

Cardiology and Angiology: An International Journal

10(4): 1-12, 2021; Article no.CA.71161
ISSN: 2347-520X, NLM ID: 101658392

A Novel Method for Measuring Myocardial Performance Index using Non-contact Ballistocardiogram System

K. R. Nishanth¹, Aashit Singh², Gaurav Parchani², Gulshan Kumar³,
Vibhor Saran², Cholenahally Manjunath¹ and Deepak Padmanabhan^{4*}

¹Department of Cardiology, Sri Jayadeva Institute of Cardiovascular Sciences & Research, Bangalore, India.

²Turtle Shell Technologies Pvt. Ltd. Bangalore, India.

³Department of Neurophysiology, National Institute of Mental Health & Neurosciences (NIMHANS), Bangalore, India.

⁴Department of Electrophysiology, Sri Jayadeva Institute of Cardiovascular Sciences & Research, Bangalore, India.

Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

Article Information

DOI: 10.9734/CA/2021/v10i430173

Editor(s):

(1) Prof. Francesco Pelliccia, University La Sapienza, Italy.

Reviewers:

(1) Abhinav M. C., Kerala Agricultural University, India.

(2) Shilpa Suresh, Sri Jayadeva Institute of Cardiovascular sciences and research, Rajiv Gandhi University of Health Sciences, India.

Complete Peer review History: <https://www.sdiarticle4.com/review-history/71161>

Original Research Article

Received 10 May 2021
Accepted 14 July 2021
Published 17 July 2021

ABSTRACT

Aim: The aim was to validate the Systolic Time Intervals (STI) measured by Ballistocardiography (BCG) with STI derived from simultaneously performed Transthoracic Echocardiogram (TTE) and attempt to create an AI algorithm that automatically calculates Tei Index from BCG tracings.

Study design: Cross-sectional study.

Place and Duration of Study: Department of Cardiology and Department of Electrophysiology of Sri Jayadeva Institute of Cardiovascular Sciences & Research, Bangalore, India, between January 2020 and January 2021.

Methodology: Two hundred seventy-four patients with clinically indicated TTE were enrolled in the study, average age was 52. Simultaneous recordings on BCG and TTE were done. 150 patients had

*Corresponding author: E-mail: deepak.padmanabhan@gmail.com;

clinically usable TTE images for accurate calculations. STI was calculated independently by operators experienced in TTE and BCG. Results were compared using Pearson's R. A proprietary AI algorithm for automatically calculating the MPI, was trained over a subset of patients. Its accuracy in detecting STI was compared to that of TTE and manually calculated STI from BCG.

Results: There was a strong positive correlation ($r=0.766$, $P<0.00$, 99%CI [0.691,0.824]) between the TTE and BCG derived MPI values. The result was validated over predetermined subgroups of subjects with reduced EF ($EF<50$) and subjects with normal EF ($EF\geq 50$). The AI algorithm had correlation of 0.54($p<0.01$) with the MPI calculated by TTE and 0.34($P<0.10$) with the manually calculated MPI on the BCG.

Conclusion: BCG derived manual and automated MPI correlates well with TTE derived MPI in a variety of EF fraction subgroups. Automated calculation algorithms for MPI derived from BCG remain a work under progress.

Keywords: *Ballistocardiogram; transthoracic echocardiogram; systolic time intervals; myocardial performance index.*

1. INTRODUCTION

Heart failure is a major cause of morbidity and mortality. Studies have shown that patients with heart failure may have gone through a phase of asymptomatic left ventricular (LV) dysfunction, where objective LV measurements reveal abnormalities in cardiac contractility, but signs and symptoms of overt heart failure are not present. [1] Also, serial assessment of LV function is important post-myocardial infarction, in individuals receiving chemotherapy with cardiotoxic drugs, dilated cardiomyopathy and infiltrative cardiomyopathies like amyloidosis, sarcoidosis. The most commonly used modalities currently for assessment of LV function include echocardiography and cardiac magnetic resonance imaging (CMR). However, the utility of these modalities in the frequent serial assessment of LV function and large-scale screening to assess asymptomatic individuals with LV dysfunction is limited due to the technical requirements and costs involved.

Myocardial Performance Index (MPI or Tei Index) reflects combined measures of left ventricular systolic and diastolic functions. It is defined as the sum of isovolumic contraction and isovolumic relaxation time divided by ejection time. [2–6] MPI has been used for the overall estimation of the LV function under a variety of diseased conditions, such as dilated cardiomyopathy, amyloidosis, coronary artery disease, heart transplantation, heart failure, as well as in prospective studies of the general population [7-16]. However, a number of studies have cast doubt on its value because of multiple reasons like poor clinical agreement with other metrics, normal values in cases of heart failure with preserved ejection fraction, low diagnostic

accuracy in subjects with heart failure and left-ventricular diastolic dysfunction and that a single value of the index fails to diagnose the actual cause.[17–19]

Currently, MPI is measured as an instantaneous value during a TTE whilst the patient is at rest. Continuous MPI values have not been reported owing to technological challenges such as unavailability of an ambulatory device to conduct cardiovascular ultrasound, the high cost of the present systems and the complexity involved in operating them that limit the measurement of MPI within hospital settings. BCG is a technique that captures the body's vibrations and recoil arising due to the cardiac expulsion of blood into the arteries and respiratory effort. [20–22] Waveforms obtained by BCG signal coincide with the specific events during the cardiac cycle. [23,24] BCG can therefore be used to calculate serial MPI values over a period of time and allow for its evaluation of these values in clinical scenarios.

