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A comparative Analysis on De-Noising ECG Signals using Discrete and Stationary Wavelet Transforms

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Abstract - *Electrocardiographic (ECG) signal is used in heart rate monitoring (HRM) devices to analyze the heart rate of a person. High processing speed along with accurate results is a requirement for this purpose. But due to various noises such as baseline noise, white Gaussian noise and muscular movement, it is necessary to remove the noises to accurately measure the heart rate. This paper compares algorithms which use Discrete Wavelet Transform (DWT) and Stationary Wavelet Transform (SWT) to detect the heart rate to de-noise ECG. The MIT-BIH Arrhythmia Database is used for reference in this work. Simulation results and its analysis using Signal to Noise Ratio (SNR) and Root Mean Square Error (RMSE) show that the SWT method is better than the DWT method.*

Key Words: Electrocardiography (ECG), Heart Rate, Discrete Wavelet Transform (DWT), Stationary Wavelet Transform (SWT), De-Noising

1. INTRODUCTION

ECG signals give the electrical activity of the heart. It is a graph of voltage versus time of the electrical activity of the heart generally obtained by using electrodes placed on the skin. The primary use of an ECG is to determine heart rate and to diagnose any cardiovascular disease (CVD). It has three main components: (i) P wave, which represents the depolarization of the atria (ii) the QRS complex, which represents the depolarization of the ventricles and (iii) T wave, which represents the repolarization of the ventricles as seen in Fig 1.

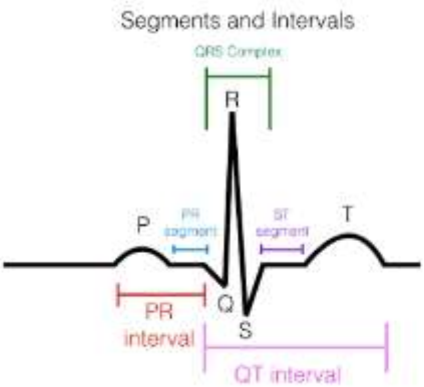

Fig -1: Normal Sinus Rhythm

Due to the rapid rise in population and increasing health concerns, automated ECG analyser has great importance. Also the field of telemedicine has gained importance in recent times. During the acquisition and transition of the signal, it gets corrupted by various noise sources. They can be due to movements of the person, electronic noise, power line interference or even involuntary muscular movements. These noise signals interfere with the non-erroneous reading of the ECG signal which makes it essential to de-noise the signal. The most common method used in de-noising is Discrete Wavelet Transform (DWT). And a newer method is used is Stationary Wavelet Transform (SWT).

In literature available, expansive forms of DWT are analysed such as double-density discrete wavelet transform, dual-tree discrete wavelet transform and double-density dual-tree discrete wavelet transform techniques [1]. An analysis based on symlet wavelet used for decomposition shows that since its structure is similar to that of ECG, it can be used effectively for ECG signal denoising [2]. Using DWT, mixed noises could be removed and various thresholding methods such as Universal thresholding, maxmin and adaptive thresholding are analysed [3-6]. Other popular methods use Empirical mode decomposition (EMD) prior to DWT [7].

Similar methods of decomposition have used SWT and universal thresholding. Comparisons of wavelet packet, lifting wavelet and SWT used in denoising ECG signals were analysed to present SWT as a better algorithm based on SNR values [8]. ECG noise reduction based on SWT have been later explored in various algorithms [9-12]. SWT has also been used to remove motion artefact noise in Ambulatory ECG signals [13].

This paper provides a comparative study on the two methods of de-noising noisy ECG signal. The outline of the article is presented as follows. Section 1 introduces ECG and its need along with the literature review of DWT and SWT used in denoising ECG. Section 2 gives a brief description of the DWT and SWT and the performance metrics are mentioned in Section 3. Section 4 and 5 gives the denoising algorithms using DWT and SWT respectively. Section 6 illustrates the experimental results and observations made and Section 7 presents conclusions based on the comparisons between the two methods. The MIT-BIH Arrhythmia Database is used in this work.

2. WAVELET TRANSFORM

Wavelet transform (WT) is capable of providing the time and frequency information simultaneously, hence giving a time-frequency representation of the signal. The two types of wavelet transforms discussed here are DWT and SWT.

