Electrocardiogram Signals Error Correction Using Empirical Mode Decomposition Based Technique

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Abstract

This paper presents the error correction of electrocardiogram signals which have been corrupted by Baseline wander and power line interference using empirical mode decomposition. The Electrocardiogram (ECG) is the electrical activity of the heart used by physicians to inspect the heart's condition. The ECG recordings are often corrupted by artefacts. One of the dominant artifacts and interference present in ECG recordings is Baseline Wander (BW) that may be due to respiration or the motion of the patients or the instruments and electromagnetic Interference (EMI) from power line. Analysis of ECG becomes difficult if BW and power line interference are embedded with the signal during acquisition. Hence BW and power line interference need to be removed for better clinical evaluation. In this paper, a technique for removing BW and power line Interference in ECG is proposed. ECG signals available at MIT-BIH arrhythmia data base were used for the investigation. The original signal from MIT-BIH is first corrupted with both BW and Power line noise. The noisy ECG signal is initially decomposed into a set of Intrinsic Mode Functions (IMFs) using Empirical Mode Decomposition (EMD) method. The IMFs containing BW are filtered using a bank of lowpass filters, the noise rank was also determined and filtered using Infinite Impulse Response (IIR) notch filter. The clean ECG signal is derived from the combination of the processed IMFs. The simulations show that the proposed EMD-based method provides very good results for BW and Power line interference removal. Compared with the wavelet transform and EMD with spectral flatness, the method used gives better Signal Error Ratio (SER) Values. At SNR of 5dB, the wavelet transform method gives an SER of 8.8000; the EMD with spectral flatness gives SER of 9.9028: while the method used in this work gives SER of 10.1630

Keywords: Baseline wander, Empirical mode decomposition, Intrinsic mode functions, ECG.

1. Introduction

An electrocardiogram (ECG) is an electrical recording of the heart activity and it is used in the heart disease diagnoses. ECG allows evaluating the rhythm and frequency of the heart work and enables investigation of the heart defects of people (Manpreet, 2011). Knowledge of ECG image for healthy and defective cases is the basis used for diagnosis of the heart diseases in patients. According to Urszula (2005), it is possible for doctors to diagnose cardiac diseases and monitor patients' conditions from the abnormal ECG waveforms. Baseline wander results in the chest lead ECG signals by coughing or breathing with significant movements of the chest, when an arm or leg is moved during the ECG data acquisition. Poor contact of the electrodes and perspiration of the patient under the electrodes. Cardiac failure and cardiac diseases are among the main causes of death in the world today (Vineet, 2010). Therefore, it is necessary to have proper methods of determining the cardiac condition of the patient which is what the paper addressed.

According to Chinchkhede et al, (2011), the ECG signal consists of six continuous electromagnetic peaks namely; PQRST and U, the P wave represents depolarization and contraction of atria, the QRS complex wave represent depolarization and contraction of ventricles and the T wave corresponds to the repolarization of ventricles.

Many researcher have worked on the removal of noise on electrocardiogram signals such as Van Alste, and Schilder (1985) who used Digital linear phase filtering method to reduce baseline wandering and power line noise in ECG signal; the major drawback of this method is the long computational time caused by the large number of multiplication involved in the filtering in the time domain or frequency domain. Besides consuming time, filtering in the frequency domain introduces computational delays and transients, and is not very suitable for real time processing.

Others are cubic spline method proposed by Mneimneh (2006) in which QRS detector may not operate correctly in the presence of high amplitude noise and baseline wander with sharp transition not accurately described by a cubic polynomial, spectrograms and Wigner-ville distributions have their own limitations.

Linear filtering method was also proposed by (Christov and Daskalov, 1999) there is overlapping between cardiac components and noncardiac contaminants in frequency, especially from 0.01 Hz to 100 Hz. the method is not efficient in eliminating such noises while keeping valid components unchanged.

In this paper, the EMD technique is proposed with modification. The noisy ECG signal was decomposed into fifteen intrinsic mode functions (IMfs). The power line interference was mostly concentrated in the first few IMFs. The number of the IMFs that are dominated by noise, referred to as the noise rank, was established. The BW is embedded in the last several IMFs; the number of IMFs that contains the BW is referred to as the baseline wander rank. The noisy IMFs are then filtered using Lowpass filter to remove the baseline wander while Infinite Impulse Response (IIR) notch filter was used to filter the power line interference.

The proposed method is unique and different from the existing methods. The EMD has been applied to the analysis of non-linear and non-stationary processes in engineering.

