HHS Public Access

Author manuscript

Sleep Breath. Author manuscript; available in PMC 2019 May 24.

Published in final edited form as:

Sleep Breath. 2019 March ; 23(1): 269–279. doi:10.1007/s11325-018-1695-6.

Noncontact identification of sleep-disturbed breathing from smartphone-recorded sounds validated by polysomnography

Sanjiv Narayan[1], **Priyanka Shivdare**[1], **Tharun Niranjan**[1], **Kathryn Williams**[2], **Jon Freudman**[1], and **Ruchir Sehra**[1]

[1]Resonea Inc., 11445 E Via Linda, Suite 2 # 224, Scottsdale, AZ 85259, USA

[2]Mayo Clinic, Scottsdale, AZ, USA

Abstract

Purpose—Diagnosis of obstructive sleep apnea by the gold-standard of polysomnography (PSG), or by home sleep testing (HST), requires numerous physical connections to the patient which may restrict use of these tools for early screening. We hypothesized that normal and disturbed breathing may be detected by a consumer smartphone without physical connections to the patient using novel algorithms to analyze ambient sound.

Methods—We studied 91 patients undergoing clinically indicated PSG. Phase I: In a derivation cohort (n = 32), we placed an unmodified Samsung Galaxy S5 without external microphone near the bed to record ambient sounds. We analyzed 12,352 discrete breath/non-breath sounds (386/patient), from which we developed algorithms to remove noise, and detect breaths as envelopes of spectral peaks. Phase II: In a distinct validation cohort (n = 59), we tested the ability of acoustic algorithms to detect AHI < 15 vs AHI > 15 on PSG.

Results—Smartphone-recorded sound analyses detected the presence, absence, and types of breath sound. Phase I: In the derivation cohort, spectral analysis identified breaths and apneas with a c-statistic of 0.91, and loud obstruction sounds with c-statistic of 0.95 on receiver operating characteristic analyses, relative to adjudicated events. Phase II: In the validation cohort, automated acoustic analysis provided a c-statistic of 0.87 compared to whole-night PSG.

Conclusions—Ambient sounds recorded from a smartphone during sleep can identify apnea and abnormal breathing verified on PSG. Future studies should determine if this approach may facilitate early screening of SDB to identify at-risk patients for definitive diagnosis and therapy.

Clinical trials—NCT03288376; clinicaltrials.org

Sanjiv Narayan, sanjivnarayan@incyphae.com.

Conflict of interest Drs. Narayan and Sehra are co-authors of intellectual property licensed to Resonea Inc., and hold equity in a company that has invested in Resonea, Inc. Ms. Shivdare was an employee of Resonea Inc. at the time of this study. Mr. Niranjan is a current employee of Resonea Inc. Drs. Williams and Freudman are paid consultant to Resonea Inc.

Ethical approval All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Informed consent Informed consent was obtained from all individual participants included in the study. No identifying information from participants was recorded.

Keywords

Sleep screening; Smartphone; App; Sleep apnea; Sleep-disordered breathing; Polysomnography; Sound; Signal processing; Fourier transform

Introduction

Sleep-disordered breathing (SDB) affects an estimated 30 million individuals in the USA alone [1], and is responsible for diverse sequelae including days lost from work, daytime sleepiness, accidents, decreased productivity, and hospitalization for heart failure and atrial fibrillation. Sleep disordered breathing is treatable with continuous positive airway pressure (CPAP) or mandibular therapy [2–4], yet many at-risk individuals remain undiagnosed and under-treated [5] due to delays in obtaining in-laboratory (polysomnography, PSG) or multichannel home sleep testing (HST) [6]. A tool for early, rapid screening by physicians, dentists, and/or patients could enable high-risk patients to be rapidly triaged for definitive diagnosis by PSG or HST and definitive therapy.

We hypothesized that normal and disturbed breathing should be detectable from ambient sound recorded from a consumer smartphone without physical contact with the patient. We reasoned that analysis of the periodicity and amplitude of breaths should detect their absence (*apnea*) or shallowness (*hypopnea*), i.e., key diagnostic components, and identify loud gasping sounds (consistent with arousals in obstructive sleep apnea, OSA). We set out to define acoustic signatures for SDB based on key diagnostic elements, which may differ from prior studies on surrogates, e.g., snores, heart rate variability [7]. For instance, Nakano et al. [8] detected snores with a smartphone that correlated with PSG, but snores may not always reflect diagnosed OSA. Other reports, while interesting, required specialized equipment and physical contact, e.g., sound analysis from a PSG mask [9] or during sleep endoscopy [10], electroencephalography [11], electromyogram [12], or oximetry [13] which may be less suited or tolerated by patients for wide at-home screening.

We tested our hypothesis by analyzing ambient sound recorded on an unmodified smartphone with no additional equipment in a prospective study of patients undergoing simultaneous PSG for suspected obstructive sleep apnea (NCT03288376). Phase I of the study involved the development of acoustic signatures for normal and abnormal breaths in a derivation cohort, while phase II validated the ability of these signatures to diagnose OSA from clinically adjudicated whole-night PSG in a separate test cohort.

Methods

Study design

We recruited individuals ≥ 21 years of age undergoing clinically indicated PSG to assess sleep-disordered breathing as part of an IRB-approved clinical study (Western IRB approval #20142343, 1½5/14), conducted from 2015 to 2016 in three AASM-accredited laboratories in the USA (see Supplement). Individuals were *included* if they had clinical suspicion for OSA ($N = 223$). *Exclusions* included prior previous PSG or HST, prior surgery for OSA, a medical contraindication for PSG, or factors that may interfere with completing informed

consent or the clinical questionnaire. Each subject had sound recordings from a consumer smartphone (Galaxy S5, Samsung corporation, Seoul, South Korea) placed on the bed-side during PSG. No patient received CPAP therapy nor was wearing a mask during recordings.

The study included $N = 91$ patients in two phases. In phase I (algorithm derivation), we selected 32 individuals from the entire dataset who provided examples of normal breathing, hypopnea, apnea, arousals, and noisy recordings. We developed acoustic analysis algorithms calibrated to these events. In phase II (validation), we randomly identified 70 patients from the dataset excluding those in phase I, of whom $N = 59$ had complete whole-night acoustic recordings. This comprised the clinical validation cohort, in whom we performed receiver operating characteristic analysis of the algorithm developed in phase I against simultaneous PSG.

Smart phone recordings at polysomnography

Sound files were recorded from unmodified smartphones. The recording protocol oriented the smartphone microphone toward the patient, < 1 m from the head of the bed. Equipment in each sleep laboratory (listed in Appendix) comprised pulse oximetry, nasal flow, ECG, respiratory effort, and EEG. PSGs were adjudicated by certified sleep technicians at each center, blinded to any smartphone analysis.

Recordings were made using the audio recording function of each smartphone. To recreate real-world settings, no attempt was made to pause recordings at times of external noise (e.g., television), speech (e.g., by the patient or staff), wakefulness, arousal, or other events. Recordings were stored on each phone's storage drive as ".wav" files, of typical size ~5 MB/min or ~2.4GB for 8 h (smaller for shorter recordings). Recordings were then exported, fully de-identified, for analysis.

