Accurate and consistent automatic seismocardiogram annotation without concurrent ECG

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Abstract

Seismocardiography (SCG) is the measurement of vibrations in the sternum caused by the beating of the heart. Precise cardiac mechanical timings that can only be obtained from SCG are critically dependent on accurate identification of fiducial points.

So far, SCG annotation has relied on concurrent ECG measurements. We have designed an algorithm capable of annotating SCG without the use any other concurrent measurement. We subjected 18 participants to graded lower body negative pressure. We collected ECG and SCG, obtained R peaks from the former, and annotated the latter by hand, using these identified peaks. We also annotated the SCG automatically.

We compared the isovolumic moment timings obtained by hand to those obtained using our algorithm. Mean accuracies for increasing levels of negative pressure were $97.61 \pm 3.39\%$*,* $93.32 \pm 5.33\%$*,* $78.28 \pm 14.29\%$*,* $58.68 \pm 17.58\%$*, and* $63.36 \pm 14.23\%$*.*

We also compared LF/HF ratios obtained from isovolumic moments to those obtained from R peaks. For indices obtained from automatic annotations, the mean differences were 0.16 ± 0.19*,* -0.10 ± 0.58*,* 0.89 ± 0.85*,* -1.22 ± 0.62*, and* 2.30 ± 1.10 *for increasing levels of negative pressure.*

1. Introduction

Seismocardiography (SCG) is the measurement of thoracic vibrations recorded from accelerometers placed on the sternum. Recent developments in MEMS accelerometer technology have rekindled research interest in the technique [1, 2].

Peaks observed in SCG have been related to significant cardiac events, the main ones being aortic valve opening (AO) and isovolumic moment (IM) during the systolic cycle. The assignment of these fiducial points was based on concurrent echocardiogram analysis with SCG morphology [3, 4]. Precise cardiac mechanical timings that can only be obtained from SCG are critically dependent on accurate identification fiducial points [5, 6].

Heart rate variability (HRV) analysis is a practical and widely used noninvasive technique to study the autonomic control of the cardiovascular system [7]. The heartbeat intervals (HBi) used for HRV analysis are predominantly obtained from electrocardiogram (ECG) R peaks.

The modern-day ubiquity of accelerometers in wearable devices and smart phones could make SCG an inexpensive data acquisition tool. Such devices have been used to obtain HBi [11–13], and the possibility of using SCG to obtain HRV indices has been reported by us [14], and others [13, 15]. In these studies, however, the identification algorithms either depended on concurrent R peak identification, or did not report the accuracy of fiducial point identification. The eventual use of SCG as a stand-alone application without concurrent ECG or photoplethysmograms, either at home or in the laboratory, depends on the accurate and consistent automatic identification of fiducial points with minimal user input.

The goal of this study was to develop and test SCG fiducial point identification software capable of returning valid HRV indices, while requiring no input from the user. A core concept for the algorithm in question was the elaboration of a function model for systolic vibration cycles, as well as an optimization function capable of accurately fitting this model to the *in-vivo* signal.

Accuracy of fiducial point identification differs importantly from the consistency necessary to obtain valid HRV indices. While HRV depends on consistent beat-to-beat identification of any one feature in systolic cycles, precise mechanical timings depend on the accurate identification of a particular fiducial point. To this end, our team has been involved in the development of an algorithm capable of correct identification of ten IM points per five minutes of recording [16].

In order to test the software's ability to correctly identify SCG fiducial points in a variety of settings, it was applied on dataset recorded from subjects who were exposed to lower body negative pressure (LBNP). Previous work on this dataset showed that HRV indices could be obtained

from manually identified fiducial points.

2. Methods

2.1. Data collection and annotation

A total of 18 participants's lower body was placed in a negative pressure chamber. Vacuum was applied to the chamber to drop the box pressure to -20 mm Hg, -30 mm Hg, -40 mm Hg and -50 mm Hg progressively. The participants were kept at each stage for 5 minutes and were returned to normal pressure at the end of the -50 mm Hg stage. If a participant exhibited a sudden decrease in heart rate or blood pressure or if they expressed any discomfort and wanted to stop, the negative pressure was immediately terminated. The protocole has been previously described in detail [5]. Signals were recorded at the Aerospace Physiology Laboratory under an ethics approval from the Simon Fraser University Research Ethics Board. Participants followed the informed consent procedure and signed consent forms.

