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Using entropy of snoring, respiratory effort and electrocardiography signals during sleep for OSA detection and severity classification

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ABSTRACT

Study objectives: Obstructive sleep apnea (OSA) is a very prevalent disease and its diagnosis is based on polysomnography (PSG). We investigated whether snoring-sound-, very low frequency electrocardiogram (ECG-VLF)- and thoraco-abdominal effort- PSG signal entropy values could be used as surrogate markers for detection of OSA and OSA severity classification.

Methods: The raw data of the snoring-, ECG- and abdominal and thoracic excursion signal recordings of two consecutive full-night PSGs of 86 consecutive patients (22 female, 53.74 ± 12.4 years) were analyzed retrospectively. Four epochs (30 s each, manually scored according to the American Academy of Sleep Medicine standard) of each sleep stage (N1, N2, N3, REM, awake) were used as the ground truth. Sampling entropy (SampEn) of all the above signals was calculated and group comparisons between the OSA severity groups were performed. In total, (86x4x5 =)1720 epochs/group/night were included in the training set as an input for a support vector machine (SVM) algorithm to classify the OSA severity classes. Analyses were performed for first- and second-night PSG recordings separately.

Results: Twenty-seven patients had mild (RDI = ≥ 5/h but <15/h), 21 patients moderate (RDI ≥15/h but <30/h) and 23 patients severe OSA (RDI ≥30/h). Fifteen patients had an RDI <5/h and were therefore considered non-OSA. Using SE on the above three PSG signal data and using a SVM pipeline, it was possible to distinguish between the four OSA severity classes. The best metric was snoring signal-SE. The area-under-the-curve (AUC) calculations showed reproducible significant results for both nights of PSG. The second night data were even more significant, with non-OSA (R) vs. light OSA (L) 0.61, R vs. moderate (M) 0.68, R vs. heavy OSA (H) 0.84, L vs. M 0.63, M vs. H 0.65 and L vs. H 0.82. The results were not confounded by age or gender.

Conclusions: SampEn of either snoring-, very low ECG-frequencies- or thoraco-abdominal effort signals alone may be used as a surrogate marker to diagnose OSA and even predict OSA severity. More specifically, in this exploratory study snoring signal SampEn showed the greatest predictive accuracy for OSA among the three signals. Second night data showed even more accurate results for all three parameters than first-night recordings. Therefore, technologies using only parts of the PSG signal, e.g. sound-recording devices, may be used for OSA screening and OSA severity group classification.

1. Introduction

Obstructive sleep apnea (OSA) is a worldwide common disease diagnosed by the gold standard of full-night attended polysomnography (PSG). Proper recording and analysis of PSG is associated with a high time and resource burden for both professional examiners and patients. Therefore, technical and scientific methods aiming at simplifying the diagnosis of OSA without the need to perform full-night PSG should be evaluated.

Snoring is highly prevalent in the general population with an estimated prevalence of 20-40% [1,2]. It is also a very common symptom of OSA, since it generally occurs in patients with a narrow upper airway,

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which is also causative of obstruction [3]. Snoring may also be an indicator for OSA and its associated sequels, like cardiovascular diseases [4] or even metabolic diseases [5]. Lately, snoring-related sounds (SRS) have come into focus for the detection of physiological signals to determine OSA and it is suggested that they carry significant information on OSA presence and severity [6]. The presence of snoring in a patient alone justifies evaluating for OSA and SRS analysis may provide an alternative to PSG for the evaluation of OSA [7].

In recent years, researchers have attempted to develop a simple and cost-effective test for diagnosing OSA by analysing SRS. These acoustic features include both intra-snore elements (such as snore rate or duration, snore index, intensity, and frequency) and inter-snore factors (such as snore time interval index, STII), often used in combination [8].

A meta-analysis by Chiang et al. [7] examined the relationship between snoring and AHI. They included several elements in their analysis. While the snoring index and snoring rate - often found in the report of a normal PSG - did not show good correlations with the apnea-hypopnea index as a proxy for OSA severity, other valuables focusing on the individual structure of the snoring sound - such as snoring intensity and snoring frequency - showed significantly better correlations. Thus, this suggests that the actual snoring signal and its microstructure provides valuable information about the presence and severity of OSA. This prompted this study, which investigated the entropy of the different and individual biosignals.

Heart rate information provides information as a proxy for autonomous activities, these parameters of overnight recordings were found competent to judge the severity of sleep apnea in previous studies [9] and frequently coincident with autonomic sympathetic nervous system activation and cortical arousal [10]. The study aimed to prove that, again, the entropy of this signal can be used to classify OSA.

