# Low-Power Wearable System for Real-Time Screening of Obstructive Sleep Apnea

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***Abstract*—Obstructive Sleep Apnea (OSA) is one of the main sleep disorders, but only 10% of the cases are diagnosed. Moreover, there is a lack of tools for long-term monitoring of OSA, since current systems are too bulky and intrusive to be used continuously. In this context, recent studies have shown that it is possible to detect it automatically based on single-lead ECG recordings. This approach can be used in non-invasive smart wearable sensors which measure and process bio-signals online. This work focuses on the implementation, optimization and integration of an algorithm for OSA detection for preventive health-care. It relies on a frequency-domain analysis while targeting an ultra-low power embedded wearable device. As it must share its resources usage with other computations, it must be as lightweight as possible. Our current results based on publicly available signals show a classification accuracy of up to 83.2% for both the offline analysis and the embedded online one. This system gives an even better classification accuracy than the best offline algorithm when using the same features for classification [1].**

## I. Introduction

Obstructive Sleep Apnea (OSA) is a common sleep disorder involving partial or complete obstruction of the upper airway. Such events last typically from 20 to 40 seconds [2]. A patient is said to have OSA when experiencing at least ten apneas in one hour and at least 100 minutes containing an apnea during an overnight recording. This disorder is an aggravating factor for different health conditions, including cardiovascular disease [3], high blood pressure [4], stroke [5] and clinical depression [6] because of sleep deprivation and oxygen lack over long periods of time. Around 4% of adult men and 2% of adult women are affected by this disorder [7].

In a context of preventive health-care, automatically detecting and screening OSA is especially interesting when targeting personalized welfare, as it can be done from home. Indeed current systems are bulky and expensive, making them only available in hospitals for the most severe cases. Thus, it leaves most of the affected population left without any kind of monitoring [8]. Detecting OSA with the lesser invasive ambulatory device, with an accessible price enables the patients to free hospitals beds and benefit from better living conditions at home, while still being monitored on the long term in case of assistance need. Furthermore, a recent group study shows a higher mortality rate on severe OSA population with respiratory help compared to other patients [9]. This lowers the incentive of a systematic external respiratory help for patients with low to moderate OSA.

Due to the significant amount of the population affected and the adverse effects of OSA on health conditions, many studies have been recently conducted on this topic. In particular, one attempt to detect OSA by only using single-lead electrocardiogram (ECG) recordings to find new and reliable ways of screening OSA with a less invasive setup than current solutions [10]. Indeed, the gold-standard measurement method for OSA detection requires a careful setup of at least 16 electrodes on the patient's body connected. Therefore, a reference database [11] has been publicly released, featuring the full single-lead ECG recordings along with the OSA annotations from a health professional.

Given the high cost of the existing medical equipment combined with its bulkiness, we investigated a way to have an efficient, cost effective and non-intrusive device for OSA detection and screening. Our contributions are the following:

- Development of an online detection algorithm for obstructive sleep apnea relying exclusively on ECG data.
- Integration of the algorithm in a low-cost and low-power embedded platform.
- Optimization of the workload to free processing power for other software tasks.

The rest of this paper is organized as follows. First, it presents the state-of-the-art of automatic OSA detection in Section II, followed by the dataset characteristics in Section III. Section IV describes the algorithm implemented with each individual part's contribution detailed. Section V will detail the target device for the algorithm integration. Section VI explains the steps followed to port the algorithm to the target and then a review of the power consumption is done in Section VII.

## II. State of the Art

The traditional way to diagnose and monitor obstructive sleep apnea is through the use of polysomnography (PSG) along with electroencephalography (EEG), electrooculography (EOG), electromyography (EMG), electrocardiography (ECG), oronasal airflow and respiratory effort and oxygen saturation [12]. This requires a lot of medical attention and equipment for usually two full nights of measurements, as well as a diagnostic made by a doctor.

All the devices available commercially or at the research state [13], [14], [15], [16], [17], only offer a simple recording of the signals. The processing and identification of OSA comes afterwards when downloading the data to a smartphone, a computer or a web-service.

