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A Preliminary Study Investigating the Quantification of Beat-to-Beat Morphological Consistency in Seismocardiogram Signals

Omer T. Inan, *Member IEEE*, Keya Pandia, Laurent Giovangrandi, Roham T. Zamanian, and Gregory T. A. Kovacs, *Fellow, IEEE*

Abstract— **Ballistocardiography and seismocardiography are both non-invasive mechanical measurements of the vibrations of the body in response to the heartbeat. The ballistocardiogram (BCG) signal represents the movements of the whole body in response to cardiac ejection of blood into the vasculature; the seismocardiogram (SCG) corresponds to local vibrations of the chest wall associated with sub-audible tissue and blood movement and audio frequency heart-valve closure dynamics. This paper focuses on methods for quantifying "signal consistency"—a quantitative measure of how morphologically similar each heartbeat in a patient's recording is compared to the ensemble average taken over the recording. Before comparing each beat to the average, known physiological sources of inconsistency—such as respiratory amplitude and timing variability—are removed, then the remaining inconsistency is quantified. Previously described methods for BCG signals are expanded to fit the high-frequency (> 20 Hz) components of the SCG. The use of this method in future work could help enable proactive management of heart disease in extra-clinical settings.**

I. Introduction

The global burden of cardiovascular disease (CVD) poses a massive threat to the physical and fiscal wellbeing of society. Recently, Murray, *et al.* outlined a migration over the past two decades in global disease burden from communicable to non-communicable (chronic) diseases—with ischemic heart disease and stroke being the first and second ranked contributors [1]. In the US, by 2030 the American Heart Association estimates that 40% of the population will endure CVD, and 24M people will die each year from the disease [2]. The problem is further compounded by the Association of American Medical Colleges projecting that Americans will have 130,000 fewer doctors than needed by 2025, because of the rapidly growing aging population, doctors retiring in the next decade, and the added 32M entering the healthcare system in 2014 under new legislation [3].

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O. T. Inan is with the Department of Electrical Engineering, Stanford University, Stanford, CA, 94305 USA (phone: 650-723-5646; e-mail: oeinan@gmail.com).

K. Pandia and L. Giovangrandi are with the Department of Electrical Engineering, Stanford University, Stanford, CA 94305 USA (e-mails: keya.pandia@stanfordalumni.org, giovan@stanford.edu).

R. T. Zamanian is with the Vera Moulton Wall Center for Pulmonary Vascular Disease, School of Medicine, Stanford University, Stanford, CA 94305 USA (e-mail: zamanian@stanford.edu).

G. T. A. Kovacs is with the Department of Electrical Engineering and (by courtesy) the School of Medicine, Stanford University, Stanford, CA 94305 USA (e-mail: kovacs@cis.stanford.edu).

These facts have kindled interest in home health monitoring solutions in a variety of publications including, but not limited to, academic journals. The Dec. 1st issue of *The Economist* strongly argued the need for cheaper and effective "self-service diagnostic technologies" [4]. In JACC, speaking specifically of congestive heart failure management, Bui and Fonarow proposed a shift from "reactive" to "proactive" care [5]. By enabling CVD patients with home health monitoring technology, therapies could be tailored to their changing needs, clinical visits could become less frequent without sacrificing quality of care, and patients could be empowered against their disease with constant knowledge of their state of health. This could result in both improved care and greatly reduced cost.

With this need in mind, researchers have recently focused on applying non-invasive sensing techniques to home monitoring: two examples of such methods are ballistocardiography (BCG) and seismocardiography (SCG). These signals were first discovered in the 1900s [6-7], but were largely abandoned in clinical settings due to the availability of more sophisticated techniques such as echocardiography, catheterization, computed tomography (CT), and magnetic resonance imaging (MRI). Unfortunately, these sophisticated technologies are unsuitable for "self-service diagnostic" use due to high cost, the need for a medical professional to administer the test, large size of the equipment, or obtrusiveness of the measurement. As a result, BCG and SCG have resurfaced as viable options for monitoring the mechanical output of the heart in the home.