Phase I: development of acoustic analysis algorithm

Analytical algorithms were created in Matlab (version 2016a, The Mathworks, Natick, MA). The $N = 32$ patients in phase I (algorithmic development) comprised 32 individuals (37.5% women) with body mass index 33.0 ± 7.73 kg/m^2 and STOP-BANG scores 4.13 ± 1.62. These patients provided breath sounds of various types. Sound was sampled at 44.1 kHz and digitized files were analyzed offline in 60–120 s epochs.

Noise reduction and signal conditioning—To identify breaths from background noise, each sound epoch was spectrally decomposed using a fast Fourier transform (FFT) using a Kaiser-Bessel window (length = 256, ß = 5). An example is shown in Fig. 1a, in which bands (color coded by frequency) represent successive breaths. A spectral magnitude-time series was created for each epoch as the median of spectral power for all frequencies at each millisecond (Fig. 1b). Each minute of the sound file was excluded if amplitudes were too low, defined a priori as (a) lowest 2 percentile of amplitudes in that epoch; (b) dynamic range < 0.75 dB.

Developing algorithms for normal and abnormal breaths—The algorithm was applied to defined breaths and non-breath sounds, referenced to a database of ambient

sounds constructed for phase I and over-read by three readers (PS, TN, RS) with discrepancies resolved by consensus. The database consisted of 12,352 breaths (386/patient) sampled from whole-night sound recordings, including annotated apnea, hypopnea, arousals (marked by loud obstructive sounds), and normal breathing referenced to PSG. We defined algorithmic acoustic signatures for each class of breath event.

Identifying discrete breaths (peaks)—Breaths were defined from the spectral magnitude-time series of the sound file. A median filter of duration 10 ms was applied to attenuate transient fluctuations, then a root-mean-squared (RMS) envelope function was applied. To identify "packets" of sound which may correspond to a breath event, each second of the smoothed signal was divided into blocks of 1225 samples. We calculated RMS envelope of window size 300 samples. Individual RMS envelopes were concatenated to form the final RMS envelope. Peak detection was applied to smoothed spectral magnitude-time series to identify an array of maxima (Fig. 1c).

Breaths B_n were defined as having onset time T_n, duration D_n, and height H_n (Fig. 1d). For each breath, we defined its largest peak, separated from other local maxima via topological prominence. Prominence mathematically defines the peak as the point above the lowest contour line (local minimum) that bounds it but contains no higher peak. If the prominence of a peak is H_n, then passing from this peak to any higher peak (i.e., another breath) requires a displacement defined as a_n, passing through lower minima. The prominence of breath B_n = H_n – amplitude of local minimum (key col.; Fig. 1d). Peaks were separated by at least 50 ms with peak width of 20 ms.

Identifying non-breath sound signals—We hypothesized that breath sounds should be discrete and periodic, while non-breath sounds (noise) may be loud, non-repeating, and/or of long continuous duration. We used frequency-domain analyses to test this hypothesis.

The enveloped spectral-magnitude time series was smoothed using a 100 point median filter (i.e., 100 out of 1224 points, ~81.7 ms). We calculated the area A_n of each spectral packet using the trapezoidal rule (dB s; Fig. 1d). Area outliers, defined liberally (to keep close to mean areas) were removed if > mean area ± 1 SD. Optimal area cutpoints for non-breath versus breathing sounds were defined from the database created for this project referenced to adjudicated simultaneous PSG.

Phase II: validation of acoustic analysis algorithm

For clinical validation, we randomly identified N = 70 individuals from our clinical study who were not used for algorithm development, of whom N = 59 had complete whole-night acoustic data. In these individuals, we created an acoustic Respiratory Index (RI) to compare the results of smartphone sound analysis against entire-night PSG. RI was computed from the numbers of abnormal breaths or apneas, and the optimum cutpoint identified which was analogous to AHI for moderate OSA (i.e., AHI > 15 events/h). RI was then evaluated for the two-bin case of normal and mild OSA (AHI < 15 events/h) versus moderate and severe OSA (AHI >= 15 events/h). Analyses were performed using open source "R" statistical analysis software, with the "OptimalCutpoints" package.

Statistical analysis

Continuous data are represented as mean ± standard deviation (SD). In phase I, the sound algorithm was developed from a database of breath and non-breath sounds created for this project, which were annotated by direct listening referenced to adjudicated simultaneous polysomnograms in each patient. Comparisons between groups were made with Student's *t* tests and summarized with means and standard deviations for independent samples if normally distributed or, if not normally distributed, with the Mann-Whitney *U* test and summarized with medians and quartiles. Nominal values were expressed as *n* (%) and compared with chi-square tests or the Fisher exact test when expected cell frequency was < 5. Multi-rater agreement was assessed using Fleiss' Kappa score.

In phase II, AHI scores from PSG in each patient were compared to acoustic respiratory index (RI) using receiver operating characteristic curves. PSG-AHI scores were assigned from each treating center, as the average of two technicians' reports blinded to acoustic analysis. From ROC analysis of RI to no/mild versus moderate/several OSA from PSG, we derived sensitivity and specificity for this endpoint.

A probability of < 0.05 was considered statistically significant for all analyses.

Results

Table 1 provides clinical details for individuals in the validation cohort, each of whom underwent smartphone sound recordings simultaneous with clinically indicated polysomnography.

Algorithmic development

Spectral decomposition of sounds during normal breathing—Figure 1 illustrates 1 min of sound recorded by a smartphone during sleep in a 72-year-old woman with body mass index (BMI) 25.7 kg/m^2 analyzed spectrally (Fig. 1a). Each band corresponds to an audible breath, of periodicity ~0.2 Hz and duration T_n = 1–2 s. Figure 1b indicates the spectral magnitude-time series, summarizing magnitudes across frequencies at each time point with peaks clearly visible. Figure 1c shows tagging of breaths for this file, using peaks from which beats were defined by parameters summarized in Fig. 1d.

Clinical derivation of optimum cutpoints for breaths, non-breath noises—We tested the algorithm for adjudicated breath events from the PSG in our development database. The ROC of peak prominence for defining breaths produced a c-statistic (area) of 0.91 (Fig. 2a). The optimum cutpoint was 0.21.

Similarly, we derived cutpoints for non-breath sounds corresponding to periods of body movement on simultaneous PSG. ROC of packet area for non-breath sounds yielded a c-statistic of 0.95 with an optimal cutpoint of 15,000 dB s (Fig. 2b).

Automatic identification of apnea—Figure 3 illustrates 1 min of sound recorded during sleep in a 55-year-old man with BMI 30.7 kg/m^2 and a history suggestive of obstructive

sleep apnea undergoing PSG. Spectral analysis (Fig. 3a), magnitude-time series (Fig. 3b), and peak detection (Fig. 3c) are shown.

Normal breaths are seen for the first 20 s of the sound file, at a rate of 0.25 Hz (one every 4 s) each of duration T_n = 1–2 s. Breaths then cease from 22 to 49 s, followed by the resumption of peaks. This period corresponded with clinical apnea (> 10 s) on simultaneous PSG (Fig. 3d), and was followed by an arousal event in which EEG, EMG, and body movement showed high activity from 50 to 60 s. During the arousal, breath-peaks are still seen on acoustic spectral analysis together with additional peaks indicating noise.

