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RESEARCH

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Enhancing visual seismocardiography in noisy environments with adaptive bidirectional filtering for Cardiac Health Monitoring

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Abstract

Background Wearable sensors have revolutionized cardiac health monitoring, with Seismocardiography (SCG) at the forefront due to its non-invasive nature. However, the substantial motion artefacts have hindered the translation of SCG-based medical applications, primarily induced by walking. In contrast, our innovative technique, Adaptive Bidirectional Filtering (ABF), surpasses these challenges by refining SCG signals more effectively than any motion-induced noise. ABF leverages a noise-cancellation algorithm, operating on the benefits of the Redundant Multi-Scale Wavelet Decomposition (RMWD) and the bidirectional filtering framework, to achieve optimal signal quality.

Methodology The ABF technique is a two-stage process that diminishes the artefacts emanating from motion. The first step by RMWD is the identification of the heart-associated signals and the isolating samples with those related frequencies. Subsequently, the adaptive bidirectional filter operates in two dimensions: it uses Time-Frequency masking that eliminates temporal noise while engaging in non-negative matrix Decomposition to ensure spatial correlation and dorsoventral vibration reduction jointly. The main component that is altered from the other filters is the recursive structure that changes to the motion-adapted filter, which uses vertical axis accelerometer data to differentiate better between accurate SCG signals and motion artefacts.

Outcome Our empirical tests demonstrate exceptional signal improvement with the application of our ABF approach. The accuracy in heart rate estimation reached an impressive r-squared value of 0.95 at −20 dB SNR, significantly outperforming the baseline value, which ranged from 0.1 to 0.85. The effectiveness of the motion-artifact-reduction methodology is also notable at an SNR of −22 dB. Consequently, ECG inputs are not required. This method can be seamlessly integrated into noisy environments, enhancing ECG filtering, automatic beat detection, and rhythm interpretation processes, even in highly variable conditions. The ABF method effectively filters out up to 97% of motion-related noise components within the SCG signal from implantable devices. This advancement is poised to become an integral part of routine patient monitoring.

Keywords Visual seismocardiography, Motion, Filtering, Decomposition, Signal, Reduction, Noise, Heartbeat, Artefacts, Health monitoring

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Inroduction

Among the rapidly developing technologies that facilitate the enhancement of healthcare and the treatment of different diseases, wearable sensors have emerged as central to the improvement of the pertinent field. Among the domains, one can notice the constant improvement of cardiac health monitoring: conventional techniques such as electrocardiography (ECG) [1] are being extended and sometimes replaced by novel techniques in the form of SCG. SCG, a non-invasive diagnostic tool that records the mechanical motion of the heart, holds much potential because, in contrast to other diagnostic tools in cardiology, it focuses on the effector organ of the heart, thus delivering great potential for biochemical treatment [2]. However, this potential has been limited in clinical applications due to significant issues, such as motion artefacts, particularly prevalent during activities like walking. These artefacts shroud the authentic cardiac signals, and thus, it becomes challenging to extract efficient and actual information from SCG recordings.

Thus, as stated before, it is evident that when the ramifications of accurate cardiac monitoring are taken into consideration, the concern of motion artefacts in SCG calls for research immediately. The question then arises: SCG signals need to be filtered in a manner that gets rid of motion noise while not losing cardiac information at the same time; how can this be done [3]? .Such research gap has established the need for new methods that would help distinguish between cardiac signals and movements. It meets an important need not only for improving the diagnostic capacity of SCG but also for broadening its use in clinical and non-clinical contexts, including prolonged ambulatory surveillance and physical training.

The importance of this research cannot be overemphasized. Cardiac monitoring is one of the most important tasks that are taken into practice because heart diseases remain the topping cause of mortality [4]. Conventional ECG is, however, widely utilized, with the major drawback of having to attach the body to the machine, which may be inconvenient for long-term monitoring. SCG, on the other hand, has the possibility of monitoring patients non-invasively, comfortably and continuously, which makes it a revolutionary step. However, it is largely marred by the problem of motion artefacts, which hitherto confined its usefulness. However, they are the main source of interference; by creating new approaches to eliminate the effect of these artefacts, SCG can be used as an alternative or as an augmentation to ECG [5]. This advancement would also be beneficial to patient outcomes, as diagnosis would be made early and accurately, and for the patient's quality of life, the monitoring process would be much easier.

Better quality of SCG signal processing can contribute to increased diagnostic accuracy of heart abnormalities, a decrease in false-positive results in clinical practice, as well as improvement in early detection and diagnosis. Higher signal clarity could help in the real-time monitoring of the heart and assist in improved patient care by coming up with relevant measures to be taken. In real-world settings, this can enhance the effectiveness of cardiac health monitoring systems by implementing elements that enhance the standard of care, cut the number of visits to local hospitals, as well as improve long-term patient outcomes at large.

In the context of the proposed research, we present a technique called Adaptive Bidirectional Filtering (ABF) to cope with the issue of motion artefacts in SCG signals [6]. ABF uses an exceptional noise cancellation algorithm that combines RMWD and a bidirectional filtering approach. This two-part process consists of the RMWD for detecting the heart-related signals and isolating them using an adaptive bidirectional filter implemented with time-frequency masking [7] and non-negative matrix factorization [8]. This two-step approach effectively helps to eliminate the temporal noise and simultaneously helps improve the spatial correlation, which also helps improve the clarity of SCG signals to a large extent.

Therefore, the rationale for this study arises from the increasing need to develop effective interventions in non-invasive cardiac monitoring. Consequently, there is growing pressure for wearable devices to become even more effective and smoothly integrated into people's lives as health-tracking technologies keep on improving. Even today's SCG methods are not adequate because of the presence of motion artefacts, despite the potential that SCG has demonstrated. In this context, our study focuses on dealing with this crucial problem, which will enrich the current understanding of the state of the art in cardiac monitoring and help expand the possibilities of developing more stable and effective health monitoring systems in the future. Of course, the application domain of this research is limited to SCG, but the principles and approach adopted in this thesis are expected to be relevant to other areas of biomedical signal processing where motion artefacts are problematic.

Therefore, it can be posited that the relevance of our research lies in the following areas: First, it offers a comprehensive workout that entails how to extract and optimize SCG signals irrespective of images created by full body motion artefacts in order to increase the efficiency of monitoring of cardiac activities. Second, the proposed system using ABF establishes a new benchmark for noise-cancellation filters in biomedical signal processing for SCG and other applications. Third, our study shows that it is possible to achieve non-invasive, continuous, real-life cardiac monitoring, which is advancement in incorporating wearable gadgets into daily life. Finally, by filling the existing gap in the literature, our research provides a basis for future advancements in the given field and adds motivation for enhanced investigations of various innovative signal-processing methods. The following description exhibit the core processes (objectives) of the study.

