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Denoising wrist pulse signals using variance thresholding technique

Corresponding author.

Tel: 9611692222
sugunagc@jssateb.ac.in

GC Suguna[1]*, **ST Veerabhadrappa**[2]

1 Assistant Professor and Research Scholar, Department of Electronics and Communication, JSS Academy of Technical Education, Bengaluru, and Affiliated to Visvesvaraya Technological University, Belagavi, KA, India, Tel.: 9611692222
2 Associate Professor, Department of Electronics and Communication, JSS Academy of Technical Education, Bengaluru, and Affiliated to Visvesvaraya Technological University, Belagavi, KA, India

Abstract

Background/Objectives: Denoising of the wrist pulse is a significant preprocessing stage for accurate investigation of the disease. The objective is to improve and analyze performance metrics of denoising techniques. **Methods/Statistical analysis:** Denoising of wrist pulse with the evaluation parameters such as PSNR, SNR, AE and RMSE has been implemented using wavelets such as Daubechies, Symlet and Biorthogonal. The performance of wavelets depends on the choice of decomposition level N and thresholding techniques. **Findings:** Variance thresholding technique showed significant improvement in Peak Signal to Noise Ratio (PSNR), Signal to Noise Ratio (SNR) and reduction in Absolute Error (AE) and Root Mean Square Error (RMSE) compared to other thresholding methods. **Novelty/Applications:** Experimental results showed drastic improvement in PSNR and SNR retaining the pathophysiological information of the wrist pulse signal for future analysis.

Keywords: Wrist pulse; SNR; PSNR; AE; RMSE; wavelets

1 Introduction

In the traditional diagnosis system of Ayurveda, wrist pulse analysis is a significant and essential tool that is extensively used for diagnosing human health. The wrist pulse signal is a pressure signal measured from the radial artery of the subject. However, wrist pulse recordings are often affected both high and low frequency such as muscle contraction, power line interference and movements, eye blink of the subject respectively. Several researchers have been reported with various denoising methods such as FIR, IIR[1], adaptive filtering, Kaiser window[2], principal component analysis (PCA), empirical mode decomposition (EMD)

[3], convolutional denoising autoencoders [4], to extract the desired wrist pulse signal from undesired artifacts [5,6]. The presence of these non-stationary artifacts can lead to wrong diagnoses of human health. Hence, wavelet-based methods are used for pre-processing of wrist pulse signals to extract desired pathophysiological information. In this paper comparison of various wavelets based denoising techniques have been implemented to improve the performance metric such as PSNR, SNR, AE and RMSE. The work mainly focuses on thresholding computation methods such as Universal threshold, Variance threshold. These thresholding methods are applied to various wavelets such as Daubechies, Symlet and Biorthogonal to evaluate performance metrics. The experimental result shows that the evaluation parameters of variance thresholding method outperformed compared to other thresholding techniques.

2 Materials and Methods

Baseline wander is artifacts of low frequency below 0.5 Hz occur in wrist pulse signal due to breathing, sneezing, eye blink and movement of the subject. These low-frequency components need to be eliminated before wrist pulse analysis for proper diagnosis. Baseline wanders present in wrist pulse, can be removed by various methods like multi-rate empirical mode decomposition, Hilbert decomposition, adaptive mean filter and high pass filter [7,8]. Low-frequency wrist pulse signals can easily interfere with 50 Hz signal during acquisition. The wavelets and thresholding techniques were applied to remove both high frequency and low-frequency artifacts

2.1 Wavelet-based denoising approaches with various thresholding methods

Wavelet transforms have great significance in denoising of wrist pulse signal. Wavelets are used for analyzing non-stationary signals both in time and frequency. In the wavelet transform, thresholding of wavelet coefficients of the filter is known as denoising [9–11].

Wavelet transform processes the noise signal with lower magnitude in higher coefficients whereas, signal with higher magnitude in lower coefficients of the filter. Wavelets use short windows at higher frequencies and longer windows at lower frequencies [12,13]. Thresholding techniques in wavelets are used to separate the desired wrist pulse signal from an undesired signal [14,15]. Wrist pulse signal of the healthy subject lies in the frequency range of 0-4Hz which uses long windows for analysis.