Spectral decomposition of sounds during movement noise—Figure 4 illustrates 1 min of sound recordings recorded during sleep in a 47-year-old woman with BMI 64.8 kg/m^2. Spectral (Fig. 4a) and spectral-peak analyses (Fig. 4b) are shown.

Period spectral bands are seen up until 40 s, which correspond to breaths with periodicity ~0.2 Hz and duration T_n = 1–2 s. However, at ~42 s, a series of rapid additional sound bands occur (Fig. 4a), which are narrow in duration (T_n < 1 s) and disturb the periodicity of peaks (Fig. 4b). The simultaneous polysomnogram in Fig. 4c shows body movement at 42–50 s, which was heard to cause these additional spectral sounds.

Automatic identification of non-breath sounds from breaths—Figure 5 illustrates sound recordings during sleep in a 55-year-old man with clinical suspicion for sleep apnea. Acoustic spectral analysis (Fig. 5a) and peak analysis (Fig. 5b) show period breaths throughout the 100-s period as well as additional non-periodic and brief sounds. The spectral magnitude-time series (Fig. 5b) shows that sounds from 22 to 30 s had fewer distinct peaks. Area analysis of this packet (Fig. 5c) was 26,613 db s, above the ROC-derived cutpoint for non-breath sounds. Auditory examination confirmed that this segment represented noise. Figure 5d shows the corresponding PSG recording.

Phase II: Clinical validation

In blinded analysis of the validation cohort, Fig. 6 shows ROC curve of the respiratory index, i.e., acoustically detected breath disturbances, compared to PSG-defined AHI ≥ 15 events/h. The c-statistic was 0.87. To optimize sensitivity for screening, the cutpoint of RI = 13.43 was selected and predicted AHI ≥ 15 events/h with a sensitivity of 93.7%, specificity of 63.0%, negative predictive value of 89.5%, and positive predictive value of 75.0%. Alternative cutpoints could be selected to provide higher specificity with expected trade-offs in sensitivity (for instance, a cutpoint of RI = 22.7 provided sensitivity 78.1%, specificity 85.2%), which could be tailored to ambient noise in the specific environment being tested.

Discussion

We show that sound recorded from an unmodified smartphone during sleep, avoiding specialized equipment and physical contact with the patient, can identify acoustic signatures of sleep disordered breathing. We first developed an algorithm to separate normal breath sounds, apnea, and arousals referenced to the gold standard of concurrent PSG. In a separate validation cohort, these acoustic signatures provided high clinical accuracy for moderate-

severe OSA at PSG. To the best of our knowledge, this is the first study to demonstrate the ability of smartphone monitoring alone to identify key breathing components of SDB, and differs from prior studies that required specialized equipment typically available only through a laboratory, or that focused on surrogate signals. Further studies should test if a screening strategy for SDB based on acoustic analysis may identify high-risk individuals who can then be referred for traditional PSG diagnosis and therapy.

Approaches for wider screening

There are several increasingly recognized challenges to screening US adults for sleep disordered breathing [14]. One potential approach may be to facilitate early and rapid screening of patients seen in family practice [15], dental clinics [16], or other venues where patients may be unaware of this diagnosis. While screening questionnaires may help identify at-risk individuals, e.g., the Berlin or STOP-BANG scores, such tools are not tailored to individual physiology and may have limited accuracy [17]. The PSG, while the gold standard for diagnosis, introduces limitations for screening [18, 19] including its in-laboratory setting, need for multiple physical connections, expense, inter-test variability including first-night effect, and variability in interpreting test results due to competing scoring criteria [20]. Improved, cost-efficient screening for SDB may enable rapid triage of high-risk individuals who are currently unscreened for gold standard PSG followed by prescription and titration of therapy as needed.

The current study extends the literature by defining acoustic signatures for SDB, i.e., which reflect pathophysiological patterns of breathing. Acoustic diagnosis offers the ultimate potential for unobtrusive, repeatable screening for sleep disordered breathing with or without attached wires or sensors. If further validated, acoustic analysis could potentially improve the value of HST [18, 19], which has experienced limited acceptance in part due to lack of physiological data. Quantification of lung ventilation (breaths) using acoustic analysis of ambient sound may provide some of this physiological information. In this way, acoustic analysis also has the potential to augment in-laboratory or home sleep testing. Some inter-observer variability of sleep studies reflect “equivocal epochs” which account for > 25% of sleep, particularly in awake/NREM, N1/N2, and N2/N3 sleep [20]. Analysis of breaths could help to understand such epochs, and provide additional information to help in coding hypopnea [21] or arousals [12].

Applicability of smartphones to health screening

Smartphone technology continues to grow worldwide with tens of millions of users in the developed and developing world, and an explosion of mobile health (mhealth) applications. These applications have great promise if applied scientifically and judiciously, but an emerging challenge is to ensure that they are appropriately tested and clinically validated to guide patient expectations. Several mHealth systems exist to record and diagnose the ECG, to measure oximetry and pulse using the light source and camera of the mobile device applied to the fingertip [22] and face [23], to assess cognitive function, to analyze actigraphy (movement) as a general index of health, and many other functions as recently reviewed [24]. Literature is emerging on the reliability of mHealth applications compared to gold

standard diagnostic screening tests, with many providing adequate approximations yet falling short of the accuracy needed for disease screening or health management [25]. The current study aims to provide a rigorous clinical validation of a novel mHealth application for screening SDB.

Prior studies using smartphones to diagnose sleep disordered breathing

Few studies have analyzed ambient sound produced by an individual during sleep to track the presence or absence of breath sounds, arousal sounds, or noisy sounds, compared to the gold standard diagnosis from PSG.

Nakano et al. used a smartphone taped to the anterior chest to analyze sound to detect tracheal snore sounds, which correlated with sleep disordered breathing (AHI > 15) on PSG with sensitivity 70% and specificity 94% [8]. These results, while impressive, may not be suitable for screening for which a higher sensitivity may be desired. Additionally, taping a smartphone to the chest may not resolve the inconvenience of current HST. Future studies should determine if abnormal breathing events may be missed by snore analysis alone (i.e., reduced sensitivity) or if normal snores in individuals without SDB are inadvertently captured (i.e., reduced specificity). Koo et al. analyzed smartphone recordings during drug-induced sleep endoscopy [26] using spectral analysis to identify the pharyngeal region of obstruction. However, sounds during drug-induced sleep endoscopy may differ from natural at-home sleep. That study and others used equipment in addition to a smartphone to detect SDB. Garde et al. used a finger oximetry analyzed by smartphone, heart rate variability, and clinical variables to train a linear classifier with acceptable accuracy for SDB [13]. Al-Mardi et al. presented a sophisticated smartphone system to combine data streams from an oximetry device, a microphone placed on the throat and an accelerometer, which showed promising correlation to OSA in a pilot study of 15 patient samples [24]. Chang et al. analyzed heart rate variability by ECG and found a moderate association with SDB [7]. These and other studies used special equipment including external microphones [9, 27, 28], oximetry [29, 30], the EEG [11], EMG [12], and movement sensors [6].

