# Feasibility of monitoring congestive heart failure with seismocardiography: a literature review

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***Abstract*—Heart failure, a condition impacting more than 23 million individuals globally, is anticipated to see an increase in its incidence. Among the various types of heart failure, Congestive Heart Failure (CHF) stands out with its hallmark of inadequate blood pumping leading to fluid accumulation in diverse body regions. Monitoring patients afflicted by CHF holds the key to better healthcare outcomes, which include timely medication delivery and reducing rehospitalization. This literature review discusses the feasibility of employing seismocardiography (SCG). SCG is a non-invasive method that relies on accelerometers to record the chest vibrations caused by cardiac activities. SCG's correlation with intracardiac filling pressures has the potential to monitor both healthy individuals and patients with heart failure, thereby reducing readmission. In addition, the integration of SCG with other wearable sensor technologies and machine learning applications can further improve diagnostic accuracy and personalized predictive models for HF progression.**

***Index Terms*—seismocardiography, SCG, congestive heart failure, right heart catheterization, mechanical vibrations, filling pressure.**

## I. INTRODUCTION

HEART failure (HF) impacts more than 23 million people globally, and according to some figures, it may reach over 37 million [1]. Heart failure indicates a gradual weakening of the heart muscle's ability to contract or the presence of mechanical issues that restrict its ability to fill with blood (Fig. 1). By definition, congestive heart failure (CHF) is not a type of heart failure, but rather a condition characterized by hyperdynamic circulation where the cardiac output is raised above normal levels. However, CHF is a long - term condition in which the heart struggles to adequately pump blood to meet the needs of the body. The heart is still beating, but it struggles to pump out the right amount of blood, which causes blood to build up in other regions of the body [2].

The pressure inside the heart during the filling phase of the cardiac cycle, known as diastole, is referred to as filling pressures. The rise in intracardiac filling pressures offers a timely indication regarding the advent of congestion in HF [3]. Increased intracardiac filling pressures and cardiopulmonary volume excess are symptoms of hemodynamic congestion [4]. Optimal administration of heart failure medication necessitates vigilantly monitoring the patient's state of congestion, achievable, for instance, through the measurement of filling pressure. Daily weight measurements are not sensitive enough to detect small volume changes, which limits their ability to forecast impending hospitalization in the majority of patients [5].

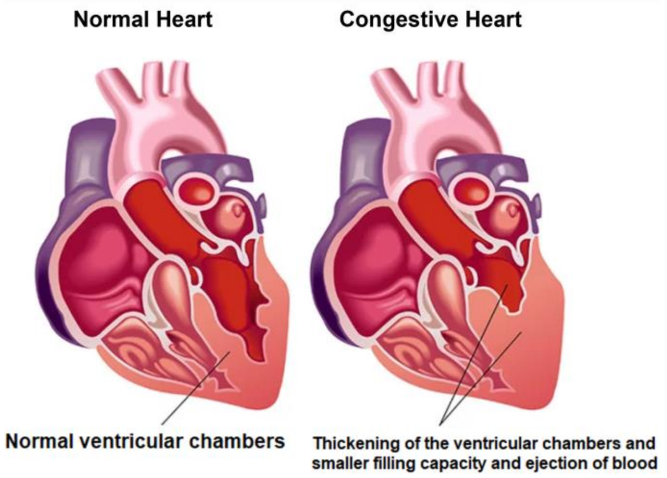

Fig. 1. Normal Heart vs Congestive Heart. Adapted from [6].

HF requires regular patient monitoring. This cannot be achieved exclusively through office visits. Reducing readmissions has become a vital quality metric, given its potential to enhance HF care and reduce costs. Implantable, wireless monitoring systems like CardioMEMS exemplify this advancement, as they include a pressure sensor implanted in the pulmonary artery (PA). Healthcare professionals receive PA pressure (PAP) readings daily and adjust treatment based on detecting hemodynamic congestion, ensuring PAP remains within an optimal volemic range (PA mean pressure within 10-25 mmHg). This proactive, hemodynamically-guided approach has proven to reduce HF-related readmissions by 37% [3]. Additionally, wearable activity devices can be used to track HF rhythm irregularities and functional status. There is, however, little proof that these devices improve HF clinical outcomes [1].

