Can the IR-UWB Radar Sensor Substitute the PSG-Based Primary Vital Signs' Measurements?

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***Abstract*—During the last decade, the development of impulse radio ultra-wideband (IR-UWB) radar sensors have led them to be considered as a viable substitute of polysomnography (PSG), the gold standard, in the acquisition of the primary vital signs of the human body, during sleep. In this work, we investigate whether radar sensor recordings of the chest and heart displacement can accurately substitute the PSG chest and heartbeat signal measurements. We develop an innovative pipeline of handling the radar-based recordings, which includes: motion detection, extraction of the respiration, heartbeat and activity vital signs and estimation of the respiratory and heartbeat rates (RR and HR, respectively). Next, we apply our proposed methodology to data from 28 subjects gathered during their sleep. Results show that the radar sensor's measurements can be comparative to those produced by the PSG. Specifically, the RR and HR frequencies, of the radar and the PSG, have average Pearson's correlation, greater than 0.9 and 0.8, respectively.**

***Index Terms*—IR-UWB radar sensor, PSG, respiratory rate, heartbeat rate, activity signal**

I. INTRODUCTION

Conducting a sleep study is the most important procedure for the identification and assessment of various sleep disorders, such as obstructive sleep apnea (OSA), a serious medical condition, that can even result in cognitive dysfunctions, cardiovascular and cerebrovascular diseases [1]. The most frequently-used diagnostic tool is polysomnography (PSG), which is widely considered the gold standard [2]. Nonetheless, the multiple on-body sensors, required for it, increase the patients' discomfort, while its long duration renders it expensive and appropriate only for use in hospitals and research settings [3].

To remedy the problems encountered during the use of the PSG, impulse-radio ultra-wideband (IR-UWB) radars have started to be extensively used during sleep studies. These sensors allow for contactless monitoring and have the ability to record the motion of the body, ranging from the micro-motion of the chest to the macro-motion of objects, or people, moving with high accuracy [4], [5].

Radar-based devices are convenient tools for sleep monitoring at home settings, as they are user-friendly and can accurately identify chest and heart oscillations. Those generated data can be subsequently used for extracting the respiratory rate, the heartbeat and the activity signal (that is the activity of the human body during sleep) which provide crucial information about sleep quality [6].

Radars are sensitive to environmental noise and the rich generated body motion information can be considered as "noise" in the context of sleep monitoring. As a result, a pipeline for noise/motion detection is used for the extraction of more accurate respiration and heartbeat signals. Specifically, the radar sensor's recordings are analyzed through a spectrogram-based approach. Spectrograms are capable of providing useful information about the body motion, through the changes of radar's characteristics over time [7]. In essence, through the spectrogram-based analysis light and intense motion can be detected and removed. To that end, the activity signal is also used, as it provides motion information that enables the researchers to exclude parts of the recordings that contain intense noise and extract, more reliably and accurately, the respiratory and heartbeat rates (RR and HR, respectively). This is an important point for consideration, given the impact that those frequencies have for a sleep study.

In this work, we investigate whether the vital signs extracted from a radar sensor are a reliable representation of those acquired from a PSG. Specifically, the chest and electrocardiogram signals acquired from the PSG are compared with those acquired from the radar by estimating the corresponding RR and HR frequencies. Moreover, from the radar data the activity signal is extracted that is used for motion detection.

The main contributions of this study are:

1) The creation of a system for the analysis of radar-based recordings which can provide three signals, namely the respiration, the heart displacement and the activity.
2) The noise treatment of the signals, that is introduced due to either body motion or environmental factors, by an innovative spectrogram-based analysis.

Simple, yet state-of-the-art, procedures are employed to provide the accurate extraction of biological signals (respiration

TABLE I
ARIA SENSING LT102 RADAR SPECIFICATIONS.

General specifications	Values
Radar's operating frequency	6.5 GHz to 8.5 GHz
Temperature operating range	$-40\,°C$ to $85\,°C$
Radar module's dimensions	36 mm×68 mm
Maximum power consumption	220 mW at 5 V
Integrated antenna aperture	$\pm 60°$ by $\pm 60°$
Typical detection range	12 m

and heart displacement) and subsequently the RR and HR. The evaluation of the pipeline was conducted mainly using the Pearson's correlation, between the PSG- and the radar-extracted results. Note that the evaluation was conducted using 28 recordings of patients with OSA disorder.

