Original Article

Efficacy of Non-contact Ballistocardiography System to Determine Heart Rate Variability

Gaurav Parchani[1] (ID)**, Gulshan Kumar[2], Raghavendra Rao[3], Kaviraja Udupa[2] and Vibhor Saran[1]** (ID)

Abstract

Background: Functions of the autonomic nervous system have cardinal importance in day-to-day life. Heart rate variability (HRV) has been shown to estimate the functioning of the autonomic nervous system. Imbalance in the functioning of the autonomic nervous system is seen to be associated with chronic conditions such as chronic kidney disease, cardiovascular diseases, diabetes mellitus, and so on.
Purpose: To evaluate the efficacy of a non-contact ballistocardiography (BCG) system to calculate HRV parameters by comparing them to the parameters derived from a standard commercial software that uses an electrocardiogram (ECG).
Methods: Current study captured an ECG signal using a three-channel ECG Holter machine, whereas the BCG signal was captured using a BCG sensor sheet consisting of vibroacoustic sensors placed under the mattress of the participants of the study.
Results: The study was conducted on 24 subjects for a total of 54 overnight recordings. The proposed method covered 97.92% epochs of the standard deviation of NN intervals (SDNN) and 99.27% epochs of root mean square of successive differences (RMSSD) within 20 ms and 30 ms tolerance, respectively, whereas 98.84% of two-min intervals for low-frequency (LF) to high-frequency (HF) ratio was covered within a tolerance of 1. Kendall's coefficient of concordance was also calculated, giving a $P < .001$ for all the three parameters and coefficients 0.66, 0.55, and 0.44 for SDNN, RMSSD, and LF/HF, respectively.
Conclusion: The results show that HRV parameters captured using unobtrusive and non-invasive BCG sensors are comparable to HRV calculated using ECG.

Keywords

Autonomic nervous system balance, Ballistocardiography, Heart rate variability, Parasympathetic nervous system, Sympathetic nervous system

Introduction

Heart rate variability (HRV) is a non-invasive method to measure cardiac function regulated by the autonomic nervous system. It is a promising tool to assess and quantify physiological, pharmacological and pathological changes in the autonomic nervous system by detecting the changes in the time intervals between consecutive heartbeats.[1] HRV analysis is traditionally done by acquiring electrocardiogram (ECG) signals and using algorithms and software that transforms these signals. ECG monitoring requires the usage of electrodes that are stuck to the subject. In clinical settings, a subject's risk outweighs the inconvenience quite easily. However,

when the subject is stable in a general ward or home setting, the inconvenience of sticking electrodes patches and the cost associated are a detriment for using ECG to measure HRV.

[1] Turtle Shell Technologies Pvt. Ltd, Bengaluru, Karnataka, India
[2] Department of Neurophysiology, National Institute of Mental Health and Neuro Sciences (NIMHANS), Bengaluru, Karnataka, India
[3] Department of Research, Central Council of Research in Yoga and Naturopathy, New Delhi, Delhi, India

Corresponding author:
Gaurav Parchani, Turtle Shell Technologies Pvt. Ltd, City Centre, #40, Ground and Mezzanine Floor, Nomads Daily Huddle, Chinmaya Mission Hospital Road, Indiranagar, Bengaluru, Karnataka 560038, India.
E-mail: gaurav@dozee.io

Continuous monitoring of the HRV indices can prove to be clinically significant in cardiac-related and other lifestyle dysfunctions because it is a reliable marker to detect sympathovagal imbalance. It can certainly add value to both prognosis and management.[1,2] Thus, it is very important to have techniques that measure HRV parameters and subsequently identify the changes in autonomic activity precisely for home e-health monitoring as well as clinical settings. In this context, our study used non-contact ballistocardiography (BCG). BCG is the unobtrusive and non-invasive system that evaluates cardiovascular functions and can be a possible solution as it does not require any physical monitoring by a technician, as compared with an ECG.[3] BCG sensors capture the vibrations generated by contraction of the ventricles of the heart and subsequent ejection of accelerated blood into the aorta.[4] BCG-based system does not require placement of any electrodes, unlike ECG, to obtain signals and can be used continuously, avoiding any uneasiness and discomfort. Although BCG systems are susceptible to noise in case of movements and posture of the subject,[5] such a system is suitable for long-term continuous data acquisition and is more helpful in monitoring the autonomic nervous system. In the present study, we evaluate the efficacy of a BCG-based device placed under the mattress of the subject to determine HRV.

