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Oxygen Saturation in Children with and without Obstructive Sleep Apnea Using the Phone-Oximeter

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***Abstract*— Obstructive sleep apnea (OSA) in children can lead to daytime sleepiness, growth failure and developmental delay. Polysomnography (PSG), the gold standard to diagnose OSA is highly resource intensive and is confined to the sleep laboratory. In this study we propose to identify children with OSA using blood oxygen saturation (SpO_2) obtained from the *Phone Oximeter*. This portable, in-home device is able to monitor patients over multiple nights, causes less sleep disturbance and facilitates a more natural sleep pattern. The proposed algorithm analyzes the SpO_2 signal in the time and frequency domain using a 90-s sliding window. Three spectral parameters are calculated from the power spectral density (PSD) to evaluate the modulation in the SpO_2 due to the oxyhemoblobin desaturations. The power P, slope S in the discriminant band (DB), and ratio R between P and total power are calculated for each window. Tendency and variability indices, number of SpO_2 desaturations and time spent under 2% or 3% of baseline saturation level are computed for each time window. The statistical distribution of the temporal evolution of all parameters is analyzed to identify 68 children, 30 with OSA and 38 without OSA (nonOSA). This characterization was evaluated by a feature selection based on a linear discriminant. The combination of temporal and spectral parameters provided the best leave one out crossvalidation results with an accuracy of 86.8%, a sensitivity of 80.0%, and a specificity of 92.1% using only 5 parameters. The median of R, mean of P and S and mean and standard deviation of the number of desaturations below 3% of baseline saturation level, were the most representative parameters. Hence, a better knowledge of SpO_2 dynamics could help identifying children with OSA with the *Phone Oximeter*.**

I. INTRODUCTION

Obstructive sleep apnea (OSA) is a sleep-disordered breathing characterized by partial or complete upper airway collapse that disrupts normal respiratory gas exchange. These obstructive events lead to oxygen desaturation, and an increase in mechanical respiratory efforts to reopen the upper airways. When the efforts are not enough and the hypercapnia (high level of carbon dioxide in the blood) level is dangerous, an arousal is generated to reactivate all the peripheral systems and respiration is restored. These desaturation episodes may occur hundreds of times during the night, with serious health implications [1]. The high prevalence of OSA determined objectively in population-based studies (2.2 to 3.8%) poses a serious threat to the healthy growth of many children [2]. The lack of oxygen during sleep can lead to daytime sleepiness, heart failure, behavioural problems and developmental delay [3].

Polysomnography (PSG), the gold standard for OSA diagnosis, consists of an overnight recording of multiple physiological signals. It requires a comprehensive sleep laboratory and the inconvenience of an overnight stay in the facility. It is highly resource intensive and confined to centralized tertiary facilities, with limited accessibility for many children, especially those located remotely. The apnea-hypoapnea index (AHI) calculated from PSG is used to characterize the severity of sleep apnea. It measures the average number of apnea and hypopnea events per hour of sleep. The relative high cost and complexity of PSG limit its capacity as a screening test. Nocturnal oxygen saturation has been proposed as an alternative to PSG, for sleep apnea detection in adults. It showed accuracy as a screening tool but comes with important limitations as a single diagnostic tool for OSA [4], [5]. While pulse oximetry is part of the standard of care for PSG, further research on its potential to provide a standalone sleep apnea screening and testing device has been encouraged [6].

The *Phone Oximeter*, is a mobile device that integrates a pulse oximeter with a cell phone. In addition to the oxygen saturation (SpO_2), it provides a photoplethysmogram (PPG), signal of blood volume changes. Combined with a pulse oximeter, the inherent capabilities of a standard mobile phone have the potential to overcome the limitations of a standalone pulse oximeter, and enable the intelligent analysis and intuitive communication of information to a health care worker [7]. Moreover, it has been demonstrated to be an intuitive tool for the operating room [8].

Our goal is to provide, with the *Phone Oximeter*, a screening device to identify children with significant sleep apnea. We hypothesize that further knowledge on SpO_2 dynamics could provide relevant information about the identification of sleep apnea. The aim of the present work is therefore, to characterize dynamic changes in the SpO_2, and use the *Phone Oximeter* as a screening tool to detect children with sleep apnea ($AHI > 5$).