2.1 Discrete Wavelet Transform

The discrete wavelet transform consists of a series of low pass and high pass filters as shown in Fig 2. Thus, on performing DWT, the signal is split into ranges of frequencies called the detail (CD) and approximation (CA) components. The lowest frequencies are found in the CA component while the higher levels of Detail components contain the higher frequencies. The steps followed to perform N level DWT is as follows:

Step 1. Select a mother wavelet that is similar to the chosen signal. The mother wavelet must also be based on the features that needs to be extracted from the signal. Based on the mother wavelet, the low pass and high pass filter coefficients are chosen.
Step 2. Apply both high pass and low pass to the signal. The output of the low pass and high pass filters are called A_i and D_i respectively where i is the i^{th} level of decomposition.
Step 3. Downsample the A_i and D_i by 2
Step 4. Use the Downsampled A_i component obtained from step 3 as the input to repeat step 2.
Step 5. Steps 2, 3 and 4 are repeated until i reaches a predefined value N.

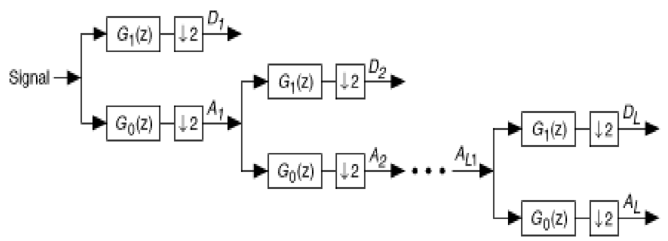

Fig -2: Block diagram of DWT where G1(z) and G0(z) are high pass and low pass filters

2.2 Stationary Wavelet Transform

Stationary wavelet transform is similar to Discrete Wavelet Transform. The signal is passed through a series of high pass and low pass filters shown in Fig 3. Unlike the DWT, the SWT does not down sample signals after every filter, instead the filter coefficients of one stage are up sampled to get the next stage coefficients. This is designed to overcome the lack of translation-invariance of the DWT. The steps followed to perform N level SWT is as follows:

Step 1. Select a mother wavelet that is similar to the chosen signal. The mother wavelet must also be based on the features that needs to be extracted from the signal. Based on the mother wavelet, the low pass and high pass filter coefficients are chosen.
Step 2. Apply both high pass and low pass to the signal. The output of the lowpass and highpass filters are called A_i and D_i respectively where i is the i^{th} level of decomposition.
Step 3. The filter coefficients for next stage is calculated by upsampling the previous filter coefficients by a factor of 2.
Step 4. Use the A_i component obtained from step 2 as the input to repeat step 2 with the upsampled coefficients obtained in step 3.
Step 5. Steps 3 and 4 are repeated until i reaches a predefined value N.

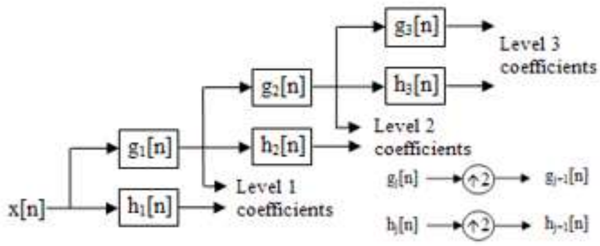

Fig -3: Block diagram of SWT where g1[n] and h1[n] are low pass and high pass filters

2.3 Mother Wavelet

There are a wide variety of wavelets available from different families. To overcome the disadvantage of having long computational time due to lengthy filters or unappealing blocks due to very short filters, Symlet 7 wavelet is used. The properties of this wavelet are near symmetric, orthogonal and biorthogonal.

3. PERFORMANCE METRICS

The following are the performance parameters based on which the two algorithms are analysed and compared:

Signal to Noise Ratio (SNR) is the ratio of signal power to the noise power, often expressed in decibels(dB). The higher the SNR, the better the signal output. SNR can be calculated using Equation 1.

$$SNR = \frac{Power\ of\ Signal}{Power\ of\ Noise\ present\ in\ the\ signal} \quad (1)$$

Root Mean Square Error (RMSE) is the root of mean of error squared present in the signal. The lower the RMSE, the better the signal output. RMSE can be calculated using Equation 2.

$$RMSE = \sqrt{\frac{1}{N}\sum(Original\ Signal - Denosised\ Signal)^2} \quad (2)$$

4. ALGORITHM BASED ON DISCRETE WAVELET TRANSFORM

The mother wavelet is chosen before performing DWT. The mother wavelet decides the filter coefficients. Once the wavelet in chosen, DWT is performed on the input noisy signal. The following are the steps to perform denoising on ECG using the DWT: The block diagram of the algorithm is shown in Fig 4.