The rest of the paper is organized as follows: Section II describes the mathematical background of the proposed methodology, Section III, presents the evaluation of the method, while Section IV discusses the conclusions.

II. MATERIALS AND METHODS

In this section the main building blocks of the proposed methodology are described.

A. IR-UWB Data Acquisition

In our experiments, an IR-UWB radar sensor was positioned next to a patient, about $50cm$ from their chest, and captured the motion of their lungs and heart. The sensor used was the Aria Sensing LT102 and its specification are presented in Table I. Generally, the procedure of capturing biological signals using a radar, involves measuring the torso displacement caused by the motion of the lungs and the heart. IR-UWB radars track the amplitude of a human body point to extract biological signals [8], by detecting and quantifying the periodic expansion of the chest. Thus, an important parameter in the extraction of those signals is the distance between the radar antenna and the human chest, which changes over time. The distance can be described by the following equation:

$$d(t) = d_0 + a_r \sin(2\pi f_r t) + a_h \sin(2\pi f_h t) \tag{1}$$

where d_0 is the nominal distance and $a_r,\ a_h$ are the mean values over the range of all possible displacements of the chest cavity caused by the respiration and the heart displacement, respectively. Moreover, with $f_r,\ f_h$ we denote the respiratory and heartbeat frequencies, respectively [9].

The IR-UWB radar sensor's acquired data consist of a 2-dimensional matrix, that is a function of the captured samples K and the radar's bins M (equal to 359 in our case). In more detail, a bin is a unit of representing and organizing the radar's captured spatio-temporal information. The total number of bins is related to the distance between the human body and the radar sensor [9]. Specifically, the radar's output can be expressed as $\mathbf{S} \in \mathrm{R}^{\mathrm{K}\times\mathrm{M}}$, where K denotes the number of samples in the sample space and M the radar's bins in fast time (in nsec).

B. Preprocessing of the Radar Recordings

As mentioned earlier, the radar's recordings belong to a 2-dimensional space, with the bins being of major importance. Between consecutive recordings, the corresponding bins have stored almost the same human body information, with the difference that each recording differs from the other usually in the amplitude of the captured signals, i.e., the magnitude of the acquired displacements. As a result, the bin with the most prominent displacement should be identified. To that end, the most well-established and simple method of finding the bin of interest is by computing the variance of each bin between all recordings and then take the bin with the maximum variance [9]. In our experimental procedure, as some patients changed position quite often, we split the matrix into N non-overlapping segments, of 120 seconds duration, and for each segment we repeated the aforementioned procedure. After that, by combining the signal's parts with the most intense human chest and heart displacement, we constructed a new signal of interest, denoted as $s \in \mathrm{R}^{1\times\mathrm{K}}$.

C. Extraction of the Activity Signal

The activity signal is among the most important signals in the context of sleep disorders. The presented methodology of detecting motion was based on the computation of the spectrogram of the extracted signal, denoted as s. Specifically, the procedure depends on the algorithm described in Algorithm 1. Inputs to the algorithm are the signal extracted from the radar-based recordings, namely s, as well as the sampling frequency of the radar, which in our case was equal to 40Hz.

Next, the spectrogram of each examination is estimated. A spectrogram is presented in Fig. 2. The algorithm detects low frequency time points, i.e., time points which present non-uniform behavior indicating the presence of a "light-tailed" distribution of motion within the signal (taking place during the time when the person was awake, yet lying in a bed). Note that the majority of time points do not include light motion i.e., they were captured during sleep. Moreover, given that the recordings took place during a sleep examination, in which people were lying in a bed, intense motion would not be present. To identify light (i.e., rare) motion (the signal samples that are presented with dark blue color in the spectrogram of Fig. 2), a threshold of 0.3 multiplied by the maximum value of the spectrogram matrix (line 9 of Algorithm 1) was applied. Having identified the areas within the signal where light motion existed, the signal was converted into a binary form by replacing the value of points where light motion existed with a value of 1, otherwise with a value of zero. To do so, a threshold denoted as $thresh$, equal to 8 or 10, was applied. Regarding the threshold value, it was important to not be excessive leading to the loss of valuable information, yet not as small as to eliminate the signal's fluctuations which could be important in differentiating patients' sleep apnea events, for instance.

