Optimising Seismocardiography for Precision Cardiac Diagnosis with Advanced Signal Processing Algorithms

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Abstract: This paper examines how the diagnosis of heart conditions is enhanced at the conjunction of modern computational methods and Seismocardiography (SCG), Without the requirement of invasive methods, SCG detects minute vibrations on the chest wall brought on by the heart's movements providing vital information on the heart function noninvasively. However, because of the complexity of the signal and the variety from person to person, the task of interpreting the signal accurately is challenging. To get beyond these obstacles, this work employs advanced signal processing techniques. In order To isolate significant frequency components from the signal the Discrete Wavelet Transform (DWT) is used. It further lowers noise in SCG signals and enhances better feature extraction. R-peaks in ECG signals are identified by The Pan-Tompkins algorithm identifies. They are then synchronized with SCG data, which allows to achieve a thorough segmentation and analysis of each heartbeat. To further refine the SCG signals interpolation techniques like Akima Interpolation and Piecewise Cubic Hermite Interpolation (PCHIP) are used to produce a continuous dataset, guaranteeing smooth and consistent signals for analysis. The SCG signals are then broken into Intrinsic Mode Functions (IMFs) by Hilbert-Huang Transform(HHT), which yields a more precise time-frequency analysis that is tailored to each individual signal. This study shows that seismocardiography (SCG) can provide accurate and non-invasive measurements of heart function by combining SCG and (ECG) data using advanced computational techniques. SCG has great potential as a reliable diagnostic tool in clinical settings, offering an easy and dependable way to assess cardiac health.

Key-Words: - Seismocardiography,non-invasive, Hilbert-Huang Transform, Signal Processing, Discrete Wavelet Transform.

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1 Introduction

Nearly half of the lives in Europe are lost every year accounting for heart and circulatory diseases. Cardiovascular illness affects millions of people across the continent and the number of occurrences has only increased in the past 25 years[2]

The vibrations of the body caused by heartbeats are recorded by using the seismocardiogram. Seismocardiography is a non-intrusive method for recording cardiac data for diagnosis The SCG collects data about the mechanical activities of the heart along with heart sounds and cardiac output[1,3]

SCG when compared to its alternative approaches in competition, it was not extensively used in clinical settings. Recent technological developments have been able to rekindle interest in the usage of SCG. It has been able to grab attention due to its advantage of enabling constant and automated surveillance along with the added benefit of emerging as a reasonably priced substitute for the current cardiac monitors[3]. The vibrations transmitted to the barrier walls of the heart at low frequencies are not effectively captured.

Since the impact is almost negligible, the nonintrusive method falls short in capturing all the disturbances and it faces difficulty in correlating them with cardiac activity. To validate the utilization of cardiac sounds for the evaluation of heart functions further research was necessary[3]

Comprehending the importance of the undulating waves and how they correlate to cardiovascular diseases was a significant challenge when interpreting SCG signals. Salerno and his team, understanding the importance of Echocardiography in the field of heart health explored the connection between SCG waves and Echocardiograms. A novel feature point-based method was used to differentiate between normal and abnormal morphologies in individual ECG and SCG cardiac cycles[11]

It is challenging to compare the outcomes among studies without standardized diagnostic protocols. Due to variations in the anatomy of the body, sensor positions and body types, the variation in SCG signal is also inevitable[13,12]. The low-frequency components of the heart are essential for recognizing heart activity. These frequencies often overlap with the other signals of the body. Improved techniques and consistent standards are thus required to make SCG a more reliable tool for interpretations[12].

The identification and marking of specific peaks of interest. In Siesmocardiogram (SCG) signals present challenges due to the complex structure and differences between individuals. This complexity poses difficulties for traditional methods for detecting peaks, particularly when compared to the identification of peaks in electrocardiogram (ECG) signals [8].