Next mechanistic and clinical steps

The present study furthers the emerging science of acoustic analysis to probe the physiology of breathing. Recording sound from an external microphone, Ben-Israel et al. developed Gaussian mixture models to detect snore, noise, and silence events with 92% sensitivity for OSA (AHI ≥ 10), and identified novel acoustic features of sleep-breathing including silence, stability, and variance of sounds and pitch [31]. Acoustic analyses may ultimately identify the level of airway obstruction [26] or airflow phenotypes associated with facial structure [32]. Clinically, acoustic screening of SDB should be tested as a gateway to definitive diagnosis by PSG or HST in diverse scenarios, to ensure that algorithms are robust to noise, varying distance of the phone from the individual, and other nocturnal variations in breathing. These studies will provide the foundation to test the ability of acoustic diagnostics to streamline referral to sleep testing or to complement existing technologies for in-laboratory testing.

Limitations

This proof-of-concept study has many limitations. First, although we used a widely available smartphone (Samsung Galaxy S5 or later), future studies should perform head-to-head comparisons of multiple smartphones. Smartphone technology has advanced so rapidly that most new smartphones today should have the capabilities of phones used in this study. Second, future studies should establish boundary limits such as distance from the user, maximum or minimum sound intensities, or acoustic qualities of the testing environment. Third, while several noise reduction approaches were applied (see analyses and Fig. 2), individual sources contributing to acoustic noise could not be identified in this clinical study to improve breath detection. This is the subject of planned controlled experiments to characterize noise that may be reflected in the PSG such as periodic leg movement, as well as those that are not reflected in PSG such as external speech or the television (which will exhibit differing periodicities to breathing), to improve the accuracy of acoustic analysis to track breathing and screen for SDB. Fourth, it is possible that acoustic analysis for SDB could ultimately be used beyond early screening; this could be tested prospectively in wider populations.

Appendix

Data for this study were recorded in American Academy of Sleep Medicine (AASM)-accredited sleep labs. Centers providing data were:

1. Peninsula Sleep Center, Burlingham CA (Mehran Farid, MD; Director)
2. Northeast Medical Group, New London CT (Amit Khanna, MD; Director)
3. Doctors Community Hospital, Lanham, MD (Riad Dahkeel, MD; Director)

Abbreviations

AHI	Apnea-hypopnea index
BMI	Body mass index (kg/m^2)
CPAP	Continuous positive airway pressure
dB	Decibel
ECG	Electrocardiogram
EEG	Electroencephalogram
EMG	Electromyogram
FFT	Fast Fourier transform
HST	Home sleep testing
PSG	Polysomnography
RMS	Root-mean-square

ROC	Receiver operating characteristic
SD	Standard deviation
SDB	Sleep-disordered breathing

References

1. Peppard PE, Young T, Barnet JH, Palta M, Hagen EW, Hla KM (2013) Increased prevalence of sleep-disordered breathing in adults. Am J Epidemiol 177:1006–1014 [PubMed: 23589584]
2. Doff MH, Hoekema A, Wijkstra PJ, van der Hoeven JH, Huddleston Slater JJ, de Bont LG, Stegenga B (2013) Oral appliance versus continuous positive airway pressure in obstructive sleep apnea syndrome: a 2-year follow-up. Sleep 36:1289–1296 [PubMed: 23997361]
3. Hoekema A, Stegenga B, Wijkstra PJ, van der Hoeven JH, Meinesz AF, de Bont LG (2008) Obstructive sleep apnea therapy. J Dent Res 87:882–887 [PubMed: 18719218]
4. de Ruiter MHT, Apperloo RC, Milstein DMJ, de Lange J (2017) Assessment of obstructive sleep apnoea treatment success or failure after maxillomandibular advancement. Int J Oral Maxillofac Surg
5. Cross NE, Harrison CM, Yee BJ, Grunstein RR, Wong KK, HC B, Marshall NS (2016) Management of snoring and sleep apnea in Australian primary care: the BEACH study (2000–2014). J Clin Sleep Med: JCSM : Off Publ Am Acad Sleep Med 12:1167–1173
6. Sands SA, Owens RL, Malhotra A (2016) New approaches to diagnosing sleep-disordered breathing. Sleep Med Clin 11:143–152 [PubMed: 27236052]
7. Chang KM (2009) Portable obstructive sleep apnea screening system using overnight ECG and a PDA-based wireless transmission system. Telemed J E Health 15:353–361 [PubMed: 19441954]
8. Nakano H, Hirayama K, Sadamitsu Y, Toshimitsu A, Fujita H, Shin S, Tanigawa T (2014) Monitoring sound to quantify snoring and sleep apnea severity using a smartphone: proof of concept. J Clin Sleep Med: JCSM: Off Publ Am Acad Sleep Med 10:73–78
9. Alshaer H, Fernie GR, Maki E, Bradley TD (2013) Validation of an automated algorithm for detecting apneas and hypopneas by acoustic analysis of breath sounds. Sleep Med 14:562–571 [PubMed: 23453251]
10. Herzog M, Plossl S, Glien A, Herzog B, Rohrmeier C, Kuhnel T, Plontke S, Kellner P (2015) Evaluation of acoustic characteristics of snoring sounds obtained during drug-induced sleep endoscopy. Sleep Breath 19:1011–1019 [PubMed: 25427818]
11. Swarnkar V, Abeyratne UR, Hukins C, Duce B (2009) A state transition-based method for quantifying EEG sleep fragmentation. Medical & biological engineering & computing 47:1053–1061 [PubMed: 19705179]
12. Amatoury J, Ali A, Younes M, Jordan AS, Wellman A, Eckert DJ (2016) Arousal intensity is a distinct pathophysiological trait in obstructive sleep apnea. Sleep 39:2091–2100 [PubMed: 27784404]
13. Garde A, Dehkordi P, Karlen W, Wensley D, Ansermino JM, Dumont GA (2014) Development of a screening tool for sleep disordered breathing in children using the phone Oximeter. PLoS One 9:e112959 [PubMed: 25401696]
14. Force USPST, Bibbins-Domingo K, Grossman DC, Curry SJ, Davidson KW, Epling JW Jr, Garcia FA, Herzstein J, Kemper AR, Krist AH, Kurth AE, Landefeld CS, Mangione CM, Phillips WR, Phipps MG, Pignone MP, Silverstein M, Tseng CW (2017) Screening for obstructive sleep apnea in adults: US preventive services task force recommendation statement. JAMA 317:407–414 [PubMed: 28118461]
15. Bailes S, Fichten CS, Rizzo D, Baltzan M, Grad R, Pavilanis A, Creti L, Amsel R, Libman E (2017) The challenge of identifying family medicine patients with obstructive sleep apnea: addressing the question of gender inequality. Fam Pract 34:467–472 [PubMed: 28334763]
16. Smith HA, Smith ML (2017) The role of dentists and primary care physicians in the care of patients with sleep-related breathing disorders. Front Public Health 5:137 [PubMed: 28664155]