Analysis of the thoracic and abdominal effort signals during the course of a respiratory event is crucial for scoring an event as obstructive, mixed or central on PSG analysis. Continued thoracic/abdominal effort during an apneic event defines the event as obstructive [11]. Because thoracic and abdominal excursion play a key role in both the pathogenesis of OSA and ultimately in the diagnosis of the disease, we also wanted to determine whether the entropy of this signal alone gives information about the presence of OSA.

Various entropy metrics are used in signal processing to describe the degree of variability and/or complexity of related information in recorded signals in the time domain. In this study, the so-called sample entropy (SampEn) was used to determine the degree of variabilty and complexity of the noise-, very low frequencies of the electrocardiogram as well as thoraco-abdominal effort signals [11]. The SampEn is the index for the complexity of the signals or activity. Thus, the value of the SampEn can also be used to determine how intensive the respective measured activity is. As a result, a conclusion can be drawn about the strength of the trigger of the activity. The aim of this study was to test whether the aforementioned SampEn metrics could be used as surrogate markers to determine the severity of OSA.

2. Methods

All patients underwent attended full-night PSG on two consecutive nights according to the American Academy of Sleep Medicine (AASM) standards at the sleep laboratory of a tertiary university medical center. All Snoring noises were collected as a part of the PSG with the help of the PSG device, Alice ® LE Headbox, Int“l (Model No: 1001929), Respironics. The PSG-embedded microphone was placed and fixed with the tape on the skin of the patient’s neck covering the larynx. The snoring sounds’ raw data was used as an input signal without additional filters. During calibration of the sensors, at the beginning of the PSG recordings, the patient was asked to both speak and snore loudly to differentiate the signals from each other. Mean PSG recording time was 8 h. Thoraco-abdominal excursions were recorded via respiratory inductive plethysmography (RIP) on thoracic and abdominal belts. Elastic bands were placed around the thorax and abdomen, and an induction loop incorporated into these bands served as a sensor that registered respiratory movements as volume changes. A single – lead electrocardiogram (ECG), in accordance with the AASM standard, was performed during the PSG. Additionally, patients’ demographic data and sleep-specific parameters were used from the PSG reports. Inclusion criteria were a recording of snoring data, ECG and thoraco-abdominal effort of more than 6 h duration during each PSG night and patients’ age >18 years. Patients with lung diseases, such as chronic obstructive pulmonary disease (COPD), asthma or a history of heart failure were excluded, since breathing difficulties in these patients may lead to breathing noises not associated with snoring.

The local Institutional Review Board (Nr. 2018-13942) provided approval for the study. The research findings are based on research and clinical practices that conform to the principles of the Declaration of Helsinki.

3. Data extraction

The curves of ECG, the thoraco-abdominal effort as well as the sound curve from SRS from both PSG-nights were extracted for each patient from four manually scored 30-s-epochs of each sleep stage (N1, N2, N3, REM, awake), which were used as the ground truth. The entire PSG recordings of both nights in all patients had been scored manually by experts in sleep medicine. Sleep stage classification was performed manually by experts in sleep medicine according to AASM criteria [12]. OSA severity decision was based on the RDI of the second night PSG. For each distinct sleep stage category, two epochs without any respiratory events and two epochs with at least one respiratory event have been chosen. The Fast-Fourier-Transformation (FFT) algorithm breaks down the heart rate into the various frequencies that make up the heart rate and displays them in a graph. A distinction is made between High Frequency (HF), Low Frequency (LF) and Very Low Frequency (VLF) bands. In this study, we focused on the VLF (0,003–0,04 Hz). Data collection from the PSG report included respiratory distress index (RDI), total sleep time (TST), time in bed (TIB), sleep efficiency (in %), mean oxygen saturation during sleep (in %), oxygen desaturation index (ODI) and arousal index (AI). This data collection served as raw data basis for the analytical evaluation by means of a support vector machine algorithm (SVM).

4. Data analysis

4.1. Sample entropy (SampEn)

The SampEn based on an algorithm developed by Richman and Grassberger [10,13]. Several variables are crucial for the calculation. To be able to calculate the SE, three variables must be known. m, r and N. m describes the so-called embedding dimension, i.e., the number of compared vectors and thus the length or width of the considered dimension. r is the mathematical tolerance. N defines the number of vectors per considered time interval. To be able to calculate the snoring entropy of a certain time classification adequately and without errors, the variables m and r must be determined consciously. The entropy power increases with increasing number of paired vectors in the embedding dimension (m and m+1). Low values of the variable m and high values of the variable r increase the number of paired vectors. In turn, too small a value for r increases the error rate [10,13]. We used in this study m = 2 and r to be 0.25 which has been described earlier [13] and also ideal for biosignal time series data.