- The primary aim of this study is to establish a reliable approach that would increase the possibility of filtering out motion artefacts from SCG signals. It is a decisive stage when enhancing the accuracy and quality of cardiac monitoring, especially if it is performed, for instance, outside of the clinical settings. The significant objectives involve the usage of the RMWD for a better evaluation and separation of the signals related to the heart and the use of dependable Time-Frequency masking and Non-Negative Matrix Factorization (NMF) with SCG signal processing for better spatial and time factors.
- The second primary goal is to design and implement the ABF that will include the data from the vertical axis accelerometer in order to offer further improvement in the distinction between SCG signal and motion artefacts. Moreover, assessing the ability of the proposed ABF technique through the enhancements in SNR and the accuracy level of the estimated heart rate is prominent.

Thus, the proposed technique of ABF for the SCG signal analysis can help address various future challenges of patient care and contribute to advancements in biomedical investigations. Thus, the approach is aimed at stressing the possibility of the ABF method's application to continuous, non-invasive, and long-term cardiac monitoring in real-life settings, which may suggest its integration into routine patient monitoring and numerous biomedical applications. It not only brings the hope of better health services for patients but, in the same breath, provides an opportunity for increased biomedicine research.

Related work

Javaid et al. [9] concentrated on utilizing the empirical mode decomposition (EMD) to mitigate the motion artefacts from the SCG signals acquired by a wearable appliance during walking. The research showed that the EMD-based de-noising approach has superiority in raising the Signal-to-noise ratio (SNR) of SCG signals and, consequently, the measurement precision of PEP during walking. Patients also demonstrated significant improvements in the distance between their resting and walking heartbeats after receiving EMD in the different walking paces. However, several limitations include the fact that the subjects were selected based on health and youth, as well as differences in signals' performance, which may be a result of different walking surfaces. Furthermore, future work should consider these limitations and come up with better SNR metrics that can be used to assess signal quality during exercise.Shafiq et al. [10] proposed a reliable technique that addresses the task of systolic time intervals (STI) annotation for SCG signals by utilizing a sliding template method. The basic approach is the construction of a primary template employing the ensemble averaging that follows the generation of the sliding template for better peak determination. The number of identified peaks for each trial was 4.7895 in the supine position and 11 in the seated position, respectively, again proving good performance on noise. The findings of the study show that the proposed method has a better performance compared to the envelope-based methods, with the limits of agreement widths reduced to as low as 16.53 s in supine and 14 ms in standing positions. The study has demonstrated that this method enables the diagnosis of heart disturbances, particularly during pregnancy. In seated trials, it takes only 49.9 ms, while in moving trials; it takes 38.2 and 62.5 ms, respectively. However, some limitations include a lower ability to deal with high amplitude momentary artefacts and a lack of proving it in a wide range of postures and activities for a reliable application in real life. Luu and Dinh [11] discuss high-motion artefact reduction techniques employing a dual-accelerometer system. It includes analogue and digital signal processing wherein the signals obtained from two accelerometers are horizontally, vertically, and diagonally arranged together and eliminate the motion artefacts during mild movement and walking. Some of the milestones include increasing the average systolic SNR by about twofold and the average diastolic SNR by about threefold during the gentle motion, in comparison to the single-accelerometer-based approaches. When it comes to walking motion, the results express even larger improvements, where systolic SNR is increased by about seven times and diastolic SNR by about 11 times. Nevertheless, the drawbacks of the study include the fact that the experiment involved multiple accelerometers, and it implies increased cost and difficulty; the results might not apply to a variety of real-world settings since further validation is recommended. Leitão et al. [12] have recently presented a high-resolution acquisition system for ECG and SCG signals using a new micro-electro-mechanical system (MEMS) accelerometer. In addition, the system also provide real time data display and data analysis function with the function of correlating ECG and SCG for all round Cardiac performance appraisal. A pilot trial comparing 22 patients to the system on physician's findings established a significant degree of heart rate congruity between SCG obtained heart rate values and ECG results with SCG derived intervals highly correlated to left ventricular ejection time as obtained using echocardiogram. The study also has to seek independent validation in different groups of patients due to the small sample size adopted in the research. D'Mello et al. [13] proposed a reliable approach to combining SCG and gyrocardiography (GCG) signals in real-time for cardiac monitoring. The basic approach comprises an online mathematical formula performed in a low-cost system developed in-house, integrated with preamplifiers that acquire SCG and GCG captured at the sternum, and the ECG is carried out simultaneously. In the system, twenty-five subjects performed by SCG–GCG obtained high heart rate, which is called ECG, and instantaneous beat identification was excellent. The computed algorithm resulted in an average computational time of 0.88 for each measurement cycle on the sampling frequency of 250 Hz, thus meaning the maximum refresh rate. The addition of the SCG and GCG measurements tapered the inaccuracies because of differences in noise rejection in the orthogonal signals. Some of these are as follows: The study was conducted only on static subjects, the results need to be tested in various conditions, and motion artefact amplitude may be problematic for the proposed technique. Zia et al. [14] put forward a new effective framework called Dynamic-Time Feature Matching (DTFM) to enhance the capability of the indexing and classification of SCG signals. The signal quality index is computed by the DTFM method as the degree of reference to a large set of templates by the SCG signal distance inverse. The characteristics of this method are that it is successful at stratifying SCG signals based on the amount of motion-artifact corruption and the utilization of the signal quality index as a feature for ensembled Quadratic Discriminant Analysis (QDA) for classifying. The proposed study was able to expedite a high percentage for detecting and identifying the misplacement of SCG sensors with an F1-score of 0.83 on held-out subjects. It is also important to underline that vital acquisitions related to the method allow the stratification of signal quality and proper classification of misplacement. However, limitations include the need to validate in different cases and conditions and the uncertainty of the SCG signals due to variability of the sources, such as the subject's condition and position of the sensors.Mora et al. [15] introduced an approach for the unsupervised processing of SCG signals. The core work employs a two-step procedure consisting of a calibration step and a modular convolutional variational autoencoder (MC-VAE) network. From the analysis of the methodology, it is revealed that it performs with excellent performance indicators, with an average precision of 98.6% for beat detection, sensitivity of 98.5% and an RMSE of 4.10 μs in the maximum difference between observed and expected intervals. Out of these three, the VAE network is especially impressive, attaining more than 90% adjusted rand score, mutual information score, completeness, and homogeneity for clustering heterogeneous SCG signals, and the network's ability to give a high likelihood of correctly identifying divergence in signal morphology. Nonetheless, the drawbacks of the specified methodology include the lower efficiency when used in noisy surroundings and the need for further research to confirm the potency of the methodology in a range of real-world circumstances in relation to different tendencies and patterns of users. In a related study, Uskovas et al. [16] use CNNs in the detection and correction of SCG-sensor misplacement. The methodology centres on training a CNN model to classify the placement of SCG sensors into five categories: right, left, upper lower, hearing, and vision. This model is tested on signals acquired from multiple subjects, which made up the test dataset for SCG signals, obtaining a classification success rate of 96.4 per cent for the misplacement of the sensors. Also, the F1 score was reported to be at 0.93 for the binary classification task of identifying whether the sensor is placed correctly (which is placed in the centre and misaligned, which is placed off-centre). Some achievements include significant minimization of misplacement errors and improved SCG signal interpretability. Nonetheless, there are several limitations of the study; the first one is the use of relatively small sample size, and the second is the lack of diverse data to enhance the generalization of the model and real-time data implementation complications because of its complexity.The work of Centracchio et al. [17] proposes a method for the automatic detection of heartbeat in SCG signals without the need to have simultaneous ECG signals. The methodology applies a template-matching approach of comparing the heartbeats, and the measure used is the normalized cross-correlation (NCC). The research was performed on SCG signals obtained from 77 patients with valvular heart disease; the sensitivity was 96%, and the positive predictivity was 97%. Also, correlation, regression, and Bland-Altman analyses of the inter-beat intervals were statistically not different with a non-significant bias ($R2$: >0.999 with inter-beat slope as 0.997, intercept as 2.8 ms in a range of ±7). This reveals the high efficiency of the proposed method and its high degree of accuracy and reliability, sometimes even surpassing more complex AI algorithms. However, there is a limitation in the identification where the selection of the heartbeat template is done manually and therefore, the method is operator dependent; the performance of the method is only tested on subjects in a stationary position in a supine position; hence, more testing needs to be done in other conditions and positions. Skoric et al. [18] proposed a new approach based onMaximum Overlap Discrete Transform (MODWT) in combination with time-frequency masking and non-negative matrix factorization for the motion artifacts rejection from SCG signals. The core work was about preprocessing SCG signals which were contaminated with real-walking vibrational noise, but it was able to provide a better estimation of heart rate by increasing the correlation coefficient, which was raised from 0.1 to 0.8 at an SNR of -15 dB. This study further revealed that the proposed algorithm could effectively eliminate motion artefacts up to an SNR of 19 dB without the help of ECG signals. Peculiarities consist of the lower efficiency of the method for very high noise levels and future research in various real-world conditions. Zheng et al. [19] proposed a method for the precise identification of aortic valve opening (AO) peaks in SCG signals for monitoring cardiac function. The main approach of the proposed method, called "Successive Variational Mode Decomposition (SVMD)", does not presuppose the number of modes, which is a common shortcoming of the existing techniques. The raw SCG signals are initially processed by filtering out the out of bands, and then, the signals are transformed into quasi-orthogonal modes before being reconstructed based on the waveform factor for an enhancement of the pulsatile AO signal. The results show a high average prediction rate (99.06%), sensitivity (99.02%), and detection accuracy (98.10%) that is much higher than those of several other state-of-the-art methods. Furthermore, the method cuts down on the maximum mean relative bias (0.03%) and the absolute error (2.11%), which proves its applicability in estimating the heart rate by using an accelerometer alone. Nevertheless, some drawbacks are the possible dependence of the method on certain datasets and the lack of sufficient testing across a wide range of conditions to prove the method's reliability.

