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Assessing the Effectiveness of Various Filtering Techniques on Seismocardiography Signals in Individuals with Valvular Heart Disease

Mahsa Raeiati Banadkooki[1], Martin Bogdan[1]
[1]Department of Neuromorphic Information Processing, Leipzig University
Augustusplatz 10, 04109 Leipzig
raeiati@informatik.uni-leipzig.de
bogdan@informatik.uni-leipzig.de

Abstract **-** Many factors, such as excessive noise and artifacts, contribute to the low-quality standards commonly encountered while interpreting Seismocardiography (SCG) signals. In this work, different types of digital filters are used to process SCG signals, and their performance is assessed in the study. Among the filters investigated were the multistage filters: the Butterworth filter (BF), Chebyshev filter (Cheby), wavelet transform (WT), Principal Component Analysis (PCA), Independent Component Analysis (ICA), Empirical Mode Decomposition (EMD), Variable Mode Decomposition (VMD), and Continuous Wavelet Transform (CWT) methods were also analysed. Performance evaluation was based on performance metrics such as Signal-to-noise Ratio (SNR), Peak Signal-to-Noise Ratio (PSNR), Peak Relative Difference (PRD), Structural Similarity Index (SSIM), and mean square error (MSE). The experimental results highlight the advantages and limitations of each filter technique. A thorough assessment of these techniques in SCG signal processing is provided. The study highlights which filters can be used effectively to obtain significant information from the SCG signals which will contribute and assist the future studies and applications.

***Keywords*:** Seismocardiography- Filtering – Artifacts- Valvular Heart Disease

1. Introduction

Seismocardiography (SCG) signal is a non-invasive method to investigate the mechanics of cardiac activity. SCG studies often encounter signal distortions due to noise and artifacts which hinder essential diagnostic information. Such sources of noise may include but are not limited to muscle contraction, respiration, and exterior electrical signals. Such disturbances complicate the process of retrieving useful information in the form of SCG signals; thus, we need the appropriate signal processing techniques.

By extension, the fundamental principle of filtering is based on the need to improve the signal-to-noise ratio and as a result, enhance the quality of the signal and its interpretation. Typically, Butterworth filter (BF), wavelet transform (WT) are common techniques for signal denoising due to their reliability and straightforwardness. Other approaches, such as Principal Component Analysis (PCA), Independent Component Analysis (ICA), Empirical Mode Decomposition (EMD), Variable Mode Decomposition (VMD), Deep neural networks (DNN), and Adaptive filtering (AF) [1-7] provide more sophisticated ways of signal denoising and enhancing detection of critical features. The choice of the filter is contingent on the attributes of the signal being analyzed. There is every opportunity to effectively increase the clarity of the signal, which makes it possible to detect those important features that are helpful in diagnosing and treating diseases or disorders of the heart. If no suitable filtering is applied, noise and artifacts lead more probable to avoidable errors and misleading conclusions.

2. Literature Review

There are many types of filters which could be employed in eliminating noise and interference associated with the heart signal. Noisy signals can be expected to produce misleading results or incorrect diagnoses when interpreting heart conditions. For instance, muscle noise can create artifact spikes in the muscle activity which look like heart events which are abnormal. In the same way, fluctuations in a framework wave signal can be caused by electromagnetic emissions that interfere with the desired portions of the waveform. Hence, filtering is important in the analysis and interpretation of biomedical signals because it removes noise and other artifacts and thereby increases analysis accuracy.

While discussing the noise challenge in bio-signals and the focus on denoising as a necessary condition in diagnosis, the authors employed wavelet transformation to eliminate noise in the ECG and EEG signals [8]. The work set out to compare two algorithms for denoising and found the wavelet approach of signal reconstruction to be superior to the wavelet approach of noise reconstruction. The evaluation covered a range of mother wavelets and initialized filters and noted that the Symlet-9 wavelet produced the best results. It also noted that for the ECG signal the Chebyshev Type I filter outperformed the Type II filter although for the EEG signals, both showed distinctive parameters.

The other research aimed at reducing the motion noise, the authors used a dual accelerometer sensor configuration to test different positions of the sensors during minor movements and walking of the patients [9]. It was concluded that the double attachment of accelerometers is a more appropriate technique than the single sensor method predominantly applied especially in the signal-to-noise ratio improvement attributes. The study concluded that the best results for detection of SCG waveforms were obtained when the sensors were mounted horizontally. However, it was also found that the motion artifact due to walking could be reduced but not removed and that the effectiveness of the techniques for noise removal depends on the location of the sensor and the frequency of the motion noise.

