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ORIGINAL ARTICLE

Apnea and heart rate detection from tracheal body sounds for the diagnosis of sleep-related breathing disorders

Christoph Kalkbrenner[1] · **Manuel Eichenlaub**[1] · **Stefan Rüdiger**[2] · **Cornelia Kropf-Sanchen**[2] · **Wolfgang Rottbauer**[2] · **Rainer Brucher**[1]

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Abstract Sleep apnea is one of the most common sleep disorders. Here, patients suffer from multiple breathing pauses longer than 10 s during the night which are referred to as apneas. The standard method for the diagnosis of sleep apnea is the attended cardiorespiratory polysomnography (PSG). However, this method is expensive and the extensive recording equipment can have a significant impact on sleep quality falsifying the results. To overcome these problems, a comfortable and novel system for sleep monitoring based on the recording of tracheal sounds and movement data is developed. For apnea detection, a unique signal processing method utilizing both signals is introduced. Additionally, an algorithm for extracting the heart rate from body sounds is developed. For validation, ten subjects underwent a full-night PSG testing, using the developed sleep monitor in concurrence. Considering polysomnography as gold standard the developed instrumentation reached a sensitivity of 92.8% and a specificity of 99.7% for apnea detection. Heart rate measured with the proposed method was strongly correlated with heart rate derived from conventional ECG ($r^2 = 0.8164$). No significant signal losses are reported during the study. In conclusion, we demonstrate a novel approach to reliably and noninvasively detect both apneas and heart rate during sleep.

Keywords Monitoring · Sleep apnea · Respiratory sounds · Heart sounds

✉ Christoph Kalkbrenner
kalkbrenner@hs-ulm.de

[1] Faculty of Medical Engineering, University of Applied Science Ulm, Albert-Einstein-Allee 55, 89075 Ulm, Germany

[2] Department of Internal Medicine II, University Hospital Ulm, Albert-Einstein-Allee 23, 89081 Ulm, Germany

1 Introduction

Sleep-related breathing disorders, also known as sleep apnea, are one of the most common sleep disorders, with a reported prevalence of 4 and 2% in adult men and women, respectively [8]. Furthermore, it has been shown that a large number of people suffering from moderate sleep apnea (> 75%) are either undiagnosed or untreated [26]. The disorder is manifested by multiple breathing cessations during the night, resulting in extensive daytime sleepiness and an elevated risk for cardiovascular disease. The most common form of sleep apnea is called obstructive sleep apnea syndrome (OSAS) and is caused by an obstruction of the upper airway, accompanied by excessive snoring. The main criteria for the diagnosis of sleep apnea is the average number of breathing pauses longer than 10 s per hour of sleep, called apnea-hypopnea-index (AHI). Here, the pauses are divided into the categories apnea (more than 90% reduction in air flow) or hypopnea (50–90% reduction in airflow) [20].

The standard method for the diagnosis of sleep apnea is the attended cardiorespiratory polysomnography (PSG). This procedure requires overnight hospitalization in a sleep laboratory or sleep center, during which several physiological signals are recorded and subsequently evaluated by trained technicians. This approach is very expensive, time-consuming, and the number of available beds is limited. Additionally, it has been reported that the extensive recording equipment has a significant impact on sleep quality which can falsify the results. On this account, several less complex but similarly reliable methods, especially for ambulatory and screening applications, have been developed. These vary mainly in the type and number of physiological signals that are recorded and automatically evaluated. Among those ambulatory methods, multiple systems using breathing sounds as the main signal for the diagnosis of sleep apnea have been proposed [7, 19].

These sounds are recorded either by ambient microphones, located in the vicinity of the patient [4, 14] or by special body sound microphones placed on the patient's neck (tracheal sounds). Pilot studies with these systems showed good agreement (> 90%) regarding AHI values when compared with standard polysomnography [17, 25].

After audio recording, elaborate evaluation procedures are necessary in order to obtain the relevant information for the diagnosis of sleep apnea. Using breath sounds recorded at the neck, a widely used approach is the calculation of envelope curves [17, 25]. Other studies found special features in tracheal sound spectrums, allowing the distinction between apnea and non-apnea phases [16, 23].

The goal of the present study was to develop a new system capable of recording movement and body sounds during sleep. Based on these signals, a method for extracting apnea events and heart rate including artifact rejection is described. The presented techniques and their successful verification are the basis for further developments towards a comfortable method for diagnosing sleep-related breathing disorders at home. The system itself was developed to make the recording process as simple as possible, minimizing the impact on sleep quality.

2 Methods

2.1 Data recording

In order to acquire breathing as well as heart sounds with a single microphone, the selection of an optimal recording position is crucial. Here, several locations on the upper body and neck were considered. In agreement with previously mentioned studies, the optimal position for recording breathing sounds was found at the neck in close vicinity to the trachea (see Fig. 1). This position also allows the acquisition of pulse sounds originating in the carotid arteries.

For sound detection, a commercially available body sound microphone was used. This microphone is part of a system called LEOSound (Heinen + Löwenstein GmbH & Co. KG, Arzbacher Straße 80, 56130 Bad Ems, Germany) developed for long-term monitoring of lung sounds in the context of diagnosing breathing disorders like asthma. However, sleep monitoring is not included in its field of application. The microphone is fixed by a double-sided, adhesive membrane also protecting the sensitive recording electronics from substances on the skin surface.

