Heart Pulse Demodulation from Emfit Mattress Sensor Using Spectral and Source Separation Techniques

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Abstract

***Introduction**: Unobtrusive bed mattress sensors such us the electromechanical film transducer (Emfit) record the heart's activity, breathing, and body movements with clinical applications ranging from epilepsy to sleep disorders. The mechanical activity of the heart recorded using these sensors is known as ballistocardiogram (BCG). However, BCG shape changes on position, patient, and mattress. **Aim**: In this study, we isolate a position-independent heart signal designed to retrieve the heart activity recorded using an Emfit mattress sensor using extended polysomnography (PSG) recordings as a reference. **Methods**: We used spectral and source separation techniques to infer the heart's Emfit Pulse (EP). We validated the resulting signal using representative 10-minute normal breathing epochs extracted from the PSG from 33 subjects and by estimating the heart rate (HR) from the EP and compared it against the electrocardiogram (ECG) using non-overlapping one-minute windows. **Results:** Results show a signal similar in shape to a photoplethysmogram (PPG) with different timings in relation to the ECG's R-peak. We found good agreement between HR with a mean absolute error (MAE) of 2.4 beats per minute (bpm) with standard deviation of 4.6bpm. **Conclusions:** A position independent heart pulse signal from the Emfit mattress sensor was obtained in a range of subjects and validated by means of HR analysis.*

1. Introduction

Unobtrusive mattress sensors such as the electromechanical film transducer (Emfit) offer great promise in measuring physiological signals from the heart —also known as ballistocardiography (BCG) and breathing. Mattress sensors have been used to monitor various conditions and physiological parameters such as breathing and heart activity [1]–[3]. Additionally, BCG has been advocated for its potential in cardiovascular monitoring [4].

Similar waveforms have been recorded using accelerometer-like sensors such as seismocardiography (SCG) [5] and gyrocardiography (GCG) [6], [7]. A recent review has studied the applications of BCG and SCG [8]. For instance, SCG [5] and GCG [9] present similar waveforms to the BCG recorded with the Emfit mattress sensor. Tadi et al. use the Doppler and ECG to reference the estimated hemodynamic variables using GCG [7]. Visual inspection of the GCG appears the same as the BCG in our experiments.

Heart activity assessment using the Emfit mattress has been previously studied and compared with accelerometers [10]. Emfit mattress has been evaluated to estimate heart rate (HR) and heart rate variability (HRV) [1], [11]. Also, recent research has benchmarked some of these algorithms [12], [13].

In practice, the BCG shapes change with the body position with respect to the mattress [14], mattress type, and sensor size and position. As a result, the I-J-K waves do not always appear visible as they are described in the literature. It also depends on sensor size, mattress type, and subject's body (weight and BMI). Hence, being unable to use similar techniques to estimate pulse transit times and count heartbeats using time-based methods. Many of these reset of position. Paalasma *et* al. use clustering methods to detect individual heartbeats and reset the algorithm by position [15]. Similarly, Brüser *et* al. re-train the peak detector after movement detection [1].

Source separation techniques based on non-negative matrix factorization have been used in single-channel source separation [16] and recovery of cardiac and respiratory sounds [17]. In this study, we use a source separation method based on the amplitude spectrogram (AS) to isolate a signal and estimate heart rate (HR) [18].

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2. Subjects and Signals

A total of 33 patients suspected of sleep-disordered breathing (SDB) took part in the study. Three recordings were omitted due to low-quality signal or electrical artefacts in the Emfit signal. In total, 24 men and six women between 25–60 years old with body mass index (BMI) varying from 22–54 kg m^2. Patients were referred to the Sleep Laboratory of Tampere University Hospital. Informed consent was obtained before recordings. The regional Ethics Committee of Tampere University Hospital area approved the study.

A full extended Polysomnography (PSG) was recorded. The PSG included a standard EEG montage, submental and bilateral anterior tibialis electromyograms (EMG), electrooculography (EOG), body position, ECG, inductive thorax and abdominal belts, piezosnore-sensor and a trachea microphone were placed on the lateral side of the neck and over the suprasternal notch of the trachea, respectively. Pulse wave and SpO_2 were recorded with a pulse oximeter (8000AA, Nonin Medical, Plymouth, MN, USA). The Emfit mattress sensor with dimensions 32 cm × 63 cm × 0.4 cm was positioned under the thoracic area under the bed mattress. The sampling rate for Emfit and ECG was set to 200 Hz for the Emfit sensor. Signals were recorded with the Embla N7000 and evaluated using sleep-staging software called Somnologica† (Flaga, Iceland).

