Automatic Sleep Apnea/Hypopnea Detection based on Nasal Airflow Signal

Tijana Sustersic[*, †], Aleksandra Vulovic[*, †], Ivan Cekerevac[⁂, ⁋], Romana Susa[⁂, ⁋], Sebastien Baumann[‡], Aikaterini Zisaki[‡], Rubén Braojos[‡], Francisco Rincón[‡], Srinivasan Murali[‡], Nenad Filipovic[*, †]

[*] Faculty of Engineering, University of Kragujevac, Kragujevac, Serbia
[†] Bioengineering Research and Development Center (BioIRC), Kragujevac, Serbia
[‡] SmartCardia Inc., Lausanne, Switzerland
[⁂] Faculty of Medical Sciences, University of Kragujevac, Kragujevac, Serbia
[⁋] Clinic for Pulmonology of the Clinical Center Kragujevac, Serbia
e-mail addresses: tijanas@kg.ac.rs; aleksandra.vulovic@kg.ac.rs; icekerevac@gmail.com; r.susa.86@gmail.com; sebastien.baumann@smartcardia.com; katerina.zisaki@smartcardia.com; ruben.braojos@smartcardia.com; fran.rincon@smartcardia.com; srinivasan.murali@smartcardia.com; fica@kg.ac.rs

***Abstract* — Sleep apnea is a common sleep-related disorder caused by the obstruction of the respiratory tract and the absence of respiratory flow. 18 million Americans are estimated to suffer from sleep apnea, out of which 80% are thought to go undiagnosed. Nowadays, apnea detection is done using a Polysomnography (PSG) test during sleeping hours, which requires that the patient spends a night in a specialized center wearing several sensors to monitor his/her state. After that, medical trained staff checks the recordings/ markings and manually corrects the scoring. This process is time-consuming, which sets the motivation for this study to provide and validate an automatic apnea detection algorithm using the raw PSG recordings of 50 patients. Apnea is detected primarily employing the nasal flow signal, combined with oxygen saturation (SpO2) for hypopnea classification. The proposed approach achieves 77.124% accuracy (SD was 7.7) with around 55.3% sensitivity and around 82.5% specificity. Such an automatic algorithm will help drastically reduce the necessary time to analyze patients' condition.**

Keywords: sleep apnea, automatic detection, nasal flow signal

I. INTRODUCTION

Sleep Apnea Syndrome (SAS) is a sleep respiratory disorder that happens when breathing is interrupted by a collapse of the upper airway at the level of the tongue or the soft palate [1, 2]. It is characterized by a complete absence or of airflow during at least 10s [3]. If the airflow is not fully blocked the episode is diagnosed as hypopnea. Depending on the respiratory effort, manifested by abdominal or thoracic movements, different types of apnea can be identified. While in obstructive sleep apnea (OSA) the respiratory effort is present, in central sleep apnea (CSA) it is not. Mixed sleep apnea (MSA) instead consists of a first part where there is no effort detected, like in a CSA episode, followed by a second part where the respiratory effort exists [4, 5]. Hypopneas are further characterized by oxygen desaturation of at least 4% [4]. According to the American Academy of Sleep Medicine (AASM) [5], the metric used to describe the SAS severity is the Apnea-Hypopnea Index (AHI). This index is calculated as the number of complete and partial apnea and hypopnea events averaged over the duration of sleep [1, 5].

Apnea events occur many times per night and, when the syndrome is severe, they can cause daytime sleepiness, insomnia, attention deficit, learning and memory difficulties, depression and irritability [3, 4]. Short-term consequences of sleep apnea also include increased heart rate and high blood pressure. More important are long-term symptoms such as poor concentration, a compromised immune system, slower reaction times and cardio/cerebrovascular problems, which are identified as risk factors for systemic hypertension, myocardial infraction, stroke, and sudden death [2, 4, 6, 7].

Sleep-related breathing disorders are usually diagnosed using Polysomnography (PSG), which is a gold standard test performed in a specialized sleep center such as Sleep Disorders Clinic or a Hospital for Pulmonary Diseases, under the supervision of technicians and doctors during the overnight sleep of a patient [1, 4]. This diagnostic tool monitors several parameters using sensors for nasal or breath airflow, oxygen saturation (SpO2), body position, movements (thoracic and/or abdominal), electroencephalography (EEG), electromyography (EMG), electrooculography (EOG) and electrocardiography (ECG) depending on the employed PSG device [1, 3]. The analysis of PSG recordings is a time-consuming process and medical staff often needs to inspect the automatic scoring made by machine in order to correct the possible mistakes [1].

