ECG DENOISING USING SECOND DIFFERENCE TOTAL VARIATION APPROACH

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***Abstract*—ECG records electrical activity of heart. These signals are low magnitude signals and are often distorted by surrounding signals of variable frequency. In this paper, a variant of total variation denoising, i.e., second difference total variation denoising approach is presented to reduce simulated noise from ECG signals of MIT-BIH database. Results obtained are compared with other techniques and are found clinically acceptable.**

***Index Terms*— ECG, Total variation denoising, Bottom-Up, Chebyshev approximation**

I. INTRODUCTION

Electrocardiography (ECG) is graphical recording the electrical activity of heart over a period of time and is recorded by placing electrodes on specific locations limbs. These electrodes detect voltage variations due to functions of heart. These recordings are used for heart related diagnosis and analysis. ECG signals consist of waves P, Q, R, S, and sometimes U [1][2]. The morphology, amplitude and timing pattern of these waves are clinically important and are shown in Figure 1.

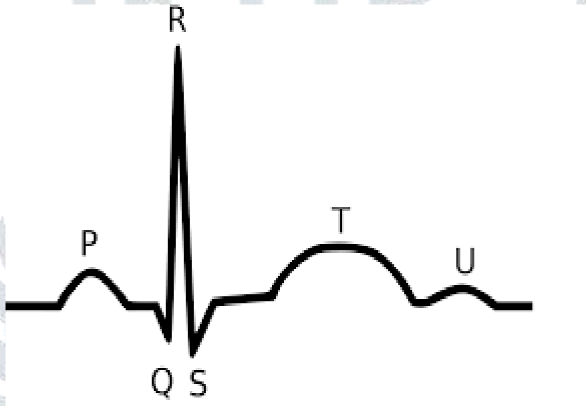

Figure 1. ECG signal (Source: Google Images)

A systematic analysis and interpretation is required to find out abnormalities in heart [3]. The magnitude of ECG signals are very low, i.e., up to 5 mV. These signals are often contaminated by various types of artifacts (noises) of high magnitude and variable frequency.Some of the common noises are due to power line inference, RF signals, electrode contact, movement of electrodes and baseline shift. These noises change the morphology of ECG signals [4]. So, it is very essential to reduce (denoise) these signalsfor accurate analysis and correct diagnosis. Since ECG signals are quasi-stationery signals, noise reduction from these signals is not so easy.

II. AVAILABLE DENOISING TECHNIQUES

Various filters were found to suppress noise from ECG signals in the last few decades. Traditionally low pass filters were utilized to reduce high frequency noise but their cut-off frequency determination was not easy [5]. Finite and Infinite impulse response filters were used to reduce baseline artifacts [6]. Other filters to reduce noises like least mean square (LMS), normalized least mean square (NLMS), transform domain least mean square (TDLMS) were also found in literature [7]. Low frequency noises were reduced using median filters in [8]. Wavelet transform were also successful in reducing noise levels to significant levels. Various filters using wavelet transform can be found in [9][10][11][12]. Neural networks and genetic algorithms were also applied to reduce noise from ECG signals [13]. An effective ECG enhancement technique using total variation was proposed in [14]. In this paper, more accurate total variation denoising method is adapted to reduce noise from ECG signals.

III. REDUCTION OF NOISE THROUGH TOTAL VARIATION

The total variation (TV) of N point discrete signal x(n), $1 \le n \le N$is defined in terms of first difference [15] as

$$TV(x) = \sum_{n=1}^{N} |x(n) - x(n-1)| \quad (1)$$

The TV of a signal measures sum of errors between consecutive points. between signal values. According to TV principle, signals with excessive and possibly spurious details have high total variation. Therefore, reducing the TV of the signal removes unwanted detail whilst preserving important details [16].

TVD is an optimization problem which minimizes the cost function (2) for reduction of noise andpreservation of sharp edges [17].

$$\arg\min_x = \left\{ F(x) = \frac{1}{2} \sum_{n=0}^{N-1} |y(n) - x(n)|^2 + \lambda \sum_{n=1}^{N-1} |x(n) - x(n-1)| \right\} \quad (2)$$

