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Adaptive Denoising of ECG Signal using Wavelet-based Wiener Filter and LMS Filtering

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ABSTRACT: The proposed work mainly focuses on reduction of EMG (Electromyogram) noise in ECG signal. The use of Wavelet Transform (WT) can be effective for suppressing EMG (muscle) noise compared to linear filtering as it provides information about both time and frequency characteristics simultaneously. The proposed algorithm reduces EMG noise using wavelet wiener filtering. Parameters of wiener filter are adapted according to the level of interference in the input signal. Important parameters used for adaptation are decomposition depth of input signal, thresholding method used, threshold size and filter banks. LMS (Least Mean Square) filtering of adaptively denoised ECG signal is also done to improve filtering performance. Testing is performed by taking ECG signal from standard MIT/BIH arrhythmia database. The proposed AWWF (Adaptive Wavelet Wiener Filtering) algorithm along with post LMS filtering provides better results by increasing SNR (Signal-to-Noise Ratio) and reducing mean square error.

KEYWORDS: ECG Signal; EMG noise; Wavelet Transform; Wiener Filtering; LMS Filtering

I. INTRODUCTION

Electrocardiogram (ECG) signals are important biomedical signals, which are reflective of an electrical activity of the heart. They form a subject of intensive research for over 100 years. ECG signals are one of the best understood signals being at the same time an important source of diagnostic information. Because of this, in the recent years there has been a steady and intensive research with the intent of developing efficient and effective methods of processing and analysis of ECG signals with emphasis on the discovery of essential and noval diagnostic information.

An ECG is a simple, noninvasive procedure. Electrodes are placed on the skin of the chest and connected in a specific order to a machine that when turned on, measures electrical activity all over the heart. Output usually appears on a long scroll of paper that displays a printed graph of activity on a computer screen.

A typical ECG signal consists of a P wave, QRS complexes and T wave. P wave is produced by muscle contraction of atria. QRS wave marks the ending of atria contraction and the beginning of ventricular contraction. T wave marks the ending of ventricular contraction.

An ECG signal recorded from a human body may contain different types of interferences. Proper denoising of ECG signal is thus necessary to separate signal from noise. Different noises in ECG signal include: 1) Power line interference 2) Electrode contact noise 3) Motion artifacts 4) EMG noise 5) Instrumentation noise. The proposed work focuses mainly on the reduction of EMG noise. EMG noise is caused by the contraction of other muscles besides the heart. When other muscles in the vicinity of the electrodes contract, they generate depolarization and repolarization waves that can also be picked up by the ECG. The extent of crosstalk depends on the amount of muscular contraction.

The common method to estimate signals which are corrupted by additive noise is to design a filter, that tends to suppress noise while leaving signals relatively unaffected. The design of filters need prior knowledge of both signal and noise, but adaptive filters have the ability to adjust their own parameters automatically and no prior knowledge of signal or noise description is needed.

Wavelets provide a flexible prototyping environment that comes with fast computational algorithms. The concept of wavelet thresholding relies on the assumption that signal magnitudes dominate the magnitudes of noise in a wavelet representation, so that wavelet coefficients can be set to zero, if their magnitudes are less than a predetermined thteshold. If a suitable wavelet is selected, the orthogonal wavelet decomposition can preserve main profile of signal of

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lower frequencies in approximate coefficients. WT results in signal decomposition, that is, highest bands with EMG noise along with some additive components of QRS complex and lower bands with more components of QRS complex.