Several studies have focused on the detection of sleep apnea using different signals, mostly focusing on reducing the amount of necessary signals to detect the apnea episodes. For example, in [4], the authors review the literature that shows that features from the ECG signal can be used to detect sleep apnea. Some researchers focus on methods such as mode decomposition to transform complex time series into a finite set of intrinsic mode functions [2] or derive a set of features that can later be used for the discrimination of apneas [1]. Other studies focused on measurement of the nasal airflow or on the evaluation of the body movements (abdominal or chest effort signals) and showed that body movements could indicate the occurrence of sleep apnea events [8]. In that sense, Almazaydeh at al. [3] based their research on the

breathing acoustic signal analyzed using a Voice Activity Detection (VAD) algorithm to measure the difference in energy of the acoustic respiratory signal during the presence and absence of breathing [3]. Another approach in apnea classification is to use the electrocardiographic (ECG) signal firstly to detect and secondly to classify apnea episodes [4]. Several features based on ECG are proposed in [9-11] to replace the information given by the respiratory signal. Varon et al. [4] proposed an algorithm, which uses two different features: changes in the morphology of the ECG and information shared between respiration and heart rate, by means of orthogonal subspace projections. Based on these two features, they claim to have achieved 85% accuracy. Another study by Corhout et al. [12], applied a technique called Empirical Mode Decomposition (EMD) on Heart Rate Variability (HRV) data and derived a signal that estimates the area under the QRS complex, which they use to detect apnea events automatically. With an initial accuracy of 88.8%, further research was done to reduce signal noise and improve accuracy [2].

A full PSG is expensive, sometimes costing up to $1000, which is not always an option for people with inadequate health insurance. Therefore, beside the PSG as a gold standard, several alternative devices have been introduced to detect SAS with a primary aim to reduce the diagnostic costs [13, 14]. In this regard, there has been an increasing interest in wearable health monitoring devices in recent years, based on e-Health and m-Health advances, which has brought academic research and industry together in order to find inexpensive and comfortable solutions for apnea detection. Some of the examples are HealthGear [6], WEALTHY [15] or Foster-Miller's health monitoring garment for soldiers [6]. Other studies such as the one done by Husemann et al [16] proposed a Personal Area Hub and developed a health care application for tracking patient compliance using an architecture for logging and subscribing to events with an implementation on a Sony Ericsson P900 smartphone. However, these devices are not properly validated and fully accepted by the end-users, since they need to overcome several clinical, technical, legal and societal obstacles, as well as improve their power consumption, privacy preservation and usability [6]. Martin et al. discuss issues that surround wearable ECG devices able to provide real-time feedback to the patient [17] highlighting that their main drawback is the lack of experimental results.

The development of more portable in a wearable manner, friendly to use and less intrusive systems is of utmost importance as demonstrated for the ever-growing interest in the field. Unfortunately, PSG is not a good candidate for sleep monitoring at home and the unfamiliar environment encountered in a sleep laboratory often influences the usual sleep pattern of patients [2, 4, 18]. Furthermore, the original test is invasive and patient intrusive, especially EEG and ECG monitoring, which require having several electrodes attached to the body to record the electrical activity [14]. In addition, such testing is expensive, time-consuming, and carried out for very limited time periods [6, 19] (typically single-night admission due to large number of patients). Furthermore, trained staff is necessary to examine and correct automatic scoring prepared and provided by the installed software connected to the monitoring devices [14, 19].

Therefore, simplified methods to reduce the time that specialists spend on processing the sleep reports [1, 3, 4, 7] would be very helpful and more comfortable for long-term testing modality and diagnosis [6]. Not many works in the literature include empirical experience of medical staff into the algorithms, which will be incorporated in this study. In this research project, we have developed an algorithm for automatic detection of sleep apnea episodes based on the nasal flow signal in combination with the ECG wave to perform artifact removal. This method for automatic detection of sleep apnea is the first step in the development of a broad independent system for monitoring sleep disorders and speed-up of sleep apnea episodes diagnosis in more flexible timelines and healthcare setups.