Adaptive bidirectional filtering

The ABF technique of SCG signal processing involves the use of RMWD to yield the wavelet and scaling coefficients of the SCG signal at different scales. Subsequently, frequencies belonging to heart signals, that is, frequencies ranging from 0.5 Hz to 40 Hz are detected, and then the SCG signal components of these frequencies are extracted. This isolated signal further goes through time-frequency masking, which helps in removing the temporal noise and offers a time-frequency masked signal. Subsequently, the NMF is used to decompose the masked signal further into a basis matrix and coefficient matrix while maintaining the spatial correlation. ABF's principal concept is based on a bidirectional filtering, which has a recursive structure using the data of the vertical axis accelerometer to distinguish between genuine SCG signals or motion artefacts. This particular filter works in both directions and helps to remove the interference from the motion to the degree of the signal. The experiment is conducted using the ABF technique to assess its performance and effect on the noise reduction of the undesired frequency band, which is illustrated using the SNR before and after filtering. To evaluate the methods' accuracy, the assessment relies on the standard metrics that demonstrate a relationship between the estimated and real values of the heart rate. Lastly, the performance of motion-artifact reduction is presented in terms of percentage, which shows the high percentage of SCG signal clarity enhancement obtained by the ABF method.

Dataset

Initially, the proposed approach is evaluated using preprocessed SCG Signal processing dataset, which is obtained from IEEE Dataport [20] contains the representations of the patient's conditions in real-time at different condition in the medical environment. The cross-sectional sample consists of 1,000 participants following the period from 10 November 2023 to 10 January 2024 in order to create a strong time frame. The records consist of a time stamp and the following key parameters: frequency of heart signal in Hz, SCG signal values in m/s^2, noise in m/s^2, and vertical axis accelerometer data in m/s^2. It also contains the heart rate indicated in BPM and the SNR values and the values are depicted in dB. Several works require SCG signal, and this dataset can be of great importance, including the investigation of the dynamic behavior of SCG signal, performance evaluation of the methods used for heart rate estimation, and evaluation of the methods to reduce the noise in the SCG signal in the biomedical signal processing area.

The kind of data and its attributes are very important in augmenting the study by capturing variable kinds of real-time SCG signals from the different patients, such as different heart rates, noise and motions. Additional vertical axis accelerometer data supplements the dataset's provision of a human ability to evaluate the characteristics of noise reduction and signal quality enhancement techniques. Such a choice makes it possible to evaluate the applicability of the proposed approach under different conditions that strengthen the method's reliability and validity. Variability in signal-to-noise ratios, heart rates, and accelerometer data allows for the assessment of the ABF method in various environments and conditions relevant to real-time cardiac monitoring. Table 1 constitutes the following attributes in the dataset with appropriate units, as well as a range of data attributes for the purposes of characteristics.

Table 1 Dataset attributes

Attribute	Specification/Ranges
Timestamp	2023-11-10 00:00:00
SCG Signal (m/s^2)	-2.5, 0.0, 1.2
Heart Rate (BPM)	60–100
Noise (m/s^2)	-1.0, 0.3, 0.8
Frequency (Hz)	0.5–40
SNR Before (dB)	-20 to -10
Accelerometer Data (m/s^2)	-0.9, 0.1, 1.5

Visual signal conversion

In order to assess the effectiveness of the proposed model in practice, it is pertinent to translate the obtained visual SCG signal into the numeric form. Therefore, the required visuals are deduced with the help of an appropriate image processing library such as OpenCV. If the image is colored, it is transformed into a black-and-white one to concentrate on the signal amplitude's intensity value. This grayscale conversion employs the weighted sum on the red, green, and blue planes. A threshold is then optional to binarize the image for a clear distinction between the signal and the background, but this depends on the quality of the image and the noise. Subsequently, the pixel intensity values are obtained along the SCG signal line. This entails ensuring one has the coordinates of the various Pixels within the image that correspond to the signal. Lastly, these pixel intensities are converted to numerical values through a calibration factor to bring back the pixel values to their original physical dimension, in this case, in terms of meters per second squared (m/s^2). These calibrated numerical data are used to analyze further and validate the signal processing model of SCG. Fig. 1 depicts the entire pre-processing procedure from the visual SCG signal to extract essential attribute for real-time testing evaluations.

