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A viable snore detection system: hardware and software implementations

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Abstract: A stand-alone, custom-made biomedical system was introduced for long-term monitoring of sleep and detection of snoring events. Commercially available electronic components were assembled for recording audio, pulse, and respiration signals. Its software was implemented for off-line processing of the acquired signals in C++ and MATLAB environments. The linear and nonlinear features of the signals were extracted and characterized using spectral energy distribution, entropy, and largest Lyapunov exponent (LLE). The performance of the system was evaluated with real physiological data gathered from 14 chronic snorers. Analysis of the cases indicated that the system identified the snoring events with an accuracy of 88.22%, sensitivity of 94.91%, and positive predictive value of 90.95%. This high level of validation confirmed the reliability and utility of the system in detecting snoring.

Key words: Biomedical equipment, biomedical signal processing, medical signal detection, sleep apnea, snore

1. Introduction

Snoring is a widespread problem affecting 20%-–40% of the population [1]. It is considered as a sleep-related breathing disorder (SRBD) and thus represents a risk factor [2]. It is common in undiagnosed obstructive sleep apnea and also prevalent in coronary artery disease, stroke, hypertension, sudden cardiac death, deep thrombosis, and diabetes [3–8].

In clinical practice, polysomnography (PSG) is the standard for recording, monitoring, and diagnosing SRBD [9]. Although PSG is thorough and reliable, the process requires a whole night's evaluation at a sleep laboratory while the subject is connected to a set of numerous sensors. It is an expensive operation and the waiting list is typically long. Also, sleep conditions are unnatural and the procedure may extend to long-term monitoring in the home environment.

Low-cost devices and techniques are required for recording and analyzing the breathing activities of a full night of sleep in a timely and accurate manner. In particular, special features are sought, such as noninvasiveness, simple operation, cost-effectiveness, efficiency in power consumption, accessibility, convenience to use in the home environment, and user-friendliness. Such devices have been developed in the past, but some still lack portability, flexibility, and long-term sleep monitoring capabilities. Others are not validated rigorously for reliability and failure [10–14].

Recent research was extended to smart phones and tablet computers, and special applications were developed, but mostly not tested, available without clinical guidance, often lacking validation, and not open-source [15–20]. For snore detection, algorithms developed in the past involved a linear regression fed by subband

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spectral energy distributions processed by principal component analysis, a hidden Markov model, and spectral-based features, the mean and covariance of features extracted from time and spectral domains, a fuzzy C-means clustering [21, 22], and wavelet transformation and features based on wavelet coefficients [23]. Other developments included ensemble methods [24] and feedforward neural networks [25], the deep learning model, and convolutional neural networks [26, 27]. With one smartphone application, snoring was detected with high sensitivity, specificity, and accuracy of 98.58%, 94.62%, and 95.07%, respectively, but the positive predictive value was only 70.38% in an at-home setting. In others, the outcomes correlated poorly with PSG when the basic sleep parameters and sleep stages were considered [28]. The detector weakly differentiated between being awake or asleep [29]. Other shortcomings included reduced processing power and media input–output capability. Applications of sleep monitoring required placing the device on a mattress. In such situations, sensor accuracy suffered due to multiple individuals being on the same sleeping surface and differences in mattress textures and materials [30]. Signal characteristics of snoring varied as the sound quality was affected by the distance from the device and the fidelity of the smartphone [31].

To address the existing issues above, the purpose of this paper is to present the construction of a new portable system, SnoreBox, for a portable home-based long-term sleep monitoring and snore detection. The following sections systematically describe the details of the unique features of its hardware and software, demonstrate the performance with real data, and discuss its validation.

2. Material and methods

2.1. Hardware design

The SnoreBox system incorporates electronic components and sensors for real-time recordings of audio, respiratory, and arterial pulse signals when attached to a person during sleep. Figure 1 shows the working structure and Figure 2 depicts the final product. The specifications associated with the components are listed in Table 1. The hardware utilizes special units facilitating ultralow power consumption, networking, and long-term storage capabilities. As a core item, the board houses analog amplifiers and filters connected to the sensors. The amplified and filtered signals are digitized at 12-bit resolution using analogue-to-digital converters (ADC) on-board. Audio is captured by a sensitive omnidirectional microphone at 8096 Hz sampling rate. Respiration is sensed from the airflow using an oronasal thermistor at a sampling rate of 1024 Hz. Pulse is recorded using a SpO2 element consisting of a light emitter as an optic transmitter and detector as a receiver. The sampling rate is 512 Hz.

