Analysis of Noise Removal in ECG Signal using Symlet Transform

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Abstract— **An ECG (Electrocardiogram) is a test used to determine the rhythmic activity of the heart. It checks for problems with the electrical activity of the patient's heart. An ECG shows the heart's electrical activity as line tracings on paper. To measure the electrical activity of the heart, electrodes are placed on the skin. Suspected myocardial infarction, seizures, etc. can be indicated by performing electrocardiography. Conventionally, 12-lead ECG is performed, where 10 electrodes are placed on the patient's limbs and on the surface of the chest. The graph of voltage versus time produced by this noninvasive medical procedure is referred to as an electrocardiogram. The ECG signal is contaminated by various noises in various stages of ECG measurement. The presence of noise in an ECG trace complicates the identification analysis. The primary sources of noise in ECG are power line interface, electrode movement noise, motion artifacts, color noise, electromyography etc. Noise removal in ECG signal is vital as these noises alter the data carried by the signal. For proper diagnosis, a pure ECG signal is required. Hence, noise removal from an ECG signal plays a vital role in biomedical field. Once the noise sources are properly characterized and understood, different types of filter designs can be used to efficiently remove noise, while preserving as much of the underlying subject information as possible. Here, we use a combination of any discrete wavelet transform (DWT) and a thresholding method for denoising. Finally, SNR is calculated to find the efficiency of the algorithm used.**

***Key words*— Electrocardiogram (ECG), Noise, DWT, Thresholding, SNR.**

I. INTRODUCTION

A. Electro Cardio Gram (ECG)

An ECG machine interprets and records the electrical impulses of the heart for diagnostic purposes. It is not a form of treatment for heart conditions. An electrocardiogram (ECG) records the electrical activity of the heart. The heart produces tiny electrical impulses which spread through the heart muscle to make the heart contract. These impulses can be detected by the ECG machine [1]. Figure 1 shows that representation of ECG signal. ECG waves are labeled using the letters P, QRS, T and U. ECG signal gives useful information about the patient's heart. Some noises may present in that signal during measurement and transmission. They are power line interference, baseline wander, electrode motion, muscle artifact and Additive White Gaussian Noise. Additive White Gaussian Noise (AWGN) is a random signal having equal intensity at different frequencies, giving a constant power spectral density. Arrhythmia is defined as an abnormal rate of muscle contractions in the heart. For clear prediction of arrhythmias, those noises must be reduced [2].

B. Wavelet Transform – Continuous Wavelet Transform (CWT)

The beginnings of wavelet transform as a specialized field can be traced to the work of Grossman and Morlet [1984]. Their motivation in studying wavelet transforms was provided by the fact that certain seismic signals can be modeled suitably by combining translations and dilations of a simple, oscillatory function of finite duration called wavelet [2]. The early results were related to what is now known as the continuous wavelet transform (CWT). Consider a real or complex value CWT $\psi(t)$ with the following properties:-

- The function integrates to zero *:*

$$\int_{-\infty}^{\infty} \psi(t)dt = 0 \quad \ldots (1)$$

- It is square integrable or, equivalently, has finite energy:

$$\int_{-\infty}^{\infty} |\psi(t)|^2 dt = 0 \ldots (2)$$

The function $\psi(t)$ is a mother wavelet or wavelet if it satisfies these two properties. Let $f(t)$ be any square integrable function. The CWT of $f(t)$ with respect to a wavelet $\Psi(t)$ is defined as

$$W(a,b) = \int_{-\infty}^{\infty} f(t) \, \frac{1}{\sqrt{|a|}} \psi^*(\frac{t-b}{a})dt \quad \ldots (3)$$

Here, a and b are real and * denotes complex conjugation. Thus, the wavelet transform is a function of two variables [3].

