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A FUNCTIONAL COMPARISON OF WINDOW SHRINKAGE SOFT THRESHOLDING TECHNIQUE WITH SOFT AND HARD THRESHOLDING TECHNIQUES FOR IMPROVED PERFORMANCE

[1]Engr. Prof. C. B. Mbachu, [2]Engr. Dr. C. I. Obinwa and [3]Agbo Okechukwu Chuks
[1&2]Department of Electrical/Electronic Engineering, Chukwuemeka Odumegwu Ojukwu University, Uli campus, Anambra State, Nigeria, [3]Department of Electrical/Electronic Technology Education, Federal college of Education (Tech.) Omoku, Rivers State, Nigeria

ABSTRACT
Thresholding techniques are pivotal in signal processing including denoising, and various estimation tasks. This article compares the functional performance of the window shrinkage soft thresholding technique with traditional soft and hard thresholding techniques. Among these techniques, soft and hard thresholding are widely used for denoising.Through theoretical analysis and empirical evaluation, the trade-offs in terms of computational complexity, denoising, and reconstruction accuracy was identified. Window shrinkage soft thresholding (WSST) function was developed based on inverted hanning window function. An Electrocardiographic signal, sampled at a frequency of 360Hz was captured from Institute of Technology-Beth Israel Hospital (MIT-BIH) online database for a duration of 5 seconds. The captured Electrocardiographic signal was loaded into a matlab environment and contaminated with a 50Hz powerline noise generated with matlab. Based on the new shrinkage function, decomposition level of 4 and daubechies 4 (db4) mother wavelet, the denoising of the contaminated Electrocardiographic signal was extensively performed using four different threshold estimation rules, namely sqtwolog, rigrsure, heursure and minimaxi threshold rules. The introduction of window shrinkage soft thresholding offers potential advantages in performance and the results demonstrate the advantages of its approach, particularly in adaptive noise environments, where it significantly outperforms conventional techniques indicating that the developed thresholding technique outperforms the existing ones as it possesses a power spectral density of -30.129 dB whereas the two existing ones possess power spectral density of -27.23 dB each which means that the developed technique effects better attenuation of the powerline noise. A narrower window than the hanning window is recommended for future work as that will give better results comparatively.

Keywords: Electrocardiographic signal, Thresholding, Denoiding, hanning window.

INTRODUCTION
Thresholding is an essential operation in signal processing, image denoising, and compressed sensing. The primary goal of thresholding is to reduce noise while retaining significant signal features. Soft and hard thresholding methods are frequently employed due to their simplicity and efficiency.

Soft Thresholding (ST) operates by shrinking values that are below a certain threshold towards zero, and **Hard Thresholding (HT)** directly sets all values smaller than a threshold to zero. While these techniques have been successful in many applications, their performance can be suboptimal in certain contexts, especially when the noise is spatially or temporally varying.

In this study introduces and compare the **Window Shrinkage Soft Thresholding (WSST)** technique, a novel approach that dynamically adjusts the threshold based on local information in a windowed region of the signal. The goal of this article is to investigate how WSST performs relative to ST and HT in terms of noise reduction, sparsity, and computational efficiency.

Descrete Wavelet Transform
The analyzing wavelet in wavelet transform can be descretised by using descrete values of the

dilation parameter "a" and translation parameter "b" to produce a descretised analyzing wavelet as shown in equation (1).

$$\Psi_{m,n}(t) = \frac{1}{\sqrt{a_0^m}} \Psi\left(\frac{t - n a_0^m b_0}{a_0^m}\right) \quad (1)$$

The wavelet transform of the signal $x(t)$ using the descretised analyzing wavelet of (1) is called discrete wavelet transform (DWT) of the signal $x(t)$ as presented in equation (2)

$$X_{m,n} = \frac{1}{\sqrt{a_0^m}} \int_{-\infty}^{\infty} x(t)\, \Psi^*\left(\frac{t - n a_0^m b_0}{a_0^m}\right) dt \quad (2.)$$

$$= \langle x(t), \Psi_{m,n}(t) \rangle \quad (3)$$

Equation (3) is the inner product of the functions $x(t)$ and $\Psi_{m,n}(t)$ as defined in equation (5)

