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Comparison of Different ECG Denoising Techniques Based on PRD & Mean Parameters

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Abstract

Baseline wandering can mask some important features of the Electrocardiogram (ECG) signal hence it is desirable to remove this noise for proper analysis and display of the ECG signal. This paper presents the implementation and evaluation of different methods to remove this noise. The parameters i.e. PRD & Mean are calculated of signals to compare the performance of different filtering methods. Wavelet Transform Method has been proved efficient method for the removal of Baseline wander from ECG signal. The results have been concluded using Matlab software and MIT-BIH arrhythmia database.

Keywords: *ECG Signal, Baseline Wander, IIR Filter, Denoise, PRD, Mean*

1. Introduction

Cardiac failure and cardiac diseases are among the main causes of death in the world. Therefore, it is necessary to have proper methods to determine the cardiac condition of the patient. Electrocardiography (ECG) is a tool that is widely used to understand the condition of the heart [1]. The electrocardiographic signal is the electrical representation of the heart's activity. Computerized ECG analysis is widely used as a reliable technique for the diagnosis of cardiovascular diseases. However, ambulatory ECG recordings obtained by placing electrodes on the subject's chest are inevitably contaminated by several different types of artifacts [3]. Commonly encountered artifacts include: Power line interference, Electrode contact noise, Motion artifacts, Baseline Drift, Instrumentation noise generated by electronic devices, Electrosurgical Noise. Baseline wander elimination is considered as a classical problem. It is considered as an artifact which produces atrifactual data when measuring the ECG parameters, especially the ST segment measures are strongly affected by this wandering. In most of the ECG recordings the respiration, electrode impedance change due to perspiration and increased body movements are the main causes of the baseline wandering [4]. The baseline wander noise makes the analysis of ECG data difficult. Therefore it is necessary to suppress this noise for correct evaluation of ECG. Many researchers have worked on development of methods for reduction of baseline wander noise. Zahoor-uddin presented Baseline Wandering Removal from Human Electrocardiogram Signal using Projection Pursuit Gradient Ascent Algorithm & shows the comparative study of the results of different algorithms like Kalman filter, cubic spline and moving average algorithms [5]. Mahesh S. Chavan*et al* has presented the Comparative Study of Chebyshev me and Chebyshev II Filter for noise reduction in ECG Signal [6]. Mahesh S. Chavan*et al* also compared the results of Butterwoth filter and Elliptic filter for the suppression of Baseline and Power line interferences [7]. Fayyaz A. Afsar et al. compared different approaches which include linear Digital filters, Adaptive filters, and Multiresolution analysis and Curve fitting for the removal of baseline drift [8].

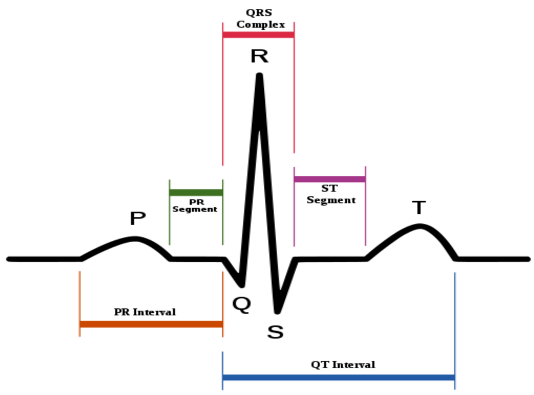

Fig-1: Normal ECG [2]

V.S. Chouhan and S.P. Mehta developed an algorithm for total removal of Baseline drift from ECG signal & deploy least square error correction & median based correction [9].

2. Implementation Techniques

2.1 Wavelet Transform

The WT is designed to address the problem of non-stationary signals. It involves representing a time function in terms of simple, fixed building blocks, termed wavelets. These building blocks are actually a family of functions which are derived from a single generating function called the mother wavelet by translation and dilation operations. Dilation, also known as scaling, compresses or stretches the mother wavelet and translation shifts it along the time axis [5, 6, 7, 8, 11, 12]. The WT can be categorized into continuous and discrete. Continuous wavelet transform (CWT) is defined by

$$\mathbf{cwt(a,b)} = \int_{-\infty}^{\infty} \mathbf{xt}\,\boldsymbol{\varphi(a,b)(t)dt}$$

Where *x (t)* represents the analyzed signal *a* and *b* represent the scaling factor (dilatation/compression coefficient) and translation along the time axis (shifting coefficient), respectively, and the superscript asterisk denotes the complex conjugation.
Ψa, b (·) is obtained by scaling the wavelet at time *b* and scale *a.*
Where *ψ (t)* represents the wavelet [5, 6, 15]. Continuous, in the context of the WT, implies that the scaling and translation parameters *a* and *b* change continuously.