In order to provide a comfortable and reliable method for recording body sounds and movement overnight, an appropriate hardware concept was developed previously described in [12] (see Fig. 2). To prove the concept of comfortable sleep monitoring utilizing body sound and movement data, a fully functional prototype including hardware as well as software

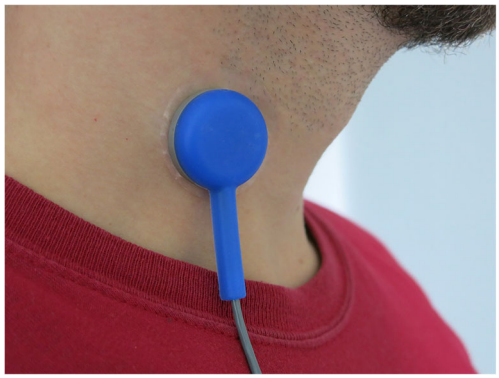

Fig. 1 Fixation of microphone on subject's neck in close vicinity to the trachea

components was developed. It is composed of two separate components. One is placed on the subject's body and contains miniaturized hardware for acquiring sound and movement (body device). The collected data is then transferred wirelessly to the second component, a laptop running a specially developed software. The data communication was realized via Bluetooth and allows for a constant stream of data from the body device to the laptop. Here, it is crucial to optimize sender as well as receiver hardware in order to minimize data loss due to connection problems. On the body side, a particularly strong antenna was used to boost the Bluetooth signal and on the opposite side, the receiver hardware was placed above the subject's head to ensure a stable and reliable connection.

For optimal information extraction from the recorded audio signal, it is important to apply appropriate analogue signal processing before sampling. Here, the main purpose is amplification to ensure that even shallow and therefore quiet breathing can be detected. Additionally, very low and very high frequency parts of the signal are removed to diminish disturbances from contact noise or aliasing effects during sampling. This results in the amplification of frequencies ranging from 30 to 2000 Hz. This should be sufficient to capture the major parts of heart and breathing sounds [18].

For the detection of movements and sleep position, an inertial measurement unit (IMU) containing an accelerometer and a gyroscope was included in the system. This allows the measurement of three-dimensional acceleration and angular velocity of the body device.

Data from microphone and IMU are sampled by a system embedded in the body device. The respective sampling specifications are 5 kHz and 10 bit for the microphone (analogue input) and 250 Hz and 16 bit for the IMU (digital input).

For the purpose of data receiving and storage, a special software application was developed. Here, the data from the body device is presented and stored. In order to ensure sufficient signal quality during initial positioning of the microphone and body device, the display shows audio data in real time (time and frequency domain). For file-oriented storage of the data, a data type called European Data Format (EDF) [15]

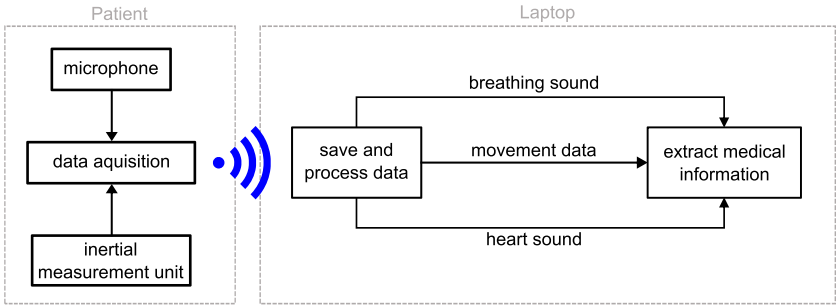

Fig. 2 Block diagram depiction of the developed hardware data acquisition and processing system

was chosen. This data format facilitates the synchronous retention of various signal channels with different sampling rates and is often used in the context of polysomnography. To summarize, the system records one channel from the microphone and six channels from the IMU (three for acceleration, three for angular velocity). The subsequent signal processing and extraction of medical information is done offline, after the recording process is finished.

2.2 Signal processing

2.2.1 Activity and sleep position

The processing of the movement data aims towards the extraction of the sleeping position and movement activity. Here, the activity is represented by a parameter ranging from 0 to 20, which indicates the intensity of the patient's movements. Details of the utilized processing techniques were previously described by Kalkbrenner et al. [13] and are not further explained here.

2.2.2 Apnea detection

The analysis of the audio signal is divided into apnea and heart rate detection. For the detection of apnea events, it is important to state that potential hypopnea events are ignored for the moment. The entire algorithm for apnea detection is divided into the sections preprocessing, drop detection, and classification. Figure 3 shows a simplified flow chart including all major steps of the process. The first step (preprocessing) aims to remove any heart sounds and noise from the raw audio recordings and results in a signal containing mostly breathing sounds. Here, an FIR bandpass filter with boundaries between 200 and 2000 Hz is used. These limits were chosen based on empirical results and related studies found in literature [17, 18, 25]. In order to remove any background noise which could hinder the detection of quiet breathing sounds, a filtering technique called spectral subtraction is applied. The procedure is based on the subtraction of a noise template from the main signal in the frequency domain [6].

The second section of the algorithm for apnea detection (drop detection) aims to identify possible apnea events by scanning the entire signal for drops in breathing sound amplitude. It is based on the procedures presented by Alshaer et al. [2, 3]. In order to facilitate understanding, the key steps of the algorithm in this section are exemplified in Fig. 4. At first, an envelope curve E1 representing every single breathing cycle is extracted by calculating the mean intensity of the preprocessed audio signal within short-term windows. During snoring, this procedure causes disproportionally high outliers which do not correlate to the amount of airflow when compared to normal breathing. Therefore, these outliers in E1 are cut off using an adaptive threshold calculated using the standard deviation of long-term windows. The blue curve in Fig. 4 represents the resulting envelope E1 whereas the blue dotted curve represents the signal before removal of the outliers.

