PPG Signal Denoising using a New Method for the Selection of Optimal Wavelet Transform Parameters

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Abstract— Photoplethysmogram (PPG) is a vital biological signal which provides valuable information related to our cardiovascular system. However, noise artifacts like high frequency noise and movement noise can corrupt the signal during recording. The success of the widely used Wavelet Shrinkage denoising method largely depends on the optimal selection of its control parameters. In this paper, we propose a new method for the selection of the Decomposition Level and Noise Threshold in PPG signal wavelet shrinkage denoising. The Crest Factor (CF) of the detail coefficient is used as a metric for the selection of decomposition level and to determine that the detail coefficient comprises noise component, noisy component or signal component. The noise components are removed and the noisy components are delimited using a level-dependent threshold, which do not demand noise estimation. Finally, the denoised signal is reconstructed from the delimited noisy components, signal components and approximate component by Inverse Wavelet Transform (IWT). Experiments are carried out using simulated PPG signals with MIT-BIH noise stress test database and real PPG signals from PPG-BP Database and Wrist PPG During Exercise Database. The denoising performance is compared with the state-of-art-methods in terms of improved Signal to Noise Ratio (SNR), Root Mean Square Error (RMSE) and Percent Root Mean Square Difference (PRD). Results shows that the proposed method yields an improved SNR of 15 dB and 37 dB at input SNR of 2 and 20 dB respectively, whereas the best of the standard methods increases the SNR by 12 dB and 28 dB for the same input SNR. Thus, the proposed method has promising research value and can invariably be applied to other biomedical non-stationary signals like ECE and EEG.

Keywords: **Photoplethysmogram, wavelet transform, wavelet shrinkage denoising, decomposition level, noise thresholding.**

1. Introduction

The Photoplethysmogram (PPG) is a non-invasive method of measuring the volumetric changes in blood in peripheral circulation. It is used to monitor blood pressure, heart rate, breathing, hypovolemia and other circulatory conditions. However, during the recording of PPG signals, the high frequency noise, caused by thermal noise and electromagnetic interference, and movement noise gets added with the signal and inevitably produce baseline drift and other distortions. Further analysis and diagnosis of vital information from the PPG signal, requires it to be noise-free. Hence, correcting the baseline drift and denoising the raw PPG signal via appropriate algorithm is of great importance.

Several frequency domain filtering methods have been proposed in the literature [Chan & Zhang 2002; Lee et al. 2007; Awodeyi, Alty & Ghavami 2013]. However, they do not always perform well on the non-stationary signals and is less effective in removing baseline wander. The mapping in the statistical methods like Independent Component Analysis (ICA) [Joseph & Titus 2014; Peng et al. 2014], is very sensitive to minor disturbances in both signal and noise. The mode decomposition-based methods [Liu et al. 2019; Karim et al. 2019] like Ensemble Mode Decomposition (EMD), Ensemble EMD (EEMD) and Variational Mode Decomposition (VMD) are shown to realize the signal segmentation and component separation effectively. However, mode mixing resulting in redundant information in the decomposition is the major drawback of these methods.

The Wavelet Transform (WT) denoising methods have been shown to be more effective than the filtering methods [Fodor & Kamath 2003] with minimum computational complexity and have been extensively used in denoising of biomedical signals Wan, et al. 2020; Zhao & Dai 2015; Zho & Cui 2015; Deng & Liu, 2015]. The efficiency of the wavelet signal denoising depends on the optimal selection of WT parameters, which includes mother wavelet function, decomposition level, Noise threshold and thresholding function. The wavelet denoising methods available in the literature, selects these parameters in a subjective manner. Also, the noise threshold value in these methods depends largely on the noise estimation at each decomposition level.

The main objective of this paper is to propose a new wavelet denoising approach for PPG signals based on an objective methodology in the selection of WT parameters, resulting in adequate removal of baseline wander and artifacts noise without signal distortion, even for weak PPG signals.

This paper is organized as follows. Section II provides a detailed review on the Wavelet Shrinkage Denoising algorithm using state-of-the-art methods and their limitations. The proposed denoising algorithm using decomposition level selection and noise threshold are described in Section III. Experimental results on denoising of PPG signals are given in Section IV for the simulated signals and real signal datasets. Finally, the concluding remarks are given in Section V.

2. WAVELET SHRINKAGE DENOISING

The wavelet shrinkage method is based on decomposing the noisy signal followed by the suppression of the detail coefficients corresponding to noise. Fig.1 illustrates the workflow of wavelet shrinkage method.

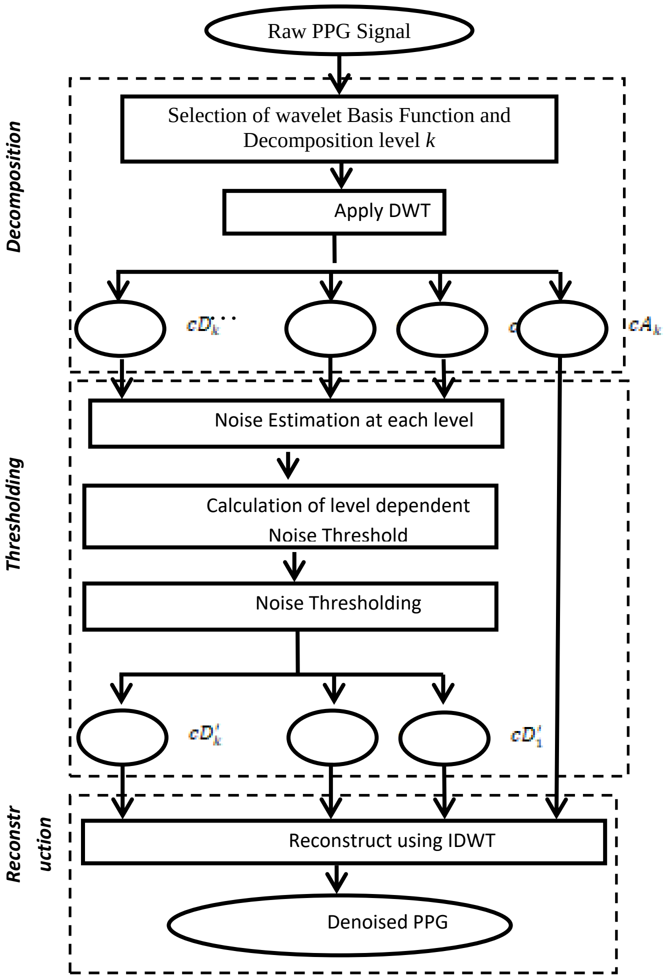

Fig 1. Flow Chart of Wavelet Shrinkage Denoising

Generally, the wavelet shrinkage denoising involves three steps:

