On the Use of Smartphones for Detecting Obstructive Sleep Apnea

Mamoun Al-Mardini, Fadi Aloul, Assim Sagahyroon, and Luai Al-Husseini

Abstract—**Obstructive Sleep Apnea (OSA) is a common sleep disorder which is characterized by recurrent blockage of the upper airway, often resulting in oxygen desaturation. Attended overnight polysomnography (PSG) has been recommended as the golden standard for the diagnostic of OSA at hospitals, which requires an expensive attended overnight stay at a hospital with considerable wiring between the PSG device and the human body. In this work, we implement a reliable, comfortable, inexpensive, and easily available portable device that allows users to apply the OSA test at home without the need for attended overnight tests. The design takes advantage of a smartphone's built-in sensors, pervasiveness, computational capabilities, and user-friendly interface to screen OSA. We extract three main physiological signals to diagnose OSA which are (1) oxygen saturation using an external oximeter, (2) respiratory effort using the smartphone's built-in microphone, and (3) body movement using the smartphone's built-in accelerometer. The signals are analyzed on the smartphone to screen the OSA. Finally, we examine our system's ability to screen the disease as compared to the golden standard by testing it on 15 subjects. Results show that 100% of the sick subjects were correctly classified as having OSA, and 85.7% of the healthy subjects were correctly classified as not having OSA. These preliminary results demonstrate the effectiveness of the proposed system when compared to the golden standard and emphasize the important role of smartphones in healthcare.**

I. Introduction

Obstructive sleep apnea (OSA) is a common disorder affecting 2-4% of the adult population [1], and it is considered to be the most prevalent sleeping disorder. In most cases, the patient is unaware of the breath stoppages because the body does not trigger a full awakening. As per the American Academy of Sleep Medicine (AASM), OSA is defined as a cessation in the airflow lasting for more than two breaths [2].

The National Sleep Foundation reported that for adults to function healthily they should obtain seven to eight sleeping hours every night [3]. Frequent obstructions of airflow during this period have a considerable influence on the performance of the human during the daytime. Attended overnight Polysomnography (PSG) is considered the golden standard for OSA diagnosis. To get an overnight OSA test, the patient should stay in a specialized sleep laboratory for more than one night, with 22 wires attached to his/her body in order to record and analyze several neurologic and cardio respiratory signals. This brings great anxiety to the patients and they may not be able to sleep well during the night. Moreover, very few hospitals can accommodate the PSG test and it is rarely found in rural areas, which makes it unavailable for everyone and costly. Because of the aforementioned complications of using PSG, a need has arisen for portable devices with acceptable accuracy, high levels of usability, and depend on acquiring fewer biological signals [2][4][5][6][7].

In this paper, we focus on implementing a portable device that is inexpensive, reliable, and accurate when compared with PSG. The proposed design makes use of the pervasiveness of smartphones by designing an Android application that is able to extract the biomedical readings from the patient and analyze them to screen and classify OSA. This screening is considered a preliminary test used to identify people at high risk of having the disease who may need further confirmatory diagnostic tests at a hospital [8].

In the proposed system, we develop an algorithm that combines and analyzes the physiological readings to reliably infer if the patient suffers from OSA. This algorithm draws from conclusions made in published literature, experimental data and tests collected in this work, and finally the consultation of a physician expert who has been actively involved in this project. All readings are analyzed solely on the smartphone without the usage of any external resources. Finally, we examine our system's ability to screen the disease as compared to the golden standard. We performed the tests on 15 subjects, 8 of whom had already been diagnosed with OSA and 7 subjects who are healthy with no symptoms. The results showed that 100% of patients were correctly identified as having the disease, and 85.7% of patients were correctly identified as not having the disease.

The rest of this paper is organized as follows: Section II includes a literature review of related research. Methods for extracting the physiological signals will be outlined in Section III. Section IV explains the algorithms used to analyze the collected physiological signals. Section V is a presentation and discussion of the results. Finally, Section VI concludes this paper.

II. Related Work

There are several systems designed for healthcare purposes. Of the systems that address obstructive sleep apnea (OSA), only a few of them depend on smartphones.

HealthGear [9] is one of the first Windows-based mobile applications that uses blood oximetry to detect sleep apnea. Cao et al. [10] also used an oximeter combined with an accelerometer in their research to diagnose sleep apnea. Their work found that body posture can provide complementary information for analyzing the respiratory movement. Other research focused on the triaxial accelerometer to diagnose sleep apnea which has been widely used for physical activity detection [11][12].

