ECG SIGNALS PROCESSED USING THE FRAMELET TRANSFORM

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ABSTRACT : ECG readings should be cleaned up since noise often appears when data is captured. Wavelet modifications are presently the most used method for standardizing ECG data. This post will explain how to leverage the Framelet domain to improve ECG readings. First, the data must be separated using the Framelet transform. After deconstruction, the images are denoised using a median-based approach. The success of the technique is evaluated by comparing the results to the wavelet transform output.
Keywords: ECG Signal Denoising, Framelet Transform, Thresholding, Wavelet Transform

1. INTRODUCTION

Electrocardiograms (ECGs) are crucial medical devices that detect abnormalities in cardiac rhythm and identify problems with the heart's electrical system. Diarrhea and extended ECG beats are indicators that someone may have a heart condition. Interferences at all levels can have an effect on the results of an ECG. Interruptions are frequently generated by muscle noise, baseline variations, power fluctuations, electrode-induced motion effects, and muscle variability. If the system is not properly constructed, power line interference at 50 or 60 Hz may occur. A chest-lead ECG reading may be erroneous if the patient's chest moves often, coughs frequently, or breaths quickly and strongly. During a limb-lead ECG, arm or leg motions may result in an incorrect readout. Baseline drift occurs when the temperature and bias of the measurement devices fluctuate. Motion effects are temporary alterations to the baseline caused by sensor movement and skin resistance variations. In certain instances, the ECG graph may show indications of excessive noise. Understanding the electrocardiogram (ECG) pattern is difficult, if not impossible, as a result of these undesirable modifications. Many data analysts employ the discrete wavelet transform (DWT). Schools teach a variety of areas, including arithmetic, science, physics, biology, and health. The wavelet transform helps to describe the behavior of the ECG data. Nagendra et al.employed the wavelet transform approach to evaluate non-stationary datasets such as ECGs, which reveal activity that fluctuates about. To clean up ECG data, apply the universal thresholding, minimax, and heuristic techniques. Poornachandra and Kumaravel developed an adjustable subband shrinking approach that reduces both hard and soft shrinkage. ECG signals were analyzed using the wavelet approach. The subband adaptive shrinkage method, which uses nonlinear hyperbolic functions, is projected to outperform the soft shrinking strategy. Then, this strategy was compared to hypershrinking, an enhanced thresholding technique based on the universal threshold. The user-supplied content contained the citation." David Donoho devised the gentle thresholding approach for removing noise from data. Compared to Visushrink techniques that rely on mean squared error, our method produced higher-quality images. Khaled Daqrouq and Mikhled Alfaouri improved their process by categorizing the data into five levels using Daubechies' wavelet function. Following extensive analysis, the region where the precise coefficients of the chaotic signal and the original signal deviated the least was identified. However, Donoho's [4] noise reduction technique was applied. An electrocardiogram (ECG) can provide useful information regarding a person's level of mental stress. As described in reference, a strategy

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based on the wavelet transform was developed to achieve this goal. Niranjana and Meenakshi suggested using Daubechies wavelets, which were developed to discriminate between pathological and normal ECG signals in the situation of ischemia.The reference has more information on how to utilize independent component analysis to remove average wander noise from ECG data.Crosstalk can be decreased using the Discrete Wavelet Transform (DWT) approach. However, there are several fundamental issues, including the difficulty in determining the best course of action, the limited availability of phase information, and the susceptibility to change. Because of these constraints, it cannot be used for certain signal processing tasks. A recent study discovered some critical information about frames. Frames outperform bases in terms of time and frequency precision. Builders can be more creative when they have a wider range of building frames to choose from. A wavelet frame requires a collection of oversampled Finite Impulse Response (FIR) filters with the appropriate properties. In,Selesnick et al. introduced the Framelet. The wavelet frame under examination has certain similarities with Daubechies' orthonormal wavelet transform. The change discussed is known as the "double density discrete wavelet transform"and it entails multiplying each scale by twice the number of wavelet coefficients that the DWT adds. It is consequently less likely to change than the DWT.The dual-tree complex wavelet transform (DT CWT) provides a number of advantages, including the ability to discriminate between multiple directions while being almost constant in many of them. Its orthogonality and symmetry properties are also improved. Recently, framelet modification has been applied to a wide range of applications. Peak Signal-to-Noise Ratio (PSNR) values in the Framelet domain usually exceed those in the Wavelet domain, with the purpose of reducing noise in grayscale pictures. Framelet can split tubular structures and outperforms its predecessors Furthermore, Framelet has been used to improve films, provide new visual data, and extract images based on their content . The use of the Framelet transform domain to remove distortion from ECG data is the study's most significant contribution. This article's subsequent sections are organized as follows: Section 2 includes more information about the Framelet change. The noise reduction strategy from Section 3 (which used the Framelet transform) is demonstrated in Section 4. This finishes section five of the study.

