Identification of Apnea Based on Voice Activity Detection (VAD)

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Abstract: We identify obstructive sleep apnea as the most common respiratory issue associated with sleep. Frequent breathing disruptions characterize sleep apnea during sleep due to an obstruction in the upper airway. This illness, if left untreated, can lead to significant health problems. This article outlines a sound approach for detecting sleep apnea and tracking it in an automated and intelligent manner. The method entails an automated identification of OSA based on the sound signal during breathing and a cardio-respiratory signals analysis for more efficient results. The suggested approach is put to the test under a variety of scenarios to verify its efficacy and dependability. The benefits and drawbacks of the suggested algorithm are mentioned further down.

Keywords: Obstructive Sleep Apnea, Breathing disorder, cardio-respiratory automatic detection, OSA.

Received: May 17, 2021. Revised: July 25, 2022. Accepted: August 19, 2022. Published: September 22, 2022.

1. Introduction

OBSTRUCTIVE sleep apnea syndrome is associated with persistent snoring and upper airway obstruction, which causes sleep disruption, changes in arterial oxygen saturation, and daytime drowsiness. It is tough to define because it can range from regular breathing to snoring, both of which have serious consequences. For clinical reasons, apnea episodes of more than 15 per hour are deemed abnormal. Each patient is unique[1].

This article describes a reliable method for automatically and intelligently identifying sleep apnea and monitoring it. The procedure includes an automated determination of OSA based on the sound signal produced by breathing as well as a study of

the cardio-respiratory signals for better outcomes. The recommended method sets itself apart by combining these two factors, and due to the innovative way the respiratory signal was processed which help us to get a very accurate detection of apnea.

According to modern research done in the United States, apnea incidence of 15 and higher was found in 9% of men and 4% of women in the workforce. Symptoms of sleep-disordered breathing were reported by 5% of men and 2% of women who were questioned [2]. These statistics show that sleep apnea is indeed a significant public health.

1.1 Diagnosis of Obstructive Sleep Apnea

The Home Sleep Apnea Test(HSAT) and other programs rely on just a few or a single measure that is gradually being created [3, 4]. There are a few high-quality HSAT devices on the market right now, but none of them is based on a single sensor. Several studies on single-channel OSA detection have yielded encouraging results. As a result, signal analysis from sensors that could be used to measure sleep apnea is a growing subject of study. Nevertheless, most single- or few-sensor OSA monitoring systems and suggested algorithms are inadequate for real-time apnea detection. Effective OSA treatment, on the other hand, is crucial since it recovers the patient's state and other consequences[5, 6].

1.2 Types of Sleep Apnea

A disorder known as sleep apnea happens when an individual stops breathing during sleep. It may be divided into three types: central, obstructive, and complex. The most common type is obstructive sleep apnea (OSA). According to multiple Trusted Sources research, OSA affects anywhere from 4% to 50% of the world's population. The prevalence of sleep apnea within every study is determined by the researchers' criteria, as well as the participants' age, gender, and body weight, as well as any underlying health concerns[7].

Males have a frequency of 22%, while girls had a prevalence of 17%, according to a 2015 review of 11 studies[8]. Understanding the various types of sleep apnea can aid people in determining what's causing their problems and obtaining the support they require[9]. Oxidative stress has been linked to sleep apnea, which has been linked to an increased risk of diseases such as diabetes, hypertension, heart problems, and strokes.

1.3 Symptoms of Obstructive Sleep Apnea

The most common type of sleep apnea is obstructive sleep apnea (OSA). It occurs when the tongue and airway are both functionally blocked. Breathing becomes extremely difficult but not improbable, when the tongue rubs against the vocal cords while sleeping, and the top of the throat and mouth then brush against the larynx[10].

OSA can induce snoring due to the vibrating of the tongue and soft palate. This can make you feel as if you can't breathe when you wake up. The lungs work properly, and the system attempts to inhale, but Apnea makes it hard to get enough air through the upper airway[11].

OSA becomes more prevalent as people grow older, and it's much more common with men, overweight people, pregnant women, and those who lie flat on their backs. The following are some of the indications and symptoms:

- Waking up at night or feeling extremely wary when awake.
- Waking up with a worrying sense.
- Gasping or struggling to breathe in the middle of the night.
- Frequent headaches.
- The feeling of having a dry mouth when you wake up.
- At school or work, you may be perplexed or unable to concentrate.

1.4 Obstructive Sleep Apnea in the World

Sleep apnea sufferers are treated in a variety of methods, depending on their symptoms or where they reside. Significant efforts are made in developed nations to identify and treat patients who experience sleep apnea. According to current studies, most instances of obstructive apnea are undiagnosed and mistreated. OSA is rarely detected in resource-constrained contexts, and diagnostic, and treatment options are either lacking or insufficient because of the high and societal repercussions, do to sum up sleep apnea is connected with a high social and financial cost.