- ***Decomposition:*** Discrete Wavelet Transform (DWT) of decomposition level k is applied to raw noisy PPG signal. At each level, the signal is decomposed into approximation coefficients (cA) and detail coefficients (cD)

$$PPG_{noisy}(t) = \sum_{n\in z} cA_k(n)\,\varphi_{k,n}(t) + \sum_{i=1}^{k}\sum_{n\in z} cD_i(n)\,\Psi_{i,n}(t) \quad (1)$$

$$cD_i(m) = \langle PPG_{noisy}, \Psi_{i,m}\rangle = \frac{1}{\sqrt{2}}\sum_n g(2m-n)\; cD_{i-1}(m) \quad (2)$$

$$cA_k(m) = \langle PPG_{noisy}, \varphi_{k,m}\rangle = \frac{1}{\sqrt{2}}\sum_n h(2m-n)\; cA_{L-1}(m) \quad (3)$$

where $cD_i(n), i = 1,2,\dots k$ represents the detailed coefficients at level i and $cA_k(n)$ represents the approximation coefficients at level k. $h(n)$ and $g(n)$ are the low pass and high pass filter of the wavelet filter bank respectively.

- ***Thresholding***: The noise variance of the detailed coefficients ($\sigma_i, i = 1,2,\dots k$) is estimated at each level and is used to determine the level dependent threshold value ($\gamma_i, i = 1,2,\dots k$) using any of the state-of-the-art threshold selection methods like universal method, Stein's Unbiased Risk Estimate (SURE), Minimax and S-median Threshold method.

The detailed coefficients are then delimited to the selected threshold values using thresholding techniques. The most common techniques are ***hard thresholding*** given by

$$cD'_{i,n} = \begin{cases} cD_{i,n};\ |D_{i,n}| \geq \gamma_j \\ 0;\ |D_{i,n}| \geq \gamma_j \end{cases} \quad (4)$$

and ***soft thresholding*** given by

$$cD'_{i,n} = \begin{cases} sgn(cD_{i,n})(|cD_{i,n}| - \gamma_i);\ |cD_{i,n}| \geq \gamma_i \\ 0;\ |cD_{i,n}| \geq \gamma_i \end{cases} \quad (5)$$

where $cD_{i,n}$ and $cD'_{i,n}$ are the noisy and denoised detailed coefficients at level *j* and index *n*.

- ***Reconstruction***: The denoised PPG signal is reconstructed from the k^{th} approximation coefficients and k detail coefficients by Inverse Discrete Wavelet Transform (IDWT)

$$PPF_{denoised}(t) = \sum_{n\epsilon z} cA_k(n)\varphi_{k,n}(t) + \sum_{i=l}^{k}\sum_{n\epsilon z} cD'_i(n)\Psi_{i,n}(t) \quad (6)$$

2.1 State-of-the-Art Methods

The optimized scale dependent threshold selection schemes are selected for the comparison with the proposed method. Other newer methods [Zhang & Bao 2003; Poornachandra et al. 2005; Lin & Cai, 2010] use improved thresholding functions to obtain better denoising. The most widely used standard denoising thresholds are

- ***Universal Threshold (sqtwolog):***

Donoho and Johnstone [Donoho 1995] proposed an optimal universal threshold based on mean square error criterion:

$$T = \sigma\sqrt{2logn} \quad (7)$$

where n is the length of the noisy signal and σ is the standard deviation of noise estimated as, $\sigma = \frac{MAD}{0.6745}$, MAD is the median of the detailed coefficients.

- ***Minimax:***

In Minimax method [Donoho & Johnstone 1998], optimal threshold is selected so as to realize minimization of maximum mean square error of the noisy signal.

- ***SURE:***

The Steins unbiased risk estimator (SURE) [Donoho 1995] is based on Steins unbiased likelihood estimation, which emphasizes the on minimizing the non-likelihood threshold.

- ***Heursure:***

Heursure [Donoho 1995] is combination of Universal and SURE method. For low SNR, Universal method is preferred whereas for high SNR, SURE method is chosen.

2.2 Limitations

- The selection of wavelets and the decomposition level k are subjective.
- The performance of almost all the standard threshold methods is influenced by the estimation of noise variance. However, there is no definite method to estimate the noise such as motion artifacts and baseline wandering associated with the PPG recordings.
- The delimitation rule is invariably applied to all the multi-level detail coefficients. However, in real scenario, there is a substantial difference in the presence of noise coefficients at various levels, which could be employed for better performance.

3. Proposed method for PPG Denoising using optimal selection of WT Parameters

The proposed method employs wavelet shrinkage with the following features:

- The wavelet is initially selected in a subjective way and the number of vanishing moments is inspected in an objective manner, which eliminates the need for soft thresholding.
- A new selection method is proposed for the determination of the decomposition level k, which greatly influence the denoising competency of the wavelet.
- An adaptive procedure is proposed for the delimitation based on the sparsity of the detailed coefficients.
- A new level dependent wavelet threshold is proposed which does not require the estimation of the noise variance in the signal.

Fig. 2.illustrates the workflow of the proposed method.

2.3 Wavelet Bases

The wavelet bases function is generally chosen to be any of the standard wavelet that resembles the signal and yields better sparsity and noise separation. Generally, the PPG signal is a two Gaussian functions model, representing the two phases of cardiac cycle namely systole and diastole. Hence, in a subjective way, it is found that the Daubechies wavelet family is better suited, compared to other standard wavelet.