An adaptive recursive least squares filter (ARLSF) was proposed [10] to remove motion artifacts from SCG signals. This was accomplished on 16 subjects who performed standing and walking on a treadmill, both SCG and magnetic scans were received. It has been proven that the filter was able to extract the heartbeat and motion artifact signals and the data obtained post-filtering served as the reference channel for the ARLSF algorithm. The method was able to detect heart signals with an accuracy of 98% including heart rate estimation while standing as well as walking.

As a different method for noise reduction of SCG signal and artifacts, a two-stage Kalman filtering (KF) model was used [11]. The methodology consisted of KF1 in minimizing the noise from the signals and estimating chest wall displacement and chest wall velocity during the different cardiac phases. Subsequently, KF2 removed low-frequency artifacts from the output of KF1. The proposed method achieved an average normalized cross-correlation of 94% for signals with a 15 dB input SNR and demonstrated superior performance compared to existing methods in terms of noise suppression while preserving diagnostic features.

In addressing motion artifacts located in the SCG signal, a process in which the SCG signal acquired from 40 people while in motion was analysed using normalized least mean square adaptive filtering has been reported [12]. Interestingly, the recognition rate for the use of this technology was 98%. Application of this technology eliminated external disturbances tracing their 32 kernel properties that proved to be the best for 32 kernel properties to a window for continuous monitoring.

The goal of this paper is to augment the robustness of the SCG signals processing through the utilization of different filtering approaches that help in the VHD recognition process. Different filtering methods have been used in the literature to remove noise from biomedical signals such as BF, Chebyshev filter (Cheby), WT, PCA, ICA, EMD, and VMD. But even with that, there are still challenges to use them for SCG signals. These obstacles greatly impede the accuracy and the reliability of our data analysis. We also wish to employ the CWT to denoise SCG signals. Such an advantage of this method lies in its ability to perform signal analysis across a range of scales therefore improving its overall resolution with appropriate filtering of the noise from the relevant signal. With this unique approach, the specific focus resides in high frequency components, which are often the most annoying noise for any SCG study. The objective of the study was to enhance the diagnostic quality of SCG signals by reducing noise in the signals and artifacts and thus contribute to the discipline. This study is also an attempt to explore the new frontiers of existing denoising techniques while reinforcing the importance of filtering during the processing of any biomedical signals.

3. Materials and Methods

The data obtained from different patients with Cardio-Mechanical relevant work published by [13] has been included in this research. It includes a dataset of 100 people suffering malfunctions of valves of the heart. They were recorded in China and United States. The information concerning data CP-01 to 70, UP-01 to 21 was obtained at the sampling rate of 256Hz and those of UP-22 to UP-30 were sampled at 512 Hz. The use of filtering methods in signal processing draws much attention and is practically necessary to improve the quality of physiological data. Noteworthy, such filters were used in study to clean the SCG signal. In the first place, the low frequencies were dealt with using a 1 Hz cutoff high-pass Butterworth filter which was applied to reduce baseline drift. For further signal processing, this signal is viewed as a reference signal. The pre-processing step comprehensively aids in the identification of useful and meaningful details from the SCG signal.

The Butterworth bandpass filter is widely used in the preprocessing of SCG, among others, to filter out noise and unwanted frequency components. The cut-off values for SCG of 0.5 Hz to 100 Hz were selected after preliminary analyses because they cut across the significant frequency bands recorded in SCG and still optimize computational resources. Furthermore, frequency modification can be done using the Butterworth high-pass filter. As the order increases so does the attenuation and the steepness of the transition band width. Thus, order of the filter should depend on specific order as well as the complexity of the system. In this manner, by adjusting these parameters for noise removal, the analysis of the SCG signal is made extremely credible since premise drift as well as noise have been effectively removed by the Butterworth filter. The order of the filter in this study was 2.