17. Chiu HY, Chen PY, Chuang LP, Chen NH, Tu YK, Hsieh YJ, Wang YC, Guilleminault C (2017) Diagnostic accuracy of the Berlin questionnaire, STOP-BANG, STOP, and Epworth sleepiness scale in detecting obstructive sleep apnea: a bivariate meta-analysis. Sleep Med Rev 36:57–70 [PubMed: 27919588]
18. Freedman N (2015) COUNTERPOINT: does laboratory polysomnography yield better outcomes than home sleep testing? No. Chest 148:308–310
19. Pack AIPOINT (2015) Does laboratory polysomnography yield better outcomes than home sleep testing? Yes. Chest 148:306–308 [PubMed: 26238829]
20. Younes M, Raneri J and Hanly P.(2016) Staging sleep in polysomnograms: analysis of inter-scorer variability. Journal of clinical sleep medicine : JCSM : official publication of the American Academy of Sleep Medicine
21. Ho V, Crainiceanu CM, Punjabi NM, Redline S, Gottlieb DJ (2015) Calibration model for apnea-hypopnea indices: impact of alternative criteria for hypopneas. Sleep 38:1887–1892 [PubMed: 26564122]
22. McManus DD, Lee J, Maitas O, Esa N, Pidikiti R, Carlucci A, Harrington J, Mick E (2013) Chon KH. A novel application for the detection of an irregular pulse using an iPhone 4S in patients with atrial fibrillation. Heart Rhythm : Off J Heart Rhythm Soc 10: 315–319
23. Couderc JP, Kyal S, Mestha LK, Xu B, Peterson DR, Xia X, Hall B (2015) Detection of atrial fibrillation using contactless facial video monitoring. Heart Rhythm : Off J Heart Rhythm Soc 12:195–201
24. Al-Mardini M, Aloul F, Sagahyroon A, Al-Husseini L (2014) Classifying obstructive sleep apnea using smartphones. J Biomed Inform 52:251–259 [PubMed: 25038556]
25. Shcherbina A and Ashley EA. (2017) Accuracy in wrist-worn, sensor-based measurements J Pers Med ;7: in press
26. Koo SK, Kwon SB, Kim YJ, Moon JI, Kim YJ and Jung SH. (2016) Acoustic analysis of snoring sounds recorded with a smartphone according to obstruction site in OSAS patients. Eur Arch Otorhinolaryngol
27. Dafna E, Tarasiuk A, Zigel Y (2013) OSA severity assessment based on sleep breathing analysis using ambient microphone. Conference proceedings : Annual International Conference of the IEEE Engineering in Medicine and Biology Society IEEE Engineering in Medicine and Biology Society Annual Conference 2013:2044–2047
28. Diaz JA, Arancibia JM, Bassi A, Vivaldi EA (2014) Envelope analysis of the airflow signal to improve polysomnographic assessment of sleep disordered breathing. Sleep 37:199–208 [PubMed: 24470709]
29. Morillo DS, Rojas JL, Crespo LF, Leon A, Gross N (2009) Poincare analysis of an overnight arterial oxygen saturation signal applied to the diagnosis of sleep apnea hypopnea syndrome. Physiol Meas 30: 405–420 [PubMed: 19332895]
30. Park JU, Lee HK, Lee J, Urtnasan E, Kim H, Lee KJ (2015) Automatic classification of apnea/hypopnea events through sleep/wake states and severity of SDB from a pulse oximeter. Physiol Meas 36:2009–2025 [PubMed: 26261097]
31. Ben-Israel N, Tarasiuk A, Zigel Y (2010) Nocturnal sound analysis for the diagnosis of obstructive sleep apnea. Conference proceedings : Annual International Conference of the IEEE Engineering in Medicine and Biology Society IEEE Engineering in Medicine and Biology Society Annual Conference. 2010: 6146–6149
32. Sprenger R, Martins LAC, Dos Santos JCB, de Menezes CC, Venezian GC, Degan VV (2017) A retrospective cephalometric study on upper airway spaces in different facial types. Prog Orthod 18:25 [PubMed: 28762153]

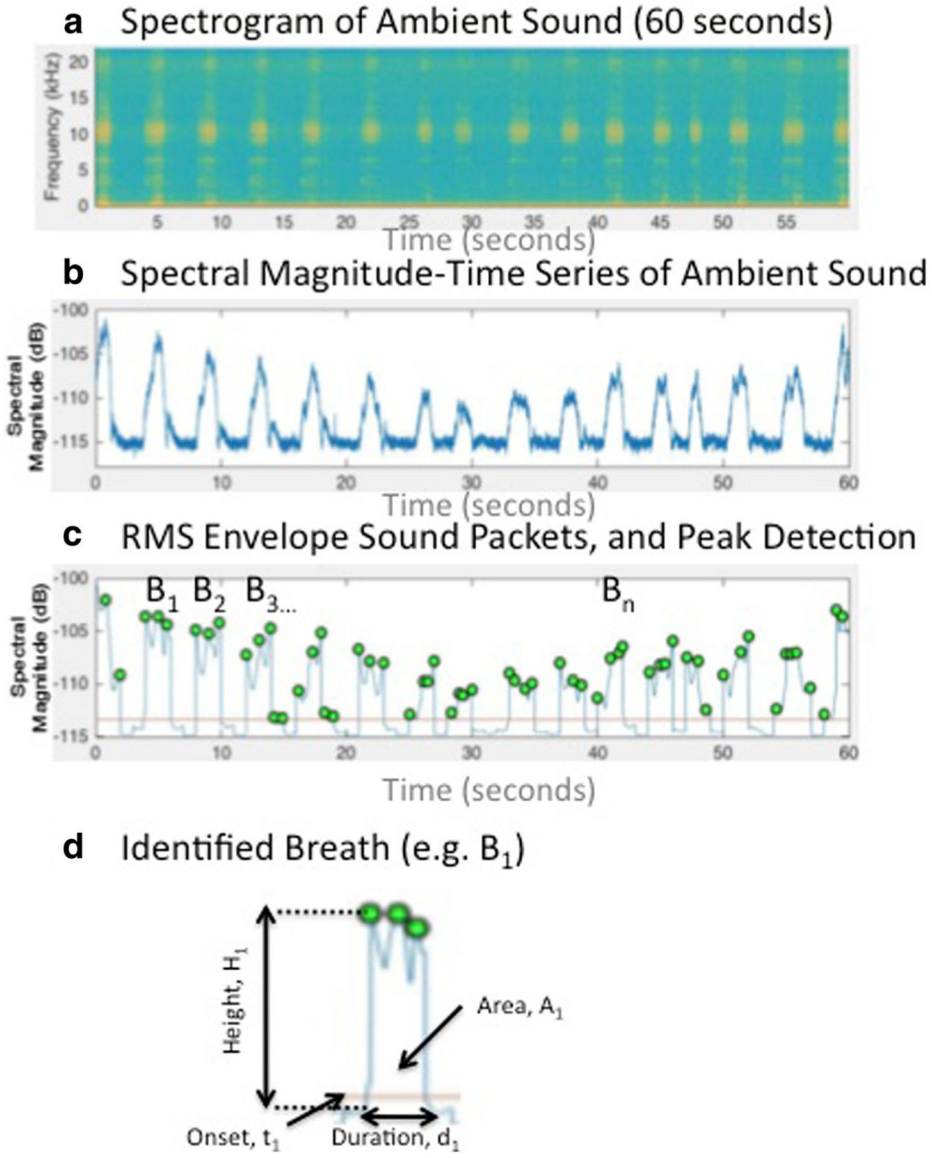

Fig. 1.

