Detection of Movement Activity and Breathing Cycles on Bioradiolocation Signals

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***Abstract*— This paper presents an algorithm for the detection of movement activity periods and breathing cycles on bioradilocation signals for sleeping subjects. The algorithm was validated using data of 27 subjects without sleep-disordered breathing, who underwent a polysomnography study in a sleep laboratory. The results of manual scoring were used as ground truth. Accuracy, specificity and sensitivity for activity period detection are 90%. Accuracy of the peak detection is 97%, and sensitivity is 98%. Our results will be useful for the development of tools for unobtrusive health and sleep monitoring.**

***Index Terms*— Biomedical monitoring, remote monitoring, signal processing algorithms.**

I. Introduction

There are four most important vital signs: heart rate, arterial blood pressure, temperature, and respiratory rate (RR). The changes in RR might be a predictor of serious illnesses and mortality [1], [2]. Moreover, RR and respiratory rate variability (RRV) are important indicators of condition of the nervous, cardiovascular, excretory, and respiratory systems. So, they might be used for health monitoring.

Usually in clinic practice respiration is monitored by respiratory inductive plethysmography(RIP), impedance plethysmography, oro-nasal pressure transducer or thermistor. However, these methods is not applicable for long-term monitoring due to their discomfort. Meanwhile, long-term monitoring of breathing might be useful for health surveillance of seniors and sedentary patients.

Thus, of particular interest are non-contact methods, which can provide essential comfort for the long-term monitoring, even during sleep, and do not have hygienic risks. One of the most promising research directions in the field is bioradiolocation (BRL). BRL is a method for the remote detection and diagnostics of biological objects based on radar signal modulation by oscillatory movements of human limbs and organs [3].

The most papers devoted to breathing monitoring by BRL are focused on RR estimation in frequency domain and verified the technology in laboratory conditions. However, breathing cycle detection in time domain might provide more information about subject condition than just RR. E.g. it is necessary for accurate sleep stage classification based on the analysis of respiratory effort. Thus, Long et al. showed that features extracted based on RRV and respiratory amplitude are informative for the task of sleep structure detection [4].

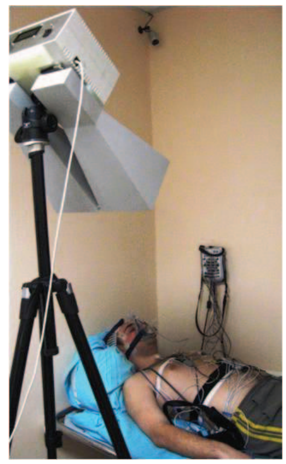

Fig. 1. Simultaneous bioradiolocation monitoring and polysomnography.

Besides, in our previous studies we used cycle-based features for sleep stage classification based on bioradilocation monitoring [5], [6]. However, the algorithm, which was used for breathing cycle detection on BRL signals, was not validated properly. We made use of RR estimated on RIP signal in time domain automatically as ground truth for the algorithm validation [7]. Moreover, it has been done on small dataset of 5 subjects.

The aim of the study is to develop and validate the algorithm for accurate detection of movement activity and breathing cycles on BRL signals for sleeping subjects.

II. Materials and Methods

A. Dataset

We analyzed the data of 27 subjects (Table I) who were initially referred to a sleep laboratory due to the suspected sleep disorders. All patients have undergone a PSG study (Embla N7000, Natus, USA), including registration of the respiratory movements by RIP. Neither Sleep-Disordered Breathing (SDB) or Periodic Limb Movement Disorder (PLMD) were confirmed in all cases. BRL monitoring was performed simultaneously with PSG (Fig. 1). We used a continuous-wave bioradar with a quadrature receiver and step-frequency modulation. It has 8 operating frequencies in the range between 3.6 and 4.0 GHz. The sampling frequency is 50 Hz. The radiated power of the bioradar is less than

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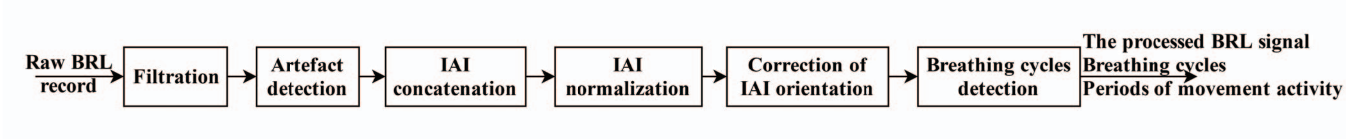

Fig. 2. Diagram of the proposed algorithm. IAI — Inter-Artefacts Intervals.

