WAVELETS BASED DENOISING TECHNIQUES FOR ECG SIGNAL

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ABSTRACT

Electrocardiogram signal may be a line graph that shows changes within the electrical activity of the heart over time. False positive reports are generated due to respiratory artifacts, motion artifacts, etc., in EKG signal. This paper is mainly aimed to suppress different artifacts in EKG signal exploitation denoising techniques like DWT, twin tree CWT, Wavelet Weiner filter. The performance of those denoising techniques is compared using the performance metric Signal to Noise ratio.

KEYWORDS

ECG, Artifacts, DWT, DTCWT, and WWF

INTRODUCTION

Electrocardiogram (ECG) plays a vital role in patient observance and monitoring and diagnosis because of its easy use and non-invasive nature. Cardiogram is the most ordinarily used biomedical signal in clinical analysis of the heart. The word "electrocardiogram" could be a combination of three words: electro, referring to electrical signal; cardio, which translates into heart; and gram that stands for recording. The recording of the electric activity of the heart is called ECG. This group of signals, called ECG, constitutes the most informative clinical signal commonly used in the diagnosis of the cardiovascular system. The schematic style of one period of the cardiogram is illustrated in Figure 1(a), and a typical healthy cardiogram signal is shown in Figure 1(b).

Fig1 (a): Characteristic wave in one cycle of a normal ECG and (b) a healthy ECG

Different Artifacts in ECG signals

A. Power line interference

It encompass 50/60Hz pickup and harmonics. The interference is principally caused by Electromagnetic interference by power cable, magnetism field (EMF) by the close machines, Stray impact of the electrical energy fields because of loops within the cables, Improper grounding of patient or the cardiogram machine. The electrical equipment's induce 50Hz signals within the input circuits of the cardiogram machine. Example, air conditioning, elevators and X-ray units that draw significant power cable current.

B. Electromyogram (EMG) Noise

The EMG noise is generated from electrical activity of the muscle. EMG consist of maximum frequency of 10 KHz. Sections of cardiogram maybe interfered and corrupted by surface electromyogram that causes difficulties in processing and analysis.

C. Baseline Wander

Baseline wander may be a low-frequency noise component present in the ECG signal. This is because of respiration, and body movement. Baseline wander have frequency bigger than 1Hz. This low frequency noise, Baseline wander causes problem in detection and analysis of peak.

D. Channel Noise

Channel noise introduces once cardiogram signal is transmitted through channels. This can be because of the Poor channel conditions. It is mainly like white Gaussian noise that contains all frequency elements E.g. AWGN

E Electrode Contact Noise

Electrode contact noise is caused by the loss of contact between the electrode and the skin, which effectively disconnects the activity system. The noise is of length 1s. Motion artifacts area unit transient bottom line changes caused by changes within the electrode-skin impedance with electrode motion. . As this impedance changes, the ECG amplifier sees a different source impedance which forms a voltage divider with the amplifier input impedance therefore the amplifier input voltage depends upon the source impedance which changes as the electrode position changes.

In terms of frequency, noise is categorized in two ways in which. Initial one is high frequency noise caused by power cable interference, EMG (EMG) generated from the chest wall, and mechanical forces acting on the electrodes. Second form of noise is low frequency noise i.e. baseline wander caused by respiration or the motion of the patients or the instruments.

VARIOUS ECG SIGNAL DENOISING TECHNIQUES

A. Discrete Wavelet Transform based ECG Signal Denoising

The basic plan of filtering technique is to boost the signal to noise ratio, in fact to cut back the background signal within the medical specialty signal. Because noise will have an effect on the reading and interpretation of the signal, a pre-processing step is fascinating before the pc analysis. Because the external noise doesn't have a selected band and its frequency is often superposed to the medical specialty frequency, it is necessary to design an intelligent model which can be adaptable to different kind of signals. It is possible with the Discrete Wavelet Transform [1, 2]. The classic technique (Donoho & Johnstone, 1994) includes 3 vital stages: the decomposition of the signal; the identification of low energy coefficients and its rejection (thresholding); and at last, the reconstruction of the new coefficients. It's shown below;

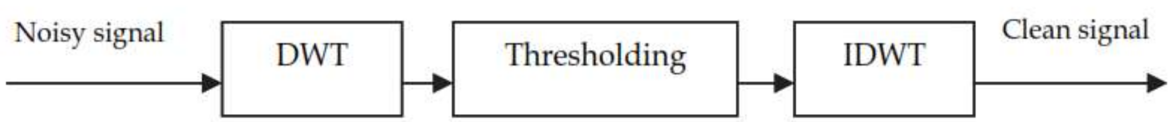

Fig 2: The filtering technique

The technique is applied for the model with additive noise, according to:

$$y=s + n$$

In the expression above y is the noisy signal, s is the ECG signal and n is the additive noise. Because the model corresponds to a linear system, the wavelet coefficients of the y are equal to the sum of the wavelet coefficients of s and the wavelet coefficients of n, according to:

If

$$Y = DWT\{y\}; \qquad S = DWT\{s\}; \qquad N = DWT\{n\}$$

Then

$$Y= S+N$$

If the external signal corresponds to white noise, its energy is thin with low amplitude. Then, the wavelet coefficients of y with low amplitude correspond to the noise of the signal. The noise is eliminated if the coefficients below a threshold area unit turned to zero (thresholding). Each stage of the Figure.2 has parameters associated with the performance of filtering. Specifically, the decomposition and reconstruction involve the base wavelet and also the variety of levels; and also the thresholding involves the threshold and the rule. The index is expounded to the length of the filter, for instance, for sym4 the length is eight. We propose choosing the base according to the similarity with the biomedical signal. In regard to the length of the filter, it's not suggested to use long filters for short time signals, for instance, if the time is 10ms, sym10 is healthier than sym45. The number of levels of decomposition (N) depends on the relation between sampling frequency and the bandwidth of the signal. An enormous N is needed if the relation is high; an initial rank is 3 to 10 levels.

Wavelet Thresholding

The various threshold choice schemes projected are VisuShrink, SURE Shrink, and Bayes Shrink. As the wavelet transform is good at energy compaction, the smaller coefficients represent noise and bigger coefficients represent the vital signal features. The smaller coefficients present in the detail subband are modified using wavelet thresholding techniques while the larger coefficients of the approximation subband are unaltered.

Hard Thresholding

The hard thresholding function is given as

$$Y = \begin{cases} X & \text{for} \quad |X| > T \\ 0 & \text{otherwise} \end{cases} \qquad \text{eq. (1)}$$

Where T, X and Y are Threshold, input, output wavelet coefficients respectively. In hard thresholding the wavelet coefficients below the threshold T are made as zero and coefficients above threshold are not changed.

Soft Thresholding:

The input-output relation of the soft thresholding function is given by

$$Y = \begin{cases} \text{Signum}(X).\max(|X| - T, 0) & \text{for} |X| > T \\ 0 & \text{otherwise} \end{cases} \qquad \text{eq. (2)}$$

From the results it's obvious that the signal is corrupted with high quantity of noise needed a lot of variety of wavelet decomposition. Whereas the signal with less quantity of noise is denoised by using less number of wavelet decomposition. Although the DWT is wide employed in signal de-noising, its application to alternative signal process issues has been hampered by two drawbacks.

Lack of Shift Invariance

This means that little shifts within the signal will cause major variations in the distribution of energy between DWT coefficients at totally different scales [3]. A method is shifting invariant if its output is independent of absolutely the location of the data within the input to process. The shift dependency happens as a result of the aliasing that's introduced by the down-sampling that follows every filtering operation.

Poor Directional Selectivity

Separable filtering of the image rows and columns produces four sub-images at every level. These sub-band images obtained using real filters that cannot distinguish between positive and negative frequency components. Therefore, every sub-band contains both positive and negative frequency components leading to poor directional selectively of the DWT.

B. Dual Tree Complex Wavelet Transform based ECG Signal Denoising

The filter bank structures for both DT-DWT are identical. Figure 3(a), (b) shows 1-D analysis and synthesis filter banks spanned over 3 levels. It’s evident from the filter bank structure of DT-DWT that it resembles the filter bank structure of normal DWT with double the complexity [3]. It may be seen as standard DWT trees operating in parallel. One tree is named as a real tree other is called as an imaginary tree. Sometimes in future discussions the real tree will be referred to as tree-a and the imaginary tree as tree-b