Spectral analysis of normal breaths in overnight sound file. **a** One minute of sound recorded from a smartphone during sleep in a 72-year-old woman. Each yellow band represents a breath. **b** Spectral magnitude-time series, emphasizing peaks (breaths). **c** Peaks and adjacent points in sound analysis. **d** Tagged features of each sound packet

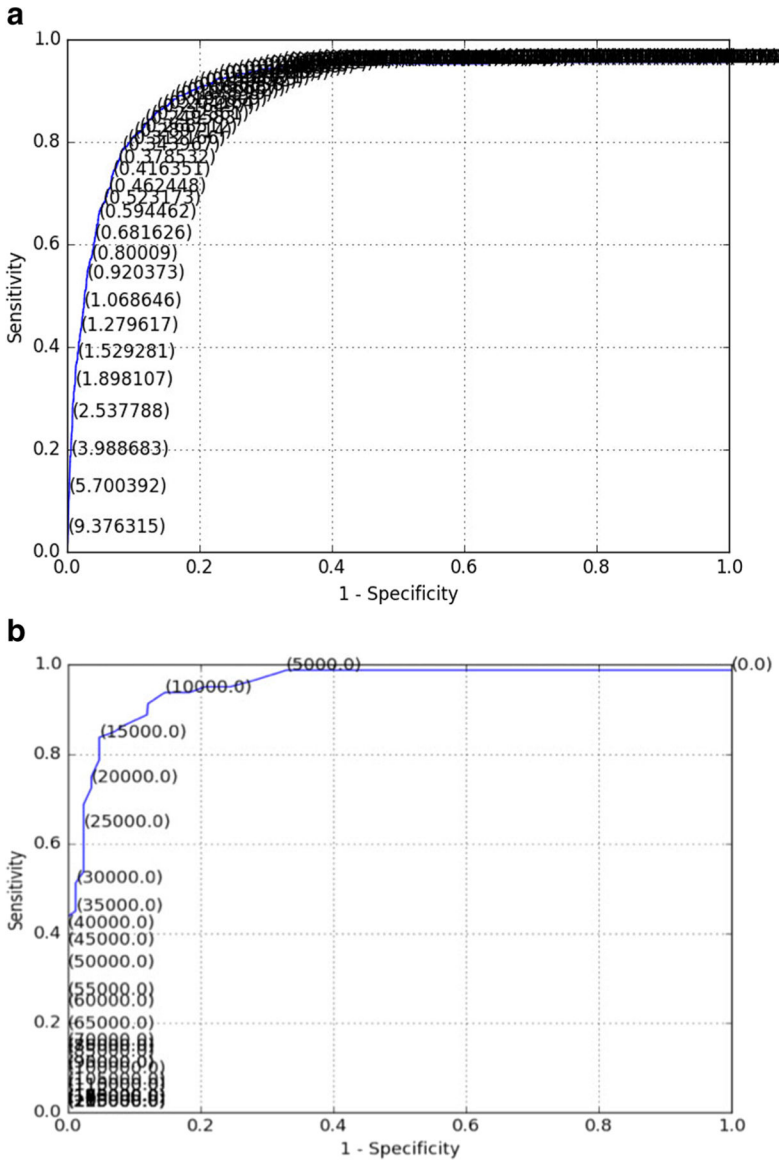

Fig. 2.

Receiver operating characteristic (ROC) curves of acoustic signatures for breaths on simultaneous PSG. **a** C-statistic for identifying breaths was 0.91, derived by varying the peak prominence parameter, with a maximum area under the curve generated at a cutpoint of 0.21. **b** C-statistic for identifying noise (non-breath sounds) was 0.95, derived by varying the packet area, with a maximum area under the curve generated at a cutpoint of 15,000 dB s

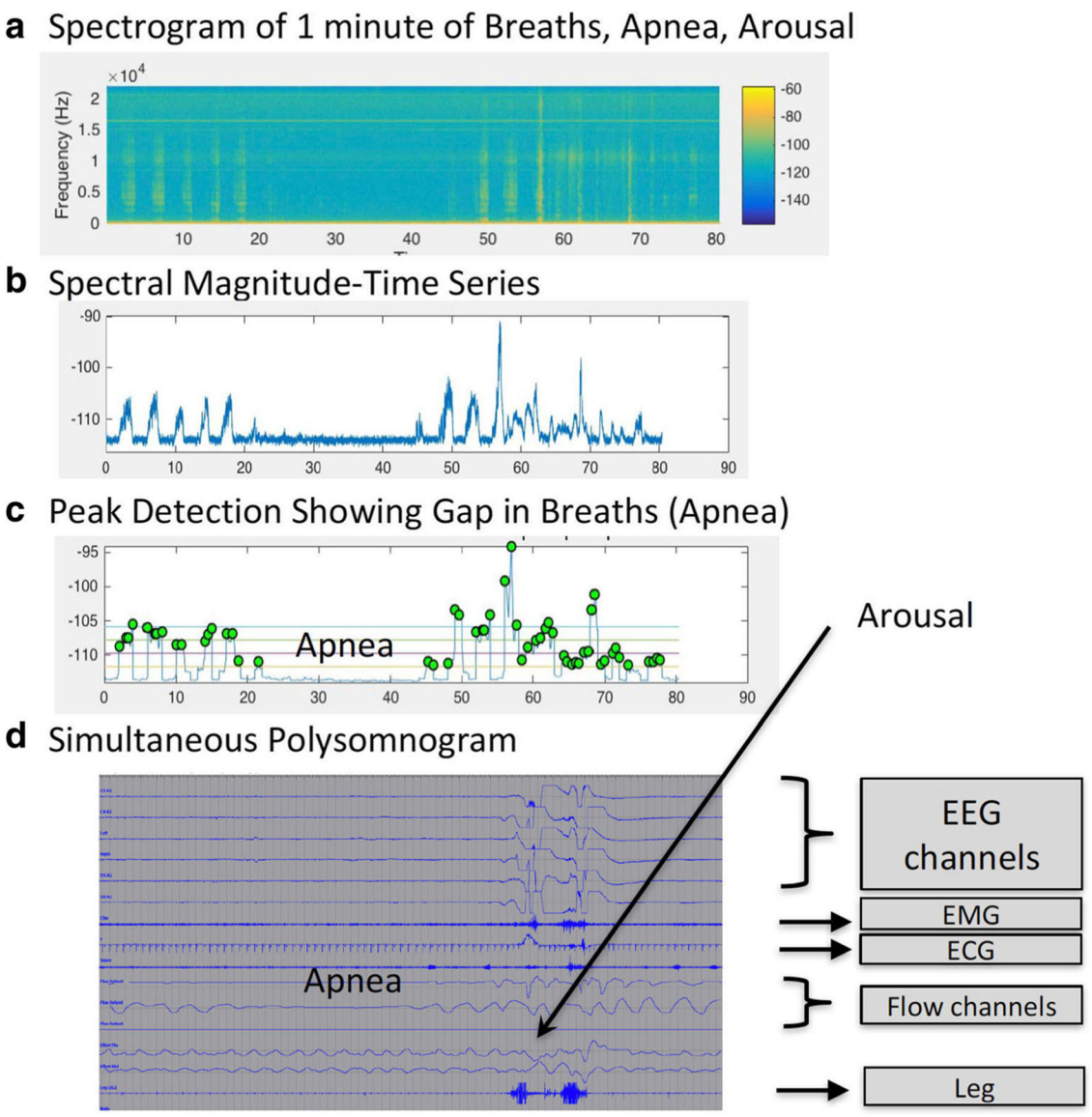

Fig. 3.