Earlier studies have shown that apart from signals obtained by the electrical activity of the heart, the vibrations of the heart during systole produce waveforms that correspond to R waves.[6] These waveforms are also called J waves, and they tend to correlate and synchronize with QRS complexes and interbeat intervals (R-R intervals).[7]

In the present study, we have used a BCG-based device to extract J-J intervals to estimate the HRV indices both in time and frequency domains, further matched and correlated with the HRV indices acquired with standard ECG devices at the same time.

Methods

Subjects

The subjects for this study were recruited randomly by visiting their homes. The mean age of the subjects in the study was 46.29 (±12.35) years. There were 17 male and 7 female subjects in the study, with a total of 54 overnight recordings totaling 425.45 h. All subjects were healthy and normal. Subjects suffering from cardiac rhythm abnormalities and having history of neurological or pulmonological diseases were excluded from the study. ECG recordings were performed at home for the whole night, and at the same time, a BCG-based device was placed under the mattresses of all the subjects. The study was in accordance with the Declaration of Helsinki, and all the subjects gave their written informed consent.

BCG Acquisition and Preprocessing

In order to find movement and artifacts, a clustering-based algorithm was employed. The incoming data was split into small instances of 5-s each. These instances were clustered together using the density-based spatial clustering of applications with noise (DBSCAN) algorithm. The 5-s instances that had movement or artifacts were grouped into a separate cluster, and HRV was not calculated for that. The red segment of the figure shows the movement captured by the algorithm in the raw data, while the green segments show nonmovement data (Figure 1).

On genuine request, the code and data can be provided to readers.

The participants of the study were asked to sleep in a comfortable location with a BCG device (Dozee) placed under their mattress for the acquisition of BCG signal. The system comprises a mesh of polyvinylidene fluoride (PVDF) based vibroacoustic sensors placed under the mattress to capture micro- and macro-vibrations generated by the body, which includes cardiac contractions, breathing, body movements, and snoring. The sensor array was attached to a data-acquisition unit sampling vibrations at a rate of 250 Hz. Figure 2 shows the setup of the device in use. Dozee VS model used for the study is manufactured by Turtle Shell Technologies Pvt. Ltd in India (www.dozee.io). It consists of the following two parts:

Sensor sheet mat: An array of piezoelectric sensors that capture the BCG signal. This mat goes under the mattress of the subject directly below the shoulder region.

Bedside pod: This is the data collection module that acquires data from the sensor mat and stores it in discrete chronological packets. This module also syncs this data to the cloud through the Wi-Fi communication controller incorporated inside.

The raw BCG signal obtained was first preprocessed to remove movements and artifacts, which result from breathing, twitches, posture change, or any other external mechanical or electrical noises. The first step of signal preprocessing involves scanning through the data for these artifacts and isolating them. This is done using a separate algorithm developed by the authors of this article. The method involves the classification of 5-s epochs as artifacts and is not based on various statistical parameters such as amplitude, range, standard deviation, and so on. After identifying these artifacts, the signal is split into multiple sub-signals such that each new sub-signal is free from all undesired artifacts. This signal is passed through the algorithm to detect J waves in the BCG signal.[8] J-J intervals thus calculated are used to find the HRV parameters.
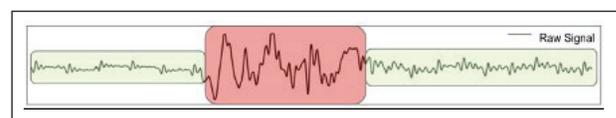

Figure 1. Movement Captured by the Algorithm in the Raw Data.