In this study the bandpass Chebyshev filter was used for the purpose of preprocessing SCG signals, considering that such filter can eliminate unwanted frequencies and noise. There are unwanted frequencies in SCG signals, and the principal task of the filter is to eliminate the frequencies outside the passes which can be defined. These defined cuts are also set during the analyses of preliminary results and were designed to lie between 0.5 Hz and 100 Hz. In this study, we have selected for the quadratic Chebyshev filter which has the benefits of moderate roll-off and minimal phase distortion. This type of filter is expected to provide stability and robustness in filtering SCG signals to allow for the relationships to be maintained and hence enable analysis that does not run the risk of being overfitted with noises. Second-order filters are also easy to implement and computationally inexpensive which makes them suitable for real-time applications whilst assuaging chances of performances against the SCG signal.

Wavelet de-noising is one of the techniques which can help in cleaning biomedical signals [14]. This is achieved through a method known as wavelet transform which expands the signal into its various frequency components. Wavelet coefficients that exceed the noise components are set to a threshold. Wavelet denoising can be useful for removing noise and artifacts from SCG signals in patients with VHD. However, it does require the right family of wavelets and thresholding parameters for best denoising. Artifacts can be defined as strong influences on the wavelet coefficients such as high frequency noise or abrupt peaks in amplitude range. Since the wavelet coefficients are sensitive to the movement of these artifacts, the artifacts may be extracted from the SCG signal. The SCG signal is recorded in 3 (X-Y-Z) directions, while the Z axes is treated as the raw SCG signal. For the purposes of reaching the filtering threshold, the SNR is computed for a threshold varying from 0.01 to 1.0 whilst aiming to determine the appropriate filtering threshold. The threshold that gives the greatest SNR is the preferred threshold as it, in essence, gives the best denoising. Generally, the threshold that resulted in the highest SNR is defined as the 'Optimal Threshold'. In this case the selection of the optimal threshold for denoising is based on this data driven algorithm which eases noise removal in SCG signals. The signal is decomposed with the help of Sym6 wavelet up to six levels. This wavelet has a greater likeness to the SCG signal. Coefficients result from the decomposition which represent different frequency components within the signal at different scales. Next, a threshold value is fixed against each of the coefficients, except for the first which refers to the approximating of the coefficients. The remaining coefficients were used to reconstruct the signal at last after denoising.

According to [3], ICA is an effective approach for noise reduction as it enables a clear distinction between the signal and noise parts. It decomposes the signal into its major building blocks and discloses the signal's configuration. SCG signal usually contains a mixture of signals which include the mechanicals of heart muscles contraction and other noise sources and disturbances such as motion artifacts from due breathing and other body movement. Now, as we stated before, we have the SCG signal in three different directions which would be x, y and z. In practice, it is stated that when ICA is applied on single sensor data (recorded in 3D), the x, y and z data is treated as 3 different channels. Though it is still a single sensor, each axis viewpoints of the relevance signal trace a close representation of the signal. This can be compared to administering multiple sensors, each of which looks from a completely different view of the picture to explain the scenario. When employing ICA in examining baseline SCG signal with different axes x, y and z, it enabled in identifying the major components which are responsible for a direct correlation to the changes in the SCG signals. Finally, noise and artifact components may eventually be suppressed, however, only those components which represent the heart mechanical activity are left. We investigated the applicability of kurtosis when selecting the denoised signals derived from Independent Component Analysis of SCG signals. The Kurtosis is defined as a measure of the 'tailedness' of a probability distribution and is usually correlated with the

Gaussianity of the signal. Based on the value of kurtosis, the signal can be classified into three categories: (a) sub-Gaussian ($K < 3$; when the signal is not too spiky), (b) super-Gaussian ($K > 3$; where the signal is more spiky than a Gaussian), (c) Gaussian ($K = 3$; which describes the situation where the signal is biased by a noise) [15]. The measurement of the components with kurtosis values close to $K=3$ is interpreted as noise.

This criterion applies in such a way as to not only improve the signal-to-noise ratio but also inhibit the loss of useful physiological information. The implications of the success of this particular methodology demonstrate context as well as the ability of the denoising algorithm to exploit non-Gaussian elements and support the enhancement of the whole SCG signal.