2 Feature Extraction and Recognition of 'R' Peaks in Signal

DataSource-
https://www.frontiersin.org/articles/10.3389/fphys.2021.750221/full

The database encompasses pertinent echocardiographic parameters associated with each subject, encompassing discharge rate, valve area, and average gradient pressure. It comprises recordings of 6 channels of 3-axis SCG and 3-axis GCG, accompanied by comprehensive patient information, demographic data (number, age, gender), recording meta information, axis definitions, and synchronized recorded ECG signals. Additionally, the database incorporates echocardiogram reports. Notably, this database stands as the inaugural collection of SCG and GCG signals obtained from cardiovascular patients.

2.1 Decomposing signals into different frequency components

A denoising algorithm based on discrete wavelet transform (DWT) enhances the SCG signal by decomposing, thresholding, and reconstructing it in a three-step process. The adaptive thresholding method improves algorithm performance, offering a time-efficient and effective denoising solution[14].

The DWT(discrete wavelet transform) analyzes signals by utilizing proportioning functions and wavelets that correspond to low-frequency and high-frequency filters[Fig.2]. Through the use of these filters, the most important are represented frequencies present in the original signal by coefficients of big wavelets in their respective frequency spectrum, while also considering their time region identification[5].

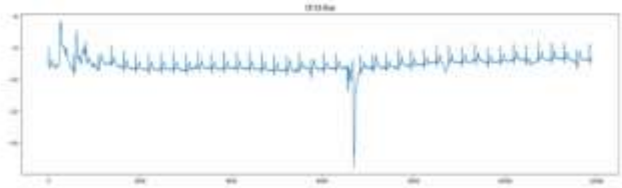

Fig.1 A sample SCG raw Signal

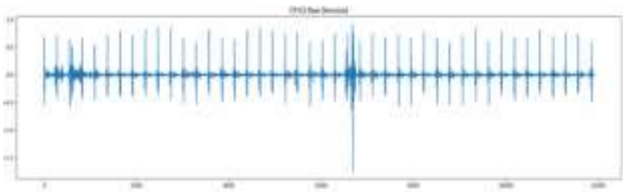

Fig.2 Resultant SCG after Discrete Wavelet Transform

The Discrete Wavelet Transform (DWT) separates noise and cardiac signals into different scales, helping to isolate low-frequency components associated with baseline wander and extracting vital features from the SCG signal for diagnostic or monitoring purposes.

2.2 QRS complex detection

Once the signal is decomposed, identifying the QRS complex allows us to align heartbeats with SCG data. Accurate detection of QRS complexes is crucial for various applications, including heart rate monitoring, arrhythmia detection, and clinical diagnosis.

During real-time processing of the signals, QRS complexes are separated by using the Pan-Tompkins method. This Algorithm is able to accurately detect heartbeats even in noisy ECG signals. It is due to this reliability the Pan-Tompkins algorithm is preferred particularly when the signals can be noisy. It is comparatively a simpler and efficient method making it perfect for cardiac monitoring. It employs custom thresholds to identify the QRS signals and additionally, it filters out common noises[15]. Finding peaks in the ECG features and figuring out their placements, heights and widths are all part of the signal processing process. Employing the algorithm on the signal aids in prioritizing the QRS complex over noise and identifying the peaks within the signal[6].

The first step in the algorithm involves the bandpass filtering of the original ECG signal given as input. The QRS complex's quick upstroke and downstroke patterns are then identified by computing the signal's derivatives. Following that the derivatives are squared. This step is done to highlight the magnitude of variations in the slope making it easier to spot the peaks in the signal[Fig.3]. Subsequently, the squared signals are processed under a moving window integrator. This procedure is specially designed to minimize other signal variations by integrating the signal over a predetermined window.

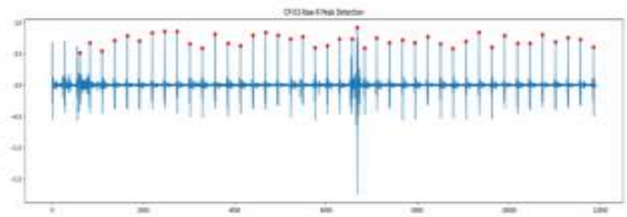

Fig.3 R Peak Detection

The integrated signal is then subjected to a dynamic threshold to determine the potential output of using QRS complexes .Peaks that surpass this threshold are then recognized as QRS complexes. To prevent multiple detections of a single QRS complex, a refractory period is frequently implemented.

