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A real-time approach for heart rate monitoring using a Hilbert transform in seismocardiograms

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Abstract

Heart rate monitoring helps in assessing the functionality and condition of the cardiovascular system. We present a new real-time applicable approach for estimating beat-to-beat time intervals and heart rate in seismocardiograms acquired from a tri-axial microelectromechanical accelerometer. Seismocardiography (SCG) is a non-invasive method for heart monitoring which measures the mechanical activity of the heart. Measuring true beat-to-beat time intervals from SCG could be used for monitoring of the heart rhythm, for heart rate variability analysis and for many other clinical applications. In this paper we present the Hilbert adaptive beat identification technique for the detection of heartbeat timings and inter-beat time intervals in SCG from healthy volunteers in three different positions, i.e. supine, left and right recumbent. Our method is electrocardiogram (ECG) independent, as it does not require any ECG fiducial points to estimate the beat-to-beat intervals. The performance of the algorithm was tested against standard ECG measurements. The average true positive rate, positive prediction value and detection error rate for the different positions were, respectively, supine (95.8%, 96.0% and ≃0.6%), left (99.3%, 98.8% and ≃0.001%) and right (99.53%, 99.3% and ≃0.01%). High correlation and agreement was observed between SCG and ECG inter-beat intervals (r > 0.99) for all positions, which highlights the capability of the algorithm for SCG heart monitoring from different positions. Additionally, we demonstrate the applicability of the proposed method in smartphone
based SCG. In conclusion, the proposed algorithm can be used for real-time continuous unobtrusive cardiac monitoring, smartphone cardiography, and in wearable devices aimed at health and well-being applications.

Keywords: seismocardiography, Hilbert transform, adaptive thresholding, heartbeat detection, biomedical signal processing, heart monitoring

(Some figures may appear in colour only in the online journal)

1. Introduction

Heart rate monitoring helps in assessing the functionality and condition of the cardiovascular system (Adamec and Adamec 2008). Heart rate monitors (HRMs) have been widely used for monitoring heart rhythm, heart rate variability (HRV) analysis, fitness and stress tests, sleep tracking and many other healthcare applications (Achten and Jeukendrup 2003). For example, a significant clinical application of HRMs is the continuous recording of heart rate and its periodicity—for strict or lenient heart rate control purposes—particularly with patients who suffer from atrial fibrillation (AF) (Van Gelder et al 2010).

In the past decade, the monitoring of cardiovascular activity by means of smart wearable or mobile systems has attracted the attention of many researchers and companies, as such systems are relatively cheap and can be utilized in most situations. Recent advances in the development of electromechanical sensors have opened a new opportunity for mechano-cardiography techniques. Miniaturized low-power, three-axis, high-resolution and low-noise accelerometers enable inexpensive access to mechanical cardiac monitoring. For example, physiological parameters such as the heart rate have been recently measured using smart devices (e.g. smart watches and smartphones), Google glasses, wristbands, weighing-scales and chest straps (Ramos-Castro et al 2012, Flatt and Esco 2013, Heathers 2013, Hernandez et al 2014, 2015, Jia et al 2015, Wiens et al 2015). Such cheap, non-invasive (and possibly disposable) heart monitors capable of long-term and frequent monitoring of the cardiac activity in an unobtrusive manner are an attractive choice for mass screening purposes as they provide immediate feedback on cardiovascular function, for example during fitness activities and stress tests.

Although there is currently a wide range of HRMs (either portable or wearable) available on the market, there is still space to improve the current technology, in particular in terms of accuracy and user-friendliness. For instance, electrocardiography (ECG) recording is the gold standard for monitoring the functioning of the heart. However, despite the undeniable capability of ECG to represent the electrical performance of the heart, it cannot be used to comprehensively investigate the mechanical activity of the heart (Wick et al 2012). Traditional ECG based HRMs are somewhat cumbersome, as they consist of multiple leads and good electrical conductance between the ECG electrodes and the skin must be achieved, which may require hair removal at the electrode locations. Typically, the current wearable or unobtrusive HRMs belong to one of two groups. One group consists of pulse wave monitors (optical or biopotential based), which are based on tracking the volumetric blood pressure variations, as in photoplethysmography, or electrical deflections due to the heart activity through the body, as in impedance cardiography and ECG. The other group includes the cardiomechanical monitors, which capture body micro-motions or chest motions (Allen 2007, Inan et al 2015) as in ballistocardiography (BCG) and seismocardiography (SCG). These cardiomechanical monitors measure the recoil forces of the body and precordial vibrations caused by the ventricular contractions, respectively (Starr et al 1939, Bozhenko 1961), and free the subject from
cumbersome wires and cables. However, BCG and SCG are more vulnerable to interpersonal variations than ECG. For example, variations in body mass index, age, sex, and somatic and health conditions may have a significant effect on the signal morphology in BCG and SCG. In addition, motion artifacts caused by body movements, position and, for example, muscle related diseases may affect the fidelity of the SCG measurement and hence the quality of the corresponding cardiac recordings (Zanetti and Tavakolian 2013, Inan et al 2015).

In this study we consider the accurate estimation of heart rate and beat-to-beat intervals from SCG signals, without the need for ECG fiducial points. A novel peak-detection method is presented based upon a combination of three-dimensional (3D) motion sensing, the Hilbert transform and adaptive thresholding. Signal processing methods and the algorithms developed for identifying particular events in the mechanical signal and extracting the cardiac time intervals (CTIs) are described. This paper is organized as follows. In section 2 we describe the SCG measurement, consider its historical background and present the SCG measurement device designed and used in this study. In section 3 we propose a new heartbeat detection algorithm for SCG and in section 4 we present statistical analysis results and comprehensively discuss the proposed method and future tasks for the further development of the method. Section 5 concludes this work.

2. Background

2.1. Seismocardiography

SCG is a non-invasive method which measures accelerations caused by respiration and myocardial motions in the chest wall (Bozhenko 1961, Zanetti and Salerno 1991). The word seismocardiography was first coined in Bozhenko (1961), and its clinical application was later introduced in Zanetti and Salerno (1991). Later, Salerno and colleagues published a paper in which they described a SCG waveform identification method for monitoring cardiac events, e.g. the opening and closing moments of the heart valves, such as the mitral and aortic valves (Zanetti et al 1991). In principle, the recording of the seismocardiogram contains useful information about the heart motions which originate from the contraction and relaxation of the left ventricle (Salerno et al 1991, Salerno and Zanetti 1991). It is worth pointing out that BCG—the recording of the ballistics forces of the body, invented by Gordon (1877)—and SCG are both unobtrusive cardiomechanical monitoring methods. However, BCG measures whole-body recoil forces in response to blood ejection into the vascular tree, while SCG measures the positional vibrations of the chest wall in reaction to the myocardial motions and respiration (Inan et al 2015).