TABLE I. The Dataset Characteristics (N = 27)

Male:Female	10:17
Age (years)	44.22 ± 15.44 (22 - 67)
Body Mass Index (kg/m^2)	27.08 ± 5.91 (17.00 - 48.00)
Apnea Hypopnea Index (episodes/h.)	2.43 ± 1.43 (0.00 - 4.90)
Wakefulness (%)	22.66 ± 12.53(5.58 - 52.94)
Sleep (%)	77.34 ± 12.53 (47.06 - 94.41)

Mean ± SD (range)

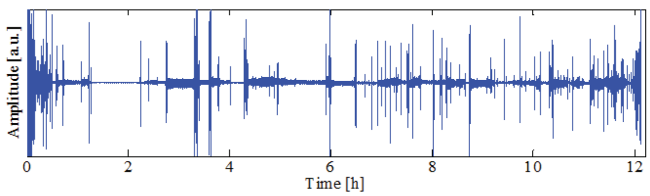

Fig. 3. A raw bioradiolocation signal.

3 mW and the maximum power density is equal to 1.36 $\mu W/cm^2$, which guarantees safety for patients during BRL monitoring.

B. Algorithm development

A raw BRL signal is presented on Fig. 3. Fig. 2 shows the diagram of the algorithm for detection of movement activity periods and breathing cycles on BRL signal. Let's consider each step of the algorithm in detail.

1) Filtration: The BRL signals were filtered with a five-order Butterworth band-pass filter with cut-off frequencies of 0.05 Hz and 0.6 Hz.

2) Artefact detection: BRL record has 2 type of artefacts — the first one (I) due to subject's movement activity, and the second one (II) due to absences of a subject in a bed. The BRL signal with the maximum mean energy were selected for the further artefact detection. The signal energy is defined as:

$$E = \int x^2(t)dt, \qquad (1)$$

where $x(t)$ — the BRL signal.

A moving window of N seconds with step of M seconds was used for the artefact detection. Criterion C was calculated for each window. An interval of the signal during the window was identified as an artefact by comparison C with a threshold value $T \times \overline{C}$, which was calculated based on mean value of $\overline{C}$ for the whole signal and coefficient T. The signal was also considered as an artefact during H seconds after the window if an artefact is detected. N, M and T were calculated separately for both artefact types with the aim to obtain better algorithm performance. If distance between artefacts is less than Z seconds, the signal during it was marked as an artefact.

Since it can be expected that an artefact period is differ by regularity, amplitude and spectral characteristics, the following parameters were considered as C:

- the signal energy (1);
- the signal entropy

$$E_n = -\sum_i x_i^2 log(x_i^2);$$

- the ratio of the spectral power in breathing frequency to the total spectral power BF/TP.

3) IAI concatenation: As described above, a BRL record consists of 16 parallel signals since the radar has I and Q quadratures for each from 8 operating frequencies. Due to changing subject's posture and radar-to-subject distance, quality of a BRL signal is altered. It is usually impossible to select the single signal suitable for the analysis during the whole night. So, after artefact detection, it is possible to split the record into Inter-Artefacts Intervals (IAI) and choose the best one from the 16 signals for each IAI. The signal with the maximum energy during IAI was chosen. The combined signal

$$S = \{IAI_1, AI_1, IAI_2, AI_2, ...IAI_n\}$$

was used in the further analysis, where AI — Artifact Interval. All AIs were replaced by zeros, and each IAI was replases by corresponding interval of the BRL signal, which has the maximum energy during the IAI.