The proposed methodology proved to be robust, although the noise was not intense. In Fig. 3, an example of an activity signal is presented. The proposed methodology has captured,

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Inputs: s, F_s
Outputs: x
Spectrogram Computation: $\mathbf{S_p}$ = $spectrogram(s,F_s)$
$\mathbf{S_p} = 10\log_{10}(\mathbf{S_p})$
Estimation of maximum spectrogram's value (in dB): $maxV = \max\left[\mathbf{S_p}(:)\right]$
Define: $N_t : length\left[\mathbf{S_p}(:,1)\right], N_f : length\left[\mathbf{S_p}(1,:)\right]$
for t = 1:N_t **do**
  for f = 1:N_f **do**
    if $\mathbf{S_p}(t,f) \leq 0.3 \cdot maxV$ **then**
      $\mathbf{S_b}(t,f) = 1$
    end if
  end for
end for
Define: $L = length(s)$
Define: $step = L/N_f$
Define: $freqs = [1 : step : L - step]$
Define: $counter = 1$
for f = 1:N_f **do**
  $part = \mathbf{S_b}(:,f)$
  $c = \sum(part == 1)$
  if $c \geq thresh$ **then**
    $\mathbf{S_b}(t,f) = 1$
    for i = $freqs(counter) : freqs(counter+1)$ **do**
      $x(i) = 1$
    end for
  end if
  $counter = counter + 1$
end for

Fig. 1. Activity signal extraction procedure.

not only the intense signal's noise (probably from motion), but also the lower amplitude noise (probably from the environment). As a result, it is evident that through the appropriate analysis of the spectrogram, the detection of human motions, both during sleep and during daytime activities, is possible [7].

D. Extraction of the Respiration Signal and the Respiratory Rate

The respiration signal is of major importance for the study of sleep and especially for the identification of sleep apneas. Thus, its accurate extraction from the radar-based recordings will result to a more accurate estimation of the RR. In our procedure, we followed the "maximum variance" process, which enables the detection of the signal's fluctuations with the maximum amplitudes. Our purpose was to estimate the respiratory rates with a simple, fast and accurate manner. The estimation of the RR was based on the computation of the power spectral density. Specifically, the first step was to split the previously extracted signal, s, into non-overlapping windows of 60 or 120 seconds duration, in order to maintain sufficient amounts of the signal's information. For each segment, if the corresponding activity signal's segment was full of zeros, the Fast Fourier Transform (FFT) was applied and

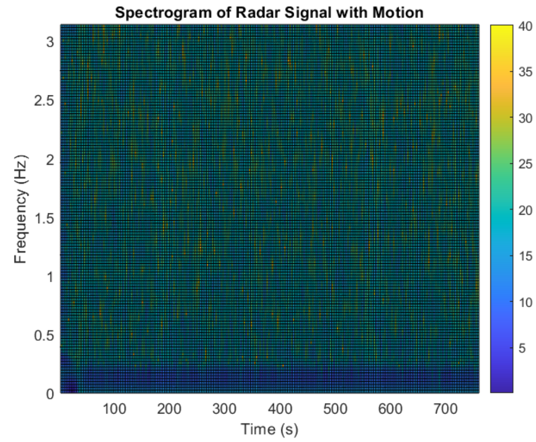
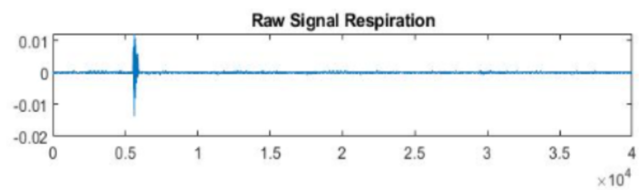
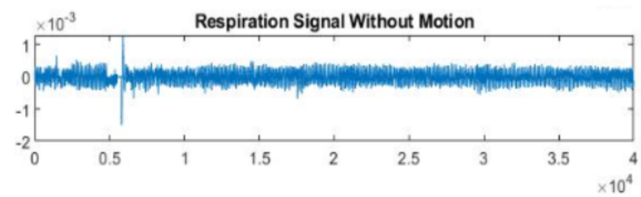


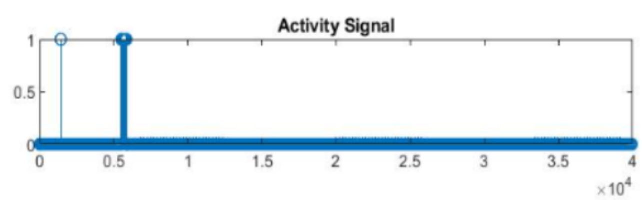
Fig. 2. An example of a spectrogram computed from patient data after a sleep monitoring procedure.



