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ECG Denoising using Wavelet Transform

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Abstract:ECG gets easily corrupted by noise and human artifacts. Denoising of ECG is very important issue in medical engineering. This paper presents the Wavelet based method that is Wavelet Transform Modulus Maxima(WTMM), for the removal of white Gaussian noise (AWGN) from ECG signal. Wavelet used here for decomposing the signal into various scales is Db6. This method basically deals with finding out the singularities and local maxima of wavelet transform is used to analyse these singularities. Hard and soft thresholding methods are used to obtain the coefficients of interest and to suppress the noise components. Inverse wavelet transform is used to reconstruct the signal.

Keywords: ECG, Lipschitz exponents, Singularities, Wavelet Transform.

I. INTRODUCTION

Electrocardiogram (ECG) is the outcome of electrical potentials in heart. The morphology of ECG and heart rate reflects the cardiac health of human. It is recorded by placing electrodes on the skin and it consists of various points in it and those are P-QRS-T. The real ECG signal from recorded of human body is always corrupted by several sources of noises such as being EMG (electromyogram) signal (a high frequency signal related to muscle activity), the BLW (the baseline wandering: a low frequency signal caused mainly by the breathing action),the electrode motion (usually represented by a sharp variation of the baseline)[3].It is a common practice to model the unwanted noise by white Gaussian noise[1].The goal of in electrocardiography is to separate the valid signal contents from the undesired noise so as to present an ECG that facilitates easy and accurate interpretation[2].Various approaches have been used to remove Gaussian white noise[4,5].We used singular point properties based on wavelet transform to remove noise[1].Singular points carry much information content in any signal[1].Wavelet is used here to detect singular points and thresholding is used to remove singular points of noise and then signal is reconstructed.

Paper is organised as follows : Section I deals with the brief introduction ,section II contains basics of ECG, section III contains literature overview, section IV contains the details of materials required and method, and finally section V shows the results and hence conclusion is drawn.

II. ELECTROCARDIOGRAM

Heart is a muscle tissue that pumps blood into body[1] The electrocardiogram (ECG) is the recording of the heart's electrical potential versus time[4].Internal conduction system of heart is responsible for the generation of ECG.ECG graphically looks like as follows:

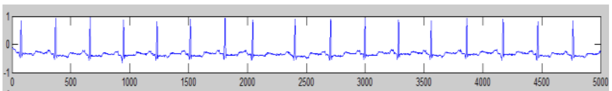

Fig. 1 Original ECG[12]

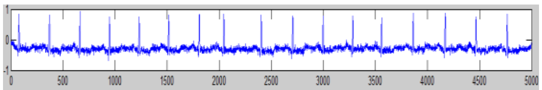

Fig. 2 Noisy ECG at input SNR 14.03 db

Noise when corrupted by noise is as shown above. Deflections shown in ECG reflect the electrical activity of heart causing muscle contraction [1].P-QRS-T, each of these points have particular and fix amplitudes and frequencies.

III. LITERATURE OVERVIEW

Various approaches have been made to denoise ECG, such as denoising using digital filters, this is based on cascading a zero-phase band pass filter, an adaptive filter, and a multi-band-pass filter.Adaptive self tunning filter structure using LMS algorithm is implemented here for removal of noise. Here multi-bandpass filter is cascaded to the previous stages to attenuate the low amplitude noise [4].

Another method of denoising is using noise residue method[9].Analysis of ECG signal shows that QRS complex has highest energy level in 2^4 scale, and in higher scales noise, baseline wander increases, so in the method adopted here signal is decomposed such that last level approximate coefficients constitute frequency band of 0-0.5Hz and then last level coefficients are set to zero and signal is reconstructed using inverse wavelet transform. Wavelet used here is 'symlet-8',the approximate coefficients at scale 2^4 constitutes spectral band(0-35Hz), wherein the most significant energies of the noise free ECG signal exist[9].

QRS complex detection is also the method adopted for denoising of ECG[5].Here QRS dominant scale and positions of R-wave are determined previously. Here R-waves are detected using continuous wavelet transform. This method is based on high peaks primarily through which threshold is decided. It is possible to remove high frequency noises by using variable window by knowing the QRS complex dominant scale and the position of every R-wave.

