Airflow from nasal pulse oximetry in the screening of obstructive sleep apnea

Xenia L.R. Hoppenbrouwer*, T. Fabius†, M. Eijsvogel†, F. de Jongh†, A. Garde*
*Biomedical Signals and Systems group
University of Twente, Enschede, The Netherlands, Tel: +31 53 489 6657
†Dept. of Pulmonology, MST, The Netherlands *Member, IEEE*

***Abstract*—**
Obstructive Sleep Apnea (OSA) is recognized as an increasing health risk, leading to daytime sleepiness and various medical conditions, such as hypertension and heart failure. Polysomnography (PSG), the gold standard to diagnose OSA, is a resource-intensive and expensive investigation confined to the hospital.

Portable home monitoring, i.e. pulse oximetry, may become an acceptable OSA screening method. The novel nasal pulse oximeter sensor (Xhale Alar) adds the possibility of combining pulse oximetry (SpO2) with airflow analysis by an integrated thermistor, which might increase the diagnostic accuracy.

In the Alar pilot study, 39 adults were measured during an overnight PSG recording together with the Alar sensor. This study aims to investigate the additional value of an airflow signal compared to SpO2 analysis in OSA screening. Both time and spectral features were extracted from SpO2 and airflow signals recorded with the Alar sensor. Leave one out cross-validation was used to develop Random Forest models in screening for apnea-hypopnea index (AHI) thresholds 5 and 10. Using both AHI $\geq$ 5 and AHI $\geq$ 10 as the diagnostic cutoff, the airflow signal shows respectively an AUC of 89% and 80% compared to 78% and 77% with SpO2 analysis, showing a higher performance using an airflow signal in screening adults for OSA.

I. Introduction

Obstructive sleep apnea (OSA) is the most common type of sleep disordered breathing and is characterized by frequent complete (apnea) or partial (hypopnea) cessations of breathing during sleep. OSA is recognized as an increasing health risk due to its high prevalence (around 10% and increasing[1]) and serious associated consequences, including daytime sleepiness, personality changes, intellectual deterioration, and various other medical conditions such as hypertension, arrhythmias, heart failure, and stroke.[2], [3] In-laboratory polysomnography (PSG), the gold standard to diagnose OSA, is accurate with a low failure rate, but is confined to the hospital, resource intensive and expensive.[4] Portable home monitoring devices might develop into acceptable methods of screening or even diagnosing OSA.[5] A variety of ambulatory devices have been developed and several studies show reasonable accuracy of portable monitors in OSA screening. Pulse oximetry is such a simple tool, a non-invasive method of measuring the photoplethysmographic signal (PPG), which visualizes the peripheral blood volume variations in tissue and the peripheral blood oxygen saturation (SpO2). Previous research showed that combining SpO2 analysis with heart rate variability analysis, improved the OSA screening performance compared to SpO2 analysis alone.[6], [7]

The Xhale Alar sensor is an innovative nasal pulse oximetry sensor that integrates a thermistor allowing the monitoring of two physiological signals; pulse oximetry and respiration. This novel simple sensor can be connected to a mobile phone to create a portable home monitoring tool to screen for patients with OSA. During this study, we measured both pulse oximetry and airflow signals with the Alar sensor simultaneously with the gold standard PSG. The goal of this study is to investigate the additional value of an airflow signal compared to SpO2 analysis in the screening of adults with OSA.

II. Alar Dataset

The Alar pilot dataset was created to validate and investigate the improvement of sleep apnea screening using a nasal pulse oximeter. In this paper we focus on the performance of airflow measurements compared to SpO2 signals in the screening of patients with sleep apnea. The Alar dataset was collected at the Medical Spectrum Twente (MST). Following ethics approval of the study protocol (K17039), 42 adults referred for overnight PSG measurement were recruited between November 2017 and July 2018. Exclusion criteria were known arrhythmia, abnormal hemoglobin or insomnia.

A. Data acquisition

The data acquisition was carried out in specialized sleep chambers at the MST, where the overnight PSG recordings were recorded by using BrainRT™ equipment (OSG, Rumst, Belgium). PSG measurement included: electrocardiogram (ECG), electroencephalogram (EEG), leg electromyogram (EMG), chest movements, pulse oximetry, nasal and oral

978-1-5386-1311-5/19/$31.00 ©2019 IEEE

airflow, audio and video recordings. Simultaneously with the PSG measurement, nasal pulse oximetry was measured with the Xhale Alar nasal pulse oximeter. The Xhale Alar nasal pulse oximeter was connected to a mobile device (Motorola Moto C Plus). The signals recorded with the Alar sensor, SpO2 (0.01% resolution), PPG (32 bit resolution) and respiration (0.001 resolution), were sampled at 80, 80 and 160 Hz, respectively.