Today, 3D SCG can easily be measured by mounting a tri-axial accelerometer sensor on the upper chest area so that the x-axis corresponds to the right-to-left lateral accelerations, the y-axis to the head-to-foot aligned accelerations and the z-axis to the dorso-ventral accelerations caused by precordial movements (see figure 1). In this work we perform peak detection on the z-axis signal, as it has the highest amplitude and as the z-axis of the accelerometer is coaxial with the heart (Inan et al 2015). To find the correct peak locations, we consider the total magnitude of the measured accelerations, and thus also use the longitudinal and lateral axes of the 3D SCG signal.

Various health and wellness applications have been proposed for SCG. Generally, electromechanical monitoring of the heart has been investigated in cardiovascular medicine for estimating hemodynamic parameters and HRV, detecting heart arrhythmias such as AF, detecting myocardial ischemia and for the treatment of acute coronary ischemia and sleep disorders (Tavakolian et al 2010, Kajbafzadeh et al 2011, Castiglioni et al 2012, Marzencki et al 2012,
In recent years, SCG has also been proposed for medical imaging applications in which the quiescent phases of the cardiac cycle can be detected by SCG for motion correction in nuclear medicine imaging and radiotherapy (Wick et al 2012, Jafari Tadi et al 2014).

2.2. Data acquisition system

For data acquisition, a hand-held system was designed for recording the electromechanical activity of the heart. This measurement system consists of a seismocardiograph, a standard three lead wire ECG system and a data acquisition board, which stores the synchronized SCG and ECG data on a memory card. A three-axis, low-power, microelectromechanical (MEMS) accelerometer (MMA8451Q from Freescale Semiconductor), with 14 bits of resolution and a physical size of 3 mm × 3 mm × 1 mm, was attached to the body of the sternum using double-sided tape without hair removal in the chest area. The measured acceleration range of the sensor was set to ±2 g. The ECG leads and the MEMS sensor were connected to the data acquisition board using shielded wires. A DC power supply including three cascaded AAA alkaline batteries was used as the input power. The data acquisition involved the measurement of acceleration (three axes of measurement) and a low power integrated analogue front-end ECG (Texas Instruments ADS1293) using a Freescale FRDM-KL25Z board to collect the data on a memory stick. The SCG and ECG data were recorded simultaneously using a custom-made acquisition system with a sampling frequency ($F_s$) of 800 Hz. In practice, a lower sampling frequency would result in smaller power consumption and computational complexity, but the chosen rate of sampling would generally be beneficial in order to investigate higher frequency (up to 320 Hz) intra-cardiac events such as the heart’s valvular activity and murmurs (Tavakolian 2010). Synchronized ECG was recorded for reference purposes. The ECG
electrodes were mounted on the right and left upper chest area, and the anterior lateral regions of the abdomen on the left and right hypochondriac. The electrodes were standard blue sensor M ECG electrodes (Ambu, Ballerup, Denmark). Data processing was performed after transferring the binary data from the memory card to the computer to convert the data to text format (.txt) using custom-made software (Jafari Tadi et al. 2014, Jafari Tadi et al. 2015). The data acquired from our prototype were processed and analyzed offline in the Matlab programming environment.

We also implemented the presented algorithm in an Android platform for real-time heart monitoring using the smartphone’s MEMS accelerometer. The design and development of the measurement systems, the Android application and post-processing algorithms of this study were performed in the TRC laboratory at the University of Turku, Finland. Figure 1 demonstrates a schematic view of the data collection designed for this study.

3. Hilbert adaptive beat identification technique

3.1. Literature review

To date, several different methods have been proposed for estimating beat-to-beat intervals in an electrical or a mechanical cardiac signal, for example see (Pan and Tompkins 1985, Benitez et al. 2000, 2001, Brüser et al. 2011, Brüser et al. 2013, García-González et al. 2013, Paalasmaa et al. 2014, Alvarado-Serrano et al. 2016). However, it should be pointed out that, in general, detecting inter-beat intervals from SCG/BCG data is much more complicated than from ECG, because the mechanical signals are often variable and inconsistent due to inter-subject morphological variations.

The current signal processing approaches for HRMs detect either the instantaneous heart rate or averaged heart rate, typically taken over several successive heartbeats. The instantaneous heartbeat detectors are based on digital filters, differentiation, adaptive thresholding (Pan and Tompkins 1985, Hamilton and Tompkins 1986), discrete or continuous wavelet transform (Sandham et al. 1998, Postolache et al. 2007, Chen et al. 2008, García-González et al. 2013, Alvarado-Serrano et al. 2016), Hilbert transform (Benitez et al. 2000, 2001, Stork 2012, Jia et al. 2015, Wei et al. 2015), classification and clustering (Brüser et al. 2011, Brüser et al. 2013, Khosrow-Khavar et al. 2013, Paalasmaa et al. 2014, Khosrow-Khavar et al. 2015), or S-transform and Shannon entropy (Zidelmal et al. 2014). These approaches can be divided into two groups: those methods which use the ECG signal to segment and process the considered SCG signal, and ECG independent methods. The approach proposed in this paper belongs to the latter group and does not require an ECG signal for heartbeat detection.

Algorithms that rely on the ECG fiducial points require ECG R-peaks for heartbeat detection and feature extraction in SCG (Pandia et al. 2012, Ramos-Castro et al. 2012, Jafari Tadi et al. 2015, Javaid et al. 2015, Khosrow-Khavar et al. 2015, Wiens et al. 2015). For example, the recently published paper by Khosrow-Khavar et al. (2015) indicated a new method for automatic annotation of high frequency components in the SCG signal by applying several signal processing techniques. This approach extracts the envelope of the SCG signal and then employs ECG R-peaks (i.e. the fiducial points) as well as a searching window technique to detect the cardiac impulses in the SCG signal. Although the method yields promising results, its motivation is completely different from the proposed work, as it assumes the use of ECG (Khosrow-Khavar et al. 2015).