We propose to validate the calculation of MPI derived from one such novel non-contact, non-invasive BCG recording device with the MPI calculated from a TTE simultaneously and attempt to create an algorithm that will automate the calculation of the MPI from the BCG tracings.

2. METHODOLOGY

2.1 Study Patients

The present study is a prospective study carried out in the Department of Cardiology in Sri Jayadeva Institute of Cardiovascular Sciences and Research (SJICR), Bangalore, India. All the

patients were explained about the study in detail. A thorough history, physical examination was done for every patient.

We excluded female patients because there was a lack of availability of female trainers for the device, patients with arrhythmias, paced rhythm, severe valvular lesions, intracardiac shunt lesions from the study. Patients who did not consent were not included in the study.

2.2 Echocardiograms

Transthoracic echocardiograms were done using a Philips iE33 echo machine by an experienced cardiologist along with 3 lead ECG. Echocardiographic examinations were performed in the left lateral decubitus position in the patients after 20-30 minutes of rest during a stable and quiet respiration period using a 1 - 5 MHz transducer. Subjects with poor echocardiographic windows were excluded from the analysis. Echocardiographic parameters were measured using standard views and techniques according to the American Society of Echocardiography recommendations. Mitral inflow and LV outflow doppler were obtained for every patient. Using Simpson's method, left ventricular end-diastolic and end-systolic diameters were measured and LV ejection fraction (EF) was calculated. The echo data were collected in the form of DICOM files. Doppler images of the blood flow were then taken and MCOT and LVET measurements were marked by an independent cardiologist. We collected data for calculation of the MCOT and LVET over 3 consecutive beats, the values of which were averaged and used for calculations.

MPI was calculated using the formula:

$$\text{MPI} = (\text{MCOT} - \text{LVET}) / \text{LVET}$$

2.3 BCG recording and evaluation

For BCG data collection and recording, a novel, non-invasive device - Dozee™, (Turtle Shell Technologies Pvt. Ltd., Bangalore) was used. This device is a thin sheet having 6 pairs of polyvinylidene fluoride (PVDF) based vibroacoustic piezoelectric sensors, 3 sensing zones and sampling rate ability of up to 1000 Hz. The heart signal in a BCG is in between 1Hz to 25Hz hence the signal with sampling more than 50 per second can be used for the study [24,25]. We limited the sampling rate for this study to 500Hz. The device is connected to an external

component which includes a data storage module, IC chips and a Wi-Fi module within it. The data was uploaded onto a cloud server for further offline evaluation.

This device was placed beneath the patient on the echocardiogram table. The timestamps of the BCG data and echocardiograms were synchronized. 3 simultaneous beats synchronized with the TTE were also used in the BCG for the calculation of the MPI.

2.4 Phase I

The collection of the data was divided into two phases. In phase I, 25 subjects were enrolled, to compare mitral and aortic valve motion on the BCG to that of an echocardiogram. The raw BCG signal was processed using the algorithm explained by Saran et al.,[26] to identify the centre peak (J-wave) of a BCG waveform. Using the identified J-wave, other characteristic BCG waves (G, H, I, K, L) were identified as shown in Fig. 1.

The time interval between H wave and K wave indicates LVET and the time interval between the G wave and L wave indicates the MCOT (Supplement 2 for further information). A comparison of MCOT and LVET calculated using BCG signal and echocardiogram is shown in Fig. 2.

2.5 Phase II

In the second phase, an independent investigator blinded to the echocardiogram data marked BCG signal based on the findings from phase I. The same beats were used to mark MCOT and LVET on the TTE and BCG. The BCG values were also averaged for three consecutive heartbeats and were used to compare it with the values measured using the TTE.

2.6 Statistics

Statistical analysis was conducted using python library (numpy and scipy). All p-values were two-sided and $\alpha = 0.01$. Pearson's correlation coefficient was used to find the relation between the values obtained from TTE and BCG. The correlation calculated was absolute, no threshold of acceptable error was ignored when calculating it. Bland-Altman plot was used to measure the agreement between MPI from BCG and echocardiogram. We also validated the result in the predetermined subgroups of reduced EF (< 50) and normal EF (≥ 50).