(a)



(b)



(c)

Fig. 3. The procedure for extracting an activity signal. (3a) Raw respiration signal from the radar recordings; (3b) The same signal'a part with reduced noise; (3c) the corresponding activity signal.

then the power spectral density (PSD) was estimated. In the literature, the number of respirations during sleep range from 12 to 20 [10], which equals to a respiration frequency between 0.2 and 0.35 Hz. As a consequence, having estimated the PSD we search for its maximum value into the aforementioned frequency range. Then, we multiply the estimated frequency with 60 in order to convert it into a respiration frequency (i.e., respirations per minute). On the other hand, in the case that the activity signal had intense motion within a segment, a linear

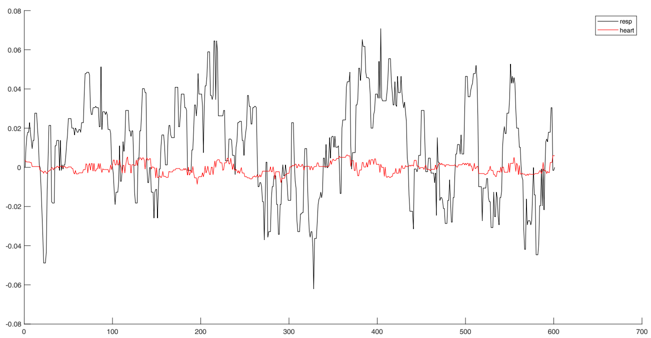


Fig. 4. Example of a radar's extracted signal. Black color denotes the respiration while red the heartbeat.

interpolation was applied that took into consideration the 2 immediate neighboring samples (both left and right).

E. Extraction of the Heartbeat Signal and the Heartbeat Rates

The heart signal is more laborious to be extracted from data of the radar-based device, as it is superimposed on top of the "stronger" respiration signal, as we can see in Fig. 4. Based on [11], the first step to reach to an accurate heartbeat signal extraction is to remove the fluctuations corresponding to the respiration frequencies. Thus, the respiratory signal extracted from the previous procedure was passed through a low-pass filter, with a cut-off frequency equal to 0.9Hz, and then through a high-pass filter of a cut-off frequency equal to 0.5Hz [10]. Finally, a median filter of order 20 was applied, for removing small signal's fluctuations, which are usually created by the system's noise (i.e., artifacts).

Having retained the most prominent fluctuations of the raw radar signal, the majority of the heartbeats have been retained as well. The final step is to estimate the corresponding HR values. Similarly to the RR estimation, for each heart displacement signal segment, if the corresponding segment of the activity signal is full of zeros, we apply peak detection. The HR is defined by counting the peaks per segment. On the other hand, in the case of a non-zero activity signal segment, again, the corresponding samples' rates were replaced with a linear interpolation that took into consideration the 2 immediate neighboring rates (both left and right).

III. RESULTS

In this section we present the evaluation of our pipeline, based on the Pearson's correlation.

A. HealthSonar Protocol – PSG Dataset

Data were collected during the HealthSonar clinical study, a one-arm observational clinical study carried out at the Sleep Disorders Center of the Intensive Care Unit located within Evangelismos Hospital at Athens, Greece. The purpose of this study was to evaluate the accuracy and validity of identifying sleep stages and apnea-related events, using data from an unobtrusive, contactless monitoring device based on an IR-UWB radar sensor compared to the same metrics as produced by data from PSG (considered the gold standard). The study was approved by the ethical committee of Evangelismos Hospital (Reference No. 198, 6/6/2022). In order to be enrolled to the study, the participants needed to be above 18 years old and able to consent to the aspects of the study before filling an informed consent form. All participants completed a clinical evaluation and underwent an attended polysomnography session. The examinations followed the "Manual for the Scoring of Sleep and Associated Events" (v2.6) of the American Academy of Sleep Medicine. Each subject was monitored for an entire night, while their sleep stages were annotated at 30-second intervals. Demographic information of the participants are presented in Table II.