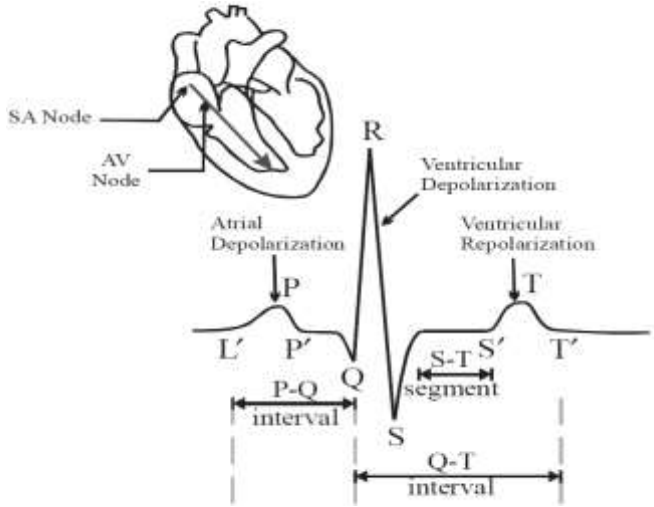

Fig. 1. Ideal ECG signal from reference [1]. The SA node causes atrial depolarization (P complex). The AV node causes ventricular depolarization (QRS complex). The T complex indicates ventricular repolarization.

C. Wavelet Transform – Discrete Wavelet Transform (DWT)

The discrete wavelet transform (DWT) is an implementation of the wavelet transform using a discrete set of the wavelet scales and translations obeying some defined rules. In other words, this transform decomposes the signal into mutually orthogonal set of wavelets. The wavelet can be constructed from a scaling function which describes its scaling properties. DWT captures both frequency and location information. The DWT can be represented as:

$$W_{\varphi}(j_o\,,\,k) = \frac{1}{\sqrt{M}} \sum_n f(n)\, \varphi_{j_o\,,\,k}(n) \quad \ldots (4)$$

$$W_{\varphi}(j_o\,,\,k) = \frac{1}{\sqrt{M}} \sum_n f(n)\, \varphi_{j_o\,,\,k}(n) \quad for\, j \geq j_o \quad \ldots (5)$$

Equation (4) provides the approximation coefficients, while equation (5) gives the detailed coefficients [3]. The inverse DWT (IDWT) is given by the equation:

$$f(n) = \frac{1}{\sqrt{M}} \sum_k W_{\varphi}(j_o\,,\,k)\, \varphi_{j_o\,,\,k}(n) + \frac{1}{\sqrt{M}} \sum_{j=j_o}^{\infty} \sum_k W_{\varphi}(j\,,\,k)\, \varphi_{j,\,k}(n) \quad \ldots (6)$$

The set of wavelets than forms an orthonormal basis which we use to decompose signal. Symlet wavelets are a family of wavelets. They are a modified version of Daubechies wavelets with increased symmetry. The Symlet transform with the best symmetry is used for computing wavelet coefficients according to the equation:

$$Symlet_{(X)} = e^{\varphi(i)\omega} \quad \ldots (7)$$

Here, X is input image, $\varphi(i)$ is Daubechies transform for each pixel i, and ω is the moment of image [4].

II. MATERIALS

A. MIT-BIH Arrhythmia Database

The ECG signal is obtained from the MIT-BIH arrhythmia database. This database consists of 48 records, obtained from the Beth Israel Hospital in Boston. Each record has sampling frequency of 360Hz. The 'header' (.hea) file gives information about the patient's age, sex and medications.

B. MIT-BIH Noise Stress Database

This database includes the diffe333rent types of noisy signals which corrupt the ECG signal during measurement. This database includes baseline wander noise, electrode motion noise and muscle artifact noise.

C. AWGN

Additive White Gaussian Noise (AWGN) is a type of noise whose mean is zero and standard deviation and variance is found to be one. AWGN is also present in ECG during measurement.

Recorded ECG signal and noise signals are taken from the respective database.

⇩

Add various noise signals individuallu to the original ECG signal

⇩

Perform wavelet decomposition on each of these nosiy ECG signals individually, using Symlet wavelet

⇩

Apply different types of thresholding methods on the Symlet decomposed signals

⇩

Denoising

⇩

Finally, calculate the SNR value for the different thresholding methods.

Fig. 2. Flow Chart

III. METHODS OF THIS WORK

A. Discrete Wavelet Transform

Discrete wavelet transform (DWT) transforms the discrete time signal to discrete wavelet representation. It changes the input signal series into the series of low pass and a high pass series of wavelet coefficient. In DWT, there are many wavelet families, such as, Symlet, Haar, Daubechies, etc. Here, Symlet wavelet of order 8 and decomposition level 5 is chosen.

B. Thresholding Techniques

Thresholding is done on the Symlet decomposed signal to remove the coefficients below a certain value. It also removes the low amplitude noise and additional noise that has occurred during the process. Here, three types of thresholding methods are used:

1) Universal thresholding

This is the basic and general thresholding method. It easily finds the accurate information of the signal. The threshold value is given by the following equation:

$$Universal = \sigma_i\sqrt{2\log(I)} \ldots (8)$$

Here, I is the number of data samples [5].