Patients with HF can live better lives and catch conditions getting worse earlier with continuous monitoring at home. However, a comprehensive evaluation necessitates insights into both the electrophysiological and mechanical health of the heart. Current Holter-based electrocardiogram (ECG) measurement devices are unable to deliver the latter [7].

With the emergence of miniaturized, cost-effective sensors, and digital health technologies, a multitude of wearable monitoring systems have been explored for tracking cardiovascular well-being, both in healthy individuals and patients with HF. Seismocardiography, a non-invasive method for measuring congestive heart failure, shows great promise [3]. This technology, introduced in the early 1990s [8], uses accelerometers, which are embedded within a wearable patch affixed to the sternum, to measure cardiac-induced vibrations on the chest. The measurement describes the mechanical activity of the heart. Previous studies have demonstrated the feasibility of monitoring hemodynamic parameters such as stroke volume or filling pressure via seismocardiography within a hospital environment [3], [9]. Consequently, this technology also has the potential for home-based monitoring of congestive heart failure.

This paper is structured to give answers to the following questions:

1. What are the physiological mechanisms underlying congestive heart failure?
2. What is the physiology of the seismocardiography signal?
3. Is it feasible to monitor heart failure progression with seismocardiography based on current literature?

The Introduction covers the first question, while the second section (Physiology of the Seismocardiography Signal) addresses question number two. The third question finds its answer in the Discussion section, and the Conclusion summarizes the main findings.

## II. PHYSIOLOGY OF THE SEISMOCARDIOGRAPHY SIGNAL

This document is divided into multiple sections. Section A presents the criteria used to select the key references. Section B presents measurement techniques used in the past. Section C discusses the physiological sources. Section D explains the SCG waveform in comparison with the ECG waveform. Section E provides an overview of the timing information extracted from the SCG signal, as previously documented in the literature. Lastly, Sections F and G describe the current open issues and recent advances related to SCG signals.

### *A. Selection Criteria*

Google Scholar was employed to identify relevant literature, prioritizing the top 100 most cited papers. For analysing the physiology of the SCG signal, the keyword "seismocardiography" yielded approximately 2900 search outcomes. Abiding by the criterion of being among the highly cited papers, three primary reviews ([10],[11],[12]) were identified to give a description of the SCG signal and the feasibility of heart failure monitoring, with the latest paper ([12]) published in 2021.

For exploring open issues and recent advances, the same keyword was used, taking into consideration the top 100 most referenced articles. Given that the most recent review was conducted in 2021, the search was restricted to papers published between 2021 and the present. Approximately 1050 results were obtained. The exclusion criteria included papers with citations lower than 5. Publications that specifically discussed congenital heart failure, filling pressures, and a better understanding of seismocardiography signals were taken into consideration.

### *B. Measurement techniques*

This section provides a short overview of the most common techniques used to measure the mechanical vibrations induced by the heart onto the chest wall.

In the past, a number of innovative techniques were put out to capture the heart's low-frequency vibrations. Among these techniques, Apexcardiography (ACG), Ballistocardiography (BCG), and Seismocardiography (SCG) have garnered considerable attention as valuable tools for discerning cardiovascular diseases. Initially, SCG relied on acceleration measurements, while ACG and BCG were based on displacement measurements. ACG and SCG recorded chest wall vibrations, whereas BCG captured whole-body vibrations stemming from center-of-mass displacements. To measure ACG, a transducer is positioned above the patient's chest wall [13]. ACG is primarily utilized for clinical diagnosis and evaluation, while SCG has the added benefit of being widely recognized as the state-of-the-art method for long-term, continuous monitoring of cardiac mechanical function in wearable applications [14].

In recent times, two alternative techniques have emerged: Gyrocardiography (GCG) and Kinocardiography (KCG). GCG has an added gyroscope soldered in the wearable patch positioned on the sternum. This introduces three extra degrees of freedom to measure the heart's angular vibrations alongside SCG [15]. On the contrary, KCG leverages BCG and SCG signals to concentrate on comprehending the body's motion resulting from the heart's contraction and blood flow [16].

### *C. Physiological sources*

Seismocardiography (SCG) signals are believed to originate from various cardiac mechanical processes, including muscle contraction, valve motion, blood flow turbulence, and momentum shifts.. Differences in these mechanical processes, provide insights about both cardiovascular physiological and pathological conditions. The SCG signal can be recorded by placing a low-noise accelerometer on the chest [10]. The information obtained from the signal can be recorded in parallel with other procedures: detection of heart electrical activity (ECG), other imaging techniques (echocardiography, cardiac magnetic resonance imaging), catheterization.