On the other hand, ECG independent methods typically suffer from strong assumptions on the mechanical waveforms, which may result in false annotation of SCG signals. For instance, methods based upon fixed threshold setting are problematic, as amplitude fluctuation in SCG/
BCG signals tend to interrupt the detection procedures. Moreover, due to inter-subject variations in the signal morphology, setting proper thresholds is a very complicated task (Friedrich et al 2010, Rienzo et al 2013). In 2013, García-González et al (2013) compared four heartbeat detectors based upon continuous wavelet transform, cross-correlation and bandpass filtering in SCGs and finally reported narrowband bandpass filtering as the best heartbeat detector. However, band-pass filtering causes additional distortion on the SCG signals which may result in quantitative inaccuracy in heart rate estimation (Zidelmal et al 2014). Recently Hernandez and colleagues detected heartbeats with the findpeaks Matlab function for feature extraction from mechanical heart signals (Hernandez et al 2015). To the best of our knowledge parameter optimization for this MatLab function is a very cumbersome task due to interpersonal variations and inconsistency between the heart waveforms for mechanical signals. Additionally, algorithms based on clustering techniques typically suffer from mis-detection of heartbeats (Paalasmaa et al 2014). In 2008, Shin et al developed a classification approach based upon template matching and cross-correlation in order to automatically detect heartbeats in BCG signals (Shin et al 2008). Later, in 2011, Brüser et al (2011) developed an unsupervised learning technique for the detection of inter-beat intervals based on k-mean clustering. However, in that study the main evaluation metric for measuring the heart rate detector performance was the coverage index—the proportion of the number of SCG/BCG inter-beat intervals to the number of ECG R–R intervals—which is not sufficient for a comprehensive comparison against ECG. Subsequently, Brüser et al (2013) and Paalasmaa et al (2014) suggested new techniques for beat-to-beat estimation based on clustering and classification in BCG signals; however, these methods had difficulty in locating a substantial amount of the inter-beat intervals. These methods achieved coverage ratios of 73% and 54%, respectively, whereas the coverage ratio in the presented work is 98%.

Methods based on calculating the average heart rate over a period of time, such as autocorrelation (Jezewski et al 2011, Nakano et al 2012, Zhu and Tian 2013), power spectral density (Hernandez et al 2014, Jia et al 2015) and wavelet decomposition (Sandham et al 1998), are usually incapable of providing information about either irregular heartbeat or rhythm variation in the inter-beat intervals, in particular for HRV analysis.

Recently, new techniques based upon multichannel data fusion, sensor fusion and sensor array structures have been used to improve the accuracy and robustness of heart monitoring (Hoog Antink et al 2014, 2015, Šprager and Zazula 2014, Zhu et al 2014, Brüser et al 2015, Jia et al 2015, Lee et al 2016). The use of multiple sensors—either measuring the same or different physical quantities—is advantageous as it offers diversity in signal acquisition. In this work we use the diversity to some extent, as the heartbeats are located from the total acceleration signal obtained as a sum over the three axes of the accelerometer; however, the application of more sophisticated data fusion methods within the proposed HABIT algorithm are left for future considerations.

3.2. Overview of the algorithm

In this paper we present an ECG independent method for the detection of the heartbeat from the SCG signal. To this end, a Hilbert adaptive beat identification technique (HABIT) algorithm was developed to detect heartbeats and to calculate beat-to-beat intervals. The timing of the heartbeat can be determined from particular wave forms in the SCG that repeat with every heartbeat. Specifically, contraction of the left ventricle (systole) yields a sharp spike in every cardiac cycle and results in aortic valve opening (AO), blood ejection and the first heart sound, S1, whose mechanical signal waveform looks like a dip–rise–dip wave (W-complex) (Sandham et al 1998, Rienzo et al 2013). This repeating waveform contains high frequency,
sharp and oscillating waves in the beginning of the systole phase. On the other hand, by the
beginning of ventricular diastole and after closure of the aortic valve (AC) the second heart
sound, S2, appears, whose mechanical signal waveform looks like a rise–dip–rise
and results in lower frequency and higher negative amplitude semi-oscillating waveforms in comparison
to the systolic waves (Rienzo et al. 2013, Tavakolian et al. 2013). In the considerations in this
paper the position of the local maximum point during the first heart sound S1 is considered
to be the timing of the cardiac impulse or heartbeat, and the local minimum point during the
second heart sound S2 is considered to be the onset of the diastolic phase in every cardiac
cycle. Figure 2 shows a set of events in a cardiac cycle for the SCG z-axis. In the measure-
ments considered in this work, the amplitudes of the cardiac cycles were typically in the
10–40 mg range. The main problem with the SCG signal is that the accelerations caused by
the valvular activity of the heart (i.e. aortic and mitral valves) yield varying waveforms, partly
due to noise and inter-subject variations. This causes inconsistency in the detection of heart-
beats since any beat-to-beat detection algorithm has to fulfill two tasks: (1) localize the heart-
beat positions accurately and (2) ensure that the heartbeat positions correspond to successive
heartbeats, i.e. that there are no falsely detected or missed heartbeats in the cardiac cycles
(Paalasmaa et al. 2014).

In the following, we present the general framework for the proposed approach, which auto-
matically finds the local maximum peaks in the systolic region across every cardiac cycle. First,
the acquired precordial vibration signals (i.e. SCGs) from a tri-axial accelerometer are filtered
and noisy components are discarded. After that, the motion artifact-free parts of the SCG data
drawn from different axes (i.e. the x-, y- and z-axes) are combined so that the magnitude of the total
acceleration is formed. The total acceleration signal denoted by \( s(t) \) is subsequently fed to the
Hilbert transform in order to extract the envelope of the fused SCG signal as an amplitude of the
analytic signal. The envelope signal—which we denote by \( A(t) \)—is next filtered by applying a
brick-wall band-pass filter to extract heart pulse waves. The \( A(t) \) signal is integrated to obtain
a very low-frequency approximation of the seismocardiogram velocity signal, which is called
the principal signal in this work. Finally, heartbeats are detected within a refinement process in
an adaptive manner. Adaptive thresholding automatically adjusts the thresholds and parameters
periodically in order to adapt to changes in systolic wave morphology and the heart rate.

3.3. Signal pre-processing

For the purposes of this study, a 3 dB bandpass fourth order Butterworth IIR filter with cut-
off frequencies of 1 and 45 Hz was first applied on each accelerometer channel, allowing the
removal of white noise, signal offset or trend. Next we removed the noisy components of the
signal (i.e. body motion artifacts) in each axis of the accelerometer and thereby only artifact-
free segments were considered for further processing and peak detection. In order to detect
these artifacts, a signal power envelope is calculated from the acceleration data using the root
mean square (rms) operation. A sliding window with a length of 500 ms and a detection thresh-
old twice the median value of the power envelope were employed to search for the noisy comp-
onents of the signals. The parts of the signal where the power envelope exceeds this threshold
are classified as motion artifacts. Figure 3 demonstrates the performance of the motion artifact
detection algorithm on an empirical noisy signal. The upper panel of figure 3 shows the enve-
lope of the signal power, where the parts exceeding the threshold are dashed and highlighted in
red. In the bottom panel of figure 3, these motion artifact parts of the original SCG signal are
detected and can hence be omitted from the subsequent analysis. It is worth mentioning that in
physiological measurements, and in particular in controlled clinical data acquisition, the par-
ticipants are asked to be as motionless as possible during the recordings. In our case, the two
main parts of the data where motion artifacts typically occurred were the beginning and end of
the recordings, as the subjects sometimes moved at these points. In total, approximately 3% of
the acquired signal considered in this work was discarded due to motion artifacts.