Computational processes of RMWD

The first of the steps involved in ABF is the identification of the signals associated with the heart and separating the samples with related frequencies. These processes are handled through RMWD. The RMWD is then taken on SCG signal $\check{S}(t)$ in order to get the scaling coefficients $\text{ʂ}_J(k)$ and wavelet coefficients, $\text{ɰ}_j(k)$. The scaling functions $\phi_{(J,k)}(t)$ and wavelet functions $\Psi_{(j,k)}(t)$ break up the given signal at various scales with different resolutions.

$$\check{S}(t) = \sum_{(j=0)}^{(J-1)} \sum_k \left(\left[\text{ɰ}_j(k) \cdot \Psi_{(j,k)}(t) \right] + \left[\text{ʂ}_J(k) \cdot \Psi_{(j,k)}(t) \right] \right) \tag{1}$$

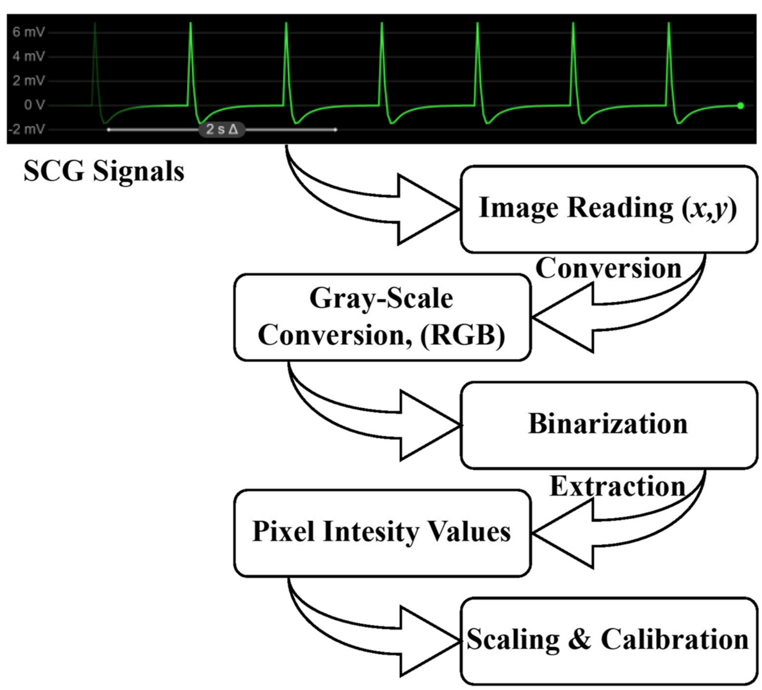

Fig. 1 Representation the signal processing stages (image reading, the process includes gray-scale conversion, binarization, pixel intensity value extraction, and ends with scaling and calibration for further analysis) for Visual SCG signals

$$\text{ȿ}_J(t) = \sum_k \left[L_J(k) \cdot \check{S}(t - 2^J k)\right] \quad (2)$$

$$\text{ɰ}_j(t) = \sum_k \left[H_j(k) \cdot \check{S}\left(t - 2^j k\right)\right] \quad (3)$$

Equations (2) and (3) are two important segments of the RMWD in Eq. (1), where a signal processing method for multi-resolution analysis for time series information. More precisely, the scaling coefficients $\text{ȿ}_J(t)$ are derived by passing the signal $\check{S}(t)$ through the low-pass filter $L_J(k)$ and then sub-sampling it at the rate 2^J. This process isolates the high-level frequency components of the given signal at the lowest resolution level. The wavelet coefficients $_j(t)$ are given by the convolution of the signal $\check{S}(t)$with the high-pass filter followed by decimation at the rate of 2^j. From this process we obtain the high frequency components, $H_j(k)$ of the signal, at different scales. Thus, RMWD involves applying the high-pass and low-pass filters with the aim of decomposing the original signal into its detailed and approximated presentation over the different scales of the frequency bands. This form of analysis is a useful method for feature extraction and the recognition of patterns and characteristics in the signal at the respective durations, which makes it a valuable tool in signal processing applications like the SCG for cardiac health monitoring. The specific wavelet functions used in RMWD for SCG signal decomposition are typically the Daubechies wavelets, known for their ability to capture both high-frequency noise and low-frequency signal features.

Detection and segmentation of Cardiac-relevant signals

Signals in the range of 0.5 Hz to 40 Hz,$(f_h = \{f | f \in \langle 0.5, 40 \rangle\})$, related to heart signals, are distinguished. Data belonging to the selected SCG signal components relative to these frequencies are extracted as$\check{S}_h(t)$.

$$\check{S}_h(t) = \sum_{(f \in f_h)} \check{S}_f(t) \quad (4)$$

Time frequency masking(TFM) and MNF

The temporal noise is then removed by applying a time-frequency mask $\pitchfork(t, k)$ to the SCG signal $\check{S}(t)$to obtain the time-frequency masked signal, $\check{S}_{tf}(t)$ which is expressed as in Eq. ($\pitchfork$ 5).

$$\check{S}_{tf}(t) = \sum_k \pitchfork(t, k) \cdot \check{S}(t) \quad (5)$$

Figure 2 illustrates a sample demonstration of TFM process for precise understanding. Later,$\pitchfork(t, k)$ signal is decomposed to obtain the coefficient matrix (C_m) and the basis matrix (B_m) such that non-negativity is ensured and spatial correlation is preserved using NMF, which can be depicted as,

$$\check{S}_{tf}(t) \approx (B_m, C_m) \quad (6)$$

The SCG signal is then factorized using NMF into two matrices: the C_m and B_m matrix. Fig. 3 shows the detailed representation of the artefact reduction method based on NMF incorporated into the ABF framework for SCG signal processing. The process starts with the input of SCG signals that include both motion artefacts and heart signals (I_{hm}), with acceleration data (I_a) that reflects the subject's movement that caused these artefacts. At the same time, a random matrix (H_0) is created, and together with the accelerometer data, it is decomposed once more using NMF to obtain the new basis and coefficient matrices. Then, the basis matrix from the SCG signal and the first part of the coefficient matrix from the combination data are utilized to construct the enhanced SCG signal. Lastly, the reconstructed signal and the accelerometer data are passed through an inverse continuous wavelet transform to get the final filtered SCG signal with less noise and artefacts for proper cardiac monitoring.