In 2015, the cost of identifying various types of sleep apnea was predicted to reach $12.4 billion in the United States. The exact global cost of identifying and treating OSA has still not been determined since a further study on the prevalence rate is required first[12][13].

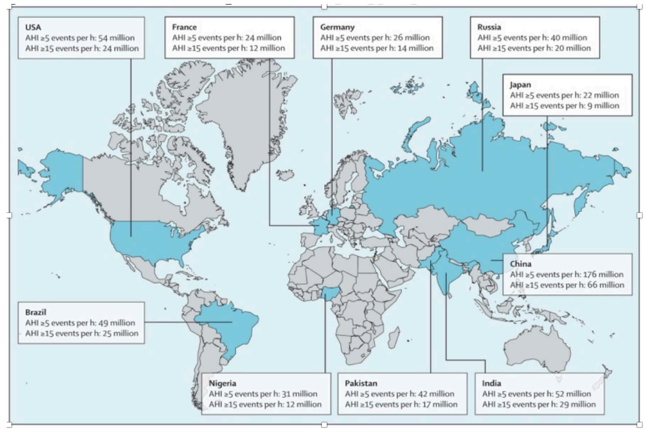

Fig. 1: According on the American Academy of Sleep Medicine's 2012 standards, the top ten nations with the largest estimated number of patients suffering from obstructive sleep apnea

Sleep apnea is linked to poor healthcare outcomes, and treating it improves the sleep-related life quality while reducing adverse clinical implications[14]. As a result, focusing on the effective treatment of OSA might be one option for minimizing linked healthcare costs and unfavorable symptoms of the disease, such as tiredness and cognitive impairment.

1.5 Related Work

For detecting sleep apnea, cardiorespiratory polysomnography (PSG) is the best model[15]. While an overnight is a must in a hospital, various respiratory factors are gathered and examined by expert professionals.

Researchers are exploring alternate analytic approaches such as home PSG and residential sleep apnea diagnostics home sleep apnea testing (HSAT), which employ monitoring systems with multiple sensors. There is other research about detecting sleep apnea using EEG[16], ECG[17], or EMG[18] signals or even by using video recording devices[19]. Even though these studies have lowered the cost of detecting sleep apnea, the inconvenience is still present. Several other techniques use breathing waves as the indicator to identify OSA have always been suggested[20][21]. Our work focuses on respiratory signals that can be simply recorded at home, thus minimizing the cost and inconvenience without affecting the system rate performance.

Those strategies need a whole nights and it is way too expensive. Moreover, it has been noticed that the extensive recording device significantly impacts sleep quality, potentially distorting the results[22]. Several less complicated but equally reliable techniques have been developed on this foundation, especially for ambulatory and scanning applications. The key distinctions are the type and quantity of

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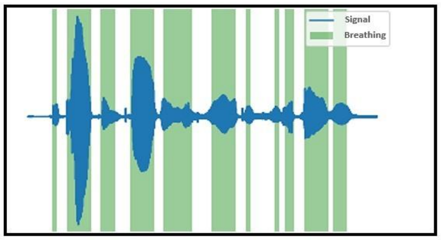
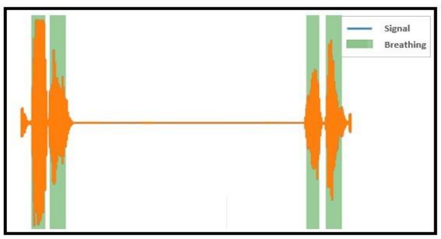
physiological signals gathered and automatically analyzed.

Polysomnography is a type of sleep study that is commonly used. After the audio recording, complicated assessment procedures are required to provide the information needed for diagnosing sleep apnea. A typical way of calculating envelope curves is to use breath sounds captured at the neck. Other studies identified distinct patterns in tracheal audio spectrums that distinguished apnea and non-apnea phases.

1.6 Proposed Work



A person with no apnea



A person with apnea

Fig. 2: Numeric breathing signals

For a vast number of people of varied ages and gender in this study, we present a unique apnea detection approach based on breathing signals. The goal of this study is to employ a variety of algorithms. Unlike previous research, the proposed method uses a threshold technique to remove unnecessary segments while keeping the ones that would be useful to detect apnea.

We examined the effectiveness of the recommended model using a range of filtering techniques, allowing us to evaluate each one's accuracy with apnea diagnosis.

2. Materials

2.1 Database

This study used a database created by Dr. Thomas Penzel of Phillips-University in Marburg, Germany, and made available through the PhysioNet website[23].The Apnea-ECG Database[24] has 70 records separated into 35 sets, with recordings ranging from 7h-10h each.