After the detection of the motion artifacts, the longest artifact-free portion of the signal—with
synchronized timestamps for each axis of the accelerometer and the ECG—was selected for

Figure 2. An electromechanical cardiac cycle (ECG–SCG): systole and diastole time
intervals are segmented with dashed lines. The S1 and S2 are first and second heart
sounds, respectively.

Figure 3. Detection of motion artifacts from mechanical signals using an rms filter.
further analysis. In the smartphone implementation of the presented algorithm, the algorithm is paused for the duration of the motion artifacts and it is restarted once the artifact ends. It might be useful to also consider motion-cancellation techniques such as those proposed in Pandia et al. (2011) and Yang and Tavassolian (2015); however, the application of such methods is outside the scope of the present work. From the selected portion of the signal, the total acceleration magnitude \( s(t) \) is obtained by calculating the vector magnitude in a sample-wise manner:

\[
s(t) = \sqrt{x(t)^2 + y(t)^2 + z(t)^2},
\]

where \( z(t) \), \( y(t) \) and \( z(t) \) represent the acceleration as measured in, respectively, the \( x \)-, \( y \)- and \( z \)-axes of the accelerometer at the time instant \( t \). The use of (1) has been previously proposed by Migeotte et al. (2011) to assess the spatial curve of the displacement vector instead of the single axis components of BCG/SCG in a microgravity environment. This technique was later used for extraction of physiological information from a free floating subject in space (Lejeune et al. 2013).

### 3.4. Hilbert transform

The Hilbert transform has become a popular operation for detecting the QRS complexes in ECG signals and a considerable amount of literature has been published on this topic (Benitez et al. 2000, 2001, Rabbani et al. 2011, Stork 2012). In this paper we assess the capability of the Hilbert transform for locating heartbeats in seismocardiogram signals. Generally, the detection of heartbeats in the SCG signal is improved by employing the Hilbert transform, since this facilitates the detection of the dominant peaks—i.e. cardiac impulses—across the signal. The envelope curve of the combined signal \( s(t) \) can thus be obtained by applying the Hilbert transform

\[
\hat{s}(t) = \frac{1}{\pi} \int_{-\infty}^{+\infty} \frac{s(\tau)}{t - \tau} d\tau.
\]

Essentially, this transform yields a 90° phase shift of \( s(t) \) and thus we can compute the magnitude of its envelope curve as

\[
A(t) = |\hat{s}_a(t)| = \sqrt{\hat{s}_a(t)^2 + \hat{s}_b(t)^2}.
\]

The envelope curve, which contains low frequency (<5 Hz) components, is subsequently fed to a brick-wall band-pass fast Fourier transform (FFT) filter with cut-off frequencies of 0.5 Hz and 3 Hz (corresponding to 30 and 180 beats per minute (bpm)), in order to obtain a waveform having the same periodicity but a significantly simpler structure than the original pulse wave. The FFT filtering is accomplished by removing unwanted frequency components in the frequency domain. In practice, we first take the FFT of the input signal, then remove the undesirable frequency bands and finally transform the remaining frequencies back to the time domain using the inverse FFT. The length of the FFT is equal to the number of samples in the considered input signal in the off-line implementation of the HABIT algorithm and equal to the number of samples in a 10 s segment in the real-time smartphone implementation. Figure 4 shows all the preprocessing steps.

### 3.5. Principal signal extraction

#### 3.5.1. Fiducial markers.

Figure 5(a) shows the reference ECG and figures 5(b)–(e) show, respectively, the SCG signals acquired from different channels (\( x \)-, \( y \)- and \( z \)-axes) and the
combined signal $s(t)$. Figure 5(f) shows the Hilbert transform of the total acceleration signal $s(t)$. As this figure demonstrates, the $A(t)$ signal has the same periodicity as the original waveform, but a simpler structure. However, there was notable inter-subject variability in the $A(t)$ signal in various seismocardiograms. We noticed that in many cases, each cardiac cycle is formed by two prominent—systolic and diastolic—peaks, of which the most prominent one, i.e. the systolic peak, is stable enough to be located for beat-to-beat interval detection. The systolic peaks originate from left ventricular activity and have a rather stable amplitude, whereas the diastolic peaks are observed as varying waveforms and amplitudes. In addition, we observed that due to inter-subject inconsistencies in $A(t)$ the systolic and diastolic peaks in some cardiac cycles appear with irregular amplitudes, which cause tooth-shaped cardiac waves. This phenomenon usually occurs in low quality SCG signals and negatively affects the accuracy of the heartbeat detection. To overcome this problem, we integrate $A(t)$. Integration transforms the acceleration to velocity and smooths the signal, and yields a sinusoid-like waveform whose frequency corresponds to the individual heart rate (see figure 5(g)) without any tooth-shaped artifacts.

The resulting signal, which is called the principal signal in the following, contains no varying or challenging components and hence peak detection can be performed in a straightforward manner. The local maxima of this signal will act as the fiducial markers which enable us to find the exact corresponding peaks in the original SCG signal, and accordingly find the most stable systolic spikes in each cardiac cycle. As the integration smooths the signal, the locations of these local maxima in the principal signal have some latency and inaccuracy in position compared to the original locations of the S1 peaks in the SCG signals. Thus, a refinement process is required, as the delayed fiducial peaks of the principal signal may affect the reliability of the considered hemodynamical parameters. The refinement process here means that the exact positions of heartbeats in the filtered SCG signals (usually the z-axis of the accelerometer) can be detected by means of the detected fiducial markers (local maxima) across the principal signal. Reliable heartbeat detection is necessary for accurate estimation of the beat-to-beat time interval variations as well as precise segmentation of the cardiac cycles. This refinement process is also critical for proper annotation of the cardiac cycles, in particular in arrhythmia detection. A detailed description of the refinement process is given in section 3.6.

### 3.6. Adaptive localization of heartbeat candidates in SCG

The refinement process for localizing the heartbeats in the SCG signal is inspired by the Pan–Tompkins method (Pan and Tompkins 1985), which has been developed for real-time
3.6.1. Initialization. Similarly to the Pan–Tompkins algorithm, we divide the initialization into two phases. In the first phase, the detection thresholds are initialized by taking first 2 s of the principal signal and then defining the thresholds based upon the signal and noise levels. The second phase requires two heartbeats or two maximum points from the principal signal to initialize the beat-to-beat interval average and limit values.