Adaptive bidirectional filtering

The ABF technique integrates both the filtered SCG signals that are obtained previously and the signals from the accelerometer to give the improved SCG signals. The core processes are interpreted as follows: measured initial signal, signal processing method in adaptive filtering, and the filtered signal obtained.

$$\check{S}_{ABF}(t) = \check{S}_{tf}(t) - \text{Å} \sum_{k=1}^{K} \left[F_C^{\check{S}} \check{S}_{ABF}(t-k) + F_C^{a} V(t-k)\right] \quad (7)$$

Equation (7) exhibits the vital computations of ABF approach for SCG signal process. This shows the SCG signal after applying the proposed method on time is called the Adaptive Bidirectional Filtering. As will be shown in more detail later on, the aim of this filter is to improve the SCG signal quality by suppressing movement related noises and random noise. The time-frequency masking $\check{S}_{tf}(t)$ is employed in the elimination of temporal noise as a preparation for the use of adaptive filtering on the SCG signal.The parameter of adaptation (Å) is a constant that determines the impact of the past filtered signal and data of the accelerometer in the adaptive filter. It basically determines the degree of influence given to preceding values which is used in the recursive filtering. The filter coefficients$\left(F_C^{\check{S}}\right)$control the degree of influence that past sample value of the SCG signal has to the present sample value of the signal. These are decided during the design of the filter with the intention of enhancing the

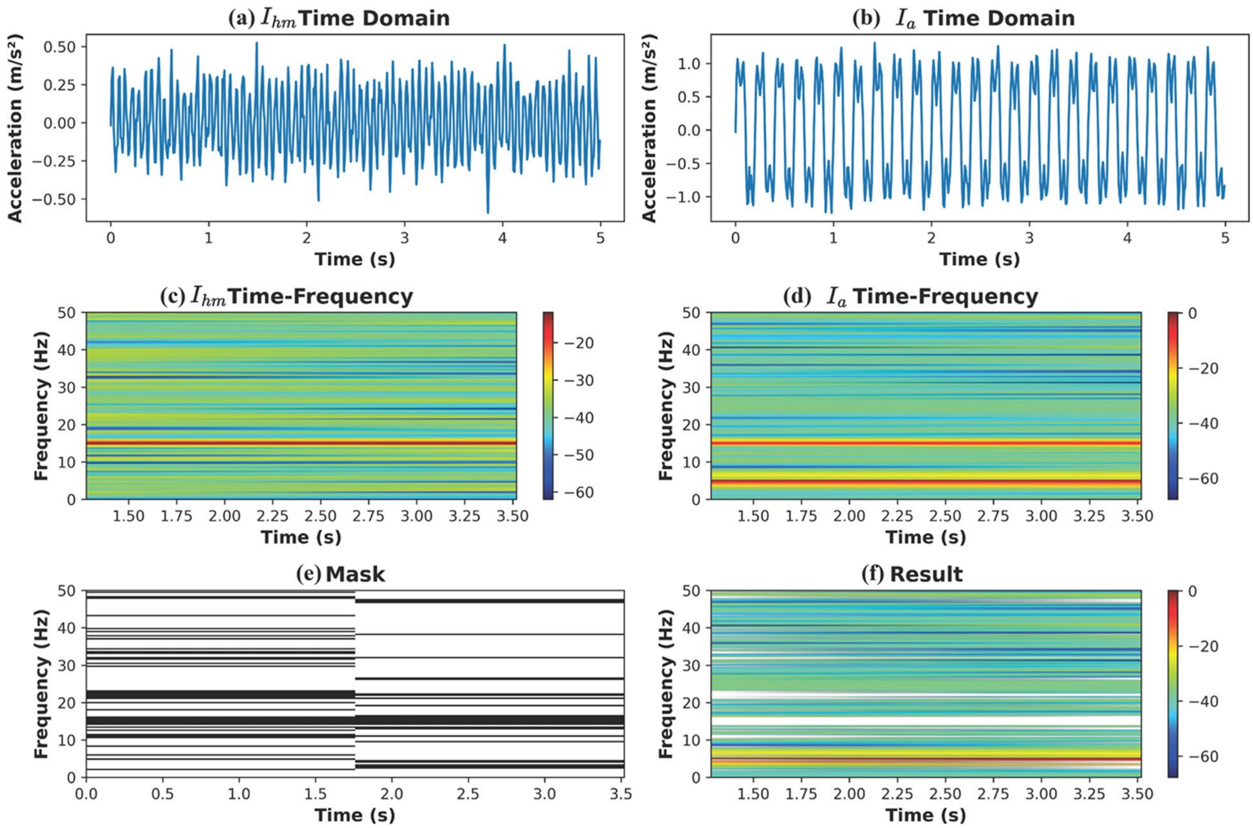

Fig. 2 Illustration of TFM that includes (**a**) Accelerometer Time Domain, (**b**) SCG Time Domain, (**c**) Accelerometer Time-Frequency, (**d**) SCG Time-Frequency, (**e**) Time-Frequency Mask, (**f**) Resulting SCG Signal

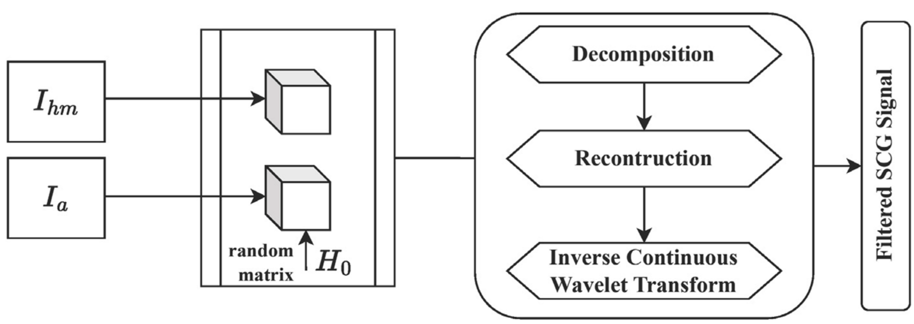

Fig. 3 Artefact reduction Process via NMF

exclusion of motion artefacts. The obtained filter values of the past signals$\left(\check{S}_{ABF}(t-k)\right)$ are placed recursively which enhances the filter to segregate the actual heart signals and artefacts. The filter coefficients $\left(F_C^a V\right)$determine the amount of past accelerometer value that are used to calculate the current filtered SCG signal that is used in the identification and elimination of the motion artefacts.

To filter the signals and distinguish between the cardiac signals and noise originating from the movement of the subject, the data from the vertical axis accelerometer $(V(t-k))$ at different times is used. Thus, this adaptive approach guarantees that the SCG signal is updated at every point in time with regard to the signal history as well as the motion context. Thus, it is very effective for real-time signal processing where the major hindrance is normally the motion artefacts. Table 2 represents the core procedure of ABF in an algorithmic way.