2. THE FRAMELET TRANSFORM

To optimize any function f(t), use a scaling function φ(t) and a wavelet function ω(t). The Framelet transform combines a scaling function (j) with two wavelet functions (ω1 (t) and ω2 (t) to work at various resolutions. The wavelet transform consists of a wavelet function and a scaling function. By extending the scope of the Framelet transform with an additional wavelet function, it is possible to detect frequencies that change with time.

Using equations (1) through (3), compute the wavelet functions and scales for the low and high pass filters. The filters hi (n) and hi (-n) must meet the optimal reconstruction criterion. When the angular frequency ω is equal to zero, Ki represents the number of zeros in Hi (ejw), where i ranges from 1 to 2. The z-transform for any sequence hi(n) is defined as follows:

$$H_0(z) = Q_0(z)(z+1)^{K_0} \quad (1)$$

$$H_1(z) = Q_1(z)(z+1)^{K_1} \quad (2)$$

$$H_2(z) = Q_2(z)(z+1)^{K_2} \quad (3)$$

K0 defines the degree and regularity of polynomials produced by shifting integer values of φ(t). K1 and K2 indicate the number of zero moments in the wavelet filters, respectively. To improve consistency, increase the value of K0 in proportion to the other two variables. Table 1 shows the analytical filters with the shortest lengths: h0 (n), h1 (n), and h2 (n).

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Table 1. Set of analysis filters

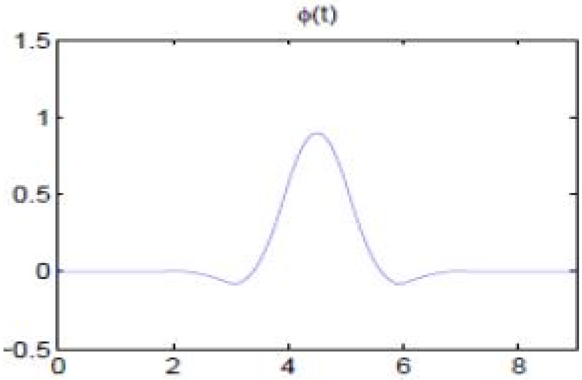
$h_0(n)$	$h_1(n)$	$h_2(n)$
0.076223	-0.020547	-0.027160
0.349088	-0.094105	-0.124388
0.602089	-0.122897	-0.130165
0.441941	0.061353	0.742137
0.060823	0.606332	-0.460423
-0.083923	-0.311319	
-0.032029	-0.118815	

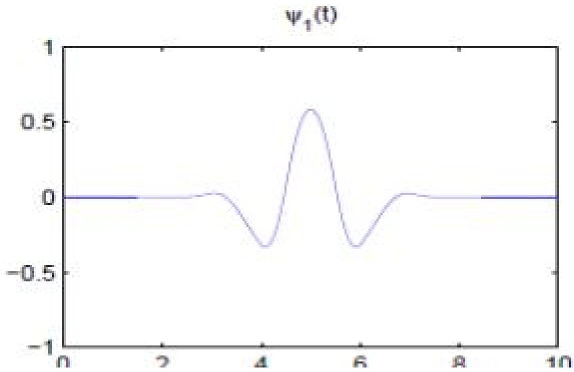
The scaling function and the two wavelet functions are defined by Equations (4) and (5).

