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Accelerometer based system for unobtrusive sleep apnea detection

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Abstract

Sleep is an essential part of human existence, as we are in this state for approximately a third of our lives. Sleep disorders are common conditions that can affect many aspects of life. Sleep disorders are diagnosed in special laboratories with a polysomnography system, a costly procedure requiring much effort for the patient. Several systems have been proposed to address this situation, including performing the examination and analysis at the patient's home, using sensors to detect physiological signals automatically analysed by algorithms. This work aims to evaluate the use of a contactless respiratory recording system based on an accelerometer sensor in sleep apnea detection. For this purpose, an installation mounted under the bed mattress records the oscillations caused by the chest movements during the breathing process. The presented processing algorithm performs filtering of the obtained signals and determines the apnea events presence. The performance of the developed system and algorithm of apnea event detection (average values of accuracy, specificity and sensitivity are 94.6%, 95.3%, and 93.7% respectively) confirms the suitability of the proposed method and system for further ambulatory and in-home use.

Keywords: Contactless measurement; accelerometer; vital signals; health monitoring; sleep apnea.

1. Introduction

People spend almost a third part of their life sleeping. Sleep is crucial to recovering our mental and physical health and well-being [1]. Along with the duration of sleep, its quality is also essential for our health [2].

Recently, the most recognized method for assessing sleep behaviour has been the adoption of polysomnography (PSG), which is recommended by the American Academy of Sleep Medicine (AASM) [3]. This procedure is the most accurate and leading sleep study, involving the monitoring of brain activity, eye movement, heart rate and

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breathing of the individual during sleep [4]. This research is typically carried out in a sleep laboratory. However, this approach is expensive, obtrusive, and time-consuming, precluding the possibility of carrying out the procedure at home [5]. This, in turn, does not allow for continuous monitoring in these conditions. In this case, the development and use of a cost-effective system for outpatient or home use are of particular interest [6].

Concerning sleep disorders that can be diagnosed using the aforementioned systems, sleep apnea disorder (especially obstructive sleep apnea – OSA) can be highlighted. From the statistics, it can be noted that sleep apnea occurs in between 3% and 50% of the population, depending on gender and age [7]. Obviously, sleep apnea affects our daily life by influencing the appearance of daytime sleepiness, fatigue or restless sleep in general. In addition, patients with apnea are at risk of developing hypertension, heart failure, brain strokes, temporary memory loss and poor concentration [8].

2. State of the Art

From a literature review on the relevance of the study, it can be noted that the determination of sleep apnea has been a relevant topic of study in recent years. For example, Khushaba et al. [9] achieved 86% accuracy in detecting central sleep apnea (CSA) compared to a polysomnography system by analysing breathing patterns using a bedside non-contact Doppler-based biomotion sensor. [10] presents a continuous respiratory monitoring system for detecting various respiratory syndromes (including sleep apnea) by tracking chest motion as a result of respiratory rhythms based on ultrasound radar detection. Using interferometry or radar technology, sleep apnea has also been successfully detected by Schellenberger et al. [11]. It is also possible to see sleep apnea at acceptable rates (90% accuracy) by covering the study area with several radars combined with a depth camera to extract skeletal information from the subject's joint coordinates [12]. 95% accuracy in identifying sleep apnea has been demonstrated by Kunczik et al. [13] by analysing facial images and measuring temperature maps of infrared images. Regarding the software component of sleep apnea detection, the continuous wavelet transform approach with filter type variation, which achieved an accuracy of 87% [8], cannot be overlooked. Barika et al. [14] presented a review of remote monitoring methods for apnea detection. A standalone system for sleep apnea detection using signals from pressure sensors placed under the mattress has shown promising results (91% accuracy) and is a cost-effective tool in the home [15]. Previously [16], we demonstrated a contactless approach using an accelerometer sensor to detect breathing. However, the possibility of detecting sleep apnea has not been considered in this work, despite the noted potential of the system to do so. In addition to that, in aforementioned works, sleep apnea was detected predominantly in 1 or 2 typical sleeping postures – on the back side of the subject or their stomach (prone position). So, the purpose of this paper is to evaluate the capability and accuracy of an accelerometer-based non-contact sleep apnea detection system and compare the possible performance of our system in different sleeping postures.

