ARTIFACTS REMOVAL OF ELECTROCARDIOGRAM USING WAVELETS

M. Durga Rani and M. Madhavi

Abstract— **Today's society is getting ever modernized by the every second. This sweep of modernization across complicated society come at a cost, health problems contributing to a major part of that. Cardiovascular diseases come under lifetime diseases. Around the world, heart diseases contribute more deaths than any other diseases. Controlling and detecting cardiovascular diseases have become one of the most challenging task in medical research. The main objective of the project is identify cardiac disorders using different signal processing techniques and to help the doctors to diagnose actual cardiac problem.**

ECG observations are often corrupted by various types of noise. In this study, we mainly focused on reduction of broad-band myopotentials (EMG) noise in ECG signal using DWT. Hence De-noising gained lot of importance. The proposed method choose the best suitable wavelet function based on DWT, using mean square error (MSE) and output SNR. The main advantage of this improved thresholding technique is retentive of each the geometrical characteristics of the first cardiogram signal and the variations with the amplitude of the varied cardiogram waveform effectively. The experimental results proves that the proposed method is improved than traditional wavelet thresholding de-noising methods in the aspects of remaining geometrical characteristics of ECG signal and in improvement of signal-to-noise ratio (SNR).Using Standard patterns and DSP in MATLAB, advantages and disadvantages of all these techniques have been studied and the best compromised solution has been determined.

Keywords:Electrocardiogram(ECG), wavelet de-noising, discrete wavelet transform, improved thresholding

I. INTRODUCTION

The heart signals are measured by using electrocardiography. These signals are collected by placing electrodes in arms, leg, and chest of our body. The ECG signal consist of six peaks and valleys, which are named as P, Q, R, S, T and U as shown in figure 1. In practical environment ECG signals are contaminated with various types of noises such as baseline wander, power line interference and Broadband myopotentials. Reduction of Broadband myopotentials (EMG) mainly concentrates in spectrum of the QRS complex [2]. With the increase of muscle activity EMG noise is occurred.

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ECG signal has a feature called non stationarity made tough task to denoise it. There are many methods to denoise this ECG signal but each method has it limitations which include poor SNR, MSE and complexity.

The use of discrete time wavelet transform (DWT) can increase effectiveness of suppression of wide-band EMG noise in comparison with linear filtering. DWT decomposes the signal containing EMG noise and some additive components of QRS complexes which are present in highest bands , and the lower bands contain more components of QRS complexes. The signal can be filtered by suitable adjustments in the transform coefficients depending on the expected level of interference. The important feature of DWT-based filtering is that it keeps additive components of QRS complexes even in the highest bands of decomposition. By using nonlinear filter the reversible DWT allows to estimate the level of noise in individual decomposition bands and proportionally adapt correction of DWT coefficients. By this method, we can achieve efficient noise suppression at the same time distortion of the ECG signal is minimized. The choice of the level of decomposition and the strategy of DWT coefficient adjustment are important factors.

II.WAVELET TRANSFORM

A wavelet is a small wave whose energy is concentrated in time, which is useful for the analysis of transient, nonstationary or time-varying phenomena. Such a wave can be expressed and analyzed as a linear decomposition of the sums and products of the coefficient and function. Consider a Example, any signal x(n) decomposition can be done by simultaneously passing it through a series of high and low pass filters with impulse responses as a(n) and b(n) respectively. The output of high pass filter is named as detailed coefficient and low pass approximate coefficients respectively.

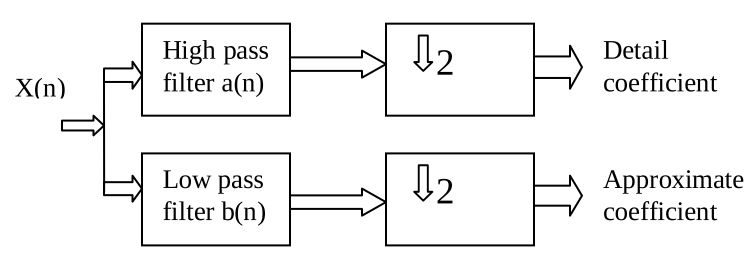

Fig 1.wavelet decomposition

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The down-sampling by 2 divides the input frequency by2, in the decomposition process. By this method of doubling the frequency resolution in further process makes the time resolution half. Increasing the levels of decomposition, which is on based user defined and application specific, will increase the frequency resolution. Unusually 3 to 5 levels are cascaded.