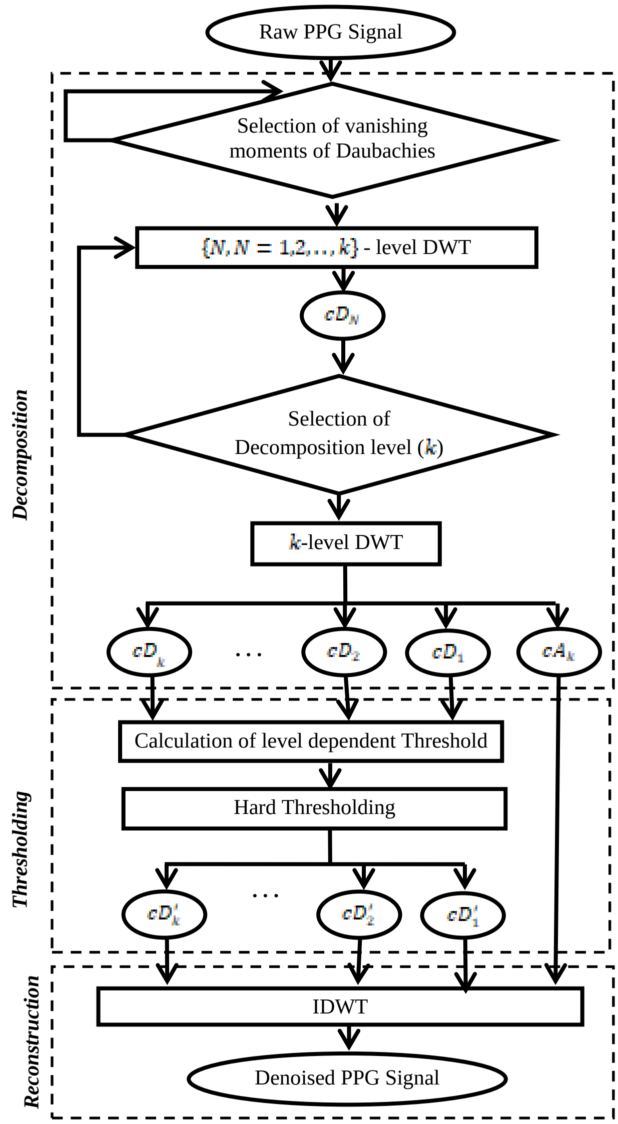

FIGURE 2. Flow Chart of Proposed Method

Algorithm 1 depicts the validation of vanishing moments of the Daubechies wavelet for the effective noise removal.

Algorithm 1 Validation of Wavelet Selection

Step 1: Generate the noise (N)that occurs in the real scenario of PPG recording, such as motion artifacts, baseline wandering & high frequency Gaussian noise. (In this work, the noise dataset from MIT-BIH Noise Stress Test Database is considered)

Step 2: Simulate the pure PPG waveform using two Gaussian function model [Wan et al. 2020] (PPG_{pure})

Step 3: Add the noise signal with PPG waveform.

$PPG_{noisy} = PPG_{pure} + N$

Step 4: Select an arbitrary vanishing moments for the Daubechies wavelet that would fit the noisy PPG signal generated, based on visual observation.

Step 5: Apply Discrete Wavelet Transform to the pure PPG (PPG_{pure}) and noise N to obtain the detailed coefficientscD_i^{PPG}& cD_i^{Noise}respectively.

Step 6: At each level, determine if the maximum of noise coefficient is less than the minimum of signal coefficient.

$\max(|cD_i^{Noise}|) < min(|cD_i^{PPG}|)$

Step 7: Tune the selection of vanishing moment in Step 4 to satisfy the condition in Step 6. In this work, vanishing moment 4 i.e., db4 is found to satisfy the above condition and is therefore used in further analysis.

3.1 Selection of Decomposition level

The selection of Decomposition level is crucial in wavelet denoising to which current methods do not define a concrete framework. In general, the decomposition level is arbitrarily chosen between 2 to 5. However, a higher-level decomposition leads to over-smoothing of the signal peaks, whereas lower-level decomposition results in poor denoising. Fig.3. illustrates the significance of proper selection of Decomposition Level, where raw noisy PPG signal from PPG-BP Database [Liang et al. 2018] is denoised at levels above and below the optimum level with Uniform Thresholding.

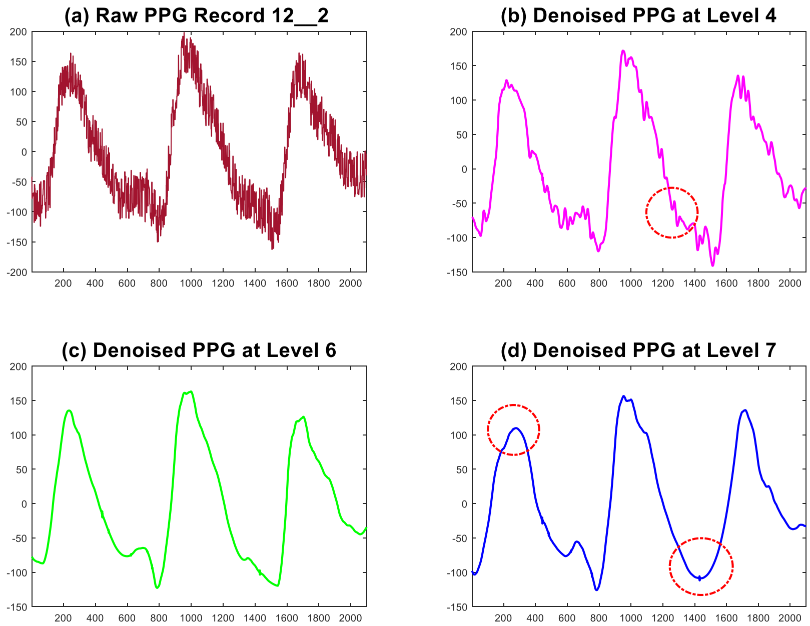

Fig 3.Illustration on Decomposition Level Selection. (a) Raw PPG signal of PPG-BP Database record 12_2 [Liang et al. 2018]. (b) Denoised with Db4 Level 4. The region of poor denoising is marked in circle. (c) Denoised with Db4 Level 5, optimized in terms of Minimum Mean Square Error (MMSE). (d) Denoised with Db4 Level 7. The over smoothed peak and valley regions are marked in circles.