The original signal $x(t)$ can be obtained from its descrete wavelet transform $X_{m,n}$ by the expression called inverse descrete wavelet transform (DWT) as in equation (4) (Sawant and Patil, 2014; Gualsaqui et al, 2018).

$$x(t) = A \sum_{m=0}^{\infty} \sum_{n=0}^{\infty} X_{m,n}\, \Psi_{m,n}(t) \quad (4)$$

Where "A" is a constant value for normalization

Inner product of two functions $x(t)$ and $g(t)$ is defined as

$$\langle x(t) * g(t) \rangle = x(t) * g^*(t) \quad (5)$$

Where $g^*(t)$ is the complex conjugate of $g(t)$

Two functions are said to be orthogonal if the inner product of the functions is zero. That is

$$\langle x(t) * g(t) \rangle = x(t) . * g^*(t) = 0 \quad (6)$$

Three or more functions are said to be orthonormal if every two of the functions are orthogonal to each other. That is four functions as an example g(t), h(t), x(t), y(t) are orthonormal if

$$[\langle g(t) * h(t) \rangle = 0, \langle g(t) * x(t) \rangle = 0, \langle g(t) * y(t) \rangle = 0,\ \langle h(t) * x(t) \rangle = 0,\ \langle h(t) * y(t) \rangle = 0,\ \langle x(t) * y(t) \rangle = 0] \quad (7)$$

Procedure for Processing of Signals by Wavelet Transform

The procedure for using wavelet transform in processing signals involves three main steps: decomposition, thresholding and reconstruction.

1. Decomposition

In decomposition the signal is separated into various components with each component having its own coefficients, by either continuous wavelet transform (CWT) or descrete wavelet transform (DWT) depending on which one that is applicable. In otherwords, what the wavelet transform does in essence is to separate the signal.In order to do this a wavelet is first chosen and the level of decomposition N is also determined after which the signal is decomposed to the level N. The decomposition operation generates two types of coefficients; the approximation coefficients and the detail coefficients. The approximation coefficients Ak are generated by applying the appropriate low pass filter and a down sampler on the wavelet-transformed signal while the detail coefficients Dk are generated by applying the appropriate high pass filter and a down sampler on the wavelet-transformed signal, where k varies from zero to infinity (Lohbare, 2022). Fig 2.2depicts a three level decomposition of a signal $x(n)$ by descrete wavelet decomposition, where LPF and HPF are low pass and high pass analysis filters respectively, and the block $\downarrow 2$ represents the down sampling operator by a factor of 2. The input signal $x(n)$ is recursively decomposed into a total of four subband signals: a coarse signal $A3(n)$ and three detail signal, $D3(n), D2(n)$ and $D1(n)$ of three resolutions.