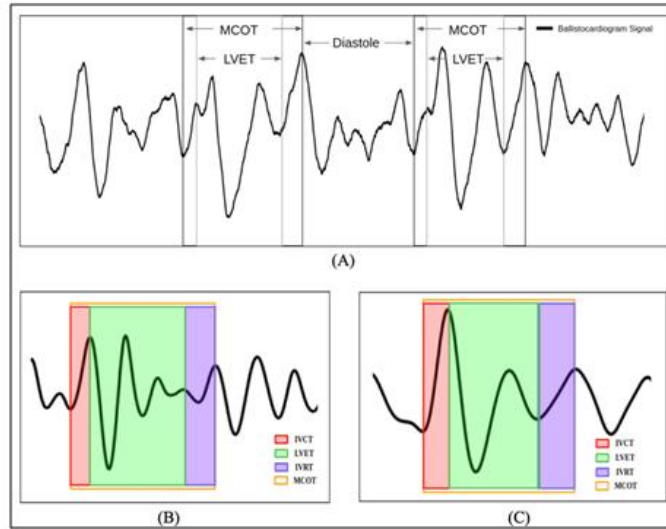


Fig. 1. Ballistogram signals - raw and model template obtained after processing. (A) Raw ballistocardiogram signal, (B) Systolic waveform type 1 (C) Systolic waveform type 2

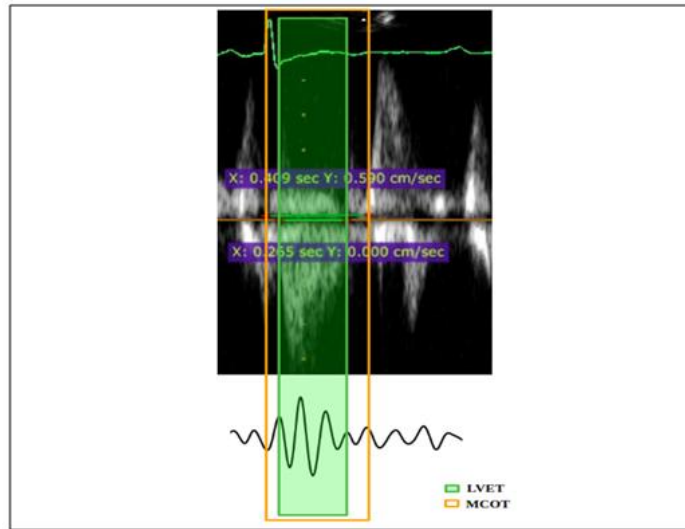


Fig. 2. TTE signal overlapped with simultaneous BCG trace for a cardiac cycle

2.7 Automation

We automated the process of filtering the BCG signal, identifying the waveform of highest confidence and measuring MCOT and LVET by building AI models by using unsupervised machine learning algorithms for pattern detection and heuristics. The results obtained from the automated calculation were then compared with the results obtained from the manual MPI detection via TTE and BCG using Pearson's correlation coefficient. Patients were chosen

randomly for the validation cohort for the validation of the automation algorithm. This has been explained in detail. (Supplement 3 for further information).

3. RESULTS

Two hundred seventy-four male patients (*age: 52±12.5 years*) were enrolled in the study. We excluded 124 patients from the final cohort for a variety of reasons, the most common one being poor TTE windows (98%). The BCG readings in

those patients who were excluded for poor echocardiographic windows were good and no artifacts were present in them. Recordings from 150 subjects qualified for analysis. The inclusion and rejection of these patients is summarized in Fig. 3.

3.1 Correlation between MPI Calculated via TTE and MPI Calculated via BCG

The mean MPI calculated using the TTE was 0.456 while the MPI calculated using the BCG was 0.448. Correlation coefficient values of MPI acquired through both methods showed a significant positive correlation of 0.766 ($P < 0.00001$, 99% CI [0.663, 0.84]) signifying a strong linear relationship. Similarly, MCOT and LVET time intervals values were also significantly

positively correlated. The complete detailed results of correlation coefficients mean absolute error and its standard deviations for all the subjects and in subgroups with reduced EF and normal EF are given in Table 1.

There was a positive correlation in the predetermined subgroups of subjects with reduced EF (<50%) and subjects with normal EF ($\geq 50\%$) with the MPI derived from the TTE.

Positive linear correlation between the values of the STI as derived by BCG and TTE are noted (Fig. 4).

The Bland Altman plot also showcases the strong degree of agreement between the 2 methods in calculating the MPI (Fig. 5).

