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Analysing Ballistocardiography for Pervasive Healthcare

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Abstract—We describe a methodology to measure ballistocardiography (BCG) signals from the body surface, using body-worn digital accelerometers to extract medically relevant information for Pervasive Healthcare. We are able to measure measuring heart rate with an 95% accuracy as well as other cardiac metrics, such as the S1-S2 interval, deviating from ECG by only 1.3%. Our results show that BCG can be a viable alternative to an electrocardiogram to provide complementary information on the heart's condition in mobile and pervasive use cases. We further show that BCG information can be detected from arm as reliably as from chest, which is especially convenient for measuring from supine positions in Pervasive healthcare applications.

Index Terms—Ballistocardiography, Pervasive Healthcare

I. INTRODUCTION

Cardiac activity-related metrics are common in both clinical and lifestyle applications. Elevated heart rate is linked to higher mortality through cardiovascular diseases [1], [2], and its variability correlates with mortality rate [3], [4]. Heart rate is also commonly used to assess e.g. the intensity of physical exercise [5] or, together with respiration, for sentiment or emotion recognition (e.g. depression) [6].

The most widely used way of performing heart-related activity monitoring has for years been electrocardiography (ECG), but with the rise of wrist-worn devices using optical heart rate monitors, Pervasive health is spurred by low-cost accurate and continuous monitoring of the heart [7]. Similarly, embedded ballistocardiographic (BCG) sensors enable contactless monitoring of heart rate [8], [9]. Whilst ECG measures the electrical heart stimulus signal, BCG records the motion differences related to the heart's movement.

Many Pervasive health BCG studies have focused on stationary sensor setups, embedded e.g. in beds, chairs or bathroom scales. However, BCG can also be sensed from wearable devices with a smaller form factor [10] and heart beat detection is feasible even within signals containing artifacts [11]. The general transition from stationary patient monitoring to Pervasive wearable devices [12] poses a possible application for wearable BCG sensors. As accelerometers are widely and economically available, a BCG system can reduce cost, requires fewer measurement points and no wet/gel electrodes.

In this work, we sense heart movement information with a body-worn BCG sensor system and compare different sensor positions on the human body for their viability of obtaining heart beat measurements. Our contributions are

Fig. 1. ECG over 2 cardiac cycles, based on [14]. The P wave, is a result from atrial depolarization that causes contraction of the atria. The PR-interval (from P wave to QRS complex) is the time required for the electrical activity to transmit from the atria to the ventricles. The QRS complex represents the ventricular depolarization that leads to contraction of ventricles and cardiac expulsion of blood. Ventricles remain contracted about 400 ms while blood flows out of the heart (ST segment). By repolarization of the relaxing heart muscle, the T wave is generated. It is broader than the sharp deflections in the QRS complex since repolarization is slower than depolarization [13].

- a low-error (1.3% compared to ECG) methodology to accurately (95%) extract pulse-related characteristics (heart-beat, S1-S2 interval, S1/S2 strength) from BCG signals with body-worn digital accelerometers.
- relation of BCG heart beat for different body locations to the corresponding ECG signal.
- detection of BCG from the arm as reliably as from the chest, suggesting measurement in supine positions for Pervasive healthcare applications.

II. BACKGROUND

A. Cardiac Cycle and Electrocardiogram

The cardiac cycle, i.e. the activity of the heart over a single heartbeat, can be divided into a systolic phase when the heart contracts and causes the blood to flow out, and a diastolic phase when the heart relaxes and refills with blood [13]. Electrocardiography (ECG) is the gold standard for measuring the phases of cardiac cycle via the electrical activity of the heart (Fig. 1). The electrocardiogram can be used to assess the (dys)functioning of the heart, as it exhibits all the major parts of a cardiac cycle as a P-QRS-T-complex. Heart rate, estimated from the RR interval, is the most common metric, as it can be used to assess the overall condition of the heart. Also other intervals, e.g. QRS and QT, can be used in assessing how the heart manages the different parts of the cardiac cycle [15].