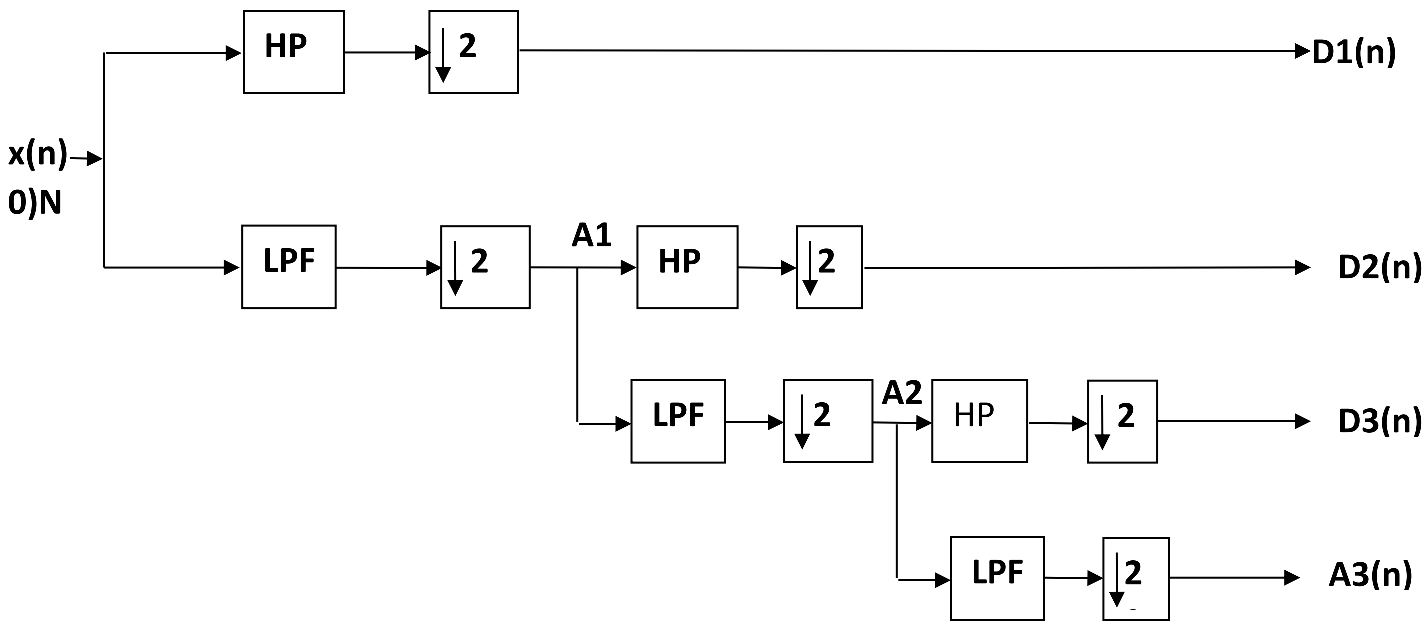

Figure 1: Three Level Descrete Wavelet Decomposition of Signal $x(n)$ (Ahmad et al, 2018).

2 Thresholding

It is established that after decomposition of noisy ECG signal into approximate and detail coefficients the coefficients that contain useful information are large compared to the coefficients of noise. Therefore, if the smaller coefficients are set to zero the noise is eliminated while keeping the important information of the original signal.This implies that one has to determine the appropriate threshold value for the wavelet coefficients of which any coefficient below the value is rejected because it amounts to noise. Standard thresholding techniques consist of hard thresholding and soft thresholding functions (Al-Timine, 2017, Mitra et al, 2014). Wavelet transformation threshold selection is very important because if the threshold value is too large or too small the signal cannot be estimated accurately.

A Hard Thresholding

This involves the process of setting to zero the elements with absolute values lower than the threshold value (Kumar et al., 2015). All the coefficients in hard thresholding below a predefined threshold value are set to zero. Mathematically hard threshold is defined as

$$y = \begin{Bmatrix} x, |x| \geq T \\ 0, |x| < T \end{Bmatrix} \tag{8}$$

Where T is the threshold value and x the wavelet coefficients

B. Soft Thresholding

Soft thresholding has better mathematical properties in comparison to hard thresholding. It is an extension of hard thresholding. It first sets the elements with absolute values lower than the threshold to zero. After setting the values to zero, it shrinks the non zero coefficients. In soft thresholding, the coefficients are linearly reduced in value. Mathematically soft threshold is defined as

$$y = \begin{pmatrix} Sig_n(x)\ (|x| - T), |x| > T \\ 0, |x| < T \end{pmatrix} \tag{9}$$

Where T is the threshold and x the wavelet coefficients. The steps of the algorithm using soft and hard thresholding are listed as follows:

1. Firstly, the received signal levels are separated by wavelets transform. Then, the received signal wavelet coefficients are calculated upto the desired level.
2. The variance (σ) of the noise is calculated using the wavelet coefficients.

$$\sigma = \frac{med(|x|)}{0.6745} \quad (10)$$

Where the med (x) denotes the median

3. The threshold value is calculated using the variance as (Al-Timime, 2017)

$$T = \sigma\sqrt{2\log(N)} \quad (11)$$

Where T is the threshold value and N the length of signal

4. Thresholding is performed using eqn (12) and eqn (13) after the calculation of the threshold value.
5. The original signal is reconstructed using the inverse wavelet transform and the retained coefficients.