Automatic detection of apnea by acoustic spectral analysis in a 55-year-old man being evaluated for obstructive sleep apnea. **a** Spectral analysis of sound, **b** magnitude-time series, and **c** peak detection show apnea between 20 and 50 ms which was detected (**d**) by simultaneous PSG in which apnea concluded with an arousal event at ~50 s (labeled) which is hinted by larger and a broader constellation of spectral peaks on acoustic analysis. Obstructive sleep apnea was confirmed on whole-night PSG in this individual

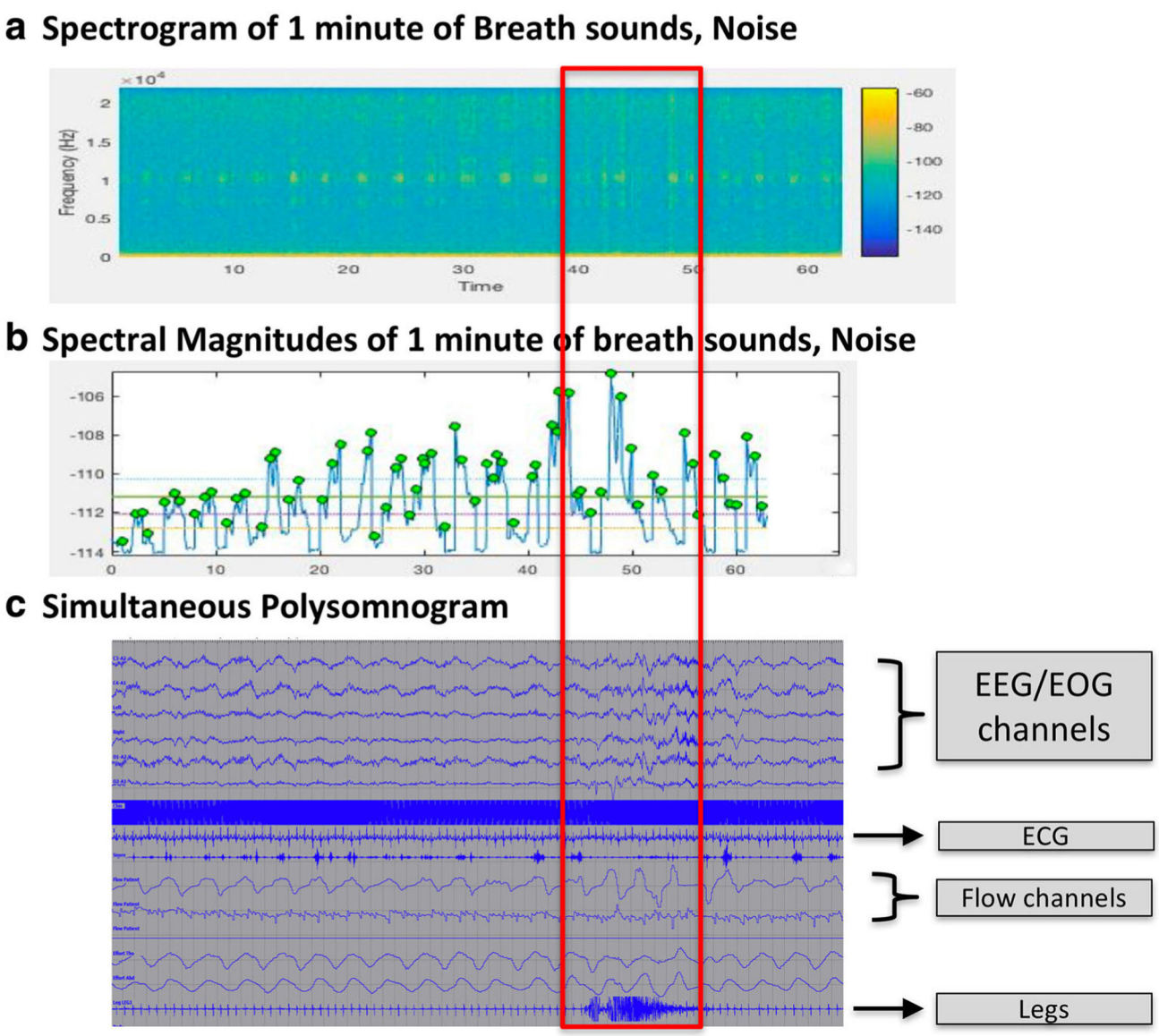

Fig. 4.

Detecting normal breaths and noise on acoustic spectral analysis. **a** Spectral and **b** peak analyses show breaths (periodic bands) until approximately 40 s, representing breaths with periodicity ~0.2 Hz (once per 5 s). At approximately 42 s, a series of rapid additional sound bands disturb periodicity and correspond in **c** simultaneous polysomnogram showing body movement at 42–50 s. Listening to audio files confirmed that this sound represented shuffling in bed/moving