3.6.2. Adaptive thresholding. The thresholds and other parameters of the algorithm are adjusted periodically—e.g. the thresholds are updated at every heartbeat—to adapt to the changing characteristics of the principal signal. As has been suggested in Pan and Tompkins (1985), the algorithm benefits from two different sets of thresholds to detect S1 peaks. One set of thresholds is used with the original filtered SCG signal from the z-axis of the accelerometer, and the other set of thresholds is used with the principal signal. Using these two sets of thresholds enhances the reliability and accuracy of the peak detection. Furthermore, the detection thresholds depend on the noise that is sensed during the processing and detecting. As proposed in Pan and Tompkins (1985), the current signal level, denoted here by $L_{\text{sig}}$, is estimated from the amplitudes of the local maxima of the signal which are above a signal threshold variable $T_{\text{sig}}$ that presents the amplitudes of recently detected S1 peaks. For example, if the amplitude of a local maximum above the signal threshold is denoted by $A_{\text{peak}}$, then the new estimate of the signal level is calculated as

$$L_{\text{sig}} = (1/8)A_{\text{peak}} + (7/8)L_{\text{sig}}.$$

The estimated noise level $L_{\text{noise}}$ is adapted analogously for local maxima below the signal threshold. The values of $L_{\text{sig}}$ and $L_{\text{noise}}$ are initialized as 25% of the maximum amplitude, and
as 25% of the mean level of the principal signal during the first 2 s of the considered segment, respectively. The signal threshold $T_{\text{sig}}$ is calculated from the estimated noise and signal levels as

$$T_{\text{sig}} = L_{\text{noise}} + (1/4)(L_{\text{sig}} - L_{\text{noise}}).$$

(5)

These adaptation parameters and equations are as originally proposed in Pan and Tompkins (1985), and the interested reader is referred to that publication for more detailed information on adaptive thresholding. To increase the robustness of the algorithm, we also employ a dual-thresholding idea inspired by the Pan–Tompkins method to find missed peaks from the SCG signal, which in turn decreases the false detection rate. In a nutshell, if no local maxima above the signal level are found within 166% of the current estimate of the cardiac cycle duration, this sub-segment will be re-investigated with lowered thresholds.

3.6.3. Heartbeat detection from SCG. After finding the local maxima from the principal signal, the location of the heartbeat of a given cardiac cycle is detected by finding the maximum value of the original SCG signal within a sliding window with a length of 400 ms, which corresponds to 320 samples. The moving window begins from the local maximum of the corresponding cycle and moves backwards to find the heartbeat within that cardiac cycle. In the SCG signal, the highest amplitude component of the systole refers to the cardiac impulse or heartbeat, i.e. $S_1$, and the presented HABIT algorithm is designed with the assumption that the amplitude of $S_1$ is larger than the amplitude of $S_2$. Inter-subject variability is a challenge in SCG-based heartbeat detection. One potential source of inter-subject variability is respiratory sinus arrhythmia (RSA). We noticed that some signals with substantial RSA have stronger $S_2$ amplitudes than $S_1$ amplitudes, which may result in erroneous classification of the $S_2$ peak as the $S_1$ peak. To mitigate this problem, a search back procedure was appended to the algorithm. If the algorithm fails to find a local maximum above the signal threshold or if it finds multiple strong peaks, a search back procedure will run in order to find the location of true $S_1$ peak. The search back window was set to 166% of the current $S_1$–$S_1$ interval, as suggested by Pan and Tompkins (1985). If no peak is detected in the search back process, the maximal detected value which lies between defined thresholds serves as a candidate for $S_1$. Figure 6 shows the positions of local maxima and $S_1$ peaks which are detected for measuring the beat-to-beat intervals. In our implementation, once a possible $S_1$ peak is found, a 300 ms refractory period is defined to avoid finding the diastolic peaks in the mechanical signal. The refractory period prevents false detection of diastolic peaks during its duration. An important feature of the presented algorithm is that each key parameter is adapted with time, which reduces the problem of inter-subject variation in the signal morphology.

The average beat-to-beat interval is calculated by two different methods. The first method calculates the mean time interval for the eight most recent $S_1$–$S_1$ intervals. The second method averages the $S_1$–$S_1$ intervals of the most recent eight heartbeats which fall within the range of 92–116% of the current $S_1$–$S_1$ interval mean value (Pan and Tompkins 1985). These two methods provide together an extensive heart rate measurement. For example, when a regular heart rate suddenly changes to an atypical one, the first method is replaced by the second method, and thereby the algorithm immediately adapts to the changed signal (Pan and Tompkins 1985).

3.7. Performance evaluation

3.7.1. Measurement scenario. In this study, the test group consisted of thirty healthy male volunteers. The demographics of the subjects were as follows for the min–max, mean, standard deviation, respectively: age (23–41, 29.15, 4.73 years), height (170–190, 178.48, 5.91 cm),
weight (60–98, 76.32, 11.20 kg) and BMI (17.53–29.4, 23.92, 3.00 kg m\(^{-2}\)). The study was conducted in accordance with the Helsinki Declaration of 1975 as revised in 2000. The cardiac recordings for this study were performed by researchers in the TRC laboratory of the University of Turku. In total, 42 recordings were obtained in this study, including thirty recordings in the supine position and 12 recording from lateral positions. Six subjects were randomly selected for measuring heart signals in two lateral positions, i.e. left and right lateral recumbent. Subjects were asked to relax for a couple of minutes before the data acquisition. All the data acquisitions were performed for up to 5 min for each subject per position.

3.7.2. Performance metrics. The performance of our algorithm was evaluated using synchronized ECG as a reference with respect to the detected heartbeats and inter-beat time intervals. In the ECG signal, the QRS complexes were detected using the Pan–Tompkins method (Pan and Tompkins 1985). The heart rate detection algorithm described in section 3 was applied to the SCG signals obtained by a three-axis accelerometer sensor. The performance of the method was assessed and computed separately for each subject by means of different statistical parameters such as the mean value of beat-to-beat intervals, precision, sensitivity, coverage, detection error rate (DER), the rms error (RMSE), the mean absolute error (MAE), and the 95th percentile error rate of the SCG inter-beat intervals and heart rates, as compared to the ECG signal.

The coverage ratio is the ratio between the total number of the measured SCG S1–S1 intervals and the total number of detected R–R intervals from the ECG. To calculate the coverage, we use the proposed peak-detection algorithm, and Pan–Tompkins for the reference ECG signal, to extract SCG heartbeat timings \(S1_i, i = 1, 2, 3, \ldots, M\) for SCG and R-peak timings \(R_j, j = 1, 2, 3, \ldots, N\) for ECG for each of the subjects. The coverage ratio between the number of S1–S1 intervals and the number of R–R intervals is then defined as

\[
\text{Coverage} = \frac{M - 1}{N - 1}.
\]
where $M - 1$ and $N - 1$ are the total number of estimated SCG and ECG cardiac intervals, respectively. A coverage ratio less than one means that a smaller number of cardiac intervals have been (erroneously) detected in SCG than in ECG, whereas a coverage ratio greater than one means that more cardiac intervals have been (erroneously) detected in SCG than in ECG.