II. MATERIALS AND METHODS

The dataset used in this study consists of continuous full recordings from 50 patients who performed a proper Sleep Study at the Clinic for Pulmonology of the Clinical Center Kragujevac[a]. The length of the signals' recordings ranges between 7 and 10 hours and the dataset includes recordings from 35 male and 15 female patients with the demographic and health characteristics detailed in Table 1.

TABLE I.
DEMOGRAPHIC AND HEALTH CHARACTERICTICS OF THE EMPLOYED DATASET (MEAN VALUES±STANDARD DEVIATION)

	Male	Female
Age (years)	53±13.5	58±11.6
AHI	32±23.1	21±16.5
Mean heart rate (bpm)	65±9.3	65±9.9
Max heart rate (bpm)	104±30.7	98±17.4
Mean SpO2	91±3.8	91±3.6
Min SpO2	77±11	78±8.25

The following parameters have been continously monitored for all the patients:

- Nasal airflow, using standard nasal pressure sensor
- Body position
- Electrocardiogram (ECG)
- Thoracic and abdominal movements, by inductance plethysmography
- Oxygen saturation (SpO2) was monitored using a pulse oximeter

Even though continuous recordings of signals for thoracic and abdominal effort were acquired, during the study, we did not further analyse the above mentioned signals in a more complex manner in order to perform apnea classification, as this is out of the current scope of the specific project and will be the topic of exploiation for future work.

Figure 1 depicts the diagram that describes the general algorithm developed in this study.

[a] website: http://www.kc-kg.rs/organizacija/klinike/klinika-za-pulmologiju

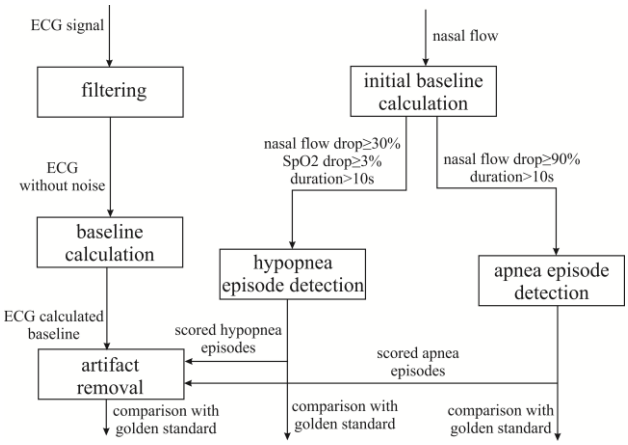

Figure 1. Proposed algorithm for automatic sleep scoring

The inputs to the general algorithm are some of the previously mentioned monitored signals, which were stored in the European Data Format (EDF) standard. The free tool Polyman (version 2.x [20]) was used to inspect these EDF files and visualize the signals before any processing. The sampling frequencies of the signals were 200 Hz for nasal flow and ECG, 500 Hz for snoring, 100 Hz for thoracic and abdominal movement and 3Hz for SpO2. Apnea detection and artifact removal were done based on the rules, which will be explained further in the text. The Gold Standard Apnea Event Scoring was initially performed automatically by the Sleepware G3 from Philips Respironics. At a second stage, the medical staff - experts inspected and corrected manually the result of the automatic pass to obtain the best possible scoring accuracy.

Since all changes in patient's sleep are monitored in comparison to the pre-event baseline or stable breathing, we calculate the baseline in the first step of the algorithm. According to the convention, the baseline is defined as the mean amplitude of stable breathing and oxygenation in the 2 minutes preceding onset of the event (in individuals who have a stable breathing pattern during sleep) or the mean amplitude of the 3 largest breaths in the 2 minutes preceding the onset of the event (in individuals without a stable breathing pattern) [5]. Figure 2 shows an example of stable breathing colored in blue.

Figure 2. Example of stable breathing

As stable breathing is not always present at the beginning of the monitoring (Figure 3), we implemented an adaptive baseline calculation to constantly update the baseline. The calculation was done based on the upper and lower envelopes of the first 120s of the input sequence and local $n(k)$ maximum values, where each maximum is calculated over a sliding window of length k=120s across neighboring elements.

Figure 3. Example of non-stable breathing

Based on the medical staff expertise and as described in the Scoring Manual of the American Academy of Sleep Medicine [5], the main rules for apnea episode detection are:

1. There must be a drop in the peak signal excursion by more than 90% of pre-event baseline using an appropriate sensor (oronasal thermal sensor, positive airway pressure device flow, or an alternative apnea sensor)
2. The duration of the interval with more than 90% drop in the signal lasts for longer than 10 seconds

By the drop in the peak signal excursion, it is meant that the amplitude of the nasal flow signal has dropped at least 90% in comparison to the baseline signal. The length of a respiratory event (e.g. apnea) is defined as the event duration.