2. Empirical Mode Decomposition

The EMD method decomposes the complicated data set into a finite and often small number of components. These components are intrinsic mode functions (IMFs). IMF satisfies the following conditions: the number of extrema and the number of zero crossings must be either equal or differ at most by one in the whole data set, at any point, the mean value of the envelope defined by the local maxima and the envelope defined by local minima is zero (Blanco-Velasco et al, 2006);(Karagiannis and Constantinou, 2010). The Empirical Mode Decomposition involves the sifting process on the signal from where Intrinsic mode Functions (IMFs) are extracted. The EMD is simple; appears naturally; does not assume anything about the signal; can be applied to a wide class of signals (Rato et al, 2008). The major advantage of the EMD is that the basic functions are derived from the signal itself (Boudra et al, 2005); (Pan et al, 2007).

2.1. Intrinsic Mode Functions Extraction

The following steps are involved:

Step 1: The ECG signal is represented as $x(t)$

Step 2: Finding all the local extrema (minima and maxima).

Step 3: Then connecting all the maxima and minima of the signal $x(t)$ using smooth cubic splines to get its upper envelop $x_{up}(t)$ and lower envelop $x_{low}(t)$.

Step 4: Finding 'mean $m_1(t)$' of the envelopes

$$m_1(t) = \frac{x_{up}(t) + x_{low}(t)}{2} . \tag{1}$$

Step 5: Getting the difference $h_i(t)$ using

$$h_1(t) = x(t) - m_1(t) . \tag{2}$$

Step 6: Regarding $h_1(t)$ as the new data and repeating steps 1-5 until the resulting signal meets the two criteria of an IMF, then define the signal as $c_1(t)$. The first IMF $c_1(t)$ contains the highest frequency component of the signal, that is, the shortest period components. The residue is given as:

$$r_1(t) = x(t) - c_1(t). \tag{3}$$

Step 7: Regarding $r_1(t)$ as the new data and repeating steps 1-6 until all the IMFs are extracted. The sifting procedure is terminated when the n[th] residue $r_n(t)$ becomes monotonic.

The original ECG signal $x(t)$ can be expressed as follows (Zhi-Dong and Yu-Quan, 2006)

$$x(t) = \sum_{i=1}^{n} c_i(t) + r_n(t) \tag{4}$$

where $c_i(t)$ represent IMFs

i represents number of corresponding IMFs

$r_n(t)$ is the residue component, all IMFs form the base functions of the signal.

The flowchart for process is shown in Figure 1

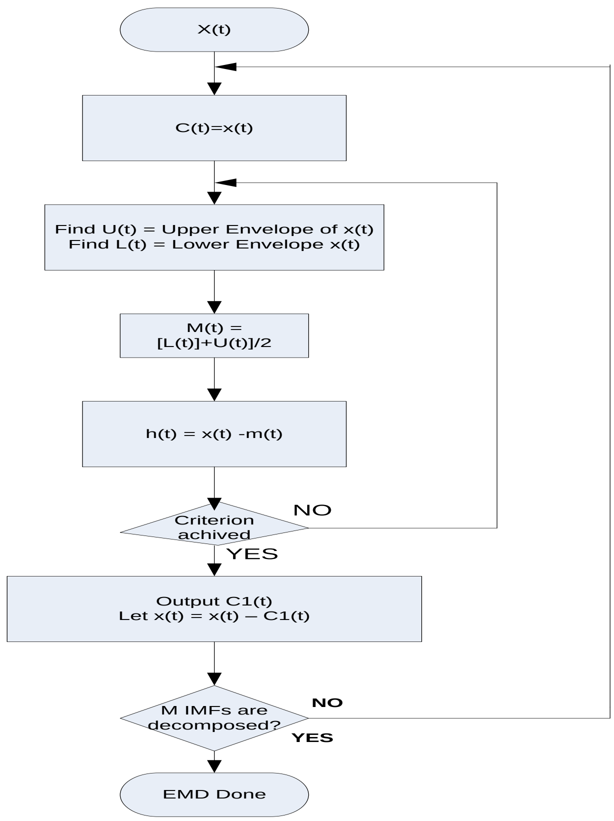

Figure 1: Flowchart for IMF decomposition.