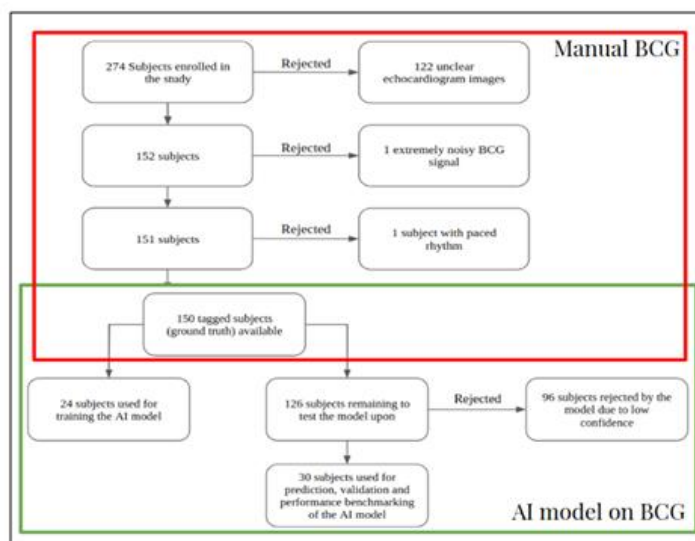


Figure 3. Flowchart of subjects enrolled for the study

Table 1. Results over all subjects and different subgroups for values obtained from TTE and BCG

STI	Pearson's R	P-value	99% CI	MAE	SD
All subjects (N = 150)					
MPI	0.766	$P < 0.00$	[0.691, 0.824]	0.075	0.068
MCOT	0.682	$P < 0.00$	[0.586, 0.759]	28 ms	19 ms
LVET	0.685	$P < 0.00$	[0.59, 0.761]	21 ms	15 ms
Reduced Ejection Fraction (N = 50)					
MPI	0.628	$P < 0.00$	[0.424, 0.771]	0.084	0.076
MCOT	0.774	$P < 0.00$	[0.632, 0.865]	27 ms	19 ms
LVET	0.710	$P < 0.00$	[0.538, 0.825]	21 ms	16 ms
Normal Ejection Fraction (N = 100)					
MPI	0.615	$P < 0.00$	[0.477, 0.723]	0.067	0.057
MCOT	0.592	$P < 0.00$	[0.448, 0.706]	28 ms	18 ms
LVET	0.586	$P < 0.00$	[0.441, 0.701]	21 ms	15 ms

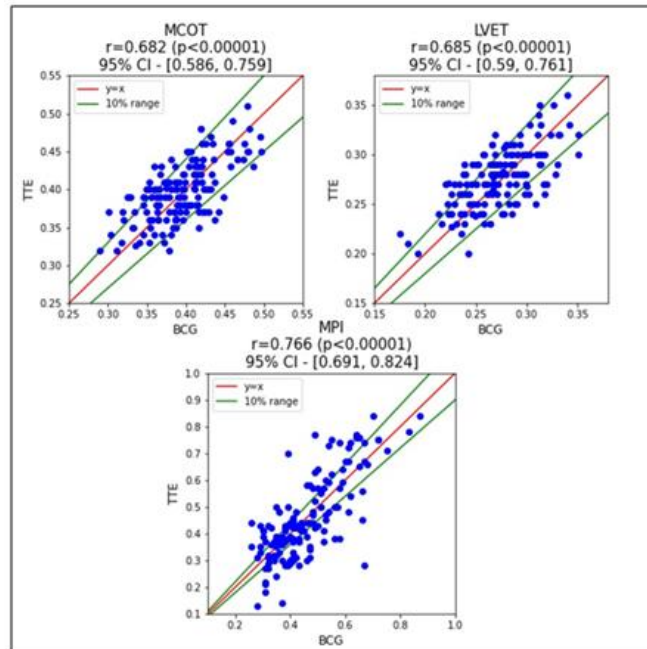


Fig. 4. Plots showing strong positive correlation between MCOT, LVET and MPI calculated manually from TTE and BCG for 150 subjects

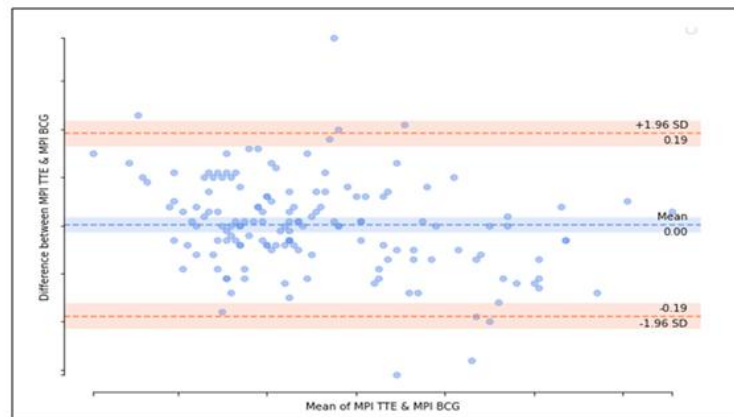


Fig. 5. Bland-Altman plot of comparison between MPI TTE & MPI BCG

Table 2. Relation between values predicted by AI model and values found from TTE and manual BCG

STI	Pearson's R	P-value	MAE	SD
BCG AI Predictions vs TTE values (N = 30)				
MPI	0.54	P<0.01	0.01	0.08
MCOT	0.60	P<0.00	20 ms	15 ms
LVET	0.72	P<0.00	14 ms	13 ms
BCG AI Predictions vs Manual BCG values (N = 30)				
MPI	0.34	P<0.10	0.084	0.076
MCOT	0.44	P<0.10	29 ms	17 ms
LVET	0.43	P<0.10	21 ms	15 ms