The suggested method relies on accurately identifying[Fig.4] the R-peak of the ECG to segment the SCG and ECG signals.[8]

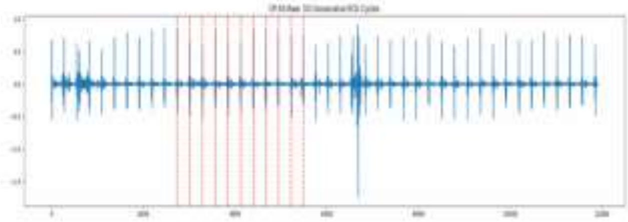

Fig.4 Detection of R-peaks in ECG Cycles.

2.3 Mapping R-Peaks to SCG Data

Aligning the R-peaks from the ECG data with the corresponding cycles in the SCG data by identifying peaks or specific features in the SCG data that synchronize with the R-peaks. After the synchronization points are identified, extract the SCG cycles that align with each R-peak in the ECG data by segmenting [Fig.5]the SCG signal into cycles.

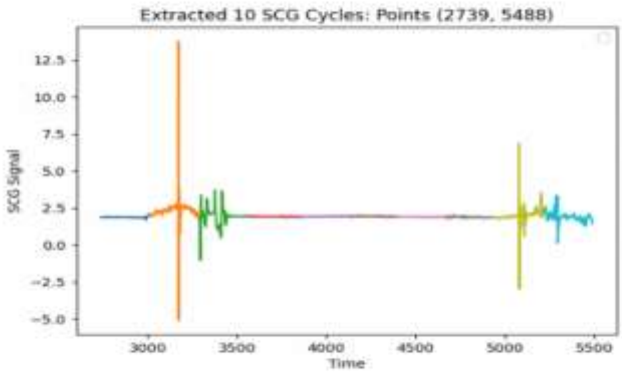

Fig.5 SCG Signal Segmentation

2.4.Interpolation

After aligning the signals, we apply interpolation to smooth the data, ensuring continuity before the Hilbert-Huang Transform is applied**.** Interpolation is particularly useful when dealing with continuous data, and it helps in creating a smooth representation of the data between discrete points One way to make sense of data is by creating a function or curve that fits the existing data points. This allows us to predict values at points within the range of the given data.

The Akima interpolation method involves the use of continuously differentiable sub-spline interpolation, which is achieved through the construction of fragmented third-order polynomials.[7]Akima interpolation is known for producing smooth curves with reduced oscillations[Fig.6] and artefacts near the data points, making it advantageous for input signals with sharp transitions or peaks.

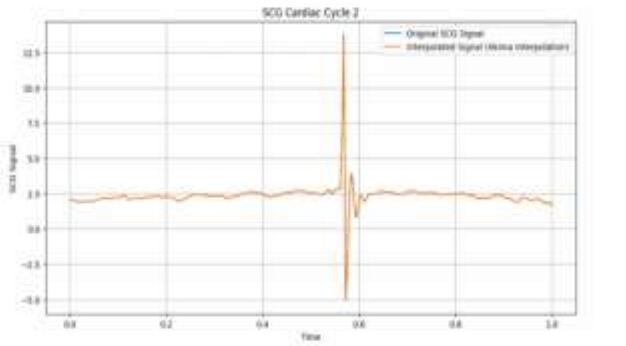

Fig.6 SCG Cardiac Cycle after Akima Interpolation

The PCHIP interpolation is designed to generate interpolating curves that maintain monotonicity. PCHIP interpolation constructs a piecewise cubic polynomial between each pair of adjacent data points. The polynomials are determined to be monotonic, and the resulting curve smoothly transitions between these polynomials. The property of monotonicity ensures that the interpolated values avoid introducing undesirable oscillations or loops between data points. This feature makes [Fig.8]PCHIP interpolation particularly well-suited for applications where preserving the monotonicity of the input signal[Fig.7] is critically important.