B. Scoring

All PSG measurements were evaluated by a specialized sleep technician who determined the apnea-hypopnea index (AHI), which is the gold standard measure of OSA severity. This AHI is computed by counting the total number of apnea and hypopneas for every hour of recorded sleep. Following the American Academy of Sleep medicine (AASM) guidelines, an apnea was defined as a complete cessation of breathing for longer than 10 seconds, and hypopneas were defined by a more then 50% reduction in airflow signal.

1) Demographic information:

Table 1 summarizes the demographic information for the Alar pilot dataset, as well as the AHI index derived from the PSG. A positive OSA diagnosis was defined as an AHI greater or equal to either 5 or 10 apnea/hypopnea events per hour. Only subjects containing a total duration of PSG and Alar recordings longer than 3 hours of reliable data were included. There were no statistically significant differences between both groups in demographics, age, BMI and total sleep time (TST) during PSG.

TABLE I
Demographic information of the Alar-database (mean +- std), comparing OSA and non-OSA groups at two AHI thresholds of 5 and 10.

		AHI threshold ≥ 5		AHI threshold ≥ 10	
	Total	OSA	Non-OSA	OSA	Non-OSA
Adults (n)	39	23	16	19	20
Male (Female)	23 (16)	15 (8)	8 (8)	13 (6)	9 (11)
Age	47 (12)	48.6 (13.4)	43.4 (9.7)	48.3 (12.9)	45.4 (11.6)
BMI	27.6 (5.6)	28.2 (5.9)	26.3 (4.7)	28.3 (6.4)	26.6 (4.5)
AHI	10.0 (8.8)	16.0 (6.3)	1.6 (1.5)	17.7 (6.0)	3.0 (4.5)
TST (hours)	10.4 (1.3)	10.3 (1.5)	10.5 (0.4)	10.5 (0.2)	10.3 (2.0)

III. Methods

Overnight SpO2 and respiration signals recorded with the Alar sensor were used for the extraction of features and creating a random forest model for OSA screening. All Alar signals were characterized in both time and frequency domain. Data analyses were performed offline in Matlab 2017a (Mathworks Inc, Natick, USA).

A. SpO2 characterization

The SpO2 samples below 50% or above 100% and SpO2 changes between consecutive samples higher than 4%, were considered physiological impossible and consequently excluded from further analysis. An overall signal quality percentage of the SpO2 signal was determined by calculating the percentage of the night the SpO2 signal was above 50%. Time domain features derived from the SpO2 signals were: mean, median, std and iqr of SpO2, lowest SpO2 and two oxygen desaturation indexes (ODI3 and ODI4, number of desaturations from baseline below 3% and 4% respectively), the Delta variability index, and the cumulative time spent between or below a certain percentage (t100-95, t95-90 and t90). Frequency domain features were characterized using a power spectral density (PSD), extracting three spectral parameters: 1) the normalized power in the modulation frequency band (consisting of a frequency interval of 0.02 Hz centered around the modulation peak located between 0.005 and 0.1 Hz.), 2) the total power, 3) the ratio between the modulation power and the total power.

B. Airflow characterization

To exclude those parts of the signal consisting of artefacts, the signal quality was evaluated using an algorithm previously applied on PPG signals.[8] The PPG signal was evaluated using this algorithm which is based on pulse segmentation and cross-correlation of consecutive pulses. The signal quality index (SQI) assigns values between 0 and 100 (with 100 being the best quality) and was applied to the airflow signal. Airflow signal segments containing a good SQI (at least 30 seconds with a SQI higher then 40) were used for further analysis and feature extraction. Time domain features derived from the airflow signals were: mean, median, std and iqr of the airflow signal. For the frequency domain features, a frequency band of interest was defined between 0.025 Hz and 0.050 Hz, corresponding to events lasting 20 to 40 seconds (reported as the typical range in duration of apnea events [9]). Four spectral features were extracted from this 0.025-0.050 Hz band from the power spectrogram: mean median, std and iqr.

C. Data analysis

Two multivariate logistic regression models were developed and validated using leave one out cross-validation (LOOCV) to classify adults at AHI cutoffs of 5 and 10. Given the size of the dataset, we perform LOOCV, where all observations except one subject are used for training and the remaining subject is used for testing the models. A stepwise selection method was applied to select the most relevant features for classifying adults with or without OSA, using a Random Forest classifier. All statistical analysis was conducted using R v3.2.0 (R Foundation for Statistical Computing, Vienna, Austra).

