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Breathing Sound Detector as a Means to Identify Possible Apneic Periods from Tracheal Sound Recordings †

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Abstract: Tracheal sound represents an easily acquired signal, particularly popular in the evolution of smartphone-based systems for Sleep Apnea Syndrome diagnosis. The syndrome is characterized by partial or complete breath cessation for at least 10 s. The developed algorithms mainly rely on neural networks focusing on the extraction of the apneic episodes' count per sleeping hour, defined as the Apnea/Hypopnea Index. Though reported highly accurate, neural networks may be severely affected by the inter- and intra-patient breathing sound variability. Alternatively, breathing detection algorithms can contribute in identifying the dominant sound patterns within the apnea events. In this work, we employ zero-crossing rate, signal power, Tsallis entropy and Shannon information to discriminate breathing from silent frames. These features are extracted independently by tracheal sound recordings from 178 patients undergoing a hospital sleep study. Apneas correspond to silent periods detected by at least one of the four features, while hypopneas correspond to periods of reduced signal power. The algorithm presents increased sensitivity (80.45%) in identifying apnea/hypopnea events (32,824 out of 40,800). Despite the non-negligible number of false positive detections, the proposed algorithm proves the dominance of the described sound pattern during apnea/hypopnea episodes.

Keywords: sleep apnea syndrome; breathing activity detection; apnea/hypopnea episode detection; tracheal sound

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1. Introduction

The Sleep Apnea Syndrome (SAS) has been gaining increasing interest since it is considered responsible for a wide variety of severe health conditions [1–3] and worsened quality of life, due to excessive daytime sleepiness and the risk of work and vehicle accidents [4]. The endeavor to develop home-based systems for SAS diagnosis, which fully comply with the criteria for high accuracy and ease of use, frequently employs the tracheal sound signal. Tracheal sound recordings are indicative of the breathing process, since contact tracheal microphones are capable to accurately monitor the vibrations of the trachea as the air flows inwards and outwards. Despite being almost ignored in the conventional process of polysomnography (PSG)—the laboratory sleep study in which a wide variety of physiological signals are recorded [5]—the tracheal sound has been proven very useful in the identification of apneic events. Indeed, an apnea event during sleep is characterized by the complete cessation of breathing or severe reduction in the inflowing air, thus it is believed to be accompanied by strong alterations in the characteristics of produced sound in the trachea [6].

An investigation of the developed systems that attempt to diagnose apnea syndrome reveals the dominance of neural networks in this field of sound classification [7]. Mainly depending on convolutional deep networks, the proposed systems classify the tracheal sound excerpts by revealing deep features in the spectrotemporal changes of the sound signal [8]. Despite the fact that the majority of these systems have been reported accurate in the development process, they are not yet capable to replace the uncomfortable test of PSG. The main restrictions they face lie in the inter- and intra-patient variability of the syndrome and the corresponding sound characteristics exhibited during apneas. Particularly, the tracheal sound may be severely altered due to the position of the body [9] and between individuals with different anthropometric factors such as weight, age and gender. The above restrictions are further extended by the recent scientific discussion on the importance of the intra-night variability of the Apnea-Hypopnea Index (AHI) [10]—defined as the average count of apneic or hypopneic events per sleep hours [11]. The exhibited variability of the AHI during the night as well as the study of different indices and factors such as the duration of each apnea event, suggests the development of systems oriented towards the apnea events detection rather than the classification of patients in groups of different syndrome severity.

Contrary to the neural networks-based approaches, breathing activity detection algorithms can assure the compliance to the above requirement for event-oriented detection. However, in order to effectively use these detectors, researchers need to reply to further questions such as: (a) what are the characteristics of breathing sound before, during and after an apnea/hypopnea event? (b) Is breathing sound expected during an apnea/hypopnea event? (c) What is the dominant sound pattern in the periods of pre-apnea, main apnea and post-apnea event? Despite several sporadic reports on these issues, these questions remain poorly studied and only a few researchers have attempted to develop systems for apnea identification based on sound breathing activity detectors. Particularly, Castillo-Escario et al. have attempted to identify apneic events by detecting extended in time, silence periods [12]. This concept eventually excludes the detection of hypopneas that are proven to be accompanied by snoring [11].

In our study, we make use of a dataset of 178 patients undergoing a complete sleep study in Sismanoglio General Hospital of Athens and we intend to respond to some of the major issues described above. Particularly, we developed five independent breathing detectors based on: the zero-crossing ratio, the signal power, the Tsallis entropy and the Shannon information and a combination of these features described in the following. Based on breathing activity detection, we identify the signal frames that are characterized by absence or severe reduction of breathing activity. The selected signal excerpts are considered candidate apneic or hypopneic events. The analysis of the results proves the dominance of this pattern among the annotated apneic events with the detector's sensitivity reaching 80.45%.