Rofouei et al. [13] extended the work done in [9-12] and developed a non-invasive, wearable neck-cuff system capable of real-time sleep monitoring and visualization of physiological signals.

Some researchers applied data mining techniques to the data recorded by the biomedical sensors, such as [5], where the authors followed data mining approaches to

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build an accurate classifier able to detect sleep apnea in a real-time fashion. However, Tseng et al. [14] developed an Android smartphone application to diagnose OSA based on some prediction rules derived by employing decision tree algorithms to a large clinical data set without using bio-sensors.

An inexpensive OSA screening technique was proposed in [4], where the authors developed an accelerometer-based system by placing an accelerometer on the suprasternal notch. They then analyzed the data using signal processing techniques implemented on a microcontroller.

III. EXTRACTING THE PHYSIOLOGICAL SIGNALS

In the proposed design, we use the smartphone's microphone to extract respiratory effort by placing it on the throat (where the obstruction happens). Oxygen saturation level is usually captured by an external pulse oximeter, which measures the oxygen level in the blood. An oximeter is a sensor that is placed on a thin part of the patient's body, usually a fingertip or earlobe, or in the case of an infant, across a foot. Body posture and movement can be detected by continuously taking the directions of the body along all axes. An accelerometer can be used to detect these movements. Researchers typically use an external accelerometer for this purpose. However, in the proposed design, we take advantage of the built-in accelerometer in the smartphone. The smartphone will be placed on the patient's arm, and body movement will be detected by calculating the displacement in the three axes (X, Y, and Z).

IV. ANALYSING THE COLLECTED PHYSIOLOGICAL SIGNALS

An apnea event is detected when there is a cessation of airflow for more than 2 breaths or at least 10 seconds [2]. Based on this definition, we need to detect the obstruction of the airflow, and the accompanied desaturation reflected in the blood. In the proposed system, we apply a pretest to find the probability of having the disease [15] and analyze three physiological signals to screen the obstructive sleep apnea (OSA). The analysis for these signals will be explained in the following subsections.

A. Oxygen Saturation

In the proposed implementation, a pulse oximeter is used to measure the oxygen level and provide continuous data transmission of a 4 byte data packet sent every second. In the proposed system, we use the oxygen desaturation index (ODI) which is defined as the average number of events per hour [16]. An event is detected if the oxygen level is below the average by 4%, and lasts at least 10 seconds. The following steps are followed to detect an apnea event using SpO2 readings [9]:

- Read oxygen level every second.
- Initial calibration phase.
  - The level of oxygen differs between individuals, therefore we need to find the average in the first few minutes, and record it.
  - An event is detected if the oxygen level is 4% below the average calculated in the previous step. Therefore, a threshold is defined as $0.96*Average$. $X = 0.96*N$, where X is the threshold and N is the average.
- Moving calibration phase:
  - After the occurrence of an apnea event, the oxygen saturation does not return to the same level just before the event. Therefore, we need to recalculate the average and the threshold again. $X\_New = 0.96*N\_New$, where X_New is the new threshold and N_New is the new average.
- If the oxygen level is detected to be lower than the defined threshold, then we have to be sure that the event lasted at least 10 seconds.
- By the end of the sleeping time, ODI is calculated. OSA is confirmed if one of the following conditions is met:
  - (ODI ≥ 10) or
  - (ODI ≥ 5) && (high pretest probability).

Figure 1 shows the oxygen level in the blood for one of our tested subjects, which is extracted from the oximeter every second. When the patient started to snore, a decrease in the oxygen saturation followed. After a few seconds, the oxygen saturation reached a level less than the threshold value that lasted for more than 10 seconds.

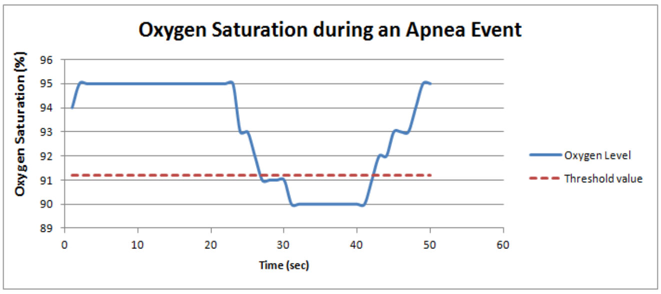

Fig 1. Oxygen saturation during an apnea event.

B. Body Movement

Based on research reported by [13] and [17], body movement may cause variation in the pulse oximetry readings. Therefore, any change in the oxygen level that is associated with body movement is eliminated.