- The filter coefficients are also selected during implementation and can be commenced with small prede-

Table 2 ABF Algorithm for SCG Signal Processing

Input: $\check{S}_{tf}(t)\check{S}_{ABF}(t-k), V(t-k), K, F_C^{\check{S}}, F_c^{a}V, \mathring{A}$ Output: Enhanced $\check{S}_{ABF}(t)$
*Begin*1.Initialize $\check{S}_{ABF}(t)$ // Initial Setup and Input Collection//setting the Filter Coefficients (for SCG Signal and Accelerometer Data)2. Computation of time-frequency masked SCG signal $\check{S}_{ABF}(t) \leftarrow \check{S}_{tf}(t)$ 3. Apply Adaptive Filtering //determining the Adaptation Parameterfor each time step *t* do*Recursive Contribution*:3.1 The influence of past filtered SCG signals is incorporated $\check{S}_{ABF}(t) = \check{S}_{tf}(t) - \mathring{A}\sum_{k=1}^{K}\left[F_C^{\check{S}}\check{S}_{ABF}(t-k)\right]$ *Motion Artifact Reduction*:3.2 Inclusion of contribution of vertical axis accelerometer data $\check{S}_{ABF}(t) = \check{S}_{tf}(t) + \sum_{k=1}^{K}\left[F_C^{a}V(t-k)\right]$ 4. Resultant Filtered SignalEnhanced $\check{S}_{ABF}(t)$ *End*

termined coefficients (with reference to the previous values of existing research) to prevent over-correction.

- Optimization is done using popular techniques that aim to maximize the signal-to-noise ratio or minimize errors. Another practical feature of real-time systems is their ability to update the coefficients with the help of the ABF techniques in accordance with the new data, which arrive in real-time applications, providing constant improvement of the SCG signal processing.
- Besides, there is an adaptation parameter provided to fine-tune the noise-removal effectiveness and the speed of reaction to the input signal's changes in comparison with other parameters (larger filter coefficients, smaller filter coefficients, slower adaptation (larger λ) and faster adaptation (smaller λ)) which can cause excessive correction or delayed filtration.

This adaptive approach guarantees that the SCG signal is updated at every point in time with regard to the signal history as well as the motion context. Thus, it is very effective for real-time signal processing where the major hindrance is normally the motion artefacts.

Experimental specifications

To implement the proposed ABF concept in the context of cardiac health monitoring and evaluate it empirically, the following software is required: an operating system (Ubuntu 20.04). Python 3.8 is used for base programming. The following are the requirements for the libraries and frameworks: for development tools, Anaconda 2020.07 is used for Python environment management. The hardware requirement is a modern computer with an advanced processor (Intel Core i7), 8 GB of RAM and an SSD with 256 GB of free storage space for optimal data management. Also, a GPU (NVIDIA GTX 1060) is used to improve the computational speed, especially in spatial correlation and other reductions, for the improvement of the ABF technique for real-time signal processing and noise reduction.

Table 3 represents the all the significant empirical parameters of ABF. The value of hyperparameters in the ABF approach is optimized with a solid rationale given to the empirical data analysis and signal processing

Table 3 Vital empirical Parametric specification of ABF

Hyperparameter	Optimal Value
Å	0.8
K	5
$F_C^{\check{S}}$	[0.2, 0.15, 0.1, 0.05, 0.05]
$F_C^{a}V$	[0.3, 0.25, 0.2, 0.15, 0.1]
$H_j(k)$	[-0.1294, 0.2241, 0.8365, -0.4829]
$L_j(k)$	[0.4829, 0.8365, 0.2241, -0.1294]
Frequency Range (Hz)	0.5–40 Hz
Sampling Rate (Hz)	256 Hz

principles. The adaptation parameter (Å= 0.8) guarantees the necessary determinative impact of the prior SCG signals, eliminating noise and other unwanted phenomena while not overemphasizing the given signal. The filter order (K = 5) is chosen as it should be long enough to give enough past data for filtering and not be too long, which takes a lot of computational resources. The filter coefficients $F_C^{\check{S}}$and $F_C^{a}V$ are adjusted so that the relative contribution of the previous SCG signals and accelerometer data is properly scaled, minimizing the artefacts. The high-pass and low-pass filter coefficients are selected in such a way that positive signal characteristics are retained while negative characteristics such as noises and motion artefacts are minimized. The filter from the RMWD filter bank like $H_j(k) = [-0.1294, 0.2241, 0.8365, -0.4829]$ and $L_J(k) = [0.4829, 0.8365, 0.2241, -0.1294]$ was chosen because the high-pass and low-pass coefficients were unique in analyzing detailed and approximated signals at multiple scales. These optimal values are obtained from RMWD filters, which are normally used to analyze signals into various frequency bands. Ranging from 5 Hz to 40 Hz, the frequencies of the signal encompass the inherent heart signal frequencies, and a sampling rate of 256 Hz will provide high-resolution data that can be processed quantitatively in great detail.

The performance of the proposed ABF technique is compared with state-of-art techniques like EMD,

Table 4 NER outcome of various methodologies

Method	Noise Reduction Efficiency (%)
EMD	85
DTFM	88
NCC	80
MC-VAE	92
ABF	97

DTFM, NCC and MC-VAE along with the traditional ABF method in order to monitor cardiac health. For the purpose of enhancing the credibility of the RMWD used in the presented approach, the RMWD performance is compared with other decomposition methods such as EMD, MODWT, and SVMD. Thus, the presented framework for the evaluation of the ABF and RMWD techniques allows for a comprehensive assessment of the techniques and proves that they provide superior performance in improving the SCG signal quality and reliability for non-invasive cardiac monitoring applications.

Performance evaluation and discussion

Table 4 reveals the Noise Reduction Efficiency (NRE in %) for different techniques of motion-artifact reduction where the ABF method turned out to be highly effective. As for EMD, the resultant NRE is about 85%, which also proves that this method has a rather satisfactory capacity for noise elimination in SCG signals. DTFM does this better, though, with an NRE of 88%, demonstrating the noise that DTFM is better capable of handling. However, as the percentage shows, NCC has slightly lower efficiency, 80%, which indicates its inability to process motion artefacts. The MC-VAE performs pretty well in making decisions with an NRE of 92% because of the enhanced machine learning features for the segregation of signal and noise. Of all the investigated methods, the ABF technique performs best with an NRE of 97%, which implies that it is highly efficient in isolating SCG signals from motion-related noise. This high efficiency is attributed to ABF's integration of the RMWD and adaptive filtering since both components are responsible for the proper identification and eradication of noise elements. The empirical data further corroborates the fact that using ABF is superior to other methods, which gives credence to the proposition that it is optimal for promoting the improvement of the quality and reliability of cardiac health monitoring facilitated via a real-time dataset.