The seismocardiography signal's mechanical vibration nature causes it to frequently be compared to or used in conjunction with ballistocardiography in literature, which is also a mechanical vibration. As a result, two classifications can be distinguished:

1. Ballistocardiography (BCG), which involves the measurement of the forces generated by the entire body during a cardiac ejection. The circulation of blood along the vascular tree induces alterations in the body's center of mass during each heartbeat. Subsequently, recoil forces prompt micromovements

in the body, ensuring the preservation of overall momentum. These motions are captured by the BCG, and they can be expressed as signals of displacement, velocity, or acceleration. It is intended to include changes in all three axes (degrees-of-freedom) [10].

2. SCG, which refers to the local chest surface recording of cardiac vibrations [11].

However, the signals are not the same. BCG measures the mechanical vibrations caused by the heart and the cardiac reaction forces acting on the entire body. SCG investigates mechanical vibrations caused by the heart. SCG and BCG are the sole two techniques encompassing both aspects: the myocardial vibrations originating from cardiac muscle contraction and the vibrations arising from arterial circulation due to blood flow [12].

When assessing BCG using a scale or force plate, it's essential to recognize that the units for SCG and BCG differ. SCG records chest wall accelerations and is expressed in mg units. In contrast, BCG depicts the displacements of the subject's center of mass on the weighing scale, which are subsequently converted to force units using the spring constant for the scale platform. As a result, the BCG is presented in units of Newtons. The mass being accelerated in SCG is different from the mass accelerated in BCG. Due to this distinction, there is currently no clear method for directly converting BCG to acceleration units or SCG to force units. Further research is needed to elucidate this conversion process [10].

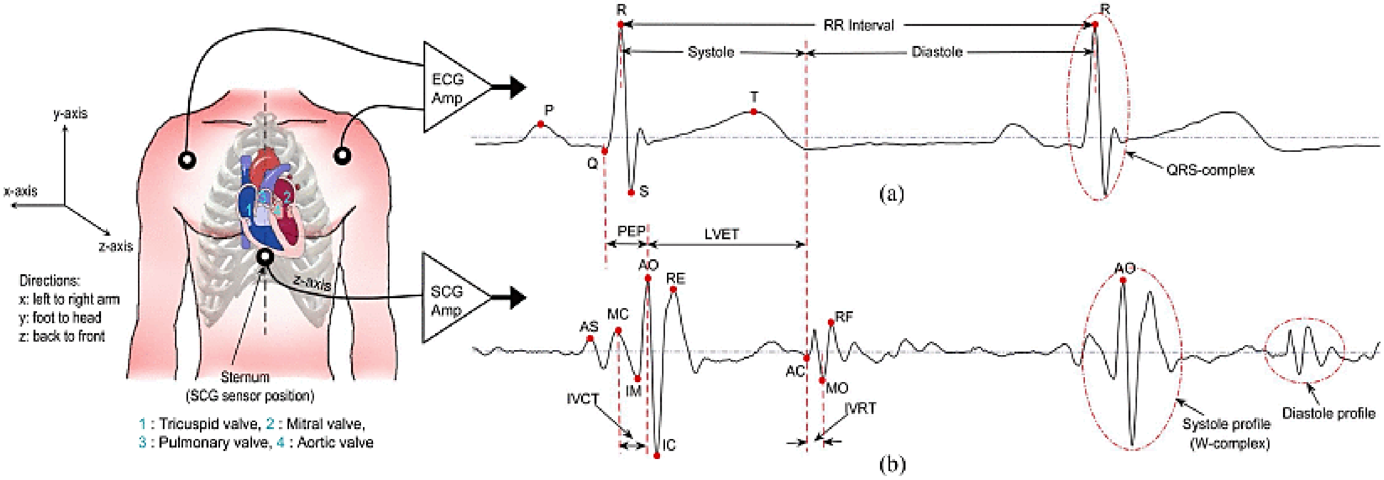

Fig. 2. The figure displays simultaneous ECG (a) and SCG (b) waveforms, accompanied by the proposed annotations from [19]. The annotations include AS (Atrial systole), MO/MC (Mitral valve opening/closure), IM (Isovolumic moment), AO/AC (Atrial valve opening/closure), IC (Isotonic contraction), RE (Rapid ejection), RF (Rapid filling), PEP (Pre-ejection period), LVET (Left ventricular ejection time), IVCT/IVRT (Isovolumetric contraction/relaxation time). Additionally, the RR (Respiratory rate interval) is also depicted. Adapted from [20]