PCA is a very efficient decomposing process which disambiguates a multivariate signal into distinct non Gaussian signals [16]. It was used to decompose the SCG signal into principal components, enhancing the extraction of relevant cardiac features. Components were evaluated using kurtosis, with higher values indicating more diagnostically significant signals

EMD technique is a method employed in signal processing for filtering signal. It entails decomposing the signal into the intrinsic mode functions which stand for individual oscillatory modes within the signal [17]. EMD decomposes the SCG signal into its Intrinsic Mode Function (IMFs) which denote different aspects of the signal. To pick out the most informative IMFs, we computed the entropy for each of the IMFs, indicating their degree of information as content and demand of its execution. The threshold entropy was usually the mean of all IMF entropies which is recommended. Entropy is a scalar measure and IMFs with values exceeding this threshold scalar were chosen to reconstruct the filtered output signal. This means that because of the provision of the threshold, scarcity of meaning imf's was made minimizes and only those imfs which were of meaning retained in the SCG signal succeeded. By concentrating attention on IMFs with higher entropy, it aims at preserving the SCG signal components associated with more meaning information overload on the signal and improving the filtration quality of the SCG signal in readiness for further analysis and diagnostic. Given this, the most useful IMFs will be those selected based on their content information due to the flexibility offered by the use of this approach in EMD troubles SCG signal processing.

VMD is a signal processing method employed to separate a broader signal into its constituent components which are called modes that encompass different frequencies and oscillatory behaviour. Because VMD is informative and signal adaptive, it is suitable for the fixation of a complex and transient signal such as the SCG signal[18]. It defines some parameters like 'alpha', 'tau', and 'K', where 'alpha' is the bandwidth constraint, 'tau' is the noise tolerance level, and 'K' is the number of modes considered. The parameters of VMD for SCG signal processing were chosen with a preference against variation and included beta = 2, tau = 2, and K = 3. Since the VMD serves as a filtering tool, the VMD is able to suppress some modes out and only leaves important modes or filtered modes for further processing. The modes can be held as exceptional elements that explain the signal and thus phenomena that are related to physiological or mechanical processes. The algorithm zone induces each mode with some frequencies that are employed in examining particular frequencies of the SCG signal within its frame. After this step, the mode frequencies are established afterward, and the last frequency known as the inaudible frequency is the first to be stripped from the signal. The limitations of the VMD filter are affected to some extent by the parameters of VMD and also the modes chosen. It is important only to consider optimal parameters for the VMD filter after careful tuning of the filter parameters along with the validation of the select filter on a validation dataset. Through an intelligent and systematic iterative procedure, it is possible to select optimal parameters for the VMD filter that yield the desired performance with respect to the target dataset or problem.

To denoise SCG signals, CWT can be precisely described as a joint time-frequency signal analysis technique which is useful in effecting the analysis of various signals in both time and frequency scale simultaneously [19]. It allows for the comprehensive tracking of changes in the frequency components of a signal through time. The first step in this more effective way of SCG signal denoising by CWT is to identify the locations of the noise components that distort the quality of the signal. The ability to analyse signals in the frequency domain is one of the greatest benefits of the CWT. Once the frequency characteristics of the signal are analysed, it is possible to identify the noise components from the targeted signal components. To eliminate the noise components, appropriate coefficients associated with these components are specifically suppressed in CWT images. The method allows removal of the noise and ensures that the stripped CWT presentation is concentrated on the signal components of interest. Also suppressed are noise components that are outside the target frequency range band which is from 0.64 to 76.8 Hz to further strengthen the efficiency of the denoising.

For practical implementation, the method is applied to the entire signal in short durations to expedite calculations. Each cycle, approximately 10 seconds long, is subdivided for localized analysis. Due to the distributed nature of scaledependent analysis, each segment undergoes CWT independently for noise suppression, and the processed segments are then combined to reconstruct a noise-free SCG signal.

4. Results

In this paper, we assess various approaches to remove noise SCG signal. The methods used were Butterworth Filtering, Chebyshev Filtering, Wavelet Transform, PCA, ICA, EMD, VMD and Adaptive Frequency Filtering via CWT to clean the SCG signal and assess their results. Due to segmentation of the signal, the task of denoising is less complex computationally and reliably removes noise components. Using high-pass Butterworth filter with cut-off frequency of 1 Hz along with the rest of the denoising techniques dramatically improves SCG signal processing. This process of denoising makes it possible to extract some useful information from the SCG signal which elevates the quality and the reliability of the acquired trials for further analysis and interpretation. Some metrics to be used for comparison for evaluation of a denoised signal are the following: SNR, PSNR, PRD, SSIM and MSE.

SNR stands for Signal-to-Noise Ratio. It is a measure to quantify the ratio of the strength or power of a signal in regard to the noise level. In other words, SNR assesses the quality of a signal by comparing the level of the desired signal to the level of unwanted noise.