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II. METHODS

A. Dataset

Following ethics approval and informed consent, 72 children referred to the British Columbia Children's Hospital for a PSG recording were recruited. The data acquisition was carried out in a dedicated facility attached to the Medical Day unit. PSG included the overnight measurement of ECG, EEG, SpO_2, chest movement, nasal airflow and video recording using the Embla Sandman S4500. The pulse oximeter sensor of the *Phone Oximeter* was applied to the finger adjacent to the one used during standard PSG. SpO_2 from the *Phone Oximeter* was recorded at a sample frequency of 1 Hz. A sleep technician scored the PSG, in 30-s epochs using standard criteria [9]. Each epoch was analyzed for the number of apneas, hypopneas, EEG arousals and oxyhemoglobin desaturation. Apnea was defined as the absence of airflow for at least 10-s. Hypopnea was defined as a reduction of airflow lasting at least 10-s associated with either a 4% decrease in the arterial oxyhemoglobin saturation or and EEG arousal. The number of apneas/hypopneas was calculated hourly to compute the average AHI. Four children were excluded from the study because the duration of their signals (PSG or SpO_2) was shorter than 3-h. Table I summarizes the demographic and clinical data of the children that were included, as well the AHI index derived from the PSG diagnosis. For this study an AHI greater or equal to 5 events per hour was considered as positive OSA.

TABLE I

DEMOGRAPHIC AND CLINICAL INFORMATION OF THE DATASET (MEAN±SD), AND p-VALUE WHEN COMPARING OSA AND NONOSA GROUPS USING THE U-MANN-WHITNEY TEST.

	OSA	*nonOSA*	$p-value$
Children (n)	30	38	-
Age	9.7 ± 4.8	8.5 ± 4.3	*n.s.*
Male(Female)*	23(7)	14(21)	0.003
BMI	24.3 ± 9.7	18.3 ± 4.9	0.014
AHI	24.29 ± 9.65	1.4 ± 1.08	<0.0001

**: The gender information of three subjects is unknown.*

B. Phone Oximeter SpO_2 characterization

The *Phone Oximeter*'s SpO_2 was characterized in the time-frequency domain. Artifacts were removed by eliminating changes of SpO_2 between consecutive sampling intervals of more than 4% per second, or any oxygen saturation below 50%. Figure. 1 illustrates a one hour-length SpO_2 signal segment, for (a) a child with OSA and (b) a child without OSA.

The SpO_2 signal was characterized in the spectral domain through the power spectral density (PSD), and in the time domain by some statistics, variability measures and indices related to desaturation episodes proposed in previous works to predict the presence of the OSA [5], [4].

1) Spectral domain: Conventional spectral analysis assumes stationarity in the signal and is therefore unable to identify pattern changes. An approach to account for such changes is to implement a time-varying spectral analysis.

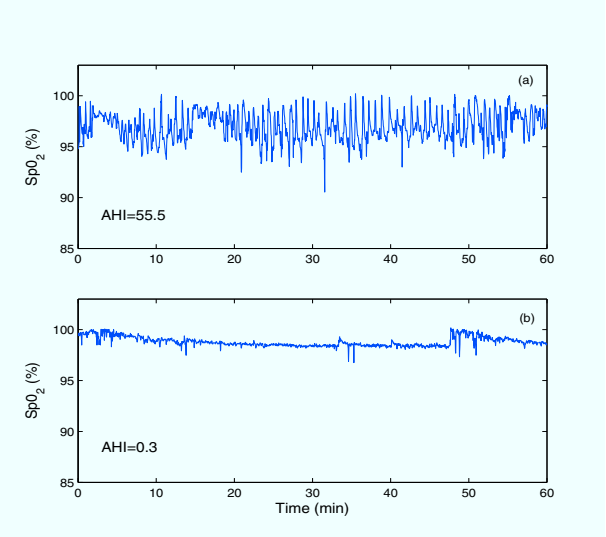

Fig. 1. One hour of the SpO_2 signal of a child (a) with OSA ($AHI = 55.5$) and (b) without OSA ($AHI = 0.3$)

Using a 90-s sliding time window with 50% overlap, the SpO_2 signal was divided into small segments that can be assumed to be stationary and therefore permit computation of power spectral density (PSD). To provide a better frequency resolution a parametric power spectral estimation was performed through autoregressive modeling.

