid. The most common sleep apnea indicators are daily sleepiness, irritability, tiredness, low concentration and impaired learning. Those factors generally produce more serious consequences such as social problems and job and traffic accidents. In addition, OSAS produces hyperactivity and low capacity to attend mental tasks during childhood [1]. Severe OSAS generates diurnal hypertension and much more cardiovascular health implications that cause the decease [2].

OSAS consists in an interruption of the airflow to the lungs produced by an upper airways occlusion. Then blood oxygen goes down across time and mechanical respiratory efforts are intensified in order to reopen upper airways. If these efforts are not sufficient 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 [3]. The open-close cycle in the upper airways produces a regular oscillatory state of pheripheral 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.

Polysomnography (PSG) is the gold standard procedure for sleep apnea diagnosis. PSG consists in an overnight recording of different electrophysiological signals. The acquisition and analysis of those signals requires human experience and specialized equipment. The last requirements and the reduced number of sleep centers makes sleep diagnosis a very expensive procedure.

In the last decade, application of different techniques for home sleep apnea monitoring has been extensively developed. Some studies have shown that photopletysmography signal (PPG) has useful information about the vascular mechanism for detecting sleep apnea [4]. PPG is a measurement of easy acquisition and provides a measure of the tissue blood volume, which is tie related to arterial vasoconstriction or vasodilatation. These vascular oscillations are generated by autonomic nervous system (ANS) and modulated by the heart cycle. Particularly during apnea, vasocontriction occurs [5] and it is reflected in the PPG signal by a decrease in the fluctuation of the signal amplitude (DAP). However, not all DAP events are related to pathologic respiration (apnea) and it seems that photoplestimography signal is sensible to other events that generate vascular activations [6].

Another electro-physiological signal very broadly studied for apnea diagnosis is the heart rate variability (HRV). HRV exhibits frequency components from 0 to 0.5 Hz, which are associated to the ANS branches. The frequency components between 0.15 and 0.5 Hz represent the vagal tone, frequencies in this band are known as high frequency components (HF). Frequencies from 0.04 to 0.15 Hz manifest the activation of both parasympathetic and sympathetic nervous and these are labeled low frequency components (LF). Finally, frequencies between 0.0033 and 0.04 give information of the slow processes such as thermoregulation.

In a previous study [7] the sympatho-vagal balance was analysed during DAPs related and not related to airflow reductions, oxygen saturation and not clear apnea episodes in normal and pathologic children. The results showed an increase on sympathetic activity during DAP events which is deeper in case of association with apnea therefore this suggest that the combination of both measures could offer

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interesting results in terms of classification performance.

The aim of this study is to evaluate if HRV analysis improve the utility of PPG signal in sleep apnea detection by distinguishing DAP episodes associated to apnea from those that are not. So the combination of DAP and HRV could be an alternative for sleep apnea screening with added benefit of low cost and simplicity.

II. Methodology

A. Data

This study includes the records of 21 children (11 boys, 10 girls) whose mean age was 4.47 ± 2.04 ($mean \pm S.D.$) years. The PSG registers were acquired in Miguel Servet Children's Hospital, Zaragoza, Spain, according to the standard methods defined by American Thoracic Society [8], using a commercial digital polygraph (EGP800, Bitmed). There were recorded six EEG channels, two electro-oculogram channels, a chin electromyogram channel, two ECG channels, air flow (oronasal thermocoupler), and respiratory plethysmography, with transducers placed around the chest and abdomen. PPG and arterial oxygen saturation (SaO_2) were recorded continuously by pulse oximetry (COSMO ETCO2/SpO2 Monitor Novametrix, Medical Systems). All of the signals were stored at a sampling rate of 100 Hz, except ECG channels whose sampling rate was 500 Hz. The PSG data were scored manually following standard procedures used to discriminate children suffering from OSAS (10 children) from those who are not (11 children).

B. DAP events detection

PPG signal was analyzed using the method described in [4] for DAP detection. This detector 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, see figure 1.

C. HRV analysis

A HRV signal processing analysis was carried out in order to obtain several time and frequency indexes to study their value for discriminate between apneic and non-apneic DAP events.