The next step of the drop detection is to generate a second envelope E2 capturing long-term changes in breathing amplitude. This is accomplished by interpolating the local maxima of single breathing cycles in the (truncated) first envelope E1 to a curve using the Piecewise Cubic Hermite interpolation method (see red curve in Fig. 4). All signal segments of the envelope E2, underlying an adaptive threshold are identified as drops in breathing amplitude. Finally, these drops and their directly adjacent segments are extracted as possible apnea segments (PAS) and examined more closely in the subsequent section of the algorithm. This part of the algorithm was designed to capture a very broad spectrum of potential apnea segments, leaving the following section the task to reject the false positive events.

The third and last section of the algorithm (classification) aims for a detailed examination of the previously extracted PAS in order to distinguish between apnea and non-apnea events. Again, in order to facilitate understanding, the key steps of the algorithm in this section are exemplified in Fig. 5. Initially, every distinct sound event in the PAS has to be detected individually in order to classify them into breathing or non-breathing events and to determine the associated air flow in every breathing phase. Similar to the previous section, the preprocessed audio signal is divided into short-term windows and the envelope E3 is now extracted by calculating the intensity

$$E = \ln\left(\frac{1}{N}\sum_{i=1}^{N} x_i^2\right) \quad (1)$$

where E is the value of the envelope, N is the number of

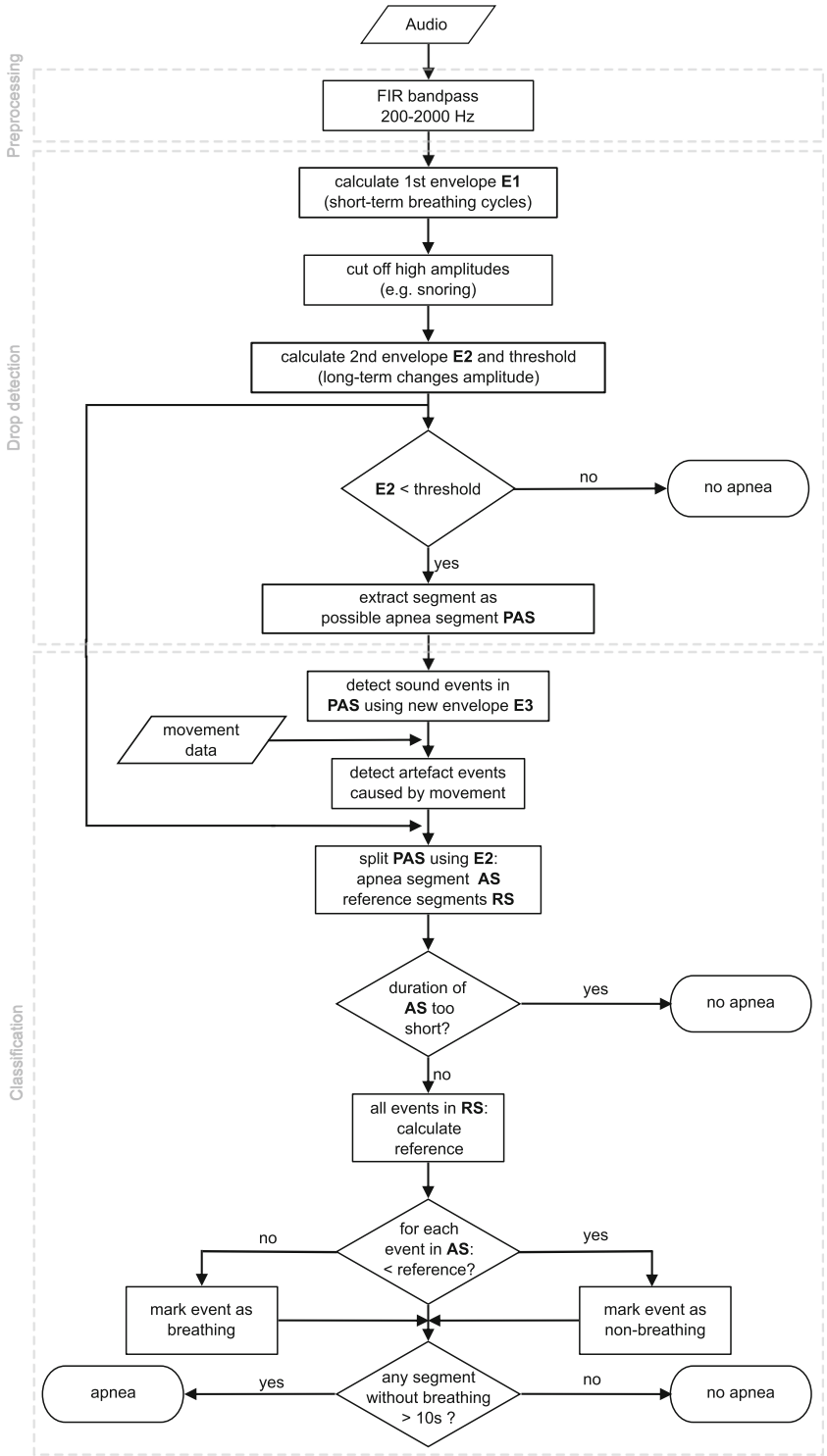

Fig. 3 Simplified flow chart including all major steps of the developed apnea detection algorithm. The entire algorithm is divided into the sections preprocessing, drop detection, and classification

samples in the window, and x_i is the ith sample in the window. This type of envelope is especially suitable for detecting different sound events separated by silence, since the logarithm quickly pushes towards very small negative values when no sound is present. After that, a variable threshold is calculated by applying a low-pass filter with a cutoff frequency at 2 Hz to the envelope curve E3. All segments of E3 overshooting this threshold are classified as sound events. In the next step, the activity signal extracted from the IMU data is used to identify events caused by motion artifacts. Here, events during which the activity exceeds a defined threshold are marked as motion artifact noise.