The coverage ratio is a basic quantitative metric to show whether or not an equal number of SCG and ECG beat-to-beat intervals have been obtained by the proposed heartbeat detection algorithm. A problem with the coverage ratio is that it fails to show whether the achieved cardiac cycles from SCG are properly aligned with those measured from ECG or not. For example there might be a situation where the S1 peak is missed or falsely detected but the coverage ratio still imprecisely shows an equal number of inter-beats for SCG/BCG and ECG due to the replacement of a missed S1 with an erroneously detected one. Thus, the coverage alone is not sufficient. Hence, we calculated the detection ability of the method by evaluating the precision or positive predictive value (PPV), sensitivity or true positive rate (TPR) and DER metrics. Sensitivity and precision evaluate the capability of the detector to find valid S1 peaks and to reject incorrectly detected S1 peaks, respectively. To calculate the above parameters, we first classified the true, false and missed detected heartbeats as follows.

For each $i = 1, \ldots, M$, a detected S1, is considered to be:

(i) true positive (TP) if

$$\exists j : |S_1_i - R_j| \leq 150 \text{ ms}$$

(ii) false positive (FP) if

$$\exists j : |S_1_i - R_j| > 150 \text{ ms}.$$  

(iii) false negative (FN), in which case the following condition is satisfied:

$$\exists i : |S_1_i - R_j| > 150 \text{ ms}.$$  

A fixed window of 300 ms located symmetrically around the R-peak in the ECG signal was used to determine the above parameters. This selection can be justified by the physiological facts that the pre-ejection period is less than 120 ms in healthy adults and that the mean left ventricular ejection time in healthy subjects is between 300–400 ms (Tei et al 1996). Thus, the selected window should contain the first cardiac sound, S1.

Using the above parameters, three performance metrics, i.e. sensitivity or TPR, precision or PPV and the DER, are calculated as

$$\text{Sensitivity or TPR} \% = \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100$$

$$\text{Precision or PPV} \% = \frac{\text{TP}}{\text{TP} + \text{FP}} \times 100$$

$$\text{DER} \% = \frac{\text{FP} + \text{FN}}{\text{total number of S1 peaks}} \times 100,$$

where TP represents the total number of TPs, FN the total number of FNs and FP the total number of FPs. Furthermore, the RMSE, the MAE and the 95th percentile ($E_{95}$) of the absolute
differences between the R–R and S1–S1 inter-beat time intervals were calculated. To compute these, we first define the \( j \)th RR-interval in ECG by

\[
RR_j = R_{j+1} - R_j,
\]

where \( R_j \) denotes the timing of the \( j \)th R-peak.

Similarly, the \( j \)th inter-beat interval in SCG is obtained as

\[
S1S1_j = S_{1j+1} - S_{1j},
\]

where \( S_{1j+1} \) and \( S_{1j} \) are consecutive heartbeats. For each R–R interval we choose the S1–S1 interval whose midpoint is closest to the R–R interval’s midpoint. For each of these corresponding intervals—here denoted by the indices \( j \) and \( k \)—we calculate the time difference as

\[
d_{error} = RR_j - S1S1_k.
\]

As a result, the RMSE and the MAE for the total number of beat-to-beat intervals (\( n \)) are obtained as

\[
RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (d_{error})^2},
\]

\[
MAE = \frac{1}{n} \sum_{i=1}^{n} |d_{error,i}|.
\]

The averaging of heart rate measurements was performed using an overlapping 10 s moving window for both SCG and ECG. Then, the RMSE of the heart rate measurements between ECG and SCG, \( RMSE_{HR} \), was calculated as

\[
RMSE_{HR} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (HR_{ECG} - HR_{SCG})^2},
\]

where \( HR_{ECG} \) and \( HR_{SCG} \) are the \( j \)th mean heart rate averaged over 10 s, obtained from the SCG and ECG signals, respectively.

4. Results and discussion

The main objective of this work is to present a new peak-detection method for estimating the beat-to-beat intervals from an SCG signal. The proposed algorithm was able to extract the beat-to-beat time intervals of all subjects except one subject, whose SCG signal was found to be too noisy. Table 1 shows the results of this algorithm for each subject, excluding the noise-contaminated one. The accurate timings of the R-peaks and S1-peaks were obtained by applying the peak-detection algorithm described in section 3.6.

The off-line computational complexity of the proposed method was assessed by measuring the computing time of HABIT on a 5 min SCG signal on a Intel(R) Core (TM) i7-6500U CPU @ 2.50 GHz with 8 GB RAM computer running the MatLab software (R2015a). This signal consists, in total, of 291 segments of 10 s durations, and the total computations required by HABIT took 2.969 s, which corresponds to approximately 10 ms per segment. In this measurement, the Butterworth band pass filter, the FFT filter, Hilbert transform and peak-detection processing time took 180 \( \mu \)s, 300 \( \mu \)s, 58 \( \mu \)s and 1 ms, respectively, per segment.

In total, 11537 (supine:9213, left:1077 and right:1247) beat-to-beat intervals or cardiac cycles were estimated using the proposed technique. On average, more than 97% of each SCG
signal was classified as free of motion artifacts and analyzed by the HABIT algorithm. The mean SCG inter-beat interval during the supine position was 962.05 ± 94.32 ms and the average heart rate was 65.88 ± 1.01 bpm. The mean inter-beat intervals for the left and right positions were 963.4 ± 37.9 ms and 937.6 ± 42.5 ms, respectively. The average RMSE error between the ECG and SCG heart rates found less than 1 bpm for all positions, as calculated errors were 0.33 bpm, 0.62 bpm and 0.45 bpm for the supine, right and left lateral positions, respectively.

Average coverage rates close to 1 were achieved for all positions as follows: supine 0.98, left 0.99 and right 1.01. The average sensitivity (TPR) and precision (PPV) rates were, respectively, 95.8% and 96.0% in the supine position, while the TPR and PPV values were 99.3% and 98.8% for the left lateral position, and 99.5% and 99.3% for the right lateral position, respectively. The average RMSE was 37.6 ms, while the MAE and the mean 95th percentile were 22.5 ms and 37.8 ms for the subjects in the supine position, respectively. These three error values (RMSE, MAE and $E_{95}$) for the two other positions were, respectively, left: 30.9 ms, 7.38 ms and 12.2 ms; and right: 26.15 ms, 10.4 ms and 28.12 ms. Furthermore, low average DERs were observed in this study (supine ≃0.6%, left ≃0.001% and right ≃0.01%). The sensitivity and precision of the proposed method were similar to the heartbeat detection method reported in Shin et al (2008) and the error metrics were similar to the beat-to-beat heart rate methods in Brüser et al (2011) and Paalasmaa et al (2014). Since the measurement set-ups, including the sensors used, are different for each of the discussed studies, and since some of the quantitative measures are missing, a direct comparison of HABIT and these methods would not be very meaningful.