3. Methods

As a prerequisite for the development of our system, it must be able to operate autonomously. This condition requires both hardware and software units of the system. This, in turn, should ensure that processes of data collection and processing can be performed without the use of external devices. This system's capability, along with its high accuracy, unobtrusiveness, and low cost, makes it affordable for home use.

3.1. Signal acquisition

The system block related to the signal acquisition should consist of the mechanical part (which provides the contact between the holder hanger and the mattress for measurements), sensor and computational unit. The mechanical part should consist of two units – a mounting to the bed frame and a spring steel plate (hanger) on which the accelerometer sensor is fitted. In [16] is presented the procedure regarding the material choice and its parameters to obtain acceptable results for respiratory measurements. The structure scheme of the system installation is shown in Fig. 1.

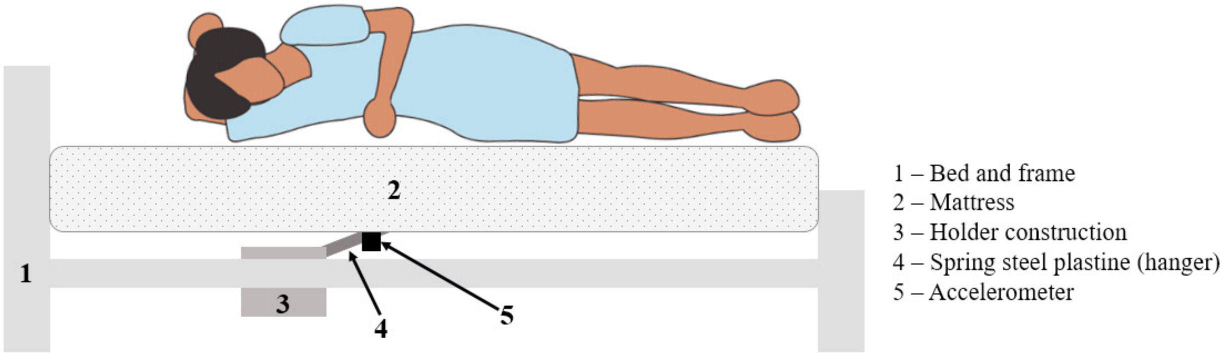

Fig. 1. The structure scheme of system installation.

In this study, we have selected the ADXL355z (Analog Devices) 3-axis accelerometer (see Fig. 2(a)) sensor for obtaining the data based on the research related to vital signals detection using this sensor [17-18]. In addition, this model of the sensor and the previous model of that product line were successfully applied to cardiorespiratory measurements [19]. The sampling frequency is 62 Hz for the accelerometer sensor, which is enough to obtain the respiratory signal. Also, as a ground truth system we have used respiration belts from SOMNO HD eco PSG (SOMNO medics GmbH, Randersacker, Germany) for obtaining the reference data. The respiratory (thorax and abdominal) signals have been recorded at a sampling frequency of 32 Hz. The belt was placed on a comfortable level for subjects.

An ESP32 module (see Fig. 2(b)) has been used as a computational unit for this system due to its compact dimensions and good compliance with the low-cost requirement. This module has an option of the obtained data transferring to the server (or cloud) via Wi-Fi usage. In addition, there is the feature to locally store each new dataset as a backup copy to a micro-SD module (which is possible to connect). This option is necessary if the system is not connected to Wi-Fi access point.

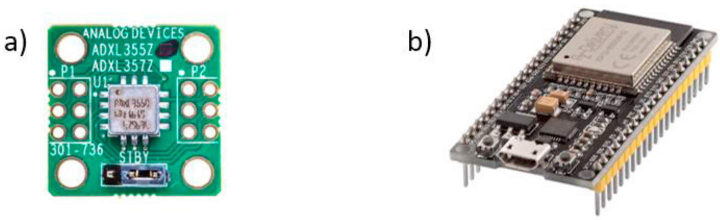

Fig. 2. (a) Accelerometer sensor (ADXL355z); (b) ESP32 computational unit.

The other important aspect is the definition of system position or, in other words, sensor arrangement. There are several positions for our system on the bed frame and related to the particular subject area – head, chest level, solar plexus, upper and lower abdomen and legs. The initial research related to the determination of the sensor position was conducted earlier [20]. However, there was not conducted the validation procedure (in other words, a comparison with ground truth), which could help to recognize the presented results surely. Nevertheless, based on the results of this research and the studies directed to accelerometer application for cardiorespiratory measurements [21-22], we have selected the sensor position at the chest level as the preferable position for our measurements. In addition, we should detect apnea events in relation to a patient in different sleeping postures (prone, right lateral, left lateral and supine) at least. The system arrangement on the frame and in relation to a subject is shown in Fig. 3 (a, b).