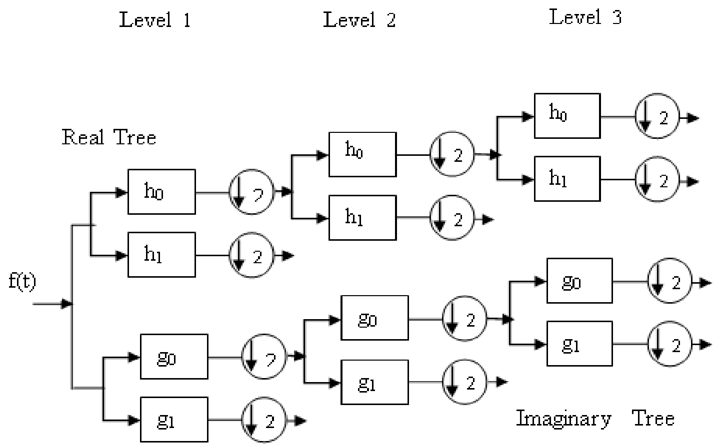

Fig 3(a): Analysis filter bank for DTCWT

Though the notation of h0 and h1 are used for all level within the real part of analysis tree, h0 and h1 of fist level are numerically totally different then the various filters at all other levels above level-1. An equivalent notion is applied for imaginary tree filters g0 and g1. The synthesis filter pairs as shown in figure 3(b) form orthogonal or biorthogonal pairs with their various counterpart filters of analysis tree as shown in figure 3(a). Each of the sub bands contains the wavelet coefficients for each imaginary and real part. Within the ±15degree, ±45degree and ±75degree directional edges within the original signal. Since the energy with every sub-band signal at any given level remains constant despite of shift, the DT-CWT is so shift invariant.

The form of conjugate filters used in 1-D DT-DWT is given as: $(h_x + j\, g_x)$. Where, h_x is the set of filters $\{h_0, h_1\}$, and g_x is the set of filters $\{g_0, g_1\}$ both sets in only x-direction (1-D)[4]. The filters h_0 and h_1 are the real-valued low pass and high pass filters respectively for real tree. The same is true for g_0 and g_1 for imaginary tree.

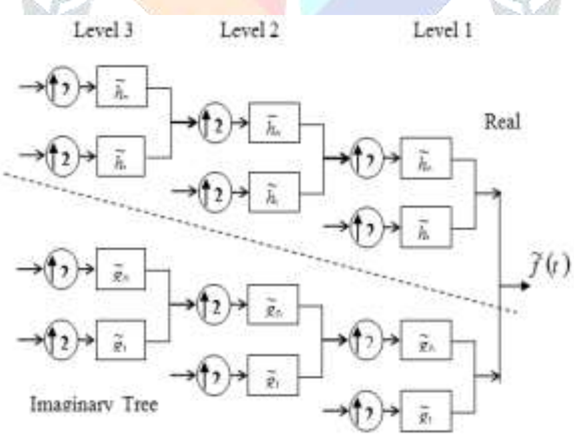

Fig 3(b): Synthesis filter bank for DTCWT

Unlike the DWT which mixes positive and negative frequencies and produces three sub-band signals at every level, the DT-CWT treats positive and negative frequencies individually and produces six sub-band pictures at every level. Every sub-band contains wavelet coefficients whose magnitudes are proportional to at least one of the ±15degree, ±45degree, ±75degree directional orientations of the input signal. As a result of positive and negative orientations taken into consideration one by one, the DT-CWT provides greater directional selectivity than the DWT.

C. ECG Denoising Using Wavelet Weiner Filter

The Wavelet Wiener filtering that consists of two stages. The primary stage is meant to estimate the noise-free signal employing a classical Wavelet filter and within the second stage is enforced the Wiener filter itself into the Wavelet domain. We have a tendency to improve this classic theme by adding a block for estimation of the input noise that sets the input parameters of this methodology. We suppose that the corrupted signal x(n) is an additive mixture of the noise-free signal s(n) and therefore the noise w(n), x(n) = s(n) + w(n), each unrelated, where n represents the discrete time (n = 0, 1,…, N-1) and N is that the length of a signal. If we transform the noisy signal x(n), using the linear dyadic discrete time wavelet transform (DTWT), to the wavelet domain, we have a tendency to get the wavelet coefficients

$Ym\ (n) = U_m\ (n) + V_m\ (n)$, where U_m (n) are coefficients of the noise-free signal and V_m (n) are coefficients of the noise, m is that the level of a decomposition and denotes m-th band. We have a tendency to be able to recover the noise-free coefficients U_m (n), from the coefficients V_m (n), using the wavelet Wiener Filtering methodology that is predicated on the Wiener filtering theory applied within the wavelet domain. The procedure is illustrated in Fig.4.

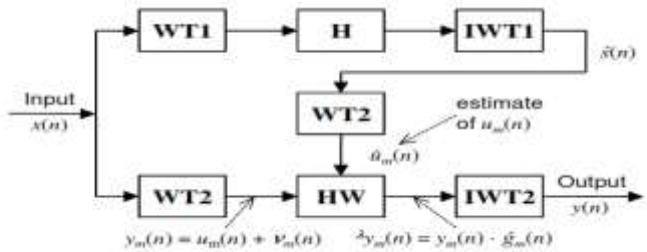

Fig4: The block diagram of wavelet wiener filtering method.