4.2. SVM classifier

The SVM classifier is an instrument for the non-linear classification of two data sets. The algorithm tries to achieve the optimal separation of two data sets by maximizing the so-called “margin” or limit of the points

of the respective data sets that are closest to each other. The mean value of the limit size reached is the optimum hyperplane. The points that are closest to each other in relation to the separating straight line are referred to as “support vectors”. Once these have been identified, the so-called “margin” or boundary is formed between these points. It must be maximized and a mean value line or a mean value level must be formed. The mean plane is called the hyperplane. Non-linear values are created, represented in an XY coordinate. These values are in a so-called “lower dimension space” and must be converted into a linear form, the “higher dimension space”, for better transfer to a graphic representation, such as the receiver operator characteristic curve (ROC). For this, the basic parameter, for example a snoring entropy value, is compared to two variables on the X and Y axis. This results in individual values for individual test subjects. To be able to represent these in the ROC as an overall value or overall result, these values are drawn mathematically from their actual points of representation, within the coordinates, onto a linear plane. In this work, all individual severity groups of patients were compared using SVM. The group without OSA was named “R" for regular, the group with mild OSA as “L" for light, the group with moderate OSA as “M" for middle and the severely ill as “H" for high. A comparison pattern resulted: L-R, L-M, L-H, M-R, M – H, H-R. Accordingly, the divergence between two groups was calculated 6 times. We compared several “parameter generators”, such as ECG, EOG and thoraco-abdominal effort, to investigate whether it is possible to determine the severity of OSA disease in patients according to the RDI value with just a few parameter generators. The comparisons should also allow to test which parameters are particularly suitable for this analysis and are diagnostically more valid than the other parameters. In this context, the following were considered: the thoraco-abdominal effort entropy, the ECG heart rate related to very low frequency ranges (ECG-VLF) and snoring entropy (snore entropy). In this work we use ROC-curves to graphically display the values calculated by SVM and the associated calculation of the area under curve value (AUC). In doing so, we asked for the possibility of comparing two data sets of different degrees of severity as ROC curves.

A flowchart of the extraction and analysis process is shown in Fig. 1.

4.3. Statistical analysis

Statistical analysis was performed with MATLABR 2015a. The demographic patient data were compared among the four OSA severity groups using a one-factorial analysis of variance (ANOVA), with group as the factor [14]. The OSA severity groups were compared using SVM. The group without OSA was named as “R" for regular, the group with mild OSA as “L" for light (RDI<15/h), the group with moderate OSA as “M" for moderate (RDI≥15/h and <30/h) and the severely ill as “H" for heavy (RDI≥ 30/h). The calculated data were then displayed into a receiver operator characteristic (ROC) curve. To test whether the entropies may be used as a surrogate marker to predict disease severity [using respiratory disturbance index (RDI) = 15/h and 5/h as cut-offs], the area under the curve value was calculated for each ROC [14].

A classifier is a parameter or a variable with a suitable optimal threshold, which is used in a classification algorithm. In this study, only binary classification was considered, e.g. classification between two different cases termed ‘positive case’ and ‘negative case’. Three main metrics evaluate the performance of a classifier —sensitivity, specificity and accuracy [15]. Age and gender were considered as a confounder in all calculations.

5. Results

A total of 102 raw data sets were collected from the Alice Sleepware system’s data memory, 86 of them (22 female, age 26-81 years) were fit for analysis. 27 patients had suffered from mild (RDI ≥5/h but <15/h), 21 patients from moderate (RDI ≥15/h and <30/h) and 23 patients from severe OSA (RDI ≥30h). 15 patients had an RDI <5/h and were therefore considered healthy/regular (R). For demographical data on the different severity groups refer to Table 1. Age and sex did not confound