Wavelets methods used for denoising of wrist pulse signal are

1. Discrete Wavelet Transform (DWT)
2. Stationary Wavelet Transform (SWT)

Discrete Wavelet Transform (DWT)

A wavelet is a short wave that possesses energy over a certain time interval. The wavelet transform decomposes a signal into its various constituent frequency bands by dilating and translating of the mother wavelet. Expressed as

$$\varphi_{a,b}(t) = \frac{1}{\sqrt{a}} \varphi\left(\frac{t-b}{a}\right) \tag{1}$$

where 'a' and 'b' are the dilating and translating parameters respectively. The wavelet transform of a signal $x(t)$ could be expressed in terms of wavelets $\varphi_{a,b}(t)$ as

$$W(a,b) = \int_{-\infty}^{+\infty} x(t)\,\varphi_{a,b}(t)\,dt\;,a>0 \tag{2}$$

Wavelet transform of wrist pulse series has been computed with the help of Daubechies wavelet 'db' to derive an additional set of features. The highest level of decomposition in the Wavelet Transform is determined based on the frequency components that are required for the specific application. Wavelet analysis of wrist pulse signal is carried with approximate and detailed coefficients of the filter at every decomposition level. At each decomposition level the length of both approximate and detail coefficients of the filter are halved, to yield a specific range of frequencies as shown in Figure 1. The frequency components of a healthy subject is in the range of 0 to 20 Hz. Universal and variance thresholding techniques are used in wavelets like Daubechies (db4,db14), Symlet wavelets (sym4) and Biorthogonal wavelets (bior3.5) to eliminate powerline and baseline interferences[16].
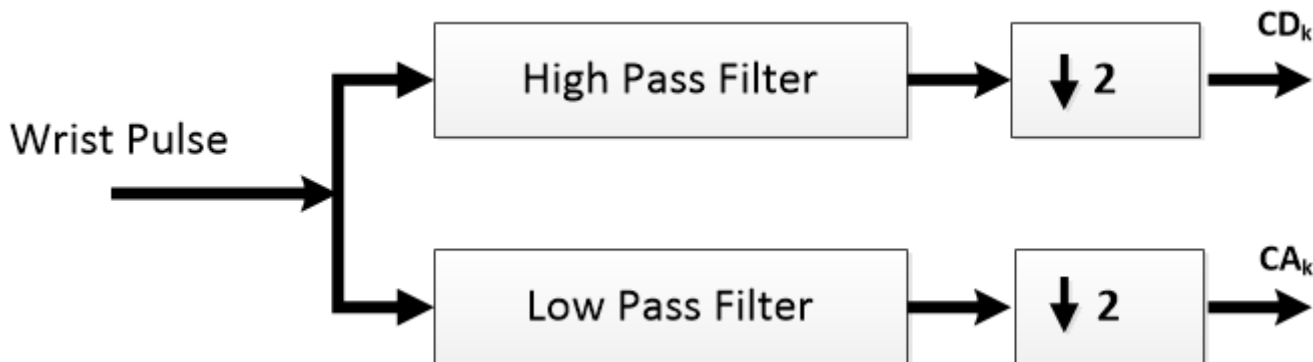

Fig 1. Discrete wavelet transform

Stationary Wavelet Transform (SWT)

Stationary Wavelet Transform is an undecimated wavelet transform where the wrist pulse signal is subjected to high pass and low pass filters to generated the approximate (cA_k) and detailed coefficients (cD_k) respectively. SWT is the same as DWT, except for the decimation factor 2. The number of samples of SWT at any level of decomposition is similar to that of input samples.

2.2 Methodology

Wrist pulse signal data is collected from the acquisition device, sampled at 500 Hz with the resolution of 14-bits/sample. Wrist pulse signal is preprocess using various wavelet methods to remove the artifacts. Denoising of wrist pulse signal using wavelets involves the following three steps as depicted in Figure 2.

1. Decomposition: Select a level N for a wavelet to be applied to the wrist pulse signal.
2. Threshold Function: Select a Threshold function (Thr) at each level to decompose of a noisy wrist pulse signal.
3. Reconstruct: Compute the Inverse Wavelet transform to obtain a noise-free Wrist pulse signal.

Figure 3 shows that decomposition level 9 with approximation co-efficient and detailed co-efficient at each level with frequency bands. The noisy wrist pulse signal sampled at 500 Hz is decomposed at different levels. At each decomposition level, the length of both approximate and detail coefficients of the filter are halved, to yield a specific range of frequencies. Wrist pulse signal of a normal subject, 0-20 Hz is prone to power line and baseline wander interference. Decomposition of approximate coefficients is considered in the preprocessing of low-frequency biomedical signals. Artifacts at each level are eliminated through