4) IAI normalization: IAIs were Z-normalized due to the huge difference in their mean energy. Z-normalization is defined as

$$IAI = \frac{IAI - mean(IAI)}{SD(IAI)}.$$

5) Correction of IAI orientation: IAI might be inverted in consequence of phase shifting of signal reflected from the subject (Fig. 4). Normal signal orientation, as we will understand it here, is the orientation when points between inspiratory and expiratory phases (peaks) is directed upwards. In its turn, inverted signal is the orientation when peaks is directed downwards. Inspiratory phase of breathing cycle is longer than expiratory phase. So, it can be expected that breathing cycle on the signal would be wider if the signal inverted. The orientation of signal during IAI was determined as follows:

- breathing cycles was detected by the search of local maximums by means of function *findpeak* from Signal Processing Toolbox in Matlab;

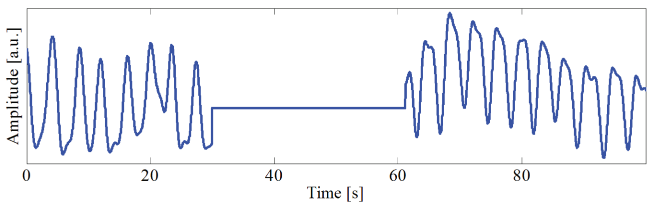

Fig. 4. The BRL signal. The signal oriented normally on the left side. The rejected artefact interval are in the center. The signal inverted on the right side.

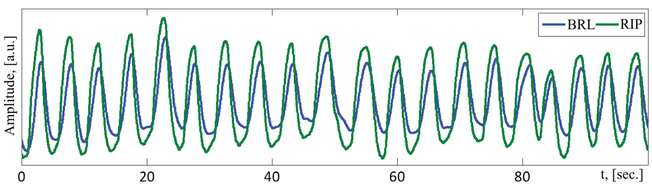

Fig. 5. Peak-to-peak synchronization of RIP and BRL signals.

- the mean width of the cycles was calculated at 0.7×peak-to-trough amplitude;
- signal were inverted and previous steps were repeated;
- if the mean width of the inverted signal were less then the IAI was flipped over.

6) Breathing cycles detection: Breathing cycles were detected by $findpeak$ function with the following arguments: the minimum peak-to-peak distance D_{min}, and the minimum peak height H_{min}.

C. Experiments

Firstly, the BRL signal was downsampled to 10 Hz since it is sample frequency of RIP signals. The BRL signal and the thorax RIP signal were manually peak-to-peak synchronized (Fig. 5). Artefact intervals and breathing cycles were manually scored. An expert detected breathing cycles by a joint visual analysis of synchronized BRL and RIP signals. The results of manual scoring were applied as ground truth. Algorithm parameters were chosen with aim to balance of specificity and sensitivity of algorithm detection and to maximize the accuracy of breathing cycle detection.

III. Results

Sensitivity, specificity and accuracy of 90% were achieved for artefact detection. The parameters of the artefact detection algorithm is presented in Table II.

Sensitivity of 98% and accuracy of 97% were achieved for breathing cycle detection during IAIs. The parameters of the algorithm is presented in Table III.

TABLE II. Parameters of the algorithm for artefact detection

	C	N,s.	M,s.	T	H,s.	Z,s.	SE,%	SP,%	AC,%
I	E	15	1	0.7	2.5	20	90	90	90
II		30	10	10^{-3}					

TABLE III. Parameters of the algorithm for breathing cycle detection

D_{min}, sec.	H_{min}	SEN,%	ACC,%
2.2	0	97%	98%

The results of automated artefact detection is shown on Fig. 6. The breathing cycle detection in IAI is shown on Fig. 7.

IV. Discussion

The sensitivity and specificity of artefact detection are 90% only. The reason is the parameters were calculated not for artefact detection, but for binary classification of each signal point as artefact or no artefact. Thus, the quality parameters is less 100% when artefact detected but its bounds differ from manual annotation.