The formula for SNR is typically expressed in decibels (dB):

$$SNR\left(dB\right) = 10 * \ \log_{10} \mathit{(Signal\ Power/\ Noise\ Power)} \tag{1}$$

A higher SNR means that the signal can be more clearly differentiated from noise which implies it is of better quality.

The MSE calculates the average value of the squared distortion between the original and processed (filtered) signals. A lower MSE indicates that a level of improvement has been achieved in the quality of the processed signal. The following is the definition of MSE:

$$MSE = \left(\frac{1}{N}\right) * \sum_{i=1}^{N} (x_i - y_i)^2 \tag{2}$$

where x_i is the originally intended signal, y_i is the modified signal, and N is a quantification of the number of samples. A low MSE reveals capped measures of distortion in the signal after filtering done to cut noise but maintaining essential characteristics of the signal.

The PSNR is used as a measure of quality control for the signal. It does so by defining the highest possible strength of the signal and weighing it against the disruptive force that affects the representation of signal.

The formula for PSNR is:

$$PSNR = 10 * \ \log_{10} \left({MAX^2}/{MSE} \right) \tag{3}$$

In the equation, the abbreviation 'MAX' refers to the highest possible signal value that can be reached. For higher values of PSNR, better quality of the signal after filtration is comparatively achieved.

PRD defines the measure of the distortion differences regarding the factors of two signals. By considering the raw signal as the reference standard and utilizing the filtered signal as the processed one, PRD provides effective estimation results for the filtering technique. The PRD is given as follows:

$$PRD = {\sum_{i=1}^{N} |x_i - y_i|} \Big/ {\sum_{i=1}^{N} x_i} \tag{4}$$

SSIM is one of the most widely used measures of the signal quality in the field of the signal processing. SSIM quantifies how structurally similar the original (raw signal) and the reconstructed signal are.

Usually, the value of SSIM lies between -1 and 1, where 1 means that the two signals are exactly the same and higher values means better likeness. On the other hand, a high distortion between two signals which SSIM score indicates will lead to lower perceptual quality.

$$SSIM\ (x,y) = \frac{\left(2\mu_x\mu_y + C_1\right)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \tag{5}$$

In this equation, μ_x, μ_y are the mean values of signals, σ_x^2, σ_y^2 are the variance and σ_{xy} is the covariance.

Table 1 shows the overall assessment of the various methods of denoising carried out to all 70 of CP data and 30 of UP data SCG signals. ICA was outstanding and was the only method that rendered a perfect SSIM score of 1.00 indicating that it is able to maintain the structural similarity of the SCG signal with respect to its original even after denoising. ICA also performed well in terms of SNR measuring 23.21, a vital factor in signal analysis because it ensures that noise is well controlled. With respect to PSNR, ICA again comes as the best with the greatest value of 47.57 thus proving that it is accurate in noise reduction without sacrificing peak signal quality. The other methods of denoising namely ICA, BF, WT, VMD, and Adaptive Frequency Filtering through CWT methods also have low MSE of 0.00 showing that these methods in particular and in general are very good at diminishing noise.

On the other hand, PCA has the worst trade-off for MSE at 0.02 which indicates high errors in noise filtering but also high levels of distortion in the signal. As for ICA, it has the best performance with the worst value of 0.08 in PDR which means that the value has the least deviations of the peaks and confirms its ability to preserve the integrity of the signal. For comparison, PCA has the highest value of 1.01 of PDR which means that the signals that have been denoised have gone through a relatively higher degree of drift which has a negative effect on the overall quality of the signal and its effectiveness for further analysis. The Cheby filter however performs satisfactorily for the two parameters as it has SNR of 3.27 and SSIM of 0.82 which are moderate and depict that the method has reduced the noise to some degree while retaining a reasonable amount of the structure of the signal. The PDR value of 0.67 however indicates that it is higher which shows more peak deviations and indicates that there is a compromise on both the integrity of the signal and its noise. In conclusion, these findings are important in assisting in the selection of the appropriate SCG denoising methods. Based on the numerous criteria evaluated, ICA was found to be the best. However, we are keen to recommend that the choice of method should be left to the end user based on the requirements of the task at hand.

