Shoe Insole Ballistocardiography as a Tool for Heart Rate Variability Estimation in Smart Insoles

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Abstract

Heart rate variability (HRV) is a noninvasive tool for assessing cardiovascular health, typically measured using ECG and PPG, which require direct skin contact. Ballistocardiogram (BCG) offers an alternative by measuring whole-body recoil forces through a piezoelectric sensor embedded in a shoe insole, eliminating the need for direct contact. This study explores the use of insole BCG to estimate HRV from short-term recordings of at least 5 min in a seated position. Simultaneous ECG and BCG recordings were obtained for 7 min from 7 subjects in sitting position. A template matching technique was used for heartbeat detection, with automatic correction for incorrect heart rate (HR) values. Temporal and spectral HRV parameters from both methods were calculated and compared. Bland-Altman analysis showed a 95% confidence interval of ±1.66 bpm between BCG and ECG HR values, within the AAMI standard accuracy limit of ±5 bpm. High statistical correlation was found in HRV parameters between the two techniques. BCG from a shoe insole is a noninvasive, comfortable, and reliable method for ambulatory cardiovascular monitoring

1. Introduction

Heart rate monitoring is one of the most relevant techniques for assessing the cardiovascular system, as it can reflect rhythm disorders such as arrhythmias. Long-term continuous heart rate monitoring allows the analysis of the heart rate variability (HRV), which is the variation in the time intervals between consecutive heartbeats. HRV is influenced by the autonomic nervous system (ANS) and several physiological mechanisms. This variability reflects ANS modulation of the cardiovascular system, making HRV analysis useful in the diagnosis and prognosis of neuropathies and cardiovascular diseases, as well as in the prediction of sudden cardiac death [1]. The gold standard technique for obtaining heart rate (HR) is the electrocardiogram (ECG). This method requires the use of electrodes and direct skin contact, which can be inconvenient for long-term recordings. In addition, the wires used in Holter monitoring systems can be uncomfortable for patients during ambulatory recordings.

One well-studied solution for heart rate monitoring is the use of pulse rate signals, which involve detecting the pulsatile component of arteries, primarily in extremities where arteries are close to the surface. Pulse rate variability (HRV) from wrist photoplethysmography (wPPG) has been validated as surrogate of the HRV in nonstationary condition [2]. Additionally, the implementation of a photoplethysmography (PPG) measurement system for heart rate monitoring in the feet has also been proposed [3].

The measurements of several parameters in the feet have experienced a growing interest due to the development of new wearable system known as smart insoles [4], which consist of the integration of a network of several sensors to measure physiological parameters such as gait kinetics [5], pressure distribution in the feet [6], temperature [7] and others. This technology offers comprehensive monitoring capabilities that are less intrusive and more comfortable for long-term use than traditional methods. Measuring cardiovascular parameters such as heart rate (HR) and heart rate variability (HRV) from the feet presents significant challenges. ECG is not suitable for this purpose because it requires a connection between both feet as the signal quality from a single foot is poor. Similarly, photoplethysmography (PPG) signals are limited by the need for direct skin contact and, like ECG signals, are hindered by the use of socks. One technique that can overcome the limitations of ECG and PPG is ballistocardiography (BCG), which measures the mechanical signals of the heart caused by the recoil forces resulting from the ejection of blood from the heart into the vascular tree [8]. HRV derived from BCG has been successfully evaluated using static mechanical interfaces, such as a force plate [9] in both supine and standing positions, weighing scale [10], and portable BCG systems such as those integrated into earbuds [11].

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The HR from BCG-based piezoelectric sensor in shoe insole has been evaluated in standing and sitting positions by placing the sensor in the heel area [12]. The use of the BCG in the standing position is impractical for long-term recordings due to its susceptibility to motion artefacts. However, it proves more practical for analyzing other parameters in ultra short-term recordings, as it maintains a high correlation in waveform and peak timing with the standard vertical weighing scale BCG. On the other hand, insole BCG in sitting position is affected by the mechanical interface (chair), which attenuate the waves around the main peak of the BCG (J-wave). This feature means that the BCG loses the properties of the standard BCG, but instead produces a signal that is easier to detect in a more comfortable position for long-term recordings, which is ideal for HRV analysis.

This work presents the analysis of the HRV measured from the BCG signal while sitting as a novel, easy and unobtrusive technique to estimate the activity of the ANS over the cardiovascular system. To do so, a comparison is performed of the main spectral and temporal parameters of HRV obtained with the insole BCG with respect to those obtained with the ECG.