The user control of the system consists of two buttons and is relatively simple to use; one button activates the signal recording while the other stops it. The signals captured by the sensors are stored in a Secure Digital Memory Card (8 GB). With this size of memory, it is feasible to operate the device over several nights without replacing the memory card. The recorded data are transferred to a PC or laptop via Bluetooth channel or the memory card for postprocessing and off-line analysis using software programs developed in-house. The SQL-SERVER 2012 express edition database was used for remotely storing the data in PC or laptop as .text files.

2.2. Software implementation

A graphical user interface (GUI) was implemented with C++ libraries running under Visual Studio.NET based software. The program enables accessing the transferred .text files, reviewing the data, and closely visualizing the signal intervals. A printout of the signals can be produced in pdf format as a hard copy.

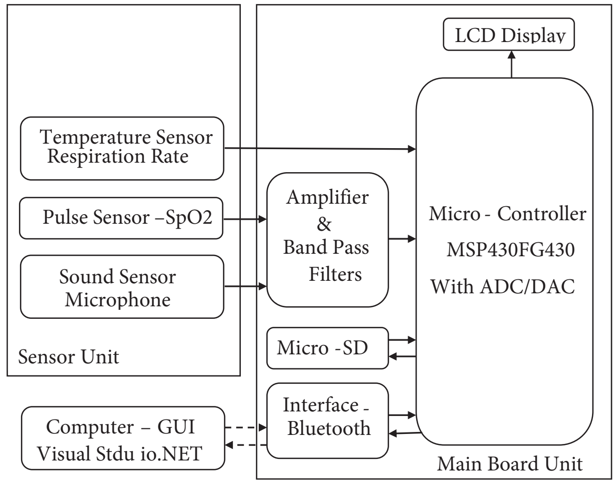

Figure 1. Block diagram of the SnoreBox system.

Figure 2. Snore detection system (SnoreBox), sensors.

Automatic detection of snoring events from the audio, pulse, and respiration signals is achieved with further off-line analysis and postprocessing. This task is accomplished at two stages using the algorithm in Figure 4. Software was implemented in-house in the MATLAB environment with the signal processing and

Table 1. Measurement feature.

Parameter	**Measured value**
Microcontroller	MSP430FG49
Memory	60KB+256B Flash Memory, 2KB RAM
Display	Alphanumerical LCD
Numbers of Channel / sensors	3 (Pulse rate, Airflow and Sound)
Recording time capacity	Approximately 6.5 MB hours
Data transmission / throughput	Bluetooth / 115.2 kbps
Power Source – consumption	3V (2*AA size battery) – 120 mAh
Size	100x68x22 mm
Weight	135 gram
Recorder	
Storage capacity	8 GB
Pulse sensor – SpO2	
Sample rate / resolution	512 Hz / 12 bits
Sound sensor – microphone	
Sample rate / resolution	8096 Hz / 12 bits
Temp. sensor – respiration r.	
Sample rate / resolution	1024 Hz / 12 bits

statistical toolbox (MathWorks, Natick, MA, USA). After reading the .text file in this program, the signals are subject to digital filtering with 0.5–5 Hz or 10–15 kHz bandpass filters to minimize the effects of digitization and environmental noise. The temporal signals are divided into nonoverlapped windows of 1-s intervals. For event detection of snoring, both linear and nonlinear features of the signals are identified and extracted for each signal segment. The specific signal features extracted are based on the spectral energy distribution, entropy, and largest Lyapunov exponent (LLE) measures. Support vector machines (SVMs) are then employed as the classifiers for detecting snoring within the corresponding signal segment.