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Translational invariant transform is the another method for denoising ECG. Here the noise is suppressed by averaging over the thresholded signal of all circular shifts. This method is fast way of implementation rather than having to do transform on the signal n times.

Here noisy ECG is shifted within the range of cycle spinning so as to get new phase shifted ECG. Transformed signal is then subjected to improved thresholding and then denoised signal is obtained by applying Inverse Discrete Wavelet Transform. Above procedure is repeated to get series of denoised signals and then average of these denoised signals is calculated to obtain final denoised ECG [11]

IV. MATERIALS AND METHODS

A. Wavelet Transform:

Wavelet is a mathematical microscope used for the analysis of signals and images. It is the time-frequency approach for the analysis of signals [6].Wavelet transforms are based on small wavelets with limited duration [6]. The wavelet transform decomposes signals over dilated and translated wavelets [6].A wavelet is function φ which belongs to $L^2(R)$ with a zero:

$$\int_{-\infty}^{\infty} \varphi(t)dt = 0$$

In the above equation it is normalised $\| \varphi \|$ =1 and centered in neighbourhood of t=0.And this means that Fourier Transform of $\varphi(t)$ is satisfies the following equation [7]:

$$\int_0^{\infty} \frac{|\hat{\varphi}(\omega)|^2}{\omega} d\omega = \int_{-\infty}^{0} \frac{|\hat{\varphi}(\omega)|^2}{\omega} d\omega = C_\varphi < \infty$$

And the Fourier transform of the wavelet φ is[1]

$$\hat{\varphi}(\omega) = j\omega\left(\frac{\sin\left(\frac{\omega}{4}\right)}{\frac{\omega}{4}}\right)^4 \qquad j^2 = -1$$

The wavelet transform of signal f which belongs to $L^2(R)$ is [6]:

$$Wf(u,s) = < f, \varphi_{u,s} \geq \int_{-\infty}^{\infty} \frac{1}{\sqrt{s}} \varphi^*\left(\frac{t-u}{s}\right)dt$$

In the equation * denotes complex conjugate, u is translating factor and s is scaling factor. For discrete applications scale factor is selected from dyadic sequence $s = 2^j$, where j belongs to set of integers [1].

Wavelet with compact support and one vanishing moment is used here which is biorthogonal quadratic spline in nature. The dyadic wavelet of digital signal can be calculated without two analysing and synthesing filter bank. Output of these filters are the wavelet coefficients of signal f(n)[1].With these filters we can decompose f(n) as follows[1]:

$$f(n) = f_s^{J+1} * S_f(2^J, n) + \sum_{j=1}^{J} f_s^j * W_f(2^j, n)$$

Where * denotes the convolution operator and $S_f(2^J, n), W_f(2^j, n)$ can be calculated by convolving f(n) and time domain coefficients of analysing filter bank[1].

B. Lipschitz exponents and Singularities:

Singularities and irregular structures carry the most important information in the signals [7].Singularity is often considered as the opposite of smoothness and can be measured by Lipschitz exponents α[1]. Fourier Transform is global and provides a description of the overall regularity of the signals, but it is not well adapted for finding the location and spatial distribution of singularities. By decomposing the signal into elementary building blocks that are well localised both in time and frequency, the wavelet transform can characterise the local regularity of signals and local of a function is often with the Lipschitz exponents [7]. Lipschitz exponents(also called as Holder exponents)is a generalised measure of differentiability of a function.[8] The decay of wavelet coefficients associated with particular event or interval of the signal with scale determines the exponent α at that event or interval. Scale behaviour of Wavelet transform can be written as [8]

$$|Wf(s,u)| \leq As^{\alpha}$$

Where A is not the function of s. Taking Logarithms on both sides we get:

$$\mathrm{Log}(|Wf(s,u)|) = \log(A) + \alpha \log(s)$$

Finding the slope of above equation produces the estimate of α [8].If a signal has singularity at any point v ,which means it is not differentiable at v, then the Lipschitz exponent at v characterises this singular behaviour[6].A function f is point wise Lipschitz α ≥0 at v, if there exists K>0,and polynomial P_v of degree m = [α] such that,For all values of t belonging to R[1],

$$|x(t) - p_v(t) \leq K|t - v|^{\alpha}|$$

A function is uniformly Lipschitz α over [a, b] if it satisfies the above equation with the constant K that is independent v. The Lipschitz regularity of f at v over [a, b] is a sup of α that x is Lipschitz α. If f is uniformly Lipschitz α >m in the neighbourhood of v, it can be verified that f is m times continuously differentiable in this neighbourhood and if α,1 at v, then f is not differentiable and v is a singular point. With this wavelet singularity can be detected [1].