In the wavelet transform, the original signal (1-D) is transformed using predefined wavelets. The wavelets are orthonormal. In discrete case, the wavelet transform is modified to a filter bank tree using the Decomposition/ reconstruction given in Fig.2.

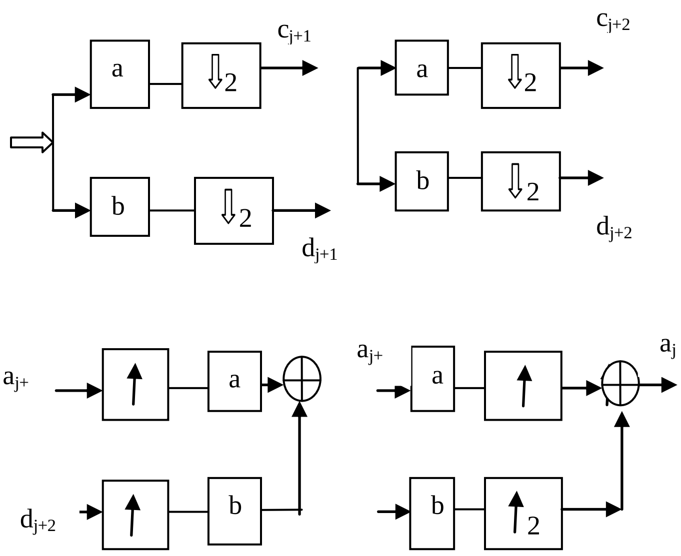

Fig 2. DWT and IDWT

The wavelet transform de-noising is based on the statement that most energy of a signal is concentrated in few coefficients whereas noise is spread over a large number of coefficients. The shrinkage step involves implementing a nonlinear threshold over these coefficients to retain the larger magnitude (signal) coefficients and nullifying the smaller magnitudes (noise).

III.THRESHOLD ESTIMATION

Since approximation coefficients contain low frequency components which are less affected by noise threshold is applied in detailed coefficients. The coefficients magnitude is compared to a threshold level, which is denoted by $\boldsymbol{\lambda}$' and an optimized value of $\boldsymbol{\lambda}$ is estimated. To estimate the threshold $\boldsymbol{\lambda}$**,** we need to calculate the noise level σ. For estimating value of σ, a popular proposed by Donoho and Jhonstone is based on the detail coefficients of the last level calculated with the help of median absolute deviation (MAD) as per the following formulae:

$$\sigma = (|x - x'|)/\ 0.6745\ (1)$$

Where, 0.6745 is the scaling factor for a normally distributed data. Further, to estimate the threshold level „$\boldsymbol{\lambda}$', a universal threshold was used which is a function of noise level „$\boldsymbol{\sigma}$' and length of signal ' k', given as:

$$\lambda = \sigma\ \sqrt{2}\ \log(k)\ (2)$$

This shrinkage step is also referred as *wavelet thresholding.*

Hard Thresholding:

$$S\ \lambda(d) = d.\ (abs(d) > \lambda)$$

IV.METHODOLOGY

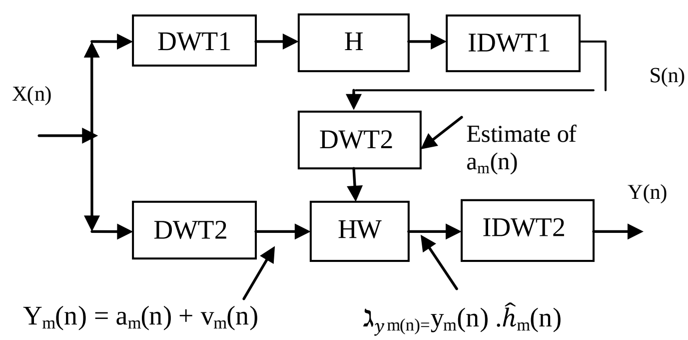

Fig Block diagram of WWF method

The above block diagram represents the WWF method. We can obtain the noise free coefficient $a_m(n)$ from the coefficient y_m (n) using WWF method [7] , [25] . The procedure for above block diagram is illustrated below.