In previous studies, schemes were presented for classifying the snore-related sounds using entropy and LLE with SVMs [32–37]. In our software, we adopted the same scheme as SVMs were reported to offer certain advantages over the others. Specifically, the SVM classifier is easy to implement, faster in training, and better in accuracy with stability/robustness, and it performs reliably with different datasets and has fewer parameters to tune and make it operational. The scope of the work was to implement a viable system with a well-established classifier [38]. Based on these features and facts, we opted to incorporate SVMs into the device. The implementation of the scheme was explained in the referenced article in detail and thus is not repeated here. However, we note that the classifier software in our implementation was further enhanced by incorporating a new feature: energy extracted from the signal. Therefore, the feature space in our analysis spans a 3D vector (energy, entropy, LLE).

3. Performance and validation tests

The performance and validation of the SnoreBox system in correctly detecting snoring events were tested with 6-h recordings of the audio, respiratory, and pulse signals acquired from 14 subjects at the Gülhane Military

Medical Sciences Sleep Laboratory (Ankara, Turkey). Based on previous polysomnographic evaluations, the recruits were clinically diagnosed as snorers (12 heavy and 2 light). Relevant information about these individuals is given in Table 2.

Table 2. The characteristics of the subjects.

Subject information	**Light snorer**	**Heavy snorer**
Number of patients	2	12
Age	31 (23–39)	46 (25–67)
Sex	1 male, 1 female	10 males, 2 females
Apnea/hypopnea indices (AHI) (apnea h–1)	2.435 (1.27–3.60)	19.56 (9.20–29.86)
Body mass indices (BMI)(kgm^2)	24.865 (23.70-–26.03)	27.95 (24.38–33)

The data from all subjects were pooled together, transferred to a PC, and reviewed using the GUI software and then analyzed with the developed SVM-based classification software after being normalized by the maximum signal intensity within the dataset (Figure 3). Based on the PSG analysis of the audio signals alone and the expert views, the entire 6-h sleeping period of each subject was evaluated. The signal was then divided into 1-s segments and each segment was manually assigned as either “snore” or “nonsnore” according to its assigned snoring level. The “nonsnore” segments contained both silence and breathing signals. Figure 4 depicts a typical segmentation based on the audio signal. The frequency and amplitude spectra of the segments exhibit different natures and characteristics. The snore segments have a few components of different frequency ranges and of high and low amplitude peaks. The breathing and silent segments have many components with similar peak values and wide frequency bands.

The first halves of the recordings (first 3 h) are used for training, i.e. for determining the boundary conditions in the space (energy, entropy, LLE) for discriminating “snoring” and “nonsnoring”. The second half (the last 3 h) constituted the testing phase where the predictions were made by the classifier software based on the previously determined discriminatory boundary conditions from the training clusters. More specifically, the training dataset was formed by random, but equal in number of 2380, segments of snoring and nonsnoring from the first 3 h of data. The testing datasets were also constructed similarly with the same segment size. The 1-s segments in both datasets were further subdivided into 50 intervals automatically, but snoring/nonsnoring assignments were retained and propagated. Considering this arrangement, the snoring and nonsnoring classes each consisted of 119,000 subsegments in either the training or testing phase. The 3D (energy, entropy, LLE) information calculated from the subsegments was then fed into the SVM-based classifier. Expert assessments of snoring and nonsnoring in the testing were considered to be correctly defined and thus were used for benchmark comparisons against the predictions of the software based on the decision boundary reached during the training. The levels of agreements and errors between the software-based decisions and the correct assignments of snoring/nonsnoring were compared using the accuracy, sensitivity, and positive predictive value (PPV). These calculations were performed according to the following formulas:

$$\text{Accuracy} = 100 * (TP + TN)/(TP + TN + FP + FN), \tag{1}$$

$$\text{Sensitivity} = 100 * TP/(TP + FN), \tag{2}$$

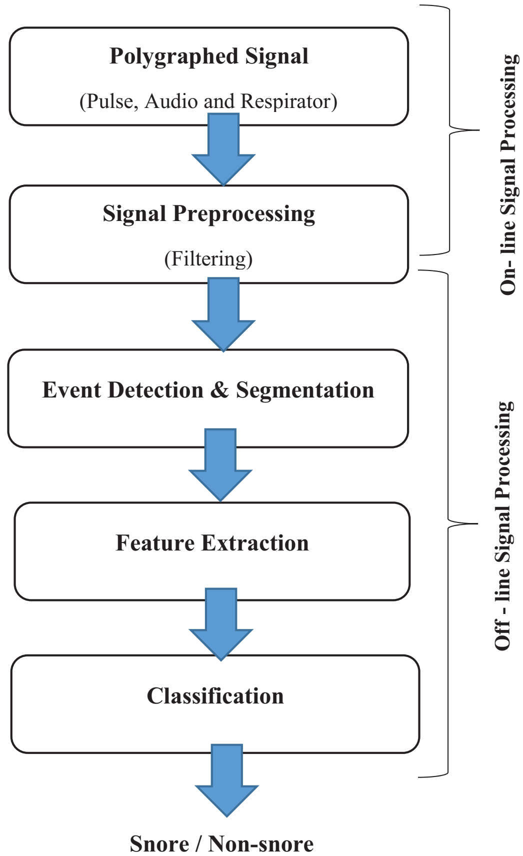

Figure 3. Snore detection algorithm.

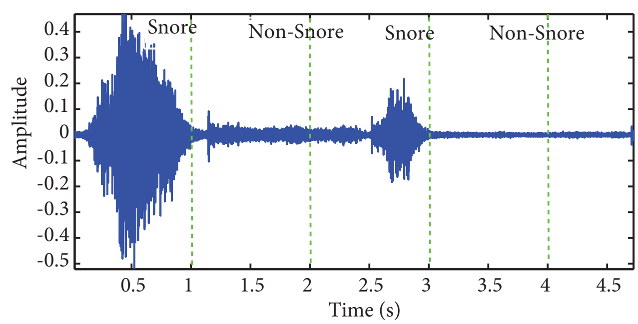

Figure 4. Segmentation of audio signal.

$$\text{Positivepredictivevalue} = 100 * TP/(TP + FP), \tag{3}$$

where TP, TN, FP, and FN correspond to the numbers of true positive, true negative, false positive, and false negative classifications of the SVM predictions of snoring, respectively.

4. Results

SnoreBox is a wearable device with belts to hang on to the body and have sensor attachments. Thus, in terms of its usage and data recording, some obstacles were met during the study. First, the sleep quality of the subject was apparently affected by the disturbance from wearing the device and sensor attachments. To accustom users to the device and to improve the data quality, subjects were trained in wearing the device two nights before the collection of the final real-time data during the night's sleep. The second obstacle was the setting of the sensors to the specified reference values, which again improved with the experience of manipulating the device. The transfer of the acquired data and review processes went with ease. Review of the signals indicated nearly the same level of background ambient noise in data from different subjects. The characteristics of the breathing and silent segments also looked similar to each other, and this in some instances caused difficulty in separating the breathing from the silent segments by the expert. The classifier software with the data and predicted snoring events runs smoothly. Figure 5 shows all the snore/nonsnore events classified by the implemented software run with a 6-h SnoreBox recording from one subject. The graph shows the features (energy, entropy, LLE) in two distinct clusters of snore/nonsnore regions distributed almost in a completely separable manner (minimal overlap) in space.

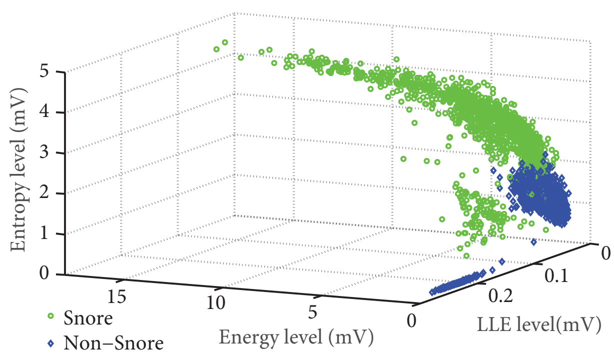

Figure 5. Distribution of the snore/nonsnore segments from the energy, LLE, and entropy features extracted from a 6-h SnoreBox recording of one subject.

Table 3 shows the performance estimated from the error analysis of device predictions against the expert assessments. The critical parameters achieved on average for the classification of snoring/nonsnoring events were: accuracy 88.22% (range 83.08%–95.12%), sensitivity 94.91% (range 84.23%–99.93%), and PPV 90.95% (range 83.22%–95.34%). These significantly high readings clearly indicate that the implemented classifier successfully and reliably detected the snoring events at high rates.