$$\Phi(t)=\sqrt{2}\sum_{n} h_0(n)\Phi(3t-n) \tag{4}$$

$$\Psi_i(t)=\sqrt{2}\sum_{n} h_i(n)\Phi(3t-n), i=1,2 \tag{5}$$

The coefficients in different sub bands of the Framelet transform are correlated. Therefore, changes in one coefficient can be compensated by its related coefficient in the other sub band. This property helps to remove the noise more effectively from the corrupted signal. The generators of a Framelet frame with parameters K0 = 5, and K1 = K2= 2 are shown in Fig. 1





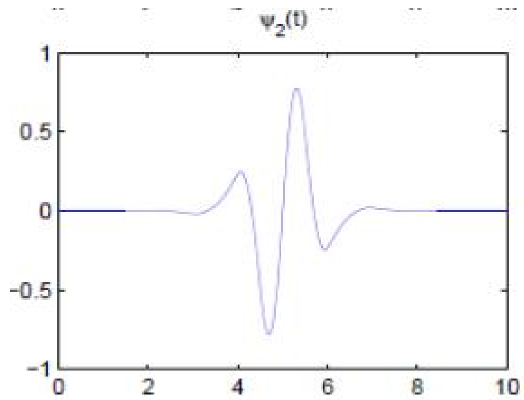


Fig. 1: Generators of a Framelet frame

3. IMAGE DENOISING USING THE FRAMELET TRANSFORM

Figure 2 uses the Framelet transform to demonstrate how the suggested denoising method breaks down ECG data. Framelet changes are performed using libraries of analysis and synthesis filters. The bank has three instruments for analysis. The low pass filter is denoted by h0 (n), whereas the two high pass filters are h1 (n) and h2 (n). First, the analysis filter bank divides the ECG signal into three subbands before transmitting it to the system. Following that, the subbands are shifted back by two. The smaller bands are broken down using the Framelet transform, followed by a cutoff. These numbers are fed into the inverse Framelet transform before proceeding to the next phase. In this adjustment, the synthesis filter bank is employed to restore the missing signal as noise. Figure 3 depicts a variety of analysis tools that the Framelet transform can use.