Interval-Dependent Thresholding

In thresholding in which the noisy signal is decomposed with the detail coefficients and the approximately coefficients, the large and small coefficients represents the low and high frequency components, respectively. Wavelet coefficients that are smaller than the threshold result are discarded, and as such the original signal is recovered from the large coefficients. In interval-dependent thresholding the threshold values are acquired independently for individual level of the wavelet transformation. Since the high and low frequency parts of the signals, have diverse features such as mean value and standard deviation, the interval-dependent threshold value is calculated separately for each level and each interval is denoised (Ustundag et al, 2017). The block diagram of the interval-dependent thresholding approach is shown in figure 2 below.

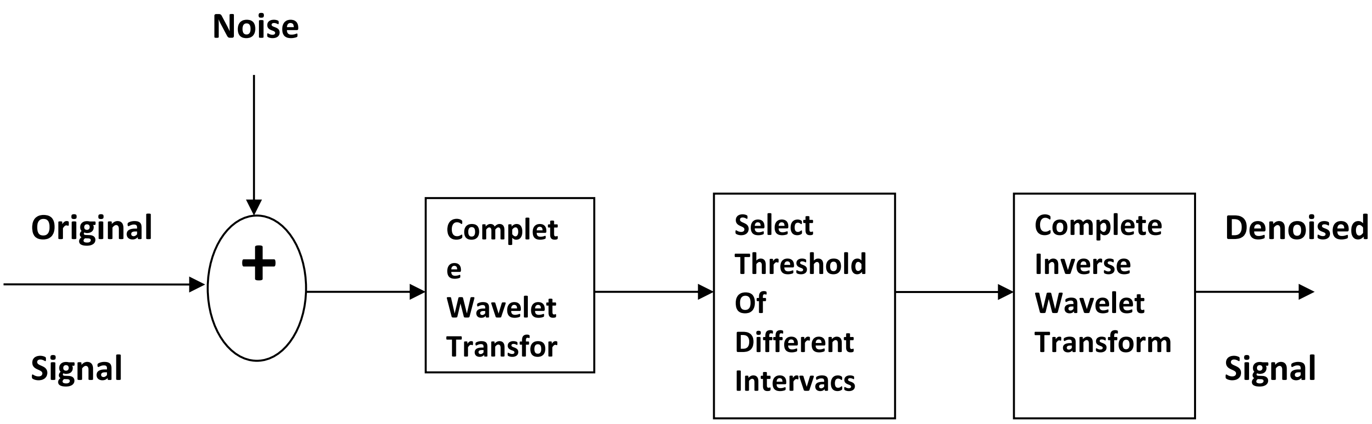

Figure 2: Block Diagram of Interval-Dependent Thresholding technique (Ustundag et al, 2017)

The algorithm of the wavelet-based interval-dependent denoising is described in the following steps:

Step 1: Decomposing the noisy signal using wavelet transform

Step 2: Noise variance at each wavelet is computed employing eqn (14)

Step 3: Computation of each level threshold utilizing eqn (15).

Step 4: Computation of the hard or soft threshold values, using the interval-dependent thresholding technique in the different intervals through eqn (13) or (14).

Step 5: The original signal is reconstructed from the retained coefficients using inverse wavelet transform.

The most essential attribute of this system is the determination of the basic threshold, for each level independently, and this enhances the algorithm functionality.