3.2 Correlation between MPI Calculated via TTE and MPI Calculated via AI Model on BCG

An AI model that was trained with the data for 24 subjects, attempted to mark the parameters for the remaining 126 subjects. It could only mark MCOT and LVET for 30 of these subjects whose data satisfied the high confidence specifications set for the model, and the remaining 96 subjects were rejected as the BCG signals did not meet the confidence specifications set for the model. For the 30 subjects, there was a linear correlation of 0.54 ($P < 0.01$) with the values of the MPI as obtained by the TTE. The results have been summarized in Table 2 and explained in detail in supplement 3.

4. DISCUSSION

This is the first study to demonstrate the utility of a non-contact novel BCG device in the calculation of systolic time intervals with potential for automated detection. There is linear correlation with the values of the MPI as calculated by a traditional TTE. The automated calculation of values correlates to the calculated BCG derived values of MPI, albeit needing additional numbers for better accuracy.

These results demonstrate that manual BCG is an effective method to measure LVET, MCOT and MPI. Portability, cost effectiveness and ease of use associated with BCG make it a promising modality to acquire MPI values on a longitudinal basis even for patients at home or in cardiac rehabilitation. The promise of summed values for MPI offers a new novel avenue to evaluate patients' functional cardiac status. It also brings a functional cardiac evaluation parameter outside the hospital and allows for potential use by the largely non-specialist workforce. The challenge of poor echocardiographic windows which may limit the calculation of STI do not seem to affect the BCG which is independent of the thoracic response to ultrasound interrogation. The calculation of the MCOT and the LVET are done on different echo windows which render the accuracy of the MPI in irregular arrhythmias lower. The BCG does not suffer from this limitation and may perhaps be more accurate since the calculated MPI is derived from the same cardiac cycle.

Various studies have attempted to calculate heart rate, myocardial performance index, LVET, autonomic responses using accelerometers

usually attached at the chest region or implanted in fabric garments.[27,28] Rienzo et al., measured RR interval and LVET beat by beat basis from ECG and seismocardiogram signals.[28] Another study assessed myocardial performance index in ischemic heart disease by analyzing left ventricular systolic and diastolic parameters at rest and after exercise using 2D echo and accelerometer device placed on the sternum.[29] Our device is able to do so just by placing it underneath the chest region even below the mattress. This removes artifacts at the device tissue interface allowing for clearer recordings. Since the device can be pre-placed beneath a mattress, the patient needs to only lie on the device post activity to be able to record the STI, whereas in each of the other devices, there is potential artifact secondary to the device tissue interface in addition to the challenges of increased chest wall motion due to the use of respiratory muscles in activity and early recovery. Since the cardiac signal activity in our device has a specific frequency and there is a conscious use of a band-pass filter tuned to optimize cardiac motion, these challenges are minimal.

The large volume of data that can potentially be generated with the use of this device presents a logistical problem for calculation of MPI. Manual calculation is possible but may not be optimal during long term monitoring for patients. Therefore, there is a need for automated detection of the MPI in the patients. Our initial attempts at automation are good but not very impressive, but is hypothesis generating for the concept. Additional data points, more clean BCG data collected under controlled environment and more patients may be needed for validation of the same as well as generation of data trends for interpretation and clinical use. The technical concept of using automated beat and interval detection has been used to generate trends in other forms of continuous monitoring and does not represent a novel concept in the handling of big data in real-time. The need for a more accurate and reproducible algorithm however remains and is one of the challenges for the future. Majority studies use unsupervised machine learning to cluster the events detected by seismocardiogram or ballistocardiogram based devices built on their waveforms [30–32]. Similar approach has been applied in our present and past studies to cluster the events using machine learning.[10]

The scope of the study is tempered by its limitations. The present study excluded women

purely out of concern for good echocardiographic windows. This is an important subset that needs evaluation in studies. Evaluation of the device in individuals with higher BMI shall also be useful to determine its versatility when it comes to body habitus. Similar correlation studies for paced beats may also be useful in the evaluation of the functional effects of cardiac resynchronization and selective conduction tissue capture. It may be a real time evaluation aide intraoperatively during the procedure thereby providing instantaneous feedback. The body and probe movements during simultaneous echocardiography led to artefacts on BCG which could be the reason for the marginally lower correlation coefficient between BCG and echo of +0.766 and the reason of such low detection rate by the AI model. The artefacts could be minimized if the procedure is conducted in a controlled environment and the subject is lying still on the bed without any disturbances around.

4. CONCLUSION

BCG derived manual and automated MPI correlates well with TTE derived MPI in a variety of EF fraction subgroups. Automated calculation algorithms for MPI derived from BCG remain a work under progress.

CONSENT

All the patients were explained about the study in detail and informed written consent was taken for participation.