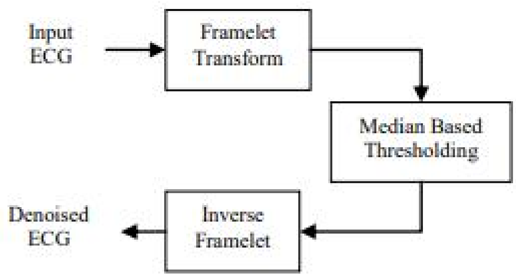


Fig 2: Framelet based denoising system

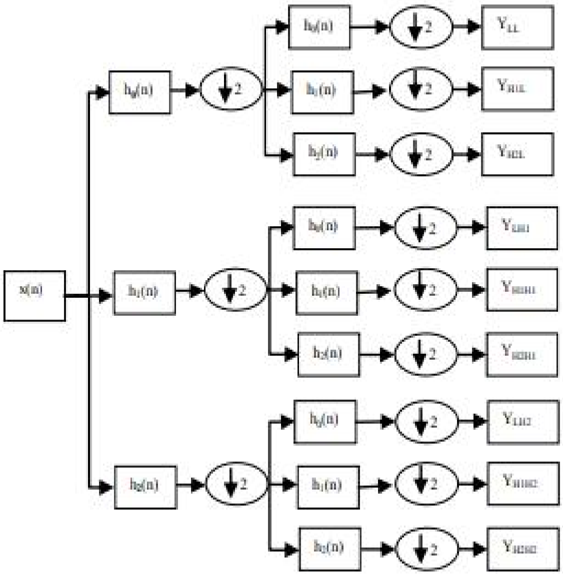


Fig 3: Analysis filter banks

3.1 Noisy Signal Generation

Several high-fidelity electrocardiogram (ECG) signals are first collected from the Physiobank database [18] to generate a noise signal. Several factors can influence ECG readings, including baseline drift, power line interference, muscular contraction, and Gaussian noise, which can create distortion. The primary purpose is to decrease Gaussian noise. As a result, combining Gaussian noise with a healthy signal produces a signal with increased noise levels. The probability density function for a Gaussian random variable x is computed using equation (6).

$$p(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{1}{2}(\frac{x-\mu}{\sigma})^2} \quad (6)$$

The symbol σ indicates the standard deviation, and μ represents the mean.

3.2 Denoising

The denoising technique is implemented in the Framelet domain. The chaotic ECG data was analyzed using the Framelet transform, which resulted in a representation of the dispersion of three discrete subbands within the Framelet domain. The deconstructed subband signals are recorded by the cell array and then sent to the thresholding algorithm for further processing. The function compares the Framelet coefficients and the estimated threshold value (T) in two steps. The next sections provide succinct explanations of fundamental concepts for reducing interference in the ECG signal.

3.2.1 Sure Shrink

SureShrink is a thresholding method that employs Stein's unbiased risk estimator to determine a distinct threshold for each subband. The Sure threshold is exactly defined as follows.

$$T = \sqrt{2}\log\frac{N\log N}{\log 2} \quad (7)$$

N denotes the number of Framelet coefficients in a specific subband.

3.2.2 Visu Shrink

The authors developed the Universal threshold [3], which is used in the VisuShrink thresholding technique. SeeShrink does not aim to achieve the lowest possible mean squared error. Some things are inexorable, while others are readily stopped. Using this technique may improve audio quality. This figure depicts the size of VisuShrink.

$$T = \sigma\sqrt{2}\log N \quad (8)$$

This depicts the amount of noise present as well as the number of samples that make up the signal.

3.2.3 Median based Threshold

The median-based filter successfully removes sub-band noise, leaving a signal that is very similar to a noise-free signal. Furthermore, the level of risk is lower than it is generally. When employing the median-based technique, the following steps are used to find the barrier:

$$T = \sigma\sqrt{2}\log N \quad (9)$$

The Framelet coefficient, or π, is the center integer in each subband.

Once a defined boundary has been established, the user can choose between a firm or flexible barrier. Above a certain threshold, framelet coefficients are preserved. Each variable's initial value is zero. When the Framelet coefficient surpasses the barrier, the ceiling lowers.

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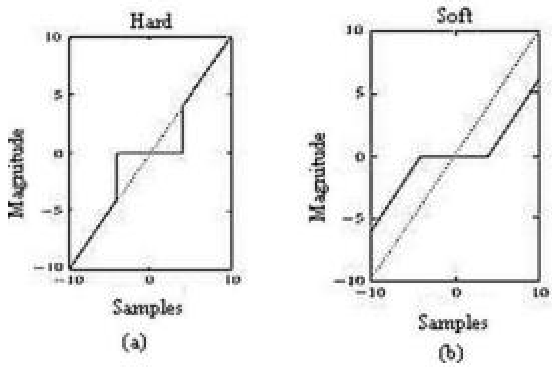
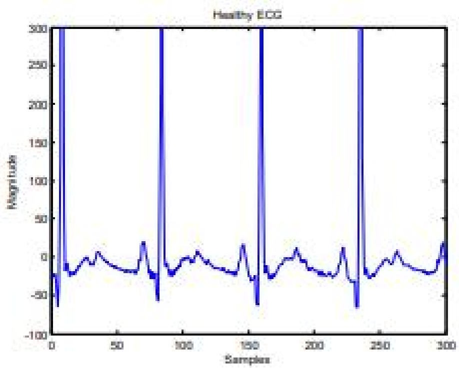