II. BCG and SCG Signals

Fundamentally, the BCG and SCG represent the low frequency vibrations of the body in response to the heartbeat: the BCG corresponding to whole body vibrations, the SCG to localized chest vibrations. For both signals, several groups are focused on measuring these signals using devices that could readily integrate into the home—weighing scales [8], beds [9], chairs [10], and miniature wearable sensors [11]—and developing algorithms or techniques for mapping characteristic features of these vibrations to clinically relevant parameters of health: cardiac output [12], contractility [13], heart rate variability [14], optimality of pacing conditions [15], and respiratory phase and apnea [16].

Recently, we have found that the beat-to-beat consistency of the signal morphology may relate to the health of the heart—specifically, the BCG signal consistency improved significantly for patients being treated for heart failure in the clinic for the duration of their visit [17]. When we began to analyze SCG signals from healthy and diseased subjects, we

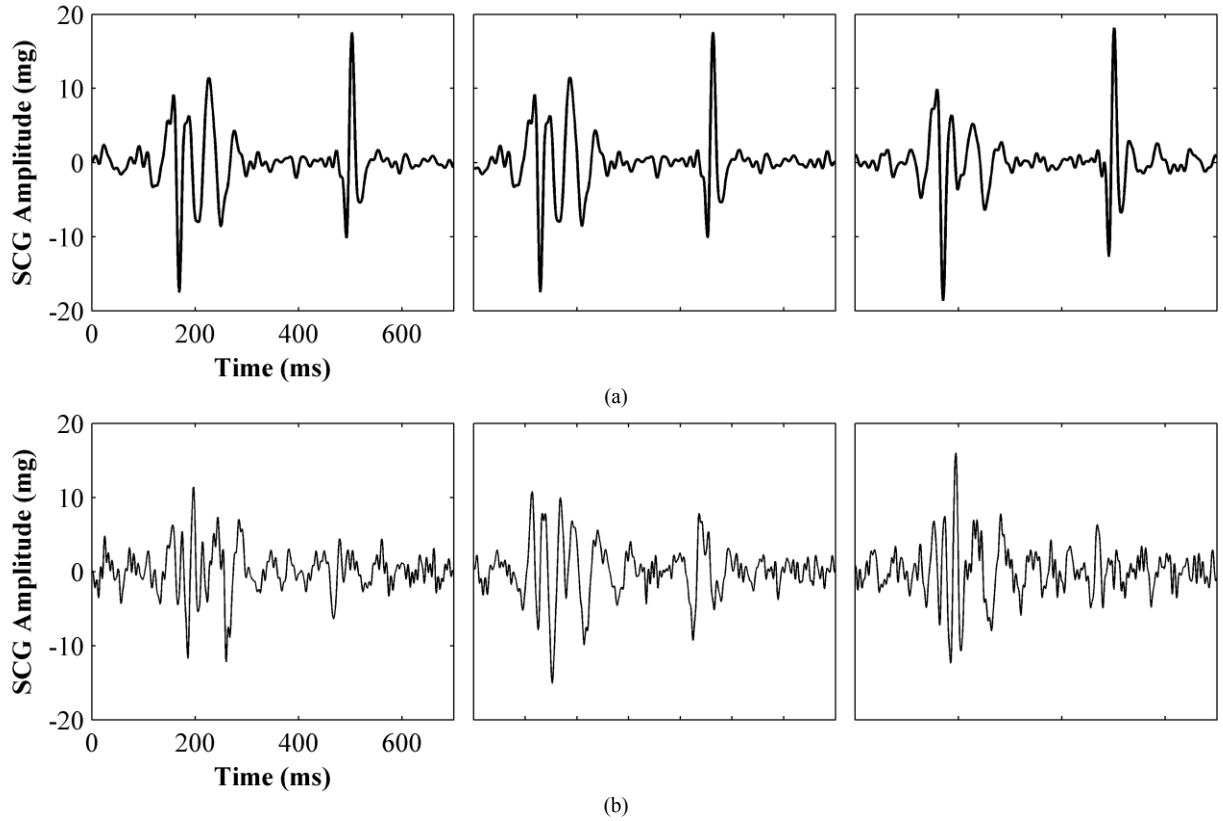

Figure 1. (a) Three successive SCG heartbeat cycles from a healthy subject. The morphology of the first and second complexes of the signal is highly consistent for the three beats, with an amplitude scaling associated with respiration. (b) Three successive SCG heartbeat cycles from a subject with pulmonary artery hypertension and heart failure. The morphology and amplitude are inconsistent for the SCG complexes for the three successive beats.

observed some striking similarities between the BCG and SCG in terms of signal consistency.

Figure 1 shows representative three successive SCG heartbeat cycles for a healthy subject (Fig. 1a) and a subject with pulmonary artery hypertension and heart failure (Fig. 1b). These signals were acquired using methods described in [16], with the SCG sensor positioned at the left sub-clavicular region of the chest, close to the apex of the heart. The three SCG beats for the healthy subject are highly consistent in morphology, with only the amplitude varying from one beat to the next due to respiration. In contrast, for the subject with pulmonary artery hypertension, the SCG beat morphology varies drastically from one beat to the next. Given these observations, we have developed preliminary methods for building on BCG signal consistency quantification [17] to analyze the SCG. The specific assumptions used for extending the methods to the SCG are based purely on physiological expectations and observations.

III. Estimating Signal Consistency

A. Estimating BCG Signal Consistency