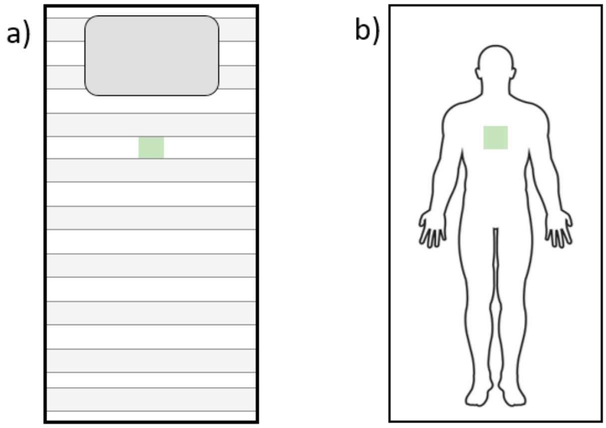

Fig. 3. (a) The system and sensor (green rectangle) arrangement in relation to the bed frame (grey lines); (b) The system and sensor (green rectangle) arrangement in relation to a subject.

3.2. Signal processing

The second central part of the described unobtrusive system is the signal processing algorithm (or software) and data visualization. The data from the sensor is stored in a .txt file with the timestamps of the start and end of record time. The actual timestamp of every signal value is also stored for possible future synchronization with other devices. The storage of raw data is important for the system's flexibility if, in addition to the proposed in this paper, signal processing is to be applied. In our study, we have considered the contribution only from one axis – Y, which corresponds to vibrations in the dorsoventral direction. This direction is perhaps the most commonly used seismocardiogram (SCG) signal axis and is thought to contain information on various phases of the cardiac and respiration cycles [23]. At the same time, we noticed the estimation's importance from each axis of the accelerometer sensor [19]. Still, the results of initial tests for the developed signal processing algorithm performed not reliable information.

The signal processing algorithm for apnea detection consists of several steps. After storing the data, the 4th-order low-pass Butterworth filter with a cut-off frequency of 0.4 Hz has been applied to the obtained signal. This step is crucial for extracting only frequencies of breathing or lower in the future. Then, the median filter was applied to signal for moving artefacts impact smoothing. As the next step, we separated the signal into four windows corresponding to each sleeping posture and removed the probable isoline drift by signal normalization.

As soon as the signal is filtered, the algorithm for recognizing apnea events is applied. For that, at the first step, we have calculated the window benchmark, which is the median value of extracted signal peaks. As the prominence value (in other words, threshold), we used 55% of this value for further signal breathing peaks extraction and apnea events recognition. It is important to determine the signal peaks related to respiration and the signal plateau corresponding to the lack of breathing (apnea). In addition, this value performs the most acceptable results in sleep apnea events detection (in comparison with lower and higher values in the range of 5%) during the initial tests. If the peak distance is more than 10 seconds, this interval is marked as an apnea event [24].

3.3. Experiment design

We have used a regular single bed (Askvoll), bed frame (Lüroy), and mattress with a dimension of 90 × 200 from IKEA (IKEA, Delft, Netherlands). We have not considered any particular requirements or customized specialties in experimental installation planning and design. All materials were wooden and widely accessible by regular users.

Before the experiment, the subjects were instructed to lie down on the bed in four typical sleeping postures: prone, right side (right lateral), supine and on the left side. We named them from P1 to P4 consequently. In addition, the experiment started in the P1 position and finished in the P4 sleeping posture. Thus, there is a counter clockwise rotation of the subject during the measurement. Also, all subjects had at least three minutes as relaxing time before collecting the data. The data measurement was 210 seconds (3.5 minutes) in each sleeping posture. The subject should simulate an apnea event of 30 seconds in length (the preferable case) three times with a 30-second resting time between each event. In total, the duration of collection 1 dataset takes 13 minutes and includes 11 apnea events. During the data collection, the subjects were instructed to behave normally with the minimum movement. However, they were informed that in case of an inconvenience, the experiment would be stopped. In addition, we notified that all participants involved in the study were informed regarding the research details and filed out the consent to data processing before the experiment.