ETHICAL APPROVAL

The study protocol was reviewed and approved by the Institutional Ethics Review Board.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

REFERENCES

1. Wang TJ, Evans JC, Benjamin EJ, Levy D, LeRoy EC, Vasan RS. Natural history of asymptomatic left ventricular systolic dysfunction in the community. *Circulation*. 2003;108(8):977–82.
2. Tei C, Ling LH, Hodge DO, Bailey KR, Oh JK, Rodeheffer RJ, et al. New index of combined systolic and diastolic myocardial performance: a simple and reproducible

measure of cardiac function—a study in normals and dilated cardiomyopathy. *J Cardiology*. 1995;26(6):357–66.

3. Davies M, Hobbs F. Prevalence of left-ventricular systolic dysfunction and heart failure in the Echocardiographic Heart of England Screening study: a population based study. *Lancet*. 2001;358(9280):439–44.
4. Weissler A, Peeler R, Roehll J. Relationships between left ventricular ejection time, stroke volume, and heart rate in normal individuals and patients with cardiovascular disease. *Am Heart J*. 1961;62:367–78.
5. Morgan EE, Faulx MD, McElfresh TA, Kung TA, Zawaneh MS, Stanley WC, et al. Validation of echocardiographic methods for assessing left ventricular dysfunction in rats with myocardial infarction. *Am J Physiol - Hear Circ Physiol*. 2004;287(5 56-5):2049–53.
6. Lakoumentas J, Panou F, Kotseroglou V, Aggeli K, Harbis P. Right Ventricular Tei Index in Children: Effect of Method, Age, Body Surface Area, and Heart Rate. *J Am Soc Echocardiogr*. 2007;20(6):764–70.
7. Dujardin KS, Tei C, Yeo TC, Hodge DO, Rossi A, Seward JB. Prognostic value of a doppler index combining systolic and diastolic performance in idiopathic-dilated cardiomyopathy. *Am J Cardiol*. 1998;82(9):1071–6.
8. Tei C, Dujardin KS, Hodge DO, Kyle RA, Jamil Tajik A, Seward JB. Doppler index combining systolic and diastolic myocardial performance: Clinical value in cardiac amyloidosis. *J Am Coll Cardiol*. 1996;28(3):658–64.
9. Poulsen SH, Jensen SE, Nielsen JC, Møller JE, Egstrup K. Serial changes and prognostic implications of a Doppler-derived index of combined left ventricular systolic and diastolic myocardial performance in acute myocardial infarction. *Am J Cardiol*. 2000;85(1):19–25.
10. Møller JE, Søndergaard E, Poulsen SH, Egstrup K. The Doppler echocardiographic myocardial performance index predicts left-ventricular dilation and cardiac death after myocardial infarction. *Cardiology*. 2001;95(2):105–11.
11. Harjai KJ, Scott L, Vivekananthan K, Nunez E, Edupuganti R. The Tei index: A new prognostic index for patients with symptomatic heart failure. *J Am Soc Echocardiograph*. 2002;15(9):864–8.

