



Unsupervised Heart Rate Variability Estimation from Ballistocardiograms

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Abstract. We propose and evaluate an unsupervised method for the estimation of heart rate variability (HRV) indices from ballistocardiograms (BCGs) recorded by a bed-mounted, electromechanical film (EMFi) sensor during sleep. After estimating the beat-to-beat intervals from the BCGs, short-term time- and frequency-domain HRV indices are computed and compared to an ECG reference. We evaluated signals recorded overnight from 8 subjects (approx. 212.000 heart beats). Our results show a good correlation (> 0.9) between BCG- and ECG-derived HRV indices and suggest that unsupervised long-term HRV monitoring using BCGs is indeed feasible.

Keywords: ballistocardiography, bed sensor, HRV, unobtrusive monitoring

1. Introduction

Heart rate variability (HRV) [Task Force, 1996] is considered to be an important non-invasive tool to assess cardiac autonomic activity [Akselrod et al., 1981]. HRV is commonly computed from beat-to-beat (RR) interval series derived from electrocardiograms (ECGs) [Task Force, 1996]. High-quality ECG recordings provide the best basis for HRV analysis. However, novel sensor modalities, with the common goal of allowing unobtrusive long-term monitoring of vital signs, have recently gained increased interest [Lim et al., 2011].

One class of these sensors records cardiac vibrations on the body surface by integrating highly sensitive mechanical sensors into beds [Alihanka et al., 1981; Brüser et al., 2011; Kortelainen et al., 2010]. The cardiac components of these sensors' signals are commonly referred to as ballistocardiogram (BCG). We have previously reported on the challenges of a reliable and automatic estimation of beat-to-beat intervals from long-term BCG recordings [Brüser et al., 2011]. Some studies implicitly used BCG-derived HRV indices, for instance, for sleep staging [Kortelainen et al., 2010]. In [Shin et al., 2011], the authors analyze HRV derived from BCGs recorded by a weighing scale. However, in their study they manually annotated each heart beat in the BCG signal. This approach, however, does not address the effect of automatic beat-to-beat interval estimation on the derived HRV, which is of course an important factor in assessing the reliability of automatic long-term BCG HRV monitoring. A very recent study compares HRV indices which were automatically derived from an under-pillow pressure sensor with pulse rate variability indices obtained from a photoplethysmogram [Zhu et al., 2012].

In this work, we analyze overnight BCG and ECG recordings of 8 subjects (over 212.000 heart beats). BCG signals were recorded using an EMFi foil sensor on top of the regular mattress. For both signals, short-term time-domain (SDNN, SDSD, RMSSD, pNN50) and frequency-domain (LF, HF, LF/HF, TF) HRV indices were estimated and compared. The entire processing of the BCG signal, from beat-to-beat interval estimation to HRV computation, was performed completely unsupervised.

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2. Methods

2.1. Data Acquisition and Beat-to-beat Interval Estimation

We performed the following analysis on the data recorded overnight from 8 healthy volunteers. The subjects (7 female, 1 male, age: 32.8 ± 13.4 years, BMI: 25.9 ± 3.7 kg/m 2) gave their informed written consent and each slept at the Boston Sleep Center, Boston, MA, USA, for one night. Throughout the night, a single electromechanical-film (EMFi) sensor (Emfit Ltd, Vaajakoski, Finland; dimensions: 30 cm x 60 cm, thickness < 1 mm), which was mounted on the underside of a thin foam overlay located on top of the regular mattress of the bed, was used to record cardiac vibrations (ballistocardiogram / BCG) of the subject lying in bed. In addition to the bed sensors, a full polysomnography was performed of which the lead II ECG signals were used as reference for the following HRV analysis.

The location of R peaks in the reference ECG were computed using the Hamilton-Tompkins algorithm [Hamilton and Tompkins, 1986]. RR interval series were derived by differencing successive R peak occurrence times. In the case of BCG signals, the automatic detection of heart beat locations is less straight-forward due to the varying morphology of individual heart beats and the increased susceptibility to motion artifacts [Brüser et al., 2011]. Hence, we used the continuous local interval estimation (CLIE) algorithm to automatically estimate the beat-to-beat intervals and heart beat locations from the BCG signals. This method does not rely on fiducial points to detect heart beats. Instead, beat-to-beat intervals are estimated by three different methods, such as the signal's autocorrelation, on a short adaptive analysis window (ideally containing two beats). These individual estimates are then combined using a Bayesian approach. The analysis window is shifted across the signal using increments that are short with respect to typical interval lengths, thus causing each interval to appear in multiple consecutive analysis windows. This property is also exploited by the algorithm to improve the robustness of the estimates.