ECG Data Acquisition

The ECG data used for comparative analysis of the study were acquired using a three-lead channel Holter machine (TLC9803). The ECG signal acquired during these recordings is processed using AD instruments LabChart 8, HRV module. The HRV module for LabChart analyzes beat-to-beat (R-R) interval variation coming from humans. The software automatically classifies beats as either normal or ectopic. It removes the ectopics before the analysis. The default settings that were used for this study are as follows:

- R-R Interval: 800–1400 ms,
- Maximum frequency: 0.5 Hz,
- Number of frequencies: 500,
- VLF: 0–0.04,
- LF: 0.04–0.15, and
- HF: 0.15–0.4.

Template Generation and Wave Detection

Data series used in HRV analysis are time series containing beat-to-beat intervals extracted from ECG or BCG signals. The QRS complex, in the sinus rhythm captured by the ECG, corresponds to the depolarization of the heart ventricles. The R wave in this complex is the most prominent feature and is therefore used to measure the heartbeat intervals by measuring the R-R intervals in successive heartbeats. On the other hand, BCG captures the contraction of the ventricles which corresponds to the IJK complex of the BCG wave. The J wave in BCG corresponds to the R wave in ECG; therefore, the J-J intervals are also used to determine the heartbeat intervals.[9] This is also represented in Figure 3.

The R-J interval is the time difference between ventricular depolarization and contraction.[10] For a subject with normal cardiac functioning, the R-J interval can vary by 20 ms. This interval varies with the hemodynamic state of the subject, which can be altered by maneuvers such as the Valsalva technique, paced breathing, and so on.[11] We assumed a variation of 10 ms during sleep for analysis in this study. This would imply a variation of a maximum tolerance of 20 ms in
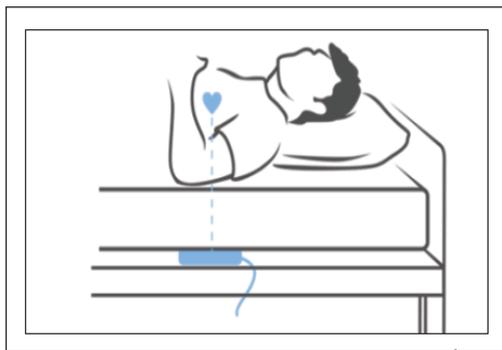

Figure 2. BCG-Based Device (Dozee) in Use.

the J-J intervals when compared with corresponding R-R intervals. As mentioned earlier, the BCG device records data at 250 Hz, which amounts to a resolution of 4 ms. This implies a maximum error of 8 ms in calculating J-J intervals. For the sake of this study, we have assumed a combined deviation of 20 ms from both the sources–variation in R-J interval and resolution of the BCG device.

HRV Analysis

The HRV parameters from BCG and ECG signals were compared for 54 overnight recordings on 24 subjects. The classical time-domain HRV parameters-standard deviation of NN intervals (SDNN) and root mean square of successive differences (RMSSD) were computed for 30-s epochs.[1] Spectral analysis of frequency-domain HRV parameters such as low-frequency (LF) and high-frequency was computed for two-min intervals. In the frequency domain, LF denotes a low-frequency band which lies in the range of 0.04 to 0.15 Hz, whereas HF denotes a high-frequency band, which lies in the range of 0.15 to 0.40 Hz.[1,12,13] The intent of the LF to HF ratio (LF/HF) is to estimate the sympathetic nervous system to parasympathetic nervous system activity balance.[2] We computed the accuracy and detection rate of SDNN, RMSSD, and LF/HF calculated using the BCG system, considering ECG as the benchmark.

