IberSPEECH 2024
11-13 November 2024, Aveiro, Portugal

Intelligent Audio-based Signal Processing for Automatic Detection of Obstructive Sleep Apnea

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Abstract

In this work, we propose a new acoustic-based method for the screening of obstructive sleep apnea (OSA) which employs breath and respiratory sounds recorded using an smartphone. In our proposed method, a set of acoustic parameters aimed at characterizing the respiratory and snore patterns of the patient are extracted from the sleep sound recordings. These include Snore Rate Variability (SVR), SET (Snore Energy Trench) parameters and Snore-to-Snore Intervals (SSI). Data fusion techniques were investigated, as well as the demographic characteristics of the subjects, which were assessed from the apnea-hypopnea index (AHI) estimated from all nightly recordings. Subsequently, a multiclass classification of each patient according to their OSA level was performed using several classifier methods, namely TabTransfomer, Support Vector Machines (SVM) and XGBoost. Real recordings made during home sleep apnea tests were used to develop and evaluate the proposed system. The TabTransformer-based classifier obtained the best results in estimating AHI severity, achieving a specificity of 0.65, accuracy rate of 0.65 and an sensitivity of 0.64, with an AUC score of 0.78. This offers the prospect of at-home screening for OSA.

Index Terms: Obstructive sleep apnea, acoustic analysis, respiratory effort, multimodal, neural network, sleep-disordered breathing, transformers.

1. Introduction

Obstructive sleep apnea (OSA) is the most common sleep-related breathing disorder in the adult population, with an estimated 1 billion adults potentially affected [1]. It is characterized by episodes of total (apnea) or partial (hypopnea) upper airway obstruction, leading to intermittent hypoxia, micro-awakenings, and increased negativity of intrathoracic pressure during inspiration [2]. OSA has significant clinical repercussions, including daytime sleepiness, impaired quality of life, neurocognitive disorders, and increased cardiovascular morbidity and mortality [3, 4].

Polysomnography (PSG) is currently the gold-standard tool for detecting OSA [5]. PSG measures multiple variables such as respiratory airflow, respiratory movements, oxygen saturation (SpO2), electroencephalogram (EEG), electrooculogram (EOG), electromyogram (EMG), electrocardiogram (ECG), and the patient's body position. Despite being the most widespread method, PSG has significant limitations, including high costs, the necessity for the patient to spend the night in a sleep lab, the requirement for administration by expert clinical personnel, and the discomfort of wearing multiple sensors throughout the night, which can affect sleep quality and diagnostic results. Additionally, manual interpretation of PSG data can be subjective and prone to errors also time-consuming and costly.

These inconveniences have contributed to the current underdiagnosis of OSA [6, 1]. For example, it is estimated that in the U.S., approximately 80% of patients with moderate to severe OSA remain undiagnosed, resulting in economic losses ranging from $60 to $160 billion annually [7]. Similarly, a recent report estimated that 85% of OSA patients in the UK are undiagnosed, and diagnosing and treating these patients could save the National Health Service £55 million and increase survival rates by 25%, reducing the risk of cardiovascular diseases, strokes, and other health issues [8].

Overall, these limitations underscore the urgent need for new, non-invasive diagnostic techniques for OSA. Using a smartphone to analyze breathing sounds during sleep emerges as an excellent candidate for OSA screening due to its convenience for at-home implementation, minimal disruption to sleep, and cost-effectiveness. Therefore, this paper aims to develop and validate a system for OSA screening based on audio recordings of snoring and breathing sounds. The proposed method analyzes whole-night audio recordings to extract a set of acoustic parameters that characterize the patient's respiratory and snore patterns. These acoustic features, combined with demographic and clinically related data, are then used in a multiclass classifier to determine the severity of OSA from the computed features.

2. Related work

OSA manifests through distinct acoustic features emitted by the person during sleep, including snores, chokes, gasps, and periods of silence. By tracking and analyzing these acoustic features, it is possible to compute parameters in the clinical scoring guidelines for OSA, such as the apnea-hypopnea index (AHI). For example, Castillo et al. [9] predicted AHI values using sound entropy from smartphone recordings attached to the chest. Saha et al. [10] estimated AHI values using a combination of oxygen saturation, tracheal sounds, and respiratory movements. Other research [11] utilized smartphone-collected sound energy, oxygen saturation, and body movement to screen for OSA.