2.2. HRV Indices

Table 1 shows the short-term HRV indices defined by [Task Force, 1996] which we chose to analyze in this study. According to the recommendations in [Task Force, 1996], 5-minute windows were used for computing the indices. The ECG and BCG signals of each overnight recording were split into synchronous 5-minute windows with 80% overlap.

Table 1. Time- and frequency-domain HRV indices.

Domain	Index	Description
Time	SDNN	Standard deviation of beat-to-beat intervals
	SDSD	Standard deviation of the differences between successive intervals
	RMSSD	Root mean square of the difference between successive intervals
	pNN50	Percentage of successive intervals which differ by more than 50 ms
Frequency	LF	Power in frequency band 0.04 - 0.15 Hz
	HF	Power in frequency band 0.15 - 0.4 Hz
	LF/HF	Ratio of LF to HF
	TF	Total power

The power spectral densities (PSDs) used for computing the frequency-domain HRV indices were estimated using the Lomb-Scargle (LS) periodogram [Lomb, 1976]. The LS periodogram is a suitable method for analyzing unevenly sampled signals, such as beat-to-beat interval data [Laguna et al., 1998], as no interpolation or resampling of the original signal is necessary. This property is especially advantageous in the case of the BCG, because BCG-derived beat-to-beat intervals can regularly contain missing or unreliable segments due to motion artifacts. These segments can easily be omitted when estimating the PSD using the LS periodogram.

2.3. Evaluation

Prior to computing HRV indices from the RR and BCG interval series, artifacts and outliers have to be excluded. Accordingly, BCG beat-to-beat intervals which were flagged as artifacts by the CLIE algorithm are automatically removed from the HRV computations. Outliers, in the RR interval series and the BCG interval series, can either be caused by arrhythmic heart beats or faulty interval estimates.

They were detected and removed from both by using a sliding window covering 41 intervals. Whenever the central interval differed by more than 20% from the mean of the remaining intervals in the window, it was excluded from the further analysis. After removing artifacts and outliers from the beat-to-beat interval series, the HRV indices shown in Table 1 were computed from both, the ECG and BCG intervals, for each 5-minute window. For each subject and HRV index pair, the correlation between the ECG- and BCG-derived HRV values was computed. First and foremost, we wanted to determine whether BCG- and ECG-derived HRV indices follow the same trends throughout the night, i.e. whether both curves have similar relative shapes. To this end, we chose the correlation coefficient over other measures of goodness, since it can account for offsets or scaling differences between the HRV curves.

Due to subjects' movements in bed, the BCG signal can be distorted for extended periods of time. This can lead to 5-minute analysis windows in which a significant portion of beat-to-beat intervals had to be excluded due to motion artifacts. In these cases, some HRV indices can not be properly estimated. We therefore introduce an artifact percentage threshold to our analysis. Each 5-minute epoch for which the percentage of excluded BCG intervals exceeds this threshold is excluded from the computation of the correlation coefficient. To assess the effectiveness of the artifact threshold in excluding potentially unreliable HRV estimates, we have varied the threshold from 0% to 99% in 0.5% increments and evaluated the effect on the mean correlation and the mean coverage, i.e. the percentage of 5-minute epochs which were not excluded by the threshold.