II. RELATED WORK

Suyi Li, Jun Lin [2] proposed an optimal denoising algorithm for ECG using stationary wavelet transform. The proposed work studies the optimal denoising algorithm for ECG based on SWT, including the selection of optimal wavelet basis, appropriate thresholding method and decomposition depth, also called level or scale. The studies highlighted three main steps in WT denoising procedure. 1) Decomposition of noisy signal using a wavelet basis 2) Shrinking the coefficients using thresholding method 3) Reconstruction of denoised signal using shrunk coefficients. In [3], the authors focused on suppression of parasite electromyographic (EMG) signals included in ECG signals with the use of wiener filtering in shift-invariant wavelet domain with pilot estimation of the signal. The proposed approach uses four-levels shift-invariant dyadic discrete-time wavelet transform decomposition for both main blocks of pilot estimation and wiener filtering. In [4], the authors presented an optimal algorithm for ECG denoising using discrete wavelet transforms. The research aims to select the optimal wavelet function and related features to achieve the best noise free signal. The wavelet denoise approach consists of three steps:1) Forward DWT 2) Thresholding 3) Inverse DWT. N.Nikolaev, Z.Nikolov, A.Gotchev, and K.Egiazarian [5] focused on wavelet domain wiener filtering for ECG denoising using improved signal estimate. The research proposes a two-stage algorithm for ECG signal denoising which combines wavelet shrinkage with wiener filtering in translation-invariant wavelet domain. In [6], the authors proposed denoising of high resolution ECG signals by combining the discrete wavelet transform with the wiener filter. The proposed work derives a filter which manipulates discrete wavelet transform coefficients in a way that minimizes the expectation of squared error. The new wiener wavelet filter allows a better adaptation of the filter to time-frequency details of the signal. The procedure is optimal in least squares sense. In [7], the authors focused on FPGA implementation of fast FIR low pass filter for EMG removal from ECG signal. The method proposes a branched tree architecture for adder connection to reduce the critical delay. The proposed architecture has been implemented on FPGA using Verilog Hardware Description Language (HDL). Angkoon Phinyomark [8] introduced and evaluated adaptive wavelet thresholding technique for estimating useful information of SEMG signal and improve application of multifunction myoelectric control system. The general wavelet based denoising procedures are composed of three steps:1) Decomposition 2) Denoising wavelet's detail coefficients 3) Reconstruction. The wavelet denoising procedure is investigated in two point views: 1) Denoising 2) Pattern recognition. The results show that Global scale Modified Universal (GSMU) method provides better performance than traditional methods.

III. PROPOSED METHOD

The paper focuses on the reduction of EMG (muscle) noise in ECG signal. The use of wavelet transform (WT) is effective for the suppression of EMG noise compared to linear filtering because it provides information about both time and frequency characteristics simultaneously. Wavelet transform results in signal decomposition,ie, highest bands with EMG noise along with some additive components of QRS complex and lower bands with more components of QRS complex. Important parameters used are decomposition depth of input signal , thresholding method, threshold size and filter banks. Choice of adequate parameters are important. Signal is separated from interference by thresholding of wavelet coefficients. Effective thresholding includes evaluation of right value of threshold and choosing right methods of thresholding.

Corrupted signal denoted by x(n) is an additive mixture of noise free signal s(n) & noise w(n).

$$x(n) = s(n) + w(n) \qquad \text{eq. (1)}$$

where n represents discrete time (n=0,1….,N-1) and N is the length of the signal

Noisy signal x(n) is transformed into wavelet domain to obtain wavelet coefficients,

$$y_m(n) = u_m(n) + v_m(n) \qquad \text{eq. (2)}$$

where, $u_m(n)$ and $v_m(n)$ denotes the coefficient of noise free signal and m is the decomposition depth.

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For calculation of threshold value, standard deviation of noise is multiplied by an empirical constant TM (Threshold Multiplier)

$$\lambda_m = TM.\sigma_{vm} \qquad \text{eq. (3)}$$

where σ_{vm} is the standard deviation of noise and it can be estimated using the median,

$$\sigma_{vm} = \frac{median(|\, y_m \,|)}{0.6745} \qquad \text{eq. (4)}$$

A. *Wavelet Wiener Filtering (WWF) Method*

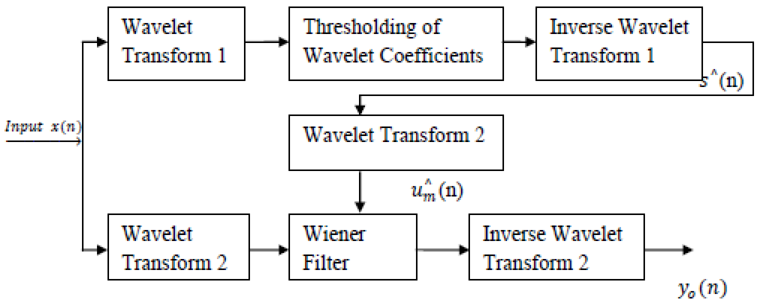

Fig.1 Block diagram of WWF method

The upper path of the scheme consists of four blocks:

- Wavelet Transform 1
- Thresholding of wavelet coefficients
- Inverse wavelet transform 1
- Wavelet transform 2

The lower path of the scheme consists of three blocks:

- Wavelet transform 2
- Wiener filter
- Inverse wavelet transform 2

Noise corrupted input signal x(n) is first transformed to wavelet domain because signal separation from noise becomes easier in wavelet domain. Threshold value $\lambda_m(n)$ is then estimated for thresholding inorder to separate signal and interference. Using inverse transform 1, estimate $\hat{s}(n)$ of noise free signal s(n) is obtained. The estimate is used to design wiener filter, which is applied to original noisy signal x(n) in transformed domain via wiener correction factor.