C. Detection and Reconstruction:

Singularities are detected by finding the abscissa where the modulus maxima converge at fine scales[6].If the wavelet φ has n vanishing moments and a compact support,then there exsists a θ of compact support such that $\varphi = (-1)^n \theta^n$ with $\int_{-\infty}^{\infty} \theta(t)\,dt \neq 0$,then wavelet transform can be rewritten as:

$$Wf(u,s) = s^n \frac{d^n}{du^n}(f * \bar{\theta}_s)(u)$$

If wavelet has one vanishing moment, wavelet modulus maxima are the maxima of the first order derivative of f smoothed by $\bar{\theta}_s$ [6].Therefore assuming that $\varphi(t)$ is the n-th derivative of a so called smoothing function,it can be shown that singular points can be detected by modulus maxima of the wavelet transform [1].Once these singular points are known straight forward optimization technique can be employed to reconstruct the signal[1].

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D.Method Used:

ECG sample is taken from MIT-BIH, this ECG signal is in pure form, white Gaussian noise is added to obtain noisy ECG. Signal to noise ratio of this noisy signal is calculated as:

$$SNR_{input} = 10log_{10}\frac{||ECG_{original}||}{||N||}$$

$||ECG_{original}||$ is power of original ECG signal and ||N|| is the power of white noise [1].Wavelet used here for decomposition of signal is Db6**.** Hard and Soft thresholding is used on the coefficients of Discrete Wavelet transform to suppress noise. Hard and Soft thresholding equations can be given as:

Hard thresholding [1]

$$\hat{d}_{j,k} = \begin{cases} d_{j,k} & if\ |d_{j,k} \geq t| \\ 0 & otherwise \end{cases}$$

Soft thresholding [1]

$$\hat{d}_{j,k} \begin{cases} sign(d_{j,k})(|d_{j,k} - t|) & if\ |d_{j,k} \geq t| \\ 0 & otherwise \end{cases}$$

Where $t = \sigma\sqrt{2logN}$,and N is number of samples and $\sigma = median(d_{1,k})/0.6745$[1].Wavelet coefficients are compared with the thresholds and based on this comparison coefficients will be adjusted to obtain the wavelet coefficients of less noisy ECG by using Inverse discrete wavelet transform. In this method thresholding is applied on individual modulus maxima of wavelet transform and thus less noisy ECG is obtained. Output SNR is calculated as:

$$SNR_{output} = 10log_{10}\frac{||ECG_{output}||}{||ECG_{original} - ECG_{output}||}$$