Step 1. Apply DWT on the noisy ECG signal.
Step 2. Perform Universal Threshold to find threshold (T) given by Equation 3.

$$T = SD\sqrt{2\log_{10} M} \qquad (3)$$

where, SD = standard deviation of the noisy ECG and M is length of signal.
Step 3. Using the selected threshold perform soft thresholding on the CD component obtained in Step 1. Soft thresholding is given in Equation 4.

$$y(t) = |y(t)| - T \ \ if\ y(t) \geq T$$
$$0 \qquad if\ y(t < T) \qquad (4)$$

Step 4. Finally, apply inverse DWT on the thresholded CD and CA to obtain the de-noised signal.

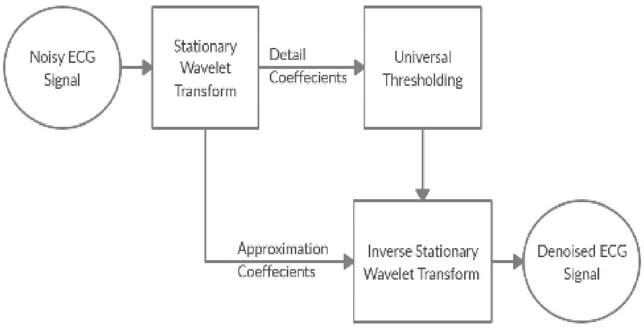

Fig -4: Block Diagram of Denoising using DWT

5. ALGORITHM BASED ON STATIONARY WAVELET TRANSFORM

The mother wavelet is first chosen before performing SWT. The mother wavelet decides the filter coefficients. Once the wavelet in chosen, SWT is performed on the input noisy signal. The following are the steps to perform denoising on ECG using the SWT: The block diagram of the algorithm is shown in

Step 1. Apply SWT on the noisy ECG signal.
Step 2. Perform Universal Threshold to find threshold (T) given by Equation 3.
Step 3. Using the selected threshold perform soft thresholding on the CD component obtained in step 1. Soft thresholding is given in Equation 4.
Step 4. Finally, apply inverse SWT on the thresholded CD and CA to obtain the de-noised signal.

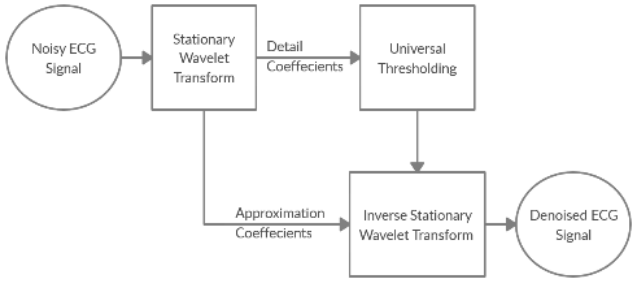

Fig -5: Block Diagram of Denoising using SWT

6. RESULTS AND ANALYSIS

The MIT-BIH Arrhythmia Database is used for analyzing the algorithms presented in the paper. Fig 6 shows a sample noise free ECG signal '103m' from the database.

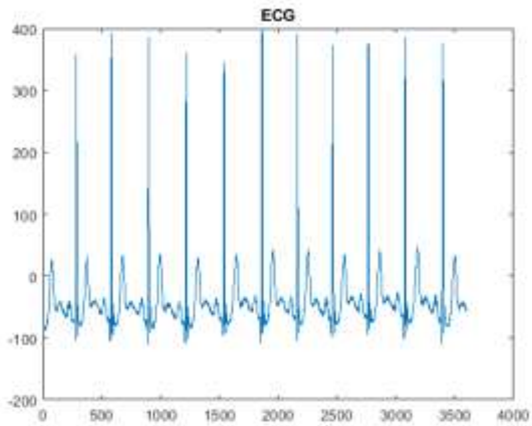

Fig -6: Noise free 100m ECG signal

Additive White Gaussian Noise (AWGN) is added to the signals with SNR ranging from 10 dB to 20 dB in varying steps of 2dB or 3dB. These noisy signals are used as input to the denoising algorithms. The '103m' signal with 15dB SNR (AWGN noise) is shown in Fig 7.

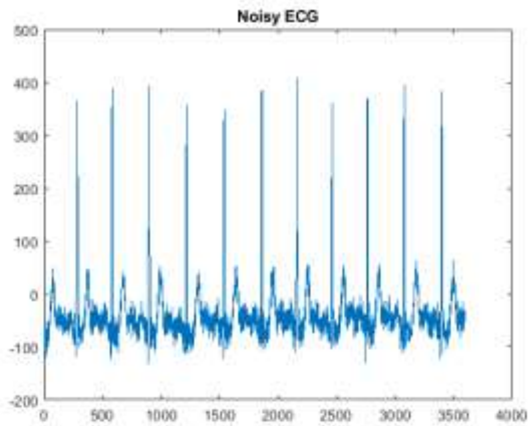

Fig -7: ECG signal '103m' with 15dB input SNR

The denoising algorithms are applied on the signals to obtain the denoised signals. The denoised signal obtained on performing the DWT based algorithm (on signal in fig 7) is shown in Fig 8. Similarly, the denoised signal obtained on performing the SWT based algorithm (on signal in fig 7) is shown in Fig 9. It can be seen that the signals are denoised and are visually clearer to analyse. The same is performed on all other input signals and the SNR and RMSE values are calculated and tabulated in Tables 1, 2 and 3.