The multilevel wavelet transform of a noisy PPG signal is depicted in Fig 4. As shown, the noise in the detail components corresponding to lower levels of wavelet decomposition is large compared to that in higher levels, due to the fact that noise contains more high frequency components. The lower level detail coefficients is found to have large number of small amplitudes corresponding to noise, whereas as the level is increased, small number of large signal amplitudes dominate the noise components.

Hence, Crest Factor (CF) of a signal serves as an efficient measure to obtain the optimum decomposition level for noise thresholding. The CF indicates how extreme the peaks are in a waveform. It is defined as the ratio of highest peak value to the Root Mean Square (RMS) of the waveform. The CF is a positive real number with minimum value of 1, indicating no peaks. The CF of the detail component at level j is given by

$$CF_i = \frac{\max(|cD_i|)}{RMS(cD_i)} \quad (8)$$

In PPG signal decomposition, the CF of detail coefficients containing only noise components is greater than 15. For coefficients containing both signal and noise component, it is found to range between 1.5 to 5. By means of extensive experiments (both simulated and real time PPG data sets) with SNR ranging as low as -12 dB to 10 dB, it is found that the CF value of 2.5 would serve as an appropriate threshold to determine the optimal decomposition level.

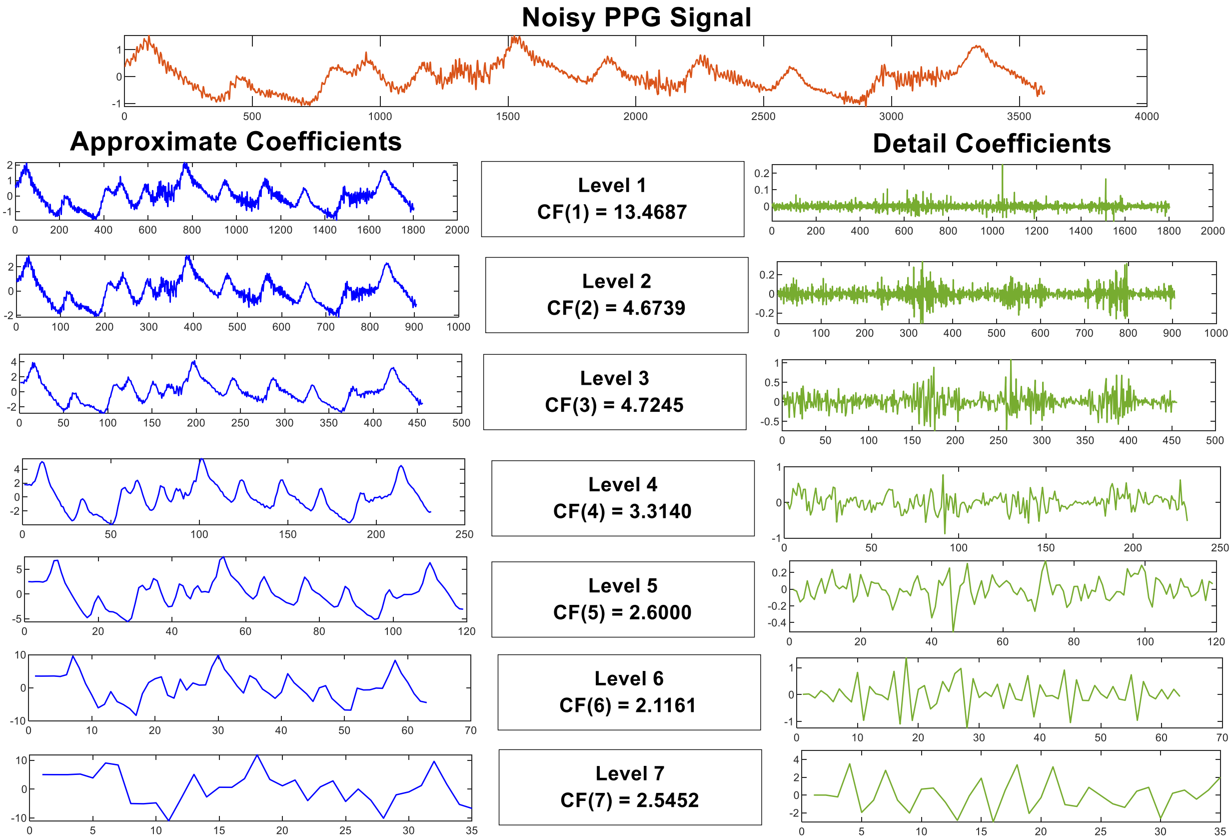

FIGURE 4. Approximate and Detail Coefficients of a sample noisy PPG and the Crest Factor values of corresponding Detail Coefficients. In a subjective manner, the decomposition at Level 5 is found to be appropriate, for which the Crest Factor is 2.6. As the level is increased further the approximate coefficient is distorted and the CF decreases below 2.5. Further increase in the decomposition level, shows a slight elevation in CF value due to the presence of fewer components of high magnitude signal component. The approximate component is heavily distorted due to loss in signal information

The Pseudo-Code of the overall algorithm for the Selection of Decomposition level is depicted below:

Algorithm 2 Decomposition Level Selection Pseudo-Code

$i \leftarrow 1$; Initialize the Decomposition level to minimum value
$CF_{(i-1)} \leftarrow 20$; Initialize the Crest Factor to a large value corresponding to the noisy coefficients
while ($CF_{(i-1)} \geq 2.5$)
DWT ← Db4 with Decomposition Level i
Determine the Detail Coefficient at Level i, cD_i
Evaluate the Crest Factor, CF_i using Equation (8)
$i \leftarrow i + 1$
end while
$k \leftarrow i - 1$; Optimum Decomposition Level

3.2 **Level-Dependent Thresholding Based on Crest Factor**

Observing at the detail coefficients and their CF value of large number of experimental PPG waveforms (both simulated and real datasets), the detail coefficients can be clubbed into three groups:

- Detail coefficients that contain only noise components i.e. $CF_i \geq 3.5$. These coefficients can be completely eliminated.