The 3-axis accelerometer integrated in the smartphone is used to measure the 3-axis accelerations of the subject body along the directions of the three axes. In the proposed system, we use a concept called Signal Vector Magnitude (SVM) proposed in [10] which reflects the motion intensity of the body. SVM is the square root of the sum of the 3-axis accelerations, the amplitude of which mirrors the motion amount of the body.

C. Respiratory Effort

The patient's airflow is recorded by attaching a microphone to the patient's throat. Frequency of breathing is different among people but experimentally has been proven to fall between {200,800} Hz [17]. Extracting this range of frequencies allows us to exclude noise and analyze the breathing signal only. Signal processing functions are required to analyze this rage of frequencies. The correctness and accuracy of these functions are first verified using Matlab software running on an external server, and then ported to the smartphone Android environment. The following steps are used to detect apnea event using respiratory effort readings:

- Read respiratory signal every second.
- Initial calibration phase:
  - ➢ The energy of the breathing signal differs between individuals, so we need to find the average in the first few minutes, and record it.
  - ➢ An event is detected if the energy is below 90% of the average calculated in the previous step. Therefore, a threshold is defined as *0.9*Average*. $X = 0.9*N$, where X is the threshold and N is the average.
  - ➢ Threshold value can vary due to the differences in the devices being used and their sensitivity [1].
- If the energy of the breathing signal is detected to be lower than the defined threshold, then we have to be sure that the event lasts at least 10 seconds.
- By the end of the sleeping period, apnea/ hypopnea index (AHI) which is defined as the average number of events per hour [2] is calculated. OSA is confirmed if one of the following conditions is met:
  - ➢ ($AHI \geq 10$) or
  - ➢ ($AHI \geq 5$) && (high pretest probability).

Figure 2 shows the energy of the respiratory effort signal for one of the subjects in our work during one minute time window. The spikes in the graph represent the snoring periods. As we can see, the snoring period is followed by an obstruction of the airway, where the energy values are less than the threshold value which is represented by the red line.

Processing the recorded respiratory effort requires filtering the signal and calculating the energy every second. The Android SDK does not contain a specific library for signal processing functions. Therefore, we have implemented the filtering functions in Android, in order to use them in extracting the required frequencies. Since the frequencies lie between 200 and 800 Hz, we have implemented and used a band pass Infinite Impulse Response (IIR) filter.

D. Determining the Final Diagnostic

At this stage, we combine the results of the analysis of the physiological signals (oxygen saturation, body movement, and respiratory effort). The analysis of the oxygen saturation and body movement is used in calculating the ODI index. On the other hand, AHI is computed using the respiratory effort analysis. Finally, we find the average of the calculated ODI and AHI and then make a decision for the existence of OSA as illustrated in the flowchart of Figure 3. After finding the average, the severity of OSA is reported based on the following categories [1]:

- Mild: $5 \leq$ Average < 15.
- Moderate: $15 \leq$ Average < 30.
- Severe: Average ≥ 30.

V. RESULTS AND DISCUSSION

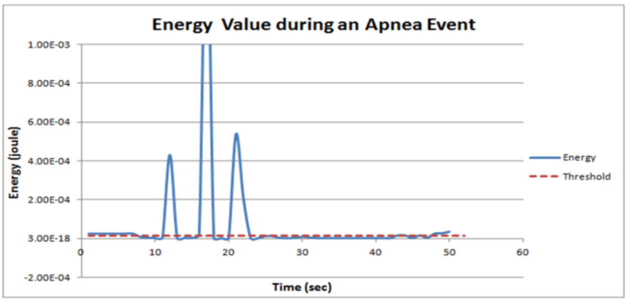

Fig 2. Energy value during an apnea event.

We performed the test on 15 subjects, 8 of which had already been diagnosed with obstructive sleep apnea (OSA), and 7 who were healthy with no symptoms. The results showed that the apnea/hypopnea index (AHI) values obtained from the proposed system are close to the values obtained using the golden standard as shown in Figure 4.

Table 1 shows the AHI values of the proposed system and the golden standard and displays the root mean square error (RMSE) value, which is important in comparing both systems statically.

When evaluating the accuracy of a clinical test, the terms sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV) are used. Sensitivity represents the percentage of sick people who are correctly diagnosed as having the disease, while specificity the percentage of healthy people who are correctly diagnosed as not having the disease. On the other hand, PPV measures the likelihood that the patient has the disease given that the test result is positive, while NPV measures the likelihood that the patient does not have the disease given that the test result is negative [18][19]. In the proposed design, we achieved 100%, 85.7%, 88.9%, and 100% for the sensitivity, specificity, PPV, and NPV respectively. Table 2 shows a comparison between the proposed system and the other portable devices.