To the first order, the BCG signal can be modeled as an underlying "template" function that is scaled in amplitude from one beat to another, and added to some unknown measurement noise. Consequently, the BCG, *y[k]*, can be modeled as follows:

$$y[k] = \sum_{i=1}^{m} a_i s[k - \tau_i] + v[k] \quad (1)$$

where *s[k]* is the underlying heartbeat "template" vector, $\vec{a}$ is the amplitude scaling vector, and $\vec{v}$ represents an additive noise term. As shown in [18], by windowing then ensemble averaging the measured BCG heartbeats, an estimate of the underlying BCG template function, *s[k]*, can be found. Furthermore, by projecting this template function onto each beat, the best least-squares estimate of the amplitude vector, $\vec{a}$, can be computed. Then, using these estimates of the signal and amplitude weighting vectors, the BCG signal can be estimated as follows:

$$\hat{y}[k] = \hat{s}[k] * \sum_{i=1}^{m} \hat{a}_i \delta[k - \tau_i] \quad (2)$$

The sample-by-sample difference between the measured BCG, *y[k]*, and this estimated BCG, $\hat{y}[k]$, provides an estimate of the measurement "noise" signal, from which the noise rms power or signal-to-noise ratio can be computed. It is important to recognize that the measurement "noise" may be due to interferences such as motion artifacts, sensor and circuit electronic noise, or **inconsistencies** in the actual underlying heart signal. If the effects of interference and electronic noise are minimized, then the ratio of "noise" to

signal power can yield a quantitative measure of the beat-to-beat consistency in the mechanical output of the heart.

B. Adapting Signal Consistency Estimation for the SCG_{HF}

The SCG signal contains low frequency sub-audible components related to the movement of blood and tissue, and higher frequency acoustic components related to the sounds generated by valve closure. For the low frequency components, the same signal consistency estimation methods used for BCG signals can be directly applied. For the higher frequency components, SCG_{HF}, two characteristics of the signal are not captured by these first order signal consistency estimation methods, and the algorithm must be adapted accordingly.

The SCG_{HF} signal, defined here as the high-pass filtered (f_{3dB} = 20Hz) SCG, contains two complexes, one associated with each heart sound, referred to here as S1 and S2. Note that the exact frequency of separation is still a subject of investigation, but in this work the "audible" frequency cutoff of 20 Hz was used. The amplitudes of S1 and S2 both vary with respiration, but not by the same magnitude, and generally out of phase with each other [19]. Capturing an amplitude term for both S1 and S2, as opposed to using a single amplitude term for the entire beat, is the first extension of the estimation method.