2. Data Collection and Annotation of Apnea Events

Data were collected from 178 patients undergoing a PSG study in the Sleep Laboratory of Sismanoglio General Hospital of Athens. Table 1 contains information on the anthropometric factors of the participating subjects that are considered to be highly related to the presence of SAS. Along with the PSG signals—among which there is a contact tracheal microphone of low quality—a separate recording system was installed. The second system is connected to a contact tracheal microphone of high quality (electret, 900 Ω impedance) with sampling frequency at 48 kHz and spectral response in the range of 350 Hz—8 kHz. The two systems are activated manually by the doctor supervising the study with an anticipated delay of a few seconds.

The audio signals recorded are stored in 24 bit WAV files and PSG signals are stored in EDF files. The low-quality contact microphone of the PSG study is employed for the synchronization of the two separately activated recording systems. The synchronization is based on Hilbert transformation, after the filtering and downsampling the high-quality audio signal (48 kHz) down to 500 Hz, which corresponds to the sampling frequency of the low-quality contact microphone of the PSG system. The synchronization process was manually inspected for all patients; the error was held below 2 s.

The annotation of the apneic and hypopneic events was performed by the medical team of the sleep laboratory of Sismanoglio, based on the PSG signals. The tracheal sound was completely excluded from the process of signals' interpretation, the events annotation and the final diagnosis extraction. The events annotation follows the updated protocol for apnea scoring. Minimum duration of the annotated events is 10 s corresponding to 3 respiratory cycles [11]. The interpretation process resulted in the annotation of 40,800 apnea/hypopnea events and in the diagnosis of each patient and their grouping into the four main SAS severity categories: Normal breathing, Mild, Moderate and Severe apnea.

Table 1. Anthropometric factors and diagnosis for all patients participating in this study.

Gender (Number of patients and %)	Male: 136 (76.4%)	Female: 42 (23.6%)	Total: 178 (100%)	
Mean age and age range (years)	Male: 58 (23–83)	Female: 58 (34–76)	Total: 58 (23–83)	
SAS severity diagnosis (number of patients and %)	Normal: 3 (1.7%)	Mild: 1 (0.6%)	Moderate: 14 (7.9%)	Severe: 160 (89.8%)

3. Breathing Activity Detection and Apnea/Hypopnea Detection from Tracheal Sound Recordings

The audio signal is segmented in frames of 150 s with an overlap of 10 s. The developed system employs four features from the audio signal excerpt of the trachea. These are the signal power, as well as three complexity metrics: the Shannon information [13], the Tsallis entropy [14–16] and the zero-crossing ratio [17]. The architecture of the system comprises of 5 independent apnea/hypopnea detectors. Particularly, the first detector is based on the extraction of the signal power in windows of 0.08 s (3840 samples) with no overlap between them. A hard threshold is applied to distinguish breathing from silent frames and breathing frames less than 0.6 s are rejected. We extract the complement of the breathing detector to result in the apnea detector (apnea detector = 1-breathing detector) and the detected periods of apnea that last less than 5 s are rejected, as too small to represent an actual apnea. Identically to the first apnea detector, we developed 3 additional detectors that are based on the three complexity metrics: the Shannon information, the Tsallis entropy and the zero-crossing ratio respectively. Examples of the operation of these four apnea detectors are presented in Figure 1.

The fifth detector is extracted by the logical operator AND applied on the three complexity metrics-based breathing detectors described above, so that a single frame is considered to represent breathing, provided it is detected by all three complexity-based breathing detectors described above. Again the frames that last less than 0.6 s are rejected. For each breathing frame we extract the average signal power so that we develop a "weighted" breathing detector illustrated in Figure 2. The list of all the values of signal power representing the detected breathing frames within the signal excerpt of 150 s are sorted in descending order and starting from the second one are applied as hard thresholds on the detector. Thus, we extract all periods of the signal in which a reduction of the signal power is exhibited in the breathing frames within these periods compared to the signal power right before and after it. Again from the detected periods we reject the ones whose duration is less than 5 s.

The final candidate apnea/hypopnea episodes for each patient result as the union of 5 sets, each one consisting of the periods detected by the corresponding independent detector. The system's sensitivity is determined by the examination only of the end point of each detected period compared with the end point of the annotated apneic event. Thus, a detected period is considered as positively identified if its end point is located closer than 10 s to an annotated apneic event.