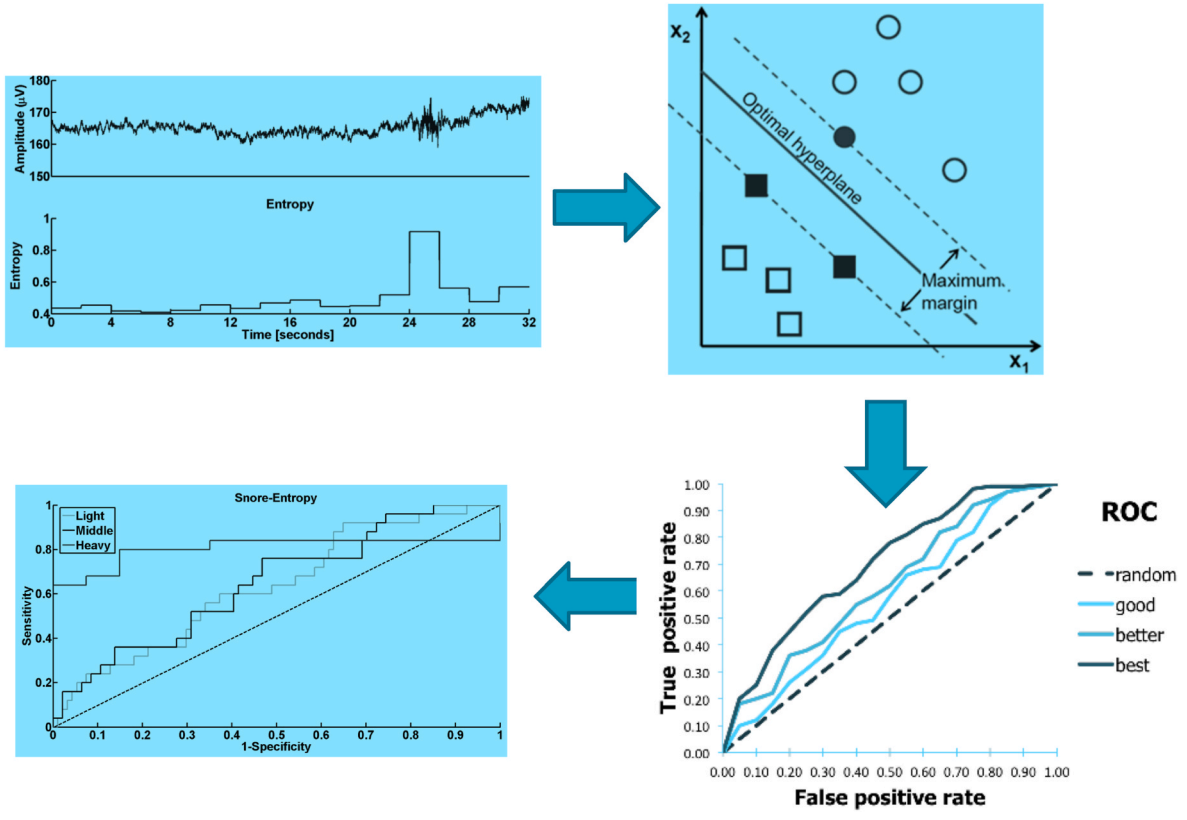

Fig. 1. Analysis Pipeline of data extraction and SVM analysis; ROC= Receiver Operating Curve.

Table 1
Clinical demographics and sleep-associated variables in the various groups of the study participants.

Group	Percentage female	Age (years)	BMI (kg/m^2)	RDI (events/hour)	t90 (SpO2 in %)	Arousal-Index (events/hour)	ODI nREM (events/hour)	ODI REM (events/hour)
Healthy (R)	27%	56.2 ± 10.3	18.9 ± 2.8	2.5 ± 1.5	0.14 ± 0.23	17.2 ± 8.8	1.9 ± 1.8	4.4 ± 5.2
Light OSA (L)	19%	54.8 ± 11.7	25.4 ± 3	11.5 ± 3.4	0.92 ± 0.02	19.4 ± 3.3	5.9 ± 2.1	10.3 ± 11
Moderate OSA (M)	19%	54.4 ± 8	27 ± 3.7	22.6 ± 4.2	3.11 ± 0.03	24.6 ± 6.4	11 ± 7.9	13.9 ± 13.2
Severe OSA (H)	17%	58.1 ± 13.1	30 ± 5.8	53.6 ± 23.1	10.3 ± 0.36	37.7 ± 17.5	39 ± 30	29.5 ± 24.3
(Anova factor group); p-values	(F(3,4.87) = 2.97; p>0.05)	(F (3,6.39) = 3.45; p>0.05	(F(3,1.29) = 89; p<0.01	(F(3,0.84) = 2305; p<0.001	(F(3,0.78) = 206; p<0.001	(F(3,0.7) = 7365; p<0.001	(F(3,1.98) = 453; p < 0.001)	(F(3,2.08) = 29; p < 0.01