V. RESULTS

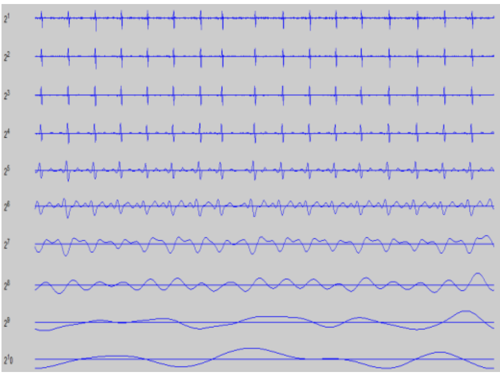


Fig3 Coefficients of ECG in various scales

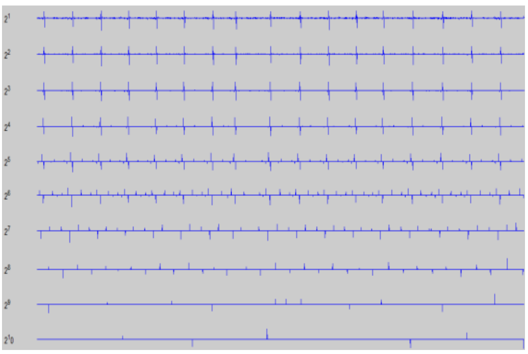


Fig 4 Modulus Maxima coefficients of ECG in various scales

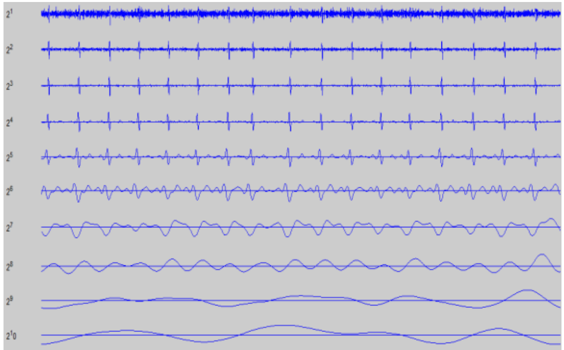


Fig5 Noisy ECG coefficients in various scales.

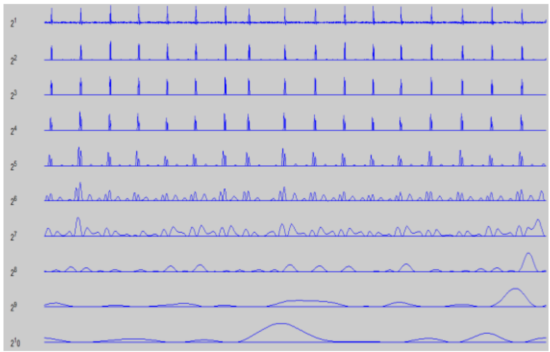
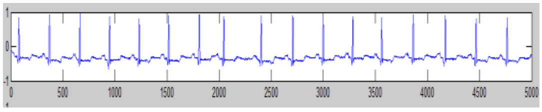
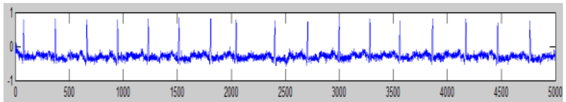


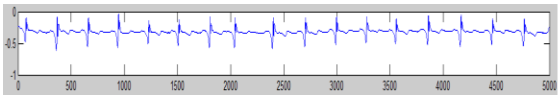
Fig 6 Modulus Maxima Noisy ECG coefficients in various scales



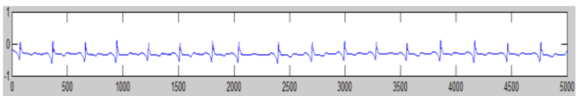
(a)



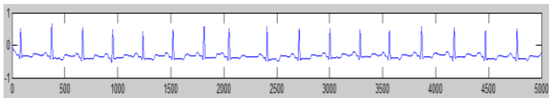
(b)



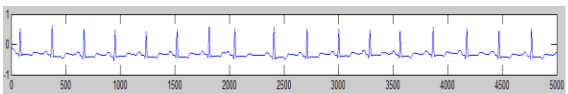
(c)



(d)



(e)



(f)

Fig 7 a) Original ECG, b)Noisy ECG, c)denoising with WT hard thresholding without local maxima, d)denoising with WT soft thresholding without local maxima, e) denoising with WT hard thresholding using Modulus maxima f) denoising with WT soft thresholding using Modulus maxima.

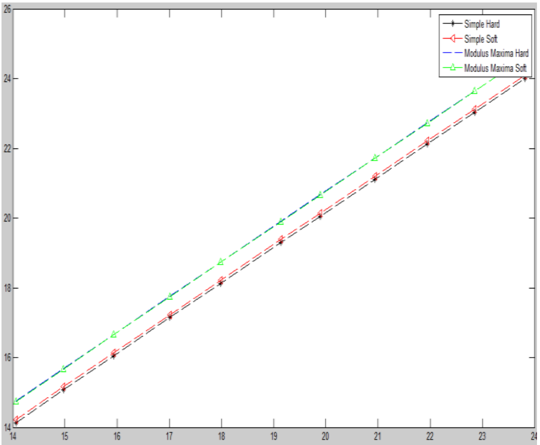


Fig8 Output SNR Versus Input SNR

VI. CONCLUSION

From the graphs and theory it can be concluded that Wavelet transform Modulus Maxima using hard, soft thresholding proves to better as compared to hard, soft thresholding using traditional wavelet transform.

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