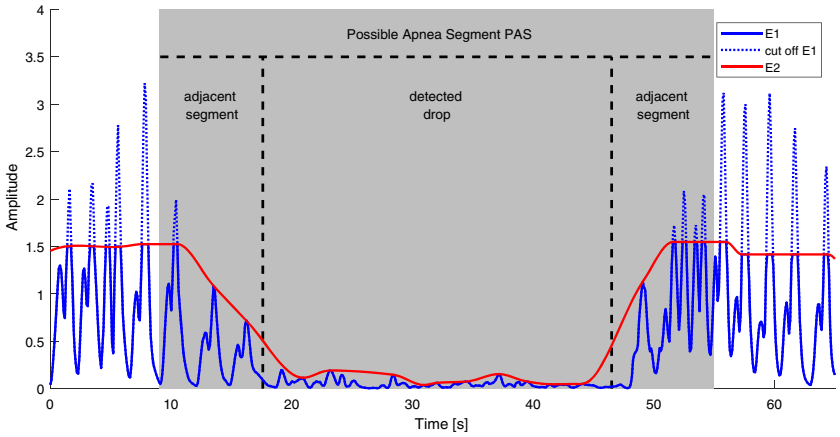

Fig. 4 Recognition of possible apnea phase. The blue (E1) and red curve (E2) are the first and second envelope curve calculated during drop detection of breathing amplitude, respectively. The dotted sections of the blue curve indicate the removed outliers of the first envelope E1 caused by snoring. The gray area marks the detected drop and its adjacent segments on each side resulting in an extracted possible apnea segment (PAS)

In order to apply the conventional definition of an apnea (see Section 1) and distinguish between breathing and apnea, the current level of normal breathing (reference) has to be known. The particular importance of this step is emphasized by the fact that the overall amplitude of the breathing sounds can vary significantly over night, mainly dependent on sleeping position. The next step of the process is therefore to determine which of the previously detected events within the extracted PAS are used as reference and which events have to be classified in breathing and non-breathing events. This is done by again employing a simple threshold operation on the second, long-term envelope curve E2 from the previous drop detection. All segments which underlie this threshold are now defined as apnea segment (AS) and all segments overshooting this threshold are defined as reference segment (RS). If the duration of AS is too short, the entire PAS is classified as non-apnea and no further analysis is done. If this is not the case, the single sound events are divided into so-called AS and RS events and the processing continues.

The next step is to relate the amount of airflow to certain features (i.e., amplitude) in tracheal sounds within the detected sound events. The relationship between airflow and breathing sounds has been the subject of various studies [10, 22, 24], resulting in the proposal of several methods to correlate the two signals. In the presented approach, Eq. (1) is used to calculate a feature value for every sound event. However, before feature calculation, possible outliers in the individual events are removed, similarly to process used in the drop detection. This is important, because sound events during apnea phases occasionally contain loud clicking noises of

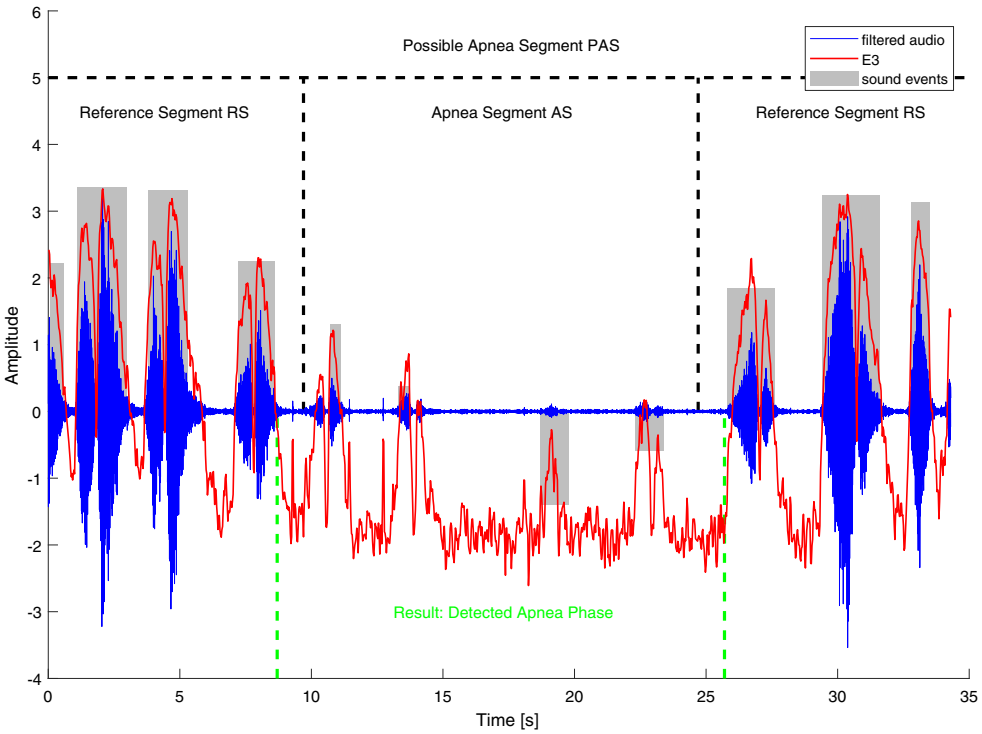

Fig. 5 Event classification within one PAS. The red curve (E3) represents the envelope curve to detect sound events using Eq. (1). The gray areas mark the detected sound events and their heights represent the value of the extracted feature (negative values stem from the use of the ln function). The feature value of the sound events in the reference segments RS define a threshold to split the events in the apnea segment AS in breathing and non-breathing. In this example, all AS events undershoot this threshold and are defined as non-breathing. Therefore, the green lines mark the area of the resulting detected apnea

unknown physiological cause. Subsequently, the reference level of normal breathing is computed by the median over the feature values of all RS events (with exception of artifact events). This makes the reference more robust against occasional outliers caused by snoring, compared to the mean. Now, it is possible to classify the AS events as breathing or non-breathing events. Finally, any phase absent of breathing (no sound event was detected or all AS events are classified as non-breathing) which exceeds a duration of 10 s is marked as an apnea phase.