The table shows sex of the participants, age, body-mass-index (BMI) in kg/m^2 and the RDI (respiratory disturbance index in events/h sleep). ODI = oxygen desaturation index in events per hour, was divided up into nREM (=non-rapid eye-movement) and REM (rapid eye-movement) sleep. RDI events include apneas, hypopneas and respiratory effort-related arousals (RERA). Healthy individuals (R, regular) had RDI ≤5 events/h, patients with mild OSA (L) had RDI = 5–15/h, patients with moderate OSA (M) had RDI = 15–30/h and patients with severe/heavy OSA (H) had RDI >30/h sleep. t90 is the percentage of TST during which the blood oxygen saturation, as measured by finger pulse oximetry, was below 90%. Numerical values are means followed by standard deviations. All numerical values are rounded up to the first decimal point. The arousal index was significantly different between group H and all other three groups ($p < 0.001$), but not between pairs of the other groups. BMI was not significantly different between group L and M ($p = 0.963$) and M vs. H ($p = 0.119$), whereas all other comparisons were significant ($p < 0.001$). As tested using ANOVA, age and sex were not confounders. PSG-associated parameters were drawn from the second night of PSG-testing.

the analysis.

The snoring SampEn of the second PSG night showed an AUC value of 0.61 and a significance value of 0.021 ($p = 0.021$) when comparing R vs. L. When R vs. M were compared, the AUC value was 0.68 and the significance value was 0.011 ($p = 0.011$). For R vs. H, an AUC value of 0.84 and a significance value of <0.001 (p< 0.001) was calculated. L vs. M gave an AUC value of 0.63 and a significance value of 0.032 ($p = 0.032$). M vs. H resulted in an AUC value of 0.65 and a significance value of 0.014 ($p = 0.014$). The comparison of L vs. H resulted in an AUC value of 0.82 and a significance value of <0.001 (p<0.001). See Table 2 for data of first and second night in comparison. Fig. 2 shows a graphic display of the comparison between group R and the other groups with a receiver operating curve (ROC). Overall, the snoring entropy showed very good results in both nights. In particular, the comparison of non-diseased patients and severely affected patients in the second night of PSG with an AUC value of 0.84, the highest overall AUC value measured in all parameter calculations, was excellent.

ECG-VLF-entropy showed in the second night an AUC value of 0.65 and a significance value of p = 0.026) when R vs. L were compared, for R vs. M, an AUC value of 0.66 ($p = 0.024$) and for R vs. H, an AUC value of 0.68 ($p = 0.004$). L vs. M resulted in an AUC value of 0.62 ($p = 0.037$), M vs. H in an AUC value of 0.65 ($p = 0.015$) and L vs. H 0.68 ($p = 0.004$). ECG VLF does not yield an AUC value greater than 0.68, making it inferior to other measured parameters as a diagnostic reference parameter for OSA severity classification. Fig. 3 shows a graphical display of the ROC comparing group R with the other severity groups.

The performed thoracic abdomen effort signal entropy in the second night showed an AUC value of 0.65 ($p = 0.021$) when R vs. L were compared. R vs. M showed an AUC value of 0.69 and a significance value of $p = 0.011$, R vs. H an AUC value of 0.75 (p<0.001) and L vs. M resulted in an AUC value of 0.6 ($p = 0.036$). M vs. H resulted in an AUC value of 0.64 ($p = 0.021$) and L vs. H in an AUC value of 0.73 (p<0.001). Fig. 4 shows a graphical display of the ROC comparing group R with the other severity groups. The collection of data for the performed thoracic-abdominal entropy calculation proved to be extremely difficult, as the raw data in the Alice Sleepware program were associated with a high error rate. In many patients, the leads of the thorax and abdomen, contained sections with significant confounding factors and thus insufficient data quality.

Table 2
Summary of comparisons of snoring- ECG-VLF- and thoraco-abdominal effort-sampling entropy (SampEn) values. Accuracy values are provided as a percentage following each AUC value and its respective p-value.