Furthermore, the time interval between the S1 and S2 complex varies for successive heartbeats because of the respiration-induced changes in the systolic ejection time [19]. As a result, a time delay term must be introduced to capture these changes in the model. With these added amplitude and time delay terms, the model then becomes:

$$y[k] = \sum_{i=1}^{N} b_i h[k-\rho_i] + c_i g[k-(\rho_i+\Delta_i)] + v[k] \quad (3)$$

where *h[k]* is the underlying template vector for the S1 complex, $\vec{b}$ is the amplitude scaling vector for the S1 complex, *g[k]* is the template vector for the S2 complex, $\vec{c}$ is the amplitude scaling vector for the S2 complex, $\vec{\rho}$ is the vector describing the heartbeat timings, and $\vec{\Delta}$ is the vector of time delays between the S1 and S2 complexes. The "noise" or inconsistency in the measurement is again captured by *v[k]*.

The S1 and S2 complexes are then treated as separate signals, and analyzed using similar methods as described in [18] for BCG signals with one important distinction—after an initial ensemble averaging computation, the beats are realigned to each other using cross-correlation. Then, a second ensemble average is computed, and is considered to be the best estimate of the underlying S1 and S2 complexes. The overall methods are summarized in Figure 2. These ensemble averages and corresponding amplitude scaling vectors are then used to estimate the SCG signal similarly to equation (2).

The estimated signal for one healthy subject and one subject with pulmonary artery hypertension are shown in Figure 3 (a) and (b), respectively, for purposes of visual observation only. Quantitatively, the consistency was computed to be 3.8 for the healthy subject, and 2.2 for the subject with pulmonary artery hypertension; however, this difference in consistency should not be over-interpreted at this point, since population studies must first be conducted. The focus of this conference paper is on presenting the methodology—future studies will then be conducted to rigorously assess the performance of these methods.

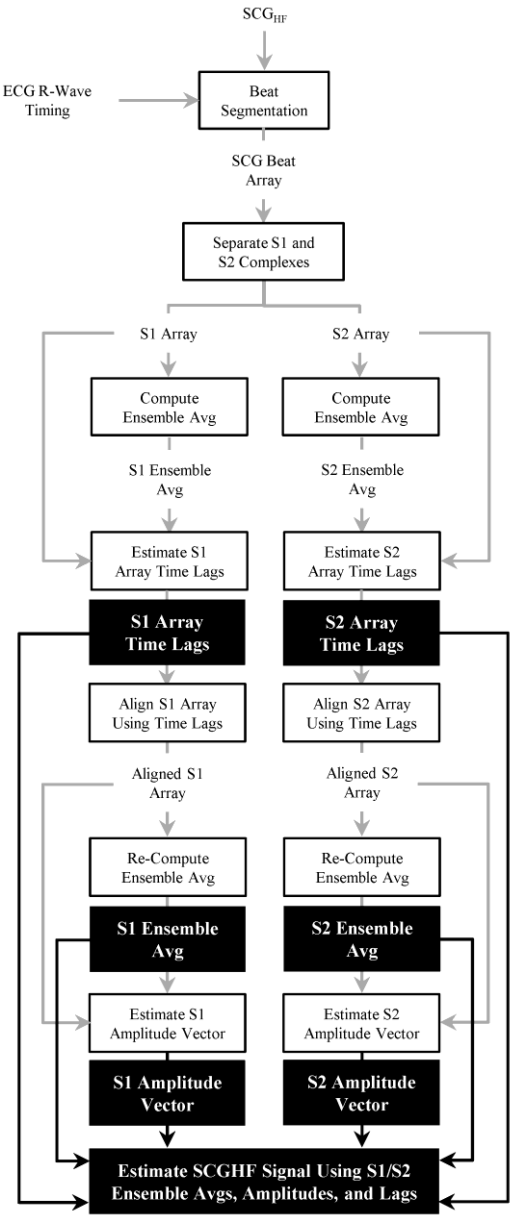

Figure 2. Signal flowchart summarizing methods for estimating the SCG_{HF} signal by decomposing into S1 and S2 complex estimation, then reconstructing the overall signal.