5. Discussion

This developmental work was motivated by the need for an affordable and at the same time reliable snore detection system. The SnoreBox system meets this need as it incorporates special signal acquisition and analysis features beyond those available commercially or described in the literature. Different analysis techniques have been suggested in the past to recognize snoring and other breathing disorders from already recorded sounds. An algorithm for detecting snoring sounds via multifeature analysis was proposed with reported classification accuracy of 94.00% when the sleep analysis was based on entropy and the classification was sum. Power spectral subtraction was used to reduce the noise [39]. Four features such as number of zero crossings, energy, normalized

Table 3. The performance validation of the SnoreBox system.

Subject	Total segment	TN	FN	FP	TP	Acc. (%)	Sens. (%)	PPV (%)
s1	19899	3699	857	1789	13554	86.70	94.05	88.34
s2	22521	575	401	2208	19337	88.42	97.97	89.75
s3	16309	2556	1204	955	11594	86.76	90.59	92.39
s4	13834	774	482	1006	11572	89.24	96.00	92.00
s5	18832	5780	1006	1965	10081	84.22	90.93	83.69
s6	16999	5687	856	1754	8702	84.65	91.04	83.22
s7	13106	1498	1758	459	9391	83.08	84.23	95.34
s8	14401	3059	1501	552	9289	85.74	86.09	94.39
s9	19551	686	409	1983	16473	87.77	97.58	89.26
s10	15720	39	11	756	14914	95.12	99.93	95.18
s11	17951	49	12	1239	16651	93.03	99.93	93.07
s12	21686	1699	757	2106	17124	86.80	95.77	89.05
s13	12786	194	252	656	11684	92.90	97.89	94.68
s14	14373	614	303	791	12665	92.39	97.66	94.12
Total	237968	26909	9809	18219	183031	88.22	94.91	90.95

Table 4. Snore sound classification studies and their accuracy results.

Study (ref. no.)	Recording type	Accuracy (%)
Ref [39]	Ambient sound	94.00
Ref [40]	Ambient sound	90.74
Ref [41]	Ambient sound	86.80
Ref [42]	Ambient sound	91.61
Ref [43]	Ambient sound	95.07
Our Study	Ambient sound	88.22

autocorrelation coefficient, and linear predictive coding analysis obtained from sound-related signals were also used to classify data into three classes with reported accuracy of 90.74% [40]. One algorithm proposed applied a spectral energy distribution to the signal segments of snoring sounds and the accuracy of the system showed variation depending on whether the snoring episode was detected from obstructive sleep apnea patients (86.8%) or simple snorers (97.3%). This system was based on principal component analysis and required training with the available snoring data and thus this limited its versatility [41]. Because of the complex nature of the acquired signals that originate from several physiological and physical conditions, nonlinear signal characteristics were examined with chaos theory. The entropy and LLE features were applied to detect the incidence of snoring and the accuracy of classifier performance of multi-SVM for snoring, respiration, and silent segments was reported to be 91.61 % [42]. With one smartphone application, snoring was detected with high sensitivity, specificity, and accuracy (98.58%, 94.62%, and 95.07%, respectively), but the positive predictive value was only 70.38% in an at-home setting [43]. As depicted in Table 3, our system exhibited accuracy of 88.22% in detecting snoring, and this performance was close to or exceeded those of the previously described approaches. Table 4 gives information about previous studies and our study's accuracy results. The present study has some limitations. First, the subjects were patients with symptoms suggestive of mostly heavy snorers. It is therefore necessary to extend the performance test to the general population. Second, the recording was performed in a single room. In the presence of a bed partner, recordings may be affected by various sound signals, including the partner's snoring. Third, the performance depended on the feature calculation and classifier parameters. Therefore, the parameters to detect snore and nonsnore events may need to be tuned more precisely. Finally, the distinction between smooth snoring and normal breathing is difficult and this may cause errors in the classification.

6. Conclusions

The SnoreBox system collectively offers affordable hardware and software solutions to fulfill the prerequisite of high fidelity signal recording from multiple channels and the follow-up analysis of the signals with sophisticated techniques in snore detection. In these regards, the system enhances the existing diagnostic tools available to sleep experts.

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