Parameter	Comparison	Area-under-the curve, (p-value) – Accuracy (in %)	
		First night	Second night
Snoring- Entropy	R vs. L	0.61 (0.043) – 61.0%	0.61 (0.021) – 61.0%
	R vs. M	0.62 (0.03) – 62.34%	0.68 (0.011) – 68.0%
	R vs. H	0.8 (<0.005) – 79.83%	0.84 (<0.001) – 84.01%
	L vs. M	0.6 (0.041) – 59.87%	0.63 (0.032) – 62.78%
	M vs. H	0.61 (0.029) – 61.43%	0.65 (0.014) – 65.43%
	L vs. H	0.79 (<0.005) – 79.23%	0.82 (<0.001) – 82.18%
ECG-VLF-Entropy	R vs. L	0.6 (0.041) – 59.78%	0.65 (0.026) – 65.0%
	R vs. M	0.61 (0.036) – 61.23%	0.66 (0.024) – 66.0%
	R vs. H	0.65 (0.024) – 65.0%	0.68 (0.004) – 68.0%
	L vs. M	0.59 (0.048) – 59.08%	0.62 (0.037) – 61.87%
	M vs. H	0.61 (0.038) – 61.23%	0.65 (0.015) – 65.43%
	L vs. H	0.65 (0.012) – 64.56%	0.67 (0.004) – 67.87%
Thoraco-abdominal effort Entropy	R vs. L	0.57 (0.039) – 57.63%	0.65 (0.021) – 65.0%
	R vs. M	0.61 (0.031) – 61.24%	0.69 (0.011) – 69.0%
	R vs. H	0.7 (<0.005) – 70.0%	0.75 (<0.001) – 75.0%
	L vs. M	0.58 (0.045) – 58.76%	0.6 (0.036) – 60.23%
	M vs. H	0.6 (0.036) –59.87%	0.64 (0.021) –64.35%
	L vs. H	0.69 (<0.005) –69.98%	0.73 (<0.001) –73.45%

6. Discussion

This study aimed to investigate whether the entropy of different physiological signals during sleep could be used as a surrogate marker to discriminate between OSA and non-OSA as well as between the different severity classes of OSA. Our results show that the intended distinction is possible in all cases, especially when using the entropy of snoring sound signals of the second night of PSG recordings.

Studies focusing on use of ECG-VLF-entropy as a diagnostic tool for OSA are sparse. Noda et al. investigated ECG-VLF prior and following positive airway pressure (PAP)-treatment. Reduction of the apnea-hypopnea-index (AHI) under PAP-treatment was associated with reduced amplitudes of VLF, supporting our thesis that VLF differs within

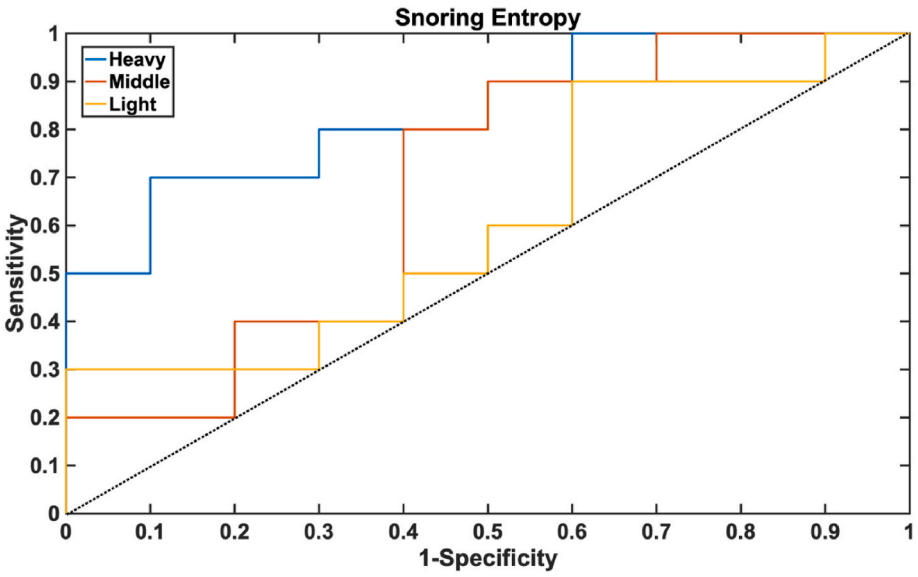

Fig. 2. Results on snoring entropy. This ROC graph shows the results of comparing the R group (i.e. the group without OSA) with each one of the other three OSA groups (L, M, H) separately.