IV. Results

Forty two adults agreed to participate in the Alar pilot study. Of these subjects, one subject had no saved PSG recording and thus no AHI information and two subjects had no Alar data stored on the phone, all three subjects were removed from data collection. The remaining 39 patients were recruited, containing 23 OSA and 16 non-OSA at an AHI threshold of 5. The sleep studies of nine additional subjects were excluded due to minimal recording or sleep time (<3 hours, mainly due to early removal of the nasal sensor (n=4)

or connection loss between sensor and phone (n=2)) or signals with low signal quality (n=3). Of the remaining subjects, 30 adults had a full data collection consisting of both PSG and Alar recordings.

Figures 1 and 2 show the ROC curves for classifying adults at AHI cutoffs of 5 and 10 respectively using SpO2 (red) and airflow (blue) analysis. The optimal model was selected using a Random Forest model, with an average of 5 features selected to build the model. At an AHI threshold of 5, the AUC obtained from the SpO2 and airflow signals was 78% and 89%, respectively. At a higher AHI threshold of 10, the AUC obtained from the SpO2 and airflow signals was 77% and 80%, respectively. For both AHI thresholds, the airflow signals provides a higher AUC performance compared to the SpO2 signals, identifying adults with OSA.

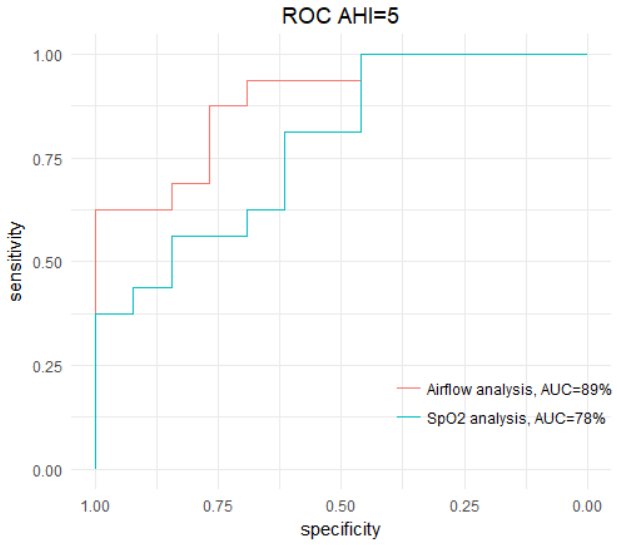

Figure 1 - ROC curve for AHI ≥ 5. The ROC was obtained using random forest with the most discriminating features applied to the Alar pilot dataset using Leave One Out cross-validation

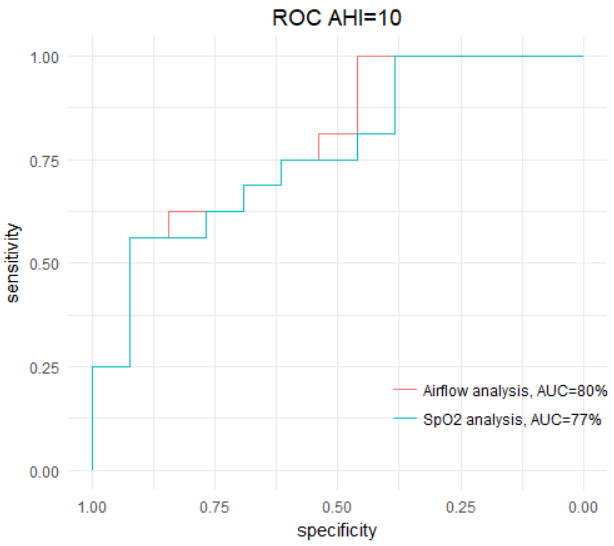

Figure 2 - ROC curve for AHI ≥ 10. The ROC was obtained using random forest with the most discriminating features applied to the Alar pilot dataset using Leave One Out cross-validation

V. Discussion

This study presents the Alar pilot study consisting of 42 recordings of adults, measured with the Xhale Alar sensor simultaneously with PSG. This pilot study investigates the preliminary use of a nasal sensor in the screening of adults with OSA, specifically the performance of airflow analysis using an integrated thermistor from nasal pulse oximetry recordings.

According to the AASM, a minimum of heart rate, oxygen saturation, and airflow analysis is required for at home sleep testing. [11] Previous at-home research showed the use of traditional finger pulse oximetry, recording both SpO2 and PPG signals, for oxygen saturation and pulse rate variability (PRV) analysis. The use of PRV (surrogate of heart rate variability) derived from the PPG signal recorded with a finger pulse oximeter has been shown to increase at home OSA detection compared to SpO2 analysis alone. [10],[12] Looking at combining multiple signals, it is also know that a cessation of breathing is best measured using an airflow signal, therefore in this study, we were interested in the screening potential of airflow signals compared to SpO2 analysis using a nasal pulse oximeter sensor. In order to assess the use of the Alar nasal pulse oximetry sensor as a screening tool for OSA, this study explored the use of two signals extracted from this sensor, SpO2 and airflow.