The first term in (3) represents the square of error in observed and denoised signal and the second term refers tothe TV within the signal. The regularization parameter $\lambda > 0$ is used to control the degree of smoothing. Literature related to selection of λ can be obtained from [18]. The TVD approach has the tendency to introduce a staircase effect [19]. The staircase effect introduces small flat regions in the denoised signal and thus it is not expected to provide clinically good results for ECG signals. For such signals, a higher-order difference can be used instead of the first-order difference in (1). So, second order TVD is proposed in this paper to reduce the noise.
The second order TVD can now be expressed as

$$TV(x) = \sum_{n=1}^{N} |x(n) - x(n-1) - (x(n-1) - x(n-2))| \quad (3)$$

Accordingly the optimization function can be formulated as

$$\arg\min_x = \left\{ F(x) = \frac{1}{2}\sum_{n=0}^{N-1} |y(n) - x(n)|^2 + \lambda \sum_{n=1}^{N-1} |x(n) - x(n-1) + x(n-2)| \right\} \quad (4)$$

Since L1 norm is not differentiable, we minimize the objective function using Majorization-Minimization (MM) algorithm.

The MM approach was developed to solve optimization problems indirectly by solving a sequence of optimization problems $G_k(x)$, instead of minimizing the cost functionF(x) directly [20][21]. The idea is that each Gk(x) is easier to solve than F(x).
The MM approach to minimize the function F(x) can be summarized as:
1. Set k = 0. Initialize x0.
2. Choose $G_k(x)$ such that
   (a) $G_k(x) > F(x)$ for all x
   (b) $G_k(x) = F(x_k)$
3. Set x_{k+1} as the minimize of $G_k(x)$.
4. Set k = k + 1 and go to step (2).

The x_{k+1} thus obtained are minima points and once interpolated, give the denoised signal.

IV. PERFORMANCE PARAMETERS

All denoising algorithms should increase signal strength by reducing the noise component. In this paper, the performance [24] of the methods is measured in terms of:

1. Signal to noise ratio (SNR) shows strength of signal component over noise. There must be increment in SNR (ISNR) value before and after denoising.
2. Maximum absolute error (MAE): It refers to the magnitude of maximum error.
3. Mean square error (MSE) is the average of error. Since MAE and MSE are error terms, so they are expected to be less.
4. Correlation Coefficient(CC) indicates similarity in between original signal and reconstructed signal. Its value near to 1 shows close resemblance between original and reconstructed signals.

V. METHODS AND RESULTS

The characteristics of ECG signals are disturbed by presence of noise. This may lead to wrong diagnosis. So, the very first stage in ECG processing is suppression of noise. Various methods related to noise suppression are pointed in section I. In almost all the papers related to ECG, the signals used for analysis are from online database. Here, we have used MIT-BIH database [22]. The signals from the database are sampled at 360 Hz with 11 bits per sample of resolution. Since in each MIT-BIH signal, a baseline of 1024 is added for storage purpose [23]. Firstly, the baseline and dc level gain of the single lead ECG signal is suitably reduced. Thenthe data is added with Additive Gaussian White Noise (AGWN) to raise its SNR level to some predefined value which in our case is 10 dB. The noisy signal thus generated is expressed by (5).

$$y(n) = x(n) + w(n) \quad (5)$$

where x(n) is signal from the database and w(n) is the noise and y(n) is the noisy signal.

These noisy signals y(n) are passes through the filter designed ,i.e., second difference TVD-MM filter. In this paper, smoothening parameter λ for reducing noise is set to 1. The results obtained by the second difference TVD is shown in Table1.

Table 1 Performance parameters for the denoising method

Record No.	**MAE**	**MSE**	**ISNR(dB)**	***CC***
101	0.0069	4.694×10^{-5}	20.0992	0.9858
103	0.0019	3.4878×10^{-6}	19.5342	0.9927
105	0.0377	0.0014	23.4918	0.9968
109	0.0974	0.0095	25.0239	0.9967
112	0.0239	5.7295×10^{-4}	30.1827	0.9912
117	0.0194	3.7542×10^{-4}	29.7502	0.9932
119	0.0126	1.5775×10^{-4}	27.6426	0.9966
124	0.0076	5.8338×10^{-5}	28.7439	0.9965
201	0.0172	2.9488×10^{-4}	19.7058	0.9916
208	0.0489	0.0489	23.8781	0.9980
212	0.0106	1.1162×10^{-4}	18.4408	0.9926

Record No.	MAE	MSE	ISNR(dB)	*CC*
215	0.1562	0.0244	15.7172	0.9859
219	0.0312	$9.7566*10^{-4}$	25.6935	0.9965
228	0.0235	$5.5154*10^{-4}$	18.8355	0.9813
232	0.0689	0.0047	14.5934	0.9401
234	0.9401	$1.1761*10^{-4}$	18.8042	0.9943

In [25], Empirical mode decomposition (EMD) and discrete wavelet transforms based techniques were compared. The lowest MSE reported for EMD and DWT for the record 101 and 103 were 0.0024 and 0.0032 respectively. Figure 2 and 3 shows the results of second difference TVD approach.