Fig.7 Original SCG Signal

Fig.8 PCHIP Interpolated Signal

Then Hilbert Transform is used to extract the instantaneous phase and amplitude information from each (IMF) Intrinsic Mode Functions. Before applying the Hilbert-Huang Transform, it's common to use interpolation for several reasons. Firstly, HHT, specifically the Empirical Mode Decomposition (EMD) part, is sensitive to data smoothness. Interpolating ensures a continuous signal, preventing inaccurate decomposition into Intrinsic Mode Functions (IMFs). Additionally, interpolation helps in handling missing data by estimating missing values, providing a complete signal for more accurate IMFs and reliable analysis. Moreover, interpolating increases the sampling rate, improving frequency resolution for a more accurate Hilbert spectral analysis. Lastly, interpolation smooths sharp discontinuities, preventing artefacts in the IMFs.

3 Problem Solution

To empirically assess the viability of the suggested technique. After performing EMD utilized within the Hilbert-Huang Transform (HHT), The subsequent action involves applying the HHT to the obtained Intrinsic Mode Functions (IMFs).

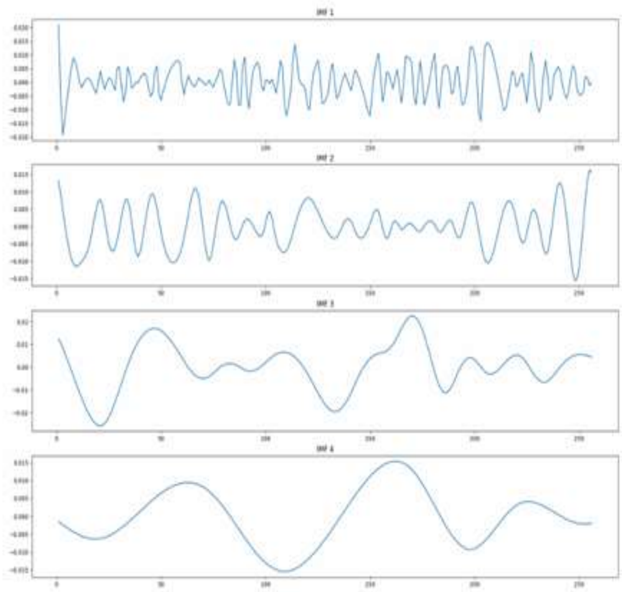

Fig.9 IMFs generated after performing EMD restricted to 4 IMFs

Applying the Hilbert Transform results in a matrix format, with each row representing an Intrinsic Mode Function (IMF)[Fig.9] and each column representing a sample point or time step. We refer to this matrix as the "HHT matrix," which contains the IMFs.

0	1	2	3	4	5
0.04007469873	0.03127851714	0.02836208414	0.0304772640	0.02894680373	0.03108502068
-0.0001337099037	-5.66E-05	-7.87E-05	-1.26E-05	2.31E-05	5.82E-05
0.05007447365	0.02589821400	0.009614896296	0.009645822019	0.008382769844	0.008311583006
0.001215277218	0.0007371598939	0.0004597703266	0.0004787083652	0.0004335839727	0.000447867436

Fig.10 HHT Matrix after restricting IMF number to 4 IMFs

The result of applying the Hilbert Transform can be arranged in a matrix format where each row represents an IMF and each column represents a sample point or time step. This matrix would be referred to as the "HHT matrix" containing the IMFs The quantity of Intrinsic Mode Functions (IMFs) generated varies for each patient, consequently influencing the dimensions of the Hilbert-Huang Transform (HHT) Matrix as the number of rows in the matrix coincides to the number of IMFs. To establish a consistent HHT Matrix across all patients, the limit is set to four IMFs per cycle[Fig.10]. Following the restriction of the number of IMFs, the dimension of the HHT matrix is 4 x 256, with "4" representing the number of IMFs generated through Empirical Mode Decomposition (EMD) and "256" denoting the number of data frames or time steps in the authentic signal.