Power spectral density (PSD): The signal $x(n)$ is modeled through an autoregressive model by

$$x(n) = -\sum_{k=1}^{p} a[k]x(n-k) + e(n) \tag{1}$$

where $e(n)$ denotes zero-mean white noise with variance σ_e^2, $a[k]$ the AR coefficients and p the model order. Once the autoregressive coefficients and the variance σ_e^2 have been estimated, the PSD of an autoregressive process is computed by means of

$$\hat{P}_{x\,AR}(f) = \frac{\sigma_e^2}{\left|1+\sum_{k=1}^{p} a[k]\cdot e^{-j\cdot 2\pi f k T}\right|^2}. \tag{2}$$

being T the sampling period. The selection of model order is a trade-off between the frequency resolution and the spurious peaks. The optimum model order was evaluated according to Rissanens minimum description length criterion $p = 10$.

Three spectral parameters were extracted from the discriminant frequency band (DB), which consist of a frequency interval (0.02 Hz) centered around the modulation frequency peak, tracked in the band from 0.01 to 0.05 Hz. The power of the DB, the ratio between the power of the DB and total power, and the slope between the modulation frequency peak and the right end of the DB, divided by the total power, were studied.

2) Time domain: The mean, median, standard deviation and interquartile range of the SpO_2 and indices like number of oxyhemoblobin desaturations from baseline below 3% and 4%, cumulative time spent below an oxyhemoblobin saturation of 92%, 90%, 88%, 86% and Δ index (a variability

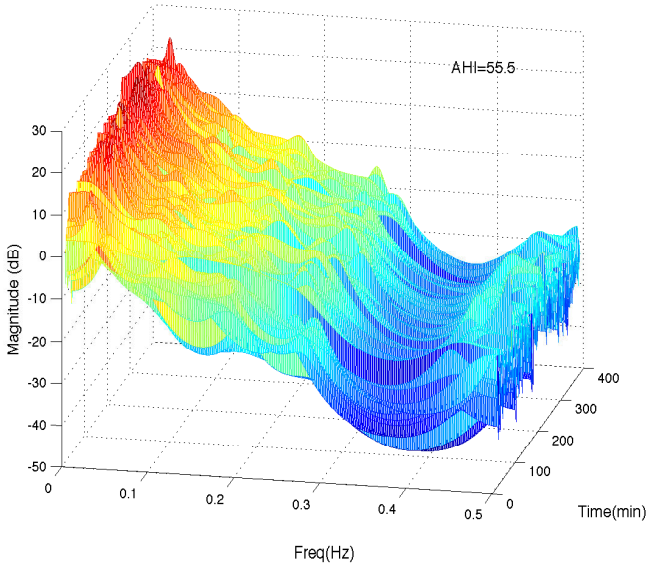

Fig. 2. Time-varying power spectrum of a child with OSA ($AHI = 55.5$).

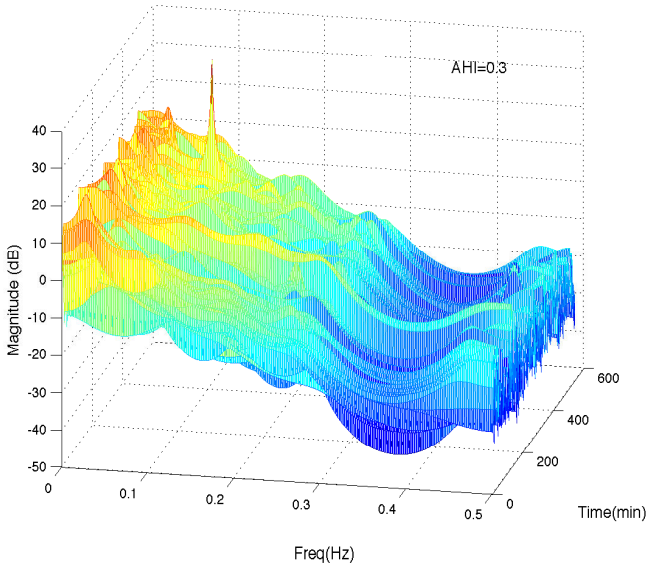

Fig. 3. Time-varying power spectrum of a child without OSA ($AHI = 0.3$)

measure of oxyhemoblobin saturation) were calculated for each time window.

C. Data analysis

The whole parameter set characterizes the behavior of the SpO_2 for each time window. However, to identify children with OSA syndrome, the statistical distribution of each time-varying parameter was evaluated. Table II summarizes the different parameters and their statistics: mean (M), median (Me), standard deviation (S), and interquartile range (I).