The position of the subject—supine or lateral positions—seems to have a rather small impact on the performance of the proposed algorithm. The results obtained for the supine position are slightly improved in comparison to the other positions, with TPR, PPV, RMSE, MAE, $E_{95}$ and RMSE$_{HR}$ of 99.5%, 99.8%, 15.1 ms, 12.9 ms, 22.5 ms and 0.16 bpm, respectively. Additionally, for two subjects (subject ID = 7 and 13) the proposed algorithm performed poorly on the z-axis of the SCG. The reason for this was the variation in the amplitudes of the systolic and diastolic peaks—likely due to substantial RSA in some cardiac cycles, S1 was stronger than S2 while for some other cardiac cycles S2 was stronger than S1. For these subjects we found that the x-axis yields more accurate results as presented in table 1(b). If for these subjects we replace the z-axis results by the x-axis outcomes, the performance metrics for the supine position become improved with TPR, PPV, RMSE, MAE, $E_{95}$ and RMSE$_{HR}$ equal to 99.14%, 99.01%, 29.6 ms, 14.26 ms, 19.24 ms and 0.21 bpm, respectively. This shows the significance of determining the best axis for heartbeat detection. Machine learning and pattern recognition could be used to automatically determine the best axis, and such methods have been previously discussed in Schumm (2010), Li et al (2014) and Tanantong et al (2014), (2015). However, we leave the application of such methods to the HABIT algorithm for future work.

Figures 7(a)–(f) show agreement and linear correlation between S1–S1 and the R–R time intervals measured by SCG and the reference ECG. Figures 7(a)–(c) demonstrate the resulting differences between beat-to-beat intervals using the Bland–Altman plot (Bland and Altman 1986) in supine, left lateral and right lateral positions, respectively. These plots indicate relatively high agreement for all positions between the inter-beat intervals achieved from the SCG signal and the ones obtained from the ECG. The middle dashed line denotes the mean difference of the SCG and ECG intervals (bias value). The upper and bottom dashed horizontal lines denote 95% confidence intervals. Table 2 shows the resulting difference values from the Bland–Altman plots of different positions. In addition to the Bland–Altman plots, figures 7(d)–(f) show the linear relationship between SCG and ECG beat-to-beat intervals, i.e. Pearson’s correlation. As can be seen from figures 7(c)–(f), very high correlation coefficients (R) were achieved in all the positions ($R^2 > 0.99$).
Table 1 and figure 7 show that beat-to-beat intervals or instantaneous heartbeats are detected with relatively high precision for most of the subjects. This makes the proposed—ECG independent—method promising for HRV analysis and other related applications such as smartphone cardioigraphy. As shown in the right panel of figure 8, heartbeat detection is feasible using the proposed algorithm on medium quality—in terms of the amount of noise—SCG signals as well. However, inter-subject variability is always a significant factor in the processing of mechanical heart signals. As such, the proposed method fails to accurately detect heartbeats in very noisy or low quality SCGs. The left panel of figure 8 shows an example of a low quality SCG signal for which accurate detection of cardiac events was difficult with the proposed technique. Additionally, the proposed method was susceptible to dynamic movements caused by, for example, exercise, intensive activity and external forces.

Further capability of the algorithm was tested in estimating two significant CTIs, namely the systole and the diastole. Since the S1 peak can be detected using the proposed technique, by applying a moving window we are also able to detect the local minima within the cardiac cycle corresponding to the second heart sound, i.e. S2 (Zanetti et al. 1991, Wick et al. 2012). The S2 timing is typically almost an imperceptible peak, which is very hard to detect without having an individual search strategy. A 250 ms long search window, starting from 200 ms after each detected S1 was defined to find the local minimum wave within each cardiac cycle. Indeed, the early systolic phase can be simply detected by finding the local minima (absolute value) inside the window. Figure 9 shows the segmented systolic and diastolic time intervals achieved by combining the method of this paper and the windowing technique proposed in Jafari Tadi et al. (2015). This segmentation process is clinically beneficial as it can be used, for example, for heart failure detection (Becker et al. 2014), for the treatment of acute ischemia using diastolic timed vibrators (Gill and Hoffmann 2010) and for motion correction in cardiac imaging (or dual gating in nuclear medicine imaging) (Wick et al. 2012, Jafari Tadi et al. 2014). Furthermore, such segmentation methods would be also beneficial for feature extraction in seismocardiograms using match-filtering techniques (Paalasmaa et al. 2014, Li et al. 2015). We would also like to point out that by detecting local maxima and minima points based on our algorithm, it is feasible to automatically annotate other cardiac events such as the AC, the mitral valve closure (MC) and the mitral valve opening (MO) using the windowing technique discussed in Jafari Tadi et al. (2015), Jafari Tadi et al. (2015). Figure 9 shows the location of cardiac events which are dominant in the SCG signal.

A limitation of the proposed algorithm is its susceptibility to noise, as the performance of the peak detection in very low quality or noisy signals is reduced considerably. As mentioned earlier, one test subject was excluded in this study due to the noise contamination in both the ECG and SCG signals. In the preliminary investigations it was noted that the quality of the signal in obese subjects with very high BMI is relatively poor compared to the low BMI subjects and therefore obese subjects (BMI > 30) were not considered in this study. Even though (Paalasmaa et al. 2014) reported that there is a moderate correlation between beat-to-beat detection proficiency and BMI, our correlation analysis showed no linear relationship between the subject’s BMI or the HRV and the method’s performance in the current study group, for which BMI < 30. Therefore, a future task is to investigate the role of the BMI value in the performance of the proposed algorithm.

In this work we considered primarily the motion artifact free parts of the z-axis of the accelerometer. As pointed out in Inan et al. (2015), the amplitude of dorso–ventral accelerations is generally better among the SCG channels, particularly when the subject lies in the supine position. However, it was noted that the amplitude of the accelerations in different axes of SCG depends critically on the position of the subject. For example, the dorso–ventral accelerations have a relatively higher amplitude while the subject is in the supine position, whereas in
Table 1. Beat-to-beat performance evaluation of the HABIT algorithm in different positions.

(a) Supine position (z-axis)

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<th>ID</th>
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<th>TPR (%)</th>
<th>PPV (%)</th>
<th>RMSE (ms)</th>
<th>MAE (ms)</th>
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σ  962.05  95.8  96.0  37.6  22.5  37.8  0.320

(b) Supine position (x-axis)

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</table>

σ  927.04  94.54  93.92  85.39  73.19  57.45  0.88

(c) Left side position

<table>
<thead>
<tr>
<th>ID</th>
<th>Mean S1 − S1 (ms)</th>
<th>TPR (%)</th>
<th>PPV (%)</th>
<th>RMSE (ms)</th>
<th>MAE (ms)</th>
<th>E95 (ms)</th>
<th>RMSE HR (bpm)</th>
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<tbody>
<tr>
<td>1</td>
<td>1074.23</td>
<td>99.2</td>
<td>99.2</td>
<td>37.1</td>
<td>5.60</td>
<td>5.00</td>
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<td>2</td>
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<td>3</td>
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<td>99.5</td>
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<td>2.39</td>
<td>5.00</td>
<td>0.193</td>
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<td>98.2</td>
<td>95.1</td>
<td>80.4</td>
<td>26.7</td>
<td>49.8</td>
<td>1.309</td>
</tr>
</tbody>
</table>

(Continued)
the lateral recumbent or sitting positions another axis may provide better acceleration signals.
Therefore a task for future work is to develop an automated procedure to estimate signal quality (Tanantong et al. 2014, 2015) and to determine the most useful axes of the accelerometer, depending on the subject’s position.

\[\text{Figure 7.} \] Bland–Altman plot (upper panels) and regression analysis plot (bottom panels) showing high agreement and a linear relationship between the S1–S1 and R–R time intervals achieved by SCG and ECG, respectively.