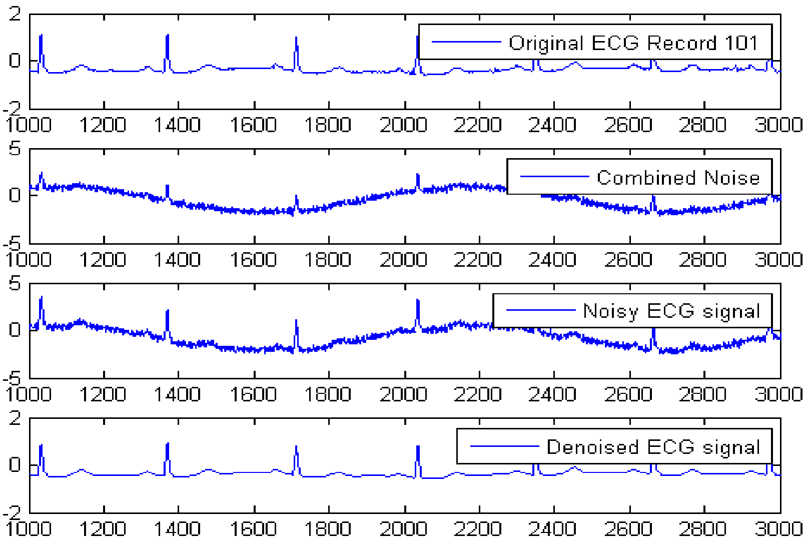

Figure 2: Original, noise, noisy and denoised results for record 101.

The maximum ISNR reported is 7dB at 10 dB noise. Our results for the same set of records are better than these values. In [26] the highest CC values, i.e. 0.9466 and 0.9779 for soft and hard thresholding using wavelets respectively were reportedwhich are lower tha n that reported in this paper.

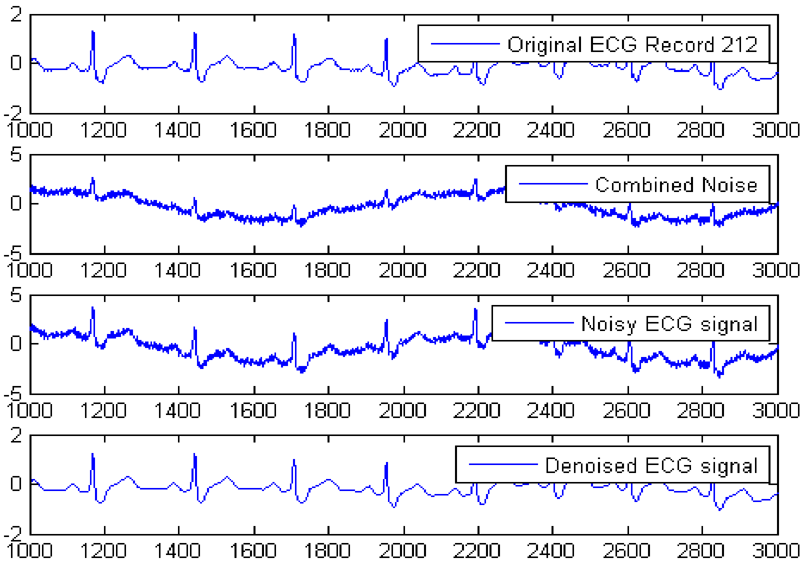

Figure 3: Original, noise, noisy and denoised results for record 212.

In this paper CC values are almost near to 1 which indicates closesimilarity in between actual and reconstructed signal. In [27] the highest SNR obtained as 12.67 dB is much lesserthat the SNR obtained in this paper. Thus we can conclude that second difference TVD improves denoising results.

VI. CONCLUSION

ECG signals are important biomedical signals and are used for diagnosis of heart related diseases. These signals are contaminated with different kind of noises of different amplitude and frequency. Addition of noises changes the shape of ECG signals and thus affects diagnosis.

So, these noises must be reduced to significant level without affecting the clinical characteristics of ECG signals. In this paper, second difference TVD approach is used to minimize the total variation of the signals. Results obtained are found to be clinically acceptable.

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