$$\hat{g}_m(n) = \frac{\hat{u}_m{}^2(n)}{\hat{u}_m{}^2(n) + \sigma^2{}_{vm}(n)} \qquad \text{eq. (5)}$$

where $\hat{u}_m{}^2(n)$ are the squared wavelet coefficients obtained from the estimate $\hat{s}(n)$and $\sigma^2{}_{vm}(n)$ is the variance of noise coefficients $v_m(n)$Noisy coefficients $y_m(n)$is processed in wiener filter block, using wiener correction factor, to obtain modified coefficients,

$$\lambda_{ym}(n) = y_m(n).\hat{g}_m(n) \qquad \text{eq. (6)}$$

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The output signal $y_o(n)$ is obtained by taking inverse wavelet transform of modified coefficients $\lambda_{ym}(n)$.

B. *Adaptive Wavelet Wiener Filtering (AWWF) Method*

Adaptive filtering is a powerful signal estimation method. If the noise follows a random pattern and the interference has non-deterministic sources, it is better to use a filter, that is adaptive to background noise to remove interference. An adaptive filter has the property of self-modifying its frequency response to change the behavior in time, allowing the filter to adapt its response to the change in input signal characteristics. Due to this capability, the overall performance and the construction flexibility, adaptive filters have been employed in many different applications.

When frequency domain adaptive filtering is applied, the Discrete Fourier Transform (DFT) is used, but it is suitable only for stationary signals, for which the statistical properties of the signal are not time varying. The wavelet transform is a time-scale representation method with a basis function, called the mother wavelet. The wavelet transform represents a signal as a sum of wavelets with different scales. In wavelet transform- based adaptive filters, the input signal is subsequently performed in subbands, and it is able to adapt to non-stationary signals. But wavelet transform thresholding in the subband is applicable, only if the signal magnitude is greater than the noise amplitude.

The WWF method has many parameters to be set manually. The most important ones are decomposition level of WT, thresholding method in wavelet domain, threshold multiplier and wavelet filter banks used in wavelet transform 1 and wavelet transform 2 blocks.

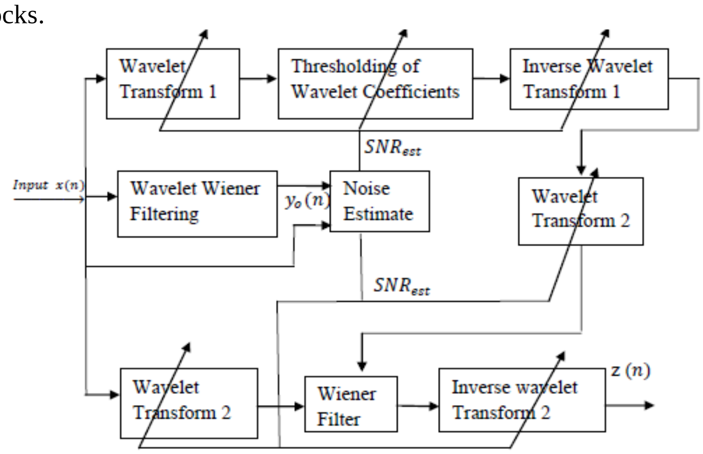

Fig.2. Block diagram of AWWF method

Here, the WWF method is improved by adding the block for noise estimate (NE). This block needs two inputs:

- Noisy signal x(n)
- Noise free signal $y_o(n)$

The difference of these two signals give an estimate of the input noise and SNR can thus be calculated. The parameters in blocks wavelet transform 1, thresholding, inverse wavelet transform 1, wavelet transform 2 and inverse wavelet transform 2 are set up using estimated SNR_{est} value.