Table 1: Information about the participant's anthropoids

Description	
No. of Subjects	70 person
Dataset Size	Size : 580.6MB
Age (year)	(27 – 58) ans
Male Patients	55 patients
Female Patients	15 patients
Body Mass (Kg)	53 – 121
Sleep Time (minutes)	430 – 585
Height	167 - 183

Four signals (a01 through a04, b01, and c01 through c03) accompany recordings (a01 through a04, b01, and c01 through c03) (Resp C and Resp A, chest and abdominal respiratory effort signals obtained using inductance plethysmography; Resp N, oronasal airflow measured using nasal thermistors; and SpO2, oxygen saturation). We used breathing recordings to support our main goal of identifying apnea using breath analysis; an overview of the database is seen at the first table.

2.2 Proposed Method

The process in general consists of using the numeric form of the recorded respiratory signal and, through a specific algorithm (explained below), we will be able to classify the signals into apnea and non-apnea signals and thus determine whether each patient has apnea or not.

The algorithm used in this study is divided into three major parts: data pre-processing, reduced detection, and classification. (for the moment, we ignored potential hypopnea episodes).

1- Data pre-processing:

In order to create a "clear" and "clean" dataset for data analysis, raw data from data extraction must first go through a sequence of steps known as data pre-processing. To enable accurate statistical evaluation, pre-processing seeks to evaluate and enhance the quality of the data.[25]
In our case we will need data pre-processing will help us remove any heart rate sound or background noise from the original audio files, leaving just breathing tones in the data.

The first part of the algorithm will follow the steps bellow:

a) Removing noises and heart sounds then producing a signal with only breath sounds.

b) Using a FIR bandpass filter (200-2000) Hz These criteria were made based on actual findings and relevant research that were identified in the literature[26][27][28].

c) Eliminating background noise for the weak breath sounds using a specific filtering method called subtraction[29].

2- Reduced detection

Finding drops and changes in the mean level of a time series or signal is the concept of reduced detection,

sometimes referred to as drop detection, in statistics and signal processing. Generally, it is regarded as a specific case of the statistical technique called change detection or shift point detection. This technique will be necessary in our system for identifying drops in breath amplitude before detecting apneic segments[30].

The second part of the algorithm will follow the steps bellow:

a) Calculating the average intensity of the audio signal after pre-processing and extracting the envelope curve E1 based on specific method cited on those researches[31][32].

b) Removing outliers due to snoring with an adaptive threshold (the standard deviation here is set at 30s).

c) interpolating the local maximum of a single respiratory cycle into the first E1 envelope.

The E2 envelope is a smooth connection of the maximum points of E1.

d) Signal segments in the E2 envelope (a connection of the maximum points of E1) below the adaptive threshold are identified as having decreasing respiratory amplitude.

e) The adjacent segments are extracted as probable apneic segments.

3- Classification

The last part of the algorithm is the classification as the name indicates. this section is used to classify the segments detected in the previous section (reduced detection) and then to classify them. the purpose of this section is to make a detailed examination of the previously extracted segment in order to distinguish apnea events from non-apnea events.

The third part of the algorithm will follow the steps bellow:

a) The sound clip is now split to small duration events, the E3 should is then be defined.

b) Using a low-pass filter of 2Hz.

Then all segments in E3 above a threshold that was calculated are labeled as sound episodes.

c) all the episodes that have an activity above a defined threshold are classified as motion noise.

d) Appling a threshold operation to the envelope curve E2. The segments below this threshold are the only one who are classified as apneic segments. If this segment is short, then there is no apnea but if not the time is divided into apneic segment and non-apneic segment.

e) Calculating the reference level for normal breathing.

f) If there is a segment with 10s and above without breathing is to be an apnea phase.

We generate a variable threshold value and apply a low-pass filter with a cutoff frequency of 2 Hz to the envelope E3. All sessions in E3 that are higher than this threshold are categorized as sound events. The noise brought on by motion artifacts is identified using the motion signal that was extracted from the motion measurement unit data. Events that have activity levels over the established threshold in this case are classified as motion artifact noise.

Then, using the decreased detection, we apply once again to the E2 long-term envelope curve. All segments are now classified as reference segments if they are above this threshold and apnea segments if they are below it. Compared to the mean value, the reference value is therefore more resistant to unintentional outliers brought on by snoring.

The flow chart in Figure 7 provides more details on the proposed system.

3. Methodology

3.1 Apnea Detection

The two most common types of auditory signals are pulse rate and apnea detection. It is worth noting that probable hypopnea activities are currently overlooked when diagnosing apnea occurrences. The apnea detection approach begins with pre-processing, Reduced detection, and finally, classification. In a basic flow chart, Figure 4 displays the framework's essential processes.