2.3 Heart beat detection

Every physiological heart beat generates two distinct peaks in the audio signal. In order to measure the heart rate, one of these two peaks has to be detected. The key steps of the algorithm can be seen in Fig. 6. The first step in the estimation of heart rate is to bandpass filter the audio signal with boundaries between 10 and 50 Hz. This is particularly useful in removing any breathing sounds and most artifacts from the raw signal, while preserving the characteristic features of the heart sound, i.e., distinctive peaks. However, during intense snoring phases, the frequency bands of snoring and heart sounds overlap each other, causing this method to fail. Therefore, the signal is rejected during these particular snoring segments. The resulting voids in the signal are handled within the following steps of the heart peak detection.

For peak identification, all local maxima in the filtered audio signal with a fixed minimal distance are detected. Subsequently, all maxima falling below the 90th percentile of samples taken from long-term windows are rejected. This threshold is represented by the black line in Fig. 6. Based on results reported in [1], it is assumed that the physiological maximum variation in the time interval between sequential heartbeats during sleep is 330 ms. Starting with the first detected heartbeat, all forthcoming peaks lying within the limits resulting from this assumption are considered as the next heartbeat. From this collection, the peak with the highest amplitude is selected as the next heartbeat (see an example of this procedure in Fig. 6). Using the newly chosen peak, the procedure is repeated in search for the next peak. In case no peak meeting the above mentioned assumption on peak distance can be detected, a new heartbeat is created by taking the mean time interval in between the last 10 heartbeats. This is obviously the case when the sound signal is rejected due to the presence of disturbances such as snoring.

Finally, the heart rate (HR) in beats per minute (bpm) is calculated using the marked audio peaks. The duration of a window including 20 marked audio peaks is used to calculate a single HR value. This window is shifted by 10 peaks for every HR value.

2.4 Data acquisition

The PSG is considered gold standard for the diagnosis of apneas and heart frequency during the night. For this study, data of ten subjects was recorded at the University Hospital Ulm. All subjects of the study were patients referred to the sleep center with suspicion of sleep-related breathing disorders. The anthropometric information of the subjects is shown in Table 1. The study was approved by the ethics committee of the University of Ulm and all subjects gave written informed consent. All subjects underwent a full-night screening at the sleep laboratory using PSG and the previously presented data collection system in concurrence. Set up of the new system was done by the medical staff after brief introduction and training. The following parameters were monitored using PSG: EEG, EMG chin, EMG leg, ECG, light, snoring, oxygen saturation (finger pulse oximeter), thoracic and abdominal effort and airflow (thermistor flow sensor). All parameters were recorded using SOMNOlab (Weinmann Geräte für Medizin GmbH + Co. KG, Kronsaalsweg 40, 22525 Hamburg, Germany).

Applying the American Academy of Sleep Medicine (AASM) 2007 standards, apneas are defined by ≥ 90% drop of baseline flow with a duration of at least 10 s and at least 90% of the events duration meets the amplitude reduction criteria [11]. After data recording, a trained technician applied the AASM criteria to manually mark apneas using solely the PSG thermistor airflow data. The soring technician was blinded to the results of the new system. The MATLAB Wavelet Toolbox and an R-wave detection algorithm [21] were used to detect heart beats in the raw ECG signal recorded by the PSG.

2.5 Evaluation of system performance

Apneas classified using the PSG are considered gold standard. Accordingly, the performance of the developed apnea detection algorithm was evaluated by calculating sensitivity and specificity as follows:

$$Specificity = \frac{True\ Negative\ Apnea\ (\mathrm{TNA_t})}{True\ Negative\ Apnea\ (\mathrm{TNA_t}) + False\ Positive\ Apnea\ (\mathrm{FPA_t})}$$

$$Sensitivity = \frac{True\ Positive\ Apnea\ (\mathrm{TPA_t})}{True\ Positive\ Apnea\ (\mathrm{TPA_t}) + False\ Negative\ Apnea\ (\mathrm{FNA_t})}$$

Whereas $\mathrm{TNA_t}$ describes the amount of correctly classified time absent of apnea, $\mathrm{TPA_t}$ describes the amount of correctly classified time of apnea, $\mathrm{FNA_t}$ describes the amount of incorrectly classified time absent of apnea and $\mathrm{FPA_t}$ describes the amount of incorrectly classified time of apnea. Furthermore, $\mathrm{TPA_n}$ describes the number of correctly classified apneas and $\mathrm{FPA_n}$ describes the number of incorrectly classified apneas.