2) Minimax Thresholding

Minimax is another global thresholding method. This method finds threshold using minimax principle.

$$Minimax = \sigma_i(0.3936 + 0.1829\ \ log_2 I) \ldots (9)$$

σ_i is the standard deviation of noise and I is the number of samples. This principle is used in statistics in order to design estimators. Since the de-noised signal can be assimilated to the estimator of the unknown regression function, the estimator is the one that realizes the minimum of the maximum mean square error obtained for the worst function in a given set [6].

3) *Heursure Thresholding*

Threshold is selected using a combination of Sqtwolog and Rigrsure methods. If the signal condition is poor the combination of both thresholding is used and gives the better result [6].

C. Denoising Steps

Signal denoising involves the following steps:

1) Decomposition of ECG signal
2) Applying different types of wavelet methods
3) Thresholding is applied to detail coefficients from decomposing operation
4) Either soft or hard thresholding is applied to detail coefficients
5) Denoising the ECG signal

D. SNR Calculation

Signal to noise ratio (SNR) gives the information about quality of signal. Higher the SNR, better is the quality of signal. SNR formula is given as follows:

$$SNR = 10\log_{10}[\frac{\sum d^2(n)}{\sum[d(n)-k(n)]^2}] \ldots (10)$$

Here, $k(n)$ is the input signal and $d(n)$ is the denoised signal.

IV. RESULTS AND DISCUSSION

This chapter focuses on the outputs obtained at each step as mentioned in the flow chart. The proposed algorithm is evaluated with the database consisting of ECG signals. By referring the given flow chart, the first step takes place. The ECG and noise signals are shown in the following waveforms – 3, 4, 5, 6, 7.