various thresholding methods. At level 3 and 9 are bands of power line inference and baseline wander interference respectively present in wrist pulse signal shown in Figure 3.
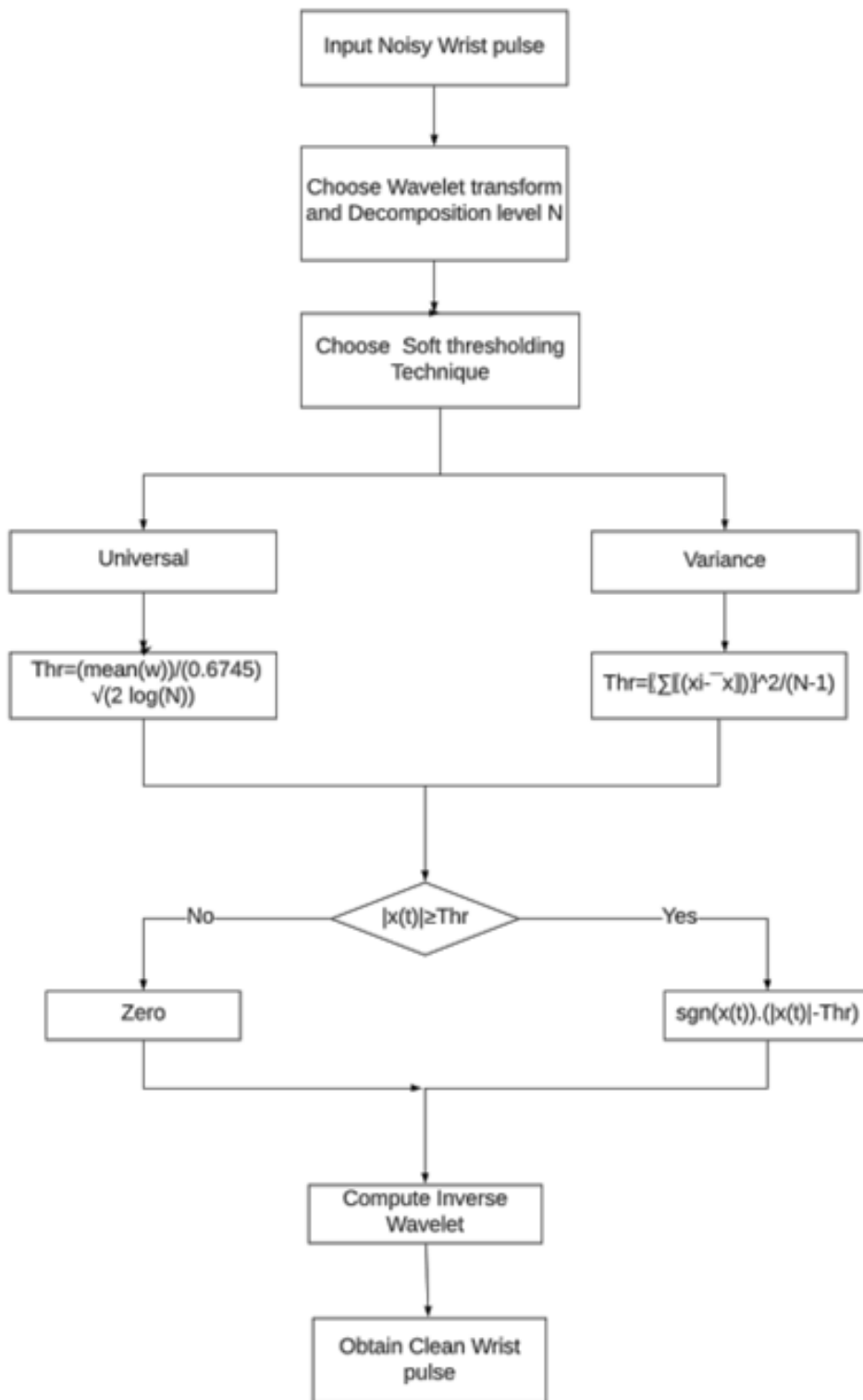