Reconstruction

The reverse process of combining the coarser approximation and detail coefficientsto yield the approximation coefficient at a finer resolution, performed by digital filtering is referred to as reconstruction in wavelet-transform based signal denoising process. The mathematical manipulation that causes the reconstruction is called the inverse descrete wavelets transform (IDWT) and the mathematical expression for the transform is as earlier presented in equation (4).

If the reconstruction mathematical manipulation is carried out by ordinary inverse wavelet transform (IWT), the mathematical expression for the transform is given as earlier given in (2) provided the admissibility of (3) is met. A three-level implementation of IDWT for signal reconstruction is shown in figure 2.4 (Elhanine et al, 2014, Ahmad et al, 2018) where LPF and HPF are low pass and high pass synthesis filters respectively, and the block $\uparrow 2$ represent the up sampling operator by a factor of 2. The four sub band signals $A3(n), D3(n), D2(n)\ and\ D1(n)$ are recursively combined to reconstruct the output signal $x(n)$. In the reconstruction the coarse approximation coefficients are applied to the low pass filter and the coarse detail coefficients are applied to the high pass filter to produce the fine approximation coefficients.

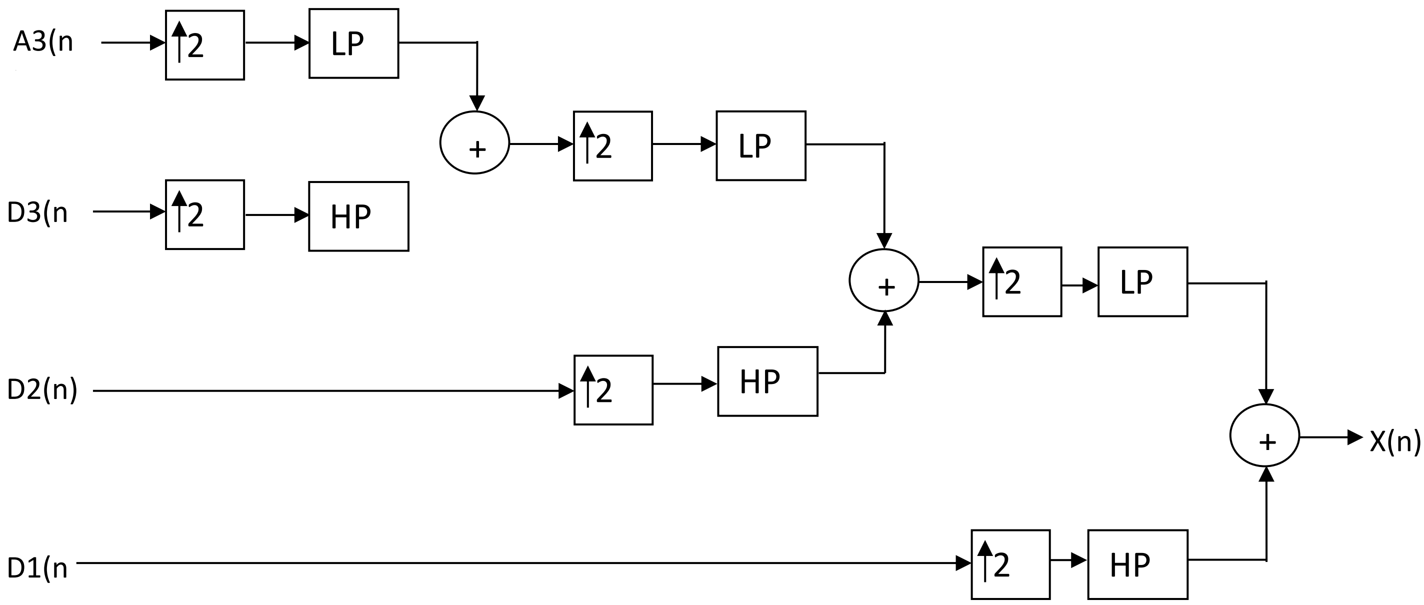

Figure 3: Three-level Implementation of IDWT for Signal Reconstruction Using Synthesis Filters (Elhanine, et al, 2014, Ahmad et al, 2018).