A Kendall coefficient of concordance correlation analysis was conducted between values of SDNN, RMSSD, and LF/HF calculated from the BCG signal and ECG signal. Cohen's standard was used to evaluate the strength of the relationship, where coefficients between 0.10 and 0.29 represent a small effect size, coefficients between 0.30 and 0.49 represent a moderate effect size, and coefficients above 0.50 indicate a large effect size.[14]

Results

The detection rate of SDNN, RMSSD, and LF/HF calculated using the BCG signal was 77.92%, 70.30%, and 76.19%, respectively, as compared with SDNN, RMSSD, and LF/HF calculated using the ECG signal. The detection rate was calculated using the following formula:

$$\text{Detection Rate} = \frac{\text{Number of Epochs from BCG}}{\text{Number of Epochs from ECG}} \times 100$$

Because of the variation in the hemodynamic state,[11] the difference in HRV parameters calculated using the ECG signal from LabChart and the BCG signal calculated by our algorithm was bucketed into three tolerance levels. For SDNN, the three buckets were with a tolerance of 10 ms, 15 ms, and 20 ms; for RMSSD, these buckets were 10 ms, 20 ms, and 30 ms; and for LF/HF, these buckets were 0.5, 0.75, and 1. Table 1 shows the distribution of epochs for each HRV

parameter in different buckets. Figure 4 shows the mean number of epochs in each bucket of SDNN, RMSSD, and LF/HF for every subject's sleep recording, whereas Figure 5 shows overnight recording for one subject and also synchrony between HRV parameters calculated via LabChart on the ECG signal with HRV parameters calculated by us on the BCG signal. Kendall's coefficient values were 0.66, 0.55, and 0.44 for SDNN, RMSSD, and LF/HF, respectively, with a *P* < .001 for all three parameters.

Discussion

A method to conveniently monitor HRV parameters for long term was presented in this work. It has been demonstrated that this method is effective and accurate compared with the gold standard to compute HRV parameters. The system used is contactless in nature and does not require technicians to install it, and it can thus work remotely.[15] This enables the collection of high-fidelity health data remotely on a mass scale and can enable a variety of research and screening. The parameters computed include–SDNN, RMSSD, and LF/HF. All the three parameters computed had a high detection rate, and the agreement was within the tolerance levels in comparison to ECG, and similar results have been observed in the studies using similar methods of detecting waveforms of BCG. The current study evaluated the feasibility of using BCG signals for monitoring HRV by extracting BCG signals such as IJK waves generated by ballistic forces both in the time and frequency

Figure 4. (a) Percentage of SDNN Epochs in Each Bucket (b) Percentage of RMSSD Epochs in Each Bucket (c) Percentage of LF/HF Epochs in Each Bucket.

Figure 5. Synchrony Between the SDNN, RMSSD, and LF/HF Computed on Lab Chart on ECG Signal With SDNN, RMSSD, and LF/HF Computed by our Algorithm on BCG Signal.

Table 1. Percentage of Epochs in Each Bucket for the HRV Parameters

HRV Parameters	Percentage of Epochs Within Bucket 1	Percentage of Epochs Within Bucket 2	Percentage of Epochs Within Bucket 3
SDNN	90.24	95.47	97.92
RMSSD	93.90	98.06	99.27
LF/HF	90.21	96.27	98.84