Since previous results indicated that IM identification is slightly more consistent than AO identification [16], our algorithm was tested on its ability to identify IM points. QRS complexes of the ECG were identified [17]. On the SCG, IM points were assigned as the local maximum following each R peak, and manually corrected. An algorithm described in detail later in this paper (subsection 2.2) was used to identify IM points without the use of R peaks. HBi obtained from R peaks and IM points were computed and resampled at 5Hz using a shape-preserving piecewise cubic interpolation method.

For all LBNP levels and participants, the time difference between automatically obtained and hand-annotated IM points was computed. The frequency spectrum of the filtered HBi time series was computed using Welch's method [18], as well as the normalized frequency-domain HRV indices.

Signal analysis was performed with Matlab 2014b (Mathworks, MA, USA), and statistical analysis with JMP 11.2 (SAS Institute Inc, NC, USA). Values reported are mean $\pm 95\%$ confidence interval. Confidence interval was computed as 1.95 times the standard error within the LBNP level.

2.2. Identification algorithm

All SCG signals were pre-annotated using a previously described algorithm [16] which uses two envelopes. The output of the algorithm returns 10-second segments of annotated SCG separated by gaps of at least 2 seconds.

The algorithm described below was developed to fill any gaps and refine individual estimations (Fig. 1).

1. *Beat-to-beat rejection*

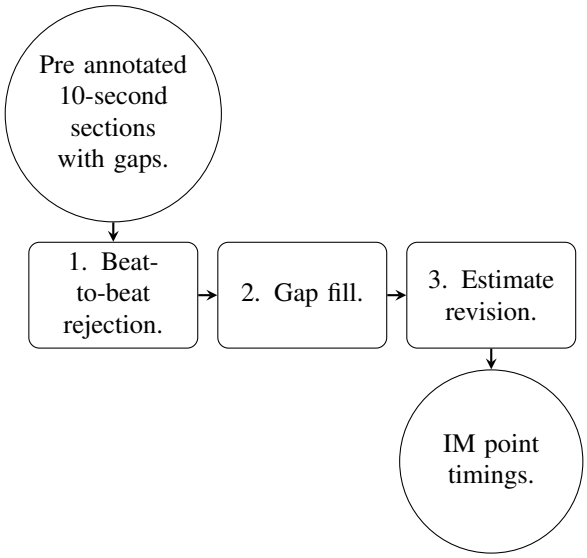

Figure 1. Summary of the isovolmic moment (IM) point identification algorithm. The input are a few very good estimates of IM points that come from a previously described algorithm and [16]. The first step rejects the set of initial estimates in which sufficient confidence was not attained. The second step fills the gaps between these few very good estimates. The last step uses the estimates, which are close to IM points, to predict the exact location of the IM points.

(a) *Computation the SCG wavelet profile.* This process created a time series used to identify AO and AC cycles. A Morlet wavelet transform of order 6 was performed on the filtered SCG signal. The sum of the resulting time-frequency power over time was then obtained, and the frequency f_p where the sum attained its maximum was computed. The profile P was then computed as the mean power for the frequencies around f_p.

(b) *Rejection of estimates.* If successive HBi differed by more than a threshold value T, the relevant estimate was rejected. Estimates were also rejected if they were closer to the immediately preceding profile peak than to the immediately subsequent profile peak.

2. *Gap fill.* The previous processes left gaps of varying width within the estimates. The gap filling process relied on picking profile peaks that minimized the standard deviation of the HBi time series, taking into account the sections immediately preceding and following the gap.

3. *Estimate revision.* For each profile peak, a 400 ms segments of the SCG signal was centered around its maximum. The median of all such segments was computed (Fig. **?? Top**). A model was then fit to this median, defined as the function

$$f(t, x_0, p, \phi_i) = A \cdot \sin\left((t - x_0) \cdot \frac{2\pi}{p}\right) \cdot \sum_{1}^{5} \phi_i \quad (1)$$

where A normalized the maximum to 1, t was time, x_0 was the time shift which is constrained to $[-30, 30]$ ms and represented the point exactly between IM and AO, p was the period which was constrained to $[20, 60]$ ms, and each ϕ_i was a compactly supported gaussian modulating the mitral closure (MC), IM, AO, and post-AO peaks, as well as a decay gaussian. The width of the gaussians was p for $i \in \{1, 5\}$ and $p/2$ for $i \in \{2, 3, 4\}$. The gaussians were centered at the MC, IM, AO, post-AO, and post-post-AO peaks, respectively. The amplitudes of the gaussians were constrained, respectively from left to right, to $[0.1, 0.6]$, $[0.3, 1]$, $[0.9, 1]$, $[0.1, 1]$, and $[0.1, 1]$. The amplitude constraints were designed from repeated observation to emulate normal signal morphology.

