EFFICIENT STUDY ON ADAPTIVE FILTER PERFORMANCES FOR DENOISING ECG SIGNALS BASED ON DWT

N. Sai Chandu [1], G. Deepika[2]
[1,2]Dept. of Electronics and Communication Engineering.
RRS College of Engg & Tech

Abstract
Electrocardiogram (ECG) signal is an instance of the real-time signal. ECG signal Filtering is an essential step in the processing of ECG signal examination and a lot of scopes required in the computer-aided diagnosis of heart. By reason ECG signals are of low ranking frequency signals and contain a lot of clinical information, and by the fact presence of other biosignals. The goal of filtering signal is to eliminate unwanted noise while maintaining important attribute of the signal. Various techniques for filtering are available thus selecting the appropriate filter for ECG signal denoising is a problem. Many research work focusing on denoising the signal for extracting important features like Extended Wavelet Transformation. The denoising signal processing techniques evaluated using by mean square error (MSE) and by improving the signal to noise ratio (SNR). Furthermore to the study, the methods above mentioned were used to eliminate the baseline wondering and high-frequency noise elements of the ECG signal acquired. Experimental results depict that analysis of different techniques of denoising and an identification of person through the ECG signal acquires best SNR values.

Keywords*:* Electrocardiography; Discrete wavelet transforms; Noise reduction; Signal to noise ratio;

I. INTRODUCTION

The electrocardiogram (ECG) is major often known diagnostic biomedical signal. It is the detailed presentation in the graphic for the human heart function and could be registered easily with surface electrodes situated on the limbs and chest. In an efficient environment during accession, various groups of artifacts in ECG signal get added. One of vital issues in biomedical signals, like the electrocardiogram, is the split up of the favored signal from noises created by power line interface, muscle artifacts, baseline wandering and motion artifacts. Since biological signals are low amplitude with low frequency in signals, they are likely subjected to noise.

The prime artifacts available in the ECG comprise Power-line Interface and Baseline Wander. Baseline wandering arises owing to respiration. Poor electrode connects and opposes the electrodes might occurs low-frequency artifacts. Sometimes, the fluctuations in temperature and slant in an instrumentation system may also produce a baseline drift. The main reason for such noise is the electromagnetic disruption from the surrounding equipment and poor conductors. The basic electromagnetic risk of cables and run or go around of the articraft can minimize the distortions occurred by electromagnetic waves. This artifact changes examine in the ECG signals, reduces the character of the signal, and yields massive amplitude signals which can resemble waveforms. Consequently, these factors mask small features that are important for clinical monitoring and diagnosis in the heart abnormalities. The solution to this problem is difficult because most biological signals and power line interface are uncorrelated. The cancelation of ECG signals equipment is important for better analysis. The withdrawal of high-level resolution in ECG signals recordings, which are unsettled by noise, is an essential issue. Two problems are considered in this thesis: one is denoising, other is the classifying of different arrhythmias. The main intention of ECG signal denoising is to discrete the carved signal constituent from the undesirable artifacts, so as to present an ECG that make a simple and exact interpretation. Due to overlying within cardiac and non-cardiac components in frequency, particularly from 0.1 Hz-100 Hz, linear filtering (filters like low pass or band pass) is inadequate to eliminate such noises, by leaving the particular components unchanged. Real-time automatic ECG diagnosis in clinical settings is of great extent to direct contact involved in diagnosing cardiac arrhythmias, which frequently emerge as consequences of a cardiac disease, and it might be life-frightening and demand immediate therapy. However, the automated categorization of ECG beats is a testing problem, as the examination and temporal analysis of ECG signal show significant disparity for patients, and under different temporal and physical conditions. The main priority of this work is to withdraw the noise in ECG signals by developing denoising methods and to classify different arrhythmia signals by extracting their distinct features.

II. DESCRIPTION

The steps followed in this thesis have been detailed below. A brief outline of the methodology is given in the flowchart Fig. 1.