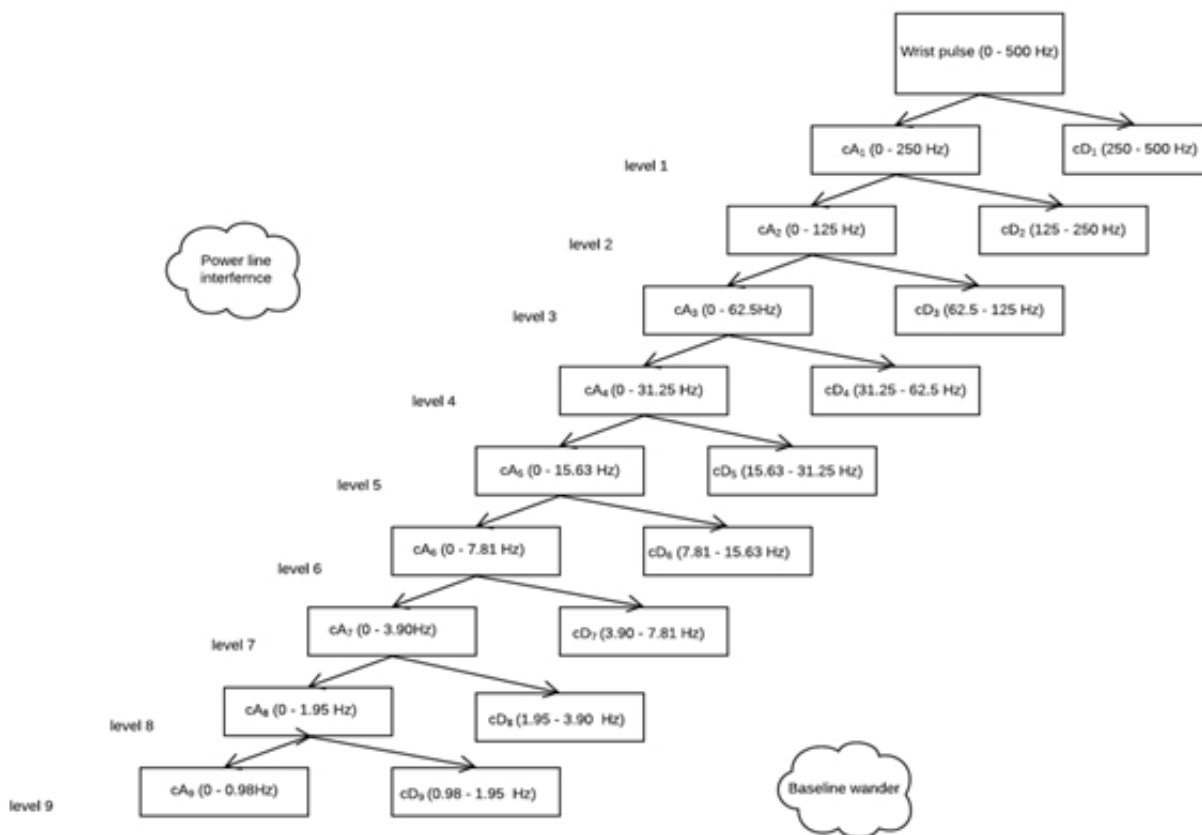**Fig 2.** Flow diagram of denoising of a wrist pulse signal

Fig 3. Level 9 Decomposition of approximation coefficient and detailed coefficient

2.3 Thresholding Techniques

Wavelet thresholding is a non-linear method, which operates on wavelet coefficients. Various thresholding functions have been developed to denoise the bio-medical signal. The most commonly used methods are hard and soft thresholding methods[17,18]. The hard thresholding method set all the coefficients less than a threshold (Thr) to zero. **Hard thresholding** could be expressed as

$$|\hat{x}(t)| = \begin{cases} 0; |x(t)| < Thr \\ x(t); |x(t)| \geq Thr \end{cases} \tag{3}$$

$|\hat{x}(t)|$ is a estimated signal after thresholding

Soft thresholding is often widely used in statistical applications and called as shrinkage wavelet. Soft thresholding reduces all the coefficients higher than Thr is given as

$$|\hat{x}(t)| = \begin{cases} 0; |x(t)| < Thr \\ sgn(x(t)) \cdot (|x(t)| - Thr); |x(t)| \geq Thr \end{cases} \tag{4}$$

where $|\hat{x}(t)|$ is threshold version of $x(t)$ at the corresponding level. $sgn(.)$ is a sign function of $x(t)$ having values as -1 and +1.

Soft thresholding method further classified as Rigrsure, Sqtwolog, Heursure and Minimaxi based on the threshold selection rules**.**

1. Rigrsure thresholding selection is an adaptive thresholding method based on the quadratic loss function. The threshold is expressed as

$$Thr = \sigma \sqrt{w} \tag{5}$$

Where σ is the standard deviation of a noisy signal

w is an approximate wavelet coefficients after decomposition.

2. Sqtwolog thresholding is a universal threshold selection rule for Gaussian noise based Median Absolute Deviation (MAD) first high-frequency sub-band. Thr is expressed as

$$Thr = \frac{mean(w)}{0.6745} \sqrt{2 \, log(N)} \tag{6}$$

N is the number of samples.

3. Heursure thresholding is a combination of rigrsure and sqtwolog thresholding. Choice thresholding method is based on SNR values of the input noisy signal. If the SNR is small, then rigrsure thresholding is adopted for better result.

