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Contactless camera-based AHI score estimation in SAS patients

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Abstract: Sleep apnea syndrome (SAS) is a common sleep-related breathing disorder characterized by recurring cessations of airflow during sleep. The gold standard for diagnosing SAS is polysomnography (PSG) which requires the patient to spend one or several nights in a sleep clinic. A PSG involves a significant amount of contact-based sensors, which leads to discomfort and deviations in sleep behavior. In this work, a contactless, multispectral camera-based approach for the autonomous detection of events of nocturnal airflow reduction is presented. The detected events are further employed in estimators of sleep diagnostic metrics, such as the apnea-hypopnea index (AHI) and the SAS stage. The AHI estimation resulted in a Pearson correlation coefficient of $r = 0.9993$. The SAS stage estimator correctly predicted the SAS stage for all three recruited patients.

Keywords: contactless, camera-based, video-based, optical, multispectral, sleep, apnea, hypopnea, AHI, SAS, OSAS, CSAS, nocturnal, respiratory event, data fusion.

1 Introduction

Sleep apnea syndrome (SAS) is a sleeping disorder characterized by recurring cessations of airflow during sleep, leading to a number of complaints, such as daytime sleepiness, concentration problems, and risk of cardiovascular diseases [1]. SAS is distinguished into two types according to the source of the cessation, namely Obstructive sleep apnea syndrome (OSAS) and Central sleep apnea syndrome (CSAS). In OSAS, airflow cessation is caused by the collapse of the upper airways due to a physical obstruction [2], as shown in Figure 1. In CSAS, the cessation is caused by a missing respiratory effort [3]. Two types of respiratory events are prevalent for both types of SAS, namely apneas (complete airflow cessation) and hypopneas (partial airflow cessation) [4]. The primary diagnosis criterion for SAS is the apnea-hypopnea index (AHI), which indicates the average number of apneas and hypopneas per hour of sleep [5].

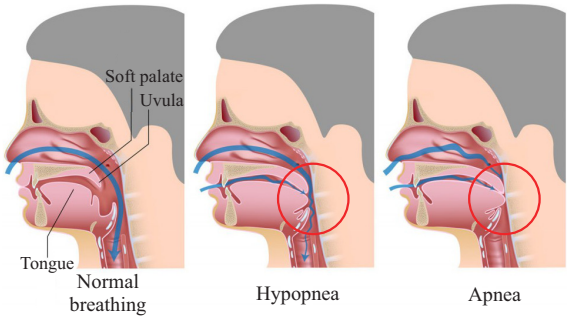

Fig. 1: Graphical representation of the upper airway obstruction leading to obstructive respiratory events [6].

SAS is diagnosed clinically in sleep laboratories via polysomnography (PSG), a multiparametric measurement involving a high number of contact-based sensors. However, a PSG involves several issues, such as patient discomfort and potentially biased results due to unnatural sleep behavior. A contactless alternative to a PSG has the potential to reduce the drawbacks of a PSG and furthermore, enable sleep diagnostics outside of sleep laboratories. A very promising direction for contactless sleep diagnostics are camera-based solutions. Cameras were first used for manual sleep scoring [7]. With the development of computer vision, automated methods have been developed. These can be divided into: (1) methods based on the analysis of respiratory motion [8–12]; and (2) methods based on the analysis of respiratory airflow [13–16].

In this work, an AHI estimation method based on respiratory airflow and multispectral remote photoplethysmography (rPPG) analysis is proposed. The goal of this study is to develop a subject-based model for AHI estimation with the differentiation among apneas and hypopneas. The AHI estimation is to be used for SAS stage classification in patients. This work is a continuation of a previously published study [13].

2 Methods

Sleep diagnostics requires data collection in the nighttime without additional sources of visible light. For this reason, a multispectral imaging device with sensors in the near-infrared

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Fig. 2: Measurement setup in the sleep laboratory.

Tab. 1: List of features extracted from the multispectral image data and physical patient data.