Fig. 2. BCG waveform. The H wave, is caused by the isometric period of ventricular contraction. The I valley marks the onset of blood ejection and occurs right after the ECG QRS complex. As the blood starts to flow down the arch of aorta, the direction of the force changes and a J peak is formed slightly after the QRS complex of the ECG [18]. The K valley is caused by the deceleration of blood due to the peripheral resistance in the aorta [19] and the reduction of heart contraction force. L and M waves derive from the ventricular relaxation after the T wave of the ECG. The final N wave occurs when the blood fills the ventricles, ending the cardiac cycle [17].

B. Ballistocardiography

While ECG measures the electrical activity of the heart's stimulus, ballistocardiography (BCG) measures the actual movement caused by the pumping motion of the heart. When ventricles contract, the blood flow causes a force which can be detected as movement on the body surface. The BCG signal can be measured from displacement, velocity or acceleration of the body in all three axis [16]. The BCG signal is strongest in the longitudinal axis (head-to-foot) but it can also be detected from the anterior-posterior axes [16]. The BCG waveform can be divided into the systolic group (H, I, J and K waves) and the diastolic group (L, M and N waves) [17] (Fig. 2).

BCG is a non-invasive method to measure the functioning of the heart. The heart rate can be measured from the interval between the J-peaks [16], comparable to the RR interval in the ECG. The amplitude of the BCG signal can be used to evaluate changes in stroke volume and cardiac output [16]. The BCG can be measured using wearable sensors, bed sensors and weighing scales. The advantage of wearable sensors is the ability to obtain data continuously through the day with the disadvantage of motion artifacts. BCG data from bed sensors can be used to evaluate the sleep quality and sleep related disorders [16]. Since BCG bed sensors are wireless, they do not disturb subject's ordinary sleep behavior [16]. The advantage of weighing scale BCG measurements is the standing position since the BCG signal is strongest in the longitudinal axis. However, difficulties in maintaining a fixed posture causes motion artifacts [16].

III. RELATED WORK

Since BCG-based healthcare applications have been dependent on fixed instruments, in contrast to our work, only few studies were conducted with digital accelerometers. A closely related study in [20] examined the viability of different body locations for the extraction of a BCG signal and found the sternum as the location with strongest BCG [20] (confirmed by our study). Table I summarizes prior work on BCG from body-mounted acceleration sensors. A BCG signal measured at any body location with an accelerometer is morphologically dissimilar to a BCG signal measured by fixed instruments [25]. In [21] wearable BCG signals from lower back and sternum

Fig. 3. FXLS8471Q 3-Axis Linear Accelerometer (BCG) [26] and Consensys Shimmer3 ECG sensor (right) [27].

are compared to a weighing scale BCG signal. The authors conclude that, even with similar anthropometrical properties, the gathered BCG signals showed intersubject variability. Jähne-Raden et al. conducted measurements using commercially available digital accelerometers, also used in this study, but with an even smaller form factor [23]. Measurements during walking were conducted by Javaid et al. [24], who were able to determine the systolic time intervals, even though strong motion artifacts existed. Our work exceeds the state-of-the-art as it combats several unanswered questions in the field, addressing the differences in BCG morphology due to sensor position, inter-subject variability and posture.

IV. MEASUREMENTS

A. Sensors

For our analysis, we recorded data with BCG and ECG sensors. The BCG data was collected using a FXLS8471Q 3-Axis linear Accelerometer with a kit containing the FRDM-KL25Z and the FRDMSTBC-A8471 boards (cf. Fig. 3). The output data rate of the accelerometer ranges from 1.563 Hz to 800 Hz and it is able to store up to 32 samples along all three axis. A sample is represented in 6 bytes and each acceleration value as 2 bytes. We collected the data via the Community edition of the Freedom Sensor Toolbox.

For our 3-channel ECG derivation after Einthoven, we employed the Shimmer3 Consensys ECG Development Kit and Consensys V1.5.0 software (cf. Fig. 3). Electrodes are connected to the left and right side on the upper chest and near left and right leg at the lower abdomen. The ECG serves as ground truth on BCG measurements.