Previous to QRS detection, we implemented a preprocessing. Nonlinear filtering technique was used for removal of the powerline interference [9]. A wavelet-based ECG delineator [10] was used for QRS detection. After that, a ECG signal spline interpolation around each QRS detection was carried out to increase resolution in time of the fiducial point up to an equivalent sampling rate of 2000 Hz. An anomalous beat exclusion rule [11] was applied in order to determine normal

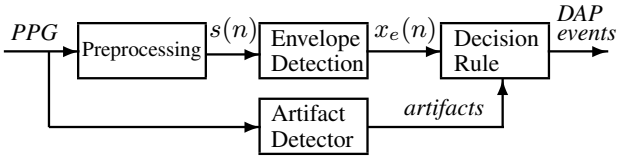

Fig. 1. DAP Detector diagram.

beats which were used for the inverse interval function (IIF) generation used in HRV.

$$d^u_{\text{IIF}}(t) = \sum_{k=1}^{M} \left(\frac{1}{t_k - t_{k-1}} \right) \delta(t - t_k) \quad (1)$$

Where t_k represent the beat location for every kth beat. Since $d^u_{\text{IIF}}(t)$ represent unevenly sampled signal, it is interpolate by cubic splines to become evenly sampled signal $d_{\text{IIF}}(n)$ so classical spectral analysis can be done. To analyze the spectral parameters of the HRV in a time-frequency plane we used the Smooth Pseudo Wigner-Ville Distribution $S_x(t, f)$, since this heart rhythm signal is clearly non stationary. This distribution show high time and frequency resolution and is characterized by an independent smoothing, in time and frequency, originated by $\gamma(t)$ and $\eta(\frac{\tau}{2})\ \eta^*(-\frac{\tau}{2})$ windows respectively and is defined as:

$$S_x(t,f) = \int\int \varphi(t-t',\tau) x(t'+\frac{\tau}{2}) x^*(t'-\frac{\tau}{2}) e^{-j2\pi f\tau} dt' d\tau \quad (2)$$

$$\varphi(t,\tau) = \gamma(t)\eta(\frac{\tau}{2})\eta^*(-\frac{\tau}{2}) \quad (3)$$

$\mathcal{P}_{\text{VLF}}$, $\mathcal{P}_{\text{LF}}$ and $\mathcal{P}_{\text{HF}}$ indexes are computed as the power in the VLF (0.0033-0.04), LF (0.04-0.15 Hz) and HF (0.15-0.5 Hz) bands respectively, as well as their normalized versions with respect to the total power $\mathcal{P}_{\text{VLF}_n}$, $\mathcal{P}_{\text{LF}_n}$ and $\mathcal{P}_{\text{HF}_n}$ and the low to high frequency ratio $\mathcal{R}_{\text{LF/HF}}$.

D. Features Set

In order to quantify the evolution of autonomic variations when a DAP event is associated or not associated to apnea, four time windows were defined in specific time intervals related to DAP events onset. Figure 2 shows a typical example of the mean d_{IIF} sequences when DAP is related or not related to an apneic episode, as well as the windows defined in relation to DAP event. Time 0 s is assigned to DAP onset. The time windows are defined as follows: a) Reference window (w_r) is located 15 s previous to the DAP event onset with a duration of 5 s. b) DAP episode window (w_d) is found two seconds before the DAP onset and lasting five seconds c) Post DAP event window (w_p) located 15 seconds after DAP onset and lasting 5 seconds d) Global window (w_g) starting at 20 seconds previous to the DAP onset and lasting 40 seconds and containing the others windows.

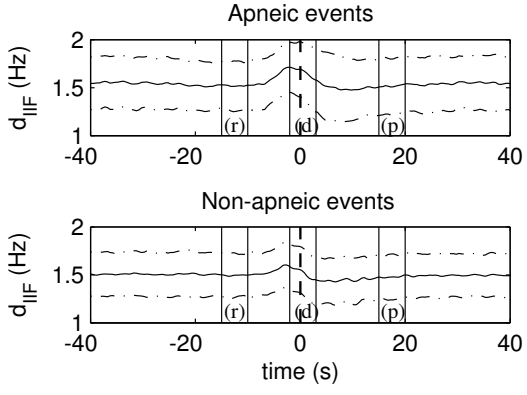

Fig. 2. d_{IIF} mean $\pm$ S.D. for apneic and non-apneic DAP events. Analysis windows (r reference, d DAP, p post-event). Dashed line at reference time indicate DAP onset.

They were extracted a series of features in order to select a set of them that could provide separation between apneic and non apneic DAP events. The set of features is formed by the mean and the variance within the four different windows (w_r, w_d, w_p and w_g) referred to the DAP detection of d_{IIF}, $\mathcal{P}_{\text{LF}_n}$, $\mathcal{P}_{\text{HF}_n}$, $\mathcal{R}_{\text{LF/HF}}$ indexes. In addition, for each index the difference between reference and DAP episode window as well as between reference and post event window was computed. In order to reduce the biovariability in d_{IIF} indexes, those were normalized by subtracting the mean value and dividing by the variance of the segment centered at the DAP event onset and lasting 5 minutes. Spectral indexes were normalized with respect to the total power. A total of 34 features were extracted.