Transforms have an important potential in signal processing issues since they can present a different representation of signals, which are more desirable for processing. Frequency domain (or transform domain) filtering, appliance in an unconventional way is used to enhance the convergence capacity of the standard LMS algorithm, by exploiting the orthogonallity property of Discrete Wavelet Transform (DWT) and related orthogonal transforms.

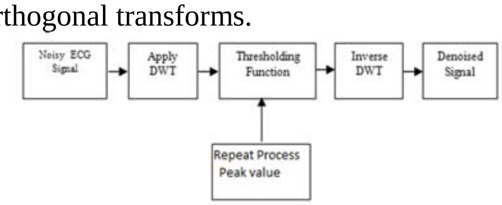

Fig.1 Block analysis of Proposed Denoising Algorithm

Frequency domain filtering is useful when Signal is statistically stationary.

- Noise is a uniform arbitrary procedure that is statistically unconventional with respect to the signal.
- The signal scope is inadequate to bandwidth note the similarity of noise (or vice-versa).
- Loss of data info in spectral bands removed by filter does not seriously infect the signal.

PLI of 50 Hz (and harmonics) is the source of inference. This inference is originated by poorly shielded nearby machinery's electromagnetic field, the stray effect of alternating current fields due to cable loops and/or trace loops in the ECG circuit, inappropriate grounding the ECG equipment or patient, etc.

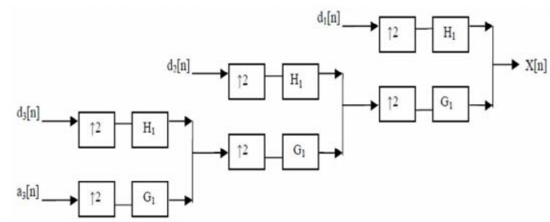

Fig.2 Wavelet-based reconstruction of signal

I. WAVELET BASED FILTERING.

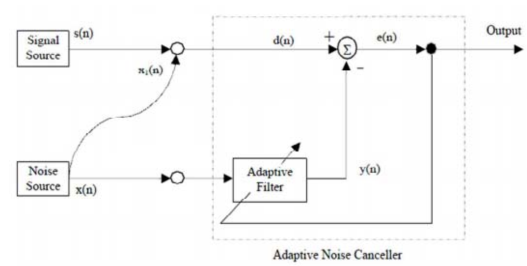

Fig.3Basic Adaptive Model

When the noise and the signal occupy fixed and different frequencies in band, conventional linear filters with firm coefficients are pre-owned to withdrawn the signal. If the features of the filter are variable and which are adaptive in changing attributes of the signal, the coefficients must vary. If the frequency band is unknown adaptive filter can be used. Adding to filter characteristics the variable, alter to changing conditions. When there's spectral overlap within signal and noise, the band absorb by noise is alters with time.

An adaptive filter behaves as a stable filter when the signal and noises are stationary. All the above-mentioned filters are applicable with-respect to noise. The LMS kind adaptive algorithm also is known gradient search algorithm by which a set of weights is calculated iteratively to obtain a minimum mean square error as,

$$w(n+1) = w(n) + \frac{1}{2}\mu[-\nabla(E\{e^2(n)\})] \quad .(1)$$

Where μ is the step-size framework and powers the convergence features of the LMS algorithm; mean square error $e^2(n)$, between the shaft output y(n) and the referral signal is given by,