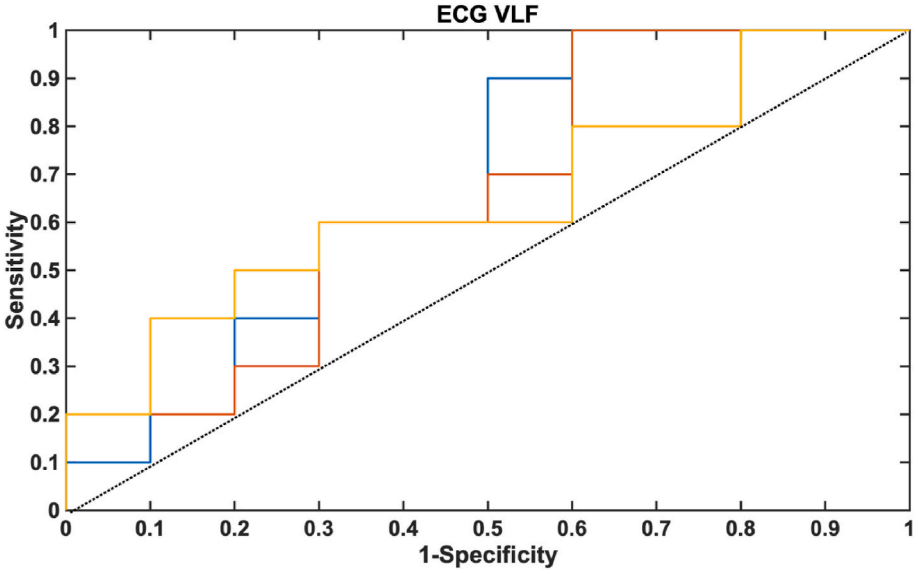

Fig. 3. Results for ECG VLF. This ROC graph shows the results of comparing the R group (i.e. the group without OSA) with each one of the other three OSA groups (L, M, H) separately.

OSA severity groups [16].

Additionally, to the best of our knowledge, the investigation of the use of thoraco-abdominal effort signal entropy alone to diagnose and classify OSA has not been previously reported in the literature. Studies on this topic mostly included the abdominal and/or thoracic excursions as part of an algorithm. Kaimakamis et al. for example developed a predictive model for the presence/severity of OSA using a linear equation and non-linear decision trees from three respiratory signals, that were extracted from two biosignals (airflow from a nasal cannula and thoracic movement) to predict OSA [17].

Although our approach with the use of the entropy of the thoraco-abdominal effort signal alone proved to be useful for both OSA prediction and distinction, results were inferior compared to results provided by the snoring signal entropy metric.

Previously, other authors have attempted to correlate the snoring signal with obstructive sleep apnea. Akhter et al. used the snoring sound of 91 patients with known OSA on polysomnography to distinguish between REM and NREM sleep by setting up an algorithm and further categorize each sleep stage as non-OSA or OSA with accuracies ranging from 80 to 86% [18]. Abeyratne et al. integrated snoring sounds into a multi-feature OSA screening tool, capturing functional, structural and spatio-temporal dependence of snoring sounds, resulting in a sensitivity and specificity of about 93% for OSA diagnosis [19]. Janott et al. were able to identify the origin of snoring sounds by coupling the sound data to sleep endoscopic findings, although accuracy was rather moderate with recall rates up to 55% [20].

A study by Sowho et al. identified snoring intensity as a reliable predictor for the presence of OSA. In contrast to our study, snoring intensity in their study was not measured by the sound profile and entropy, but by the mean peak inspiratory sound. They could identify a peak sound “cut-off” at 53 dB. Based on their results, above this 53 dB-threshold, patients had predominantly manifest OSA [21].

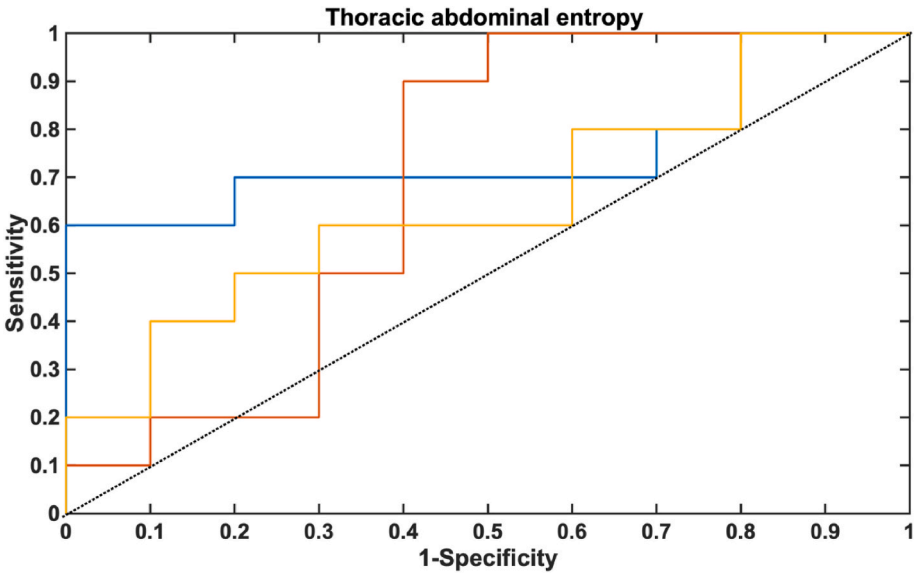

Fig. 4. Results for thoraco-abdominal effort signal entropy. This ROC graph shows the results of comparing the R group (i.e. the group without OSA) with each one of the other three OSA groups (L, M, H) separately.