Examples of apnea events are colored in yellow in Figure 4. Windows of 10s were used to score apnea events and the maximum duration of an apnea event was limited to 60s.

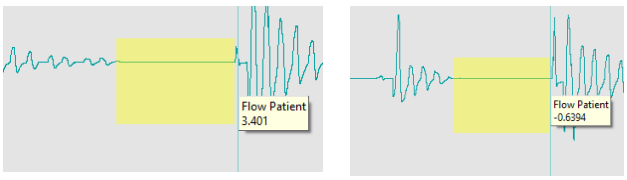

Figure 4. Examples of apnea events

Analogously, the main rules for hypopnea episode detection are:

1. There must be a drop in the peak signal excursion by more than 30% of pre-event baseline using an appropriate sensor (as previously mentioned)
2. The duration of the more than 30% drop in the signal lasts for longer than 10 seconds
3. There is a minimum of 3% oxygen desaturation from pre-event baseline or the event associated with an arousal

Examples of hypopnea events are colored in yellow in Figure 5.

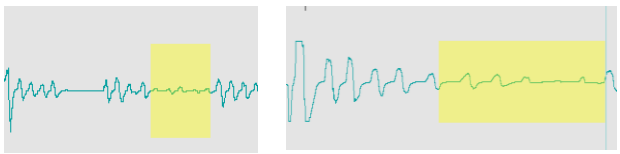

Figure 5. Examples of hypopnea events

The tool that is used to generate the apnea/hypopnea report is only considering the basic rules described before, so if there is an artifact, the underlying algorithm would still score it as apnea/hypopnea. In that case, manual correction would be necessary. Typically, specialized medical staff performs this manual scoring by selecting the area of the artifact and marking it as an awake stage. To this end, the ECG signal is used to identify artifacts. Examples of artifacts are given in Figure 6. Yellow parts of nasal flow would be automatically scored as apneas by the tool, if there were no manual scoring.

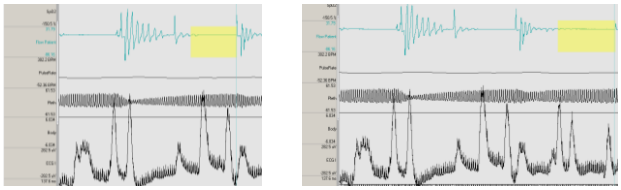

Figure 6. Examples of artifacts that should be excluded from event scoring

To automate this process, a third order low pass filter was firstly used for filtering the ECG signal with a cut off frequency *0.06/(freq. ECG/2)*, where *freq.ECG* is the sampling frequency of the ECG signal. Additionally, zero-phase filtering was used to have zero phase distortion and

no delays in the filtered signal. No additional decimation/sampling frequency reduction was necessary. The filtered ECG signal will be the output of the first block served as an input to the baseline calculation and apnea detection. Artifact removal was carried out removing a full apnea episode based on the quality of the ECG signal. In other words, if the ECG signal is not normal for an automatically detected apnea event, the whole episode is removed. We defined abnormal ECG as an excerpt of signal in which the amplitude for that window is larger than the amplitude of the baseline with some added tolerance. Baseline is calculated based on the first 15 minutes of the ECG signal.

Comparison with manually scored events was done before and after artifact removal. Standard statistical measures of diagnostic accuracy, sensitivity and specificity were calculated based on Equations 1, 2 and 3.

$$sensitivity = \frac{TP}{(TP + FN)} \quad (1)$$

$$specificity = \frac{TN}{(TN + FP)} \quad (2)$$

$$accuracy = \frac{TP + TN}{(TP + TN + FP + FN)} \quad (3)$$

TP indicates true positives, TN true negatives, FP false positives and FN false negatives. It must be emphasized that TP, TN, FP and FN are calculated per window. In order to classify a window as apnea/hypopnea window, a constant threshold (currently set to windowThreshold = 5/30) is used. This means that if apnea duration is longer than 5s in a window of 30s length, a whole window will be classified as apnea/hypopnea window. This is done for both the reference and our suggested automatic scoring. In this way, we were able to reduce the potential problems that can occur between the scoring performed by the expert and the one calculated by our algorithm. This situation can happen because our system has incorporated predefined rules for the exact ending of the apnea/hypopnea event, whilst the marks made by the experts may denote the end of the episode subjectively based on experience.