Because of the absence of online analysis of the recorded signal, we aimed at researching and developing such a device, using an already existing hardware architecture (*c.f.* Section V).

The methods are developed based on a publicly available database [11] providing full ECG recordings released for stimulating research on detecting OSA using only signle-lead ECG recordings. While the published works targeted an offline analysis using a computer/cloud system, our main contribution in this paper is to develop methods that can directly run on a mobile device. In general, latest works [1], [18], [19] analyzed the power spectrogram of heart-beat intervals series to classify patients. This is due to the presence of a notable shift on the power distribution as presented in the spectrum in shown in Fig. 1. Indeed, during OSA events, the signal's power in the lowest frequencies of the spectrum rise significantly therefore this feature is relevant for automatic OSA detection.

Feature extraction of the ECG morphology from the recordings such as the amplitude, pulse energy and duration of specific deflections present in the ECG (R, S and T waves) has also been investigated [1], [18], [19]. These characteristics are useful as complementary features to improve the classification. Time-domain feature extraction and processing has also been considered [1], [20], [19]. The best accuracy [18] of 92.5% is nevertheless obtained by a combination of different features extracted from the frequency-domain (power spectral density and time-frequency maps) as well as from the ECG morphology (heart-rate, S-wave amplitude and pulse energy). The main drawback of this solution is that it is a manual classification and not an automatic one.

When considering a fully automatic classification algorithm, the reference for comparison will be the one from [1] because it is the one achieving the best results when using only the spectrogram power and it is the one giving the most details about its results in terms of accuracy, sensitivity and specificity. When using only the frequency derived for the RR-peaks, the final accuracy reported is 80.3% with a sensitivity and specificity of respectively 73.9% and 84.2%. The other publication mentioning the sensitivity and specificity is [20] but it does not use any spectral analysis. It reached an accuracy of 85.6% along with 72.1% sensitivity and 91.2% specificity.

As we aim at keeping the global software complexity and processing workload as low as possible, we chose to use only the frequency spectrum of the intervals between two R peaks (RR) without paying the energy cost of extracting more features. This specific case has been considered by [18] and [1] where the reported accuracy is respectively 78.9% and 79.2% for minute-by-minute classification. Combining this with other features extracted from the ECG enabled the latter [1] to reach the score of 89.8%. However, this solution requires a heavier CPU active time which prevents the use of our device for long-term screening.

To the best of our knowledge, this paper is the first to propose an online solution for OSA detection on a wearable device which is recording and processing the ECG before analyzing it for the existence sleep-apnea events.

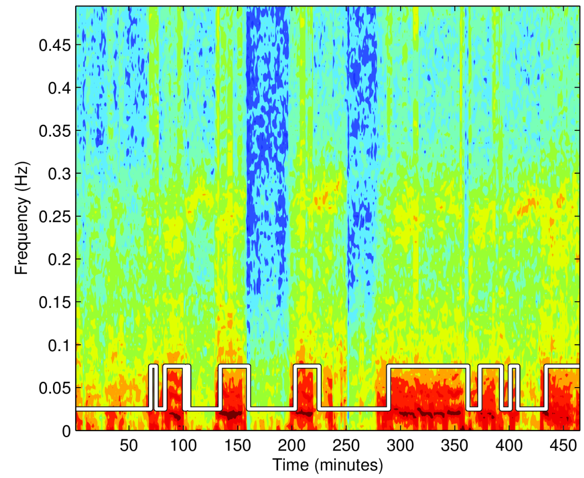


Figure 1. **Spectrogram of the log-power for the recording `x32` with the labeled OSA overlayed in white as a logic signal.**

## III. Apnea-ECG benchmark recordings

The recordings used for comparing the results are publicly available on Physionet in the apnea-ecg database [11]. The 70 single-lead ECG recordings were sampled at a frequency of 100Hz and manually labeled minute-by-minute by an expert for sleep apnea and hypopnea events, without distinction between both. The used beat annotations were provided along with the files by Physionet, coming from an automatic delineation without any specific correction.