The superiority of the ABF method in terms of noise reduction efficiency can be explained by numerous factors and changes in the design and operating principles. RMWD breaks down the SCG signal into different levels and enables one to filter out signals related to the heart from the noise in different frequency ranges. This multi-scale approach helps to considerably eliminate not only high-frequency noise but also motion artefacts of low frequency. In contrast to the other forms of wavelet transforms, the RMWD retains redundancy in the signal, which assists in preserving the signal's characteristics while enhancing the removal of noise. The ABF method analyses the signal in a forward and backward manner, which helps to improve resolving power. This bidirectional approach aids in reducing phase distortions and makes sure that the filtering is bilateral, thus improving the efficiency of noise elimination. In bidirectional filtering, the structure of the filtering operation is recursive in order to fulfil the adaptive nature due to the change in the characteristics of motion artefacts. The filter also successfully modifies based on the vertical axis accelerometer data to properly distinguish between the actual SCG signals and motion-generated noise. Preprocessing of the SCG signal involves time-frequency masking; this is aimed at removing the temporal noise in the SCG signal. This kind of masking is useful in eliminating the noise that happens at certain times while not destroying the shape of the signal.

Figure 4 illustrates the r-squared values for various motion-artifact reduction techniques, including EMD, DTFM, NCC, MC-VAE, and ABF, across different SNR levels from 0 to -25 dB. At 0 dB SNR, the ABF method achieves the highest r-squared value of 0.95, indicating its superior initial accuracy in heart rate estimation compared to other methods. As the SNR decreases to -5 dB, ABF maintains a strong performance with an r-squared value of 0.9, outperforming DTFM, NCC, and MC-VAE, which show values of 0.621, 0.8, and 0.8, respectively. At -10 dB SNR, ABF continues to demonstrate robust noise reduction capabilities with an r-squared value of 0.75, which is prominently higher than the other approaches. This trend persists at lower SNR levels, with ABF maintaining higher r-squared values at -15 dB, -20 dB, and −25 dB, where it achieves 0.67, 0.6, and 0.57, respectively. These results clearly indicate that ABF's integration of RMWD and adaptive filtering techniques effectively isolates and mitigates motion artefacts, ensuring accurate SCG signal processing even in highly noisy environments. In contrast, the other methods show a more pronounced decline in performance as noise levels increase, underscoring ABF's superior noise reduction efficiency and resilience in challenging conditions.

NMF ensures that the spatial characteristics of the signal SCG remain invariant while minimizing noise. Since it breaks the signal into non-negative matrices, the separation of signal components with respect to their spatial

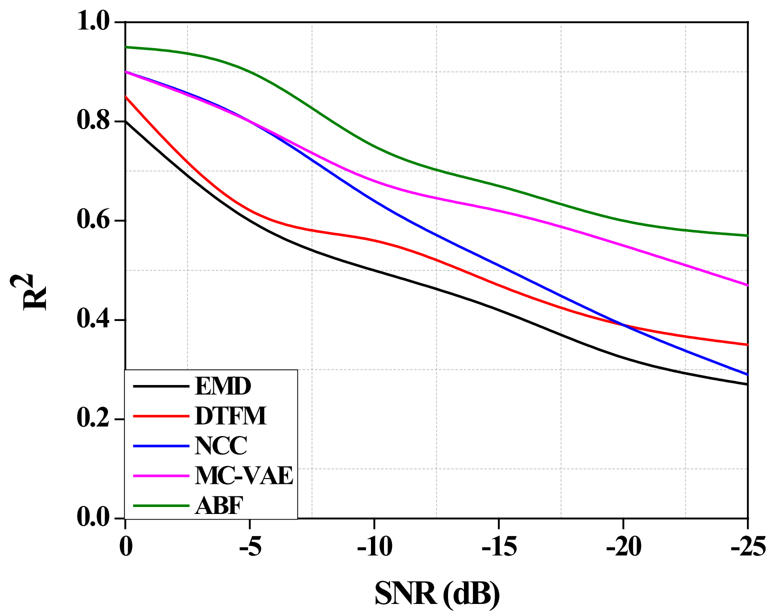

Fig. 4 Comparison of R-squared values of different motion-artefact reduction techniques of different SNR bands

Table 5 Computation timing of various methods in the process of motion- artefact reduction process

Method	Computational Time (s)
EMD	5.2
DTFM	7.8
NCC	4.1
MC-VAE	12.5
ABF	8.3

dependencies is easier with the help of NMF. The use of NMF, along with accelerometer information, simplifies the removal of major types of dorsoventral motion that, in most cases, can be considered as sources of artefacts in SCG signals. The ABF method's parameters, such as the filter coefficients and adaptation parameters are selected to attain maximum noise reduction. Such fine-tuning helps to ensure that the specifics of the SCG signals are optimally processed in the framework of the method.

Table 5 represents the computational times of the motion-artifact reduction methods such as EMD, DTFM, NCC, MC-VAE, and ABF are as follows, which are proportional to the algorithmic complexity of the methods and their processing capability. EMD, with a computational time of 5.2 s, employs an iterative sifting process that, while effective, is moderately time-consuming. DTFM, taking 7.8 s, involves extensive calculations in the time-frequency domain, which contributes to its higher computational demand. NCC, the fastest among the methods with a time of 4.1 s, relies on simpler cross-correlation computations, making it more efficient but less robust against complex noise.MC-VAE, with the longest computational time of 12.5 s, utilizes advanced deep learning models and extensive training processes, providing high accuracy at the cost of increased computational resources. ABF, at 8.3 s, balances complexity and efficiency by integrating RMWD and adaptive bidirectional filtering. This approach improves noise reduction without substantially increasing the computational complexity, which indicates that ABF provides better artefact suppression without inordinate processing time; therefore, it can be implemented as a viable solution for real-time SCG signal processing in cardiac health monitoring.

RMWD and adaptive bidirectional filtering minimize the trade-offs of noise reduction efficiency and computational time in the ABF method. Compared with other methods, such as NCC, ABF has far better noise reduction capabilities, but it still consumes less time than deep learning models like MC-VAE. ABF has a computational time of 8.3 s, indicating a practical level of real-time SCG signal processing by providing a moderate artefact suppression with relatively low complexity (exhibits enough artefact suppression and moderate complexity to establish the real-time possibility of the SCG signal processing in real-life). However, to achieve an even greater noise reduction, the filter complex may have to be raised, which might pose a problem in terms of computational time and thus restrict the real-time capacity of the application.