The ECG signal of the PSG was used to evaluate the performance of the developed heart beat detection algorithm. To compare audio and ECG-based heart rate, the same method

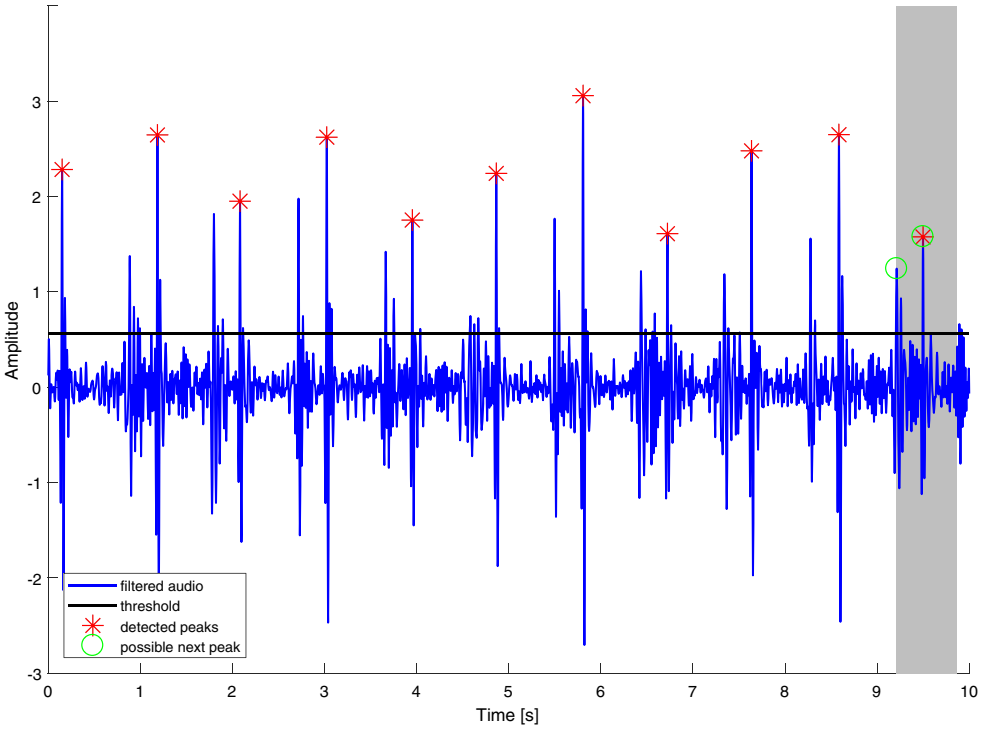

Fig. 6 Peak detection of typical heart sounds. The blue curve represents the bandpass filtered (10 to 50 Hz) audio signal. The red stars mark the detected heart peaks. The gray area represents the time interval for the next heart peak based on the assumed 330 ms maximum time variation between two heartbeats. The green circles mark all possibilities for the next heart peak. The black line represents the threshold based on the 90th percentile of the current signal window. All peaks below this threshold are discarded

for calculation of heart rate from single peaks was used (20 peaks with 10 peak shift). The agreement of both methods was analyzed using correlation as well as Bland-Altman analysis.

3 Results

3.1 Apnea detection

The results of the developed apnea detection algorithm are displayed in Table 2. Ten recordings with an overall duration of 4185 min were evaluated. These consist of a total of 681 apnea events detected using PSG, ranging from 2 to 247 apnea events per recording. The algorithm classified 630 apnea events correctly (true positive) and 52 incorrectly (false positive). Considering correctly and incorrectly classified time intervals a sensitivity of 92.8% and a specificity of 99.7% was calculated. The deviation in the sensitivity of subject 4 stems from the low total number of apnea events occurring (2 of 3 apneas classified correctly).

Table 1 Anthropometric information of subjects

Subject ID	Age	Sex	Weight (kg)	Height (cm)	BMI
1	71	M	91	181	27.8
2	41	F	98	168	34.7
3	72	M	130	181	39.7
4	57	F	80	163	30.1
5	37	M	110	186	31.8
6	43	F	123	173	41.1
7	83	M	78	165	28.7
8	58	M	110	185	32.1
9	57	F	80	160	31.3
10	56	F	59	165	21.67
	ø 57.5 ± 1-4.7		ø 95.9 ± 2-2.4	ø 172.7 ± 9.8	ø 31.9 ± 5.7

3.2 Hear rate detection

The results of the correlational and Bland-Altmann analysis are shown in Fig. 7. The correlation analysis revealed that audio HR was strongly correlated with ECG HR (coefficient of determination r^2 = 0.8164). The sum of squared errors (SSE) was 4.5 bpm. Using Bland-Altman Analysis, a mean ± 1.96 SD difference between audio HR and ECG HR of − 1 ± 10 was calculated. The coefficient of variation (CV) was 8.4%.

4 Discussion

A novel system including a fully functioning prototype capable of recording movement and body sounds for sleep monitoring was developed. The system consists of a device worn by the user including a body sound microphone attached at the neck and an IMU. Data is wirelessly transferred to a laptop where the data is stored for subsequent offline analysis. The

Table 2 Results of apnea detection

Subject ID	Apnea events PSG	TPA_n	FPA_n	Duration (min)	TNA_t (s)	TPA_t (s)	FNA_t (s)	FPA_t (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

TPA_n number of correctly classified apnea events, FPA_n number of incorrectly classified apnea events, TNA_t correctly classified time absent of apnea, TPA_t correctly classified time of apnea, FNA_t incorrectly classified time absent of apnea, FPA_t incorrectly classified time of apnea

developed system is easy to set up and offers a high comfort compared to conventional sleeping monitors. This was also previously investigated in [12].