But not only the sound event itself has been used previously for OSA diagnosis. In addition, irregularities in snoring like inter-event-silence seem to correlate with sleep apnea. Ben-Israel et al. found a correlation of this silent time interval with the AHI [22]. Mesquita et al. have also been able to distinguish between regular and non-regular snoring event patterns; again, the time interval between snoring was examined and it was found that patients with severe apnea had shorter time intervals between regular snoring events [23].

Roebuck et al. used multiscale entropy (MSE) to both diagnose OSA and classify its severity on 858 overnight sound recordings. The noise events were labelled in the first breath after apnea (choke), snoring and other noise events. Whereas the event classification by more traditional speech analysis algorithms reached an accuracy of 76.9%, the accuracy for OSA severity classification using MSE entropy increased to 80% [24].

Wang et al. used spectral entropy and sampling entropy to distinguish snoring from non-snoring sounds on PSG. Especially with use of sampling entropy a high accuracy of 94% was achieved [25]. Kim et al. developed a complex system of acoustic signal biomarkers that also succeeded in diagnosing and classifying OSA; in their study, a standard PSG microphone was used [26].

Furthermore, the influence of snoring on the organism as well as different organ systems seems to be greater than initially assumed. Most of the consequences of disturbed night sleep have always been associated with upper-airway-collapse and apnea. Recently, however, more and more studies show that snoring alone - with or without concomitant OSA - can be associated with adverse effects for the organism. A study by Taylor et al. showed that heavy snorers without OSA had greater carotid remodelling, in terms of carotid intima-media thickness and carotid inter-adventitial diameter, than non-heavy snorers [27]. In a another study the snoring index in OSA patients was the single strong indicator of the presence of non-alcoholic fatty liver [5]. Further, snoring alone without any concomitant OSA may be associated with a systemic pro-inflammatory profile, therefore increasing cardiovascular risk in snorers [28].

A limitation of our study is that snoring sounds were not individually checked on extraction, meaning that they could not be separated from other breathing-related sounds that may occur during the night. However, the entropy of the snoring sounds proved to be the best parameter despite this possible confounder. There was no significant difference in BMI on OSA groups L vs M and M vs H, and still these groups were distinguishable by the three entropies. But it is a limitation of the study that our control group significantly differed in BMI and consisted of patients with a significantly lower mean BMI than the other three groups. This could have affected our results. As a consequence, the effect of the BMI on the different signal entropies should be further investigated.

A strength of our study is the relatively high number of participants and well-distributed number of OSA-positive participants. Also, a high number of sleep epochs were analyzed, leading to a high amount of significant results. Moreover, and most importantly, we could test and replicate the results in the same individuals on two consecutive sleep study nights.

The fact that the entropy results of the second night are even more accurate than those of the first night suggests that this signal entropy method may work better when patients are accustomed to the recording conditions and thus have a sleep more similar to the sleep in the well-known home milieu. This in turn may be a further argument for this method being more suitable for home-like conditions and not in-lab PSG conditions.

If the preliminary, hypothesis-generating results of this study could be replicated in larger confirmative studies, then there would be reason to suggest that patient-owned devices, such as smartphones or similar, which have a microphone, could be possibly sufficient for OSA diagnosis and OSA severity classification in the future.

7. Conclusion

The applied entropy method for sleep-associated physiological signals, especially for snoring sounds, may facilitate the screening or even diagnosis of OSA, since an extensive recording of multiple channels in either PSG or home sleep apnea testing would not be necessary. In this exploratory study the classification between OSA patients of varying degrees and non-OSA patients was clearly feasible. Especially the distinction between non-OSA and severe OSA individuals can be achieved with a quite high degree of accuracy. These promising results should give rise to further research in this area.

CRediT authorship contribution statement

K. Bahr-Hamm: Conceptualization, Validation, Data curation, Writing – original draft, Writing – review & editing, Visualization. **A. Abriani:** Conceptualization. **A.R. Anwar:** Writing – review & editing.

H. Ding: Writing – review & editing. **M. Muthuraman:** Conceptualization, Methodology, Software, Validation, Data curation, Writing – review & editing, Visualization, Project administration. **H. Gouveris:** Methodology, Writing – review & editing, Supervision, Project administration.

Declaration of generative AI and AI-assisted technologies in the writing process

No generative AI or AI-assisted technologies were used in the writing process.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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