

Multichannel Bed Pressure Sensor for Sleep Monitoring

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Abstract

A bed sensor with multiple pressure sensitive non-contacting electrodes has been applied for unobtrusive monitoring during sleep. The novelty is in using multichannel algorithms to improve extraction of the heart rate and respiration signal from the recorded ballistocardiographic (BCG) data. Heart rate is extracted by using a sliding Fourier Transform, and after averaging the sensor channels in the frequency domain, the attained resolution enables to detect individual heart beat intervals (HBI) and estimate the heart rate variability (HRV). The respiration signal is calculated from the low pass filtered BCG signals by updating the linear coefficients with an adaptive principal component analysis (PCA) model. In comparison to the reference ECG R-R interval, the relative error of the HBI has been 0.40 % with 88 % measurement coverage for the healthy subjects during normal sleep. The error of the respiratory rate estimated from the bed sensor has been 1.5 % in comparison with the respiratory inductive plethysmogram (RIP). For the group of patients having different kinds of suspected sleep disorders, the measurement coverage varied a lot between subjects due to increased movement artifacts. In this case, some examples of detecting respiratory disorders with bed sensor signals are shown.

1. Introduction

A widely studied approach for an easy to use portable sleep monitoring system is based on electrocardiogram R-R interval (ECG RRI) measurement and the heart rate variability analysis [1]. In this paper, we will present sleep monitoring with a less obtrusive bed sensor, which is using non-contacting pressure electrodes to measure the ballistocardiographic (BCG) signal instead of ECG. Corresponding studies with different kind of bed sensors cover the range from the sleep research [2] to home based well-being applications [3]. In addition to heart rate, the bed sensors enable measurement of respiration signal and movement activity, which obviously improves sleep analysis and detection of sleep problems. Sleep

laboratories use many different methods like the respiratory inductive plethysmogram (RIP) or the airflow measurement for the detection of the respiration disorders, as well as a wrist actigraph, EMG electrodes or inclinometer sensors are often used for the movement activity monitoring.

Sleep disorders have high relevance as a co-morbidity of heart failure (HF). Sleep apnea occurs in 4 % of men and 2 % of women in the general population, between the ages of 30 to 60 years; but is much more common in HF patients: 40 % ... 50 % of those with chronic HF, and up to 80 % in acute HF [4].

1.1. Bed sensor

The dynamic pressure signal obtained with the bed sensor enables unobtrusive monitoring of several different physiological signals of the sleeping subject. Heart beat muscle movement and blood pulsation is found in the high frequency component of the BCG signal and respiratory movement is found at the lower frequency band with corner frequency of approximately 1 Hz. However, the frequency range of heart beat and respiration may overlap somewhat, because the respiration movement cycle is asymmetric, having shorter inspiration phase in comparison with the expiration phase. In addition, respiratory air flow may cause higher frequency vibration and snoring sounds, which might obscure detection of the weak heart beat signal. Body movements cause the strongest signal component for the bed sensor and occasionally may prevent detection of the heart beat and respiration, but at the same time, movement activity periods can be used to detect restless sleep, arousals and longer waking states. Analysis of the static pressure distribution over the whole mattress area would enable detection of the sleeping posture, and has been applied by commercial bed mattress manufacturers to optimize the comfort feeling. However, the dynamic pressure sensors have better sensitivity for the BCG signal detection in the sleep analysis. Several different sensor materials exist for pressure sensitive foils, like PVDF and Emfit [5].

2. Methods

We applied multichannel methods for the extraction of both heart rate and respiration signal from the bed sensor, although with different approach for each. A simple averaging over all the sensor channels would not provide the optimal result. The shape and timing of the heart beat signal varies a lot between different sensor channels, and we can improve the heart rate extraction by averaging the signal channels in the frequency domain, which is presented in the section 2.1. The respiration movement signals can have phase differences and even different movement direction, depending on the sensor locations below the subject. We applied principal component analysis (PCA) to compose the linear model giving maximum signal variance, and so forth improved the sensitivity for the extraction of the respiration signal, which is presented in the section 2.2. Both the heart rate and respiration are non-stationary and we had to use sliding time window algorithms. These methods are implemented also with DSP for on-board processing.