TABLE II
PARAMETER DESCRIPTION AND STATISTICS

P; M_P, Me_P, S_P, I_P	Power of DB
R; M_R, Me_R, S_R, I_R	Power ratio
S; M_S, Me_S, S_S, I_S	Slope of DB
$M_{\mathbf{Sp0_2}}$; $M_{M_{Sp0_2}}$, $Me_{M_{Sp0_2}}$, $S_{M_{Sp0_2}}$, $I_{M_{Sp0_2}}$	Mean SpO_2
$Me_{\mathbf{Sp0_2}}$; $M_{Me_{Sp0_2}}$, $Me_{Me_{Sp0_2}}$, $S_{Me_{Sp0_2}}$, $I_{Me_{Sp0_2}}$	Median SpO_2
$S_{\mathbf{Sp0_2}}$; $M_{S_{Sp0_2}}$, $Me_{S_{Sp0_2}}$, $S_{S_{Sp0_2}}$, $I_{S_{Sp0_2}}$	Stan. dev SpO_2
$I_{\mathbf{Sp0_2}}$; $M_{I_{Sp0_2}}$, $Me_{I_{Sp0_2}}$, $S_{I_{Sp0_2}}$, $I_{I_{Sp0_2}}$	Interq. range SpO_2
Δ; M_Δ, Me_Δ, S_Δ, I_Δ	Δ measure
2%; $M_{2\%}$, $Me_{2\%}$, $S_{2\%}$, $M_{2\%}$	# desat. $\leq 2\%$
3%; $M_{3\%}$, $Me_{3\%}$, $S_{3\%}$, $M_{3\%}$	# desat. $\leq 3\%$
T_{92}; $M_{T_{92}}$, $Me_{T_{92}}$, $S_{T_{92}}$, $I_{T_{92}}$	Time below 92%)
T_{90}; $M_{T_{90}}$, $Me_{T_{90}}$, $S_{T_{90}}$, $I_{T_{90}}$	Time below 90%)
T_{88}; $M_{T_{88}}$, $Me_{T_{88}}$, $S_{T_{88}x}$, $I_{T_{88}}$	Time below 88%)
T_{86}; $M_{T_{86}}$, $Me_{T_{86}}$, $S_{T_{86}}$, $I_{T_{86}}$	Time below 86%

In this study, we used linear discriminant analysis to identify children with OSA. Using the statistics extracted from each parameter distribution, a feature selection algorithm was applied. The parameters that provided the best classification accuracy, maintaining a good sensitivity-specificity balance were selected, using leave one out crossvalidation [10].

III. Results

A. Illustration of the method

Figures 2 and 3 illustrate the performance of the time-varying PSD applied to a child with and without OSA, respectively. From these figures it is clear that the power in the DB ($0.01 - 0.05$Hz) defined by the modulation of the SpO_2 is much higher in children with OSA due to oxyhemoblobin desaturation events, than in children without OSA.

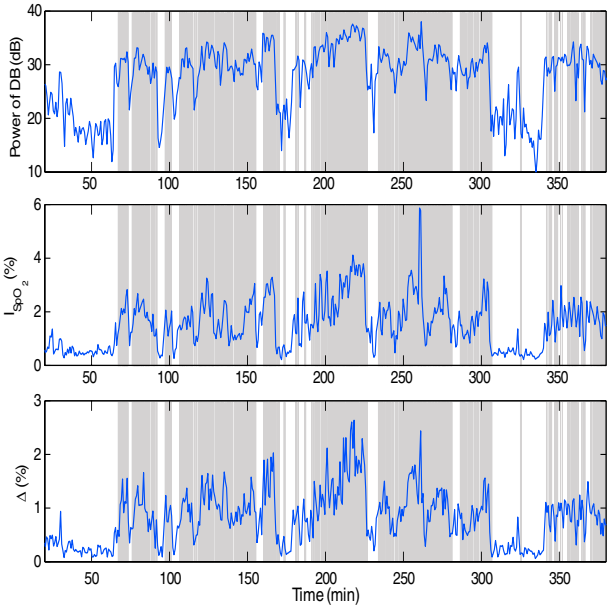

Fig. 4. Temporal evolution of (a) power of the DB, (b) interquartile rage of the SpO_2 and (c) Δ variability measure, together with the apnea events (in red), for a child with OSA.