12. Møller JE, Egstrup K, Køber L, Poulsen SH, Nyvad O, Torp-Pedersen C. Prognostic importance of systolic and diastolic function after acute myocardial infarction. *Am Heart J.* 2003;145(1):147–53.
13. Årnlöv J, Lind L, Andrén B, Risérus U, Berglund L, Lithell H. A Doppler-derived index of combined left ventricular systolic and diastolic function is an independent predictor of cardiovascular mortality in elderly men. *Am Heart J.* 2005;149(5):902–7.
14. Parthenakis FI, Kanakarakis MK, Kanoupakis EM, Skolidis EI, Diakakis GF, Filippou OK, et al. Value of Doppler index combining systolic and diastolic myocardial performance in predicting cardiopulmonary exercise capacity in patients with congestive heart failure: Effects of dobutamine. *Chest.* 2002;121(6):1935–41.
15. Toumanidis ST, Papadopoulou ES, Saridakis NS, Kalantaridou AT, Agapitos E V., Nanas JN, et al. Evaluation of myocardial performance index to predict mild rejection in cardiac transplantation. *Clin Cardiol [Internet].* 2004;27(6 suppl. 3):352–8.
16. Årnlöv J, Ingelsson E, Risérus U, Andrén B, Lind L. Myocardial performance index, a Doppler-derived index of global left ventricular function, predicts congestive heart failure in elderly men. *Eur Heart J.* 2004;25(24):2220–5.
17. Gillebert TC, Leite-Moreira AF, De Hert SG. Load dependent diastolic dysfunction in heart failure. *Heart Fail Rev.* 2000;5(4):345–55.
18. Gutgesell HP. Novel index relating both isovolumetric contraction time and isovolumetric relaxation time to ejection time. *J Am Soc Echocardiogr.* 1997;10(7):781–782.
19. Gillebert TC, de Veire N Van, De Buyzere ML, Sutter J De. Time intervals and global cardiac function. Use and limitations. *Eur Heart J.* 2004;25(24):2185–6.
20. Starr I, Rawson AJ, Schroeder HA, Joseph NR. 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.* 1939;127(1):1–28.
21. Scarborough WR, Davis FW, Baker BM, Mason RE, Singewald ML, Lore SA, et al. A ballistocardiographic study of 369 apparently normal persons. An analysis of “normal” and “borderline” ballistocardiograms. *Am Heart J.* 1953;45(2):161–89.
22. Kim CS, Ober SL, McMurtry MS, Finegan BA, Inan OT, Mulkamala R, et al. Ballistocardiogram: Mechanism and Potential for Unobtrusive Cardiovascular Health Monitoring. *Sci Rep.* 2016;6(1):1–6.
23. Crow RS, Hannan P, Jacobs D, Hedquist L, Salerno DM. Relationship between seismocardiogram and echocardiogram for events in the cardiac cycle. *Am J Noninvasive Cardiol.* 1994;8(1):39–46.
24. Brüser C, Stadlthanner K, De Waele S, Leonhardt S. Adaptive beat-to-beat heart rate estimation in ballistocardiograms. *IEEE Trans Inf Technol Biomed.* 2011 Sep [cited 2021 May 24];15(5):778–86.
25. Albukhari A, Lima F, Mescheder U. Bed-embedded heart and respiration rates detection by longitudinal ballistocardiography and pattern recognition. *Sensors (Switzerland).* 2019;19(6):1451.
26. Saran V, Kumar G, Dhawan U, Parchani G. Unsupervised Identification of Cardiac Contraction through Ballistocardiography. In: *Biomedical Engineering and Sciences (IECBES).* Sarawak, Malaysia: IEEE-EMBS; 2018. p. 42–7.
27. Dinh A, Bui FM, Nguyen T. An accelerometer based system to measure myocardial performance index during stress testing. In: *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS [Internet].* Institute of Electrical and Electronics Engineers Inc.; 2016. p. 4877–80.
28. Di Rienzo M, Vaini E, Castiglioni P, Merati G, Meriggi P, Parati G, et al. Wearable seismocardiography: Towards a beat-by-beat assessment of cardiac mechanics in ambulant subjects. *Auton Neurosci Basic Clin [Internet].* 2013;178(1–2):50–9.
29. Korzeniowska-Kubacka I, Kuśmierczyk-Droszcz B, Bilińska M, Dobraszkiewicz-Wasilewska B, Mazurek K, Piotrowicz R. Seismocardiography - A non-invasive method of assessing systolic and diastolic left ventricular function in ischaemic heart disease. *Folia Cardiol.* 2006;13(4):319–25.
30. Antink CH, Mai Y, Ranta J, Tamiceriu A, Brüser C, Leonhardt S, et al. On the Performance of Bed-Integrated Ballistocardiography in Long-Term Heart

- Rate Monitoring of Vascular Patients. In: Computing in Cardiology. IEEE Computer Society; 2019.
31. Gamage PT, Khurshidul.Azad M, Taebi A, Sandler RH, Mansy HA. Clustering Seismocardiographic Events using Unsupervised Machine Learning. In: 2018 IEEE Signal Processing in Medicine and Biology Symposium (SPMB). 2018. p. 1–5.
 32. Taebi A, Solar BE, Mansy HA. An Adaptive Feature Extraction Algorithm for Classification of Seismocardiographic Signals. 2018 Mar 27 [cited 2021 May 24];
 33. Starr I. The relation of the ballistocardiogram to cardiac function. *Am J Cardiol.* 1958;2(6):737–47.

APPENDIX

1. Mitral inflow and left ventricular outflow time intervals were used to measure left ventricular ejection time (LVET) and mitral valve closing opening time (MCOT). Supplement Fig. A1 shows the mcot and LVET phases marked in a single echocardiogram dicom loop captured as part of the study. In this case MCOT is 409 ms and LVET is 265 ms.

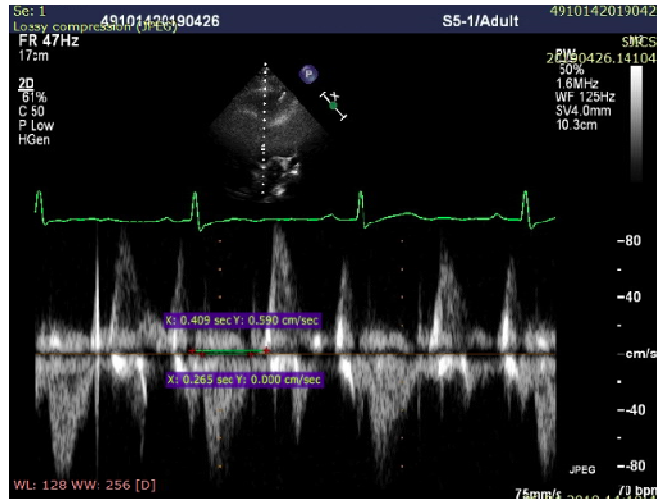


Fig. A1. One of the 2D Doppler Echocardiogram Dicom loops captured during the study