B. Subjects

All subjects ($n=6$, $m=2$, $f=4$, $\text{age}=\pm 1$) were made familiar with ECG and BCG sensors and with the data collection steps.

C. Measurement Process

Measurements were conducted in three states: lying, sitting, walking (cf. Fig. 4). BCG devices were attached at the locations depicted in Fig. 4. ECG electrodes attached according to the manufacturer's recommendation [28].

While lying, the BCG sensor was placed freely atop subject's chest. In other states and body parts it was secured with double-sided tape or with a flexible band in direct contact to the skin. Subjects were instructed to avoid unnecessary movement and to breath normally. Two dedicated laptops collected BCG and ECG data (sampling rate 512 at 200 Hz for both) and

TABLE I
RELATED WORK ON WEARABLE BCG SENSING

	Goal	Sensor	subjects	Method	Findings
[20]	Strength of BCG across body locations	A MEMS accelerometer	4	Sing Spectr Anal.	Strongest at sternum and parietal bone.
[21]	Compare BCG: sternum & lower back vs. weighing scale	Custom electronics, BCG weighing scale	5	2 nd derivative BCG comparison	Derivatives homologous. ACC location matters and subject-dependent.
[22]	Study the change of posture (sitting vs. supine positions) in BCG.	EMFi (electromechanical film), fixed	7	–	Sitting and supine positions clearly distinguishable in BCG signal
[23]	Specific. for small BCG sensor board.	Four accelerometers	5	BCG aver. sum	Board produces good quality BCG
[24]	Estimate systolic time intervals whilst walking with wearable BCG.	Several accelerometers	4	DTW	Combining multiple accelerometers reliably estimates systolic intervals.

Fig. 4. Illustration of the measurement locations (marked in red) for lying, sitting and walking subjects on the left.

Fig. 5. Processing workflow for electro- and ballistocardiogram data.

synchronization was achieved via 'sync-artifacts' induced by light manual taps on the hardware. Each measurement lasted about 5 minutes, yielding roughly 300 heartbeats.

V. METHODS

For signal processing (cf. Fig.5), first, signals are synchronized. Then, BCG and ECG are processed separately to yield frequency-filtered BCG data along with exact heartbeat timings (ECG). The latter is then used to segment the BCG data for BCG waveform extraction related to cardiac activity. Processing was performed via Matlab (version 2018a) signal-processing and wavelet toolboxes.

1) *Preprocessing*: During the preprocessing, (1) the channels with highest signal-to-noise ratio (SNR) are selected, (2) channel time frames are synchronized (via 'sync-artifacts', cf. section IV-C), and (3) regions of interest are selected manually (by excluding leading and trailing samples contaminated with

movement). In practice, these are the channels with BCG axis perpendicular to the body (z-axis), and any upper torso-leg lead pair of ECG.

2) *ECG Processing*: The ECG signal was further processed by removing the power line interference (applying a 50 Hz notch filter), detrending the baseline drift (fitting and subtracting a low-order polynomial), and by correcting the drifting time frame (linear scaling to match BCG and ECG). Finally, heartbeats were detected from the processed ECG data by peak localization with manually defined thresholds.

3) *BCG Processing*: The frequency contents of preprocessed BCG were determined by a continuous wavelet transform [29] employing analytic Morse wavelets (cf. Fig. 7). The relevant frequency range, i.e. the band that carries most of the heartbeat-induced vibrations, was determined by visually distinguishing the periodic components in the scalogram. Non-relevant frequencies were excluded via zero-phase filtering.

4) *Segmentation and Artifact Extraction*: The timings of R-waves, extracted from ECG, were used to segment the BCG signal. In practice, BCG samples were 700 ms long, starting 200 ms before the R peak, and ending 500 ms after it. An example result of windowing for a single measurement after the artifact removal is presented in Fig. 6 (left).