A method for extracting possible apnea events was established and described. With a sensitivity of 92.8% and a specificity of 99.7%, the algorithm shows a similar performance in comparison to other sound-based methods [2, 4, 17, 25], confirming its capability to reliably detect apnea events. This result was achieved by combining three unique signal processing steps, utilizing both audio and movement data to detect apnea events. During preprocessing, any heart sounds and noise from the raw signal were removed. The drop detection identifies possible apnea events by scanning the entire signal for drops in breathing amplitude. During classification, the previously extracted segments of possible apneas are inspected in detail in order to distinguish between apnea and non-apnea events. The movement data is used to facilitate this process by using it to detect motion artifacts in the sound signal.

Most mobile sleep monitors use thermistors to record airflow and thus detect apneas and hypopneas. However, it was reported that using solely the thermistor method to measure respiratory airflow provides poor results [5], since the thermistor fails to reliably detect nasal as well as oral breathing. In contrast, breathing sounds recorded at the trachea are independent of breathing route [17]. However, body sound recorded at the trachea has been reported to be affected by the individual anatomy of every patient [9]. Additionally, it can be observed that the breathing sound amplitude can change with sleeping position without altering the airflow. This makes the reliable estimation of airflow from sound data challenging. Here, this issue was resolved by constantly updating the reference for normal breathing to distinguish between apnea and non-apnea events. It has been shown that this method can compensate for the change in breathing sound amplitude.

The main weakness of the algorithm is the lack of hypopnea event detection. The Apnea-Hypopnea Index (AHI) is one of the most important parameters used to quantify the severity of sleep apnea and can therefore not be calculated with the proposed method. Therefore, an appropriate evaluation of the diagnostic capability of the developed system is still pending. Full analysis of the PSG results which also included hypopnea events revealed that the major part of false positive apnea events in subjects 5, 8, 9, and 10 are misinterpreted hypopnea events. The attempt to simply adjust classification thresholds to distinguish between apnea and hypopnea events was infeasible since it caused a high number of false positive hypopnea events, especially in recordings with less than 20 total apnea events. By AASM standards, hypopneas are defined by at least 30% reduction in air flow including an event-related arousal and/or more than 3% oxygen desaturation [11]. Without information about oxygen desaturation or arousals, the correct classification of hypopneas is challenging. It has been shown that the feature used for apnea detection is fit to distinguish between breathing and non-breathing. However, this feature fails to detect a certain reduction in air flow. Therefore, other sound features are needed in order to detect hypopneas in a reliable manner. In the current study, the data simply failed to provide enough distinct hypopnea events to develop and subsequently validate a method for hypopnea detection. Therefore, further studies will be necessary to investigate the sound properties during hypopneas. In order to facilitate the hypopnea detection, current research efforts in our group are directed towards the integration of an oximetry sensor into the cone of the body sound microphone. This would add another channel to the system without affecting its current simple setup.

The detection and calculation of HR using the presented method offer certain benefits. It is interesting to note that heart sounds recorded at the neck are very dominant across all

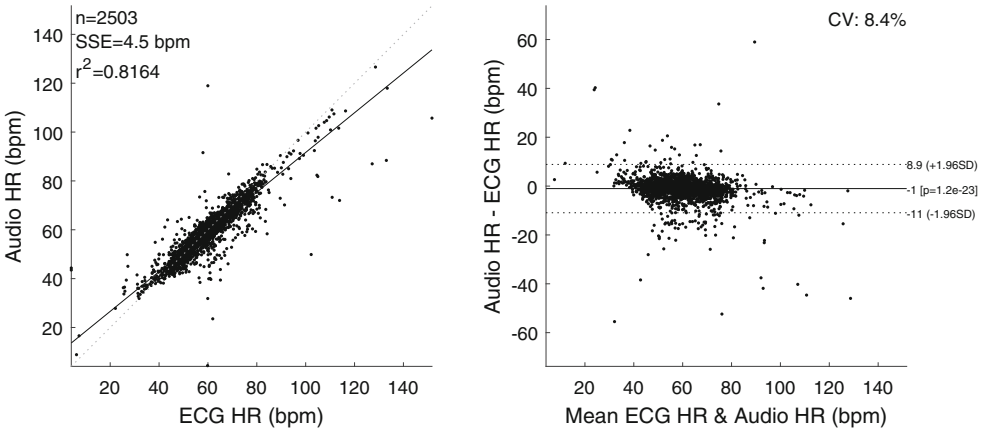

Fig. 7 Correlation (left) and Bland-Altman (right) plot of the relationship between the ECG heart rate (HR) and the audio HR. Correlation: r^2, coefficient of determination; SSE, sum of squared errors; *n*, number of data points; Bland-Altmann: lines indicate the bias and the limit of agreement (±1.96 SD); CV, coefficient of variation

recordings. This finding, while preliminary, suggests that heart sounds can easily be recorded independent of sex, age, or BMI of the patient. However, there are limitations to this method. During snoring episodes, heart sound extraction from the recorded audio signal is severely disturbed. This may also apply if the patient is talking or moving thus creating loud noise within the audio signal. Therefore, heart rate is interpolated during those sections. A fast change in heart rate may get missed and other diagnostic relevant information like heart rate variability cannot be calculated accurately. The results of correlation and Bland-Altman analysis encourage these assumptions. On the one hand, a high correlation between ECG HR and audio HR can be observed. Furthermore, the bias is very low and seems to be constant from 40 up to 100 bpm ECG HR. On the other hand, audio HR tends to be low if ECG HR is over 100 bpm. The mean ± 1.96 SD difference and widely scattered outliers mostly reflect errors due to interpolation. This leads to the general conclusion that calculation of HR using tracheal audio is only suitable to give a reliable trend of HR and long-term changes during the night.