VI. CONCLUSION

The Obstructive sleep apnea (OSA) is a potentially serious sleep disorder, which is characterized by repetitive pauses in breathing during sleep. Polysomnography (PSG) is the golden standard in diagnosing OSA, but it requires an attended overnight test in the hospital, and imposes high cost and discomfort to the patients. In an effort to relieve patients from the requirements dictated by PSG, researchers have experimented with various home-bound and inexpensive techniques for detecting OSA. Due to the popularity of smartphones and their powerful computational capabilities, we propose an OSA detection technique that makes use of the built-in sensors in the smartphone. This detection platform extracts and analyzes physiological signals including oxygen saturation, body movement, and respiratory effort with the final output being a reliable screening and classification of OSA. Upon examining our system's ability to screen the disease as compared to polysomnography, we tested the application on 15 subjects. The results showed that 100% of patients were correctly identified as having the disease, and 85.7% of patients were correctly identified as not having the disease. These results demonstrate the effectiveness of the system as compared to the golden standard and emphasize the important role that smartphones can play in healthcare in the future.

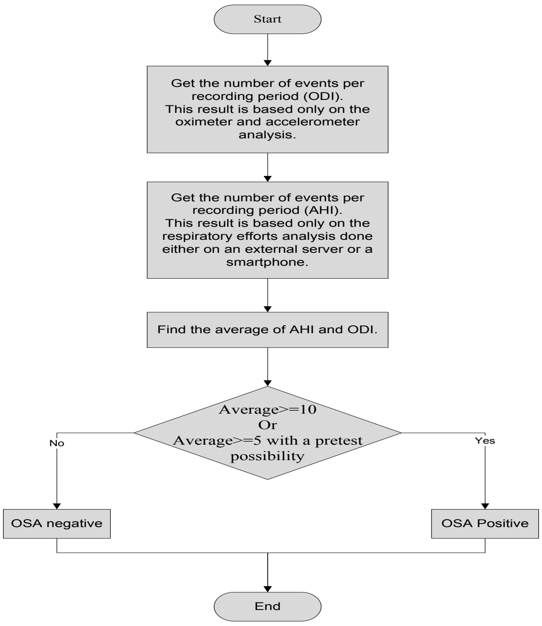

Fig 3. A flow chart explaining the steps needed to determine the final diagnostic.

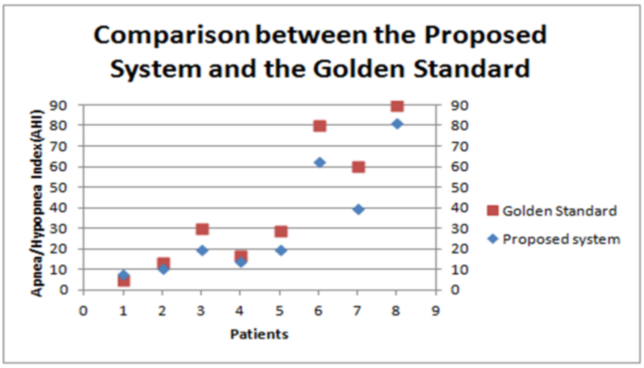

Fig 4. Comparing the proposed system and the golden standard.

Name	Proposed System		Golden Standard		Error²
	Severity	AHI	Severity	AHI	
Patient 1	Mild	8	Mild	5.2	7.8
Patient 2	Mild	10.8	Mild	14	10.2
Patient 3	Moderate	19.8	Severe	30.2	108.2
Patient 4	Moderate	15	Moderate	17	7.8
Patient 5	Moderate	19.6	Moderate	29	88.4
Patient 6	Severe	62.8	Severe	80.7	320.4
Patient 7	Severe	39.7	Severe	60.6	436.8
Patient 8	Severe	81.1	Severe	89.9	77.4
Total					1057
RMSE					32.5

Table 1. Comparing the proposed system and the golden standard.

Previous Work	Number of Participants	Sensitivity	Specificity
Burgos et al [5]	70	96%	96.1%
Oliver et al [9]	20	-	-
Rofouei et al [13]	3	Only one subject was compared against the golden standard, and it was correctly diagnosed.	
Tseng et al [14]	540	-	-
Mont. et al [34]	52	88%	83.3%
Yadollahi et al [16]	40	88.9%	92.3%
Proposed system	15	100%	85.7%

Table 2. Comparing the sensitivity and specficty of the proposed model against other OSA portable devices.