Data recordings with the bed sensor have been made in two sleep laboratories; one at the Finnish Institute of Occupational Health (FIOH, Helsinki, Finland) and one at the Sleep Centre of Tampere University Hospital (TaUH, Tampere, Finland). Both healthy subjects and patients with suspected sleep problems have been measured, and ethical permissions were obtained for all of these studies. The first bed sensor prototype included up to 160 measurement channels over the whole mattress area, using Emfit sensor material (Emfit Ltd., Vaajakoski, Finland). For the final recordings performed in TaUH, the bed sensor included eight PVDF sensor channels (acquired from Measurement Systems Inc.), placed into four rows and two columns and covering overall area of $0.7 \text{ m} \times 0.7 \text{ m}$. We did not find any significant difference in accuracy for the extraction of the heart rate and respiration signals between these different bed sensor assemblies.

Comparison of the heart beat interval has been done against the reference ECG R-R interval signal. The reference for the respiration signal has been the Respiratory Inductive Plethysmogram (RIP) belt on both thorax and abdomen.

2.1. Heart rate extraction with Cepstrum

We used Fourier transform to extract the heart beat interval from the channel averaged cepstrum, which is defined as the inverse Fourier transform of the logarithm of spectrum [6]. The spectrum for the BCG heart beat signal is composed of the peaks at the harmonic frequencies of the fundamental heart beat frequency. This periodicity in the spectrum is shown as a peak value in the cepstrum located at the corresponding HBI lag time.

In a previous publication [7], we calculated the cepstrum only for those time windows including presumably two consequent heart beats in BCG signal. Figure 1 shows BCG signal for a period of three heart beats including two HBI values to be estimated. The uppermost graph shows one measurement channel of the bed sensor. Fourier transform time window for the first HBI period is shown with blue color and the following period is shown with red color. The middle graph shows the logarithm of the spectrum and the lowermost graph shows the cepstrum when the both are averaged between all measurement channels. The first HBI result with blue color is 0.86 seconds and the following is 1.2 seconds.

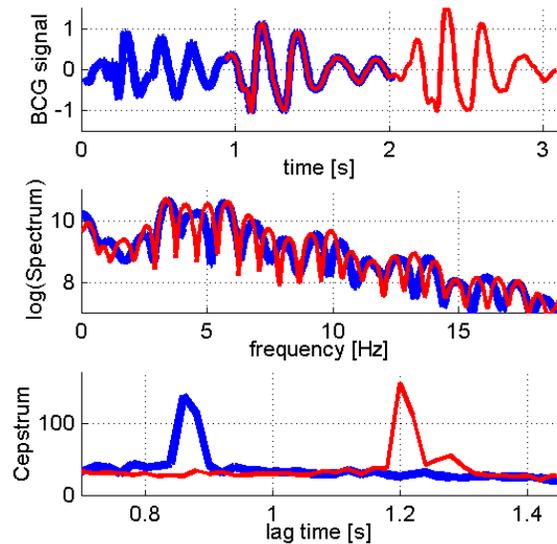


Figure 1. Two consequent heart beat interval periods and corresponding spectra and ceptra.

In our DSP algorithm we use a sliding Discrete Fourier Transform (DFT) to update the cepstra at 0.1 seconds time intervals. The DFT is updated with sliding data window by adding the new value and subtracting the old value from the previous DFT result for each frequency bin, as presented by Keith Larson from Texas Instruments [8]. The final HBI values are selected from the time-cepstra maximum values.

When we are extracting heart rate from the BCG signal, the optimal data window length contains exactly two heart beat pulses. Or, other way around; to compose the cepstrum at some lag time value, we should use about twice longer data window length. In our method, we calculate a multitude of sliding DFT blocks with several different data window lengths, and so forth we can assume that the optimal result for cepstrum at the lag time τ can be achieved from the DFT using a data window length of $N = 2\tau$. We can minimize processing by taking the inverse DFT for the cepstrum only for a specific frequency band of each DFT block.

2.2. Respiration extraction with PCA

During relaxed sleep the main source for the middle body movements is respiration. We estimated respiration movements from the first principal component score of PCA model applied on the low-pass filtered bed sensor signals. From all possible linear projections for dataset x , the first principal component score will give the signal with maximum variance [9], and thus shall improve sensitivity for the extraction of the respiration. In addition, the PCA model loads coefficients show the distribution of signal variance over the sensor mattress, and could be used to estimate e.g. the sleeping position.