Description of a Denoising System

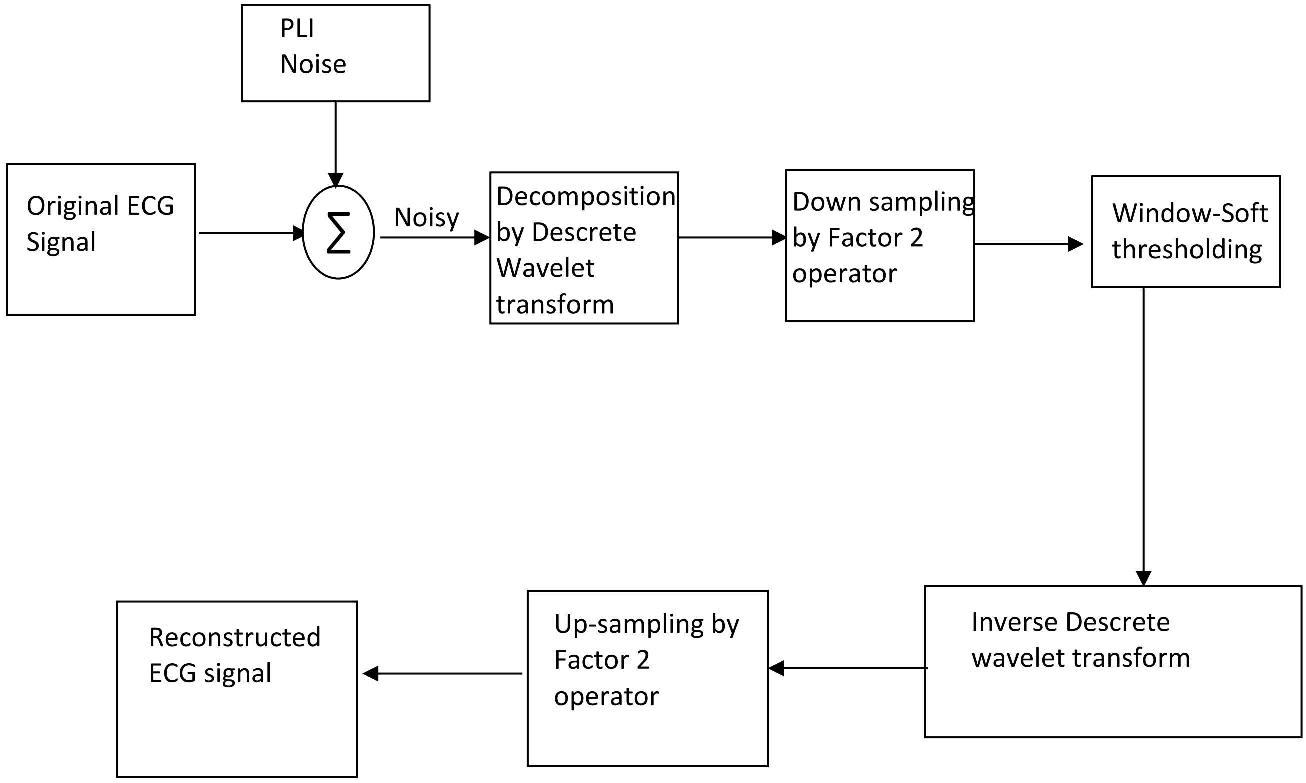

Figure 4: Block diagram of ECG Denoising System

The system functions by capturing an original ECG signal from MIT-BIH database and sampled with a sampling frequency of 360Hz and loading it into a matlab environment and 50Hz powerline noise added to it to constitute a noisy ECG signal. The noisy ECG signal is subjected to level 4 decomposition to generate approximation and detail coefficients using descrete wavelet transform with Daubechies (Db4) as the mother wavelet. This decomposition is realized through analysis filters. The coefficients are passed through the thresholding unit for interval dependent soft thresholding and shrank with the developed window thresholding shrinkage function (WTSF). After shrinkage the output signal is made of denoised filter coefficients that require reconstruction to obtain a denoised ECG signal. The reconstruction is realized by performing inverse descrete wavelet transform (IDWT) on the output coefficient using synthesis filters after which it is applied to up-sampling operator to perform up sampling operation by a factor of 2 to fix in the coefficients previously eliminated by down sampling after signal decomposition.