$$e^2(n) = [d^*(n) - w^T x(n)]^2 \quad \ldots (2)$$

The gradient weights in the equation (2) can real-time as

$$\nabla_w(E\{e^2(n)\}) = -2r + 2Rw(n) \quad \ldots (3)$$

II. ECG Signals using DWT

In this research, by using decomposition four methods are suggested for denoising ECG signals. Two methods are adaptive filter structures, other is DWT. An adaptive filter is an inherent choice for the transfer of power line interface, as it can regulate its coefficients as stated by certain algorithms. It's an effective signal estimation method for Least Mean Square algorithm developed is familiarly used adaptive filtering algorithm, and it's a simple in computation. A two-level adaptive filter used at the early stage is to divide the interface. Notch filters are fixed frequency filters, and unable to use in a varying signal environment. Adaptive filter aims at diminishing the errors to withdraw the estimated and the original signal. This error is fed back as the input to the next level of iteration. Thus, an adaptive filter is the better choice for the time-varying noise environment. The two-level adaptive filters will have command over the phase and the signal magnitude. Two methods are proposed; one by giving the referral signal and followed by extracting the exact band of power line interface by placing a BPF in the path of the reference signal. Facing changes with regard to characteristics in noise, automatically there will be a change in the DWTs also. The performance of this approach is compared with the effects of the wavelet and notch filters, and the plots are shown in Figure 4. Although the analysis is time-consuming, better denoising performances are obtained.

Each component represents one component of the signal, the first function captures the high-frequency position of the actual signal and consequently, the representation of signal is constructed from fast oscillations (high frequency) to slow oscillations (low frequency). The wavelets also knew as modes or components, which are acquired by using the process called sifting. Depending on the selected settings, the signal is separated into less or more components. This is mentioned as the resolutions of the decomposition, similar to using unconventional window sizes at the short time or choosing different wavelets in the DWT behaves as a "wavelet-like" adaptive filter bank for Gaussian noise. It is possible to restore the information from start to the longest and shortest periods. The difference within the reconstructed information from overall the actual data is extremely small, and therefore, the completeness of the decay is validated Haiyong Zhang & Qiang Gai (2006).

The major advantage of the DWT is the basic functions are derived from the signal itself. Thus, the examination is robust in oppose to the conventional methods, where the basic functions are constant. The DWT is building on the serial extraction of energy-related with numerous intrinsic times scaling of the signal, initializing from finer spatial scales to rough ones. The decomposed levels will distinct the frequency given in the noisy ECG signal.

If the signal x(t) decomposes as follows

$$x(t) = \sum_{i=1}^{N} c_i(t) \quad \ldots \ (4)$$

the frequency of c (t), c (t), … , c (t) is decreasing. So the low-frequency levels in signals can be written as

$$x_L(t) = \sum_{i=L}^{N} c_i(t), 1 \le L \le N \quad \dots (5)$$

The high-frequency signal levels can be represent as

$$x_H(t) = \sum_{i=1}^{H} c_i(t) \quad 1 \le H \le L \quad \dots (6)$$

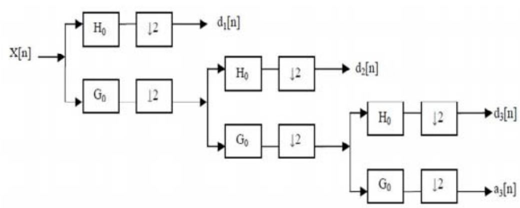

Fig.4 Decomposition of Signal

The signal filtering is accessed by DWT based with the signals detail and average coefficients, so the initial step is to initiate the wavelet coefficients, the following step is to scale the coefficients build on the thresholding methods mentioned above. The last step is to recreate the signal from the coefficients with IDWT.

Wavelet thresholding algorithm consists of major steps:

1. Apply DWT on a noisy ECG signal and obtain different intrinsic mode functions. The representation of decomposed signals can be the sum of total signals and one residue. This can be given as

$$x(t) = \sum_{i=1}^{N} c_i(t) + r(t) \quad \dots (7)$$

2. Choose wavelet coefficients with DWT.
3. Remove the noise by scaling the average coefficient noises by applying the algorithm to the detail coefficients.
4. Generate the filtered information from the coefficients with IDWT.
5. The residue signal, that is a monotonic signal, has the frequencies of range 0.5 Hz and shows baseline wandering. So discard the residue signal, r(t).
6. Finally, add the signal dominant threshold levels; the partially reconstructed noise free ECG signal is obtained.