The outcomes of the Hilbert Transform, particularly the instantaneous frequency, are frequently portrayed through time-frequency representations. Spectrograms [Fig.11]or time-frequency plots facilitate the comprehension of how the signal's frequency characteristics evolve. These visual aids have a vital function in elucidating the temporal dynamics of the signal's frequency content. The techniques was chosen because it effectively analyzes nonlinear and nonstationary data, unlike traditional methods that assume data linearity and stationarity[16].This adaptive, localized approach allows for detailed time-frequency-energy analysis through Hilbert Spectral Analysis, making HHT particularly useful for complex, naturally occurring processes.

To create a spectrogram, you need to split the EEG signal into short, overlapping segments, utilize the Fourier Transform on each segment to extract its frequency spectrum, and then represent these spectra as a function of time[9]

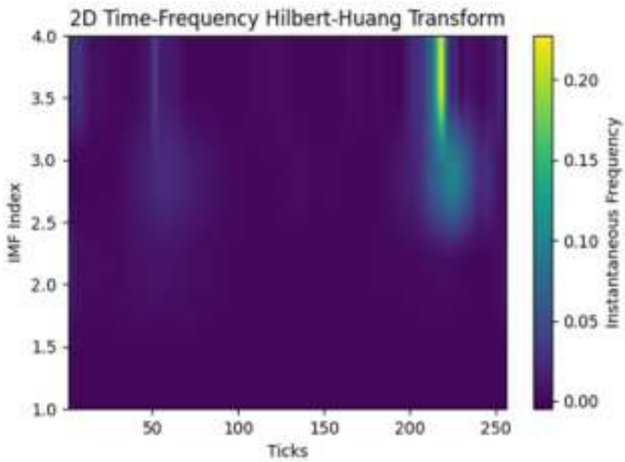

Fig.11 Hilbert Spectrogram

Unlike traditional methods, HHT does not rely on predefined basis functions, making it more flexible and capable of adapting to the unique characteristics of SCG signals. The potential applications of HHT in biomedical signal processing, such as in electrocardiograms (ECG) and electroencephalograms (EEG), suggest that it could become a standard tool for analysing a wide range of physiological signals.

4 Future Work

Applying the HHT to other bodily signals beyond SCG could significantly open up novel developments in biomedical signal processing. Expanding the usage widens the understanding of various physiological processes. The study lays a groundwork for further investigations in the future wherever time-varying signals are commonly found like geophysics and vibration analysis. Building on the findings of the study exploration on combining HHT with other analysing techniques, like STFT or CWT might add to new development in hybrid approaches. Particularly, considering the computational complexity of HHT, optimising it to a clinical scale is necessary to accentuate its efficiency. In future areas of research of HHT in SCG analysis, it is crucial to address the inaccurate decompositions produced due to mode mixing in EMD.

5 Conclusion

In summary, The study emphasizes the importance of yielding the true potential of seimocardiograhy(SCG) for evaluating cardiac functions. An innovative tool alone is used in combination with other advanced methods for feature extraction and R-peak detection in ECG signals. It highlights the use of the Discrete Wavelet Transform and the Pan-Tompkins algorithm for optimising the methodology discussed and applied to SCG data. Using HHT for time-frequency analysis is a superior way to extract meaningful features from the data. Through the systematic advancements in computational techniques used and the improvement of the signal processing algorithm enhance this work and show that SCG can offer great potential in precise cardiac assessments.Further careful development on this innovation and validation of new procedures is a great advantage to the field of cardiac assessment. Overall, the results and methodologies presented in this study open the door for additional research and development of non-invasive diagnostic tools. These cutting-edge diagnostic instruments have the potential to revolutionize patient care.

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