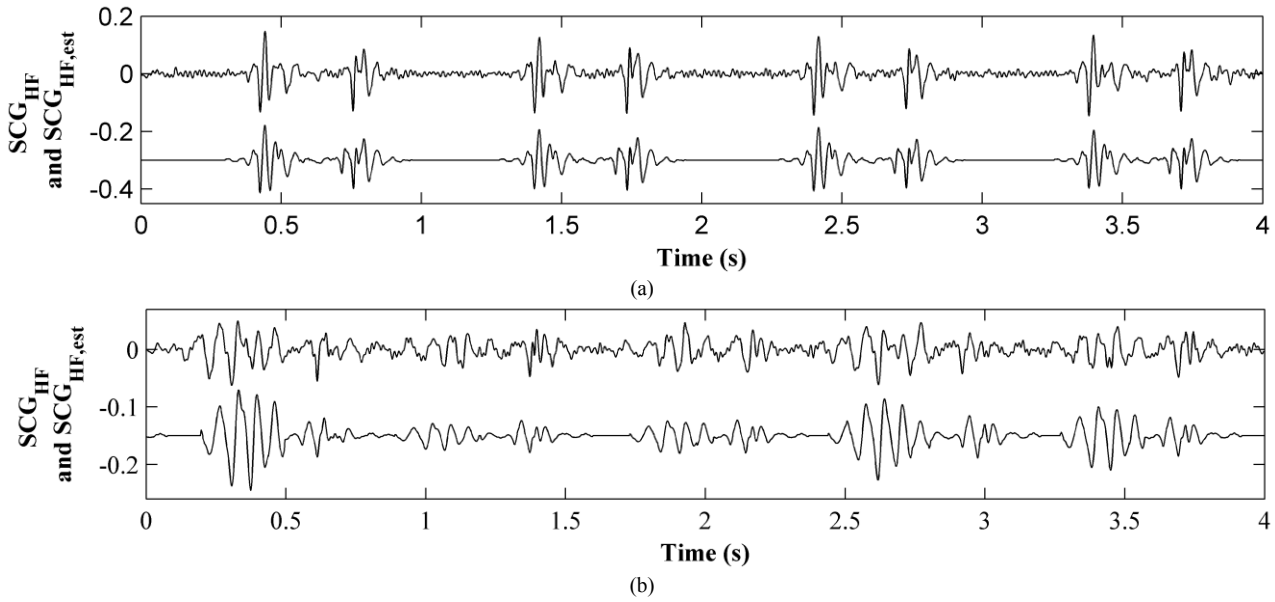

Figure 3. (a) SCG_{HF} signal (top) and estimated SCG_{HF} (bottom) for a healthy subject. Visually, the beat-by-beat consistency in the signal morphology was adequately captured by the estimation methods. (b) SCG_{HF} signal (top) and estimated SCG_{HF} (bottom) for a subject with pulmonary artery hypertension. The signal morphology changes more significantly from one beat to the next, but the consistent components are adequately captured by the model visually.

IV. Discussion and Conclusion

Unlike the ECG, both the SCG and BCG are relatively low SNR signals that can unfortunately be corrupted by motion artifacts, electronic noise, and other interferences. As a result, the analysis of these signals requires a new set of tools, beyond what is available for the ECG, to determine the effects of disease on the signal morphology, and to then use this knowledge in patient care applications. In this work, the concept of monitoring the beat-to-beat morphological consistency of the SCG was introduced and explored, by expanding on an algorithm that was previously developed for BCG signals. In future work, the differences between signal consistency for healthy and diseased subjects will be quantified using age and gendered matched populations. Furthermore, other methods such as cross-correlation may be explored for quantifying the similarity of each heartbeat to the averaged beat rather than simple subtraction.

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