III. RESULTS AND DISCUSSION

The results show 77.124% accuracy (SD was 7.7) with mean sensitivity around 55.3 and specificity around 82.491. One example of apnea events scored by medical staff and our automatic tool is given in Figure 7. Visual comparison of the reference scoring made by the expert (first row) with the scoring of our system (second row) can be seen. Reference scoring has distinctions among different types of apnea (cf. colored legend in Figure 7), which will be incorporated to our algorithm in future iterations. Other signals such as SpO2, body movements and ECG signal can also be observed in this figure.

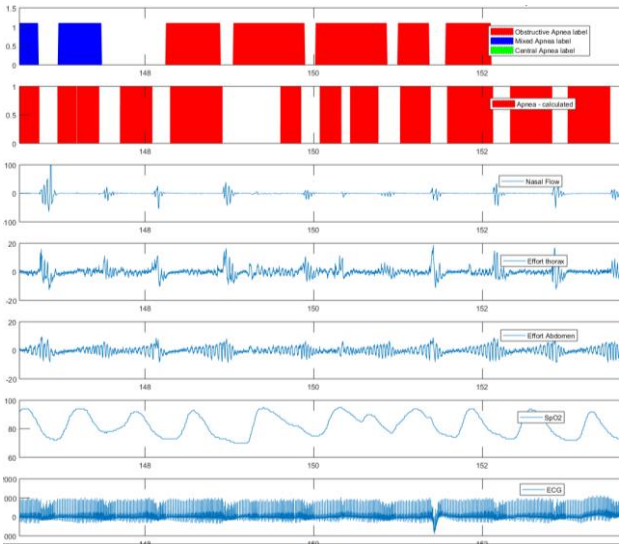

Figure 7. Reference and automatic apnea scoring per window

In addition, numerical values for some patients are given in Table 2.

TABLE II.
STATISTICAL MEASURES FOR SOME PATIENTS BEFORE ARTIFACT REMOVAL

Patient number	Sensitivity	Specificity	Accuracy
3	32.828	72.114	57.479
15	57.598	88.007	73.273
22	56.554	82.299	71.650
31	76.879	87.470	80.278
41	45.399	89.227	77.751

Comparison by window between the manually scored signal and our system for one patient is given in Figure 8. It can be seen visually that apnea scoring per window of the reference signal is matching the apnea scoring per window obtained by our algorithm at most points.

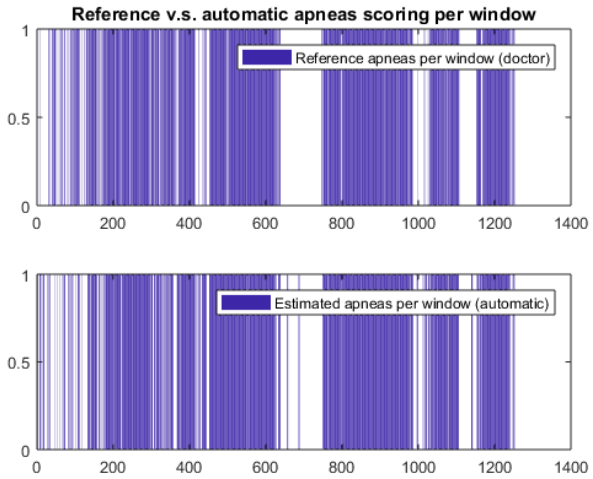

Figure 8. Reference and automatic apnea scoring per window

Based to the current state of the art by running a proper cross validation analysis, Varon et al. [4] obtained between 71% and 73% accuracy using SVM-based algorithms and up to 84% accuracy using combined LS-SVM algorithms, tested on the Physionet database. When

they tested the same approach on the Leuven dataset, accuracy was higher, achieving up to 86% using SVM and around 80% using LS-SVM. Wong et al. [14] report 0.92 sensitivity and 0.86 specificity on evaluation of AHI based on a nasal flow-monitoring device for obstructive sleep apnea (OSA) in comparison to AHI estimation of a PSG. The main drawback of this work is that it does not report accuracy nor describes the methodology of detecting the presence of obstructive sleep apnea using a single-channel nasal flow-measuring device. Mijovic et al. also compare their findings with the results of Corthout et al. in terms of classification performance [2]. They report 0.83 accuracy for detection of OSA by Empirical Mode Decomposition on Tachogram and discuss that apneic and borderline subjects are not so well separated compared to the work of Corthout et al., showing that the algorithm proposed by Corthout et al. outperformed in specificity, but was less accurate. Although our results are comparable to the current state-of-the-art showing around 77% accuracy, we must emphasize that these results are obtained only based on pure pre-defined rules for scoring and no additional machine learning is implemented.