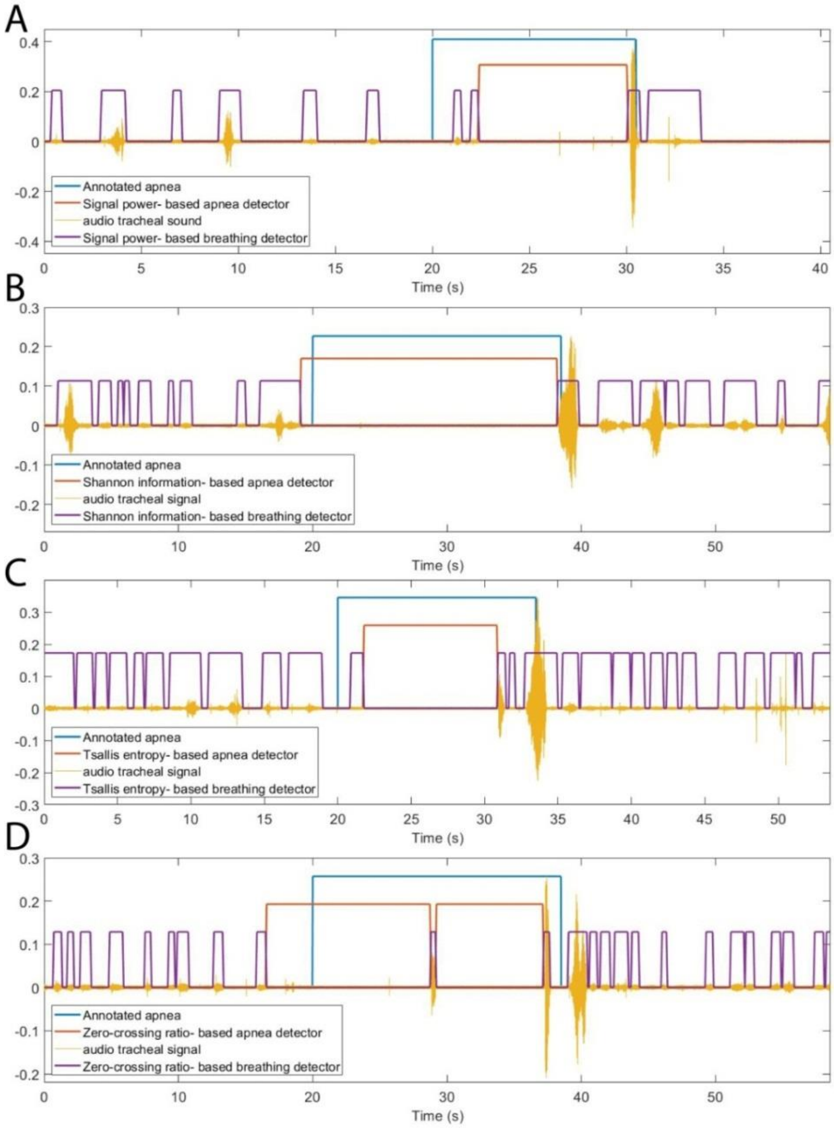

Figure 1. Examples of audio excerpts from different patients subjected to the four independent features for breathing activity detection, from A to D: the signal power-based detector, the Shannon information detector, the Tsallis entropy detector and the zero-crossing rate detector. The corresponding apnea detectors are extracted by the complement of the breathing detector provided that each period of positive apneic/hypopneic activity lasts at least 5 s. The y axis values correspond to tracheal sound amplitude while for all detectors (both apnea and breathing) illustrated in the plots the amplitude is equal to 1, despite the fact they are presented at different levels in order to facilitate figure's interpretation.

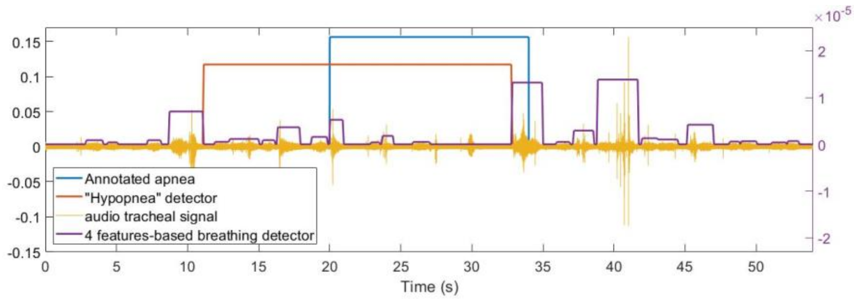

Figure 2. Example of an episode considered as hypopnea since sound is present within the event. Three complexity metrics are used to detect breathing: Tsallis entropy, Shannon information and zero-

crossing ratio. The mean signal power is extracted for all detected breathing frames resulting in a weighted breathing detector illustrated in the plot as "4 features based- breathing detector". The weights of the detector correspond to the mean signal power and are given in y axis on the right. The candidate hypopnea event is detected in the regions of the signal where the weight detector exhibits reduced amplitude with respect to its value right before and after the detected period. The left axis corresponds to the audio sound amplitude. The detectors amplitude is always equal to 1 except for the case of weighted detector whose amplitude is given according to the right axis.