Abbreviations: SDNN, standard deviation of NN intervals; RMSSD, root mean square of successive differences; LF/HF, low-frequency/high-frequency.
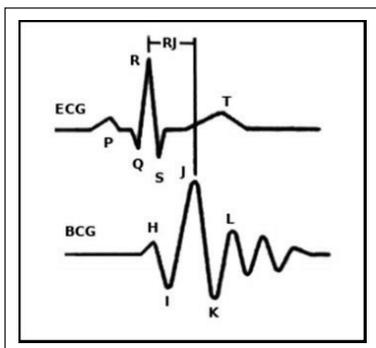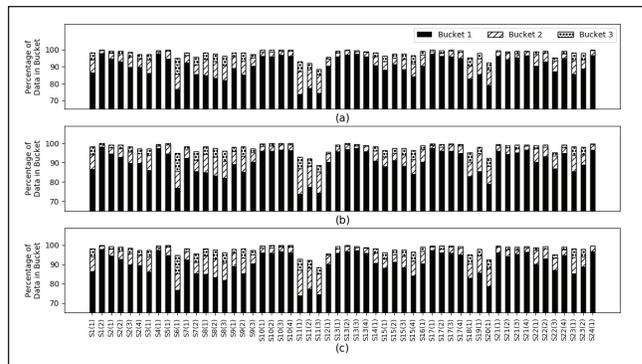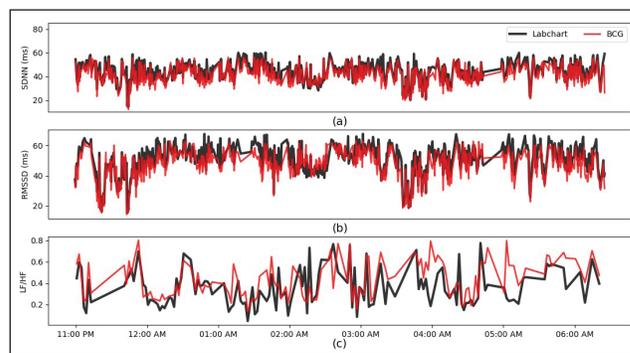

Figure 3. Representation for ECG and BCG for a Heartbeat.

domains. Despite having different methods of collecting data of cardiac cycle such as ECG, BCG, photoplethysmography, phonocardiogram, and so on, many studies analyzed the raw data to calculate the HRV with different algorithms such as time-domain algorithms, frequency-domain algorithms, and wavelet-domain algorithms applied on waveforms.[3,16–18] Recent information technology revolutions have made an outstanding impact on the current monitoring of heart rate, HRV parameters, and breathing rate on a continuous basis both in wearable and nonwearable devices by applying different methods of detection of vital signals.[19–21] But it is difficult to detect HRV parameters during body movements and artifacts arising from twitches or posture change.

Conclusion

The presented work can serve as a base to conduct research studies and screening exercises on a large population in the field. The system presented is cost-effective, intuitive, and can work remotely. Moreover, it does not come in contact with the subject and does not hinder the lifestyle or sleep of the subject in any way.