However, calculating wavelet coefficients for every possible scale can represent a considerable effort and result in a vast amount of data. Therefore discrete wavelet transform (DWT) is often used. The WT can be thought of as an extension of the classic Fourier transform, except that, instead of working on a single scale (time or frequency), it works on a multi-scale basis. This multi-scale feature of the WT allows the decomposition of a signal into a number of scales, each scale representing a particular coarseness of the signal under study. The procedure of multiresolution decomposition of a signal *x*[*n*] is schematically shown in Fig. 1.

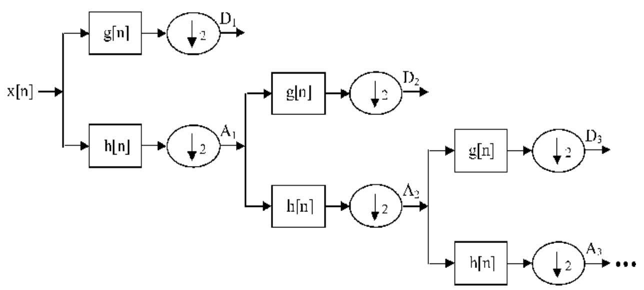

Fig-2: Sub Band Decomposition of Discrete Wavelet Sub Band Decomposition of Discrete Wavelet Transform Implementation; G [N] is the High-Pass Filter; h [N] is the Low-Pass Filter.

Each stage of this scheme consists of two digital filters and two down samplers by 2. The first filter, *g* [·] is the discrete mother wavelet, high-pass in nature, and the second, *h* [·] is its mirror version, low-pass in nature.

The down sampled outputs of first high-pass and low-pass filters provide the detail, *D*1 and the approximation, *A*1, respectively. The first approximation, *A*1 is further decomposed and this process is continued as shown in

Fig. 2. All wavelet transforms can be specified in terms of a low-pass filter *h*, which satisfies the standard quadrature mirror filter condition:

2.2 The Kalman filter

The Kalman filter, also known as linear quadratic estimation (LQE), is an algorithm that uses a series of Measurements observed over time, containing noise (random variations) and other inaccuracies, and produces estimates of unknown Variables that tend to be more precise than those based on a single measurement alone. More formally, The Kalman filter operates recursively on streams of noisy input data to produce a statistically optimal estimate of the underlying system state. The filter is named for Rudolf (Rudy) E. Kalman, one of the primary developers of its theory. The Kalman filter has numerous applications in technology. A common application is for guidance, navigation and control of vehicles, particularly aircraft and spacecraft. Furthermore, the Kalman filter is a widely applied concept in time series analysis used in fields such as signal processing and econometrics. The algorithm works in a two-step process. In the prediction step, the Kalman filter produces estimates of the current state variables, along with their uncertainties. Once the outcome of the next measurement (necessarily corrupted with some amount of error, including random noise) is observed, these estimates are updated using a weighted average, with more weight being given to estimates with higher certainty. Because of the algorithm's recursive nature, it can run in real time using only the present input measurements and the previously calculated state and its uncertainty matrix; no additional past information is required. It is a common misconception that the Kalman filter assumes that all error terms and measurements are Gaussian distributed. Kalman's original paper derived the filter using orthogonal projection theory to show that the covariance is minimized, and this result does not require any assumption, e.g., that the errors are Gaussian.[1] He then showed that the filter yields the exact conditional probability estimate in the special case that all errors are Gaussian-distributed.