Fig 4: (a) Hard Threshold (b) Soft Threshold

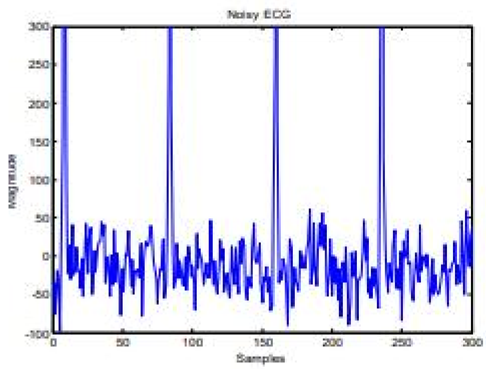
Simply said, everything exceeding the predetermined limit will drop in value. If these things fall below a certain threshold, they are taken into account. When a number approaches the cutoff, it remains the same. Figure 4 shows how the two threshold-setting strategies work.

4. RESULTS

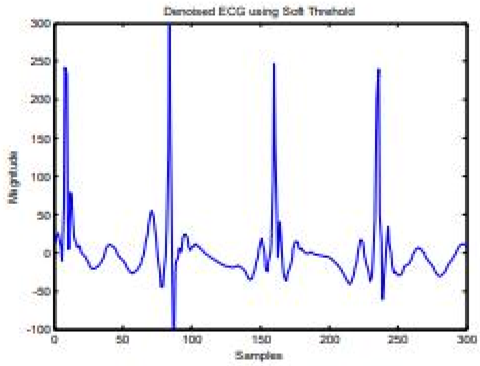
The planned insertion of Gaussian noise to the ECG records prior to processing decreases their accuracy. Every warning is followed by a minute. It adjusts the amount of Gaussian noise applied to an ECG output that is noise-free. There was no noise at all and fifty percent noise in the experiment.



(a)



(b)



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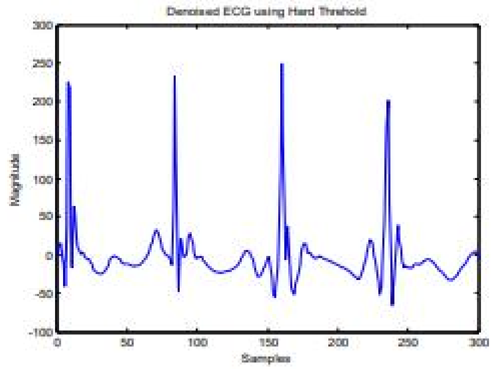

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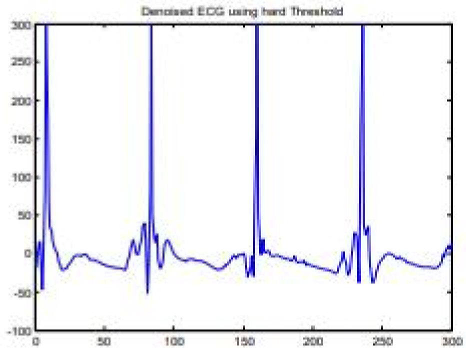

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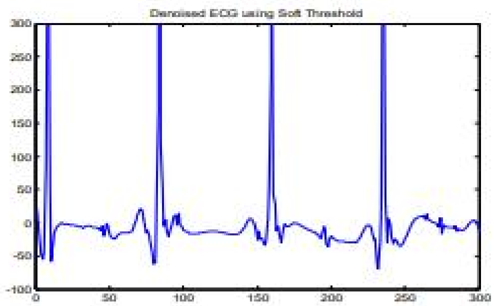

(f)

Fig 5: (a) Healthy ECG Signal (b) ECG Signal with 30% noise (c)Denoised ECG signal in DWT domain with soft threshold (d) Denoised ECG signal in DWT domain with hard threshold (e) Denoised ECG signal in Framelet domain with hard threshold (f) Denoised ECG signal in Framelet domain with soft threshold