The quality criterion which is used to evaluate the success of whole denoising process is achieved SNR of output signal y(n).

$$SNR_{out} = 10.\log_{10} \frac{\sum_{n=0}^{N-1}[s(n)]^2}{\sum_{n=0}^{N-1}[y(n)-s(n)]^2} \qquad \text{eq. (7)}$$

SNR improvement is given by,

$$SNR_I = SNR_{out} - SNR_{in} \qquad \text{eq. (8)}$$

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For calculating SNR, noise free signal s(n) is needed. Model of noise free signal is created by filtering of ECG from MIT/BIH database corrupted by artificial noise w(n). Model of EMG noise is created by filtering random noise using a shaping filter H(f) which is given by the expression,

$$H(f) = \frac{f_h^{\,4} f^2}{(f^2 + f_l^{\,2})(f^2 + f_h^{\,2})^2} \qquad \text{eq. (9)}$$

where $f_l = 60\,Hz,\ f_h = 120\,Hz$

Right power of noise is set to achieve required SNR_{in}. It is done by multiplying noise by a constant A.

$$x(n) = s(n) + A.w(n) \qquad \text{eq. (10)}$$

Where A is given by the expression,

$$A = \sqrt{\frac{\sum_{n=0}^{N-1}[s(n)]^2}{10^{\frac{SNR_{in}}{10}} \sum_{n=0}^{N-1}[w(n)]^2}} \qquad \text{eq. (11)}$$

Step by step process is as follows:
Step 1: SNR is set from 0 to 30 dB in steps of 5 dB
Step 2: Randomly select first combination of parameters (shown as bold in table I)
Step 3: Generate random EMG noise
Step 4: Change decomposition level from 2 to 6
Step 5: Filter signal for each decomposition level
Step 6: Choose decomposition level at which achieved SNR is highest
Step 7: Do the same with Threshold Multiplier, Thresholding method and both filter banks
Step 8: Using the above obtained parameters, different blocks are adapted

Decomposition Level	Thresholding Method	Threshold Multiplier	Filter Bank WT1	Filter Bank WT2
2	**Hard**	1	**Db4**	Db4
3	Soft	1.2	Bior4.4	**Dmey**
4	Garrote	.	.	.
5		.	.	.
6		**6**	Sym6	Sym6
5	3	11	7	7

Table.I. Investigated parameters for adaptation

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C. *Adaptive Wavelet Wiener Filtering (AWWF) Method with Post LMS Filtering*

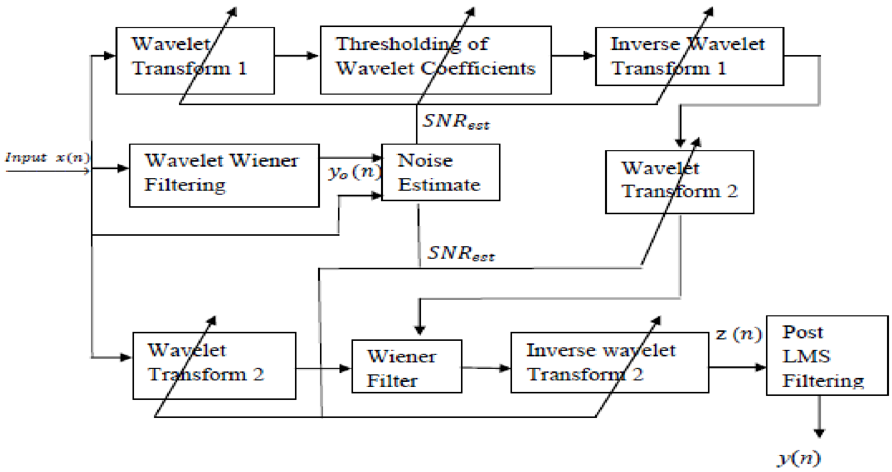

Fig.3. Block diagram of AWWF method with post LMS filtering

IV. SIMULATION RESULTS

The performance evaluation is done using MATLAB R2015a. MATLAB is a high-performance language for technical computing. It integrates computation, visualization, and programming environment. The ECG signal used for testing are from MIT/BIH database. The artificial noise used was generated using normalised random function.

Fig 4 (a) shows the noiseless signal. It is obtained by prefiltering the ECG signal (using an averaging filter) taken from the MIT/BIH database. Fig 4 (b) shows the noisy signal. It is created by adding randomly generated noise to ECG signal. The noise is shaped to EMG spectrum before addition using a shaping filter. Fig 4 (c) shows the denoised output after Adaptive Wavelet wiener filtering. For input SNR of 20 dB, output SNR of 21.5385 dB was achieved.