Using both AHI ≥ 5 and AHI ≥ 10 as the gold standard cutoff for the diagnosis of OSA, the airflow signal recorded with the thermistor shows a higher performance in screening adults for OSA compared to SpO2 analysis (respectively AUC of 89% and 80% for airflow analysis, compared to 78% and 77% for SpO2 analysis).

Although the addition of airflow in OSA screening seems to add valuable information to improve the performance, future event-by-event comparison with apnea/hypopnea events from the PSG can show a more quantitative view on whether each apnea event can be accurately detected with only one nasal thermistor.

The real setting for the proposed OSA screening tool is at home. This device is a portable, easy-to-use sensor, which was not experienced as unpleasant by the patients. A future study will concentrate on repeated measures with the Alar device both at the hospital and at home. This way the comparison can be made between hospital and at home measurement, and the performance of the proposed method can be investigated in the real at home environment.

This study described the use of a novel nasal pulse oximeter and multivariate random forest models using both SpO2 and airflow signals to screen adults for OSA. The information provided by an airflow signal provides additional information to identify adults with OSA, underlying the potential for nasal pulse oximetry to improve the at-home OSA screening compared to conventional finger pulse oximetry.

ACKNOWLEDGMENTS

The authors would like to thank the clinical staff of the sleep laboratory at the Medical Spectrum Twente for their continuing support.

REFERENCES

[1] P. E. Peppard, T. Young, J. H. Barnet, M. Palta, E. W. Hagen, and K. M. Hla, "Increased prevalence of sleep-disordered breathing in adults," *Am. J. Epidemiol.*, vol. 177, no. 9, pp. 1006–1014, 2013.

[2] Z. M. Abdelsattar *et al.*, "The Impact of Untreated Obstructive Sleep Apnea on Cardiopulmonary Complications in General and Vascular Surgery: A Cohort Study," *Sleep*, vol. 57, no. 8, pp. 1205–10, 2015.

[3] N. M. Punjabi, "The Epidemiology of Adult Obstructive Sleep Apnea," *Proc. Am. Thorac. Soc.*, vol. 5, no. 2, pp. 136–143, 2008.

[4] C. A. Kushida *et al.*, "Practice parameters for the indications for polysomnography and related procedures: an update for 2005.," *Sleep*, vol. 28, pp. 499–521, 2005.

[5] N. A. Collop *et al.*, "Clinical guidelines for the use of unattended portable monitors in the diagnosis of obstructive sleep apnea in adult patients. Portable Monitoring Task Force of the American Academy of Sleep Medicine.," *J. Clin. Sleep Med.*, vol. 3, no. 7, pp. 737–47, 2007.

[6] P. Dehkordi, A. Garde, W. Karlen, D. Wensley, J. M. Ansermino, and G. A. Dumont, "Pulse rate variability compared with Heart Rate Variability in children with and without sleep disordered breathing," *Conf. Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, vol. 2013, no. December, pp. 6563–6566, 2013.

[7] A. Garde, P. Dehkordi, W. Karlen, D. Wensley, J. M. Ansermino, and G. A. Dumont, "Development of a screening tool for sleep disordered breathing in children using the phone oximeter," *PLoS One*, vol. 9, no. 11, 2014.

[8] W. Karlen, K. Kobayashi, J. M. Ansermino, and G. A. Dumont, "Photoplethysmogram signal quality estimation using repeated Gaussian filters and cross-correlation.," *Physiol. Meas.*, vol. 33, no. 10, pp. 1617–29, 2012.

[9] D. J. Eckert and A. Malhotra, "Pathophysiology of adult obstructive sleep apnea.," *Proc. Am. Thorac. Soc.*, vol. 5, no. 2, pp. 144–53, 2008.

[10] A. Romem, A. Romem, D. Koldobskiy, and S. M. Scharf, "Diagnosis of obstructive sleep apnea using pulse oximeter derived photoplethysmographic signals," *J. Clin. Sleep Med.*, vol. 10, no. 3, pp. 285–290, 2014.

[11] American Academy of Sleep Medicine, "Standards for Accreditation of Out of Center Sleep Testing (OCST) in Adult Patients," 2013.

[12] A. Garde, P. Dehkordi, D. Wensley, J. M. Ansermino, and G. A. Dumont, "Pulse oximetry recorded from the Phone Oximeter for detection of obstructive sleep apnea events with and without oxygen desaturation in children," in *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, 2015, vol. 2015–Novem, no. September, pp. 7692–7695.