The upper path of the scheme consists of four blocks: wavelets transform WT1, modification of the coefficients within the block H, the inverse wavelet transforms IWT1 and also the wavelet transform WT2. The lower path of the theme consists of 3 blocks: the wavelet transform WT2, the Wiener filter within the wavelet transform HW and also the inverse wavelet transform IWT2. Coefficients modification within the block H is usually performed by thresholding [6, 7]. We have to set a suitable thresholding method and the threshold level, which should be dependent on a noise level (its standard deviation σ_vm) present in the signal in each band m. The levels of threshold λm are often modified by constant TM (the Threshold multiplier), λ_m = TM. σ_{vm}. The standard deviation of the noise is computed within the wavelet domain between two consecutive QRS complexes.

We get the estimate s ̃(n), when the inverse transform IWT1, that approximates the noise-free signal s(n). This estimate is employed to style the Wiener filter (HW), that is applied on the original noisy signal x (n) in WT2 domain (lower path), via Wiener correction issue

$$\hat{g}_m(n) = \frac{\hat{u}_m^2(n)}{\hat{u}_n^2(n) + \sigma_{vm}^2}$$

Where u ̂m^2are squared wavelets coefficients obtained from the estimate s ̂ (n) and σ^2_{vm} is that the variance of the noise coefficients $v_m(n)$ in m-th band. We process the noisy coefficients $y_m(n)$ within the block HW, using above described Wiener correction factor, to obtain modified coefficients

$$\lambda_{y_m(n)} = y_m\ (n)\,.\,\hat{g}_m(n)$$

The output signal y (n) is obtained by the inverse wavelet transform IWT2 of the modified coefficients λ_{ym} (n).

RESULTS & DICUSSIONS

The EKG signal is taken from the MIT-BIH arrhythmia data base-PhysioNet and denoised using some arbitrary denoising techniques and denoised signal is considered as clean or reference EKG signal.. As Gaussian noise thought-about as linear combination of artifacts such as Respiratory artifact, motion artifact, power line interference and electromyogram noise etc., that is present in EKG signals. The Gaussian Noise that is added to clean ECG signal in different amounts ranging in steps of 10dB. So obtained noisy signal is subjected to totally different denoising techniques mentioned during this paper particularly Discrete Wavelet Transform based EKG signal Denoising, twin Tree Complex Wavelet Transform based EKG signal denoising, and EKG Denoising

Using Wavelet Weiner Filter. The performance of those ways is evaluated through the metric signal to noise quantitative relation SNR. The SNR values of various denoising techniques are tabulated in table no.1.

Table 1: Comparison of SNR values for denoising techniques

Input SNR in dB	Output SNR in dB for Different Denoising Techniques					
	DWT				DTCWT	WWF
	db8	sym9	coif4	bior3.9		
0	3.4119	3.4107	3.4169	3.3420	3.8642	**11.9190**
10	13.2306	13.2127	13.2698	12.6861	12.6003	**20.8078**
20	25.2347	25.2460	25.2360	24.1946	26.7784	**27.0970**
30	31.5731	31.9735	31.6190	31.8935	**33.2901**	30.4853

From the Table.1 it's determined that the performance of wavelet wiener filter is best than DWT and DTCWT based denoising techniques when the noise is within the range of 0dB – 20dB. Because the wavelet wiener filter technique estimates the noise present within the EKG signal it's effectively suppresses the artifacts present in signal. For less quantity of noise DTCWT based mostly denoising technique is acting higher than that of the remaining two. Fig 5 a-e represents clear EKG signal, noisy EKG signal with SNR 20dB and its denoised version obtaining using DWT, DTCWT, and WWF.