Development of the Window Shrinkage Soft Thresholding (WSST) Function

Shrinkage is a technique for shrinking or further reducing the coefficients of the detail coefficients after thresholding. It is part of soft thresholding. The function of thresholding is to remove all coefficients below the threshold value and retain all coefficients equal or above the threshold value. But in soft thresholding the retained detail coefficients after thresholding are further modified by shrinking them to further remove noise component coefficients. First, the threshold value is determined by using the appropriate thresholding rule. Threshold rule is a method of determining the threshold value to be applied in the processing. There are various thresholding rules in existence such as universal, minimaxi, rigrsure and heursure thresholding rules (Negendra et al, 2013, Devnah et al, 2015). SURE standards for Stein's unbiased risk estimate. In this research the universal thresholding rule will be used to determine the threshold value. The threshold value for universal thresholding rule is given (Nagendra et al, 2013, Bhargava and Choubey, 2017) as

$$T = \sqrt{2\log(N)} \quad (3.68)$$

If the data is not normalized with respect to noise standard deviation, then the threshold value is given (Nagendra et al, 2013, Kumar and Patel, 2012, Theja and Varadavajan, 2023, Madhukar et al, 2017, Georgieva-Tsaneva and Tcheshmedjiev, 2013) as

$$T = \sigma_n\sqrt{2\log(N)} \quad (15)$$

where T is the threshold value, N, the number of data samples and σ_n is the standard deviation of the noise component. The standard deviation of the noise σ is given by

$$\sigma_n = \frac{MAD}{0.6745} \quad (16)$$

where MAD represents the median absolute deviation of the coefficients of noise components.
After obtaining the threshold value, the next step is to shrink the detail coefficients using any appropriate shrinkage function.
The researcher's input in this work is to develop a new shrinkage function for the detail coefficients shrinkage.The window considered here is an inverted hanning window function. The hanning window function is as shown (Babu et al, 2015, Mbachu, 2015, Mbachu and Offor, 2013) in equation (3.70)

$$w(n) = 0.5 - 0.5\cos\frac{2\pi n}{N}, 0 \leq n \leq N \quad (17)$$

The inverted hanning window function is therefore given as

$$w(n) = 1 - (0.5 - 0.5\cos\frac{2\pi n}{N}), 0 \leq n \leq N \quad (18)$$

For the purpose of the work the limit of n in equation (3.71) is $1 \leq n \leq N$
The decomposition detail coefficients are denoted by Dk., while the window coefficients are given by w(k)
where k and n vary from 1 to N, the number of samples. The new developed shrinkage function is as stated in (3.72)

$$D(w) = \begin{Bmatrix} sgn(Dk.w(k))(Dk.w(k) - T) |Dk.w(k)| > T \\ 0 \qquad otherwise \end{Bmatrix} \quad (19)$$

where D(w) is the denoised signal coefficient sequence, T, the threshold value, Dk.w(k), the unshrunk product of detail coefficient and window coefficient sequence. Equation (19) is called window shrinkage softthresholding (WSST) function.A block diagram depicting the position of the shrinkage function in the denoising scheme of ECG is Figure 6.