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REFERENCES

[1] M. Berger, A. Oksenberg, S. Silverberg, E. Arons, H. Radwan and A. Iaina, "Avoiding the supine position during sleep lowers 24h blood pressure in obstructive sleep apnea (OSA) patients," in *Journal of human hypertension*, 11(10), 657-664, October 1997.

[2] S. Quan, J. Gillin, M. Littner and J. Shepard, "Sleep-related breathing disorders in adults: Recommendations for syndrome definition and measurement techniques in clinical research," in *Sleep*, 22(5), 667-689, 1999.

[3] National Sleep Foundation (NSF). Available: *http://www.sleepfoundation.org*

[4] C. Bucklin, M. Das and S. Luo, "An inexpensive accelerometer-based sleep-apnea screening technique," in *Proc. of the IEEE National* on *Aerospace and Electronics Conference*, 396-399, July 2010.

[5] A. Burgos, A. Goñi, A. Illarramendi and J. Bermudez, "Real-Time Detection of Apneas on a PDA," in *IEEE Trans. on Information Technology in Biomedicine,* 14(4), 995-1002, July 2010.

[6] M. Hamada and M. Lida, "Home monitoring using portable polygraphy for perioperative assessment of pediatric obstructive sleep apnea syndrome," in *The Tokai journal of experimental and clinical medicine*, 37(3), 66-70, September 2012.

[7] R. Gao, L. Yang, X. Wu, T. Wang, S. Lu and F. Han, "A phone-based e-health system for OSAS and its energy issue," in *IEEE International Symposium on Information Technology in Medicine and Education*, vol. 2, 682-686, August 2012.

[8] C. Free, G. Phillips, L. Felix, L. Galli, V. Patel and P. Edwards, "The effectiveness of M-health technologies for improving health and health services: a systematic review protocol," in *BMC research notes*, 3:250, October 2010.

[9] N. Oliver and F. Flores-Mangas, "HealthGear: automatic sleep apnea detection and monitoring with a mobile phone," in *Journal of Communications,* 2(2), 1-9, March 2007.

[10] Z. Cao, R. Zhu and R. Que, "A Wireless Portable System with Micro Sensors for Monitoring Respiratory Diseases," in *IEEE Trans. on Biomedical Engineering,* 59(11), 3110-3116, Nov. 2012.

[11] Y. Lee, S. Jung, Y. Seo and W. Chung, "Measurement of Motion Activity during Ambulatory Using Pulse Oximeter and Triaxial Accelerometer," in *Proc. of the IEEE International Conference on Convergence and Hybrid Information Technology*, vol. 1, 436-441, Nov. 2008.

[12] W. Dargie, "Analysis of Time and Frequency Domain Features of Accelerometer Measurements," in *Proc. of IEEE International Conference on Computer Communications and Networks*, 1-6, Aug. 2009.

[13] M. Rofouei, M. Sinclair, R. Bittner, T. Blank, N. Saw, G. DeJean and J. Heffron, "A Non-invasive Wearable Neck-Cuff System for Real-Time Sleep Monitoring," in *Proc. of the IEEE International Conference on Body Sensor Networks*, 156-161, May 2011.

[14] M. Tseng, H. Hsu, C. Chang, H. Ting, C. Wu and P. Tang, "Development of an Intelligent App for Obstructive Sleep Apnea Prediction on Android Smartphone Using Data Mining Approach," in *Proc. of the IEEE International Conference on Ubiquitous Intelligence & Computing / Autonomic & Trusted Computing*, 774-779, Sep. 2012.

[15] T. Penzel, A. Blau, C. Garcia, C. Schöbel, M. Sebert and I. Fietze, "Portable monitoring in sleep apnea," in *Current Respiratory Care Reports*, 1(2), 139-145, June 2012.

[16] F. Chung, P. Liao, H. Elsaid, S. Islam, C. M. Shapiro and Y. Sun, "Oxygen desaturation index from nocturnal oximetry: A sensitive and specific tool to detect sleep-disordered breathing in surgical patients," in *Anesthesia & Analgesia,* 114(5), 993-1000, May 2012.

[17] A. Yadollahi and Z. Moussavi, "Acoustic obstructive sleep apnea detection," in Proc. of the *IEEE International Conference on Engineering in Medicine and Biology Society*, 7110-7113, 2009.

[18] A. Lalkhen and A. McCluskey, "Clinical tests: sensitivity and specificity," in *Continuing Education in Anaesthesia, Critical Care & Pain,* 8(6), 221-223, 2008.

[19] R. Mangrulkar and S. Gruber, "Patients and Populations: Medical Decision-Making." Available: *http://open.umich.edu/education/med/m1/patients-pop-decision-making/fall2011*