Simulation Results

The execution of each classifier is analyzed regarding the classifying accuracy and computation time. Few of the classes are misclassified because of the nature waveform being alike to the other classes. Automated detection of captures using ECG is an extent that extremely increased its sources in the health sector and is fetching gain in a population where inadequate knowledge regarding the disease and its effects are noted to the mass.

Mean Square Error (MSE)

Mean Square Error is the computation of signal cause and position at estimating the amount of similarity/accuracy or, the amount of error/falsification within the signals and is situated on the prediction that one signal is of flawless original, while other is contaminated by errors.

$$\mathbf{MSE} = \frac{\sum_{M,N}[I_1(m,n) - I_2(m,n)]^2}{M * N} \quad \dots (8)$$

In the equation (8) represents M (rows) and N (column) of the given input signal.

Peak Signal to Noise (PSNR)

Peak Signal-to-Noise Ratio abbreviated as PSNR, characterizes the ratio within the maximum achievable power of a signal and degraded noise that influences the similarity of its presentation. It is generally expressed regarding the logarithm decibel scale. It can be simply evaluated via MSE.

$$\mathbf{PSNR} = 10 \log_{10} \left(\frac{\mathrm{Max}^2}{\mathrm{MSE}}\right) \quad \dots (9)$$

In the equation (9) Max represents the peak value of the ECG signal. The higher the value of PSNR better is the constancy of the signal.

Specificity

Specificity is an arithmetical measurement used to calculate the representation of analysis. It can also refer to as the true negative rate which estimates the percentages of negative values which are accurately recognized. It is generally expressed with regards to a percentage.

$$\text{Specificity}=\frac{\text{Number of true negative decisions}}{\text{Number of actual negative cases}} \quad \ldots (10)$$

Sensitivity

Sensitivity is another numerical calculation used to indicate the number of positive data which are exactly analyzed. It is also the referral to as true positive rate. It is commonly expressed regarding the percentage.

Accuracy

Accuracy is stated as the final extent to which an estimated value confirms to a true or obtained value. Accuracy is computational of correctness. The ultimate performance of any classifier based accuracy. It is normally indicated by the percentage.

The residual power line interface can be interfering with the exact representation of ECG wave boundaries. This affects the proper measurement of the RR intervals. Digital notch filters are majorly used but need a narrow band frequency. Since the spectra of noise and signal are overlapping, the notch filters to eliminate the 60 Hz signal component, further to the noise component. One cannot directly perform the noise subtraction from the signal, as the referral signal may have a different phase with the input signal. Subtraction procedures are very easy and simply implemented with less computational complexity. The SNR values for subtraction methods are high, with a less mean square error. The eminence of the reconstructed signal is good, the contrast to the adaptive methods. High SNR results are obtained, whatever the amount of noise.

The indirect subtraction method outperforms all the other proposed methods. The first level obtained after the reduction of a noised ECG signal, taken as the referral signal for subtraction. Since the input signal is taken as the reference, there are no phase differences. Increases in the PSNR value indicate the better character of the signal denoised.

Proposed Methods	SNR	MSE	PSNR
Partial reconstruction	41.22	0.037	14.29
DWT	43.05	0.0078	25.53
Adaptive	41.49	0.005	23.12
LMS	52.81	0.004	24.74
IDWT	64.68	0.000058	35.68

Fig.5 Equivalence of the proposed methods for (%) noise level

An SNR improvement of 42 dB is obtained at 25% noise level, by the direct subtraction method. The SNR value of 52 dB is obtained at 10% and 25% noise levels for various frequency bands. As the result of the contaminating noise increases the performance is better, irrespective of the frequency of interference. Subtraction methods are simple, as no adaptation and control parameters are required to tune the frequency change.