2.2. Stopping Criterion

In practice, after a certain number of iterations, the resulting signals do not carry significant physical information. To prevent this, boundary conditions are adopted, and then the sifting process is stopped by limiting the normalized standard deviation

The normalized standard deviation (NSD) is defined as:

$$NSD = \sum_{t=1}^{T} \frac{\left[x_i(t) - x_i(t+1)\right]^2}{\left[x_i(t)\right]^2} \tag{5}$$

When NSD is smaller than a threshold ‘T’, the first IMF is obtained and this procedure iterates till all the IMFs are obtained. In this case, the residual is either a constant, or a monotonic slope or a function with only one extremum (Wu and Huang, 2004).

3. Proposed Method

3.1. Synthetic Noise and Baseline Wander

The first lead of record 103 from MIT-BIH Arrhythmia database was chosen. The first 2000 samples are taken for the evaluation. Power line interference consists of 50/60 Hz and its harmonics which was modelled as sinusoids and a combination of sinusoids with amplitude up to 50 % of the peak- to-peak of ECG amplitude. 50Hz power line noise is simulated using the MATLAB software package. The noise level corresponds to the peak-to-peak amplitude of 0.15 mV. The baseline wander generated is a low frequency White Gaussian Noise. The noise has a frequency of 0.3HZ. The Gaussian noise was filtered by a Lowpass filter, the filtered signal is the baseline wander added to the signal already corrupted by power line interference. The original signal 103.dat and the corrupted signal are shown in Figure 2.

The original ECG signal after EMD, yields sixteen IMFs as shown in figure 3; while the corrupted ECG signal after decomposition resulted in fifteen IMFs as shown in figure 4.