E. Classifier

A linear discriminant analysis was used to separate between DAP events related and not related to apnea episodes (G_a and G_n). Let $\mathbf{y_i} = [y_{1i}, y_{2i}, ..., y_{di}]$ be a row vector with d values where each column represents a feature value from ith DAP. And suppose we are interesting to assign $\mathbf{y_i}$ to class k of the c possible classes, then the discriminant value f_k for each class is evaluated from the following equation:

$$f_k = \boldsymbol{\mu}_k \boldsymbol{\Sigma}^{-1} \mathbf{y}_i^T - \frac{1}{2} \boldsymbol{\mu}_k \boldsymbol{\Sigma}^{-1} \boldsymbol{\mu}_k^T + log(\pi_k) \tag{4}$$

where T represents the transpose and $\boldsymbol{\mu}_k$ is the row mean vector obtained from the whole N_k training vectors belonged to the class k. In order to evaluate $\boldsymbol{\mu}_k$ let N be the total number of $\mathbf{y_i}$ in the training set , then $\boldsymbol{\mu}_k$ is obtained by:

$$\boldsymbol{\mu}_k = \frac{1}{N_k} \sum_{i=1}^{N_k} \mathbf{y}_{ik} \tag{5}$$

For an LD classifier $\boldsymbol{\Sigma}$ represents the pooled covariance and its is evaluated as:

$$\boldsymbol{\Sigma} = \frac{1}{N-c} \sum_{k=1}^{c} \sum_{i=1}^{N_k} (\mathbf{y}_{ik} - \boldsymbol{\mu}_k)^T (\mathbf{x}_{ik} - \boldsymbol{\mu}_k) \tag{6}$$

Finally, π_k represent the prior probability that $\boldsymbol{y_i}$ belongs to a class k. A practical way to evaluate π_k is :

$$\pi_k = \frac{N_k}{N} \tag{7}$$

However, it is possible to eliminate this term of the the discriminant equation if $\boldsymbol{y_i}$ has the same probability for all classes. Finally $\boldsymbol{y}_i$ is assigned to the class, k with higher f_k.

F. Features selection

For training the classifier, a total of 268 DAP events were extracted. These DAP events were clustered in two groups: apneic DAPs (Ga) and non apneic DAPs (Gn) based on the physiology of apneic events. 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 when DAP event is not correlated to neither airflow reduction nor SaO_2 decrement. A summary of the clustering is presented in Table I.

TABLE I

CLUSTERING OF DAP EVENTS

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

Feature selection can be addressed in different ways, wrap method is the one used in this work, it consists in selecting the features based on the classifier performance by adding gradually one more feature and selecting the one, in combination with the features selected previously, which provides the highest classification accuracy.

G. Clinical Study

To evaluate the improvement of adding HRV information for OSAS diagnosis based on PPG, a clinical study was carried out. Complete night PSG recordings were split into 1-hour length fragments. These one hour PSG fragments were labeled as control, doubt or pathologic based on SaO_2 desaturation in order to later being able to evaluate the classifier accuracy for these fragments. To establish this separation, a baseline level β, corresponding to the SaO_2 signal mode of the entire night recording, was considered. In all recordings $\beta \geq 97\%$ and the probability of this mode value was higher than 0.3 from a bin resolution of 1%. Total time intervals with SaO_2 signal below $\beta - 3\%$, $t_{\beta-3}$, was calculated for each fragment. PSG fragments were classified according to the following criteria:

$$\begin{array}{cc} t_{\beta-3} < 0.9 \text{ minutes} & \text{control} \\ 0.9 \text{ minutes} < t_{\beta-3} < 3 \text{ minutes} & \text{doubt} \\ t_{\beta-3} > 3 \text{ minutes} & \text{pathologic} \end{array} \tag{8}$$

This imply a minimum of 5% of the time with evident oxygen desaturation to be consider as pathologic, which corresponds to a severe OSAS criteria of 18 apneas/hour having a mean duration of 10 seconds. For control group the threshold corresponds to 5 apneas/hour. Table II shows the classification for PSG fragments.