Figure 5 visually compares the performance of four signal decomposition methods: EMD, MODWT, SVMD, and

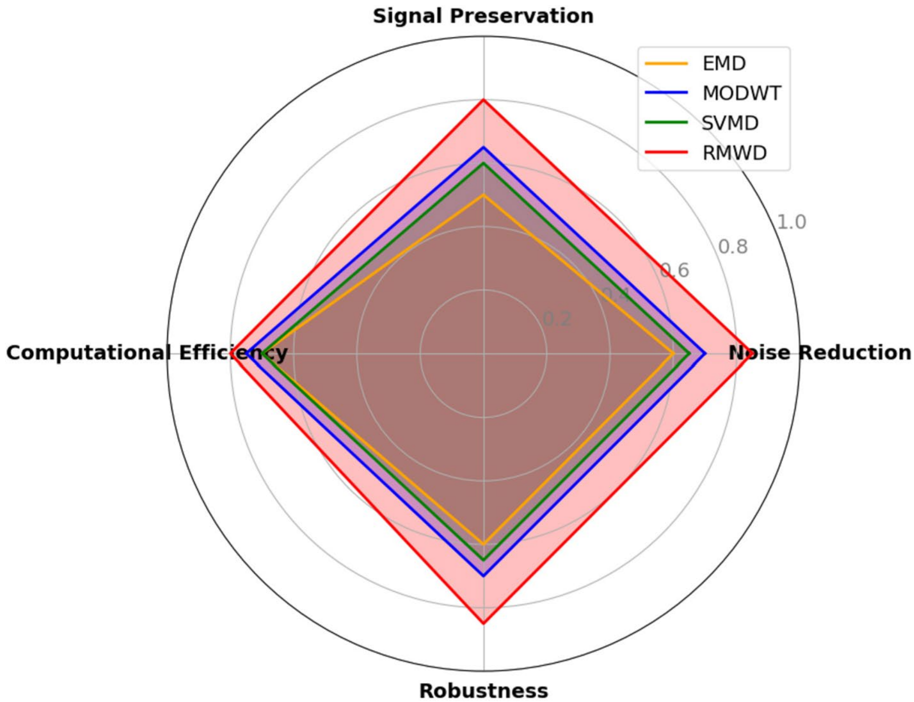

Fig. 5 Performance analysis of various methods during decomposition process

RMWD—across four critical metrics: reducing the noise level, preserving the signal, computational complexity, and the signal's ability to be accurate in different environments. Each axis represents one of these metrics, with values ranging from 0.0 (centre) to 1.0 (outer edge). Analyzing the results presented from the resultant, it can be realized that RMWD (in red) is higher than the other methods in all the categories and consistently preserves higher values in all of them with a special emphasis on Noise Reduction and Signal Preservation. This means that RMWD is well dedicated to the best decomposition efficiency by protecting the SCG signals and simultaneously minimizing noises while enriching computational capacity and stability.

MODWT (blue) and SVMD (green) have moderate results in all the evaluations, and EMD (orange) has relatively lower efficiency, particularly in noise reduction and signal preservation. It is obvious from this outcome that RMWD, in its actuality, was effective and far superior to the other methods in dealing with the SCG signal decomposition for health monitoring of the heart.

Figure 6 exhibits the SNR values (1000 samples) provided by the dataset (before) that are compared for the evaluation of ABF filtering performance, which is expressed in dB. The SNR before filtering reflects the initial quality of the SCG signal, often degraded by motion artefacts. The SNR, after filtering, indicates the effectiveness of the methodologies in enhancing signal quality by reducing noise.

The current ABF method also has constraints in terms of patient profiles and motion environments as the filter coefficients are fixed. The method may not perform sufficiently stably and effectively at varying or unpredictable motion conditions, for instance, in the case of increasing velocities. Moreover, minor latency and computational load may occur due to the fixed filter coefficients, especially when adapting to dynamic or unpredictable motion environments. Possible solutions to these challenges in future research can include the use of ML filter coefficients to adapt dynamically to patient data and motion contexts. Moreover, incorporating DL models for feature extraction and signal classification in SCG signals could enhance the capability of anomaly detection in the proposed system and enhance the stability of the cardiac monitoring system.

Conclusion and future work

From the findings, the suggested ABF technique that incorporates RMWD demonstrates significantly high effectiveness in improving the quality of the SCG signal due to a diminished amount of motion artefacts. Comparisons with real estate data reveal that ABF offers a greater amount of superior noise reduction than methods like EMD, DTFM, NCC and the MC-VAE, superior r-squared score across numerous signal-to-noise ratios, and consistently positive outcomes even in suboptimal conditions. Owing to the usage of bidirectional filtering,

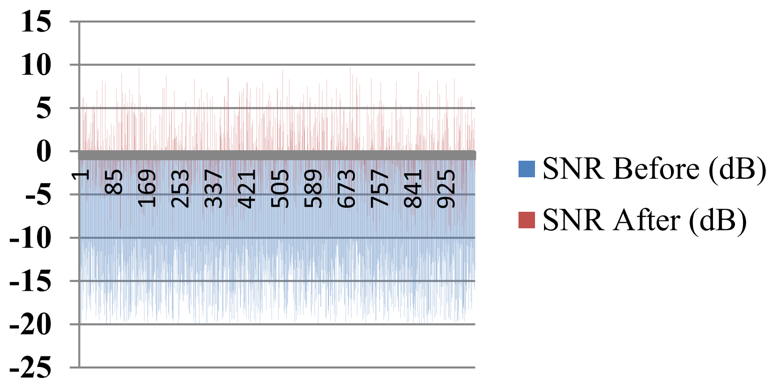

Fig. 6 SNR Evaluation before and after the performance of ABF

time-frequency masking, and non-negative matrix decomposition, which are all used in ABF, accurate isolation and rejection of noise over the signal of interest have the advantage over other methods in computational complexity. It decreases and reschedules the motion artefact and is based on the vertical axis accelerometer data using the recursive structure, which is inherent in the method used. This advanced approach results in significant improvements in SNR, as illustrated by the substantial elevation of SNR values before and after filtering. On average, the application of the ABF technique is seen to be a very efficient and reliable method to non-invasively diagnose heart diseases using wearable sensors owing to its better decomposition effect as well as its ability to eliminate motor noise proficiently. For this reason, this technique is regarded as a major advancement in the field of cardiac diagnosis, offering the prospect of increased accuracy and reliability of SCG signals with reduced motion artefacts in real-life clinical applications.

The potential future study on the ABF technique is the incorporation of machine learning algorithms for optimizing the filter coefficients as per the patient profile and different motion environments, which will enhance the cardiac surveillance of the patient. Furthermore, the development of models such as deep learning models for automatic extraction of features and classification of the SCG signals improves the anomalies' detection.

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Authors' contributions
G.N took care of the review of literature and methodology. C.R.B has done the formal analysis, data collection and investigation. M.T.R has done the initial drafting and statistical analysis. T.E.Y has supervised the overall project. All the authors of the article have read and approved the final article.

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Availability of data and materials
The datasets used for the findings are publicly available at https://ieee-dataport.org/documents/seismocardiography-scg-signal-processing-dataset.

Declarations

Ethics approval and consent to participate
Not Applicable as the research is done on the publicly available dataset.

Consent for publication
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Competing interests
The authors declare no competing interests.

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