The recordings come from a set of 32 subjects, healthy and with obstructive sleep apnea. From those subjects, four contributed to four recordings each, two contributed to three recordings each and 22 contributed to two recordings each. The dataset is divided in two groups of 35 recordings, one for training and one for testing. In each group, the amount of apnea events represents around 50% of the data.

The time range of the recordings goes from 6h 41min to 9h 38min, with an average duration of 8h 12min. The normal breathing time varies between 11 and 535 minutes whereas for the disordered breathing, it ranges from 0 to 534 minutes. The amount of breathing-disordered minutes was used to classify the patients in three different groups: the control group C showed less than 5 minutes of disordered breathing, and the apnea group A was defined as having 100 or more minutes of disordered breathing. The remaining cases were classified in the group B as being borderline.

The training set of 35 recordings has been used for tuning the parameters and the test set for assessing the performance of the algorithm. No files have been left out or were modified in any way using an offline pre-processing.

## IV. Sleep-apnea detection algorithm

We chose to build an algorithm suitable for embedded processing, targeting a wearable device for non-invasive and personalized health care. Therefore, as it is an low-power device, the algorithm should be efficient, yet simple and easy to integrate. It will be part of an existing data flow processing already developed (Fig. 2) and must work online to raise an alert whenever a problem occurs during the screening.

Compared to the state-of-the-art, we decided to lower the overall algorithmic complexity while keeping good results by focusing exclusively on a frequency-domain processing for two reasons. First, this is the feature which yields the best results when used alone. Second, a time-frequency conversion block is already available in the considered device as shown in Fig. 2.

In the context of frequency analysis based algorithms, the power in bands close to 10-40 mHz is always identified as an important feature to monitor, so we based our development on this specific feature, improving the results by adding one stage of pre-processing and another of post-processing.

Our implementation follows the flowchart in Fig. 3: the ECG is recorded by the device, then filtered and delineated to retrieve the R-wave peak. There is an optional single-beat correction step before the final ECG analyses. Each block of the sleep apnea detection will be detailed hereafter. The blocks' respective parameters have been optimized on the training set one after another until reaching convergence.

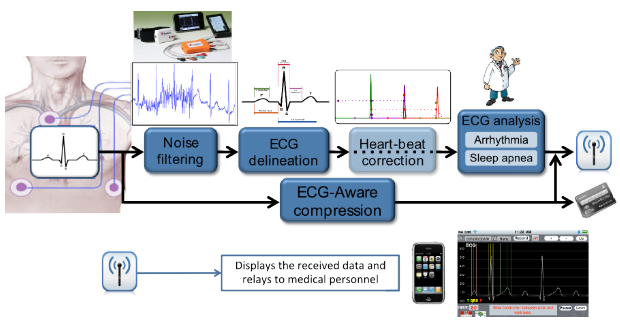


Figure 2. **Processing blocks integrated in the device. The OSA analysis has been integrated within the *ECG analysis* block**

## A. *Pre-processing: Thompson filtering*

Detecting and removing outliers is important because they have strong negative effects on the time-frequency conversion [21]. We chose to do this data-validation thanks to a Thompson filter, which is applied on the series of RR-intervals. The Matlab implementation is provided by [22] whereas the C version was developed specifically taking into account the constraints of the platform and the specificity of the data. This filtering is more generic than a single-beat correction, such as [23], because it simply deletes the outliers without any correction but does not adversely affect the results as the amount of data removed is small.

We did an automatic parameter sweep to find the optimal setting for the filtering varying its strength from 0% to 1% with 0.2% steps, and then up to 10% with 0.5% steps. The results in Fig. 4 shows that small values give the best results. This can be explained because of two phenomenons. First, a small number of values have a significant impact on time-frequency conversion so they need to be filtered out with a weak filtering.