4. Results

For the evaluation of system work, we have conducted a study with 10 datasets from 3 participants (all subjects are males). The weight range of these testing persons was (60-75) kg, and the height was from 170 cm to 184 cm. Table 1 shows the statistical data of recruited subjects.

Table 1. Demographic case of recruited subjects in the study.

Subject	Age	Weight	Height	Number of collected datasets
1	40	60	170	3
2	26	70	178	4
3	25	72	182	3

110 apnea events (30 events for prone, right lateral and supine sleeping postures and 20 for left lateral) with a length of 30 seconds (according to the plan) were simulated. Timestamps of imitated apnea were noticed in an experiment protocol and additionally by a polysomnography system with respiration belts too. It is important to note that the simulation of apnea events lasting 30 seconds was complicated during the experiment for one subject. Therefore, the participant simulated two apnea events in 30 seconds, which were also successfully detected by the developed algorithm. Figure 4 (a, b) shows the visualization of this dataset with examples of detected apnea events (cyan horizontal line) for obtained respiratory signal compared with the signal from the ground truth.

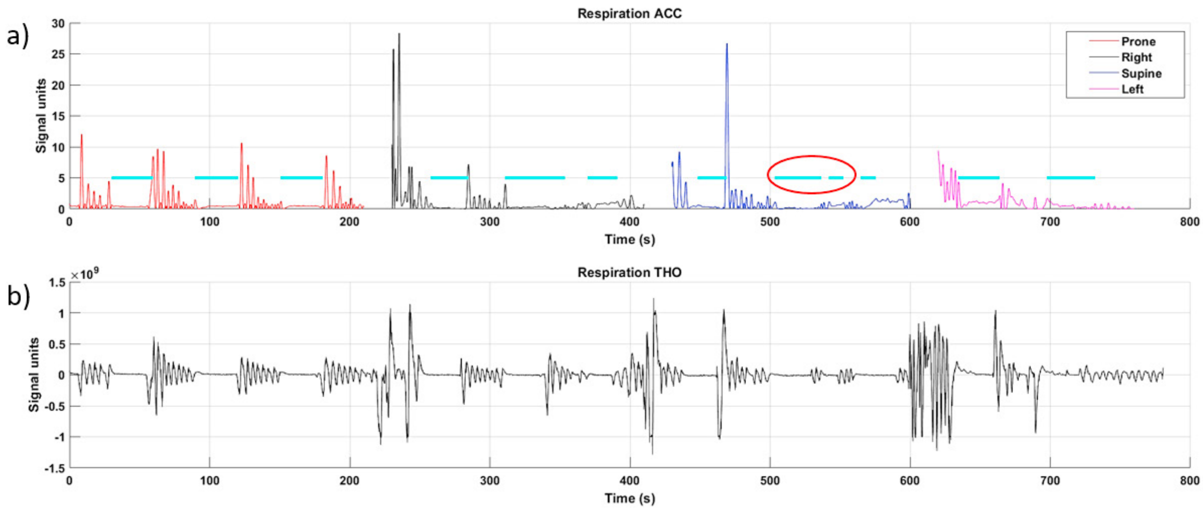

Fig. 4. (a) The processed signal. Red ellipsoid highlights two successfully closely detected apnea events; (b) The reference respiratory signal from the ground truth.

As mentioned, this study aims to estimate the system performance in general and for each considered in the research sleeping posture. For that, the obtained signal was initially divided into 30-second windows to identify a breathing or apnea event in each window. Figure 5 (a – e) shows the results of detected apnea events for prone, right lateral, supine and left lateral positions and in total, respectively.

a) **PRONE POSITION**

		Reference	
		Apnea	No apnea
Predicted	Apnea	30	1
	No apnea	0	39

b) **RIGHT LATERAL POSITION**

		Reference	
		Apnea	No apnea
Predicted	Apnea	27	3
	No apnea	2	38

c) **SUPINE POSITION**

		Reference	
		Apnea	No apnea
Predicted	Apnea	28	2
	No apnea	4	36

d) **LEFT LATERAL POSITION**

		Reference	
		Apnea	No apnea
Predicted	Apnea	19	1
	No apnea	1	29

e) **TOTAL**

		Reference	
		Apnea	No apnea
Predicted	Apnea	104	7
	No apnea	7	142

Fig. 5. (a) Confusion matrix of detected apnea events in a prone position; (b) Confusion matrix of detected apnea events in right lateral position; (c) Confusion matrix of detected apnea events in supine position; (d) Confusion matrix of detected apnea events in left lateral position; (e) Confusion matrix of detected apnea events in total.