Pre-processing removes any heart rate or background noise from the original audio files, leaving just breathing tones in the data. A FIR bandpass filter [200-2000] Hz is employed in this example. These settings were selected based on published research [27,28]. A filtration process known as spectral reduction is used to reduce ambient noise that may interfere with recognizing breathing patterns[29]. This approach works by eliminating noise dents from the spectrogram's underlying signal.

The system's second component is Reduced detection, crucial for identifying probable apnea episodes. To aid in further explanation, Figure 5 depicts this section's most significant parts of the algorithms.

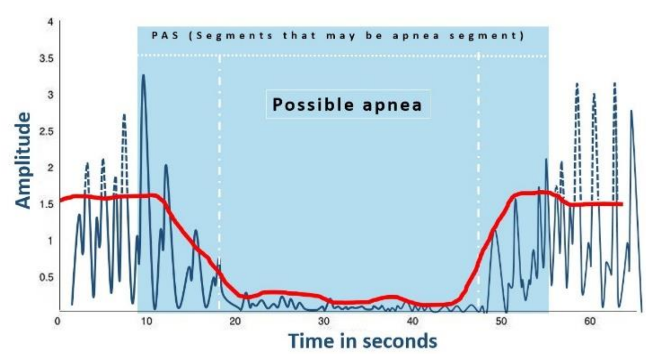
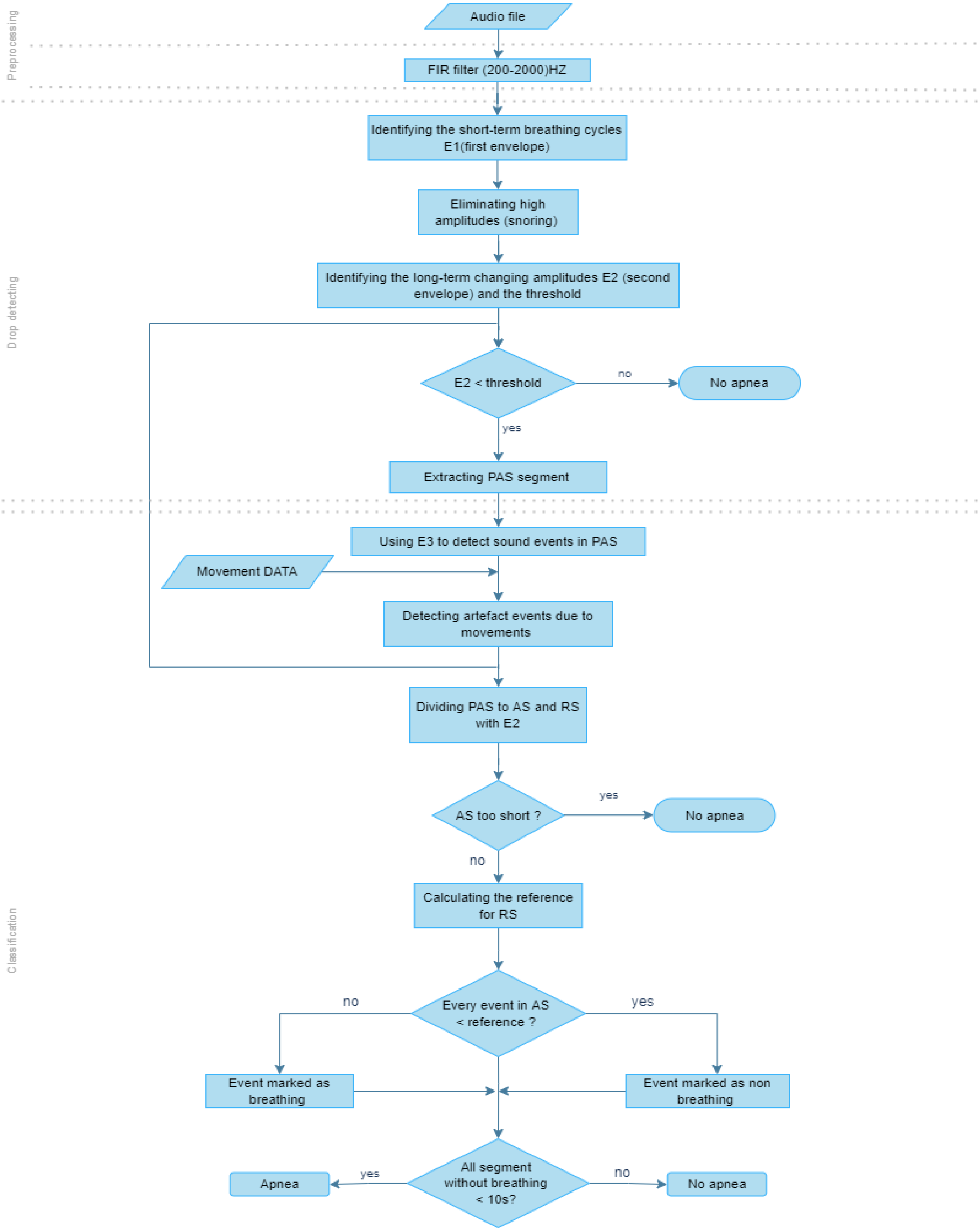