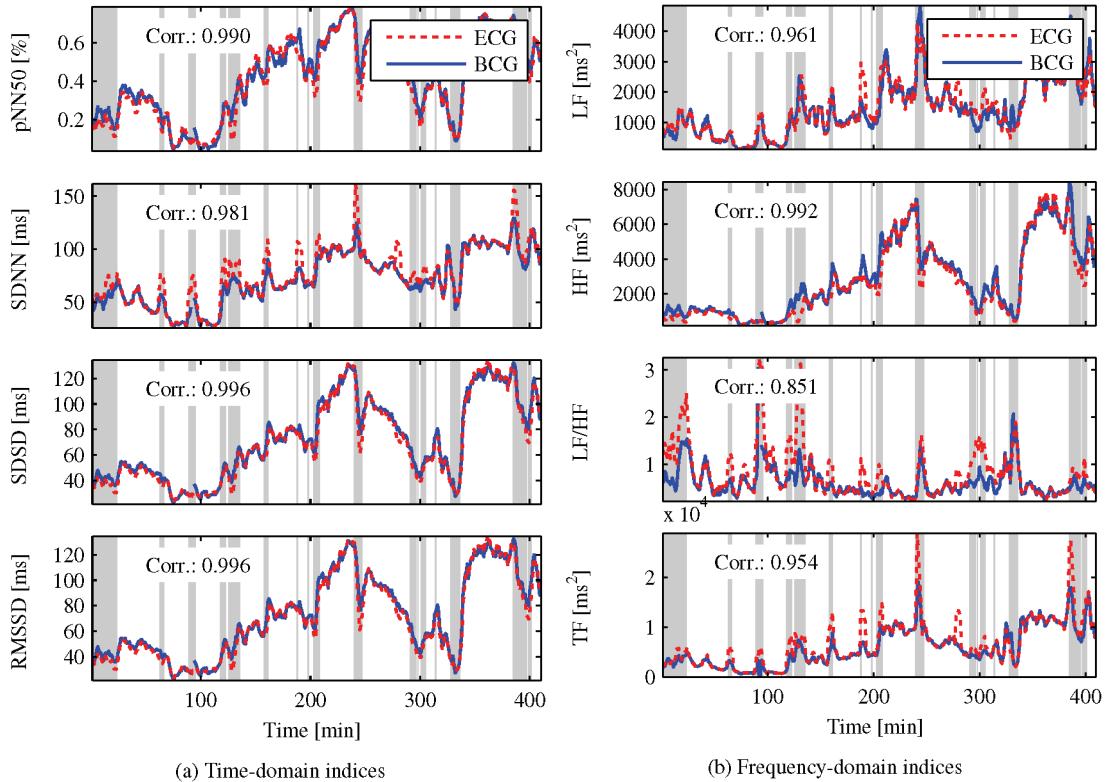


Figure 1. Time- and frequency-domain HRV indices derived from the BCG signal of Subject 4 compared to those derived from the ECG RR series. Shaded intervals were excluded due to BCG artifact corruption exceeding 10% of the respective 5 min. analysis window. Correlation coefficients were calculated for the remaining (white) regions.

3. Results

Figure 1 shows the ECG- and BCG-derived HRV indices of Subject 4 throughout the course of the night. In this example, the artifact threshold was set to 10%. The shaded intervals in Fig. 1 highlight the segments which were excluded due to exceeding this threshold. All indices, except LF/HF, show a good correlation between the ECG- and BCG-derived HRV.

The correlation coefficients and the coverage of all subjects are given in Table 2. These values were also computed using an artifact threshold of 10%. The table also gives the relative errors between the underlying BCG beat-to-beat intervals and the ECG RR intervals for each subject.

Table 2. Correlation coefficients for each subject and HRV index with an artifact threshold of 10% as well as the relative estimation error of the underlying BCG beat-to-beat interval series.

	S01	S02	S03	S04	S05	S06	S07	S08
<i>RR Error</i>	0.47%	0.72%	0.64%	0.57%	0.69%	1.01%	1.04%	1.06%
<i>LF</i>	0.906	0.641	0.946	0.961	0.901	0.948	0.946	0.931
<i>HF</i>	0.940	0.965	0.844	0.992	0.920	0.956	0.970	0.944
<i>LF/HF</i>	0.921	0.588	0.599	0.851	0.845	0.891	0.922	0.867
<i>TF</i>	0.918	0.677	0.854	0.954	0.928	0.802	0.922	0.840
<i>pNN50</i>	0.979	0.942	0.829	0.990	0.885	0.931	0.982	0.963
<i>SDNN</i>	0.949	0.814	0.948	0.981	0.934	0.893	0.961	0.908
<i>SDSD</i>	0.920	0.968	0.869	0.996	0.909	0.973	0.986	0.957
<i>RMSSD</i>	0.920	0.968	0.869	0.996	0.909	0.973	0.986	0.957
<i>Coverage</i>	69.2%	69.4%	66.4%	74.1%	95.5%	85.9%	73.1%	80.9%