After artifact removal, we have noticed that the statistical measures changed depending on the patient. The results show that total average accuracy with removed artifacts is 76.5%, average specificity raises to 87% and average sensitivity drops to 62.67%. These results show that the overall specificity is improved after artifact removal, but the sensitivity is reduced, which means that deeper analysis of the tolerance selection and ECG signal should be done. This will be the focus of interest in future studies. Numerical values for same patients shown in Table II are shown in Table III after performing artifact removal.

TABLE III.
STATISTICAL MEASURES FOR SOME PATIENTS AFTER ARTIFACT REMOVAL

Patient number	Sensitivity	Specificity	Accuracy
1	30.051	74.823	58.137
15	56.66	88.712	73.182
22	53.932	82.827	70.875
31	76.538	87.470	80.046
41	45.399	89.227	77.751

A progress towards the automatic apnea detection incorporating the experience of medical staff is made. Nasal flow is the cornerstone in this study, which is complemented with information from oxygen saturation (SpO2) to identify hypopnea. As mentioned previously, thoracic and abdominal movements were not currently examined to differentiate between obtrusive, central and mixed apnea. This will be of interest in future research as well as the correlation of the measured signals with the signals measured by SmartWearable, a Swiss made wearable device manufactured by SmartCardia S.A[b], able to perform homecare monitoring at a reduced cost when compared with standard PSG.

Machine learning algorithms or fuzzy logic in combination with experience from trained medical staff will be explored in the future.

[b] website: http://www.smartcardia.com/

IV. CONCLUSION

In this study, we have proposed an automatic algorithm for apnea/hypopnea scoring based on experience from trained medical staff. The results based on the analysis of nasal flow, oxygen saturation (SpO2) and artifacts in the ECG signal, are very promising since no complex machine learning method is required. Such an automatic algorithm would enable the conception of a system to perform home monitoring of sleep during more than one night, reducing the diagnosis costs and the time required for the manual scoring by an expert.

The continuous recordings have been done, apart from the Golden Standard Device, by the SmartWearable for cross validation purposes, as the Wearable which will be used as a screening tool. This will provide an easy solution to the end-users with a small, comfortable, easy to wear, accurate tool based on sensors, algorithms and a mobile app that can help them even to self-screen for sleep apnea in their own bedrooms, at a later stage in the near future. This will be part of future analyses in the framework of sleep disorders research. Future research will also include apnea and hypopnea classification into obstructive, central and mixed events to obtain a better insight into sleep-related disorders.

ACKNOWLEDGMENT

Part of this research is supported by Ministry of Education, Science and Technological Development of Serbia, with projects OI174028 and III41007.

REFERENCES

[1] N. Selvaraj, and R. Narasimhan, "Detection of sleep apnea on a per-second basis using respiratory signals," In Engineering in Medicine and Biology Society (EMBC), *35th Annual International Conference of the IEEE*, pp. 2124-2127, July 2013.

[2] B. Mijović, J. Corthout, S. Vandeput, M. Mendez, S. Cerutti, Van S. Huffel, "Detection of obstructive sleep apnea by empirical mode decomposition on tachogram," *4th European Conference of the International Federation for Medical and Biological Engineering*, Springer, Berlin, Heidelberg, 2009, pp. 247-251.

[3] L. Almazaydeh, K. Elleithy, M. Faezipour, A. Abushakra, "Apnea detection based on respiratory signal classification" *Procedia Computer Science*, vol. 21, pp. 310-316, 2013.

[4] C. Varon, A. Caicedo, D. Testelmans, B. Buyse, S. Van Huffel, "A novel algorithm for the automatic detection of sleep apnea from single-lead ECG," *IEEE Transactions on Biomedical Engineering*, vol. 62, no 9, pp. 2269-2278, 2015.