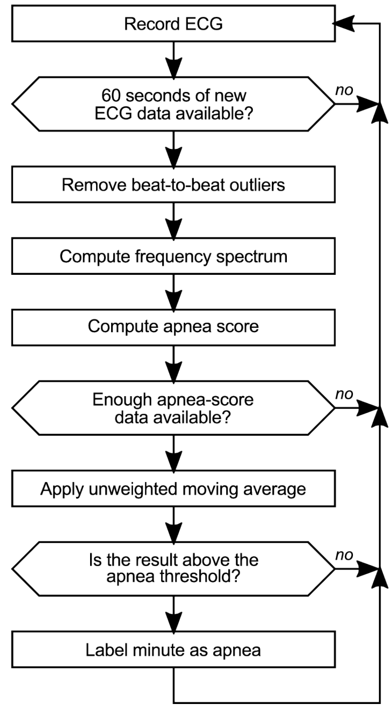


Figure 3. **Flowchart of the proposed OSA screening algorithm**

Second, using a strong filtering also removes meaningful data by being over-selective thus decreasing the resulting accuracy. Therefore, a balanced value between those two extremes can improve the results up to 5%.

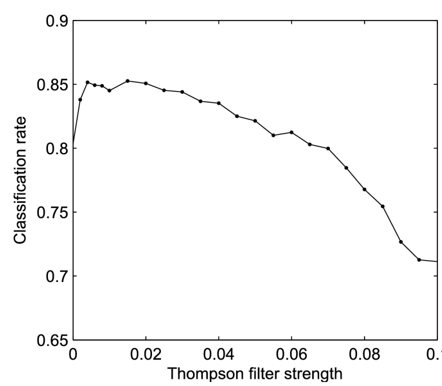


Figure 4. **Evolution of the accuracy depending on the strength of the Thompson filter.**

## B. *Apnea scoring*

Once the data has been filtered, the apnea-score can be computed using the signal's power spectrum. We define this score as being the relative power in the apnea-band compared to the total signal power when working on a five minutes window. After an additional noise-filtering step, this score will be the value used for discriminating an apnea-minute and a non-apnea minute.

As there is no defined gold-standard of the frequencies of the apnea-band to be used for estimating OSA events from an ECG recording, we automatically tuned the frequency-band.

We tested the change of frequency-band bounds, focusing on improving the classification accuracy. From an exhaustive exploration of all possible frequency bands from 0Hz to 0.1Hz, we obtained 2D-maps of accuracy such as the one displayed in Fig. 5. The apnea frequency-band bounds are readable on the axes, and the classification accuracy is linked to the color in the graph. From the figure, we notice a clear frequency interval regarding the lower bound of the band ranging from 10mHz to 18mHz while the upper bound has more tolerance, from 45mHz to 75mHz. This whole area gives good classification results which are reaching 76% in the illustrated case where no data correction nor validation is integrated in the global algorithm.

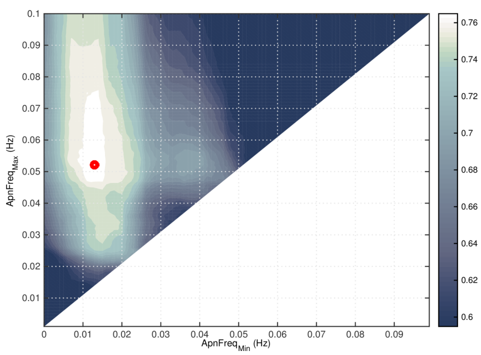


Figure 5. **Classification accuracy rate for OSA when varying frequency band bounds. The circular dot is placed at the position of the best frequency band.**

## *C. Apnea-score smoothing*

The reference minute-by-minute sleep-apnea labels reveal that OSA is a signal which changes at a low frequency: it is unlikely to have a single minute containing an apnea event in a long period of non-apnea sleep and vice-versa. Therefore, we need to track the evolution of the apnea-score over several minutes. We implemented this feature using a simple unweighted moving average.

In the same way we tuned the Thompson filtering strength, we optimized the moving average window length. When using a length of 15±4 minutes, there is classification accuracy increase of 3% to 4% depending on the specific configuration of the previous processing blocks.

# V. Target device

We will be targeting a device developed by SmartCardia (Fig. 6) [24]. It is an energy-effective wearable device providing a single-lead ECG recording with a 24 bits depth digitization at a frequency from 250Hz to 16kHz, skin-conductance and respiration evolution. The latter is measured using additional electrodes by impedance pneumography. The impedance change due to chest movement and blood oxygen saturation is captured using proprietary circuitry. The device is equipped with the STM32L151RDT6, an ultra-low-power 32-bit microcontroller which can operate at a maximum frequency of 32 MHz. It features 48 kB of RAM, 384 kB of flash storage and analog peripherals including a 12-bit ADC.