<table>
<thead>
<tr>
<th>Table 1. (Continued)</th>
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<tbody>
<tr>
<td>ID</td>
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<td>-----</td>
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<td>5</td>
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<td>6</td>
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<tr>
<td>5</td>
</tr>
<tr>
<td>6</td>
</tr>
<tr>
<td>α</td>
</tr>
</tbody>
</table>

\[\text{Note:} \] ID and α denote the subject number and the mean value of each column, respectively.

Therefore a task for future work is to develop an automated procedure to estimate signal quality (Tanantong et al. 2014, 2015) and to determine the most useful axes of the accelerometer, depending on the subject’s position.
Table 2. Statistical analysis results based upon the Bland–Altman method.

<table>
<thead>
<tr>
<th>Position</th>
<th>Bias (ms)</th>
<th>Upper LOV (ms)</th>
<th>Lower LOV (ms)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Supine</td>
<td>0.08</td>
<td>6.6</td>
<td>-6.5</td>
</tr>
<tr>
<td>Left</td>
<td>0.30</td>
<td>11</td>
<td>-12</td>
</tr>
<tr>
<td>Right</td>
<td>0.12</td>
<td>7.8</td>
<td>-8.1</td>
</tr>
</tbody>
</table>

*Note:* LOV denotes the level of agreement or 95% confidence interval, i.e. the upper and bottom dashed lines in each Bland–Altman figure. The middle line denotes the mean/bias value. (LOV = mean ± 1.96 × standard deviation)

Figure 8. A very poor quality and noisy SCG signal from z-axis (left) and heartbeat detection from medium quality SCG signal by applying the proposed method (right).

Figure 9. The upper panel shows the segmentation of systole and diastole phases using the S1 peaks, S2 peaks and windowing technique. The S1 and S2 regions are denoted by pink circles and blue squares (solid line), respectively. The bottom panel shows the averaged cardiac cycle (bold red color waveform) over more than 100 cycles for one of the subjects. Cardiac events such as MC, AO, AC and MO can be detected using the method published in Jafari Tadi et al (2015).
To test the real-time capability of the proposed algorithm, we implemented it as an Android application for smartphone-based heart monitoring. With the Android application, the SCG signals are continuously streamed from the smart device’s accelerometer and are processed by buffering and dividing the input data into 10 s segments. The sampling frequency of the smartphone’s accelerometer is set to 200 Hz by default. Each segment is processed by the HABIT algorithm in order to estimate the average heart rate over that 10 s segment, and is subsequently displayed on the smartphone’s screen. In our implementation, a new 10 s segment is processed—and the result on the screen is updated—every second, which means that successive segments overlap by 9 s. The current implementation is developed for proof-of-concept purposes, and in further development of the application we will consider, for example, the effect of different durations of the segments on the accuracy of the heart rate estimation, on the computational complexity and on the robustness of the algorithm against variations in the signal morphology. Figure 10 illustrates the preliminary version of the developed smartphone application for real-time heart rate estimation.

Figure 10. Real-time heart monitoring using smartphone devices. The smartphone simultaneously reads the vibration signals from a built-in tri-axial accelerometer sensor and transmits to a custom-made Android application where the HABIT algorithm is running to measure the heart rate and inter-beat variations periodically.

Figure 11. HRV under pre-exercise and after-exercise conditions.

To test the real-time capability of the proposed algorithm, we implemented it as an Android application for smartphone-based heart monitoring. With the Android application, the SCG signals are continuously streamed from the smart device’s accelerometer and are processed by buffering and dividing the input data into 10 s segments. The sampling frequency of the smartphone’s accelerometer is set to 200 Hz by default. Each segment is processed by the HABIT algorithm in order to estimate the average heart rate over that 10 s segment, and is subsequently displayed on the smartphone’s screen. In our implementation, a new 10 s segment is processed—and the result on the screen is updated—every second, which means that successive segments overlap by 9 s. The current implementation is developed for proof-of-concept purposes, and in further development of the application we will consider, for example, the effect of different durations of the segments on the accuracy of the heart rate estimation, on the computational complexity and on the robustness of the algorithm against variations in the signal morphology. Figure 10 illustrates the preliminary version of the developed smartphone application for real-time heart rate estimation.

An additional investigation of the Android application was conducted by measuring the SCG when a subject is in a relaxed situation (pre-exercise condition) and immediately after a heavy workout using an exercise-bike (after-exercise condition). The results indicate that
the proposed algorithm is able to detect the heartbeats under both conditions (see figure 11). Furthermore, we assessed the performance of the proposed algorithm on a healthy subject who has reoccurring arrhythmia, namely atrial tachycardia or ectopic atrial tachycardia. The duration of this measurement was 30 min and the subject was asked to lie in a supine position. The evaluation metrics for this subject for TPR, PPV, RMSE, MAE, E95 and RMSEHR were, respectively, 99.15%, 99.4%, 40.4 ms, 13.4 ms, 40 ms and 0.3 bpm, and we note that HABIT correctly detects the heartbeats even from the more irregular segments. However, we noticed that during aggravated motions the HABIT algorithm fails due to heavy motion artifacts. A weakness in the proposed heartbeat detection technique is thus its vulnerability to the high motion dynamics present, for example, during training. The utilization of a motion mitigation technique is thus left as an important future task.

5. Conclusion

In this paper we have presented a real-time capable SCG-based heart rate monitoring algorithm and its Android platform implementation. The proposed adaptive heart rate estimation algorithm, HABIT, is based on applying the Hilbert transform on the total acceleration signal, and on performing adaptive thresholding on the filtered signal. To assess the capability of the proposed algorithm we recorded and analyzed SCGs and ECGs from 30 participants in three different positions. The statistical results show that the method is accurate, and could be used for suitable e-health and well-being applications. The proposed method does not use ECG to detect the heartbeats, which separates it from many other SCG/BCG heartbeat detectors, which require ECG fiducial points to operate. Future investigation within this topic includes the application of the developed method on other sensor modalities such as gyroscopes, load-cells and force sensors. Also, the smartphone application based on HABIT for unobtrusive and continuous cardiomechanical monitoring, HRV estimation and CTI analysis will be developed further.

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