4. Minimaxi thresholding is a statistical mathematical computation that represents the noise threshold. Minimax uses a fixed threshold chosen to yield min-max performance. Thr is represented as

$$Thr = \begin{cases} 0; & N \leq 32 \\ \frac{mean(w)}{0.6745} \left(0.3936 + 0.10829 \log_2 N \right); N > 32 \end{cases} \tag{6}$$

5. Variance thresholding

A variance thresholding technique is based on the variance of approximated coefficients of the filter. Variance is statically defined as the average of the squared difference from the mean of approximate coefficients.

$$Thr = \frac{\sum (x_i - \bar{x})^2}{N-1} \tag{7}$$

x_i - i^{th} approximate Coefficient of Wavelet

$\bar{x}$ - the average value of x approximate Coefficients

$$|\hat{x}(t)| = \begin{cases} 0; |x(t)| < Thr \\ sgn(x(t)) \cdot (|x(t)| - Thr); |x(t)| \geq Thr \end{cases} \tag{8}$$

Where $|\hat{x}(t)|$ is variance threshold version of $x(t)$ at the corresponding level.

Variance based thresholding improves evaluation parameters SNR, PSNR and reduces AE, RMSE.

2.4 Evaluation parameters of the denoising techniques are[19]

1. Signal to Noise Ratio (SNR): SNR is the ratio of denoised wrist signal power to noisy signal power in decibels (dB). Higher the SNR, denoised wrist pulse signal power is high could accurately diagnose the disease.

$$SNR \, (dB) = 10 log_{10} \left(\frac{Denoised \, Wrist \, pulse \, signal \, power}{Noisy \, wrist \, pulse \, power} \right) \tag{9}$$

2. Peak Signal to Noise Ratio (PSNR): PSNR is the ratio of square of maximum peak denoised wrist pulse signal to mean square error.

$$PSNR(dB) = 10\log_{10}\left(\frac{\text{Maximum Peak of the Denoised Wrist pulse}^2}{\text{Mean Square Error}}\right) \qquad (10)$$

3. Absolute Error (AE): AE is defined as an absolute difference between denoised wrist pulse signal and noisy wrist pulse signal.

$$AE = \|\hat{x}(t) - x(t)\| \qquad (11)$$

where $\widehat{x}(t)$ denoised signal and $x(t)$ is a noisy wrist pulse.

4. Mean Square Error (MSE): MSE is defined as the mean squared error between noisy wrist pulse signal and denoised wrist pulse signal. Typically, MSE should approach zero.

$$MSE = \frac{1}{N}\sum_{k=1}^{N}(y_k - \widehat{y}_k)^2 \qquad (12)$$

Where N is the number of samples

y_k - is actual values

$\widehat{y}_k$ - is predicted values

5. Root Mean Square Error (RMSE): RMSE defines as the square root of MSE. Expressed as

$$RMSE = \sqrt{MSE} \qquad (13)$$

3 Results and Discussion

A study was carried out involving 56 healthy subjects include both male and female with an average age of 25.3 years. Procedure and norm was explained to subject before acquiring the wrist pulse and analyzed using MATLAB software tool. Table 1 show that the universal thresholding and variance thresholding technique's evaluation parameters of Daubechies 4, Symlet 4, Biorthogonal 3.5, and Daubechies 14 wavelet at a decomposition level 5 of 56 healthy subjects. Figure 4 depicts the comparison of evaluation parameters of various wavelets using universal thresholding and variance thersholding methods. The PSNR and SNR evaluation parameters increased from 17.32 ± 5.83dB and -0.33 ± 1.47 dB in Universal thresholding method to 41.72 ± 9.48dB and 26.98 ± 4.48dB respectively in Variance thresholding method using db4. Figure 5 depicts variance thresholding method as better pulse contour and fiducially points (onset, peak and dicrotic notch) compared to universal method. A pulse contour and fiducal point of the wrist pulse contains abundant information of the subject. This information of denoised signal with variance method could be useful for future analysis compared to the universal method. AE and RMSE of the denoised pulse wave significantly decreased from 0.75± 0.69μV and 0.18± 0.17μV in the Universal thresholding method to 0.06 ± 0.11μV and 0.02 ± 0.04 μV respectively in the Variance thresholding method. Variance thresholding method has significantly less error compared to the universal threshold method. The variation of these evaluation parameters of all subjects is as shown in Figure 6. Comparing to the conventional wavelet method, EMD, improved EMD[20], the proposed variance threshold method showed significant results.

Table 1. Evaluation of denoising parameters of healthy subjects using universal thresholding and variance thresholding methods.