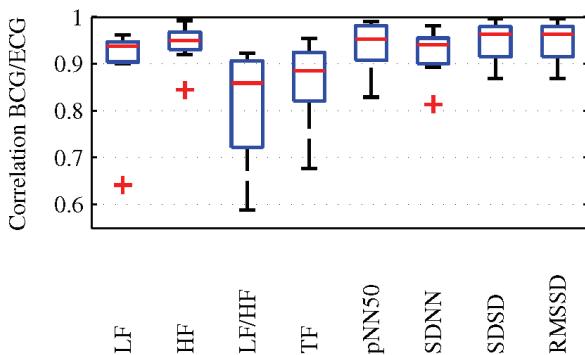
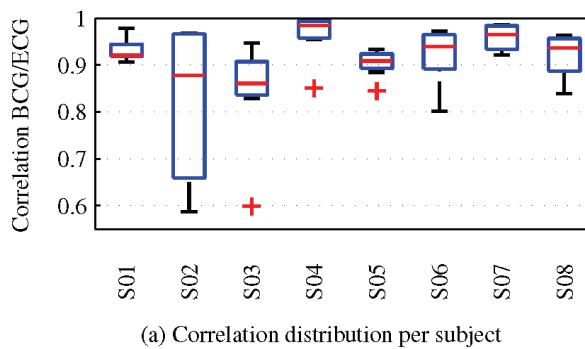


Figure 2. Distribution of the correlation among BCG- and ECG-derived HRV indices per (a) subject and (b) index. The correlations were computed using an artifact threshold of 10%.

Figure 2 shows boxplots of the correlation distribution for (a) each subject and (b) each HRV index. The latter clearly shows that LF/HF and TF achieve the lowest correlations among all indices. In the case of LF/HF, this is to be expected since errors in the estimation of LF and HF propagate to the computation of LF/HF and can even be amplified. For instance, a 10% overestimation and underestimation of LF and HF, respectively, leads to a 22% error in the values of LF/HF. For the other indices, we can report mean correlation of 0.933. As shown in Fig. 2a, there also exists an inter-subject variability in the correlation coefficients. Subjects 2 and 3, in particular, show some outliers well below a correlation of 0.8.

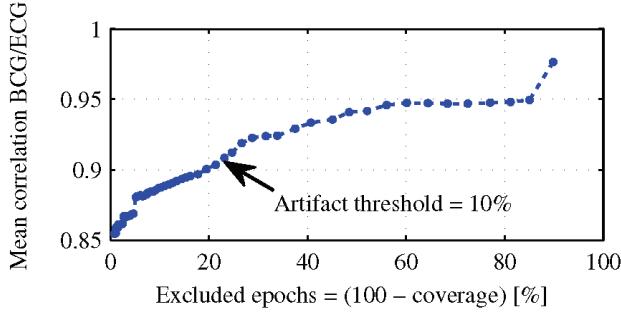


Figure 3. Mean correlation over all subjects and HRV indices versus the percentage of excluded epochs under varying artifact thresholds.

Figure 3 shows the effect of various artifact thresholds on the mean correlation and coverage, which were computed over all subject and HRV indices. As intended, increasing the threshold excludes more segments and increases the mean correlation.

These preliminary results show that a fully automatic extraction of standard time- and frequency-domain HRV parameters from bed-mounted BCG sensors is indeed feasible. The observed differences between ECG-HRV and BCG-HRV can be attributed to two major sources. Firstly, the intrinsic differences between the timings of the electrical heart activity measured by the ECG and the mechanical activity recorded by the BCG. Secondly, the interval estimation errors introduced by artifacts in the BCG signal and through the automatic interval estimation algorithm. However, further research is necessary to investigate for which applications of HRV the achieved degree of agreement is sufficient.

4. Conclusions

We extracted a set of common short-term HRV indices from BCG signals recorded by an unobtrusive bed-mounted EMFi sensor. The entire analysis process was performed using completely unsupervised algorithms. This includes the estimation of beat-to-beat intervals from the BCG, the detection and exclusion of artifacts and outliers as well as the computation of HRV indices. We demonstrated that such an unobtrusive, fully automatic system can provide surrogate HRV data with a satisfying correlation.

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