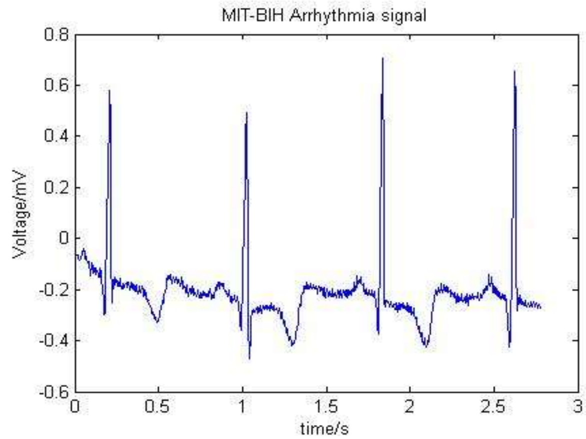

Fig. 3. ECG signal

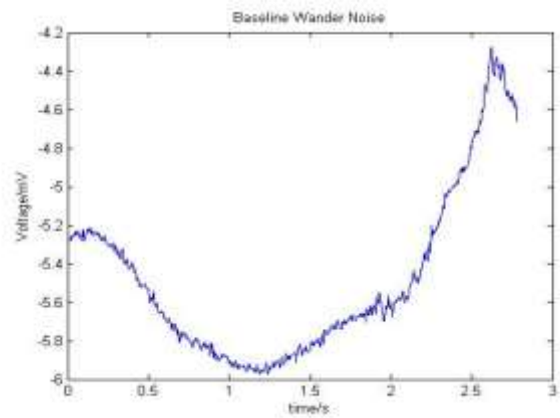

Fig. 4. Baseline Wander Noise

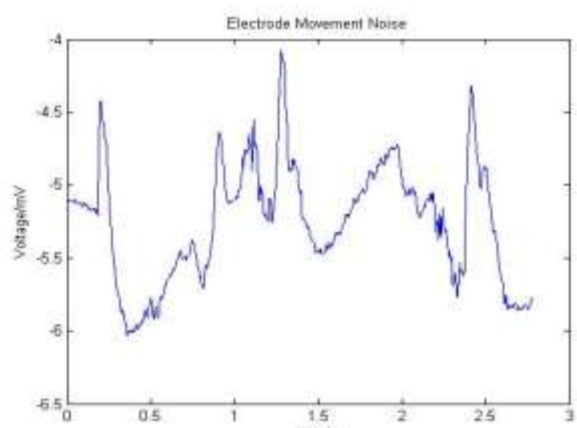

Fig. 5. Electrode Movement Noise

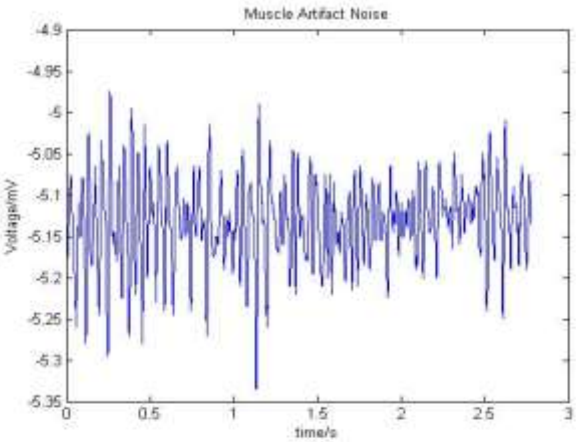

Fig. 6. Muscle Artifact Noise

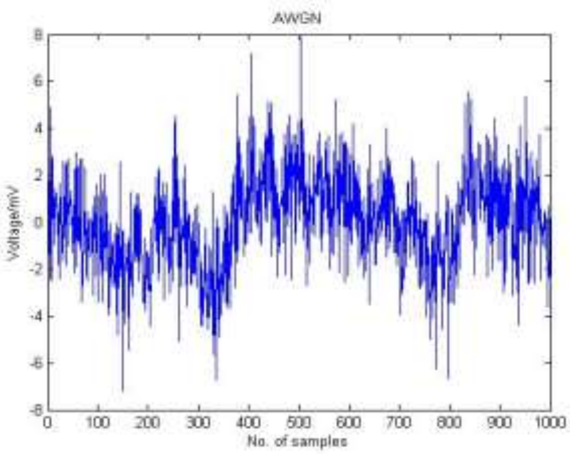

Fig. 7. Additive White Gaussian Noise

A. Results obtained for noisy signals

In Step 2, the mentioned noise signals are added to the input ECG signal individually to get four noisy ECG signals. The following figures are obtained:

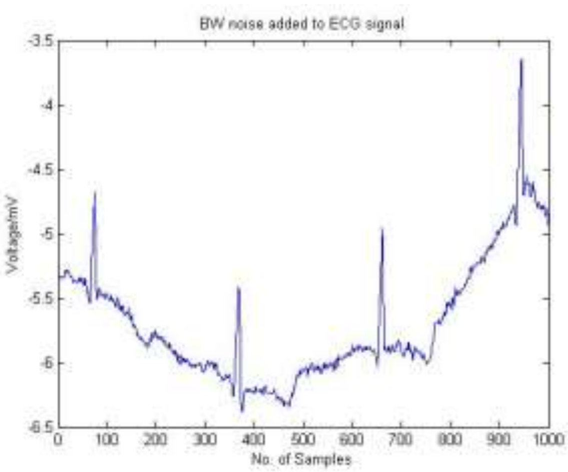

Fig. 8. BW noise added to ECG signal

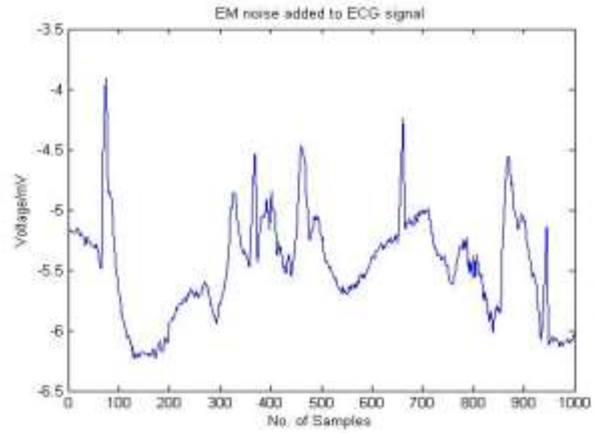

Fig. 9. EM noise added to ECG signal

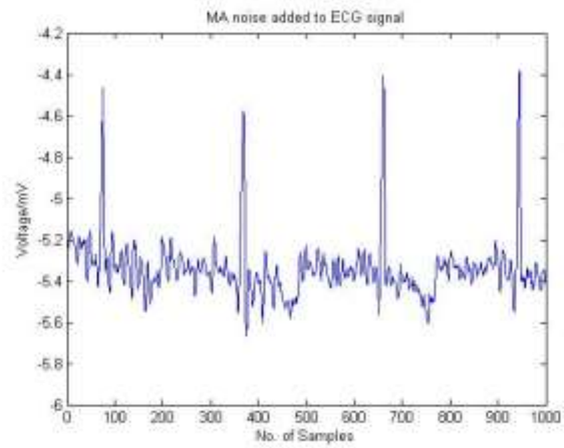

Fig. 10. MA noise added to ECG signal

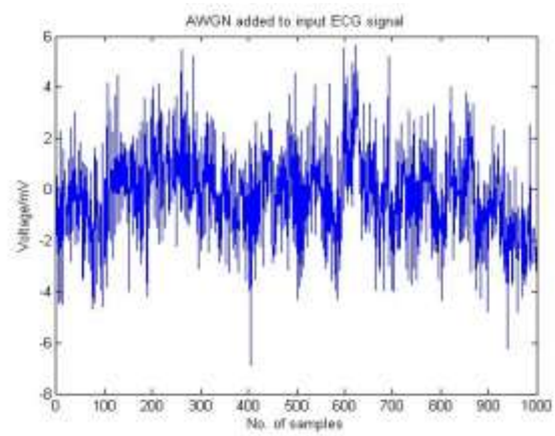

Fig. 11. AWGN added to ECG signal

B. Results obtained for denoised signal

Noisy ECG signals are decomposed by making use of Symlet wavelet in step 3. For removing noise from the noisy signal, different types of types of thresholding, such as, universal, minimax and Heursure methods are applied in step 4. The following figures show the denoised output signals.