The measurement properties of the respiration signal are approximately stationary while the sleeping position is not changed. Therefore, we could use the same PCA model during quite long periods, but however a new model might be needed whenever body movements appear, and so forth we decided to update the PCA model with an arbitrary choice of one minute long epochs. Any additional body movements during each epoch, shown as strong variation in the signal, would cause poor quality for the modeling. Therefore, we check the quality of each model by testing the regularity of the resulted scores signal over the epoch length, and in case of artifacts, remove the short movement period from the epoch and run the model again. During the longer movement periods the PCA model shall not be updated until the new epoch contains enough relevant data. By comparing the model coefficients between consequent time intervals we can get also information about any changes in the sleeping position.

The bed sensor measures the dynamic force caused by respiration movements which can be converted to estimate the respiration volume by integrating the output signal. The reference respiratory belt measurement RIP detects respiration volume more directly, as a variation in the cross-section area of the body. Because the PCA model is affected by the variance of the signal but not by the polarity, we had to track for the correct respiration movement direction by the assumption that the inhalation shows a sharp peak in the signal in comparison with the longer exhalation valley. In this way, the PCA model was automatically biased in the correct polarity for 90 % of time epochs in our test data, and for the rest of the epochs, we could easily correct the polarity by comparing the model load coefficients with the preceding epochs.

3. Results

The performance of the bed sensor during normal sleep has been studied already in [7] based on measurements at FIOH. Averaged over six healthy subjects, the percentage error of the heart beat interval was 0.40 % in comparison with the reference ECG R-R interval, and the error of the

respiration cycle in reference with the RIP belt on thorax position was 1.5 %. The sleep time with sufficient signal quality was automatically selected, and the corresponding measurement coverage was in average about 90 % but varied strongly between subjects. Low signal quality was relating to the movement artifacts and also on arrhythmia episodes in case of the heart rate measurement.

A group of 28 patients, age between 48-63 years, including 13 females and 15 males, and having different kind of suspected sleep problems, were measured at TaUH. The measurement coverage was only 80 % in the average, and the average error of the HBI was 1.8 %. By leaving out the two most difficult subjects, having both strong arrhythmia and movement artifacts, and by averaging over the remaining 26 patients, the coverage was 86 % and the HBI error improved to 0.9 %, which would be more sufficient for the further sleep modeling.

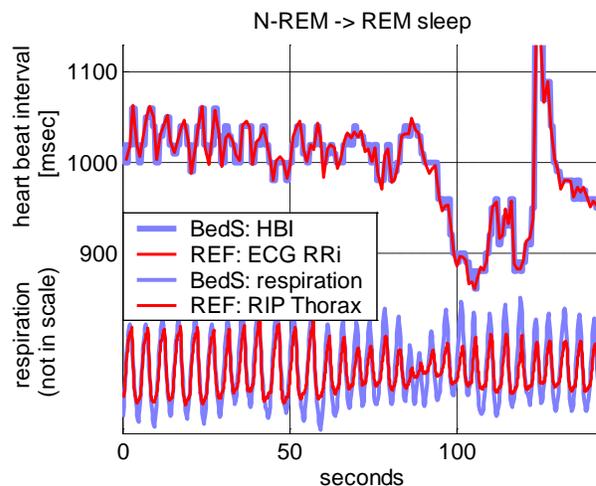


Figure 2. Heart rate and respiration measurements during switching from non-REM to REM sleep at $t=90$ seconds.

Bed sensor sleep analysis is based on the heart rate variability (HRV) during sleep, and Figure 2 shows a typical example of the heart rate fluctuation during switching from non-REM to REM sleep. During the non-REM sleep in the first 90 seconds of the Figure 2, the heart rate varies in synchronization with the respiration cycle. Relative amplitude of this variation is only about 5 % and a good accuracy of the heart rate extraction is needed to detect this. After the 90 seconds time stamp, the subject switch to the REM sleep and the heart rate starts to fluctuate stronger but with low frequency, and the respiration induced faster variation disappears. The blue colored bed sensor HBI signal match well with the reference ECG RRI and in the lower part of the graph the bed sensor respiration signal is shown together with the reference respiratory belt signal.

Figure 3 shows cardiorespiratory signals during obstructive apnea with manual annotation. The first graph

shows the reference RIP signals (belt on thorax with red color and on abdomen with blue color), and the second graph shows the bed sensor respiration signal together with the smoothed amplitude curve. The third graph shows the reference SpO₂ measurement which has been used for the desaturation annotation. The lowermost graph shows the heart rate measurements, for the bed sensor HBI with blue ‘o’ marks and the reference ECG RRI with red curve.