The first 3 blocks such as DWT1, H and IDWT1 represents the classic wavelet filtering method. The upper part consists of 4 blocks such as wavelet transform DWT1, threshold H, inverse wavelet transform IDWT1 and DWT1. The lower part consist of the wavelet transform DWT2, the wiener wavelet Domain HW, and inverse wavelet transform IDWT2.

Using the inverse transform IDWT1, we estimate S(n), which approximate the noise free signal S(n). This estimate is used to design the Weiner Filter HW, which is applied to the noisy signal X(n) in the DWT2 domain in the lower path using wiener correction factor [2], [26] .

$$\hat{h}_m\ (n) = \frac{\hat{a}_m^2\ (n)}{\hat{a}_m^2\ (n) + \sigma_{vm}^2\ (n)}$$

where $\hat{a}\ {}_m^2(n)$are the squared wavelet coefficients obtained from the estimate $s(n)$, and $\sigma 2\ \ y_{m(}n)$ is the variance of the noise coefficients $v_m(n)$ in the mth band, estimated using (2).We process the noisy coefficients $y_m(n)$ in the HW block, using the previously described Wiener correction factor, to obtain the modified coefficients

$$ƛ_{ym}(n) = y_m(n) \cdot \hat{h}_m(n).$$

Adaptive Wavelet Wiener Filtering method (AWWF):

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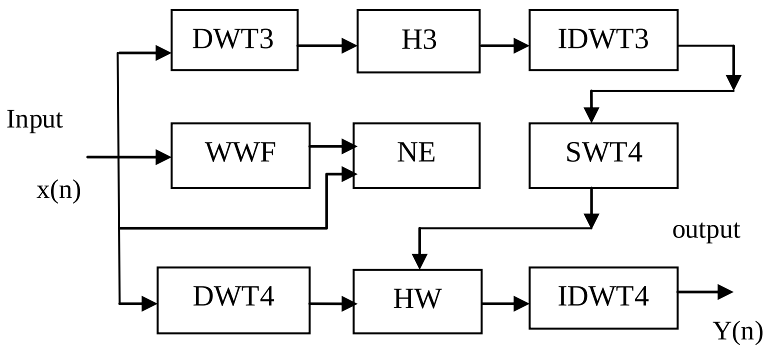


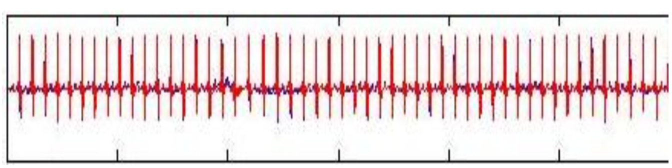
Fig 3.Block diagram of AWWF Method

To solve this problem we improved WWF by adding a block known as NOISE ESTIMATOR (NE).To estimate the noise it need two inputs one from noisy signal X(n) and another from noise free signal Y(n) obtained by WWF. The difference between signals gives an estimate input noise from this we can calculate the SNR. The parameters in the blocks are DWT3, H3, IDWT4, DWT4 and IDWT4 are set up using the estimated SNR_{est} value. Here for different level of interference we need to find out parameters individually. Because the problem here is we don't know correct setting of individual blocks.