- Detail coefficients that contain both noise and signal components with small magnitudes i.e., $2.5 < CF_i \leq 3.5$. These coefficients have to be delimited by appropriate threshold value.
- Detail coefficients with large amplitude signal components i.e. $CF_i \leq 2.5$. These components can remain unchanged.

The selection of thresholding value is critical, since poor selection may lead to poor denoising or signal distortion during reconstruction. The standard wavelet denoising threshold would often require a noise variance estimation algorithm at each level.

There is no definite procedure to estimate the noise present in PPG signals and widely used general algorithms results in different values.

A new level dependent threshold is proposed which depends on the CF value of the detail components.

$$\gamma_i = \alpha * \max |(cD_i)| \tag{9}$$

Where $\alpha = CF_i / CF_1$ is the adjustment parameter. Since, CF_1 corresponds to the CF of the 1st level detail component cD_1, which contains only noise, the highest value of threshold obtained is $\gamma_i^{max} = \max|(cD_i)|$. Thus, all-noise detail coefficients are delimited to zero. Fig.5. depicts flowchart of the thresholding process.

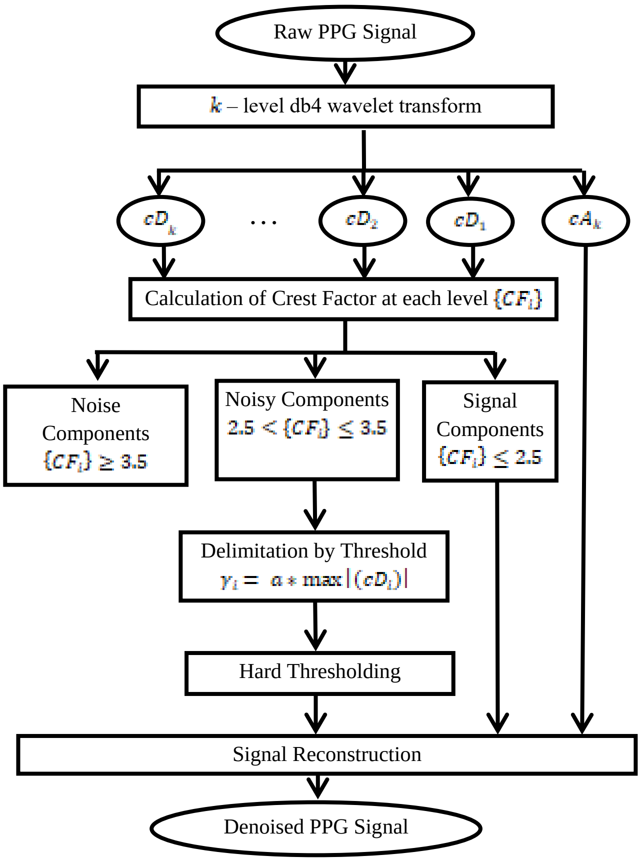

Fig 5. Flowchart of the Proposed Thresholding Process

4. EXPERIMENTS AND RESULTS

The proposed algorithm is evaluated in both simulated PPG signal and the real PPG dataset and the performance is compared with state-of-the-art methods. The following metrics are used as quantitative performance indicators in this study.

- The output SNR indicates the noise reduction level at the denoised output. The larger the output SNR, the better is the performance of the denoising method.

$$SNR_{output} = \frac{\sum_{n=1}^{N}[x(n)]^2}{\sum_{n=1}^{N}[x(n) - \hat{x}(n)]^2} \tag{10}$$

- The Root Mean Square Error (RMSE) indicates the variance between original signal and the denoised one. The smaller the RMSE, smaller is the difference.

$$RMSE = \sqrt{\frac{1}{N}\sum_{n=1}^{N}[x(n) - \hat{x}(n)]^2} \quad (11)$$

- The SNR Improvement (SNR_{imp}) is another useful assessment parameter which is a measure of the improvement of output SNR in comparison with that of the input.

$$SNR_{imp}\,[dB] = SNR_{output} - SNR_{input} \quad (12)$$

- The percentage Root Mean Square Difference (PRD) denotes the recovery performance by measuring the error between original and denoised signal. The smaller the PRD, better is the reconstruction.

$$PRD = \sqrt{\frac{\sum_{n=1}^{N}[x(n)-\hat{x}(n)]^2}{\sum_{n=1}^{N}[x(n)]^2}} * 100 \quad (13)$$

4.1 Evaluation on Simulated PPG Signal

The Synthetic photoplethysmogram generation using two Gaussian functions, proposed by Tang et al., [2020] is used to simulate the PPG waveform.

$$x(t) = a_1 \exp\left(-\frac{1}{2}\left(\frac{t-\theta_1}{b_1}\right)^2\right) + a_2 \exp\left(-\frac{1}{2}\left(\frac{t-\theta_2}{b_2}\right)^2\right) \quad (14)$$

The optimal parameters for excellent PPG are
$a_1 = 1.0000, \theta_1 = -1.5161, b_1 = 0.6303, a_2 = 0.1999, \theta_2 = 0.8186,\ b_2 = 1.0225$. [Tang et al. 2020].

MIT-BIH Noise Stress Test database [Moody, Muldrow & Mark 1984] is used for generating realistic Baseline wander and motion artifacts. The '*noise1'* of *'bw.dat'* and *'ma.dat'* datasets are added with the simulated PPG signal at various SNRs. The noisy PPG and its spectrum are shown in Fig.6 for various SNR.

The Selection of Decomposition level (Algorithm 2) is applied to the noisy PPG signal $y(t)$, to obtain the optimum level k at every input SNR. Table.I shows the CF value of the detail coefficients at different SNRs. The following observations are made:

- The Crest Factor of the detail coefficients at level 1 is generally greater than 10. This corresponds to the all-noise coefficients at the lowest level.
- At level 2-4, the CF value decreases to around 3, due to the increase in small number of high amplitude signal coefficients and decrease in the large number of small amplitude noise components.
- The CF value falls below 2.5, at level 4-6, depending on the SNR of the input signal. This is the optimum level, where the signal components dominate the noise components.
- Towards, higher levels of decomposition i.e. for CF values below 2.5, the detail components contain only signal coefficients and the CF value is slightly increased.