Sleep recordings were scored by the standard scoring method by a clinical neurophysiologist (Iber 2007). The apnea-hypopnea index (AHI) was estimated as the number of obstructive apnoea and hypopnea events per hour of sleep (Berry et al. 2012). Arousals were scored according to the criteria of the American Sleep Disorders Association (ASDA 1992).

Representative normal breathing (NB) epochs were selected for a maximum duration of 10 minutes per patient by an experienced neurophysiologist. NB periods did not contain snoring, apneas or hypopneas. NB epochs were divided into 60s non-overlapping epochs for further analysis.

3. Methods

*Signal Pre-processing***:** The Emfit signal was filtered with a high-pass finite impulse response (FIR) filter designed with a Hamming window, with a cut-out frequency 6Hz and a 1Hz transition band.

Emfit pulse (EP) estimation: The procedure is depicted in Figure 1. The Emfit signal was filtered with a low pass filter (LPF) at 40 Hz and decimated by a factor of 5. The resulting signal was filtered using a modified discrete cosine transform (MDCT) 12-unit bank filter followed by halfwave rectification and a low pass filter. Next, the short-time Fourier transform (STFT) of each resulting signal is estimated. Eight of the 12 resulting spectrograms were selected to calculate the non-negative real-valued tensor using Kim and Park's Matlab implementation [19]. A schema of the signal isolation is shown in Figure 1. Similar schemas have been used in monaural sound source separation [20]. The resulting signal was then up-sampled to 200Hz as in the original Emfit signal to compare with other signals from the dataset and to increase the accuracy.

*HR estimation***:** HR is estimated using the resulting EP. This method has multiple parameters that can be tuned to produce a sinusoidal-like signal suitable for spectral and time peak detection methods. The heart rate (HR) is estimated using spectral estimation in the following manner: The separated EP is segmented into 1-minute epochs. An initial HR estimate is calculated at minute-to-minute values. This *naïve* method is a method designed to be a bit more robust to temporary low SNR due to artefacts. The 1-minute epochs are divided into 10-second windows with a 50% overlap. This window is chosen for simplicity: several windows have been used in literature, from 8s to one minute [1], [11], [13]. The spectrum of each of the windows is estimated using Lomb-Scargle using an oversampling factor of 4.

Subsequently, the peaks between [0.6–1.7] Hz are estimated; these correspond to [42–102] bpm. The maximum peak is compared with the lower 90^{th} percentile of the peaks. Then, if its height is two times the standard deviation of their distribution, it is marked as the prominent peak. If there are prominent peaks in the 1-minute epoch, the heart rate is estimated using the median of the 90^{th} percentile of the prominent peaks. If no prominent peaks exist, the median of the 90^{th} percentile of the peaks is used.

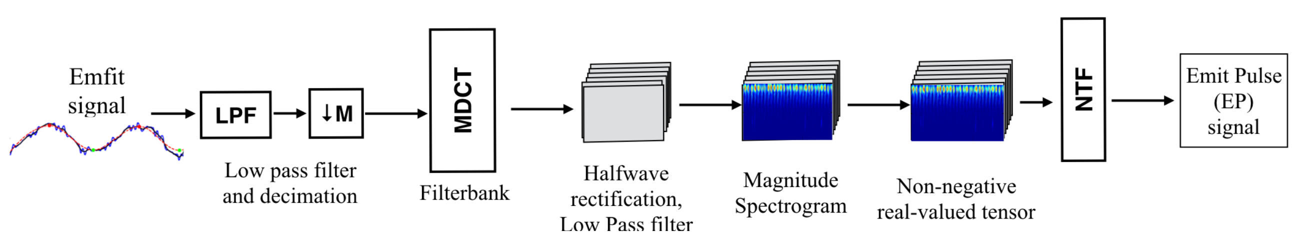

Figure 1. Schema of the source separation signal. NTF: Non-negative tensor factorization. MDCT: modified discrete cosine transform. LPF: low pass filter.