Now the objective is to classify these one hour fragments based on the DAP per hour ratio. This classification will be done both just with the DAP coming from the DAP detector in section II-B, r_{DAP}, and with those classified as apneic DAP events with the methodology presented in II-E, r^a_{DAP}. ROC curves were calculated for both indexes and the optimum thresholds in terms of maximizing sensitivity Se and specificity Sp were established. In addition, Wilcoxon non parametric statistical analysis was carried out for both indexes in order to evaluate their discriminant power between groups.

Since we are interested in having a label attached to a patient, we need a rule to determine when a patient with a given number of pathological fragments is considered as

TABLE II

PSG FRAGMENTS CLASSIFICATION

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

pathologic subject. For that, the percentage of time under pathologic fragments based on r_{DAP} and r^a_{DAP} was analysed. The threshold for this percentage was selected for maximizing Se and Sp. From the total of 21 children, six subject were excluded because only less than 4 hours had ECG and PPG signals of acceptable quality, so 15 registers were included in this study corresponding to 8 OSAS and 7 normal according to clinical diagnosis.

III. RESULTS

The best features for classification obtained by the wrap method were: the mean of normalized HF within global window ($\overline{\mathcal{P}}^{w_g}_{\text{HF}_n}$), the mean of the LF/HF ratio within global window ($\overline{\mathcal{R}}^{w_g}_{\text{LF/HF}}$), the variance of the d_{IIF} signal within DAP event window ($\sigma_{d^{w_d}_{\text{IIF}_n}}$) and the difference of the mean of the d_{IIF} within reference window with respect to DAP window ($\Delta\overline{d}^{\,w_r-w_d}_{\text{IIF}\,n}$). Results about PSG fragments and subject classification are shown in Table III. The inclusion of HRV information improves the PSG fragments classification accuracy in 12.3% reaching at values of 72.7% and 80% for sensitivity and specificity, respectively. In addition, the Wilcoxon statistic analysis shows a higher discriminant power between pathologic and normal for r^a_{DAP} ($p = 0.0061$) than for r_{DAP} ($p = 0.0225$). ROC curves in Fig. 3, varying thresholds in r_{DAP} and r^a_{DAP}, demonstrate the advantage of including HRV information. As for subject classification, the improvement in accuracy is 6.7% obtaining values of 87.5% and 71.4% for sensitivity and specificity respectively.

IV. DISCUSSION AND CONCLUSIONS

Photopletysmography 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. However, its high sensibility could produce misdetections and overestimate apneic episodes. Generally, in most of the studies PPG has been directly related with the cardiac function given as results a measure of the Pulse Transition Time (PTT) [12]. PTT gives a quantitative measure of the time that a pulse wave needs for passing from one arterial to another one. OSAS produces a PTT decrement because the sympathetic activation produces heart rate increment, higher stroke volume and vasoconstriction, which in turn, generate pulse wave acceleration. However, some other physiological events such as slow paced breathing and deep inspiratory gasp [13] induce also variation in the PTT that could be confused with sympathetic activations. However, this integration looses important information that could be obtained from the spectral parameters of heart rate. Dynamic of heart rate and its spectral parameters offer time and frequency information that discriminates between small cardiovascular variation and more severe ones, like when an apneic episode occurs. However, when only spectral parameters are used to discriminate apnea, spectral parameters loss sensibility since there is not a pre-screening of the potential apneic events as the DAP detection provides, improving the sensitivity and specificity values. In conclusion HRV analysis improve the utility of PPG signal in sleep disorder diagnosis so the combination of DAP and HRV could be an alternative for sleep apnea screening with the added benefit of low cost and simplicity. Nevertheless, extended studies are needed to corroborate the potential of PPG signal in conjunction with HRV analysis in diagnosing sleep disorders.

TABLE III

PSG FRAGMENTS CLASSIFICATION RESULTS

	PSG Fragments classification			Subjects classification		
Index	S (%)	S_p (%)	Accuracy (%)	S (%)	S_p (%)	Accuracy (%)
r_{DAP}	81.8	64.3	66.7	75	71.4	73.3
r^a_{DAP}	72.7	80	79	87.5	71.4	80

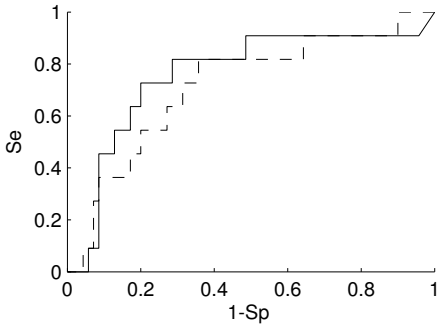

Fig. 3. ROC curves for r_{DAP} (dashed line) and r^a_{DAP} (solid line).

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