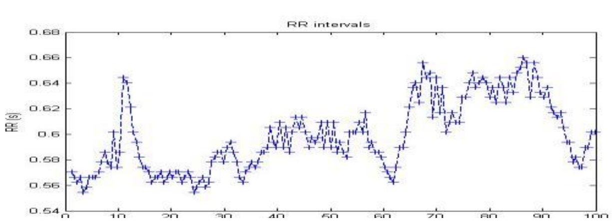
V. RESULTS

The ECG signal which is used here for testing are taken from standard CSE database. This signal consists of 2 sets of 125 practical 12 lead and 3 lead ECG signals. With a sampling frequency of 500HZ and quantization step of 5μv ECG signal will be recorded for 10s.

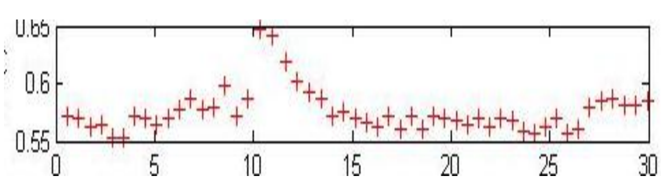
If filter whole data base using AWWF, SNR value increases greatly. The average improvement of SNR and SNR_i changes with the noise level. From the below graphs e can see it gives a clear idea of SNR improvement by using AWWF method.



RAW ECG SIGNAL



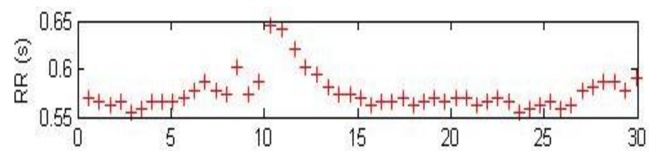
RR INTERVAL



RR interval after WWF

In WWF many parameter has to be set manually. Multiplier place an important role to decompose WT. Setting of proper input parameters had a great influence with filtering Threshold Results. Due to this reasons it became very difficult to set suitable input parameters.

TABLE-1



RR interval after AWWF

BASIC GROUPS OF INVESTIGATION PARAMETERS

Dec.level	Thres	TM	WT3	WT4
2	**HARD**	1	Haar	Haar
3	Hyperbolic	1.5	**dB4**	db4
4	Garrote	2	Sym2	Sym2
5	Semi-soft	-	-	-
6	Soft	20	dmey	Dmey
5	5	15	53	53

Dec.level-decomposition level, Thres-Thresholding method, TM-Thresholding Multiplier

TABLE-2

Example of iteration with ending condition

Iteration	Dec.level	Thres	TM	WT3	WT4
0	6	Hard	21	db4	dmey
1	4	Hard	4.5	sym2	bior 4.4
2	4	Hyperb.	4.5	rbio1.3	sym4
3	4	Garrote	4	db4	coif2
4	4	Garrote	4	db4	sym4
5	4	Garrote	4	db4	sym4
6	4	Garrote	4	db4	sym4
7	4	Hyperb	4.5	db4	sym4
8	4	Hyperb	4.5	Sym5	sym4
9	4	Garrote	4.5	db4	sym4
10	4	Semi soft	4.5	db4	sym4
11	4	Garrote	4.5	db4	sym4
12	4	Garrote	4.5	db4	sym4
13	4	Garrote	4.5	db4	sym4

Dec.level-decomposition level, Thres-Thresholding method, TM-Thresholding Multiplier

TABLE-3
Comparison of results with tested methods

Method	LF	WF	WWF	AWWF
Mean Imp.[db]	-4.4	6.3	6.6	10.5
STD.Imp.[db]	8.1	3.5	3.7	2.3
Computational cost [sec]	0.002	9.54	0.04	0.3

VI.CONCLUSION

The proposed technique Adaptive Wavelet Wiener filtering results is very effective when compared with simple wavelet filtering. In AWWF method setting of suitable parameter value and their estimate of noise level had a great impact on performance of filtering algorithm. By considering above factors effective noise suppression was done with less significant changes in the noise power. Due to this adaptive nature AWWF filter deal with dynamically changing noise. By applying this method on various ECG signals which are corrupted by EMG noise had a great Improvement in its SNR ratio.

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