## D. SCG waveform

Although the precise link between SCG waves and cardiac activity is not fully understood, numerous studies have explored this relationship. For instance, researchers have noted that SCG exhibits a low-frequency wave during atrial systole, a high-amplitude wave during ventricular systole, an extra wave during early ventricular filling, and several relatively high-frequency waves coinciding with the first and second heart sounds, which correspond to the opening and closing of the mitral valve [11]. Additionally, it was shown that SCG is helpful in measuring cardiac intervals like the left ventricular ejection time (LVET) and electromechanical systolic pre-ejection period (PEP) [17].

Delineating the SCG waveform involves identifying specific reference points (fiducial points) and estimating time intervals between these points, which hold clinical significance for interpreting cardiovascular system abnormalities.

Current research focuses on identifying these reference points within an SCG signal and correlating them with the ECG to discern physiological events taking place during a cardiac cycle [18].

Fig. 2 illustrates the simultaneous recordings of ECG and SCG waveforms. The heart consists of two distinct compartments separated by a septum, each comprising an atrium and ventricle. These chambers are further divided by atrio-ventricular and semi-lunar valves. An SCG signal can facilitate the identification of different phases of the cardiac cycle. These phases include: mitral valve opening/closure (MO/MC), aortic valve opening/closure (AO/AC), isovolumic contraction/relaxation time (IVCT/IVRT), rapid filling (RF) of blood through the ventricles, rapid ejection (RE) of blood from the ventricles, and isovolumic movement (IM) [19].

Accurate assessment of the SCG signal's fiducial points, such as the IM, AO, and AC, is one crucial criterion for its usage in a clinical environment [20].

In the study conducted by Rai et al. in 2021, a review of experiments aimed to determine the most easily detectable fiducial points using SCG. Based on precision and sensitivity, the effectiveness of different proposed techniques was evaluated. Some fiducial points were identified with the aid of ECG as a reference, while others were detected without ECG reference. The results indicated that the most noticeable peak in the SCG signal, namely the AO peak, was the most easily detectable. Interestingly, a specific experiment yielded the most favorable outcomes for AO detection. This success can be attributed to the combined analysis of the SCG signal with the GCG signal, which captures both angular cardiac vibrations and regular vibrations, ultimately enhancing the accuracy of detection [12], [15]. The annotations presented in Fig. 2. represent one of the initial sets of annotations, which have been experimentally compared to the echocardiogram signal and are associated with well-known physiological events. Annotation plays a crucial role in improving the comprehension of the signal by labeling specific points, known as feature points, within the acquired signal. In SCG, both fiducial and feature points are employed for annotation, but they differ in their definition and purpose. Fiducial points are utilized to determine the timing of cardiac events, while feature points are utilized to extract information about the heart's mechanical activity. Depending on the annotation technique used, a varying number of feature points can be identified.

In the study conducted by Rai et al. in 2021, the annotation processes for the SCG signal were categorized into four groups: temporal envelope-based with ECG, temporal envelope-based without ECG, machine learning-based, and visual inspection and comparison-based.. This classification was based on experiments carried out on patients where both SCG and ECG signals were simultaneously recorded. In certain cases, ECG recordings and ultrasound images were also obtained. It is important to note that each annotation process comes with its own limitations. For instance, the Envelope-based with ECG method may not be effective for all patient groups [12].

## E. Extracted parameters

Seismocardiography presents the opportunity for continuous monitoring of cardiac activities, both in clinical settings and at home. SCG enables the observation of the duration the heart dedicates to specific cardiac activities and stages, providing valuable insights into its functioning. These time measurements are commonly known as cardiac time intervals (CTI). SCG finds application in monitoring cardiac health and identifying various cardiac conditions by extracting different parameters linked to physiological events.