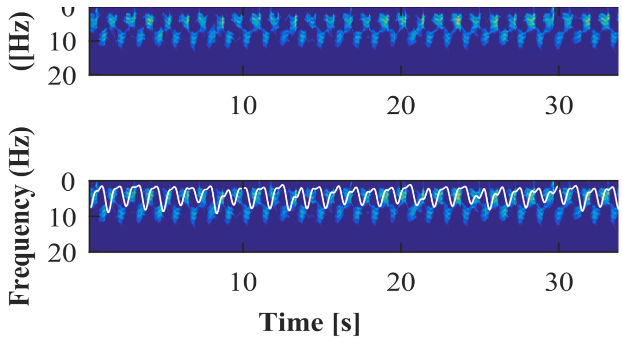

Figure 2. Emfit spectrogram and resulting Emfit Pulse (in white)

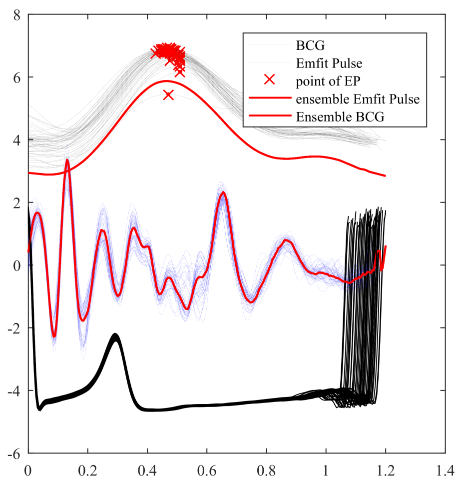

Figure 3. Overlap of the time signal ballistocardiogram (BCG), the isolated emfit signal / Emfit Pulse (EP), and electrocardiogram (ECG).

4. Analysis

HR performance evaluation: HR performance evaluation was evaluated using the mean absolute error (MAE) (of the HR for each minute epoch:

$$MAE = \frac{1}{N-1} \cdot \sum_{i=1}^{N} HR(i) \qquad (0.1)$$

where i is the index of the minute-to-minute epoch. Additionally, the standard deviation (SD) of the mean errors across all patients. Inter-subject variability is measured using the mean of the MAE, and the SD of the MAEs. The SD provides insight into the robustness against the inter-patient variability.

5. Results

Figure 2 shows the spectrogram of one of the subjects, which shows the systolic and diastolic cardiac cycles. Overlapping the spectrogram, the ECG, and EP was depicted.

Figure 3 shows an overlap of the BCG with the EP, BCG, and ECG. The variability of the ECG can be shown in the latter part of the ECG signal. The peak of the signal appears to be after the P-wave.

Quantitative results are shown in Table I. Two of the subjects—marked with an asterisk—showed irregular ECG patterns causing the ECG-HR algorithm to fail; hence the approximated HR epoch average using Somnologica software (Embla, Iceland) was estimated for those two patients. Average MAE and deviation were MAE 2.4 ± 4.6bpm.

Table I. HR estimation results expressed in mean absolute error (MAE).

SID	**P**	**MAE**	**SD**	**SID**	**P**	**MAE**	**SD**
1	S	8.71	19.98	16	R	0.89	0.9
2	L	0.68	0.5	17	L	1.44	0.96
3	L	0.29	0.33	18(*)	S	2.5	0
4	R	0.58	0.38	19	L	1.3	0.45
5	R	0.46	0.64	20	S	1.17	1.16
6	L	1.15	1.02	21	R	0.65	0.24
7	R	0.65	0.24	22	L	0.4	0.44
8	R	0.65	0.48	23	R	1.55	1.4
9	R	0.35	0.31	24	S	22.9	2.1
10	L	1.2	1.13	25	R	0.8	0.91
11	L	1.75	1.19	26	L	11.75	16.11
12	S	0.63	0.43	27	R	0.7	0.35
13	L	0.95	0.73	28	P	3.67	2.78
14	S	1.76	2.78	29(*)	S	1.27	1.12
15	R	0.68	0.55	30	R	1.01	1
				Total		2.42 ± 4.58	

Note: MAE: mean absolute error; SID: Subject ID; P: position. (*) Subjects whose HR reference is an average from Somnologica software.

6. Discussion and Conclusion

We presented a method to demodulate a heart pulse using amplitude. The resulting signal, the Emfit pulse, appears in every heartbeat and has a similar shape. On the spectrogram, systolic and diastolic times are clearly visible.

The accuracy of the results is similar to some studies that report errors between 3.8–5 bpm [13]. Brüser reports much better results [1].

Most methods implementation use segmentation methods to discard epochs, reducing the coverage, in search of noise free epochs. The more holistic approach by Pröll [13] reports errors in 100% coverage. Nevertheless, when the SNR is low, usually due to body movements of any kind, the heartbeat is unlikely to be obtained, making näive or statistical methods —such as reporting previous HR the same or interpolating between clean epochs—suitable. However, they would not be factual but rather guesses.

In this study, we use clean breathing epochs for the analysis to validate and present the method. We obtain a signal that is similar to the PPG which will potentially ease existing approaches.

Finally, our restuls on the spectrograms, we believe that deeper analysis of spectral signal would be useful for cardiovascular evaluation in steady position and points to future research directions.

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