List of extracted features	
centroid	maximum
mean	median
min	distance
entropy	fundamental frequency
human range energy	interquartile range
absolute difference	mean difference
mean absolute deviation	neighbourhood peaks
peak-to-peak distance	power bandwidth
RMS	skewness
slope	spectral distance
spectral kurtosis	spectral positive turning points
spectral spread	sum of absolute difference
wavelet entropy	gender
aggregated age	aggregated height
aggregated weight	aggregated BMI

(NIR) and far-infrared (FIR) spectrum is used. For enhancing the measurement in the NIR spectrum, narrow-band NIR light-emitting diodes (LED) are employed. A detailed description of the measurement system is provided in [13, 17]. For the data collection, a patient study is conducted in the sleep laboratory of the University Hospital Essen. Three symptomatic patients, which were referred to the sleep laboratory with a suspected SAS for an initial diagnosis are enrolled in the study. The patient data sample is presented in Table 2. A PSG is performed with all patients and serves as a reference for the camera-based measurement. The measurement setup in the sleep laboratory is shown in Figure 2.

The collected multispectral image data is processed into three time-series signals: (1) rPPG signal at a central wavelength of 780 nm obtained from the forehead; (2) rPPG signal at a central wavelength of 940 nm obtained from the forehead; and (3) respiratory airflow signal in the FIR spectrum obtained from the subnasal region [13]. The extracted time-series signals are firstly preprocessed, then data snippets containing respiratory events are extracted and labeled with reference to the PSG data and finally fused in a respiratory event database. The extracted data snippets are fixed to a length of ten seconds. Events that last longer than ten seconds are divided into multiple ten-second-long snippets. The fused data is then fed into a feature extraction stage in which 30 individual features are calculated from each spectral signal. A list of the extracted features is provided in Table 1. The features serve as inputs to a random forest classifier (RFC), which is modeled to classify among normal breathing intervals, apneas, and hypopneas. The training of the RFC model is performed via leave-one-subject-out cross validation (LOSOCV). The hyperparameter tuning of the RFC is shown in Table 3.

For the AHI estimation, a linear regression (LR) model with a LOSOCV is trained. The model is built with three features: (1) the number of detected apnea snippets; (2) the number of detected hypopnea snippets; and (3) the measured sleeping duration. The equation of the resulting LR model is given in Equation 1. The coefficient β_0 represents the offset, while the coefficients β_1, β_2, and β_3 are weights of the input features x_1, x_2, and x_3. The estimated AHI score is used to predict the SAS stage based on the following criteria: (1) SAS existent if AHI > 15; (2) SAS nonexistent if AHI ≤ 15.

$$AHI_{Est}(x_1, x_2, x_3) = \beta_0 + \beta_1 \cdot x_1 + \beta_2 \cdot x_2 + \beta_3 \cdot x_3 \quad (1)$$

3 Results

The subject-wise results of the three-class respiratory event classification among normal breathing, hypopneas, and apneas are presented in form of a confusion matrix in Figure 3. By reducing the task into a two-class classification problem (by merging apneas and hypopneas into a single class), an overall accuracy of 0.82, a sensitivity of 0.73 and a specificity of 0.92 are achieved.

The results of the AHI estimator based on the LR model from Equation 1 and the results of the SAS stage estimation are presented in Table 4. The AHI estimation resulted in a Pearson correlation coefficient of $r = 0.9993$. The SAS stage estimation is correct with all three subjects. A comparison with the SAS stage classification results obtained in related studies is presented in Table 5. Four related studies did not obtain an SAS estimation because the study was either related to infant apnea [14], included only healthy control subjects [15], or did not involve an SAS estimation [8, 16].

Tab. 2: Overview of the patient sample included in the study.

Pat.	Gender	Age (years)	Height (cm)	Weight (kg)	BMI	AHI	ODI	Sleep time (h)	Recorded sleep time (h)
1	male	27	188	105	29.70	14.50	9.4	5.45	4.86
2	male	48	180	98	30.20	11.93	33.7	2.85	1.64
3	female	51	172	85	28.70	29.00	34.6	6.23	3.61