The specificity was not calculated for breathing cycle detection since there are not true negative class here (non-breathing-cycle). The results of breathing cycle detection is competitive with other studies where the cycles were detected in time domain on a signal of respiratory movements. Thus, Navarro et al. [8] achieved sensitivity of 97% in breathing cycle detection on signals from neonatal intensive care unit. Daluwatte et al. [9] achieved sensitivity of 94% on respiration signals collected during hemorrhage in a conscious ovine model. However, these studies used methods other than BRL for the registration of respiratory movement.

To the best of our knowledge, this is the first study devoted to breathing peak detection on BRL signals recorded over whole night sleep. In similar study, Vasu et al. [10] tested their algorithm only on selected 10 minutes intervals. Our results will contribute to the development of tools for unobtrusive sleep and health monitoring

V. Acknowledgements

The authors thank Anna Komarova for her help with manual data annotation. This work was supported by the grant of Russian Foundation for Basic Research (Project No. 16-07-01096 A).

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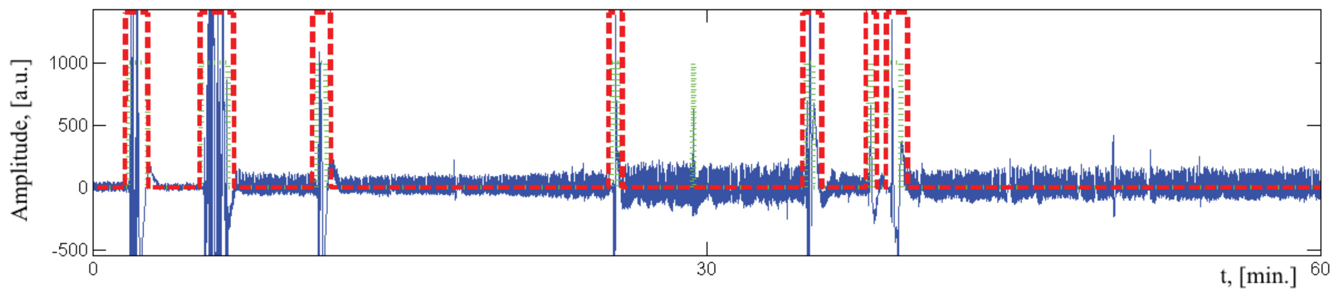

Fig. 6. Manual (dotted line) and automated (dashed line) detection of artefact intervals.

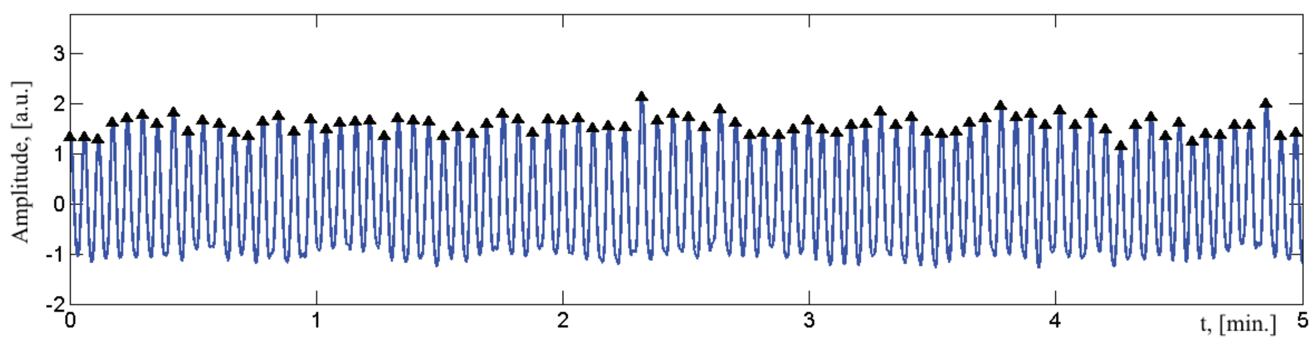

Fig. 7. Automated breathing cycle detection.

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