Fig. 4: Recognizing of probable apnea phase

Fig. 3: *The flow diagram highlights each key stage in the proposed apnea diagnosis system*



4. Methodology

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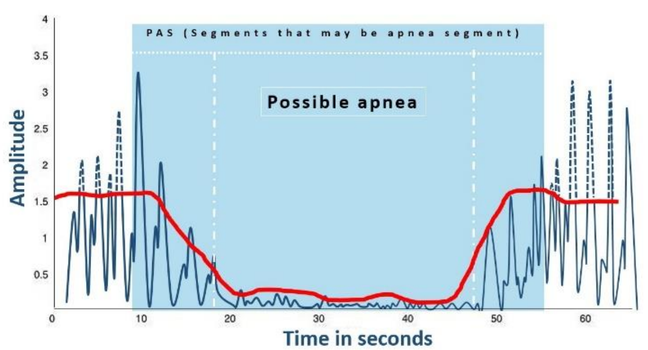

Fig. 4: Recognizing of probable apnea phase

To identify the early stages of sleep apnea. The first and second envelope curves created during breathing amplitude Reduced detection are blue (E1) and red (E2), respectively. All the deleted examples concerning E1 are then induced by noise are depicted by a dotted portions of the blue curve. The blue zone on either side reflects the observed decrease and its neighboring segments, resulting in a potentially retrievable apnea segment (PAS).

First, most pre-processed audio inputs are detected over short-term frames to construct an envelope curve E1 representing each breathing cycle. Compared to regular breathing, snoring creates disproportionally huge outliers that do not match the airflow volume. As a result, using a thresholding technique for the lengthy frames' typical fluctuation, all the anomalies in the first envelope are removed. In Figure 5, the resultant E1 is shown in blue, while the signal before outliers were removed is shown in the blue line curve.

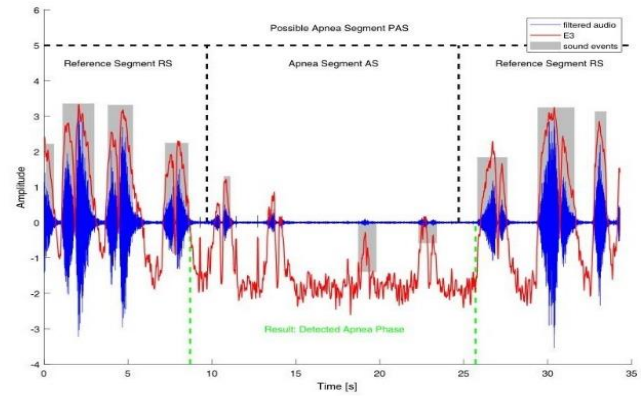

Fig. 5: Recognizing of probable apnea phase

We can observe the event categorization inside a single possible apnea segment(PAS) in this graphic. The envelope contour used by Eq 1 to identify sound occurrences is represented by the red contour (E3). The lengths of the gray surface, which identify the recorded sound occurrences, signify the intensity of the selected features. The feature rate of the audio signals in reference segment(RS) establishes a cutoff to distinguish between respiratory and non-respiratory episodes in the apnea segment.

In this illustration, all apnea segment(AS) occurrences come up short throughout this cutoff and are classified as non-respiratory. The region of the following identified apnea is thus shown by the green curves.

E2, a second envelope that detects long-term respiratory amplitude changes, is created as part of the Reduced detection technique. The Nonlinear Cubic Hermite interpolation method converts the local maxima of the (truncated) starting E1 into a curve (see a red curve in Figure 5), Various research have looked at the connection between air circulation and breathing noises [33-35]. Within an adaptive threshold, breathing amplitude decreases are detected in all signal parts of the second envelope. Finally, these decreases and the segments immediately around them are flagged as probable apnea segments (PAS) and investigated further in the algorithm's next phase. This algorithm phase's goal was to detect a wide range of probable apnea segments while keeping the rejection of false-positive occurrences to the following part.