The setup of the developed monitor was performed by trained medical staff but without attendance of technicians. There were no recordings where a significant amount of data was lost or unusable. This finding illustrates the simple set-up and suggests the applicability of the developed hardware in home monitoring. Furthermore, unlike most ambulatory sleep monitors, the developed system provides a heart rate monitoring without the need for additional pulse oximetry or ECG thus reducing wiring and the interference with the patient's sleep. It can therefore be suggested that using less sensors leads to a better sleep quality and therefore to more reliable results.

The present study holds several advantages and limitations. Although all subjects were recruited with a suspicion of sleep apnea, the PSG results covered the entire spectrum from no to severe sleep apnea. Additionally, the sex, age, and BMI distribution cover a wide range of different individuals, suggesting that the results are applicable to the general population. Nevertheless, the number of subjects needs to be expanded in future studies. Additionally, since it is of great interest how the proposed system performs at home without medical supervision, any future studies should be performed in a home setting.

An unanticipated finding was that breathing as well as snoring can be detected by visually inspecting the acceleration and angular velocity data of the IMU. This is rooted in the fact that any movements or vibrations of the chest are transferred to the body device mounted there. This is an important finding and should be addressed by future research. The IMU signals could be utilized to facilitate the detection snoring and to distinguish between obstructive sleep apnea (paused breathing despite breathing effort) and central sleep apnea (paused breathing without breathing effort). Additionally, it is possible that this accumulation of physiological data can be used for an expanded sleep analysis including sleep staging. Additional research should be undertaken to investigate this suggestion.

5 Conclusion

It has been shown that the presented system is capable of adequately detecting apneas in a clinical setting using a unique detection algorithm. Novel features of the system in relation to comparable methods are the utilization of movement data and the capability to detect heart rate. By developing a fully functioning prototype, it has been shown that the recording system is highly reliable and more comfortable than existing ambulatory sleep monitors due to its minimalistic sensor setup. However, the main shortcoming of the system is the missing detection of hypopnea events, crucial for AHI estimation. Future research efforts will focus on including the detection of these events in the existing algorithms, as well as expanding the current capabilities towards a more holistic sleep quality assessment.

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Compliance with ethical standards

Conflict of interest The authors state no conflict of interest. Informed consent has been obtained from all individuals included in this study. The research related to human use has been complied with all the relevant national regulations, institutional policies and in accordance the tenets of the Helsinki Declaration, and has been approved by the authors' institutional review board or equivalent committee.

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Christoph Kalkbrenner was born in Leipzig, Germany, in 1989. He received the B.Eng. degree in biomedical engineering from the University of Applied Sciences Ulm in 2012, and the M.Eng. degree in biomedical engineering from the University of Applied Sciences Ulm in 2013. Since 2013, he has been a Ph. D. student in the medical faculty of the University Ulm in cooperation with the Department of Mechatronics and Medical Engineering of the University of Applied Science Ulm. His research interest includes signal processing, motion tracking, and all areas of sleep-related diagnosis.

Manuel Eichenlaub was born in Landau, Germany, in 1990. He received the B.Sc. degree in biomedical engineering from the University of Applied Sciences Furtwangen in 2013 and the M.Eng. degree in biomedical engineering from the University of Applied Sciences Ulm in 2015. From 2015 to 2016, he served as an academic employee in the Department of Mechatronics and Medical Engineering at the University of Applied Sciences Ulm. He is currently a Ph.D. student at the School of Engineering at the University of Warwick, UK. His research interest includes signal processing, machine learning, and mathematical modeling.

Dr. Stefan Rüdiger was born in Meißen in 1975. He has studied medicine in Berlin (Germany). He has become a medical specialist in Internal Medicine and Pulmonology in 2014 and received his dissertation in 2015. For 10 years he has been working in Ulm University Hospital currently as a senior physician at the Division of Pulmonology at the Department of Internal Medicine II at the University of Ulm. His research interests include molecular abberations of lung cancer.

Dr. Cornelia Kropf-Sanchen has studied medicine at Ulm (Germany), Aberdeen and Newcastle (UK) and Boston (US), finishing her studies in 2003. She received her dissertation in 2007 and has become a medical specialist in Internal Medicine and Pulmonology. Her further specialization included Sleep Medicine (2012) and Palliative care medicine (2013). She is currently working as a senior physician at the Division of Pulmonology at the Department of Internal Medicine II at the University of Ulm.

Professor Wolfgang Rottbauer born in 1967 studied medicine at the Universities of Regensburg, Wuerzburg (both Germany) and at Columbia University in New York. In 1994 he started his professional and scientific career as resident and research fellow at Heidelberg University Hospital. From 1998 until 2002 he worked as postdoctoral scientist at Harvard Medical School with Prof. Marc Fishman. In 2002 he returned to Heidelberg University where he finished his clinical training in cardiology and established scientific research on zebrafish. He was offered and accepted the chair as Head of the Department of Internal Medicine II (Cardiology, Angiology, Pneumology, Sports and Rehabilitation Medicine) at Ulm University in April 2010. Within the Department of Internal Medicine II, the pneumology division focuses next to other lung specific issues on sleep-associated diseases in the context of cardiovascular disorders.

Rainer Brucher was born in Zell a.H., Black Forest, Germany. He received his degree in Electrical Engineering and PhD in Biomedical Engineering at the University of Karlsruhe (KIT), Germany. After an industrial period of six years developing ultrasound instrumentations he started his professorship of Medical Electronics and EMI-compliant Circuit Design at the University of Applied Sciences Ulm in the year 1990. His research interest includes ultrasound sonography, cerebral hemodynamics and emboli detection combined with patient's monitoring, sleep diagnosis and patient's monitoring for theranostics.