[5] R. B. Berry, R. Budhiraja, D. J. Gottlieb et al., "Rules for scoring respiratory events in sleep: update of the 2007 AASM manual for the scoring of sleep and associated events: deliberations of the sleep apnea definitions task force of the American Academy of Sleep Medicine,". *Journal of clinical sleep medicine: JCSM: official publication of the American Academy of Sleep Medicine*, vol. 8, no 5, pp. 597, 2012.

[6] N. Oliver, F. Flores-Mangas, "Healthgear: Automatic sleep apnea detection and monitoring with a mobile phone," *JCM*, vol. 2, no. 2, pp. 1-9, 2007.

[7] T. Young, M. Palta, J. Dempsey, J. Skatrud, S. Weber, S. Badr, "The occurrence of sleep-disordered breathing among middle-aged adults," *New England Journal of Medicine*, vol. 328, no 17, pp. 1230-1235, 1993.

[8] A. Ng, J. Chung, M. Gohel, et al., "Evaluation of the Performance of Using Mean Absolute Amplitude Analysis of Thoracic and Abdominal Signals for Immediate Indication of Sleep Apnea Events," *Journal of Clinical Nursing*, vol. 17, no. 17, pp. 2360-2366, September 2008.

[9] M. Bsoul et al, “Apnea medassist: real-time sleep apnea monitor using single-lead ecg,” *IEEE Trans. Inf. Technol. B.*, vol. 15, no. 3, pp. 416– 427, May 2011.

[10] P. De Chazal et al, “Automated processing of the single-lead electrocardiogram for the detection of obstructive sleep apnea,” *IEEE Trans. Biomed. Eng*., vol. 50, no. 6, pp. 686–696, Jun 2003.

[11] K. Kesper et al, “ECG signal analysis for the assessment of sleepdisordered breathing and sleep pattern,” *Med. Biol. Eng. Comput.*, vol. 50, no. 2, pp. 135–144, February 2012.

[12] J. Corthout, M. O. Mendez, A.M. Bianchi, T. Penzel, S. Van Huffel, S. Cerutti, “Automatic screening of Obstructive Sleep Apnea from the ECG based on Empirical Mode Decomposition and Wavelet Analysis,” *EMBC Proc. vol. 30, International Conference of the IEEE Eng. in Med. and Biol. Soc.*, Vancouver, Canada, 4 pages, 2008.

[13] W. W. Flemons, M. R. Littner, J. A. Rowley, et al., “Home diagnosis of sleep apnea: a systematic review of the literature: an evidence review cosponsored by the American Academy of Sleep Medicine, the American College of Chest Physicians, and the American Thoracic Society,” *Chest*, vol. 124, no. 4, pp. 1543-1579, 2003.

[14] K. K. Wong, D. Jankelson, A. Reid, et al., “Diagnostic test evaluation of a nasal flow monitor for obstructive sleep apnea detection in sleep apnea research,” *Behavior Research Methods*, vol. 40, no 1, pp. 360-366, 2008.

[15] R. Paradiso, “Wearable health care system for vital signs monitoring” *In Proc. IEEE Int. Conf. Information Technology Applications in Biomedicine*, pages 283–286, 2003.

[16] D. Husesmann, C. Narayanaswami, and M. Nidd, “Personal mobile hub,” *In Proc. Intl. Symp. Wearable Computers (ISWC’04)*, pages 43–49.

[17] T. Martin, E. Jovanov, and D. Raskovic, “Issues in wearable computing for medical monitoring applications: A case study of a wearable ecg monitoring device,” *In Proc. Intl. Symp. Wearable Computers (ISWC’00)*, pages 43–49, 2000.

[18] H. Steltner, R. Staats, J. Timmer, M. Vogel, J. Guttmann, H. Matthys, and J. Christian Virchow, “Diagnosis of sleep apnea by automatic analysis of nasal pressure and forced oscillation impedance”, *American Journal Of Respiratory And Critical Care Medicine*, vol. 165, no 7, pp. 940-944, 2002.

[19] H. Nakano, T. Tanigawa, T. Furukawa, and S. Nishima, “Automatic detection of sleep-disordered breathing from a single-channel airflow record,” *European Respiratory Journal*, vol. 29, no 4, pp. 728-736, 2007.

[20] B. Kemp, and M. Roessen, “Polyman: a free(ing) viewer for standard EDF (+) recordings and scorings,” *Sleep-Wake Research in the Netherlands*, vol. 18, pp. 71-73, 2007.