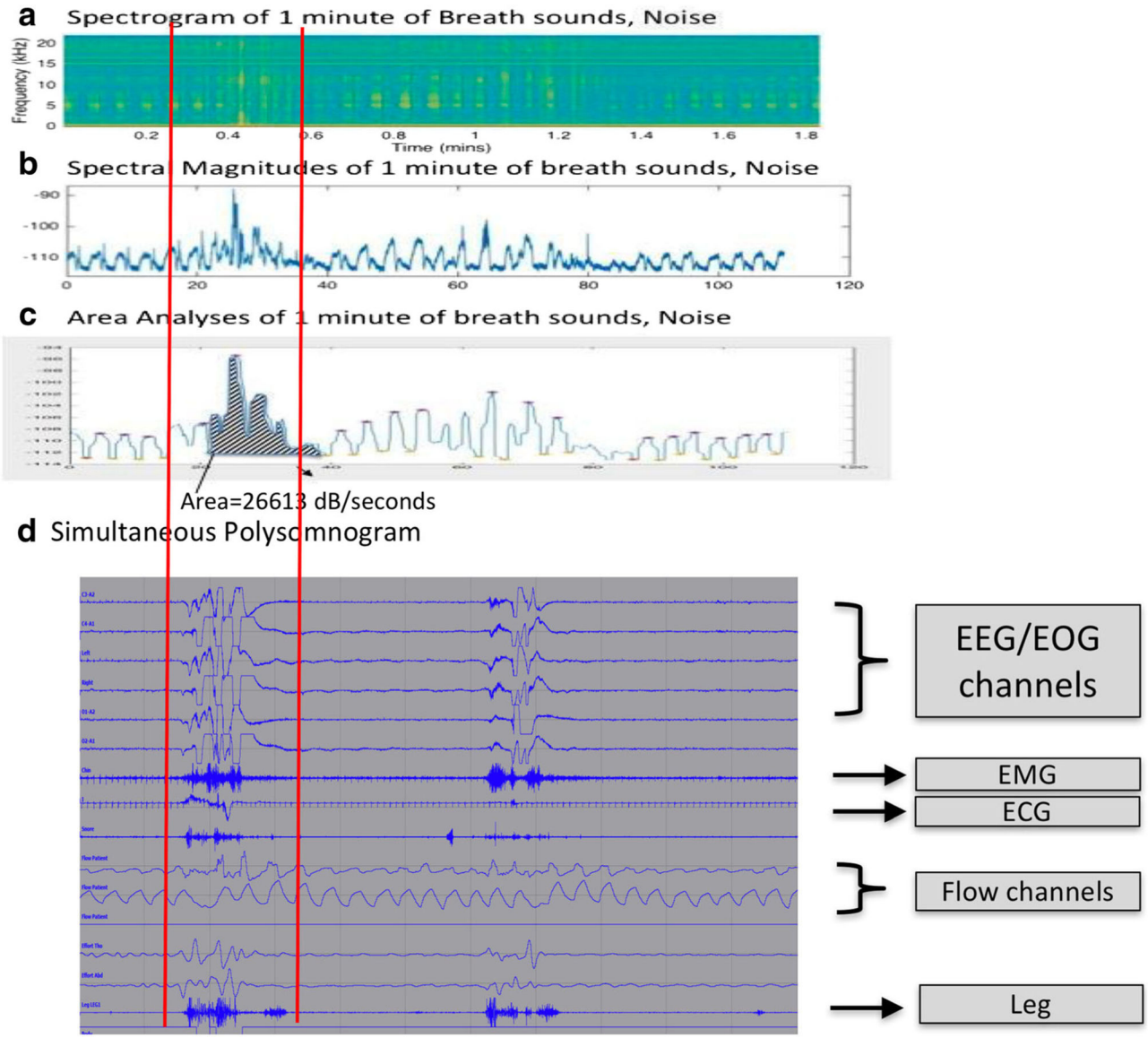

Fig. 5.

Automatic quantification of non-breath sounds by acoustic spectral area. **a** Acoustic spectral analysis and **b** peak analysis from magnitude-time series indicate periodic breaths, as well as additional non-periodic and brief sounds. Spectral magnitude-time series shows sounds from 22 to 30 s that coalesce without distinct periodic peaks. **c** Area analysis of this packet gives area 26,613 db s, above the ROC-derived cutpoint for noise (non-breath sounds). Auditory examination verifies that this segment of the file represents likely movement noise. **d** Simultaneous polysomnogram confirms movement, shown by the leg channel movement as well as high-frequency activity on multiple other channels

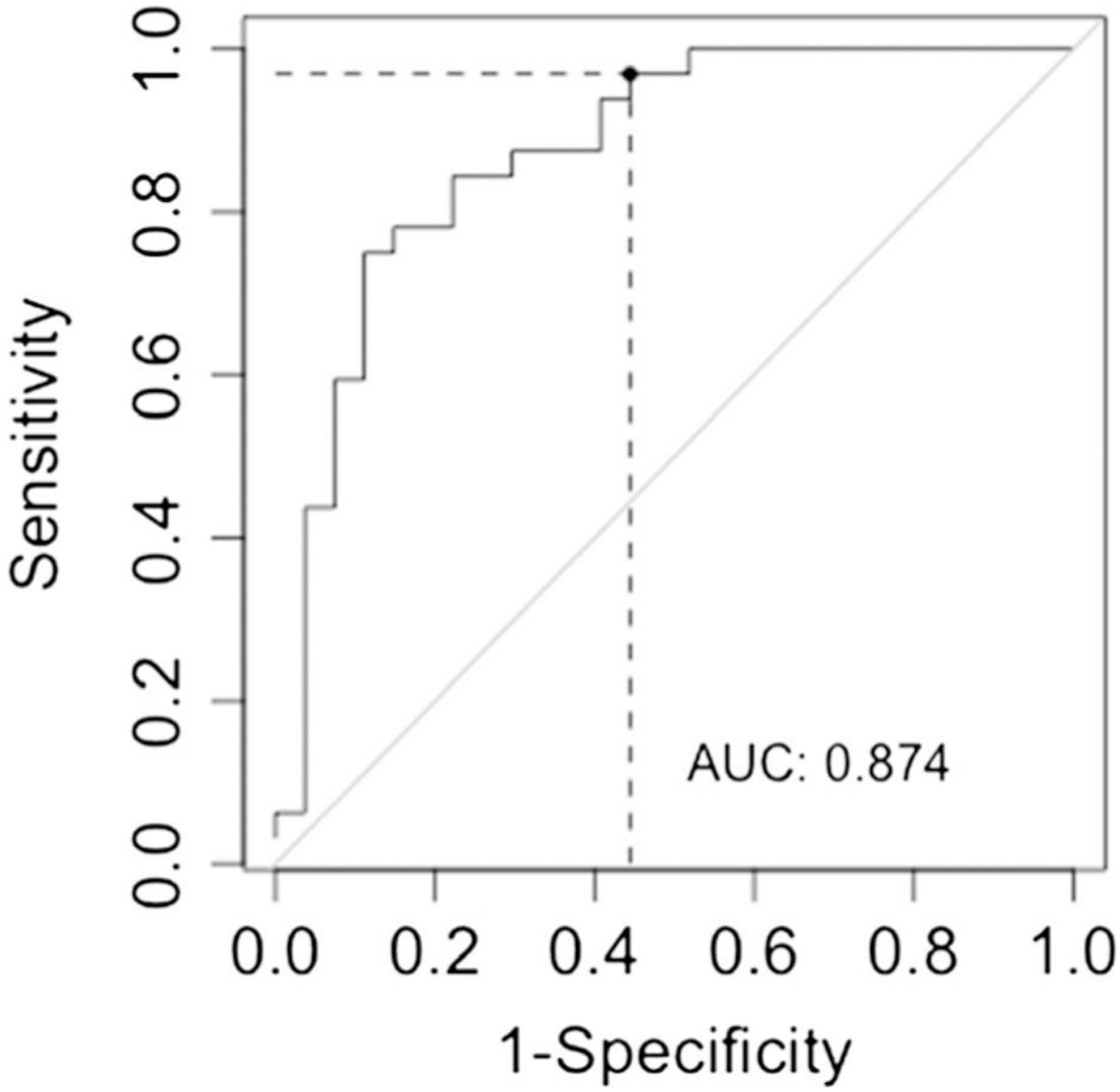

Fig. 6.

Testing acoustic algorithm against whole-night PSG in validation cohort. Receiver operating characteristic (ROC) curve for whole-night acoustic respiratory index for diagnosing OSA on PSG. **a** AHI on PSG < 15 events/h versus **b** AHI on PSG > 15 events/h. The c-statistic was 0.87

Table 1

Clinical characteristics of validation cohort

	Patient characteristics
N	59
Age, years	52.9 ± 15.1
Male/Female	39/20
Height/m	1.70 ± 0.10
Weight/kg	94.1 ± 25.4
Body mass index, (kg/m^2)	32.6 ± 9.54
Hypertension, % (*n*)	27.1% (16/59)
STOP-BANG score	3.59 ± 1.33
Apnea/Hypopnea Index (per hour)	30.0 ± 32.0
No. with AHI < 5	11
No. with 5 < AHI < 15	15
No. with 15 < AHI < 30	15
No. with AHI ≥ 30	18
Prior OSA therapy or surgery	0