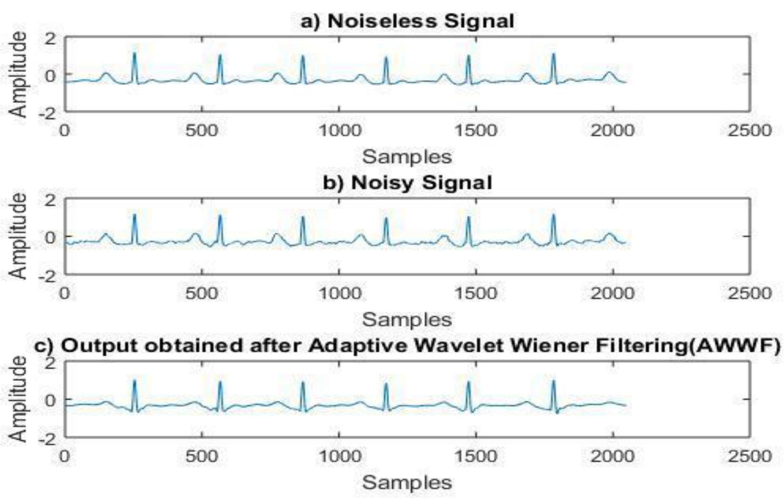

Fig.4. (a) Input noiseless signal, (b) noisy signal obtained by adding EMG, and (c) output obtained after AWWF filtering for input SNR 0f 20 dB

Fig 5 shows the comparison between two output waveforms, that is, the one obtained after adaptive denoising and the one obtained after post LMS filtering of AWWF output. Adaptively denoised output is again post filtered using LMS filter for further noise reduction. While the AWWF output achieved an SNR of 21.5385 dB, LMS filtered output

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achieved an SNR output of 25.8814 dB. Mean square error also reduced from 0.0072 to 0.0034 for an input SNR of 20 dB.

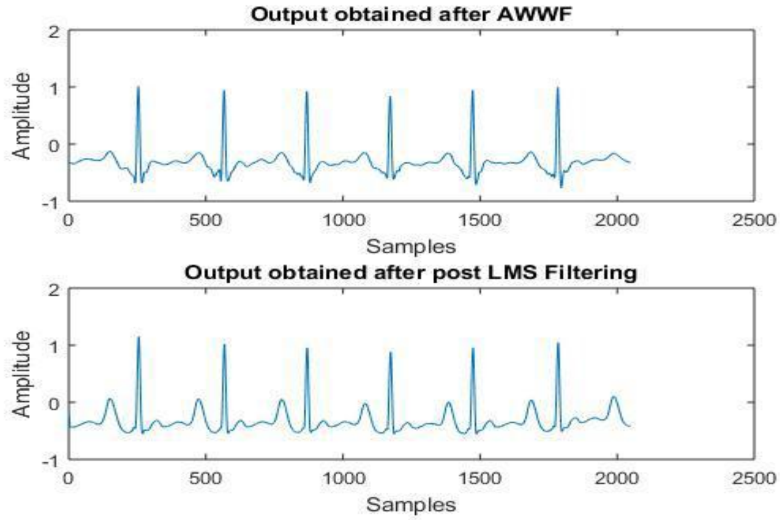

Fig.5. Output obtained after AWWF filtering and post LMS filtering for input SNR of 20 dB

Table II shows the achieved SNR and mean square error. After adaptive denoising of ECG signal, the peak SNR achieved by the denoised output was found to be 21.5385 dB, while the output obtained after post LMS filtering of AWWF signal achieved an output SNR of 25.8814 dB corresponding to an input SNR of 20 dB. Mean square error for the first case was found to be 0.0072 while it was found to be 0.0034 for the second case. Thus the peak SNR showed an increase and at the same time mean square error showed a decrease resulting in an improved performance.

Methods used	Peak SNR(dB)	Mean Square Error
After adaptive denoising	21.5385	0.0072
After post LMS filtering	25.8814	0.0034

Table.II. SNR and mean square error obtained for $SNRin=20\ dB$

V. Conclusion

The survey of the works and findings done by various researchers on ECG signal denoising shows that the use of dicrete time wavelet transform (WT) can increase effectiveness of suppression of wide-band EMG noise in ECG signal compared with linear filtering. The WF and WWF methods use fixed parameter setting, and therefore cannot properly respond to changes in the signal, and filtering fails. The root causes for the problem is examined and found that adaptation of filter coefficients according to the level of interference in the input signal is necessary to improve the filtering performance.

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The proposed method denoises ECG signal adaptively. Suitable filter banks and other parameters of wiener filter are chosen with respect to highest SNR obtained and adaptation is done by using these parameters. Denoising procedure is implemented using wavelet transform, wavelet decomposition, thresholding, and wiener filtering by application of wiener correction factor. Threshold value is set adaptively based on standard deviation of noise at decomposition levels. Denoised output is processed using a post processing LMS filter for further noise reduction. The results showed an improvement in achieved SNR and it also showed a reduction in mean square error.

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BIOGRAPHY

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