Given the internal capabilities and connectivity possibilities, it can work as a fully autonomous device for several hours

| Formula | $age = 20$ | Ref. |
|---|---|---|
| $HR_{max} = 208 - 0.7 \times age$ | 194 bpm | [25] |
| $HR_{max} = 220 - age$ | 200 bpm | [26] |
| $HR_{max} = 205.8 - 0.685 \times age$ | 192 bpm | [27] |
| $HR_{max} = \frac{203.7}{1+exp(0.033\times(age-104.3))}$ | 191 bpm | [28] |
| $HR_{max} = 2178 - 0.85 \times age$ | 200 bpm | [29] |

Table I. Maximum heart-rate given the age

Estimating the maximum heart-rate can be done using different formulas. We applied each of them in the case of a healthy adult where the heart-rate reachable is the highest, that is to say 20 years old.

of recording, uploading the recorded data to a base station when one becomes available. For example, a Bluetooth® Low-Energy compliant smartphone can be used for that, which can afterwards be used to display the data on-screen, upload it to a remote medical web-service or even raise an alarm if a critical condition is detected. In case of a web-service, it can be used by the patient's attending physician to manually check the data. Another use can be for anonymized population-wide statistical studies.

Figure 6. **The target device has a credit-card form-factor and can be used both hand-held or in a chest strap band.**

# VI. Optimization and integration of the algorithm in the target device

The algorithm has been ported from an offline Matlab implementation to a online and embedded C one. The initial classification accuracy is 83.4%.

To prevent runtime hardware faults triggered by dynamic memory allocation, we dedicate enough memory at compile-time for the arrays used to store and compute the data. As the apnea-scoring block needs to work on five minutes of data, we decided to allocate enough memory to store 1000 beat-to-beat intervals. This is the theoretical maximum number of heart-beats which can occur under normal conditions according to the estimators available in Table I.

## *A. Thompson filtering tuning*

The original implementation of the Thompson filtering can use different estimators for the averages and standard deviations used in its internal processing. The default estimator, *biweight*, is less prone to be much affected by erroneous values but it comes at the price of an increased computational load as it uses a more advanced statistical modeling of the input. In the case of the *biweight* method, it requires finding the median value of the input vector as well as the median absolute deviation from the median value. In other terms, it involves extra-memory for duplicating the input data, generating another vector derived from the input data and sorting them both before computing the *biweight* mean and average. When moving from *biweight* to the usual average and standard deviation, the results are decreasing by only 0.4%, which is a very good situation because the simplification of the internal processing brings both comparable results and lowers the use of both memory and CPU time.

Another improvement was applied thanks to the knowledge we have on the dataset. Indeed, when computing the Thompson filtering, we need an intermediate $\tau$ variable which is derived from the inverse cumulative distribution function of the Student's distribution. Fig 7 shows that for a filter strength of 1% and an input length from 200 to 1000, the value of $\tau$ can be approximated as constant. For the variations of strength considered, changing the filter strength only changes the vertical scaling. This interval corresponds to our maximum bounds of heart-rate from 40bpm to 220bpm for the required five minutes window of apnea-scoring. We chose the constant to be the $\tau$ value given for a vector length of 325 as this is the average number of beat-to-beat intervals in five minutes of sleep [30]. This optimization has no effect on the final classification outcome.

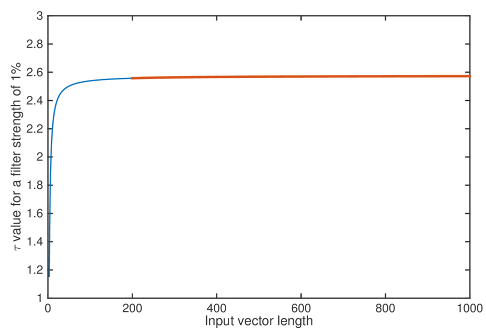


Figure 7. **$\tau$ value computed by the Thompson filtering for a strength of 0.01. The relevant input vector length in our situation is from N=200 to N=1000.**

### B. *Fast-Frourier Transform optimization*

Computing the spectrum of the input signal is done using the Lomb normalized periodogram. The implementation used [31] is really lightweight and dedicated to processing heartbeats on a low-power platform, albeit not really exact. It takes a vector of RR intervals and timestamps as inputs, resamples it, and fits the closest power of two required for the analysis.