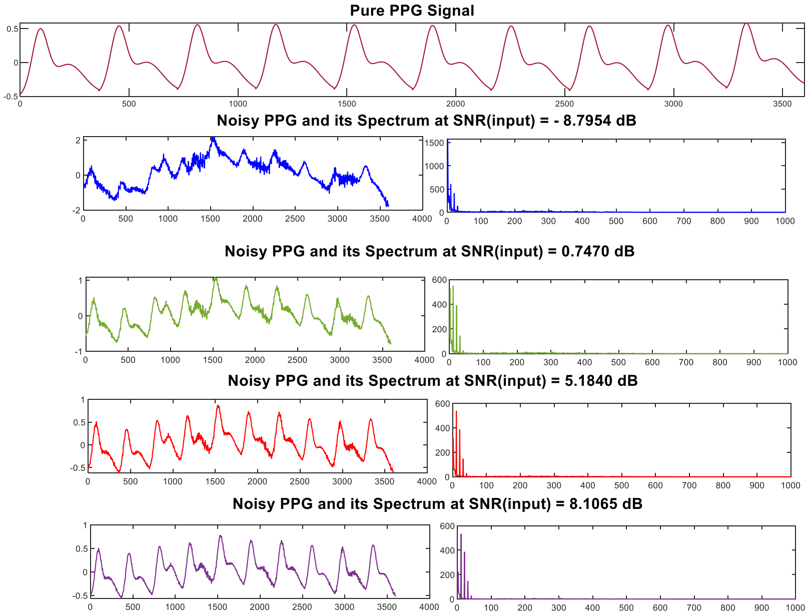

Fig 6. Noisy PPG Signal and its corresponding Spectrum at various SNR

TABLE I

THE CREST FACTOR (CF) VALUES OF THE DETAIL COEFFICIENTS AT VARIOUS DECOMPOSITION LEVELS FOR VARIOUS SNRS.

SNRinput (dB)	**Decomposition Levels**							**Optimal Decomposition Level**
	1	**2**	**3**	**4**	**5**	**6**	**7**	
-14.816	13.4968	4.6753	4.7249	3.3145	3.2622	2.6645	1.9576	6
-5.2736	13.4977	4.6772	4.7232	3.3126	2.6528	2.154	2.1046	5
-0.8366	13.4738	4.6783	4.7207	3.3083	2.4474	1.9912	1.1259	4
4.2688	13.3534	4.6785	4.7129	3.2929	2.0623	2.0085	2.1399	4
8.7058	13.0084	4.673	4.694	3.2523	1.7582	2.0125	2.157	4
12.4185	12.3138	4.6558	4.6582	3.1724	1.6934	2.0138	2.1598	4
14.4319	11.6867	4.6356	4.6232	3.096	1.6753	2.0141	2.1629	4

The noisy PPG signal is then decomposed using ‘db4’ at the selected optimal level k. The detail coefficients with CF value greater than 3.5 are set to zero. Thresholding is applied to the detail coefficients with CF value in the range 3.5 to 2.5. The detail coefficients with CF value below 2.5, remain unchanged.

In this work, the performance of the state-of-the-art methods such as Universal Threshold, SURE and Minimax are compared with the proposed one in denoising at different noise levels. The decomposition level k that results in minimum MSE compared to other levels is chosen for the standard methods.

Fig. 7 shows the Denoising effect of the standard and the Proposed methods at SNR=-0.8366 & 7.4628 dB. It is seen that though the Universal method provides better performance among the standard ones, there are local distortions at the signal points with high noise. Minimax method, which shows a better performance than SURE, corrects the baseline drift to a large extent still with significant fluctuations. The proposed method is found to remove the baseline noise, fits the sources signal even in peaks and valley points and shows very little distortion at SNR= -0.8 dB.

The performance metrics of standard and proposed methods at various levels of input SNR are shown in Fig. 8. It can be seen that the denoising effect of the proposed method shows marginal improvement than the standard methods at very low SNR while significant improvement is achieved at SNR > 5dB. The universal method outperforms other standard methods especially at high SNR.

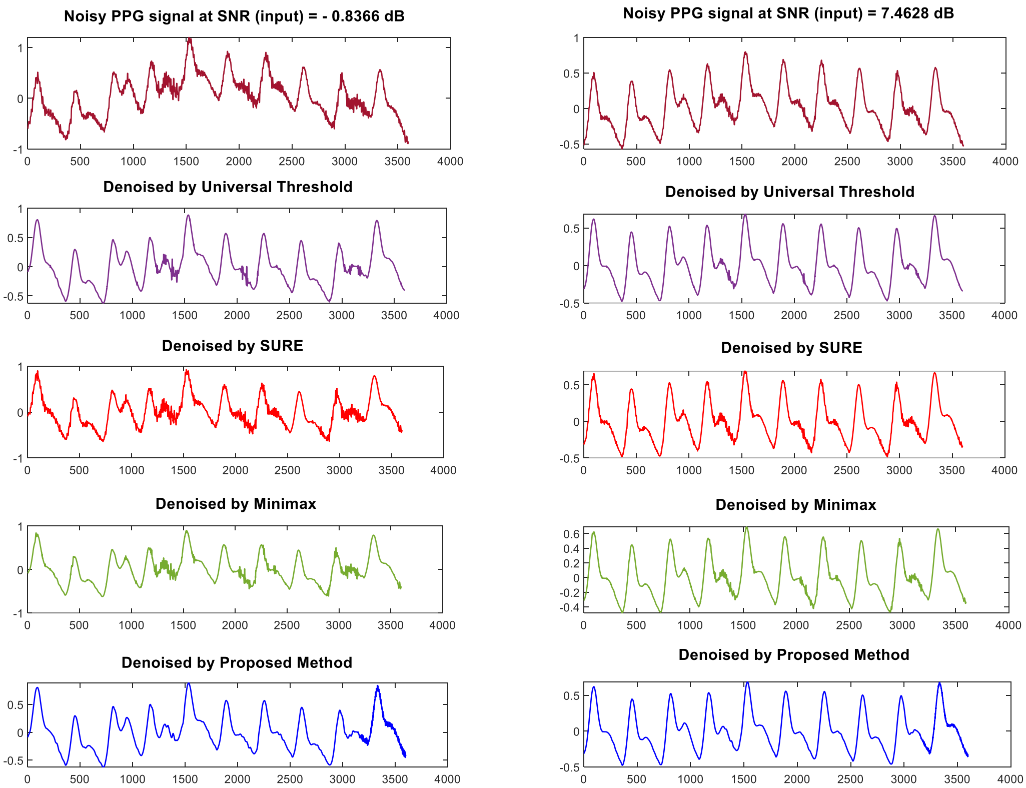

Fig 7.Denoising effect of the standard and the Proposed methods at SNR=-0.8366 & 7.4628 dB