The model was fitted by a simplex search method [19], implemented in Matlab as fminsearch, to minimize a custom distance function. The result was assumed to represent a generic systolic cycle for the participant, for the particular LBNP level.

A model was then fitted analogously to each identified systolic cycle. This process implicitly returned timing estimates for MC, IM, and AO points.

3. Results

Accuracy results are shown in Figs 2 and 3.

The HRV ratio LF/HF was computed for each level of LBNP and all subjects. Indices obtained with IM points were compared to those obtained from RR intervals. For indices obtained from hand annotations, the mean differences were -0.08 ± 0.34, -0.24 ± 0.50, -0.34 ± 0.43, -0.70 ± 0.64, and -1.07 ± 0.77 for increasing levels of LBNP. For indices obtained from automatic annotations, the mean differences were 0.16 ± 0.19, -0.10 ± 0.58, 0.89 ± 0.85, -1.22 ± 0.62, and 2.30 ± 1.10 for increasing levels of LBNP.

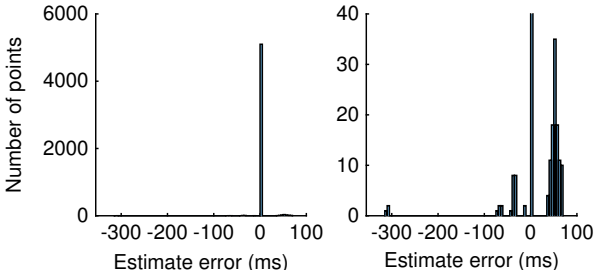

Figure 2. Histogram of the estimation errors of the algorithm at baseline for all participants. The mean error is 0.72 ± 0.30 ms. **Right** A truncated version of the histogram on the **left** highlighting the inaccuracies. The groups of errors centered at $\approx \pm 50$ ms represent errors wherein either the previous or subsequent peaks were misidentified as the isovolumic moments. The few errors near -300 ms represent diastolic cycles mistaken for systolic cycles.

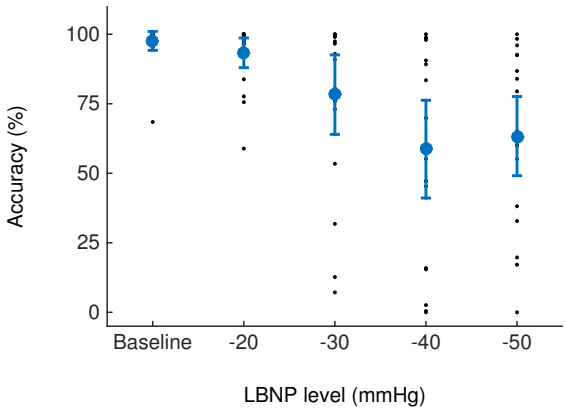

Figure 3. Mean accuracy of isovolumic moment (IM) identification for each level of lower body negative pressure (LBNP). For each subject, accuracy is computed as the percentage of automatically annotated IM points that are identical to hand-annotated IM points. Values are given as mean $\pm$ confidence interval.

4. Discussion

A new algorithm for the identification of the IM fiducial point on SCG without the use of ECG was tested in its accuracy and consistency across levels of LBNP.

The methodology described in this study distinguishes itself importantly from previously described algorithms by its modelling, which was able to overcome the difficulties created by multiple extrema in the vicinity of true fiducial points. The modelling also allowed for concurrent estimation of all systolic fiducial points, as well as a representation of participants' general SCG morphology.

The accuracy of IM identification was tested by the comparison of the timings obtained automatically to timings obtained by hand-identification. This accuracy reached above 97 and 93% when analyzed at baseline and -20 mmHg of LBNP, respectively. At baseline, 17 participants in a total of 18 had an identification accuracy of over 95%.

The consistency of the IM point identification was tested by comparing HRV indices as obtained from R peaks to those obtained from hand-identified IM points and automatically identified IM points. At baseline and -20 mmHg of LBNP, these indices were not statistically different from 0. They had small mean difference, small standard error and most importantly, 17 and 16 participants out of a total of 18 had an accurately estimated LF-HF balance.

These levels of consistency and accuracy at baseline and -20 mmHg indicate that the algorithm is adequate to perform SCG analysis without concurrent ECG at levels of orthostatic and cardiovascular stress equivalent to 5 min-

utes of -20 mmHg of LBNP or below. Furthermore, it was accurate enough to obtain precise continuous mechanical timings that can only be obtained with SCG, as well as consistent enough to obtain HRV indices. The results open opportunities for stand-alone applications of SCG for home use as well as in laboratories.

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