2. Materials and methods

2.1 BCG and ECG measurements systems

The measurement system proposed in [12] was used to measure the BCG and ECG signals. The BCG measurement setup consists of a piezoelectric sensor (DT4 028K Measurement Specialties, Inc.) placed in the heel area of the shoe insole and coupled to a charge amplifier with a low cut-off frequency of 0.5 Hz, followed by a first-order high-pass filter with the same cut-off frequency of 0.5 Hz. A third-order Butterworth low-pass filter with a cut-off frequency of 20 Hz was used to limit high-frequency noise. An ECG lead I was used as a reference for HRV analysis. The signal was filtered between 0.5 Hz (first order) and 40 Hz (first order) and amplified by 1000.

2.2 Measurement protocol

ECG and BCG were simultaneously recorded for 7 min from 7 healthy subjects by placing the foot in the shoe insole while seated. The measurements were taken in the facilities of the Escola d'Enginyeria de Telecomunicació i Aeroespacial de Castelldefels of the Universitat Politècnica de Catalunya where the subjects gave their informed consent to participate. The Ethics Committee (C.P.–C.I. PI22/031) approved the study.

2.3 Signal processing

In order to detect BCG signals, we propose a method based on the correlation between a template signal and the BCG signal. For template generation, a reference signal such as the ECG was not used, instead, the template is generated by assembling 500 ms windows from the minimal points of the upper envelope of the BCG signal (Fig. 1). Once all the windows are assembled (Fig. 2), the template is obtained by applying Woody's method for a robust mean [13].

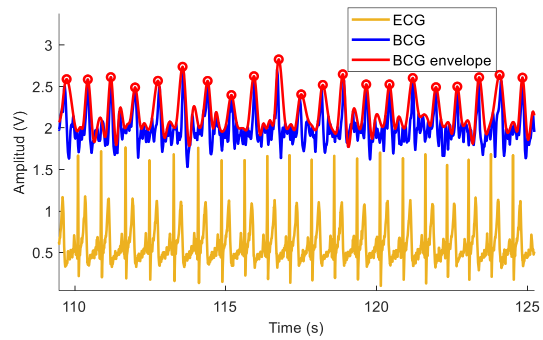

Fig. 1. BCG and ECG signals, and the upper envelope of BCG for template generation.

The convolution result of the template and the BCG signal generates a new BCG signal that can be easily detected with a simple peak detector with a minimal distance of 500 ms to avoid as much as possible false negatives. HR values were obtained by the timing differences of the main peak of the BCG, the J wave.

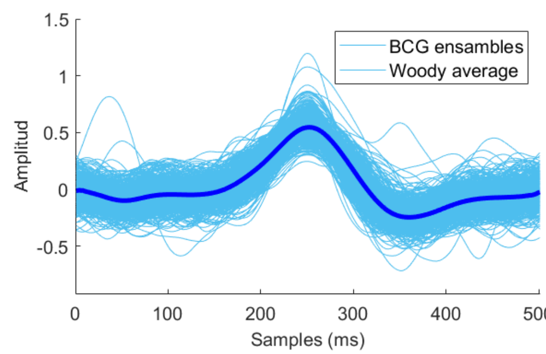

Fig. 2. Ensemble of BCG segments and the template by applying the Woody's method.

As BCG is a cardiac mechanical signal, it's more sensitive to motion artefacts in standing position than in sitting position. Anyway, the integrity of the BCG signal can be compromised by the slightly voluntary or involuntary movements of the foot. The false positive (FP) can be easily identified in the BCG tachogram typically as abrupt JJ interval changes (Fig 3). To estimate the missing true values of JJ intervals from BCG, a mean of the previous values of the JJ intervals was used.

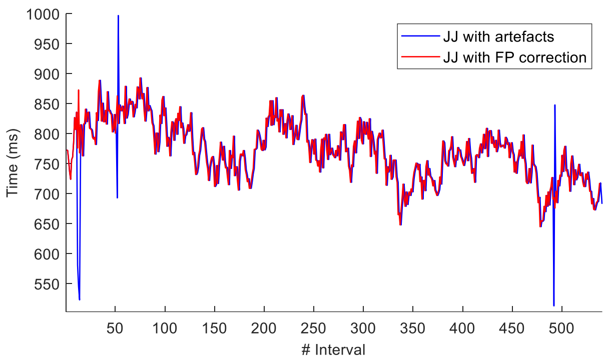

Fig. 3. RR and JJ series with a correction of FP detections for the HRV analysis.