2.3 Smooth function

Extracting the baseline by moving average directly may attenuate the QRS complexes, since the output of moving average around R-wave peaks is usually high. In order to preserve QRS complexes precisely, we design a weighting function based on the gradient in the neighborhood area of the current position. The weighting function is named the gradient varying weighting function and is defined as follows:

The Kalman filter, also known as linear quadratic estimation (LQE), is an algorithm that uses a series of

$$w[n] = \frac{1}{d + |x[n+k] - x[n-k]|}$$

Where *n* is the current position of the ECG signal, *x*[*n*] is the current value of the ECG signal, *k* the window size we specified for computing the gradient in the neighborhood, and *d* is a constant to balance the influence of the gradient. All of the parameters can be designed for specific requirements. In (1), we can distinguish QRS complexes from other parts of the ECG signal by choosing the proper window size *k*. The suggested value for *k* would depend on number of samples for QRS complexes in this way; we can obtain a smaller weighting value in the location with a larger gradient, such as the QRS complex, and obtain a larger weight in the location with a smaller gradient. In Fig. 2, the behavior of the gradient varying weighting function in (1) is presented. It can be observed that the values of *w*[*n*] are smaller when encountering QRS complexes.

2.4 FFT Filtering

fftfilt filters data using the efficient FFT-based method of *overlap-add*, a frequency domain filtering technique that works only for FIR filters.

y = fftfilt (b, x) filters the data in vector x with the filter described by coefficient vector b. It returns the data vector y. The operation performed by fftfilt is described in the *time domain* by the difference equation:

$$y(n) = b(1)x(n) + b(2)x(n-1) + \cdots + b(nb+1)x(n-nb)$$

An equivalent representation is the *z*-transform or frequency *domain* description:

$$Y(z) = \left(b(1) + b(2)z^{-1} + \cdots + b(nb+1)z^{-nb}\right)X(z)$$

By default, fftfilt chooses an FFT length and data block length that guarantee efficient execution time.

If x is a matrix, fftfilt filters its columns. If b is a matrix, fftfilt applies the filter in each column of b to the signal vector x. If b and x are both matrices with the same number of columns, the i-th column of b is used to filter the i-th column of x.

y= fftfilt (b, x, n) uses n to determine the length of the FFT. See Algorithm for Information.

y = fftfilt (GPUArrayb, GPUArrayX, n) filters the data in the GPU Array object, GPU Array X, with the FIR Filter coefficients in the GPU Array, GPU Array b. See Establish Arrays on a GPU for details on GPU Array objects.

3. Measure of Performance

3.1 Percent Root Mean Square Difference

PRD One of the most difficult problems in ECG compression applications and reconstruction is defining the error criterion. The purpose of the compression system is to remove redundancy and irrelevant information. Consequently the error criterion has to be defined so that it will measure the ability of the reconstructed signal to preserve the relevant information. Since ECG signals generally are compressed with lossy compression algorithms.

A way of quantifying the difference between the original and the reconstructed signal, often called distortion. The most prominently used distortion measure is the Percent Root mean square Difference (PRD) that is given by

$$\text{PRD} = \sqrt{\frac{\sum_{n=1}^{N}(x[n] - \hat{x}[n])^2}{\sum_{n=1}^{N}(x[n])^2}} \times 100.$$

Where x[n] and [n] are the original and reconstructed signals of length N, respectively. The PRD indicates reconstruction fidelity by point wise comparison with the original data.

3.2 Mean

The Root Mean Square error (RMSE)of original signal and de-noised signal is given by the following Equation