4. The Use of the Apnea Detection System as Autonomous System for Apnea Diagnosis

The possibility to use the above detection system to extract the total count of apnea events per patient has been examined by extracting the precision of the system (see Section 5.3), additionally to the sensitivity of it as determined above. Specifically, the total count of detected candidate events, comprising both true and false positive detections has been extracted after a process of combination of detected events: The detected candidate events of the algorithmic process were grouped so that sequencing episodes that are separated by a time frame of less than 6.5 s are considered as a unique detection. This assures optimum performance of the developed system as two apneic episodes should be separated by at least one breathing cycle—3–5 s, thus a minimum of 13 s between the ends of the two episodes.

5. Results and Discussion

5.1. The Dominant Pattern in Tracheal Sound Apnea/Hypopnea Episodes

In order to investigate the performance of the developed algorithm we counted as true positive detections all identified episodes whose end time was less than 10 s away from an annotated apneic/hypopneic episode. The developed algorithm succeeds in detecting the end of 32,824 apnea and hypopnea episodes among a total sum of 40,800 annotated events in the used dataset. Thus, the achieved detection sensitivity is 80.45%. The corresponding sensitivity validated separately for the main categories of apneic events, as these are defined in the AASM protocol for apnea scoring are: 83.05% for Obstructive apneas, 90.35% for Mixed apneas and 87.31% for Central apneas, resulting in a total sensitivity of 84.54% for all apnea events. The sensitivity for hypopneas is 68.22%. This can be explained by the fact that some hypopneas are expected to be accompanied by severe snoring (increased audio signal power) even when snoring or heavy breathing sound is not present in the pre-hypopnea and post-hypopnea period [11]. Additionally, we noticed that in case that both the end and the start of the detected periods are used for the estimation of the sensitivity, with the criterion remaining the time distance of less 10 s, the derived sensitivity is 68.12%. The above results indicate the dominance of the followed pattern in the vast majority of the apnea and hypopnea events. Interestingly, the pattern initially followed for hypopnea detection (Figure 2) identifies obstructive apnea events where inhalation effort is present in the corresponding audio excerpts without being followed by an exhalation.

5.2. The Contribution of each Feature in Apneic/Hypopneic Events Detection

Each particular feature and the corresponding Apnea detectors have been studied in terms of contribution to the identification of apnea/hypopnea events. The signal power based apnea events detector is exclusively responsible for the identification of 2827 events (8.6% of all detected episodes), meaning that these events would not have been detected if the signal power based detector was not included in the system. Interestingly the contribution of the hypopnea detector is exclusively responsible for 8698 episodes (26.5% of all detected events), while the Shannon information-based detector, the Tsallis entropy and the zero-crossing rate exhibite a much lower degree of contribution with the corresponding events count being: 164 events (0.5% of all detected events), 124 events (0.4% of all detected episodes) and 532 events (1.6% of all detected episodes) respectively. Despite lower contribution of these features, the aforementioned counts prove the importance to include all selected features in the episodes identification, since all features are necessary to achieve the high sensitivity of the system. Additionally, Table 2 summarizes the sensitivity and the precision of each particular detector separately.

Table 2. Sensitivity and precision of each particular detector.

	Sensitivity	**Precision**
Signal power-based detector	52.64%	51.61%
Shannon information-based detector	35.02%	40.19%
Tsallis entropy-based detector	36.87%	42.31%
Zero-crossing ratio-based detector	37.59%	46.85%
“hypopnea” detector (as described in Section 3)	53.20%	35.99%

5.3. The Use of the Detector as an Autonomous System for SAS Diagnosis

Based on the process of combination of detections that is described in Section 4, we extracted the final count of true and false positive detections, resutling in the estimation of the systems precision. The maximum achieved precision per patient is 80%, however the mean precision for all patients is 33%. The non-negligible number of false positive detections that is observed, renders imperative the use of additional features or classification systems to distinguish between false and true positive detections and the detection system described here cannot be used autonomously.

6. Conclusions

We have developed and validated the performance of an apneic/hypopneic episodes detection system, employing four features applied independently on the tracheal sound signal of breathing activity during sleep. The features include the signal power, the Tsallis entropy, the Shannon information and the zero-crossing rate. The sensitivity of the system is proven to be very high for apneic events reaching 84.54% and slightly lower for hypopneas reaching 68.22%. While the detection system requires further analysis of the detected episodes to exclude false positive detections, it is proven than the followed pattern dominates the tracheal signal during apnea episodes and sets the basis for time localization of respiratory events during sleep.

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