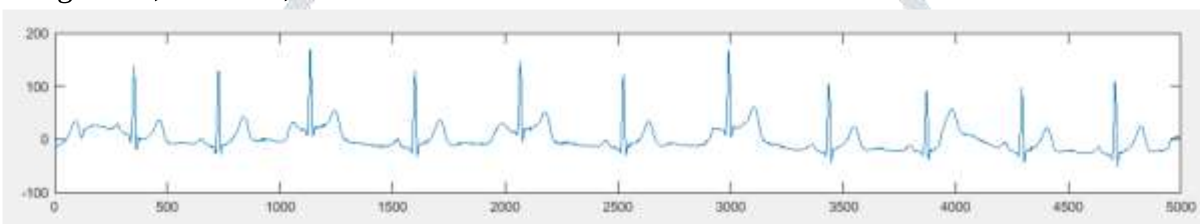

Fig 5(a): Clean ECG Signal

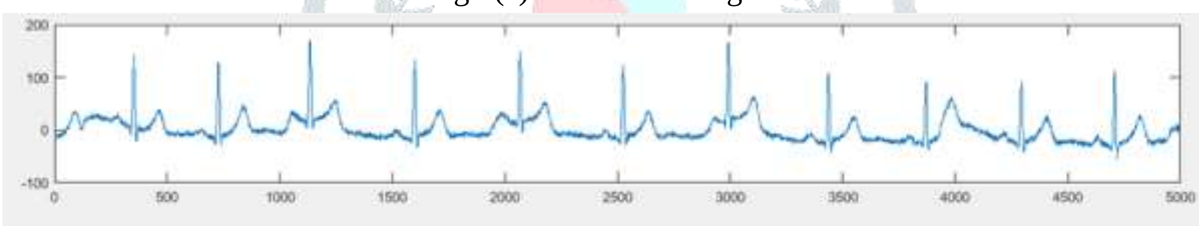

Fig 5(b): Noisy ECG signal with SNR 20dB

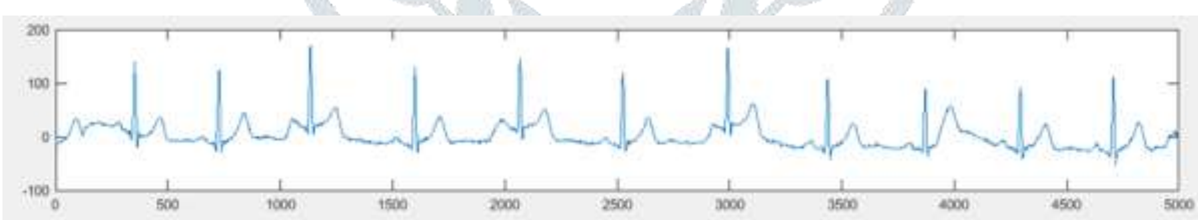

Fig 5(c): Denoised ECG signal using DWT

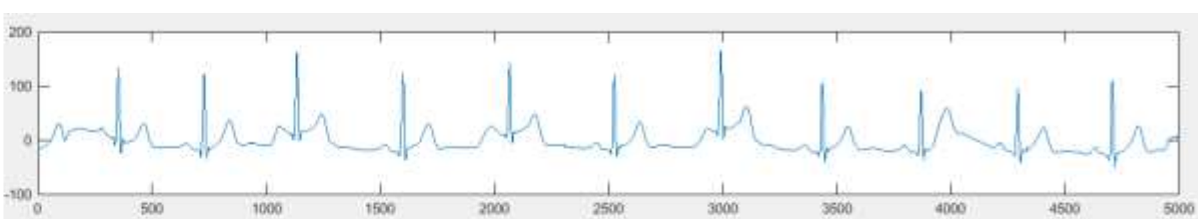

Fig 5(d): Denoised ECG signal using DTCWT

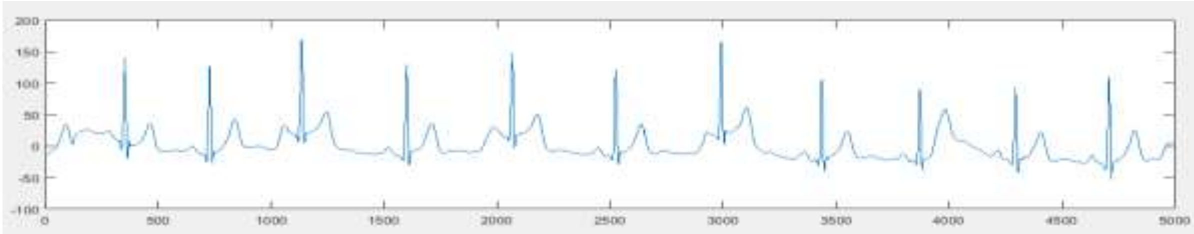

Fig 5(e): Denoised ECG signal using WWF

CONCLUSION

For removing artifacts from ECG signal completely different denoising techniques are applied. Performance of denoising techniques using DWT & DTCWT is relatively lesser than WWF for the noisy signal that are corrupted in large amount. Because the wavelet wiener filtering techniques estimate the noise present within the ECG signal before treatment, it's effectively suppressing the artifacts present within the signal.

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