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Noise signals are first broken down into their component parts at the single-level level before being transformed with wavelet and Framelet. Following that, Sureshrink and the proposed median-based thresholding technique are used to remove the disturbance. Simultaneously, it was discovered that the signal that had been denoised following the single-level collapse was not clear enough and contained frequency inconsistencies. Multi-level decomposition was then used on levels 2, 3, and 4, and the denoising process was repeated for both areas. In the Framelet domain, the median-based thresholding strategy outperformed a four-level decomposition. Figure 5 shows an ECG signal and the outcomes of denoising it with the wavelet and framelet domains. Equation 10 calculates the Signal-to-Noise ratio (SNR), which is used to determine the strength of the denoised signal.

$$SNR(dB) = 20\log_{10}\frac{\sigma}{\sigma_n} \qquad (10)$$

The symbols πn and π represent the standard deviations of the cleaned signal and noise, respectively. Table 2 compares the SNR values obtained in both regions using the moderate and strong thresholding procedures. The results reveal that the median-based approach's mild thresholding method produces a higher signal-to-noise ratio (SNR) in the Framelet transform domain than the Sureshrink strategy in the wavelet transform domain. To show the difference in signal-to-noise ratio (SNR) values between the Framelet and wavelet domains, a large batch of stochastic signals with 30% noise variation can be generated. Figure 6 shows the signal-to-noise ratio (SNR) values for data collected using the Framelet and soft cutoff wavelet approaches. The employment of two high frequency filters improves framelet SNR values and facilitates frequency identification.

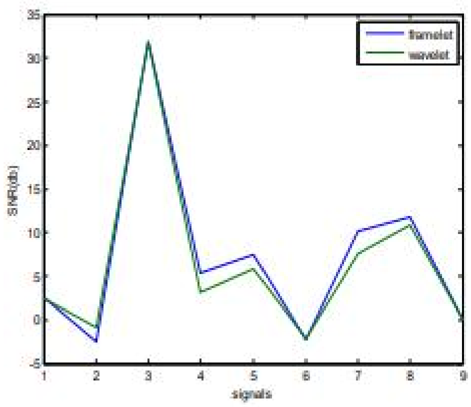

Fig 6: SNR values in Framelet and Wavelet domain with soft thresholding at noise level =30%

Table 2. Comparison of SNR of various ECG signals fordifferent noise levels

Signal	Noise Level Variance (%)	Wavelet (Sureshrink)		Framelet (Median based)	
		Hard Thresh old	Soft Thresh old	Hard Thres hold	Soft Thresh old
		SNR (dB)	SNR (dB)	SNR (dB)	SNR (dB)
a04m	20	8.070	8.041	6.778	9.689
	30	3.871	3.121	3.486	5.837
	40	-0.439	0.053	1.187	2.910
a05m	20	9.956	10.450	7.763	11.681
	30	5,618	5.870	4.748	7.928
	40	2.572	2.315	2.030	5.245
a07m	20	12.38	12.337	10.490	13.628
	30	8.103	7.537	6.590	9.760
	40	4.492	4.754	4.374	6.735

5. CONCLUSION

This publication presents a systematic methodology for effectively implementing Framelet domain methods to remove noise from electrocardiogram (ECG) data. The unusual ECG data is analyzed using the Framelet transform. The signal is then filtered in the Framelet domain using a median-based thresholding algorithm. Furthermore, this study shows that combining multilevel Framelet decomposition with mild thresholding achieves better results than aggressive thresholding alone. The performance

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research findings show that the median-based thresholding method outperforms the SureShrink algorithm in terms of Signal-to-Noise Ratio (SNR). The experimental results show that framelet-based denoising approaches outperform wavelet-based methods in terms of signal-to-noise ratios (SNR). This can ultimately be used to evaluate a wide range of photos and movies. Furthermore, the outcomes of these various data formats can be compared using different denoising algorithms.

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