TABLE II
DEMOGRAPHIC INFORMATION OF THE STUDY PARTICIPANTS.

No. of subjects	28
Age range	23-68 years
Weight range	55-155 kg

The PSG data used for our analysis included the following sensors' signals:

1) the "chest" signal, responsible for recording the patient's respiration. Its sampling frequency was equal to 32 Hz.
2) the "ECG_{LA}" and the "ECG_{RA}" signals responsible for acquiring the heart beats. The sampling frequency was equal to 256 Hz. The final electrocardiogram (ECG) signal was computed by the formula:

$$ECG = ECG_{LA} - ECG_{RA} \quad (2)$$

It is worth mentioning that the signals, from both PSG and radar, were synchronized and the radar-based activity signal was also used in the analysis of the PSG recordings, in order to clean the signals from the patients' motion while improving the synchronization.

B. PSG-based RR and HR

In order to estimate the corresponding RR and HR frequencies from the chest and ECG signals, we followed the procedure described on Section II. Briefly, for the estimation of the RR, the chest signal recorded from PSG was split in 120-second windows and for each window the PSD was estimated based on the FFT transform. The most prominent frequency of the PSD was considered as the respiratory rate for each window. Regarding the HR, again, the signal was split in windows of similar duration and through a peak detection process, the peaks of the ECG, having amplitude greater than a specific threshold, were identified. This threshold was defined in the range of $[0.4-0.6]$ of the maximum signal's amplitude.

For the estimation of both HR and RR, the regions of activity (as described in Section II-C) were fitted with a linear curve produced by linear interpolation, which took into consideration the 2 immediate neighbors (left and right).

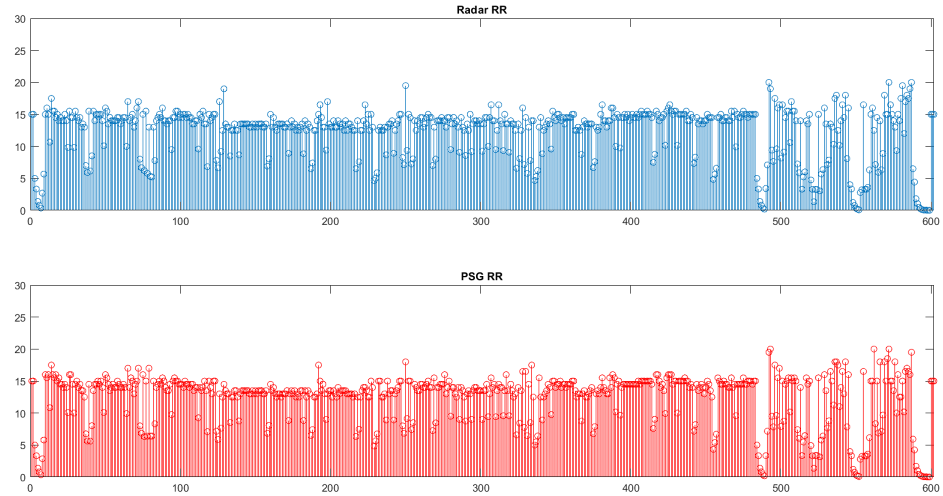


Fig. 5. The RR values for 5 randomly selected patients during their monitoring procedure as produced by the radar-based device (top) and the PSG system (bottom). The window duration is 120 seconds.