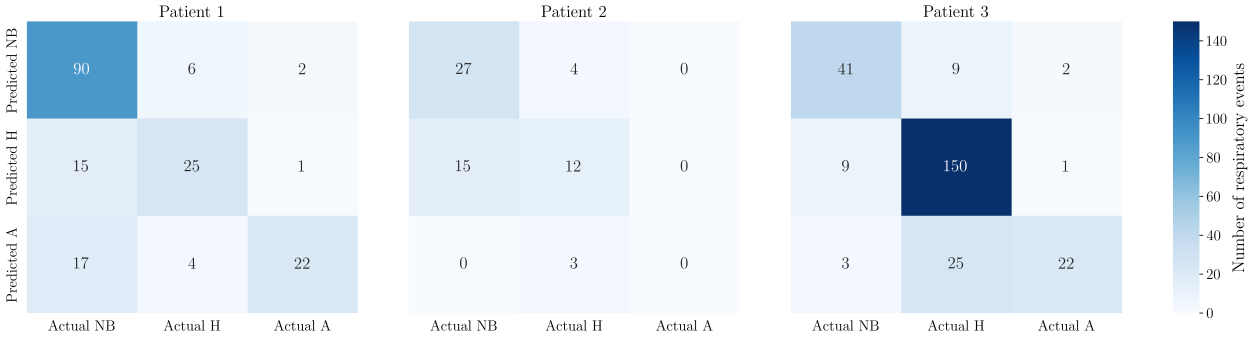

Fig. 3: Confusion matrix of subject-based respiratory event classification (NB - normal breathing; H - hypopnea; A - apnea).

Tab. 3: List of hyperparameters set for the random forest classifier.

Hyperparameter of random forest classifier			
n_estimators	100	criterion	gini
max_depth	8	min_samples_split	2
min_weight_fraction_leaf	0.0	min_samples_leaf	10
max_features	sqrt	max_leaf_nodes	none
min_impurity_decrease	0.0	bootstrap	true
oob_score	false	n_jobs	none
random_state	90	verbose	0.0
warm_start	false	class_weight	none
ccp_alpha	0.0	max_samples	none

Tab. 4: Regression and classification results for AHI score and SAS stage estimation.

Patient	AHI_{True}	AHI_{Est}	SAS_{True}	SAS_{Est}
1	14.5	13.9	no	no
2	11.9	13.0	no	no
3	29.0	20.9	yes	yes

Tab. 5: Performance comparison with related studies.

Study	Study size	SAS estimation accuracy
Alić et al.	3	1.00
[9]	21	0.90
[10]	41	0.83
[11]	50	0.98
[12]	59	0.81

4 Discussion

The results presented in this work and in the publications mentioned in the literature overview in the introduction show that camera-based systems have the potential to be used for sleep diagnostic purposes. Nevertheless, there are still several important questions that need to be addressed and further investigated in the future. The majority of studies in the published literature on camera-based sleep diagnostics still lack a deeper classification of respiratory events, which is significant for establishing a correct diagnosis and selecting a treatment plan for SAS patients. A correct differentiation based on the source of the respiratory event (central, obstructive, or mixed) combined with the correct estimation of the amplitude of the event (apnea or hypopnea) is important for correct clinical care [3].

Approaches that analyze respiratory motion can primarily detect central events due to the lack of respiratory effort. However, they still lack the possibility of detecting obstructive events, since respiratory effort remains present in obstructive events. Regarding the amplitude of the event, the approaches mentioned in the literature overview predominantly categorize hypopnea and apnea as a single class. On the other hand, approaches that analyze respiratory airflow have the issue of differentiating between the source of the event. In order to differentiate among the source of the event, it is necessary to examine the measured airflow signal more closely and analyze it based on attributes that physicians use in manual PSG classification. Another interesting aspect is the use of rPPG signals in respiratory event detection. Besides [13], no other publication is obtained that uses rPPG signals for this purpose. However,

several works have already proven that a robust respiration rate detection via rPPG is possible [18]. Furthermore, in the feature selection process in this study, it is noticed that features from the rPPG signals contribute to the classification task equally well as the FIR airflow signal. This shows that the use of NIR rPPG signals in nocturnal respiratory event detection is an approach that needs to be further investigated.

In this preliminary study, a correct SAS stage classification is achieved for all three enrolled patients. However, it must be noted that this sample is not large enough to deliver reliable conclusions. The achieved results present a promising starting point for a larger patient study.

5 Summary and Future Work

This work demonstrated a multispectral camera-based approach for AHI estimation and OSA stage classification on a small dataset of symptomatic patients. By a combined approach with rPPG analysis in two separate NIR spectra and a respiratory airflow analysis in the FIR spectrum, it is possible to differentiate among apneas, hypopneas, and normal breathing and use the detected events for a subject-based estimation of the AHI score and the SAS stage.

After obtaining promising initial results, the collection of a larger dataset of symptomatic SAS patients and healthy control subjects is currently in progress. By obtaining more data, especially from patients who experience central and mixed apneic events, it will be possible to investigate whether both the source and the amplitude of respiratory events can accurately be determined via remote camera-based measurements.

Author Statement

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