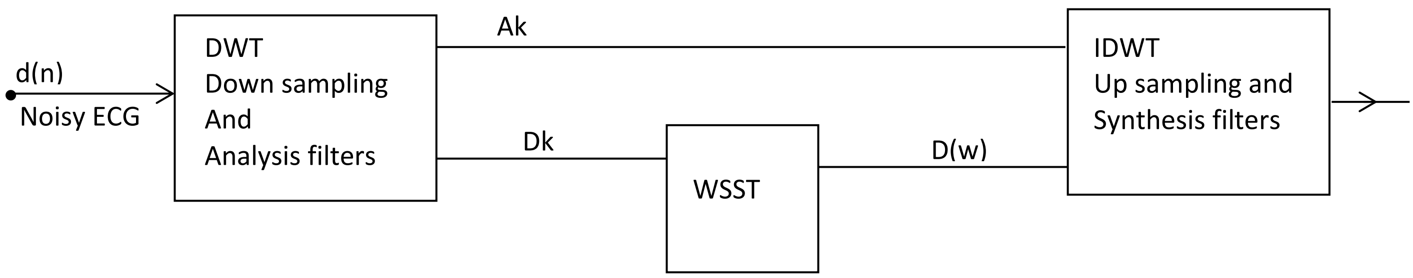

Figure 6: ECG Denoising Scheme Showing the Position of the Window shrinkage Function

Comparison of the Developed WSST and Other Existing ThresholdingTechniques
Using the optimum decomposition level of five, most effective threshold estimation rule of minimaxi, and mother wavelet of db4, performance of the developed technique and two main existing thresholding techniques of conventional soft thresholding and hard thresholding techniques were compared.
Comparison of PSD, SNR, MSE α MAE of ECG Denoised with WSST, Soft α Hard Techniques

Thresholding Type	Developed WSST	Soft Thresholding	Hard Thresholding
PSD	30.129	27.23	27.23
SNR in dB	31.5643	64.2446	64.2446
MSE	0.0209	7.9540E-004	7.9540E-004
MAE	0.8223	0.2121	0.2121

Table1: Comparison of WSST with Soft and Hard Tresholding Techniques

The results from table 1 depicting the comparison of the developed WSST with the existing soft thresholding and hard thresholding shows that the developed WSST is better in removing the powerline noise at the normalized frequency of 0.1 radian because it has highest PSD value, implying better attenuation of the noise. However, because of the fact that the window used in the developed technique is not very narrow, it slightly reduced the amplitude of some useful signals and since SNR is calculated from amplitude to amplitude difference between the original signal and the denoised signal, the SNRs of the signals denoised by soft thresholding and hard thresholding are higher than that denoised by WSST. Also, the MAE is calculated from the highest amplitude difference between original signal and the denoised signal, for the same purpose of amplitude decrease of useful signal by the window, the MAE of the ECG signal denoised by soft thresholding and hard thresholding are smaller than that of the developed WSST. This does not suggest that the noise is high in WSST or that the MAE is very high in WSST because these reduced signal amplitudes are still useful signals. Amplification after thresholding can be used to improve the results of the WSST or by applying very narrow window function that will minimize useful signal amplitude reduction.

CONCLUSION

The work developed a new thresholding technique called window shrinkage soft thresholding (WSST) technique which was used to denoise ECG signal of powerline interference by wavelet transform and thresholding. The wavelet used for the decomposition is db4 and the initial decomposition level is 4. The performance of the technique was evaluated by comparing with existing techniques (soft and hard thresholding) with attenuation of the powerline noise at 50Hz in the denoised ECG signals through their power spectral density responses. The attenuation values showed that the developed technique is effective. Other criteria for evaluation are the signal to noise ratio, mean square error and maximum absolute error and each criterion confirmed the effectiveness of the developed technique.

RECOMMENDATION

This work is recommended for cardiological equipment manufacturers to improve the performance of their electrocardiographic test equipment and instruments. The technique can also be deployed to other areas of signal processing like denoising of electroencephalographic EEG), electromyographic (EMG), electrooculographic (EOG) and audio signals as it may also perform in those areas. In terms of future work, a very narrow window is recommended for the shrinkage application as it will decimate the noise only without affecting the wanted signals in any form.

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