Classical machine learning techniques have also been explored for OSA screening. In [12], a Gaussian mixture model-based system was developed to analyze acoustic features from speech signals of 93 subjects, effectively differentiating between OSA and non-OSA patients. Discriminative features such as vocal tract length and linear prediction coefficients were selected to train the model. Specifity (sensitivity) values of up to 86% (84%) were achieved by the system, indicating potential for OSA screening tool development. More recently, deep learning approaches have shown significant promise in this

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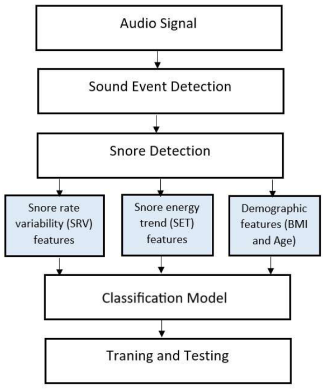

Figure 1: *Block diagram of the proposed acoustic-based method*

field. In [13], a convolutional neural network (CNN)-based system was proposed that computed AHI values from spectrogram images of tracheal sounds. In [14], CNNs were used to detect snoring from ambient sound recordings and analyze active snore noises with a smartphone.

Most previous studies used controlled sleep clinic data, limiting their applicability in home settings. An exception to this is the study [15], which described a CNN-based system to screen for OSA by analyzing sleep breathing sounds recorded with a smartphone at home. Audio recordings made over a whole night were divided into 30s segments and AHI values were predicted for each segment using a CNN. When evaluated over a sample of 103 participants, the system achieved a sensitivity of 79% and a specificity of 80% when screening for moderate OSA, while the sensitivity and specificity when screening for severe OSA were 78% and 93%, respectively.

Our study takes a different approach by using the previously unused TabTransfomer classifier and by using a database with patients with other respiratory pathologies, the COVID-19.

3. Materials and methods

3.1. Dataset

A total of 80 participants were recruited in 2022 from the Sheffield and Greater Manchester area in the UK, comprising 41 male and 39 female individuals. The dataset included cardio-respiratory data collected using Home Sleep Apnea Testing (HSAT) SOMNOTouch RESP devices, as well as sleep breathing sound data recorded via smartphones. Participants were recorded for at least two nights each in their own homes, resulting in a total of 170 nights of recordings. All participants were suffering from long-COVID at the time of the recordings and scored 3 or higher on the STOP-Bang questionnaire[1]. Both the HSAT and audio recordings underwent a sanity check procedure, leading to the exclusion of 70 nights. This left 100 valid nights of recordings from 59 participants (29 males and 30 females). The 59 participants included in this study had an average age of 41 years (SD = 11 years) and an average body-mass index (BMI) of 29 (SD = 6). Patients were classified into 4 levels of OSA according to their AHI score, with 3 being the most severe and 0 for healthy patients.

3.2. System description

Figure 1 presents a block diagram of the proposed acoustic-based method for OSA screening. Initially, the audio signal is downsampled to 16 kHz and denoised to enhance its quality. Subsequently, relevant sound events, such as snoring sounds and apneas (defined as silence periods exceeding 10 seconds), are automatically detected within each audio segment. These events are then utilized to extract a set of acoustic features, as detailed in Table 1. These acoustic features, combined with basic demographic information such as age and body mass index (BMI), are used to train multiclass classification models to assess the severity level of OSA. In the following, more details about the processing blocks in Figure 1 are given.

3.3. Acoustic features

To characterize respiratory and snore patterns during sleep, our system extracts a set of acoustic features from the preprocessed audio signals for each participant from snoring events. The preprocessing steps include converting the audio to mono, downsampling it to 16 kHz, and applying Wiener-filter denoising to enhance its quality. Based on previous studies [16, 17, 18], we consider the following types of acoustic features for OSA screening and classification, as summarized in Table 1.

It should be clarified that Snore-to-Snore Intervals (SSI) are the time intervals between consecutive snoring episodes estimated from sounds. It can provide information about breathing patterns and the presence of obstructive events during sleep. More information on how to calculate it can be found at 3.3.1.