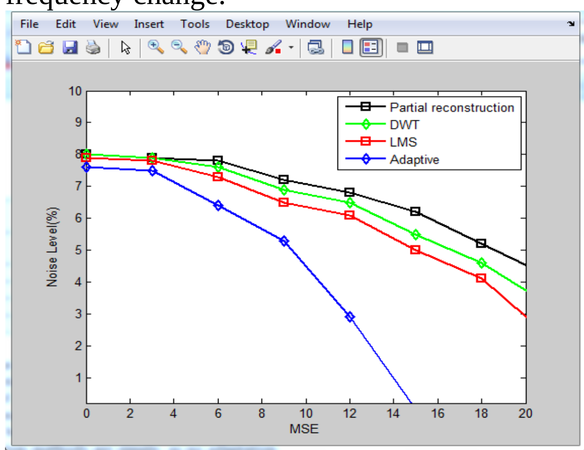

Fig.6 Equivalence of the MSE of various techniques at different noise levels (%)

Equivalence of the SNR of various DWT based techniques at different noise levels (%)

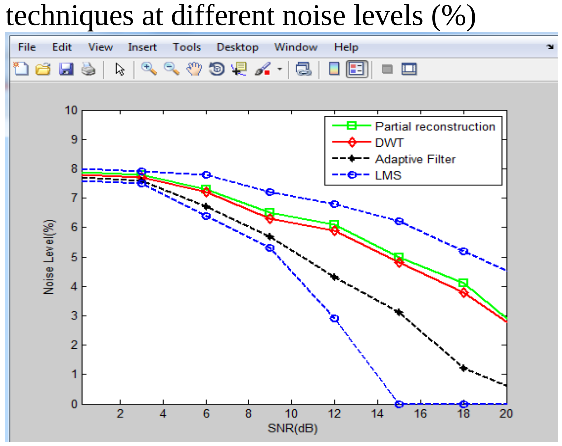

Fig.7 Equivalence of the SNR of various techniques at different noise levels (%)

A comparative analysis is carried out by extracting morphological and secular features from ECG signals and better performance is accomplished by SVM features classification both with regards to classification accuracy and computation time.

CONCLUSION

Various possible techniques are presented and implemented in MATLAB. The application of these procedures in power line interference elimination and baseline wander removal is also studied. The simulation results are discussed and compared with those of the existing methods. The correlation of the denoised ECG signals using various methods is evident that subtraction methods are more efficient in denoising and with less computational complexity.

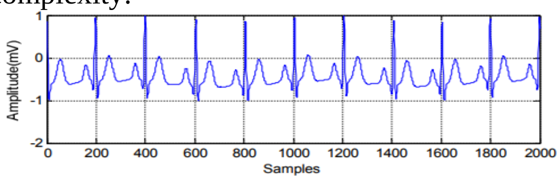

Fig.8 denoised signal based partial reconstruction

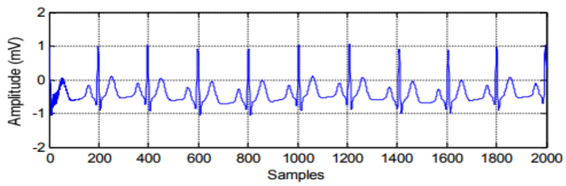

Fig.9 Denoised ECG signal using Adaptive filtering

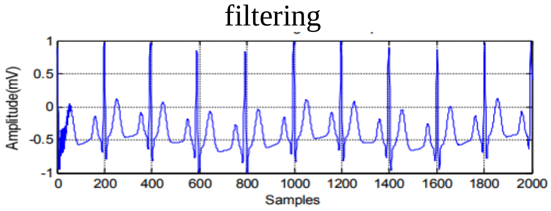

Fig.10 Denoised ECG signal-DWT

The classification of signals into more than one class is a challenging process, as it should be adaptable to a new patient's data. The support vector machine finds application in various fields. The SVM with unusual kernels is the future scope of this work.

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