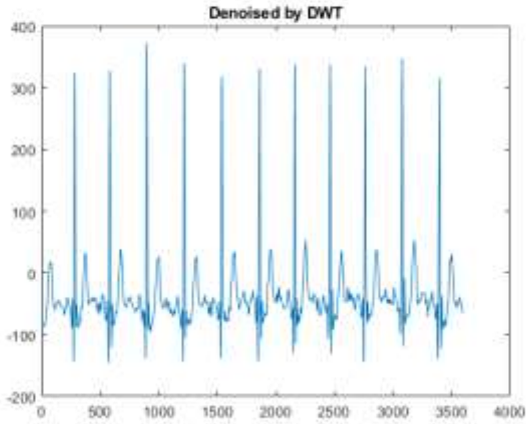

Fig -8: Denoised signal using DWT based algorithm

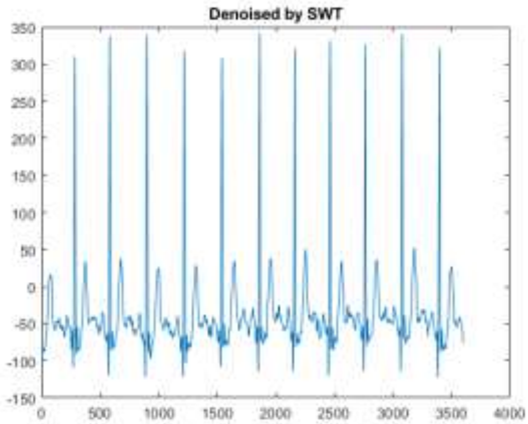

Fig -9: Denoised signal using SWT based algorithm

Noise level of 10dB is added to the fifteen randomly chosen signals and the results for both SWT denoising and DWT denoising methods are tabulated and shown in Table -*1*. The Root Mean Square Error and SNR is also calculated for a 100m input SNR signal and is tabulated in

Table -2. and Table -3 respectively for SNRs varying from 5dB to 20 dB. The lower the RMSE, the better is the signal. Also, Higher the SNR, the better the signal.

7. CONCLUSION

The ECG signal is used for finding the heart rate and in the diagnosis of cardiovascular diseases. These signals are affected by various noises which can be denoised effectively using wavelet transform. The two methods analysed in the project are Discrete Wavelet Transform and Stationary wavelet transforms. The universal thresholding is applied on the detail components of both the transforms and on reconstruction the two denoised signals were compare. The performance is evaluated based on the Signal to Noise ratio and Root Mean Square Error. It is found that the algorithm with SWT has higher SNR and lower RMSE compared to DWT algorithm. These simple yet effective algorithms can be used to denoise ECG signals both in medical equipment and also in-home health devices.

Table -1: SNR comparisons for signals with input SNR 10dB

Input	DWT method	SWT method
100m	14.4047	15.3243
101m	15.0330	15.6539
103m	12.9381	14.2390
105m	17.1473	18.3974
106m	12.0991	14.0412
107m	17.1203	17.8164
108m	18.1834	18.5385
109m	18.8530	19.2345
114m	15.3928	16.1829
116m	16.3652	17.1717
200m	16.5690	17.4516
215m	12.4422	13.6512
222m	12.3819	12.7522
230m	13.7674	14.8352
234m	13.6670	14.4776

Table -2: SNR comparisons for 100m signals

Input SNR (dB)	Output SNR (dB)	
	DWT method	SWT method
5	11.9687	12.7105
7	13.3607	14.1269
10	14.4047	15.3243
12	15.4861	16.4139
15	16.0522	17.0019

17	17.6678	18.7407
20	21.9929	22.1395

Table -3: RMSE comparisons for 100m signal

InSNR (dB)	InRMSE (dB)	RMSE of DWT method	RMSE of SWT method
5	0.6740	0.3088	0.2804
7	0.5353	0.2594	0.2352
10	0.3793	0.2268	0.2019
12	0.2921	0.2010	0.1789
15	0.2150	0.1883	0.1671
17	0.1723	0.1755	0.1536
20	0.1232	0.1689	0.1466

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