- **Time-domain features**: are used to analyse and describe temporal signal variability. They provide information on different aspects of the signal, such as total variability, short- and long-term fluctuations, and regularity. **SDSS**: Standard deviation of SSIs of the whole night. **cSS1**: Count of successive SSIs that differ by more than 1 s. **RMSSD**: Root mean square of successive SSI differences of the whole night. **SDSD**: Standard deviation of successive SSI differences of the whole night. **SRV triangular index** : Integral of the density of the SSI histogram divided by its height [19]. **TISS**: The baseline width of the distribution measured as a base of a triangle, approximating the SSI distribution.
- **Frequency-domain features**: Relative power of the very-low-frequency (VLF) band (0.0006–0.008 Hz), low-frequency (LF) band (0.008–0.03 Hz) and high-frequency (HF) band (0.03–0.08 Hz). **LF/HF** : Ratio of LF-to-HF power.
- **Non-linear features**: are used to evaluate the complexity and structure of the time signal, they can detect complex patterns and dynamic characteristics of the signal. **S**: Area of the ellipse which represents total SRV. **SD1**: Poincaré plot standard deviation perpendicular to the line of identity. **SD2**: Poincaré plot standard deviation along the line of identity. **SD1/SD2**: Ratio of SD1-to-SD2. **DFA**: Detrended fluctuation analysis, which describes short-term ($\alpha 1$)and long-term ($\alpha 2$) fluctuations of SRV. **SampEn** : Sample entropy (entropy embedding dimension = 2, tolerance distance = 0.2 * standard deviation), which measures the regularity and complexity of a time series. **MSE**: Multiscale entropy (scale: 2, 4, 6, 8, 10), which measures the complexity of fluctuations over a range of time series.
- **SET**: are indicators of time complexity and asymmetry in time series. They are used to analyse the variability and structure of the signal.**SET Percentile**: SET percentile of the 10-90%. **SET ss**: Sample statistics for all concatenated WES values:mean, variance, skewness, kurtosis, minimum, maximum, median, standard deviation and interquartile range.

[1] http://www.stopbang.ca/osa/screening.php

Table 1: *Parameter descriptions for time-domain, frequency-domain, non-linear features, SET and demographic.*

Parameter	Unit	No
Time-domain features		
SDSS	s	1
cSS1		1
RMSSD	s	1
SDSD	s	1
SRV triangular index		1
TISS	s	1
Frequency-domain features		
VLF relative power	%	1
LF relative power	%	1
HF relative power	%	1
LF/HF	%	1
Non-linear features		
S	s	1
SD1	s	1
SD2	s	1
SD1/SD2	%	1
DFA $\alpha1$		1
DFA $\alpha2$		1
SampEn		1
MSE		5
SET		
SET Percentil	%	8
SET ss		9
SET SamplEn		5
Demographic		
Age		1
BMI		1

SET SampEn: Sample entropy of concatenated SET values.

- **Demographic**: In addition to the acoustic parameters, patient demographic parameters are taken into account. A larger number of parameters than those shown in the table are available, but only age and BMI are used as they have been shown to be the most relevant in the study of OSA.

More technical details about the extraction of the acoustic features are given in the following subsections.

3.3.1. Sound and Snore event detection

It follows the study's hypothesis that the occurrence of sleep-disordered breathing events perturbs the continuous occurrence of snoring events. Therefore, exploiting the temporal variability of snoring can help characterise the periodicity of occurrence of these events and help estimate AHI without explicitly detecting apneas and hypoapneas.

To detect sound events, the energy vector is calculated from the RMS and an adaptive energy threshold is calculated by applying a median filter of order 5 and a 90th percentile. If the event exceeds this threshold it is considered sound and if there is a silence greater than 10s it is hypoapnea, finally nearby events are merged.

The concept of SVR is proposed to characterise changes in snoring events. Snoring can occur in clusters separated by relatively long intervals, which should not be included in the time series of SSIs used to calculate SVR features. Therefore, before extracting SVR entities, the first step is to calculate all SSIs and then separate the snoring clusters based on these distances.