We removed artifacts based on sample-to-sample cross-correlation (comparing pair-wise correlation between samples to their average). Artifact-free samples show a significantly higher correlation metric so that they are easy to isolate. As threshold for rejection we selected 10 % below the median of the cross-correlation metric.

5) *Sample Averaging*: An average heartbeat waveform was computed separately for each subject as a simple average over artifact-free samples (cf. Fig. 6 (right))

6) *Purely BCG-Based Heartbeat Detection*: In deployment situations without ECG reference, the continuous wavelet transform of the preprocessed BCG data can be used for reliable heartbeat detection. As the frequency content of a single heartbeat is well-defined and relatively similar across different subjects, it can be used to distinguish individual beats, provided that frequency contents of the noise do not overlap with the bandwidth of interest. The average frequency contents of a heartbeat, as measured from the chest, are presented in Fig. 7(a). Comparing average magnitude of relevant frequency contents to non-relevant ones, a cardiac activity map can be constructed per time instance (Fig. 7(b)). Under ideal

Fig. 6. An average heartbeat BCG waveform for a single subject (left); waveforms of about 300 heartbeats recorded in one session (right). Contraction and relaxation-related activity can be seen around 0 ms and 350 ms, respectively.

circumstances, this method provides a similar SNR as ECG, with both contraction (S1) and relaxation (S2) clearly visible.

7) *BCG-Based S1-S2 Detection*: We can further distinguish the first (S1) and second sounds (S2) by searching for smaller secondary peaks close to the detected primary peaks distinguished as heartbeats. The related other secondary peak might occur on either side since a found primary peak might be either S1 or S2. The secondary peaks are kept or discarded depending on their height and distance from the closest primary peak with respect to the average over all peak pairs. After identifying all peak pairs, they are sorted into first and second.

VI. RESULTS AND DISCUSSION

A. Viable Measurement Locations

We investigated the viability of BCG measurement locations at different body locations (left and right pectoral muscle, sternum, upper arm, forearm, wrist and upper thigh). We assess the viability of a body-location by comparing the spectral density of the raw data from each measurement to base noise (determined by running 1 minute measurements with the sensor placed on a tabletop). Thereby, the biological part of the power spectrum can be distinguished as differing from the noise, and the heartbeat-related part as highly periodic components (Fig. 7 (top)).

The spectral densities recorded at each location are depicted in Fig. 8. Strongest signals are measured on the left pectoral muscle and on the sternum, but they have differing peak frequency contents (22 Hz and 11 Hz, respectively). On the chest, the difference in signal amplitude is directly related to the distance from the heart, and the location-dependency of frequency contents is most likely explained by different acoustic properties of the intermediate tissue.

Based on the spectral density, signals from extremities also carry some relevant signal, but in practice only the arm and forearm were deemed viable. The choice of measurement locations becomes more crucial when assessing the two components of the heartbeat. The second part of the cardiac cycle, at around 350 ms, is visible also outside the chest region, but its intensity compared to the noise becomes low (Fig. 9(b)).

B. Average Heartbeat

Heartbeat waveforms averaged from about 100 samples measured simultaneously from chest and arm, and processed

TABLE II
HEARTBEAT METRICS EXTRACTED FROM ECG AND BCG.

•	HR _{ECG} (BPM)	HR _{BCG} (BPM)	S interval $\pm \sigma^2$ (s)
S1	76.59	78.98	0.36 ± 0.01
S3	70.73	69.77	0.35 ± 0.01
S4	58.50	58.49	0.35 ± 0.13
S5	45.43	46.04	0.27 ± 0.05
S6	63.40	63.82	0.33 ± 0.01

as outlined in section V, are presented in Fig. 9. Both chest and arm clearly exhibit acceleration caused by the initial ventricular contraction and ejection at around 0 ms, but the signal caused by trial contraction at around 350 ms is only visible on the chest as a second, smaller peak. If the subject is in upright position, e.g. sitting, the magnitude of acceleration is reduced, but the waveform remains highly similar (Fig. 10).