Considering the values presented before, we can estimate the system performance metrics such as accuracy, specificity and sensitivity. Table 2 shows the values of mentioned parameters for each sleeping posture and in general.

Table 2. Evaluated metric of system performance.

Sleeping posture	Accuracy, %	Specificity, %	Sensitivity, %
Prone	98.57	97.50	100
Right lateral	92.86	92.68	93.10
Supine	91.43	94.74	87.50
Left lateral	96	96.67	95
Total	94.62	95.30	93.69

5. Discussion

Based on the data presented in the previous section, the system performs promising results. So, the average values of accuracy, specificity and sensitivity are 94.6%, 95.3%, and 93.7% respectively. In addition, we can notice that these evaluation metrics are better for a prone position (sleeping posture) and are similar to average values in a supine position. The metric values for both lateral positions are a bit lower than average but not significant. Obviously, the results relating to the prone position (accuracy, specificity and sensitivity 98.6%, 97.5%, and 100%, respectively) should be higher than for the other positions because of the better contact between the breast and the mattress, resulting from the chest expansion on the contrary direction to the accelerometer sensor and more effect on the system and sensor during respiration. In addition, we noticed an increase in accuracy in both lateral positions compared to the supine position. This is due to the fact that the subject's chest is usually in close contact with the mattress during the measurement, which is the reason for the more accurate detection of inhalations, exhalations and apnea events at the same time as the reference systems and in general. Also, we can report about the same peculiarities and dependencies in the results (for the most part) for the specificity and sensitivity of our developed system and algorithm. Moreover, we should remind that the sensor and system were placed at the chest level, which confirms quite promising results. A the same time, the sensor position didn’t consider at this level but in other places, for example on the right or the left side from the bed center. The obtained results for this system using a similar methodology in signal processing part outperform the results presented earlier [15].

Regarding the possible limitations of our study, we should declare that we have collected the data only from male subjects with similar physical and almost identical anthropometric conditions. Moreover, we have obtained the data with apnea simulation, or in other words, more similar to central sleep apnea (CSA), which prevalence is lower than obstructive sleep apnea (OSA) worldwide. Summarizing this, we conclude that it is important to expand the further investigation not only on the way of study group extension (different gender, ages, height and weight etc.) but also in different physical conditions of tested subjects if it’s possible.

6. Conclusion and outlook

According to the achieved results (average accuracy of 94.6%, specificity of 95.3% and sensitivity of 93.7%), this non-invasive and unobtrusive system based on the accelerometer sensor has a good potential of the proposed approach for sleep apnea detection. The level of accuracy is similar to the one considered in the introduction section techniques and methods. At the same time, the presented system is related to novel modern approaches with significant advantages in relation to other technologies. The considered system has hardware and software blocks that could be installed under the bed in a user-friendly way. Based on the measurements in an unobtrusive way, we can confirm the system works in autonomous mode, which is one of the device's requirements. Meanwhile, there is an option to connect some external devices if required. Thus, we can declare that this system can be relevant in hospitals, rehabilitation centres and even in the home.

Despite several advantages, such as a simple design combined with effective and low-cost hardware and contactless opportunity to measure, the proposed system, in conjunction with the processing algorithm, still has potential for improvement (in addition to the suggestions offered in the previous section).

For instance, one of the options for improvement of the hardware part is the upgrade of the mechanical holder due to the drift shift of the hanger and its mechanical wear over time. The last one could be solved by regularly changing the spring steel plastine. So, this upgrade can probably increase the quality of the obtained signal and signal-to-noise ratio. Besides that, we have simulated only apnea events in our study, which is some of the obstacles to providing more significant results. However, this system could be extended for the continuous monitoring of respiration (this opportunity was mentioned earlier). For that, we need to improve the signal processing method (in other words, the software part) by applying the adaptive filter or, for example, continuous or discreet wavelet transform. The work on this extension is currently being done, as well as hardware improvement. Also, we should consider the performance of this algorithm and system when calculating the contribution to the output signal from 3 axes as described in [19]. Furthermore, the proposed system and approach could be used as a part of a system for sleep study of sleep phase recognition in combination with the algorithms presented in [25].

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