The third and last phase of the algorithm (classification) tries to properly assess the previously extracted PAS to discriminate between apnea and non-apnea occurrences. The essential phases of the algorithm in this section are depicted in Fig.5 to facilitate comprehension. Each sound event in the probable apnea segments should be detected separately to discriminate between breathing and non-breathing episodes. Then the related airflow in each breathing phase should be computed.

The pre-processed audio signal is separated into small intervals, and the third envelope is obtained by calculating the amplitude, as in the preceding portion.

$$E = ln\frac{1}{Ns}\sum_{i=1}^{N} Z_b^2$$

E stands for the envelope size, the total number of samples in the window stands for Ns, and the sample selection is Zi. Because the logarithm quickly pushes to minimal negative numbers when there is no noise, this form of the envelope is suitable for distinguishing various sound occurrences isolated by quiet. The final waveform is then subjected to a reduced filtration with a stopband of (2 Hz), which is used to determine a fixed limit. Sound episodes are E3 portions that go over this threshold.

The active signal retrieved from the inertial measurement unit is then employed to detect episodes produced by the movement sound effects in the following step. Movement artifact noise develops when activity exceeds a certain threshold.

The present average breathing level (reference) should be known to use the basic definition of apnea and distinguish between breath and apnea. The importance of this stage is underscored by the fact that, depending on sleeping posture, the overall volume of breathing sounds can change significantly during the night. After then, the method determines which of the previously identified episodes in the retrieved probable apnea segment should be employed like a referencing, then those segments get categorized to be a respiratory segment or not. In the next step, the long-term part of the second envelope curve, repeat the basic threshold approach employed in the Reduced prior detection. All segments below that level are already referred to as apnea segments, while those above it is referred to as reference segments.

The next stage is to link the quantity of airflow to specific tracheal sound properties (such as amplitude) within the good episodes that have been recorded. Different strategies for connecting airflow and breathing sounds have arisen from various investigations of the two signals. Eq No (1) is employed in the technique provided to determine an attribute for each sound occurrence. On the other hand, individual event outliers are deleted before feature calculation, much like Reduced detection works. This is important because loud clicking noises might occur during an apnea attack.

Within a particularly probable apnea, episodes are classified. The envelope curve that recognizes sound episodes using Eq is represented by the red color E3 (1). The heights of the grey patches represent the feature extraction value. In contrast, the grey sections reflect the detected sound occurrences (negative values stem from using the ln function). The good episodes in the reference segments have a feature value. RS defines the referent segments. Because all apnea segment episodes fall below that rate, they get classified as not-breathing. As a consequence, the green colors indicate where apnea was found.

Since relying just on respiratory signals may not always produce better insights in some instances, we conducted a cardio-respiratory study; more details are shown below.

4.2 Cardio-respiratory Signal Processing

The human body is affected physiologically and physically by the functioning of the respiratory and cardiovascular systems[36, 37]. Based on the human eye's low spatiotemporal acuity, most of these impacts are undetectable to human drivers, but in biological and clinical contexts, they can be very instructive[38,39]. The cardiorespiratory signal can be retrieved based on the following methods:

- SKIN COLOR CHANGES.
- ARTERIAL PULSE MOTION.
- CHEST MOTION.
- HEAD MOTION.

Since relying just on respiratory signals may not always produce better insights in some instances, we conducted a cardio-respiratory study; more details are shown below.

4.3 Protocol

After the signal acquisition, and for a time period chosen., we studied three intervals that will lead the apnea detection