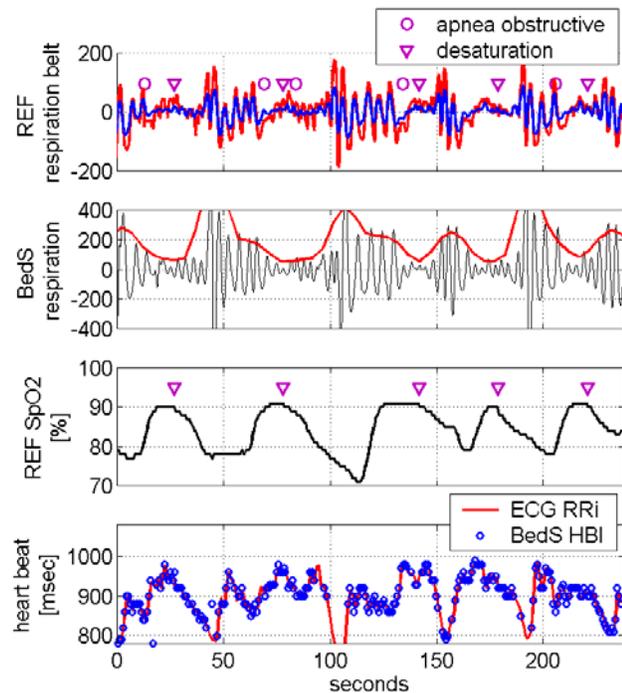


Figure 3. Bed sensor and reference signals during apnea period.

The bed sensor respiration signal follows well with the respiration belt signals, showing the large variation in the amplitude during the periodical breathing and apnea periods. The resulted blood oxygen variation could be predicted based on the respiration effort. Also, the heart rate is varying in the similar manner, although the bed sensor cannot detect the heart beat interval during the strongest movement artifacts.

4. Conclusions

A bed sensor with multichannel non-contacting pressure electrodes have been tested for sleep monitoring. The heart rate signal is extracted from the channel averaged Fourier transform and cepstrum. The respiration signal is calculated by adapting the linear channel coefficients with a sliding PCA model. In the both cases of heart rate and respiration signal, the simple averaging over the BCG signal channels would not provide as good accuracy. To prove the presumed benefit of our multi-

channel approach, it would be interesting to have a comparison with some commercially available bed sensor systems which are usually based on one large sensor foil.

The extracted heart rate, respiration and movement activity signals can be applied for further sleep analysis. The accuracy of the heart rate measurement is critical for the HRV based sleep modeling, because the respiratory induced HF-HRV component can be weak especially for the elderly people. The robustness of the respiration signal measurement shall also be critical for analysis of the respiratory sleep disorders, mainly because of the increased movement artifacts during apnea.

Acknowledgements

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References

- [1] Redmond SJ, Heneghan C. Cardiorespiratory-Based Sleep Staging in Subjects With Obstructive Sleep Apnea. *IEEE TBME* 2006; 53.
- [2] Alihanka J, Vaahtoranta K, Saarikivi I. A new method for long-term monitoring of the ballistocardiogram, heart rate, and respiration. *Am J Physiol* 1993; 240:289-297.
- [3] Paalasmaa J, Waris M, Toivonen H, Leppäkorpi L, Partinen M. Unobtrusive Online Monitoring of Sleep at Home. Submitted for 34th IEEE EMBC, August 28 - September 1, 2012, San Diego, USA
- [4] Rao A, Gray D. Impact of heart failure on quality of sleep. *Postgrad Med J* 2005;81:99-102.
- [5] Lekkala J, Tuppurainen J, Paajanen M. Material and operational properties of large area membrane type sensors for smart environments. XVII IMEKO World Congress, June 22-27, 2003, Dubrovnik, Croatia.
- [6] Oppenheim AV, and Schafer RW. Discrete-time signal processing. Prentice-Hall International, Inc. 1998: 768-825.
- [7] Kortelainen J, Virkkala J. FFT averaging of multichannel BCG signals from bed mattress sensor to improve estimation of heart beat interval. 29th IEEE EMBC, August 23-26, 2007, Lyon, France
- [8] Texas Instruments: Digital Signal Processing Solutions, User's guide, TMS320C3x general-purpose applications, SPRU194, January 1998, chapter 6.8.
- [9] Morrison DF. Multivariate Statistical Methods. second edition, McGraw-Hill International Editions, 1978, 415 pages, pages 266-288.

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