| **Cardiac Phase** | **Parameter Extracted** | **Physiological Event** | **Interval/Ratio** |
|---|---|---|---|
| Systolic | $S_1 S_2$ | First and second heart sound | MC − AC |
| | $QS_2$ | Total systole interval | Q − AC |
| | Q–I | Interval from onset of QRS to $S_1$ | Q − MC |
| | PEP | Pre-ejection period | Q − AO |
| | LVET | Left ventricular ejection time | AO − AC |
| | IVCT | Isovolumetric contraction time | MC − AO |
| | PEP/LVET | Contractility coefficient | (Q − AO)/(AO − AC) |
| Diastolic | LVFT | Left-ventricular filling time | MO − MC |
| | RVFT | Rapid ventricular filling time | MO − RF |
| | IVRT | Isovolumetric relaxation time | AC − MO |
| Global | MPI | Myocardial performance index | (IVCT + IVRT)/LVET |

Table 1. Cardiac time intervals and parameters extracted for cardiac health monitoring. Adapted from [12].

Both the systolic and diastolic stages of the cardiac cycle are determined by CTIs. A comparison of the different extracted intervals is presented in Table 1. For detailed information on the extracted parameters and the methodologies used for extraction, check reference [12].

## F. Open Issues

Among the three reviews conducted on SCG signals, certain unresolved matters persist in this field, while others have been tackled to improve the understanding and practicality of SCG signals. In Table 2, the primary open issues are listed in the first column, and the table is updated to include the latest research outcomes included in the review paper from 2021. The second column presents the research articles that discuss the corresponding open issues. Open issues that have recently appeared (since 2021) and were not included in the last review paper are highlighted in blue. Only the open issues with blue-colored references are described in this context, as the others have already been discussed in previous reviews.

Initial endeavors to utilize SCG for cardiac diagnosis encountered obstacles such as bulky instrumentation size and uncertainty regarding signal characteristics and variations among different subjects. However, recent progress in sensor technologies and signal processing techniques has spurred numerous new studies, providing improved understanding of these challenges. Considering the substantial impact of cardiovascular disease on morbidity and mortality rates, along with the significant costs of healthcare, there has been growing impetus for further research to reevaluate the feasibility and utility of SCG in diagnosing and monitoring cardiac function [11]. Enhanced comprehension of these challenges holds the potential to boost the quality of signal processing techniques, diminish SCG signal variability and noise, and ultimately result in a more precise delineation of SCG features for diagnostic and monitoring purposes.

| **Open Issues** | **References** |
|---|---|
| Effects of respiration [18],[19] | [23],[24],[25] |
| Subject motion, and postural position [7],[10],[26] | [7],[26],[27],[28],**[29]** |
| SCG variability: gender, age, health conditions. | **[16]**,[30] |
| SCG variability: cardiac contractility, heart rhythm | More research is needed |
| Adherence of the sensor to the signal waveform or quality | [31] |
| Digestive state and mood of the patients [11] | More research is needed |
| Facilitate clinical practice | [11] |
| Reference values for different groups of people including a variety of body kinds, sizes and ages [10] | More research is needed |

Table 2. Open Issues and current References.

In **[29]**, a robust framework for estimating cardiac time intervals using SCG signals in the presence of vehicle vibrations is proposed. The method effectively removes external vibrations by decomposing the corrupted signal and utilizing heartbeat features to separate vehicle noise from the SCG signal. In order to validate the proposed methodology, generated simulated SCG data that had been corrupted by vehicle-related factors was obtained. This data was added to clean SCG. The study showcased a significant reduction in Root Mean Square Error (RMSE) of AC detection after applying the denoising method and achieved high accuracy in AO detection. The proposed model for mitigating vehicle vibration interference in SCG timing features could have crucial implications for the implementation of wearable cardiovascular monitoring systems in out-of-hospital settings. By improving the reliability of these features in noisier environments, the coverage and applicability of algorithms using SCG timing features can be extended beyond controlled clinical environments.

In reference [16], a groundbreaking technique known as kinocardiography (KCG) was introduced. This innovative method involves the fusion of both SCG and BCG signals to record and analyze myocardial functions. By combining these two signals, the KCG approach utilizes 12 degrees-of-freedom to precisely capture the intricate body motion arising from myocardial contractions and blood flow within the cardiac chambers. The KCG parameters derived from the combined BCG/SCG signals demonstrated high repeatability, and the gender of the volunteers did not influence the final results.

### *G. Recent Advances*

Remarkable strides have been achieved in the realm of continuous and non-invasive monitoring of cardiovascular function, thanks to recent breakthroughs in the study of SCG signals.