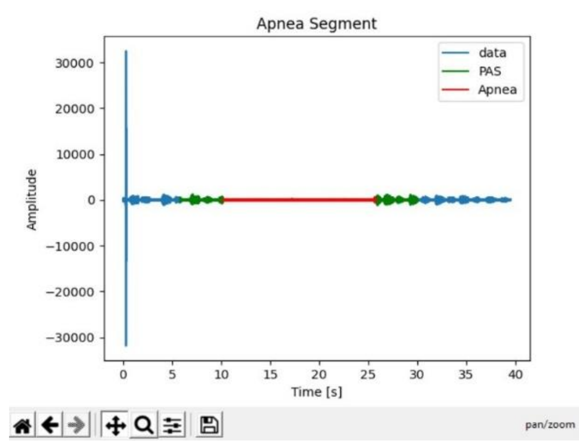

Fig. 6: Apnea detection simulation

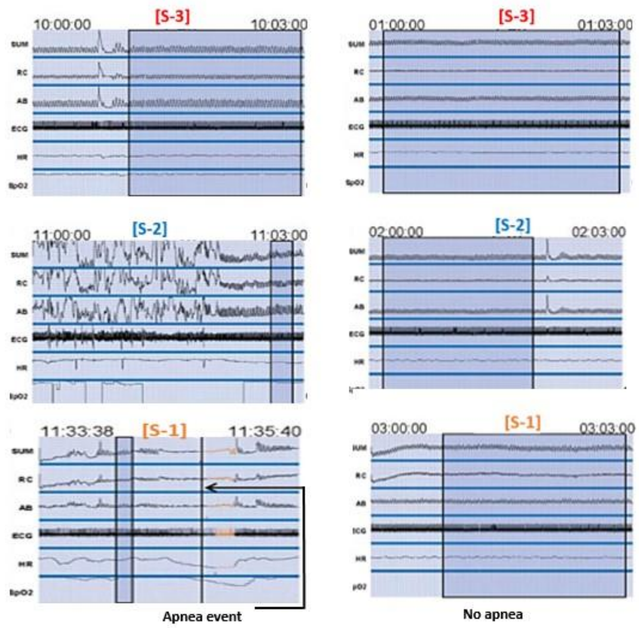

Fig. 7: A sample full set of the examined time period collected.

- [S-1]: Refers to the 75s that were recorded after the time period chosen.

- [S-2]: Refers to the 3 minutes recorded up to 1 hour prior to the chosen time period.

- [S-3]: Refers to the three minutes recorded one hour prior to the [S-2] period.

we created sample complete sets of studied intervals in linear arbitrary models with a random slope and intercept. 3-min automatically recorded segments were accessible up to 2 hours S-2 and up to 1 hour before to the occurrence of interest for each epoch of conventional.

These reference intervals must last at least 15 seconds after the cycle began; they should involve at least three breaths, be devoid of motion artifacts, and last 15 seconds after any activity. Then we classified any breathing arrest lasting more than 5 seconds as an apnea incident. Unfortunately, because of the lack of data, we could not afford to include this part in our application, more details and intimations are included in the research's cited [40, 41].

5. Results

5.1 Results Statistics

The results of the detection are shown in bellow. A total of ten audios, the total of the running time is also presented below. There are between 2 and 247 apnea episodes in each recording.

Table 2: Detailed description of sleep health study database

Subjects	Sex	Height	Age
No.1	F	140	70
No.2	F	160	41
No.3	M	170	72
No.4	F	162	50
No.5	M	168	37
No.6	F	150	43
No.7	M	174	80
No.8	M	165	57
No.9	F	150	57
No.10	F	159	56

as for:

- TNA: the length of time without apnea that has been appropriately categorized.
- TPA: stands for the total amount of accurately classified apnea time.
- FNA: the length of time without apnea that was mistakenly categorized.
- FPA: represents the amount of apnea time that has been erroneously categorized.
- TPA: stands for the total number of apneas that have been appropriately classified.
- FPA: the number of apneas that are wrongly categorized.

we were able to find six hundred and thirty episodes true positive(TP) and fifty-two wrong ones false negative(FP). if we consider true and wrong classified time segments a sensitivity of ninety-two percent and a specificity of ninety-nine percent.

We can see that our system was able to provide high results compared to other systems, while minimizing costs and disruptions without affecting system performance.

for other systems such as those based on EEG, EMG or ECG, if they rely on a single measure to minimize cost and time, the performance of the system decreases significantly. and if they combine these measures (EEG, EMG, ECG), the performance of the system will increase, but the time and cost will increase significantly, as these techniques require clinical assistance, leaving our system the best performing and least expensive.

Even for systems that rely on video recording data, there is evidence that they are only useful for infants.

5.2 The System Performance

The sensitivity and specificity of the devised apnea detection algorithm were calculated as follows to assess its performance:

$$Specify = \frac{TNA}{T\,NA + FPA} \qquad Sensitivity = \frac{FPA}{TPA + FNA}$$

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Table 2: Detailed description of sleep health study database

Subject ID	Apnea events	TPAn	FPAn	Duration (min)	TNAt (s)	TPAt (s)	FNAt (s)	FPAt (s)	Sensitivity	Specificity
1	35	32	1	464	27,105	721	47	12	93.9	99.9
2	14	13	2	434	25,777	227	20	25	91.9	99.9
3	2	2	4	230	13,712	42	0	46	100.0	99.7
4	3	2	5	417	24,915	35	18	65	66.0	99.7
5	247	230	18	460	22,469	4520	397	229	91.9	98.9
6	19	16	4	449	26,504	351	29	79	92.4	99.7
7	23	21	1	457	26,936	429	33	24	92.9	99.9
8	182	170	8	421	21,359	3631	219	103	94.3	99.5
9	102	96	5	411	22,092	2361	161	63	93.6	99.7
10	54	48	4	442	25,434	947	100	61	90.5	99.8
SUM	681	630	52	4185	236,303	13,264	1024	707	ø 92.8	ø 99.7