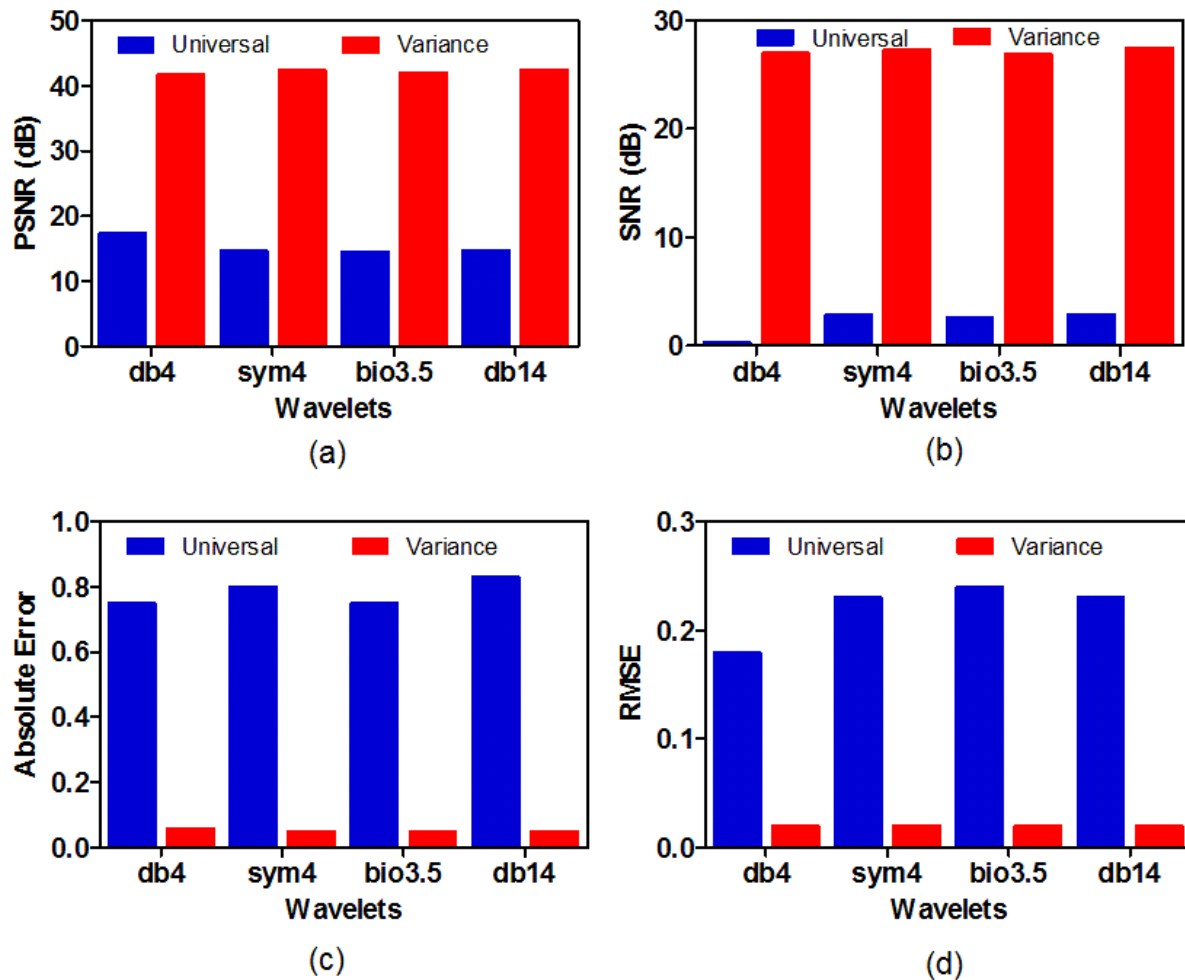| Wavelet/Threshold		Universal					Variance				
Parameters		PSNR	SNR	AE	RMSE	STD	PSNR	SNR	AE	RMSE	STD
db4	AVG	17.32	-0.33	0.75	0.18	0.11	41.72	26.98	0.06	0.02	0.22
	SD	5.84	1.47	0.69	0.17	0.09	9.48	4.48	0.11	0.04	0.18
sym4	AVG	14.77	2.84	0.80	0.23	0.22	42.35	27.27	0.05	0.02	0.21
	SD	5.29	0.75	0.77	0.21	0.18	9.40	4.42	0.11	0.04	0.17
bior 3.5	AVG	14.42	2.59	0.75	0.24	0.21	41.99	26.88	0.05	0.02	0.21
	SD	5.25	0.74	0.73	0.21	0.17	9.43	4.49	0.09	0.04	0.17
db14	AVG	14.77	2.92	0.83	0.23	0.22	42.50	27.42	0.05	0.02	0.21
	SD	5.29	0.74	0.78	0.21	0.19	9.41	4.44	0.08	0.04	0.17