In [32], a novel measurement technique named Forcecardiography (FCG) has emerged. This cutting-edge approach leverages a piezoelectric sensor to accurately measure the local forces exerted on the chest wall due to the heart's mechanical activity. Interestingly, FCG's heart sounds component showed the highest similarity to SCG signals, and FCG provided accurate timings for the aortic valve opening (AO) marker and pre-ejection periods (PEP) estimates. In a separate study [33], the primary emphasis was placed on extracting valuable information concerning ventricular emptying and filling events from the SCG signal. This paper compared two techniques for monitoring cardiac mechanical activity: SCG and FCG. The study concluded that the proposed approach, which incorporated double integration of SCG , yielded a novel displacement signal. Notably, this newly derived signal exhibited a low-frequency component remarkably similar to that of FCG.

Presti et al. 2021 [34], presents a soft wearable system (SWS) based on fiber optic technology for multi-point heart rate monitoring, demonstrating its feasibility on healthy volunteers. This SWS design allows simultaneous recording of SCG signals from various measuring sites and adheres well to the body.

In another recent research study [3], machine learning algorithms were harnessed to estimate changes in pulmonary artery mean pressure (PAM) and pulmonary capillary wedge pressure (PCWP) during right heart catheterization (RHC). This estimation was achieved through a thorough analysis of wearable SCG signals. The results suggest the potential use of wearable SCG signals as an alternative to CardioMEMS for longitudinal monitoring of intracardiac filling pressures in remote HF management, with the potential to reduce rehospitalization. However, further validation and clinical studies are required.

A recent investigation [35] focuses on the respiratory implications of SCG, proposing a U-Net-based cascaded framework to estimate respiratory rates (RR, see Fig. 2) from ECG and SCG signals. The framework introduced in this study enhances the pervasive and accurate measurement of RR by utilizing convenient and comfortable ECG and SCG measurement systems. Furthermore, another research paper [36] highlights the versatile utility of SCG data for monitoring both respiratory and cardiac rates. The suggested method is tested on 20 healthy persons before and after exercise while they are able to sit properly in a chair for monitoring. The accuracy found is comparable to earlier studies.

In [37], a multimodal wearable biosensor is introduced, capable of measuring both SCG and ECG signals to estimate stroke volume (SV) in patients with congenital heart disease (CHD) through machine learning. The non-invasive nature of the biosensor offers a convenient and patient-friendly approach to cardiac function evaluation. With the capability of remote monitoring, patients with CHD could benefit from continuous and real-time cardiac assessments, contributing to more personalized and proactive healthcare interventions. However, the paper emphasizes the importance of conducting further longitudinal studies with larger populations to validate the accuracy and generalizability of the proposed model.

## III. DISCUSSION

Worldwide, HF has a huge impact. The hallmark of CHF is the heart's ineffective pumping, which results in blood accumulation in the body. Monitoring HF patients is crucial to reducing readmissions and improving care with quick medication. For non-invasive HF monitoring at home, SCG, utilizing wearable patches with accelerometers, shows promise. The SCG signal can be easily detected by placing a low-noise accelerometer on the chest, giving vital information on cardiovascular health. This non-invasive method provides an invaluable way to assess the function of the heart. SCG signal analysis entails comparing the signal to reference echocardiogram images or ECG waveforms. Researchers and medical practitioners can evaluate the heart's function and obtain a deeper understanding of cardiac dynamics thanks to this comparative technique.

SCG offers the capability to extract cardiac timings and metrics associated with various physiological processes. The performance of the heart at various stages of the cardiac cycle is shown by these extracted metrics, which provide important information about the heart's function. There are numerous methods for annotating SCG signals, each having its own drawbacks and uses.

Recent developments in continuous and non-invasive cardiovascular monitoring focus on: forcecardiography, investigating SCG signals from multiple body sites, using machine learning to track intracardiac filling pressures, creating a U-net based framework to calculate respiratory rate, and introducing a multimodal wearable biosensor to calculate stroke volume in patients with congenital heart disease using machine learning.