The initial configuration required allocations of single-precision floating-point arrays of length 2048 which exceeded the target's available memory. Compromises had to be made regarding the oversampling factor and maximum frequency to compute so it could fit in arrays half as long. Lowering the oversampling factor by 25% as well as the maximum frequency from 0.83Hz to 0.50Hz was enough to meet the memory requirements. Thanks to several tuning iterations of the parameters, the lowering of the precision of the FFT is balanced to keep as good results. The final accuracy reaches 83.2%, which is only 0.2% lower than our reference offline implementation.

| Operation | Current (mA) | Duty cycle (%) | Average current (mA) |
|---|---|---|---|
| ECG acquisition | 0.435 | 100 | 0.435 |
| ECG delineation | 10.5 | 1.67 | 0.175 |
| Apnea processing | 10.5 | 1.68 | 0.177 |
| Idle time | 2.10 | 96.65 | 2.030 |
| Total | | | 2.816 |

Table II. CURRENT USED FOR OSA DETECTION ON THE TARGET DEVICE

## VII. ENERGY CONSUMPTION

After porting the algorithm on the device, measurement of the processing time on the device shows that on 141 apnea computations, the average time was 1.004 seconds and the standard deviation was 0.025 seconds. As such processing occurs at each time one full new minute of data is available, the duty cycle is as low as 1.67% which leaves computational power for other operations such as feature extraction of the R-peaks from the ECG signal.

In the case where the device is only used for OSA detection, the energy consumption results are reported in Table II. The ECG measurement is active 100% of the time, therefore it is a constant current draw. Concerning the software, two main parts are required: the ECG delineation to detect the heart-beat and the OSA detection. In both cases, the microcontroller is in its active state, consuming 10.5mA. The rest of the time, when no computation is running, the CPU is in an energy-saving mode drawing 2.10mA. Summing the individual consumptions weighted according to their individual duty cycles gives an average current consumption of 2.816mA. As the battery is rated at 710mAh, the total lifetime to expect is 252 hours, which is equivalent 10.5 days.

## VIII. CONCLUSION

There is a high rate of OSA in the population combined with a very low percentage of persons being monitored for this condition. This is explained because this health problem is under-diagnosed, expensive and bulky to monitor and has no directly lethal consequences. Nevertheless, it is known to be an aggravating factor for other life-threatening conditions linked with the vascular system and it affects everyday's life because of sleep deprivation. All those points motivated the work described in this paper with the research and development of a non-intrusive wearable system for online detection of OSA events which can be used for long-term screening.

The existing wearable devices dedicated to OSA always record the data for an offline processing after having transmitted the data to another device, whether it is a smartphone, a computer or an online service. None of them have integrated the full ECG recording, delineation and analysis on the same low-power and low-energy device. As for the algorithms, the literature recognized the importance of a frequency analysis of the beat-to-beat series. The main drawback from our point of view is that they focus on offline analysis, which means that many more features can be extracted and used for the classification of OSA. In the context of a wearable device, each additional operation comes with a processing cost which adversely affects the battery-life.

Considering the state-of-the-art, we decided to develop a non-intrusive wearable and autonomous solution to record and process ECG for OSA classification. Therefore, we implemented and optimized an online algorithm for OSA detection relying on a single feature extrated from the ECG. We integrated it in an affordable ultra-low-power device and we lowered the workload to save the battery life leave the option of adding additional diagnostics algorithms.

In the end, we reached 83.2% accuracy for a minute-by-minute classification while running on the device for more than 10 days. This is 2.9% better than the existing offline algorithms relying on the same ECG feature.

## IX. Acknowledgment

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