Table 1 : Comparison of Different Filtering Techniques

	SSIM	***SNR***	***PSNR***	***MSE***	***PDR***
BF	0.95	9.71	34.09	0.00	0.34
Cheby	0.82	3.27	27.69	0.02	0.67
ICA	1	23.21	47.57	0	0.08
PCA	0.69	1.32	24.51	0.02	1.01
WT	0.95	19.23	34.94	0.0	0.13
EMD	0.87	7.83	32.32	0.01	0.47
VMD	0.98	12.23	36.98	0.0	0.25
Adaptive Frequency Filtering via CWT	0.95	13.34	39.84	0.0	0.24

Besides the quantitative evaluations that were done, figure 1 also showed some images of these filtering techniques to provide the reader with a first impression of these techniques according to the degree in which they could protect signal features and reduce noise.

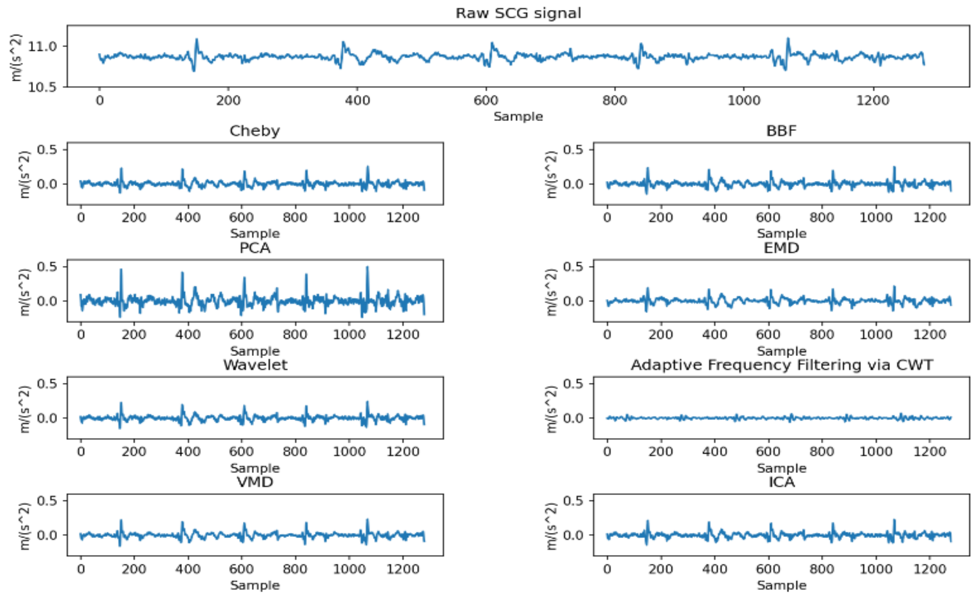

Figure 1: the visualizations for the eight different filtering methods to the raw signal. Each method exhibits distinct characteristics in terms of noise reduction and signal preservation

6. Conclusion

In summary, this research reviewed different digital filtering methods in SCG signal processing which were intending to improve the retrieval of useful information as well as noise and artifacts interference. Butterworth filter, Chebyshev filter, WT, PCA, ICA, EMD, VMD and CWT were included into the study for comparison. The performance evaluation was done using SNR, PSNR, PRD, SSIM, and MSE.

The results of the study emphasize the necessity of a systematic selection of the related denoising methods for SCG signals. Even though ICA offered the best performance, this decision should be made in a more comprehensive way, considering the application specifications and the inevitable balancing between the degree of noise elimination and the quality of signals being measured. In this sense, the integrative approach of quantitative measures, qualitative measures, and diversity of the evaluation facilitates a comprehensive evaluation and assists in identifying the best-dominated noise removal technique that suits the situation at hand.

To build upon existing research, Adaptive Frequency Filtering via CWT was presented as a new way of filtering SCG signals. This technique utilizes the strength of CWT to remove unnecessary unwanted noise components in SCG signals in both time and frequency domains, thereby enhancing the SCG analysis by targeting the removal of the time frequency components of the high frequency noise. The extensive review of numerous filtering techniques including illustrations and different evaluation criteria should be helpful to researchers and practitioners working in the field of biomedical signal processing. Noise and artifacts are the aim of these filtering techniques, which are considered to enhance the SCG signal processing techniques especially during the diagnosis of valvular heart disease. This study demonstrates a remarkable progress that contributes towards improvement of the denoising methods by advancing the synthesis of filters for utilization in biomedical signal processing.

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