### A. Advantages of SCG for CHF Monitoring

1. Non-Invasiveness: Noninvasively obtaining cardiac information using SCG is advantageous. Healthcare professionals can obtain valuable cardiac data by placing a low-noise accelerometer on the patient's chest, avoiding more invasive procedures such as catheterisation. SCG improves on the traditional technique by providing more accurate readings.
2. Continuous monitoring: SCG provides the ability to continuously monitor heart mechanical function. Unlike conventional methods, SCG enables continuous observation of the heart's activity across time. With this benefit, early deterioration of cardiac health can be diagnosed in advance for timely medication.
3. SCG waveform analysis: SCG waveform analysis offers crucial information about how the heart works. Healthcare personnel can better comprehend the mechanical activity and coordination of the heart during various periods of the cardiac cycle by carefully analysing the unique features and intervals (cardiac time intervals) included in the SCG signal. Assessing heart performance and spotting any anomalies or abnormalities is made much easier with the use of this information.
4. Complementary to other methods: SCG serves as a complementary diagnostic method alongside other established cardiac evaluation techniques. When combined with traditional methods like ECG, serologic testing, echocardiography, and cardiac MRI, SCG can offer a more comprehensive and multidimensional assessment of cardiac health. The integration of SCG data with data from other diagnostic modalities enhances the accuracy and completeness of the diagnostic process, providing a more holistic understanding of a patient's cardiac status.
5. Home-Based Monitoring: HF patients can comfortably monitor their heart function from the comfort of their homes by using small and portable SCG sensors. The use of home-based monitoring devices lessens the frequency of hospital visits and enables patients to easily include cardiac evaluation into daily routines. A sense of empowerment is also fostered in HF patients by home-based SCG monitoring as they actively take part in their own healthcare. It makes it possible for patients to keep in touch with their medical staff and get timely input and support, resulting in more proactive and patient-centered care.

### B. Limitations, challenges and future research

1. SCG origins: There is still more to be done, despite the fact that various research attempted to identify the physiological source or sources of the SCG signals. Intrathoracic pressure and breathing are two extra-cardiac elements that may have an impact on SCG signals. So taking these factors into account may further clarify the sources of SCG.
2. Interpretation Complexity: Although SCG holds promise in delineating particular phases of the cardiac cycle, the precise correlation between SCG waves and cardiac activity remains not entirely comprehended. This level of intricacy could potentially impede the widespread adoption of SCG for HF monitoring until further research unravels the underlying connections.
3. Lack of Standardization: Currently, there is no standardized method for annotating SCG signals and defining specific reference points. This lack of standardization makes it challenging to compare results from different studies and hampers the widespread clinical use of SCG.
4. Open issues such as signal characteristics, variabilities, including sensor placement, health conditions and noise reduction in SCG signals require further research and resolution.
5. Despite recent advances, additional research and longitudinal studies are essential to validate the efficacy and generalizability of the proposed models and techniques.
6. The majority of current data collecting methods rely on irritable contact sensors that are connected to the skin. So effective contactless SCG detection methods would be required.

### C. New Insights

1. Combined Use with Gyrocardiography: Recent research suggests that combining SCG with gyrocardiography (GCG), which measures the angular vibrations of the heart, can improve the detection accuracy of certain fiducial points in SCG. This highlights the potential of integrating multiple wearable sensor technologies to enhance SCG's capabilities.
2. Novel Annotation Techniques: Researchers are exploring new approaches for annotating SCG signals. These include using machine learning algorithms to identify specific cardiac events and developing standardized annotation protocols to ensure consistency across studies.

### D. Hypotheses

1. With the emergence of various measurement techniques, much of the research is currently concentrated on comparing these different techniques. In light of this, I propose the development of a single wearable patch capable of acquiring multiple signals, such as SCG, ECG, GCG, and FCG. Such an efficient

at-home data acquisition system would enable regular monitoring, leading to improved accuracy in HF diagnosis. Moreover, it would offer researchers the opportunity to delve deeper into the morphology of the heart signal, fostering further advancements in the field.