The steps for calculating the SSI series followed are based on the snore estimation system proposed in [20], which follows the recommendations of studies[17, 18]

Figure 2 shows an example of the result of the audio pre-processing, where the top panel shows the original audio and the Wiener filtering; the middle panel shows the energy of the signal, the sound events and the possible apnea events (silences of more than 10s) around 1:00, 1:15 and 1:30 minute in Figure 2; and the bottom panel shows the evolution of the SSI. This audio corresponds to patient nº10, who presents a high level of AHI

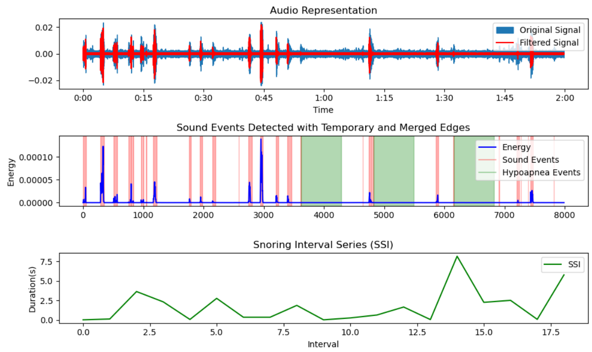

Figure 2: *Audio pre-processing result patient 10 with three OSA.*

(label severe = 3).

3.3.2. Extraction of SVR and SET parameters

After obtaining the SSI per group and for the whole night, features are extracted from SSI that can then be used in the estimation of the AHI and the classification of OSA severity. For the frequency domain features, the VLF, LF and HF bands were empirically chosen by dividing the VLF, LF and HF frequency bands typically used for HVR [21] analysis by 5, as the heart rate (60-100 beats per minute) is on average 5 times faster than the respiratory rate (12-20 times per minute) during rest. A total of 22 all-night ISS features are obtained.

Trends in the energy of consecutive snoring events are collected in different features that we call SET. The calculation is performed using the Root Mean Square Error (RMSE) to represent the amplitudes of a snoring event and the SSI between consecutive snores for each group of snores. We work with groups of 4 snoring events and their time stamps, where $RMSEs \geq 1$ and $RMSEs = SET \times \text{TimestampsMatrix} + b$, where b is the intercept of the fitted linear model, representing the initial value of the RMSE at time zero. These are then concatenated to describe the final SET features for the whole night, seen in 1.

3.4. Classification models

We evaluated three models for OSA severity-level classification: support vector machines (SVM) [22], extreme gradient boosting (XGBoost) [23], and TabTransformers [24], an artificial neural network [25] model designed for tabular data, in our case the features extracted from the audios, modeling using contextual embeddings. These models were assessed for classifying OSA into the four severity levels (0: healthy, 1: mild, 2: moderate, 3: severe). For the SVM classifier, we used standard parameters from the *Scikit-learn* library [26], to compensate for the imbalance between the data of different classes, the weights of the classes are adjusted to give more importance to the minority class, using the parameter *class_weight='balanced'* . The XGBoost classifier was configured with a *softmax* objective function for the four-class classification. Additionally, we tuned the following hyperparameters using *RandomizedSearch* from the *Scikit-learn* library across 100 iterations and five folds: (i) number of epochs (10-90), (ii) learning rate (0.01-0.2), (iii) maximum tree depth (1-5), (iv) minimum sum of instance weight needed in a child (1-9), and (v) the proportion of column subsamples when building each tree (0.5-0.9). The TabTransformer model was finetuened with the following parameters: a batch size of 32, 42 features (corresponding to the sum of

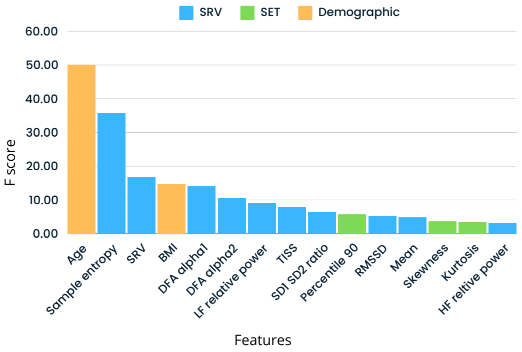

Figure 3: *Features with the top average importance scores.*

the characteristics SRV, SET and demographic characteristics) , an embedding dimension of 32, 8 multi-head attention heads, 6 encoder layers, a feedforward dimension of 128, a regularization rate of 0.1, and a learning rate of 5×10^{-5}. The classifier was trained over 25 epochs to prevent overfitting.