Table 3: Apnea detection statistics

5.3 Filtering Options

The filtering part play a major role in the process of apnea detection. We used a FIR filter bandpass (200-2000) Hz. we tried looking for different filterers that can be used by our system and we conducted a parallel comparison of each filter and its effect on the result of apnea detection. the filters information's are shown below:

a) CHEBYSHEV FILTER:

The Chebyshev category I filter optimizes the pace of cutoff seen between passband and stopband of the sound quality at the price of passband ripple and phase response noise [42].

b) HILBERT FILTER:

The harmonic spectrum's lower half is wiped out, converting the real-valued input to a reinforced one [43].

c) THOMSON5 (BESSEL) FILTER:

With minimal ringing in the linear system, the analog Bessel filter does have a maximum uniform group delay and a fully linear phase reaction.

Bessel is an analog filter by definition. The bilinear shift is used to build digital Bessel filtering, although the frequency sensitivity of the analog filter is not preserved. As a result, for harmonics below around fs/4, it is only nearly right. To get a bandpass filter that is as flat as possible at high frequency[44].

5.4 Filtering Comparison

Table 4: Filters statistics

Filters type	No of TD	No of FD
CHEBYSHEV	7	1
HILBERT	8	2
THOMSON	6	4

6. Discussion

An innovative sleep monitoring technology has been developed that allows people to identify apnea without exerting too much effort.

This technique was created and supplied for recognizing probable apnea episodes. This method was approved in further research that deployed different methods and tools. They demonstrate their ability to identify apnea episodes regularly [20].

Four different filtering procedures were used to make a more efficient experiment, and three significant stages were needed to process the signals. All heart noises or disturbances from the initial file during pre-processing were eliminated. The Reduced detection detects potential apnea episodes by analyzing the whole signal and trying to find some scraps in the respiratory amplitude to discriminate between apnea and non-apnea episodes. Finally, the apnea diagnostics get done in the classification stage. This system does a very in-depth analysis of all the signals so that any apnea episodes get detected during all the processing stages.

Comparing our system to other systems, we can see that it was able to deliver superior outcomes while minimizing expenses and interruptions without degrading system efficiency. If other systems, such those based on EEG[16], ECG[17], or EMG[18] rely on just one technique to cut costs and time, the system's performance suffers greatly. and if they combine these measurements (EMG, EMG, and ECG), the system's performance will improve, but the time and cost will considerably increase because these techniques demand clinical support, even if we count video recording-based solutions, they are only helpful for young children. making our system the best-performing and least costly.

The algorithm's weakest spot is that it fails to detect hypopnea episodes. Although Apnea-hypopnea index(AHI) is usually the must study measurement that we should focus on to detect OSA but unfortunately we can't use this it in this study. According to a thorough review of the PSG data that included hypopnea episodes, most false-positive apnea episodes in subjects five and eight are misread hypopnea episodes. Changing classification levels to distinguish between apnea and hypopnea episodes proved impracticable since the study showed that we have many false-positive hypopnea episodes, and this is so clear and repeated in files with a number of apnea occurrences that is under than twenty. According to American Academy of Sleep Medicine (AASM) standards [45], hypopneas are identified as a droption in airflow of at least 30%, incident excitation and an air dehydration of much more over 3%.

Heart beat retrieval from the captured audio stream is greatly interfered with during snoring bouts. This could also be the case if the patient is talking or moving loudly while recording an audio signal. Thus, throughout certain parts, heart rate is adjusted. Other diagnostically significant information, such as heart rates, could be estimated with sufficient accuracy, making it possible to miss a rapid shift in pulse rate.

The proposed study has several pros and downsides. Even though all of the patients were chosen because they were suspected of having sleep apnea, the findings encompassed the whole spectrum of sleep apnea from none to severe. The sex, age, and BMI distributions also contain a wide variety of people, indicating that the findings apply to the broader public. Nonetheless, future research needs to include a larger participant pool. Future research should be conducted in a home situation since it would be fascinating to examine how the suggested system functions without medical supervision.

7. Conclusion

Apneas can be detected in a clinical context using the disclosed technique. The system's use of data acquired and ability to estimate heart rate are distinguishing characteristics compared to certain other technologies. Due to its fundamental sensor arrangement, compared to current mobile sleeping trackers, the tracking system proposed has proven to be way more dependable and pleasant and also bought high results throughout the development of a fully functional prototype in other research. The device's fundamental flaw is its failure to identify hypopnea episodes required for AHI calculation. Future research will concentrate on incorporating these episodes into existing algorithms and enhancing present capabilities to provide a more comprehensive assessment of sleep quality.

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