2. Mitigating Vehicle Vibration Interference in SCG for wearable cardiovascular monitoring. One of the open issues in the field of SCG is the interference caused by external vibrations in wearable cardiovascular monitoring systems. Unwanted vibrations can contaminate the SCG signal, leading to inaccurate timing features and reduced signal quality. However, a recent study proposes a robust framework for mitigating vehicle vibration interference in SCG signals. By introducing this technique into a wearable patch, noise caused by subject motion/postural position may be considerably reduced and the reliability of SCG timing features in wearable cardiovascular monitoring systems can be improved, enabling more accurate diagnosis and monitoring of cardiac function in real-world, out-of-hospital environments.
3. Machine Learning Applications for Congestive Heart Failure: The utilization of machine learning algorithms to analyse extensive datasets comprising SCG, ECG, and other relevant sources holds immense potential in creating precise and personalized predictive models for CHF progression. These advanced models have the capability to revolutionize treatment optimization and risk stratification strategies. Furthermore, machine learning algorithms can aid in risk stratification, categorizing patients based on their likelihood of experiencing specific cardiac events.
4. Integrating SCG with Telemedicine: Combining SCG with telemedicine platforms can enable remote monitoring of heart failure patients, providing timely interventions and reducing hospital readmissions. Exploring the effectiveness of this integrated approach could improve patient outcomes and healthcare efficiency.
5. Incorporating SCG into Heart Failure Rehabilitation: Assessing the role of SCG in heart failure rehabilitation programs could help in designing personalized exercise regimens and monitoring patients' response to rehabilitation efforts.

### *E. SCG related to filling pressure*

Inan et al. 2018 proposes a non-invasive method for assessing cardiovascular hemodynamic changes at home. The method involves measuring the SCG waveform before and after a controlled exercise called the 6-minute walk test (6MWT).
The SCG signal comprises time-domain waves, as depicted in Fig. 2, which correspond to events like the opening and closing of the aortic valve and the rapid ejection of blood into the aorta. In healthy individuals, exercise induces significant alterations in the waveform's shape and timings. For instance, the IVCT shortens as a result of elevated sympathetic tone, which compresses the SCG waves over time and increases the high-frequency components. The main hypothesis of the research was that decompensated patients with HF would exhibit significantly fewer changes in the SCG signal during the 6MWT compared to compensated patients. Decompensated patients are less apt to raise their cardiac performance in response to exercise because they have less cardiovascular reserve. Alterations in intracardiac filling pressures are intricately linked to variations in stroke volume, presenting an indirect means of assessing both intracardiac filling pressures and cardiac contractility [9].

If the previous study focused on healthy individuals, recent advances have extended the application to HF patients using machine learning algorithms to estimate alterations in PAM and PCWP during RHC through the analysis of wearable SCG signals. Various SCG signal segments were analysed to understand important segments providing relevant information about changes in PAM and PCWP. Specifically, changes in SCG during the early systole (isovolumetric contraction period, IVC) were most relevant for PAM, while changes during the late diastole (AS) phase were most relevant for PCWP. Another recent study demonstrated the feasibility of estimating stroke volume in patients with CHD [12].

Monitoring congestive heart failure (CHF) using SCG is highly feasible and promising. Abovementioned studies have successfully tested SCG on both healthy individuals and HF patients, providing valuable insights into cardiac dynamics. The identification of key components such as isovolumetric contraction time (IVC period) and the opening of the aortic valve through strengthens the credibility of SCG as a reliable tool for CHF assessment. Additionally, in recent developments, respiration rate (RR) was also estimated from the SCG signal, announcing additional characteristics to take into account for an improved understanding of the SCG signal.

Overall, the research into SCG and its relation to filling pressures provides promising evidence for its use in monitoring heart failure patients and potentially reducing readmissions. By accurately measuring filling pressures through SCG, healthcare professionals can adjust treatment in a timely manner, leading to better management of heart failure and improved patient care.

## IV. CONCLUSION

In conclusion, monitoring congestive heart failure (CHF) using SCG holds great promise as a non-invasive and continuous method for assessing cardiac mechanical function. It complements other diagnostic methods and enables the extraction of valuable cardiac time intervals and parameters associated with physiological events. Recent advancements in SCG and related technologies, such as gyrocardiography and machine learning, enhance its capabilities and potential for remote monitoring, leading to reduced rehospitalization of HF-related patients.

However, challenges remain, including the need for further research on SCG genesis, interpretation complexity, lack of standardization, and signal characteristics variabilities.

Addressing these issues will be crucial to expanding the widespread clinical use of SCG for CHF monitoring. Additionally, the integration of SCG with other wearable sensor technologies and machine learning applications can further improve diagnostic accuracy and personalized predictive models for congestive heart failure progression.

Finally, the research findings regarding SCG and its relation to filling pressures support its feasibility and potential in monitoring CHF patients, reducing readmissions, and improving overall patient care and management.

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