2. BCG data from Dozee (shown in use in supplement Fig. A2 below), was processed through an algorithm to identify the heart beats in the ballistocardiogram waves. This algorithm is already explained in another paper (Saran et al) to identify J-waves from the BCG data.[26]

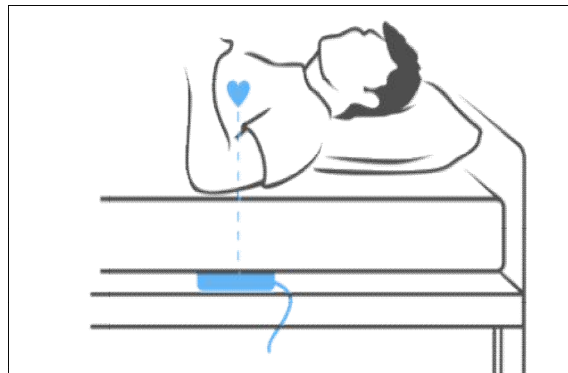


Fig. A2. Dozee device in use

Around the beats identified, characteristic waves (G, H, K and L) were identified manually over 25 subjects by synchronizing time from echocardiograms and BCG signals and observing repeating patterns over multiple beats and over multiple subjects. These waves, shown in Fig. A1, are formed by systolic and diastolic events of the heart, like opening and closing of valves, contraction and relaxation of heart chambers. In ballistocardiogram G wave which is a downward deflection, represents the time when the mitral valve closes and the systole starts and subsequent isovolumetric contraction begins.[20,33] H wave is an upward deflection, which occurs towards or after the end of the first heart sound and correlates with the opening of the aortic valve. K wave represents the time when the aortic valve closes, and isovolumetric relaxation begins. The position of the K wave is variable in different identified waveforms. L

wave marks the time when the Mitral Valve opens, and the diastole begins.[33] Furthermore, these waves and the templates generated (Fig. A1) are used in the next part of the pipeline to identify points that mark the stages in a heartbeat - closing and opening of the mitral valves and the aortic valves - which help in identifying the duration of the components used in calculating the MPI values for each beat.

3. Creation of the automated algorithm for the calculation of STI

We built AI models by using unsupervised machine learning algorithms for pattern detection and heuristics, by taking 24 out of 150 patients randomly as reference subjects. The algorithm identified the respective points to mark MCOT and LVET on these 24 subjects' BCG tracings using the values marked by the cardiologist on the TTE. This was then further used to automatically identify the MCOT and LVET on the remaining 126 subjects. 96/126 subjects were rejected by the model because of unclear data or low confidence data allowing us to test the model on 30/150 subjects (Fig. A3).

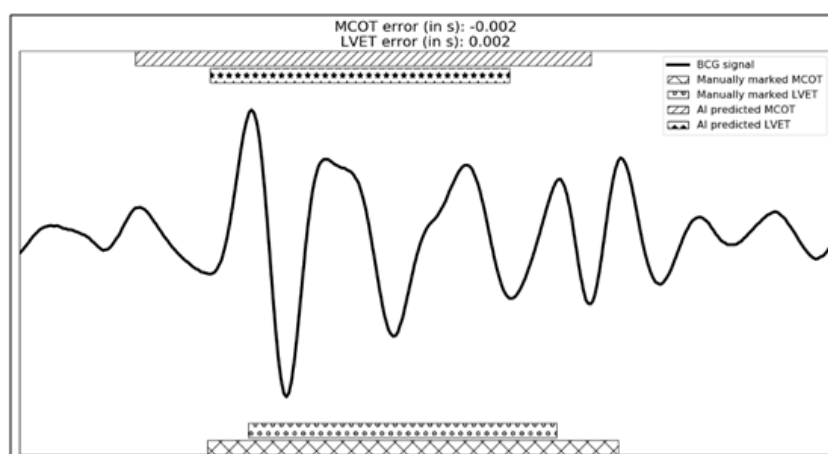


Fig. A3. MCOT and LVET marking on BCG signal by the AI model for the same subject

4. Correlation of the automated algorithm for the calculation of STI with that of the manual detection of MPI via BCG and TTE

The Pearson correlation coefficients between MPI, MCOT and LVET derived from the automated BCG model and TTE were 0.54 ($p < 0.01$), 0.6 ($p < 0.001$) and 0.72 ($p < 0.0001$) respectively. Detailed results given in Table 2, which also compares the predicted values by the AI model and the independent investigator. Supplement Fig. A3 shows the MCOT and LVET markings on BCG signals by the AI model and manually by the independent investigator.

© 2021 Nishanth et al.; This is an Open Access article distributed under the terms of the Creative Commons Attribution License (<http://creativecommons.org/licenses/by/4.0>), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Peer-review history:

The peer review history for this paper can be accessed here:
<https://www.sdiarticle4.com/review-history/71161>