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Soriginal - Sdenoised)^2}$$

4. Results

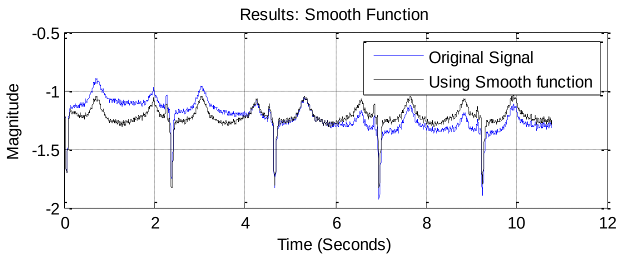

Fig-3: Denoising output using smooth function

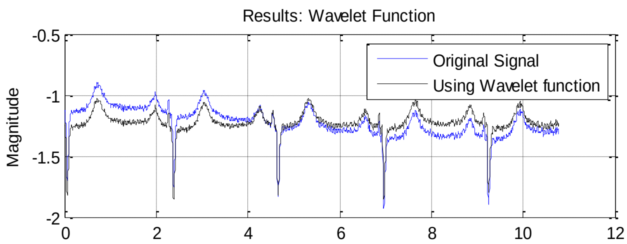

Fig-4: Denoising output using wavelet function

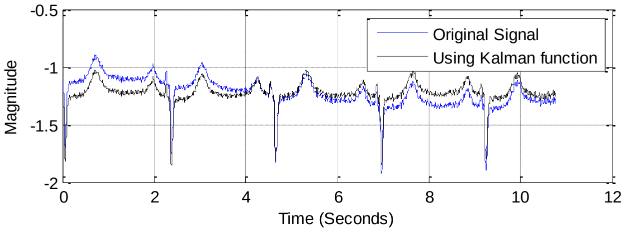

Fig-5: Denoising output using Kalman function

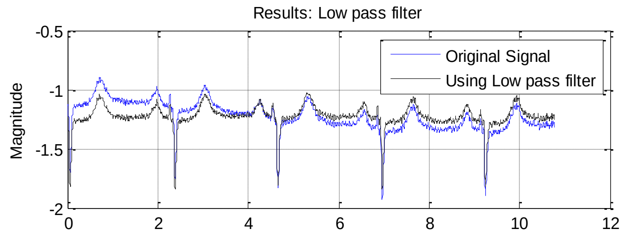

Fig-6: Denoising output using low pass filter

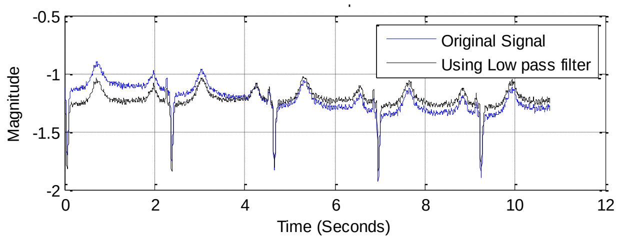

Fig-7: Denoising output using FFT

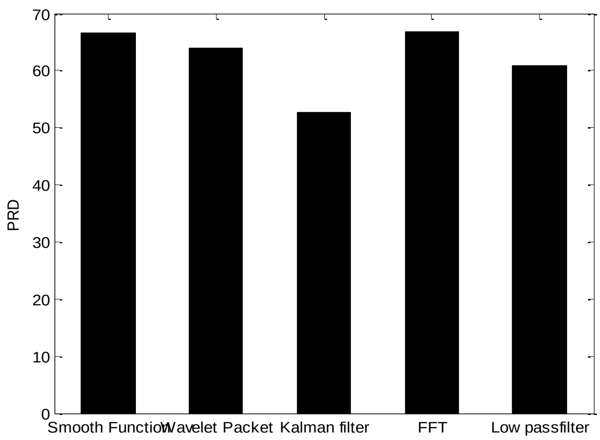

Fig-8: Wavelet Packet Kalman Filter (PRD)

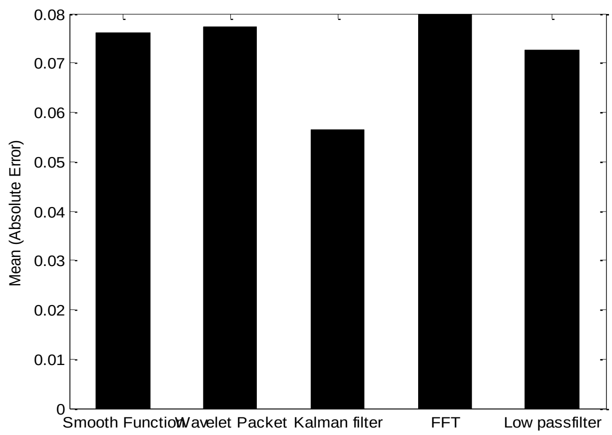

Fig-9: Wavelet Packet Kalman Filter (Mean)

5. Result and Discussion

ECG is the prime human physiological signal which can be used for various clinical applications to detect the healthiness of the human being. Therefore the proper processing and detection of ECG is very much important. Since many decades various methods have been used for processing and accurate detection of human cardiac signal. In the last two decades many researchers and scientists have been using the methods based on Wavelet transforms and found that this Wavelet transform is more suitable for analyzing the non stationary, pseudo periodic ECG signal. Still there is lot of scope of Wavelet transform to be used for analyzing ECG signal. The suitability of Wavelet transform depends upon the proper selection of moth wavelet along with properties. In this paper we made an attempt to give an overview of various wavelet techniques used by the researchers for processing ECG signal. We hope that this material will be helpful particularly for beginners who are interested to work in this field.

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