Fig 4. Comparison of evaluation parameters of various wavelets using universal thresholding and variance thresholding methods ((a) PSNR (b) SNR (c) Absolute Error (d) RMSE)
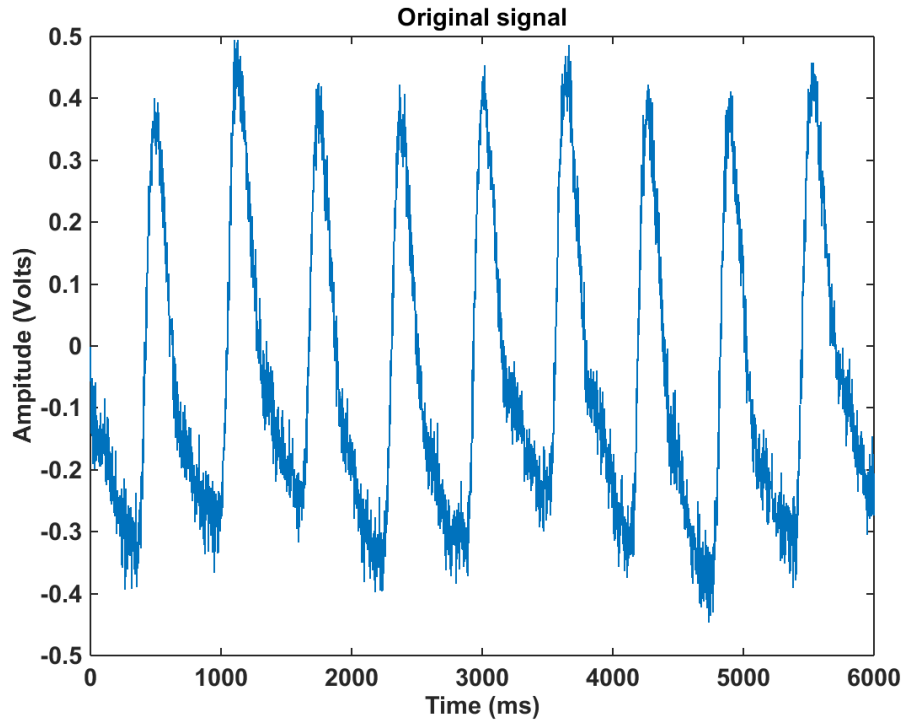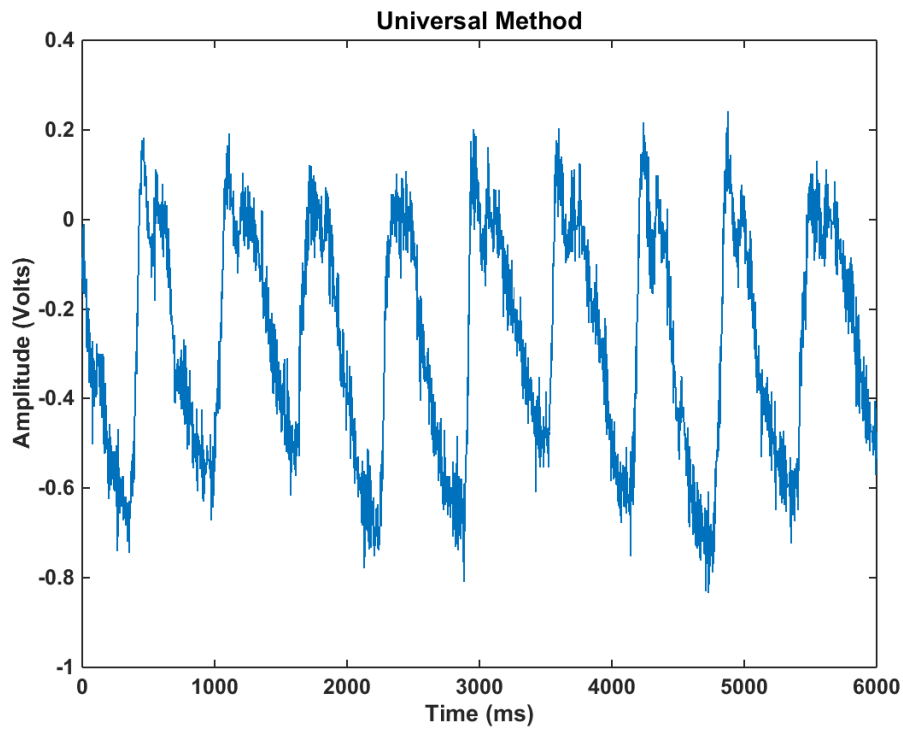
Fig. 5a: Original noisy wrist pulse