Authors' Contribution

Statement of Ethics

Declaration of Conflicting Interests

Funding

ORCID iDs

Gaurav Parchani https://orcid.org/0000-0001-8401-9355

Vibhor Saran https://orcid.org/0000-0003-0101-1310

References

1. Malik M, John Camm A, Thomas Bigger J, et al. Heart rate variability: Standards of measurement, physiological interpretation, and clinical use. *Circulation* March 01, 1996; 93(5): 1043–1065. https://www.ahajournals.org/doi/abs/10.1161/01.CIR.93.5.1043.
2. Eckberg DL. Sympathovagal balance. *Circulation* November 4, 1997;96(9):3224–3232.https://www.ahajournals.org/doi/10.1161/01.CIR.96.9.3224.
3. Martín-Yebra A, Landreani F, Casellato C, et al. Studying heart rate variability from ballistocardiography acquired by force platform: Comparison with conventional ECG. In: Computing in Cardiology, *IEEE Computer Society*, 2015, p. 929–932.
4. Gubner RS, Rodstein M, and Ungerleider HE. Ballistocardiography; an appraisal of technic, physiologic principles, and clinical value. *Circulation* 1953; 7(2): 268–286.
5. Inan OT, Migeotte PF, Park KS, et al. Ballistocardiography and seismocardiography: A review of recent advances. *IEEE J Biomed Health Inform* July 2015; 19(4): 1414–1427.
6. Pinheiro E, Postolache O, and Girão P. Theory and developments in an unobtrusive cardiovascular system representation: Ballistocardiography. *Open Biomed Eng J* November 5 2010; 4(1): 201–216.
7. Starr I, Rawson AJ, Schroeder HA, et al. Studies on the estimation of cardiac output in man, and of abnormalities in cardiac function, from the heart's recoil and the blood's impacts; the ballistocardiogram. *Am J Physiol Content* July 31, 1939; 127(1): 1–28. https://journals.physiology.org/doi/abs/10.1152/ajplegacy.1939.127.1.1.
8. Saran V, Kumar G, Dhawan U, et al. "Unsupervised Identification of Cardiac Contraction through Ballistocardiography," 2018 IEEE-EMBS conference on biomedical engineering and sciences (IECBES), Sarawak, *Malaysia*, 2018, pp. 42-47, DOI: 10.1109/IECBES.2018.8626652.
9. Scarborough WR, Talbot SA, Braunstein JR, et al. Proposals for ballistocardiographic nomenclature and conventions: Revised and extended. *Circulation* September 1956; 14(3): 435–450. https://www.ahajournals.org/doi/10.1161/01.CIR.14.3.435.
10. Alametsä J, Palomäki A, and Viik J. Short and longer term repeatability of ballistocardiography in a sitting position with EMFi sensor. *Med Biol Eng Comput* August 19, 2011; 49(8): 881–889. https://link.springer.com/article/10.1007/s11517-011-0746-y.
11. Inan OT, Etemadi M, Wiard RM, et al. Noninvasive measurement of Valsalva induced hemodynamic changes on a bathroom scale ballistocardiograph. *In: Proceedings of the 30th annual international conference of the IEEE engineering in medicine and biology society, EMBS'08: "Personalized Health care through Technology," IEEE Computer Society*, 2008, p. 674–677. https://pubmed.ncbi.nlm.nih.gov/19162745/.
12. Munoz ML, van Roon A, Riese H, et al. Validity of (ultra-) short recordings for heart rate variability measurements. *PloS One* 2015; 10(9): 1–15.
13. McCraty R and Shaffer F. Heart rate variability: New perspectives on physiological mechanisms, assessment of self-regulatory capacity, and health risk. *Glob Adv Health Med. GAHM LLC* 2015 4, 46–61. http://journals.sagepub.com/doi/10.7453/gahmj.2014.073
14. Cohen J. The effect size index: D. *Statistical Power Analysis for the Behavioral Sciences*. 1988, 2, 284–288
15. Sadek I, Biswas J, and Abdulrazak B. Ballistocardiogram signal processing: A review. *Heal Inf Sci Syst* December 16, 2019; 7(1): 1–23. https://link.springer.com/article/10.1007/s13755-019-0071-7.
16. Sviridova N and Sakai K. Human photoplethysmogram: New insight into chaotic characteristics. *Chaos, Solitons and Fractals* August 1, 2015; 77: 53–63.
17. Khandoker A, Ibrahim E, Oshio S, et al. Validation of beat by beat fetal heart signals acquired from four-channel fetal phonocardiogram with fetal electrocardiogram in healthy late pregnancy. *Sci Rep* December 1, 2018; 8(1): 1–11.
18. Kim CS, Ober SL, McMurtry MS, et al. Ballistocardiogram: Mechanism and potential for unobtrusive cardiovascular health monitoring. *Sci Rep* September 8, 2016; 6(1): 1–6.
19. Sharma P, Hui X, Zhou J, et al. Wearable radio-frequency sensing of respiratory rate, respiratory volume, and heart rate. NPJ *Digit Med* December 1, 2020; 3(1): 1–10. https://doi.org/10.1038/s41746-020-0307-6.
20. Reeder B and David A. Health at hand: A systematic review of smart watch uses for health and wellness. *J Biomed Inform Academic Press Inc* 2016; 63: p. 269–276. http://dx.doi.org/10.1016/j.jbi.2016.09.001.
21. Brüser C, Stadlthanner K, De Waele S, et al. Adaptive beat-to-beat heart rate estimation in ballistocardiograms. *IEEE Trans Inf Technol Biomed* September 2011; 15(5): 778–786.