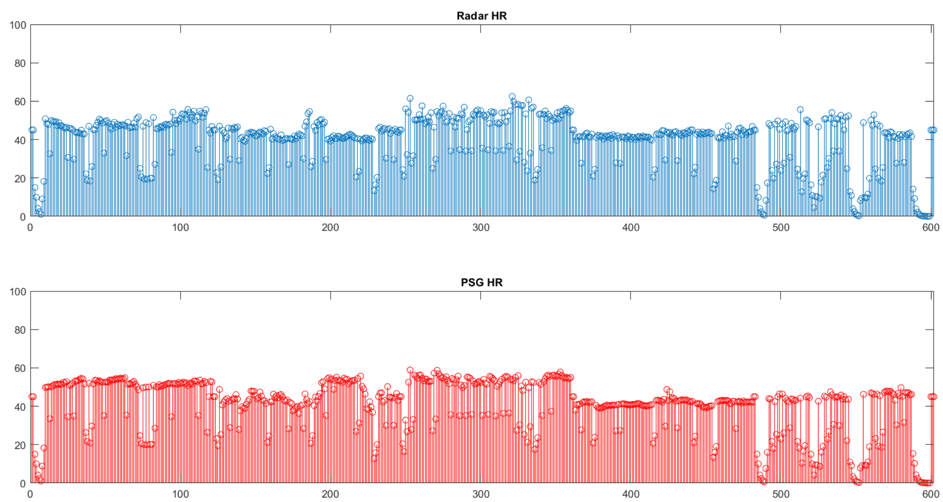


Fig. 6. The HR values for 5 randomly selected patients during their monitoring procedure as produced by the radar-based device (top) and the PSG system (bottom).

C. Performance Evaluation

In our analysis, the results were evaluated through 2 main metrics, i.e., the Pearson's correlation and the intraclass correlation coefficient (ICC) between the RR and HR measurements derived from the IR-UWB radar sensor and the measurements derived from the PSG system, as it was also used in [1]. The evaluation results can be seen in Table III. Note that the analysis was performed using windows with a duration of 120 seconds. Regarding the ICC values, the average correlation between the RR and the HR, as was extracted from the data radar and those of the PSG, was equal to 0.98 and 0.89, respectively.

In Fig. 5 and 6, we observe the RR and HR values for 5 selected patients during their monitoring procedure. Each spike corresponds to a rate derived from the analysis of a window of 120 seconds duration. As we can observe, especially for the case of the RR, the values estimated from data of both systems are very close, as it is verified by the high Pearson's correlation values and the ICCs. Notice that all raw frequencies were converted to represent the number of respirations and heart beats, respectively.

It is worth mentioning that after changing the window's duration to 60 seconds, the correlation values were lower and almost reached 0.8. Although still a high correlation, this result implies that our methodology has as a limitation the samples

TABLE III
PEARSON'S CORRELATION OF RR AND HR RATES BETWEEN THE RADAR SENSOR AND THE PSG SYSTEM.

Patient ID	Respiratory	Heartbeat
1	0.99	0.88
2	0.95	0.91
3	0.96	0.98
4	0.97	0.71
5	0.93	0.81
6	0.95	0.96
7	0.98	0.95
8	0.99	0.67
9	0.93	0.83
10	0.98	0.89
11	0.93	0.90
12	0.99	0.97
13	0.98	0.46
14	0.99	0.69
15	0.99	0.99
16	0.94	0.97
17	0.97	0.98
18	0.91	0.96
19	0.95	0.97
20	0.95	0.98
21	0.94	0.96
22	0.93	0.97
23	0.96	0.88
24	0.79	0.95
25	0.91	0.95
26	0.88	0.93
27	0.98	0.98
28	0.99	0.99
Average	0.95	0.90

we take into consideration. As a result, the 60-seconds duration seems to not be able to provide sufficient information for the procedure to estimate the rates with more accuracy.

IV. CONCLUSIONS

The goal of this study was to investigate whether the radar sensor can accurately substitute PSG, especially in the case of respiratory rate and heartbeat estimation. The analysis was focused on constructing an innovative pipeline which takes into consideration the radar-based recordings, represented by a 2-dimensional matrix and results in the following clinical information:

1) the respiration and heart displacement signals,
2) the respiratory and the heart rate, as well as
3) the activity signal (activity of the human body).

Results prove that the presented simple and fast procedure for processing the radar-based data generates accurate respiration and heart displacement signals, that are highly correlated with the corresponding PSG signals, considered as the ground truth. Moreover, the procedure for extracting the activity signal, was shown to be effective, leading to an improved performance in extracting the aforementioned signals, as well as estimating the corresponding frequencies.

Our methodology was accurate for most of the patient cases that was tested on, highlighting that it is robust to different patients' characteristics and also to different sleep patterns. Overall, the methodology is simple and fast, and the data analysis does not require a large number of external parameters apart from the cut-off frequencies of the low-pass and high-pass filters utilized for the heart displacement signal extraction, as well as an appropriate threshold for the extraction of the activity signal. However, our methodology has to be further tested using complementary features which can provide more information about the detection of the OSA.

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