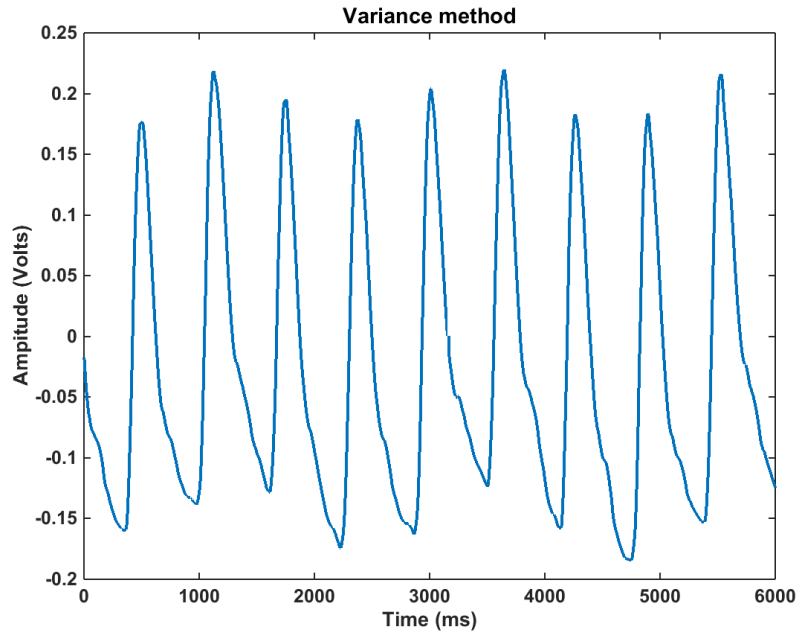Fig. 5b: Denoising with universal method

Fig 5. c: Denoising with variance method

Figure 5: Denoising waveform using universal method and variance method ((a) Noisy wrist pulse signal (b) Denoised waveform using the universal method (c) Denoised waveform using variance method)
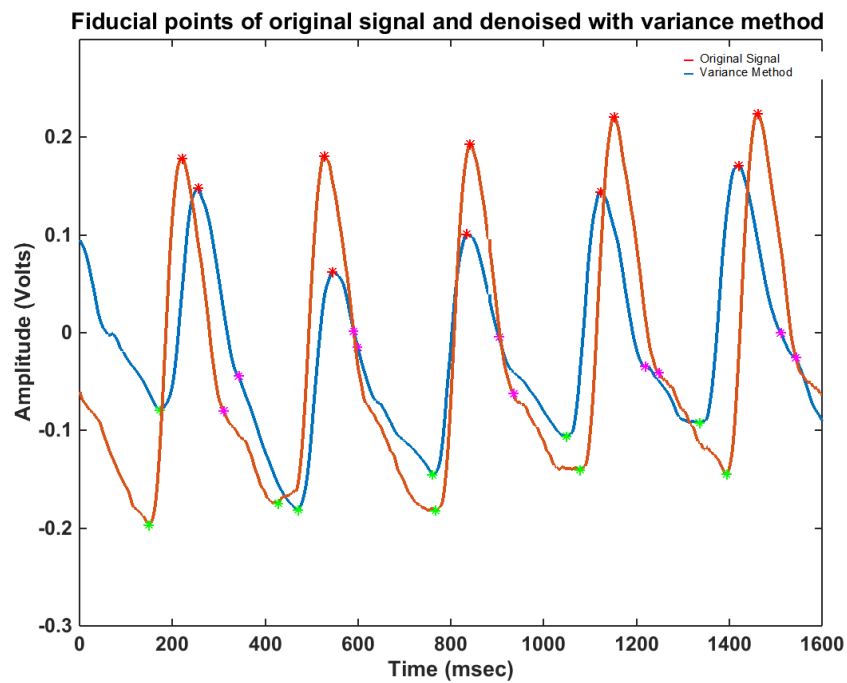

Fig 6. Fiducial points (Onset, Peak and Dicrotic notch) of original and denoised with db4 signal

The pulse contour using the variance thresholding method in shown Figure 6 clear depicts peak, the transition of pulse and notch of the pulse compared to other wavelets using universal thresholding techniques. Figure 6 shows that the original pulse signal is subjected to the Butterworth filter to remove the noise and later on to delineator. Onset, Peak and Dicrotic notch of wrist pulse (original and denoised signal) are obtained through the delineator method. The pulse rate of the subjects is calculated with **82.17 ± 12.6 (mean ± SD).**

4 Conclusion

In this study, denoising of wrist pulse with the evaluation parameters such as PSNR, SNR, AE and RMSE has been evaluated using wavelets such as Daubechies, Symlet and Biorthogonal. The performance of wavelets depends on the choice of decomposition level N and thresholding techniques. The variance thresholding technique quantified drastic improvement in PSNR, SNR and reduction in AE and RMSE compared to the Standard Universal thresholding technique. Wrist pulses signal denoised with variance method retains relevant information for future analysis. Variance thresholding method could be used for pre-processing of the bio-medical signals.

Acknowledgement

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