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Ecg Denoising Using Total Variational Approach

Om Prakash Yadav | Bhilai Institute of Technolgy ,Durg,(CG) 8966000053.

Shashwati Ray | Bhilai Institute of Technology , Durg ,CG, India.

ABSTRACT

The ECG signals which are quasi-stationary in nature are important signals for the diagnosis and treatment of heart related diseases. These signals get corrupted by various types of disturbances. This paper presents a Majorization-Minimization technique to optimize the total variation in the signal and also focuses on effect of smoothening parameter over quality of denoised signal. The results show significant change in signal to noise ratio and effect of smoothening parameter over quality of reconstructed signal.

KEYWORDS | ECG signal, Total Variation Denoising, Signal to Noise ratio, Root Mean Square Error

INTRODUCTION

ECG signal is a record of electrical potential generated due to contraction and expansion of heart. The Signal consists of P, QRS Complex, T and sometimes U waves (refer fig 1). The amplitude and duration of the ECG contains useful information and must not change during analysis [1].

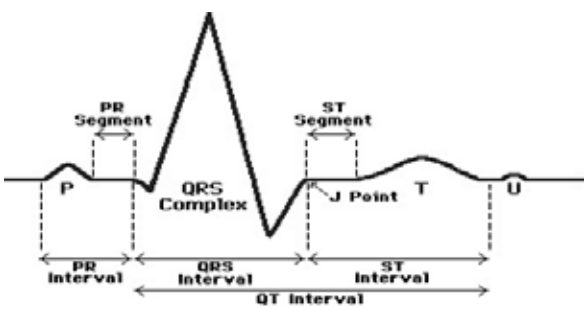

Figure 1. ECG Signal

During acquisition of the ECG signals noise, artifacts and interferences may degrade its quality. The noises may be due to power line interference(PLI), external electromagnetic field interference, body movements, electrode contacts etc. So it is essential to reduce noises to extract the efficient morphology of ECG signal for correct analysis and diagnosis [2].

Several denoising techniques have been proposed over past few decades to reduce noises present in ECG signals. Digital Infinite Impulse Response (IIR) filter were used to reduce the effects of power line (50/60Hz) interference (PLI) and baseline wander from ECG signals [2]. Inspite of its simple design, it has the drawback of increased filtering time, memory and incapability to filter the highly non-linear signals. An adaptive filtering method which causes inter-beat variations, have been used for reducing the PLI noises [3], [4]. The Wiener Filter (WF) is the optimal linear filtering technique in the Minimum Mean Square Error (MMSE) sense for stationary signals, but it is not expected to provide good results for ECG [5].

ECG being a non-stationary signal, the irregularities are not periodic and do not show up all the time, but is noticeable at certain irregular intervals. The most difficult problem faced in automatic ECG analysis is the large variation in the morphologies of ECG waveforms. In some related works, filtering approaches have been proposed based on time-frequency or wavelet transforms, and timescale WFs [6].

Wavelet Denoising (WD) is now most commonly used for denoising of signals [7], [8], [9]. A soft thresholding method for the shrinkage of the noise components in the wavelet domain were proposed by Donoho and Johnston [10], [11]. Mahmoodabadi et al. proposed an ECG feature extraction system based on the multi-resolution wavelet transform [11]. Shantha et al. suggested designing optimal discrete wavelet a method which uses based orthogonal filter bank for cardiac signal [12]. Nikolaev et al. suggested a two-step algorithm for removing of Electromyogram (EMG) artifacts from the ECG using Wavelet Domain Wiener Filtering [13]. However, selection of appropriate wavelet function, thresholding methods and thresholding rule play an important role in signal denoising [14].

Statistical techniques such as Principal Component Analysis (PCA) [15], Independent Component Analysis (ICA) [16], [17], and Neural Networks (NNs) [18] have also been used to extract a statistical-based model of the signal and noise, allowing the removal of in-band noise by discarding the dimensions corresponding to noise. Although these are powerful in-band noise filtering schemes, the model is not only fairly arbitrary but also extremely sensitive to small changes in either the signal or the noise unless the basis functions are trained on a global set of ECG beat. A two stage algorithm for supression of EMG artifacts using Wavelet domain filtering [19] has been investigated by Nikolay and Atanas in 2000 and maximum 5 dB improvement of signal to noise ratio is observed.

TOTAL VARIATION

Total Variation (TV) concept was introduced by Rudin, Osher and Fatem [20]. It is an optimization approach for noise reduction and preservation of sharp edges of signals. This technique has advantages over simple techniques, that it is remarkably effective at simultaneously preserving edges whilst smoothing

away noises in flat regions, even at low signal-to-noise ratios. Along with denoising, it is used for deconvolution, interpolation, compressed sensing, etc. In this work we apply the TV filtering algorithm to remove white Gaussian noise from ECG signal.