3.5. Model training and evaluation

For evaluation, the database is randomly divided into two sets, a training set (80%) and a test set (20%). We will perform hyperparameter fitting by cross-validation on the training set and use the validation set to compare models. For this we will use the library of *Machine Learning Scikit-learn* library and its *sklearn.model.selection.train.test.split* function to split the subsets randomly into training and test. We evaluated model performance using accuracy, sensitivity, specificity, F-1 score and AUC score, calculated from the ROC curve and confusion matrix. Training was performed using *leave-one-fold-out* cross-validation at the subject level.

4. Results

4.1. Exploratory analysis

Firstly, we aimed to identify the most predictive features (acoustic or demographic) for OSA severity-level classification. We trained an XGBoost classifier and obtained importance scores for each feature type, indicating their utility in constructing the model's decision trees. This allows for ranking and comparison of features based on their contribution to classification accuracy improvements. Figure 3 presents the ranking of the top 15 features selected by the XGBoost technique for our dataset, where the F score indicates the relevance of this characteristic, the higher it is, the more it influences the detection of OSA. As can be seen, demographic features such as age and BMI are among the top five features for our problem. This is not surprising, as there is ample evidence supporting the relationship between these attributes and OSA-related parameters such as AHI [27, 28]. It is also observed that the SVR characteristics occupy more relevant places than the SET characteristics, with simple entropy being the most important of the SVR characteristics and petencil 90th the most important of the SET characteristics.

4.2. OSA classification results

The results obtained for each classifier are shown in table 2. They have been obtained by calculating the metrics per class and then performing a weighted average across all classes. We can see that the three classifiers achieve considerably low sensitivity, accuracy rate and f-1 metrics. This is mainly due to the imbalance of the data since class 3 is not detected by the models, which results in worse metrics. The worst of these is the SVM, which shows that this model is less robust to mismatches in the distribution, as well as being the least consistent. This underlines the importance of obtaining other metrics such as the AUC score or ROC curve, all of which are above 0.5, showing that no prediction is random.

Table 2: *OSA classification results weighted average.*

	XGBoost	SVM	TabTransformers
Sensitivity	0.67	0.55	0.64
Specificity	0.55	0.61	0.65
Accuracy Rate	0.59	0.42	0.65
F-1 Score	0.58	0.42	0.64
AUC	0.8	0.87	0.78

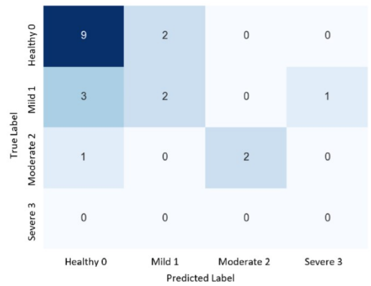

Figure 4: *Confusion matrix TabTransformer model.*

If we look at the confusion matrix from the evaluation of the TabTransformer model (20 nights) in Figure 4, which gets the best metrics, shows that the model performs reasonably well in classifying classes 0 and 2, but struggles with classes 1 and 3. This may be acceptable or even preferable in scenarios where false positives have a high cost, but there is room for improvement in identifying all positive instances to increase the sensitivity and hence the F1-score. To improve performance, more training data could be collected from the under-represented classes.

5. Conclusions

Robust screening for OSA in a real home environment during sleep is a difficult task. There are two main problems: 1) ambient sound recordings may be affected by background noise; 2) the mismatch between OSA classes affects the models considerably. This paper proposes a novel solution by exploiting the temporal pattern of sounds and the integration of complementary information from acoustic signal characteristics and patient demographics. It has been evaluated using three types of classifiers, from the more conventional SVM to the more novel Transformer-based classifiers, the latter being the most appropriate for this purpose, offering a cost-effective domestic solution for an accurate and reliable assessment for a first screening. Future work will investigate ways to automatically resort to single-mode approaches when data are not available.

6. Acknowledgements

This work was partly supported by Innovate UK Knowledge Transfer Partnership (KTP) 012741 and UKRI MRC IAA Grant Ref: MR/X502728/1, and by grant PID2022-141378OB-C22 funded by MICIU/AEI/10.13039/501100011033 and by ERDF/EU.

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