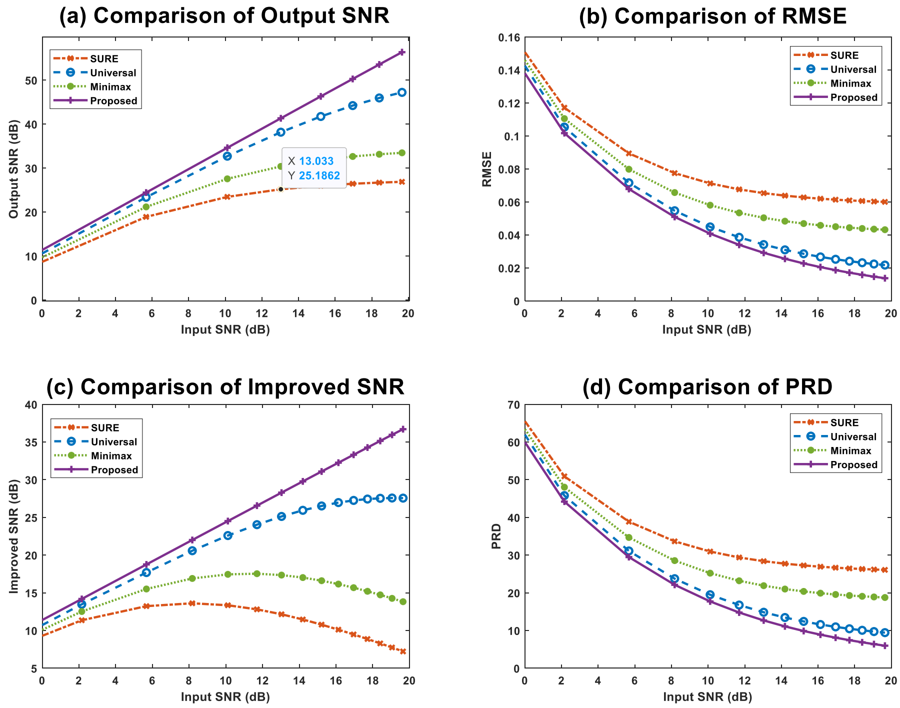

Fig 8. Comparison of the Performance metrics of standard and Proposed Methods. The proposed algorithm with adaptive decomposition level outperforms other standard methods with fixed decomposition level. Significant improvement is found at input SNR > 5 dB

4.2 Evaluation on PPG-BP Database

The proposed method is evaluated against the standard methods on PPG-BP Database [Liang et al. 2018], a health dataset for the non-invasive detection of cardiovascular disease (CVD), containing 657 data records from 219 subjects. The dataset covers an age range of 20–89 years and records of diseases including hypertension and diabetes.

The PPG records with different noise levels and chosen and denoising is performed using standard and proposed methods. The decomposition level for the standard methods are chosen in a subjective manner, based on physical observation as done in most of the existing methods.

Fig.9 shows the denoising effect at various records. It is found that the proposed method with adaptive decomposition level results in outstanding denoising performance. At low noise levels, the universal method performs better than other standard methods and approaches to that of the proposed one.