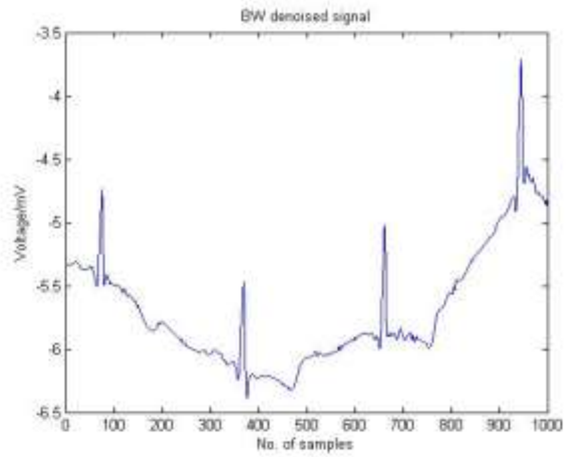

Fig. 12. BW denoised signal

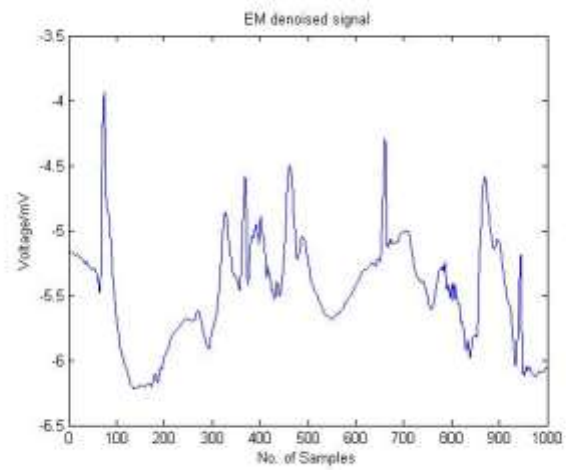

Fig. 13. EM denoised signal

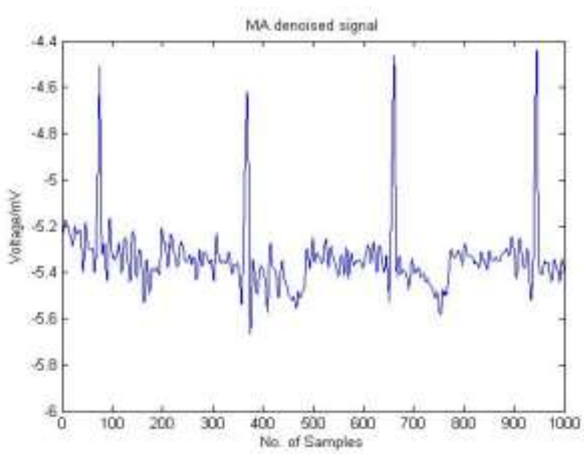

Fig. 14. MA denoised signal

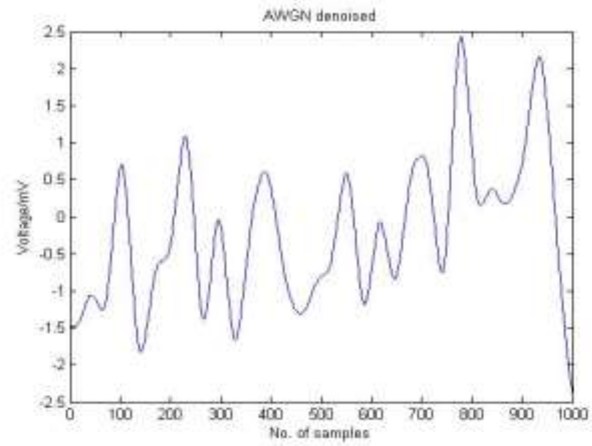

Fig.15. AWGN denoised signal

C. Results obtained for SNR improvement values

Finally, the SNR values are calculated for different thresholding methods, as shown in the following tables

TABLE I SNR VALUES FOR RECORD NO. 100

Thresholding Method	SNR Improvement Values			
	BW Noise	EM Noise	MA Noise	AWGN
Universal	03254	0.3371	0.3474	0.2191
Minimax	0.3255	0.3372	0.3475	0.2191
Heursure	0.3256	0.3373	0.3475	0.2191

TABLE II SNR VALUES FOR RECORD NO. 101

Thresholding Method	SNR improvement values			
	BW noise	EM noise	MA noise	AWGN
Universal	0.3219	0.3334	0.3434	0.2729
Minimax	03219	0.3333	0.3434	0.2729
Heursure	0.3219	0.3334	0.3434	0.2659

TABLE III SNR VALUES FOR RECORD NO. 102

Thresholding Method	SNR improvement values			
	BW noise	EM noise	MA noise	AWGN
Universal	0.3215	0.3329	0.3426	0.0846
Minimax	0.3215	0.3329	0.3426	0.0850
Heursure	0.3215	0.3329	0.3427	0.0846

TABLE IV SNR VALUES FOR RECORD No. 103

Thresholding Method	SNR improvement values			
	BW noise	EM noise	MA noise	AWGN
Universal	0.3336	0.3454	0.3564	0.3765
Minimax	0.3336	0.3454	0.3564	0.3736
Heursure	0.3336	0.3453	0.3564	0.3765

TABLE V SNR VALUES FOR RECORD No. 201

Thresholding Method	SNR improvement values			
	BW noise	EM noise	MA noise	AWGN
Universal	0.3210	0.3320	0.3420	0.2863
Minimax	0.3210	0.3320	0.3420	0.2856
Heursure	0.3210	0.3320	0.3420	0.2868

V. CONCLUSION

This paper proposes an efficient method to remove noise from ECG signal. First, base and gain present is removed from the ECG signal obtained from MIT-BIH arrhythmia database. Then, the respective noises- baseline wander, electrode movement, muscle artifact and AWGN are added individually added to the above ECG signal. These noisy ECG signals are decomposed using Symlet wavelet. By decomposing them, the detailed and approximation coefficients are obtained. Then, different thresholding techniques are applied to the detailed coefficient to obtain threshold signal. Finally, denoising of threshold signal is done and SNR is calculated for all of the above mentioned noised. Compared to other thresholding methods, the Heursure method gives better results. This work can be further expanded to various performance evaluation such as SNR improvement value, mean square error, root mean square error (R.M.S.E) and percent root mean square difference. For proper diagnosis of ECG signal, the signal has to be noise-free. These noises are usually low frequency signals and hence, simple filters are also sufficient for the process. In this paper, Symlet wavelet is used as it orthogonal, has nearly linear phase and itself resembles a pure ECG signal.

ACKNOWLEDGMENT

The authors are grateful to Dr. Mohan Manghnani, Chairman, New Horizon College of Engineering (NHCE), Bengaluru, for his encouragement for carrying out this work. They are thankful to Dr. Manjunatha, Principal, New Horizon College of Engineering, Bengaluru, for his encouragement for doing this research work. They are also ever grateful to Dr. Sanjay Jain, Professor and HOD, ECE Dept., New Horizon College of Engineering, Bengaluru, for providing the necessary backbone support to proceed on this endeavour. Finally, we are highly indebted to our parents for encouraging to excel in our chose fields.

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