Figure 4 shows the overnight dynamic of three of the most statistically significant (p-value < 0.001) parameters comparing OSA and nonOSA children. It can be observed

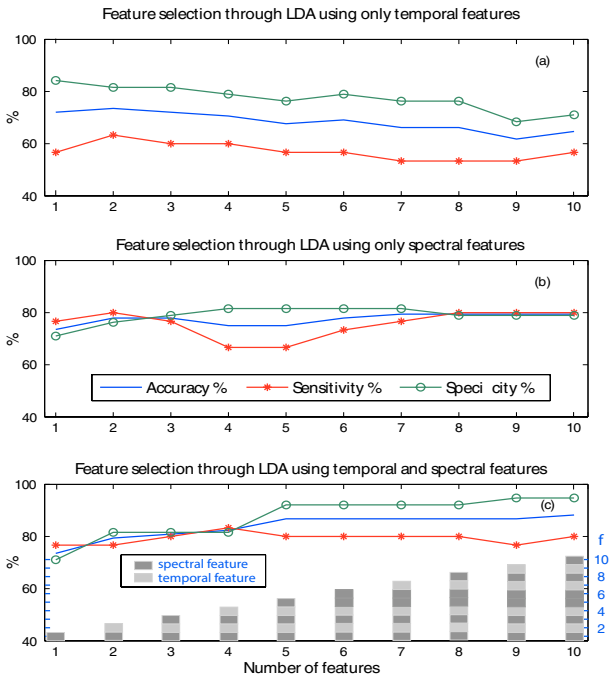

Fig. 5. Accuracy, sensitivity and specificity of the feature selection based on a linear discriminant analysis using (a) time features, (b) spectral features, (c) combination of temporal and spectral features.

that the power in the DB and the variability of the SpO_2 signal, reflected by the interquartile range of the SpO_2 and Δ index, increase significantly during sleep apnea events.

B. Classification

Figure 5 shows the performance of the feature selection in terms of accuracy, sensitivity and specificity classifying OSA and nonOSA children, whenever a new feature was included to the linear discriminant. The classification results using only temporal features (Figure 5.a), spectral features (Figure 5.b), and a combination of both (Figure 5.c) were studied. It can be observed that spectral parameters tend to perform better than temporal parameters identifying OSA patients and that the classification accuracy improves slightly using the combination of temporal and spectral parameters. Table III shows the mean, standard deviation and p-value of the most discriminant features chosen by the feature selection algorithm using temporal and spectral features (see Figure 5.c). Using 5 features (3 spectral and 2 temporal) and a linear discriminant analysis we achieve an accuracy of 86.8%, a sensitivity of 80.0%, and a specificity of 92.1% classifying OSA and nonOSA subjects. These results marginally increase to 88.2%, 80% and 94.7%, respectively using 10 features (6 spectral and 4 temporal).

IV. Discussion

In this work, time-varying characterization of the *Phone Oximeter*s SpO_2 signal in the time and spectral domain is proposed to detect children with OSA. The SpO_2 is characterized by spectral parameters extracted from the PSD and statistics, variability indices, number and duration of oxyhemoblobin desaturations. After a feature selection, an

TABLE III

Features selected to classify OSA vs nonOSA (mean±sd) and p-value using the U-Mann-Whitney test

	Feature	OSA	nonOSA	p-value
f1	Me_R	0.63 ± 0.07	0.57 ± 0.05	< 0.0001
f2	$S_{3\%}$	0.58 ± 0.28	0.42 ± 0.21	0.01
f3	M_P	424 ± 503	282 ± 395	0.007
f4	$M_{3\%}$	0.14 ± 0.18	0.06 ± 0.08	0.02
f5	M_S	1.06 ± 0.29	0.85 ± 0.17	< 0.0001
f6	M_R	0.62 ± 0.07	0.57 ± 0.04	< 0.0001
f7	M_Δ	0.38 ± 0.18	0.28 ± 0.10	0.001
f8	S_S	1.03 ± 0.29	0.88 ± 0.28	0.001
f9	I_Δ	0.31 ± 0.18	0.20 ± 0.07	< 0.0001
f10	I_S	1.02 ± 0.21	0.84 ± 0.13	< 0.0001

accuracy of 86.8%, sensitivity of 80.0%, and specificity of 92.1% is achieved with a linear discriminant using a set of 5 features from the time and spectral domain. As a preliminary study, these results allow consideration of the time-varying characterization of the SpO_2 signal as a suitable tool to provide further knowledge of oxygen saturation dynamics and to identify children with OSA. This characterization could permit the use of *Phone Oximeter* as a sleep-screening tool to identify children with significant sleep apnea.

V. Acknowledgments

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