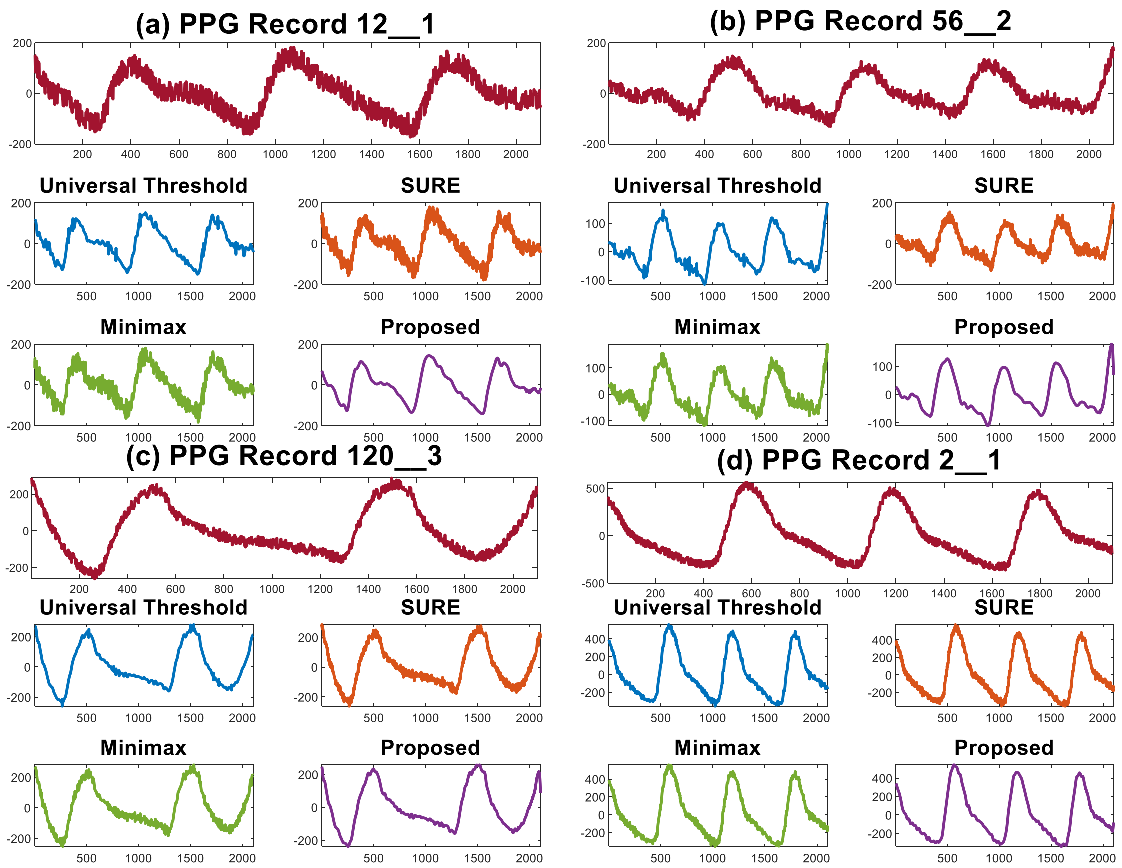

Fig 9. Denoising effect of the standard and the Proposed methods on few records of PPG-BP Database

4.3 Evaluation on Wrist PPG During Exercise Database

The proposed method is evaluated against the standard methods on Physionet [Goldberger et al. 2000] Wrist PPG During Exercise Database [Jarchi & Casson 2017]. This database contains wrist PPGs recorded during walking, running and bike riding. Simultaneous motion estimates are collected using both accelerometers and gyroscopes to give multiple options for the removal of motion interference from the PPG traces.All signals were sampled at 256 Hz. Records from 8 participants aged 22—32 are present. Fig.10 shows the denoising effect at various records.

For the walking and running records, the database contains the raw PPG and motion signals. The universal method and proposed methods almost perform same level of denoising in these signals. However, the performance of universal threshold only depends on subjective analysis in the selection of decomposition level, while in the proposed method the adaptive algorithm is deployed.

For the cycling records, large amounts of high frequency noise were present in the PPG traces. Hence, PPG traces were low pass filtered prior to conversion. The proposed method outperforms other standard methods in these signals.

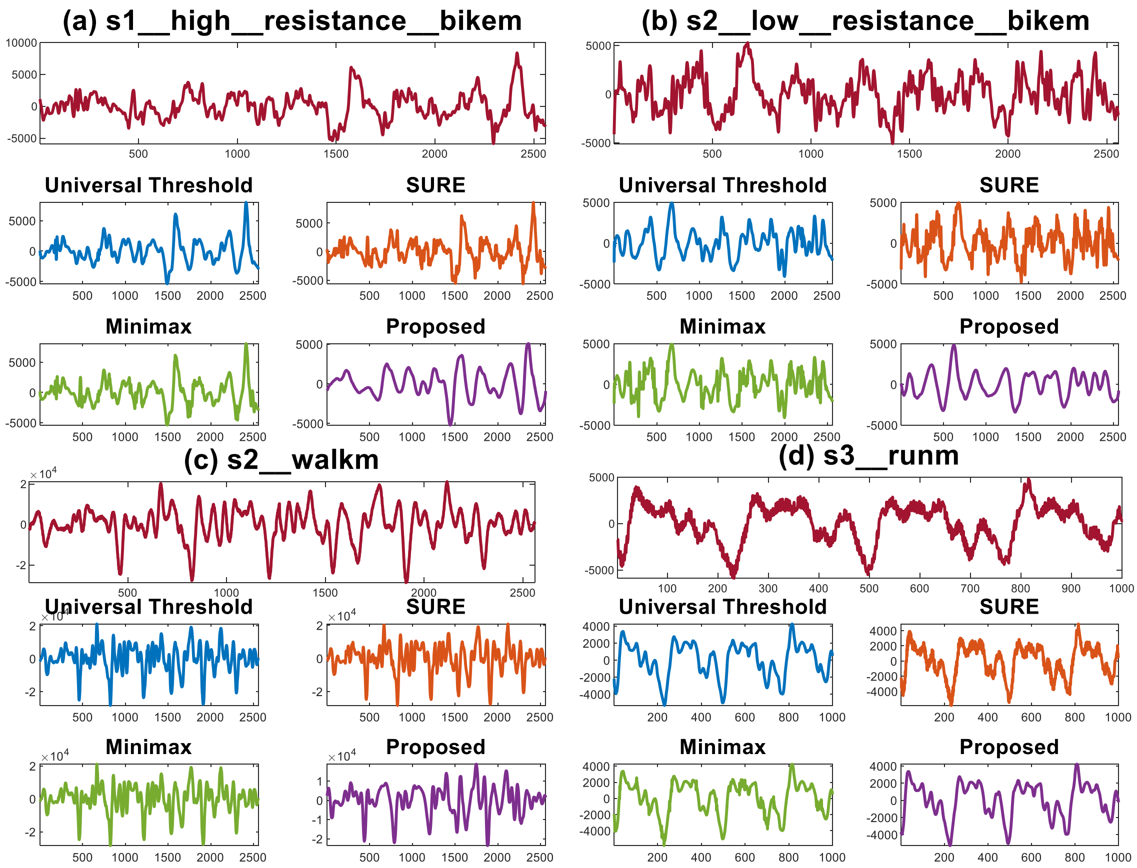

Fig 10. Denoising effect of the standard and the Proposed methods on few records of Wrist PPG During Exercise Database

5. Conclusion

In this paper, an extensive methodology for the selection of optimal WT parameters i.e., wavelet bases, decomposition level and noise thresholding is proposed for PPG signal Wavelet Shrinkage denoising. The method is based on Crest Factor which is a simple metric with less computations but effective in determining noisy coefficients. The new method is compared with Universal threshold, SURE and Minimax methods by a large number of simulations on modeled and real time PPG datasets. The results show that the new method is superior to other standard methods in terms of quantitative performance metrics, computation involved and effective removal of baseline wander and noise artifacts, while preserving the signal characteristics. The proposed method yields a marginal improvement to the universal threshold at low SNR, provided the WT parameters of universal threshold are optimized in terms of MMSE by trial and error. However, at SNR>5 dB, the proposed one outperforms the standard ones at a significant rate. Thus, the new method based on Crest Factor has promising research value and can invariably be applied to other biomedical non-stationary signals like ECE and EEG.

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