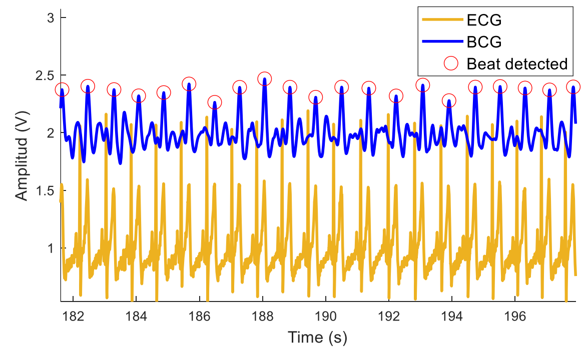

Fig. 4. J-wave peak detection of the BCG signals.

2.4 HRV analysis

In order to evaluate the agreement between HR values obtained from BCG with those obtained with the ECG reference signal, a first test was made by using the Bland-Altman plot [14]. Finally, both temporal and frequency HRV parameter were obtained and compared in accordance with the current recommendations [1] by using Kubios HRV Analysis Software®. For time domain analysis the following parameters were obtained: the mean NN interval, the standard deviation of all NN intervals (SDNN) and the root mean square of differences (RMSSD) of successive NN intervals. The estimated frequency domain parameters were power in the very low frequency band (PVLF), which refers to the component of the HRV power spectrum for frequencies below 0.04 Hz; power in the low frequency band (PLF) for the range 0.04 Hz to 0.15 Hz; and power in the high frequency band (PHF) for the range 0.15 Hz to 0.4 Hz. Finally, the LF/HF ratio was obtained. This ratio is a valuable tool for understanding the autonomic regulation of cardiac function and the balance or imbalance of autonomic nervous system activities.

3. Results and discussion

Figure 4 shows an example of beats detection in BCG signals. It can be seen that, after convolution with the automatically generated template, the signal quality is improved and is easier to detect. The objective of the proposed method is to maximize the J-wave peak, especially when the amplitude is weak. Once the FP were corrected from the BCG tachogram the Bland-Altman plot was obtained, in which the 95% confidence interval was ±1.66 bpm from the overall recordings, which is lower than the accuracy limits recommended by the AAMI standard for HR meters of ± 5 bpm (Fig. 5).

This agreement between the time series is evidenced by high statistical correlation in most of both temporal and frequency parameters of HRV with both techniques (Table 1). Both temporal and frequency parameters of heart rate variability show a correlation coefficient greater than 0.95, demonstrating a strong correlation with statistical significance, as the *p*-value for all recordings was less than 0.001.

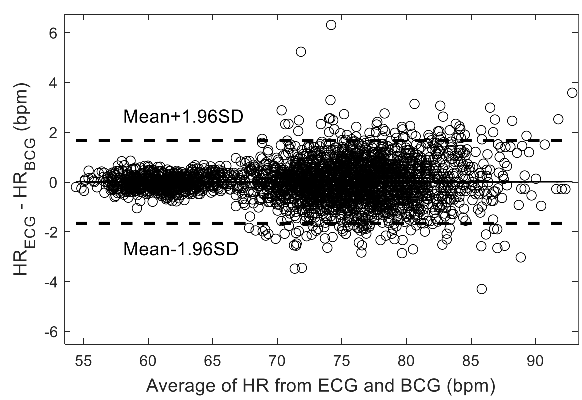

Fig 5. Bland Altman plots of the average difference of the HR from ECG and the HR from BCG in sitting position (*SD*= 0.849).

Table 1. Pearson's correlation coefficient for HRV parameters from ECG and BCG.

Parameter	r
RRmean (ms)	0.998**
SDNN (ms)	0.974**
RMSSD (ms)	0.953**
PVLF (ms^2)	0.999**
PLF (ms^2)	0.999**
PHF (ms^2)	0.990**
LF/HF	0.993**

***p* <0.001

This minimal difference could be related to the origin of the signal, as the mechanism of genesis is different between the RR interval and the JJ interval. The genesis of the vertical BCG is related to blood pressure gradient in the aorta [15], therefore the heartbeat extracted from the BCG can slightly change due to pulse propagation inherent dynamics. On the other hand, the BCG signal measured in the sitting position is systematically dampened by the mechanical interface, in this case, the chair, which could contribute to minimal differences in the HRV indexes.

4. Conclusion

Measuring HRV with a BCG in a seated position by embedding a piezoelectric sensor in a shoe insole has been shown to give results very similar to those obtained with ECG. This method has several advantages, including its non-invasive and comfortable nature, making it suitable for continuous daily monitoring. However, there are limitations such as sensitivity to motion artefacts and the need for a controlled sitting position to ensure signal accuracy. Despite these challenges, measuring BCG while seated can be a promising tool for effective and convenient HRV monitoring. It also contributes to the development of smart insoles that address the challenge of monitoring heart rate from the foot without the need to remove socks.

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