TOTAL VARIATIONAL DENOISING

The TV of a signal measures how much the signal changes between signal values. Total variation denoising (TVD) is based on the principle that signals with excessive and possibly spurious detail have high total variation.

According to this principle, reducing the total variation of the signal subject to it being a close match to the original signal, removes unwanted detail whilst preserving important details such as edges. The output of the TV denoising 'filter' is obtained by minimizing a particular cost function [21].Total variation denoising assumes that the noisy data *y(n)* is of the form

where *x(n)* is an approximately piecewise constant signal and *w(n)* is white Gaussian noise.The total variation of an *N* point signal *x(n),* 1≤ n ≤N is defined as [22]:

The *N* point signal *x* is represented by the vector

TVD estimates the signal x(n) by solving the optimization problem

where the first term represents the mean square error between the original noisy signal and the reconstructed signal. The regularization parameter λ controls how much smoothing is performed. Increasing λ gives more weight to the second term which measures the fluctuation of the signal *x(n).* For large noise levels λ should be larger.

MINIMIZATION-MINORIZATION(MM) TECHNIQUE

Majorization methods solve minimization problems by replacing a complicated problem by a sequence of simpler problems. Solving the sequence of simple optimization problems guarantees convergence to a solution of the complicated original problem. Convergence is guaranteed by requiring that the approximating functions majorize the original function at the current solution [23].

Let x and y εR, f and g be real valued functions on R^n. Then the function g majorizes the function f *at* y *if*

- $g(x) \geq f(x)$ for all x
- $g(y)=f(y)$

ALGORITHM

The MM approach to minimize the function *F(x)* can be summarized as:

1) Store the ECG signal as data and set the number of data points
2) Set λ=different values ≥1
3) Set number of iterations as 20
4) Set $k = 0$. Initialize $x(0)$.
5) Choose $G_k(x)$ such that
a) $G_k(x)>F(x)$ for all x
b) $G_k(x) = F(x^{(k)})$
6) Set $x^{(k+1)}$ as the minimizer of $G_k(x)$.
7) Set $k = k + 1$ and go to step (5).

The above algorithm is implemented over the ECG signal which is taken from MIT-BIH database.

EXPERIMENTS

The ECG signals are taken from MIT-BIH database [24].The duration of the signal was 10 seconds and are sampled at 720Hz sampling frequency with 11 bits per sample of resolution. The signal is then distorted with addition of white Gaussian noise to make signal to Noise ratio (SNR) of the distorted signal as about 20dB.

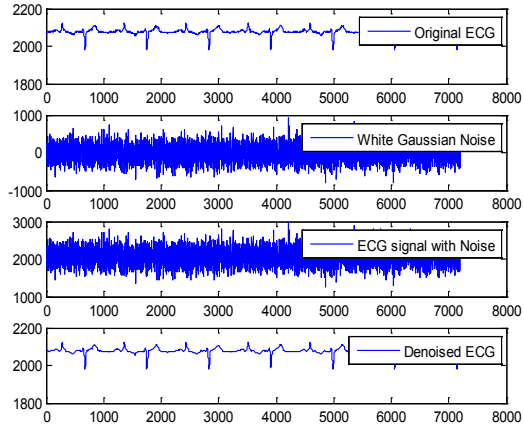

Figure 1: Original ECG, Noise, Noisy ECG and denoised signal

The figure 1 shows original signal, white Gaussian noise, Noisy signal and denoised ECG signal. The whole process is carried out in Matlab. The signal is then denoised using TVD MM approach. The results obtained are indicated in table 1.

TABLE – 1
Performance Matrix for ECG signal

λ	SNR_i	SNR_o	RMSE	Correlation Coefficient
1	20.1350	26.8433	0.5149	0.9995
2	20.0296	25.9312	0.6211	0.9993
3	20.0431	25.3426	0.7014	0.9910
4	20.0756	24.9649	0.7653	0.9989
5	20.0400	24.6562	0.8192	0.9988

The SNR represents the signal strength as compared to noise and is measured before and after application of TVD MM approach. Root Mean Square Error(RMSE) indicates difference in predicted and actual values. Correlation coefficient measures how the predicted values follow the original signal.

From the table ,we can see a significant improvement in SNR(about 4-6 dB).The value of SNR decreases with increase in λ. This may be due to its quasi-stationary behaviour. The obtained value of RMSE increases as we increase the value of smoothening parameter. It indicates that error increases with increase in λ upto certain extent. Similarly it can also been observed that correlation coefficient value decreases with increase in λ. Selection of λ plays crucial role for denoising of signals which are variable in nature. Better results may be expected for linear sections of any signal.

CONCLUSION

In this paper TVD technique using MM approach is used to reduce white Gaussian noise from ECG signals. The signals sampled at 720Hz, taken from MIT-BIH database were used from analysis purpose. The results show that increase in smoothening parameter increases error when applied to complete wave. The results may be improved by segmenting ECG signals. Additional parameters may be included for further analyzing the robustness of the technique.

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