The difference in waveforms between chest and arm occur since the fast and intense ventricular contraction propagates a pressure pulse along the arterial system, that is distinguishable throughout the body. On the contrary, the relaxation and refilling of the heart is a more subtle and tardy process, and thus practically invisible outside the upper torso region.

C. Heartbeat Detection

We determined heart rates and S intervals with a single BCG sensor, following the methodology outlined in sections V-6 & V-7 (cf. Fig. 7 (bottom)). The BCG-based heartbeat monitor achieved an accuracy of over 95%, and deviated on average from the ECG-based heart rate by 1.3%.

Results for individual subjects are presented in Table II. Noteworthy is the stability of the S interval. Due to excessive movement artifacts, the standard deviation for Subject 4 is comparably high (130 ms). This, however, does not seem to affect the heart rate, and indeed random movement artifacts mistaken for S1 tend to cancel each other out over longer periods of time. We remark that this method is stable reliably finds S2 with low SNR (cf. for subject 5 in Fig. 11).

D. Measurements from a Walking Subject

Detecting the heartbeat from a walking subject proved to be non-feasible with our setup. Although the sensor can technically pick up the BCG signal while walking, the artifacts caused by upper torso movement and pacing are considerably stronger any relevant BCG signal. To assess these artifacts, reference signals or advanced signal filtering is required, such as e.g. Savitzky-Golay polynomial smoothing [30]. However, with the setup used in this study, the frequency content of movement artifacts pervades the frequency range of the heartbeats, thereby rendering the filtering unsuccessful. Similarly, synchronized multi-sensor setups for artifact cancellation are beyond the technical capabilities of the setup used.

VII. CONCLUSION

We have investigated the recording of BCG data for Pervasive healthcare with a simple accelerometer. A signal processing pipeline based on continuous wavelet transform

(a) Continuous-time scalogram for the BCG signal recorded from chest

(b) Mean intensity of ECG/BCG heartbeats.

Fig. 7. BCG heartbeat detection and cardiac activity over time

Fig. 8. Spectral density of BCG different body locations. The noise level is equal for both plots, scaling differs for extremities.

(a) Average heartbeat BCG waveforms for chest and arm.

(b) Average heartbeat BCG scalograms for chest and arm.

Fig. 9. Average heartbeat BCG waveforms and scalograms for measurements from chest and arm. Notice the different scaling of the magnitudes in scalograms.

(a) Average heartbeat BCG waveforms for a single subject lying and sitting.

(b) Average heartbeat magnitude scalograms for a single subject lying and sitting.

Fig. 10. Average heartbeat BCG waveforms and magnitude scalograms for a single subject lying and sitting. Notice different scaling of the scalograms.

Fig. 11. Average heartbeat waveforms for all six subjects.

spectrography was created. Additionally, the viability of the approach was validated at different location across the body, and boundaries were tested. Upper torso and upper arm were determined to be most viable locations due to their strong SNR for heartbeat detection. For the assessment of the second heart sound, only the chest region features sufficient SNR. An average acceleration waveform of a heartbeat for each subject was determined, and its relation to cardiac physiology was discussed. The waveform varies from subject to subject, potentially due to sensor placement. Furthermore, we proposed a method for a method to determine heart rate and S1-S2 interval from a single BCG-sensor measurement. The heart-rate yielded an accuracy of over 95% with a fairly stable S1-S2 interval across all the subjects. In the future, further analysis methods could be constructed based on this methodology to assess more features of the cardiac cycle. For instance, the presented methodology can be expanded for within-cardiac-cycle characterization to assess e.g. the relative strengths, durations and stabilities of S1 and S2. We further show that BCG information can be detected from arm as reliably as from chest, which is especially convenient for measuring from supine positions in Pervasive healthcare applications.

BCG measurements of a moving subject have not been possible due to excessive noise caused by step recoil. We assert that in future research some high-frequency components of the noise might be reduced through improved coupling of the sensor to skin, thus decreasing free oscillatory movements.

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