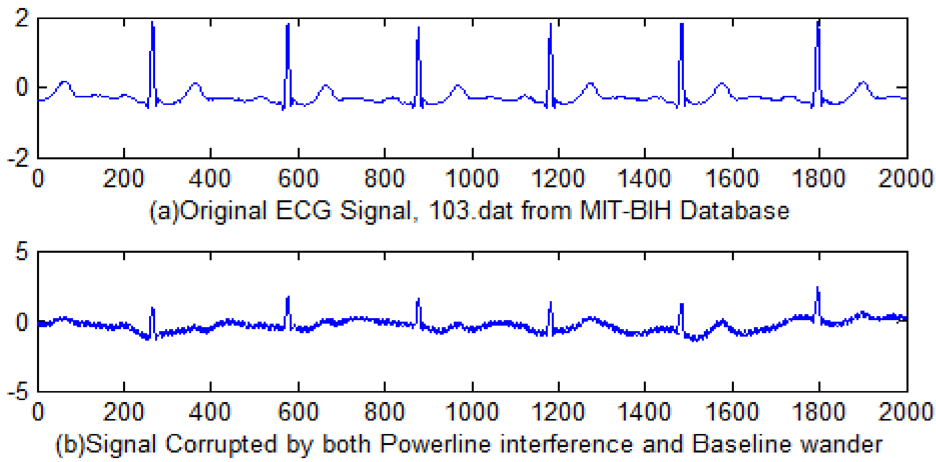

Figure2; (a) original ECG signal, (b) Corrupted ECG signal

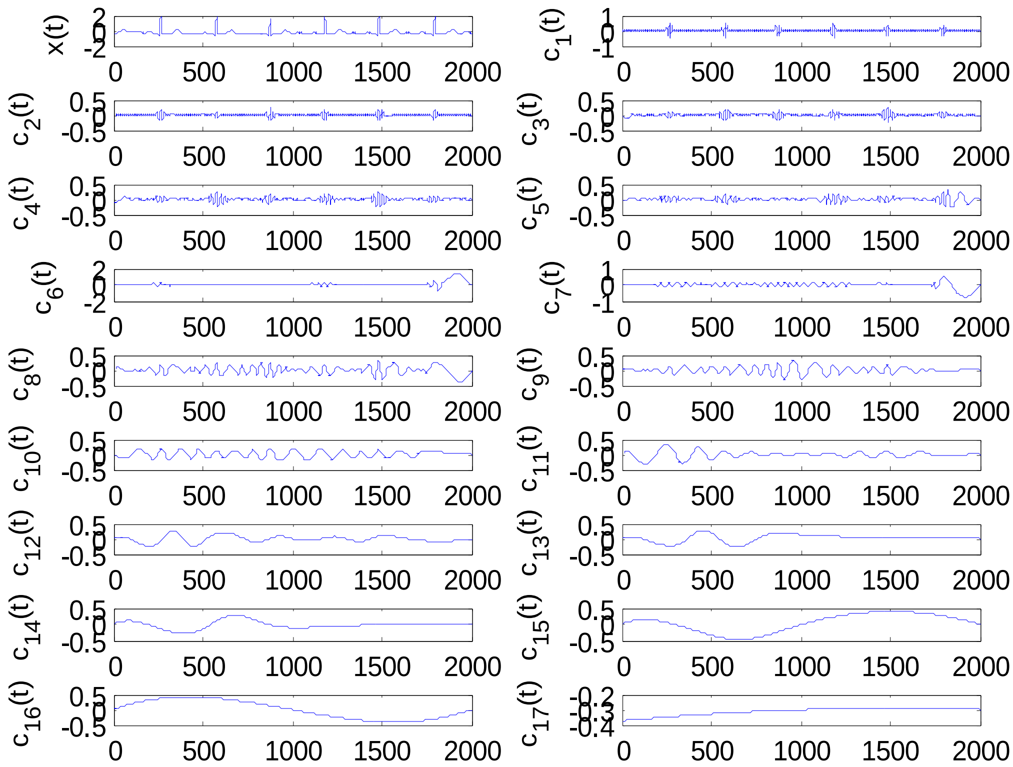

Figure 3: Original ECG decomposed to its IMFs using EMD.

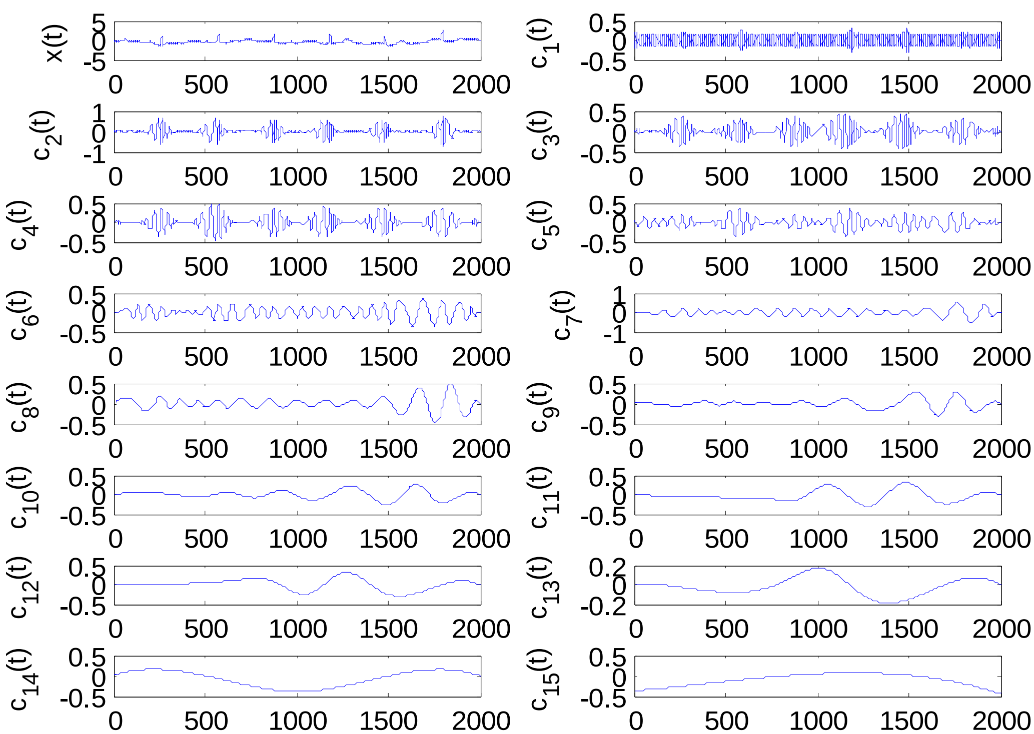

Figure 4: Noisy signal decomposed into its IMFs using EMD.

3.2. Noise Ranking

For ECG signals, the IMFs average value is usually non-zero, while the average value of the contaminating noise is zero. To remove the Power-line interference in EMD, therefore, a statistical analysis is carried out based on this fact. As can be seen from Figure 4, the first few IMFs contain the power-line interference; hence, a statistical test was performed on the IMFs starting from the first one to determine how many of the IMFs are to be filtered to remove the Power-line interference with minimum distortion to the significant features of the ECG signals under study.

$$P_0 ; mean\left[\sum_{i=1}^{K} C_i(t)\right] \neq 0 \tag{6}$$

$$P_1 : mean\left[\sum_{i=1}^{K} C_i(t)\right] = 0 \tag{7}$$

Zero (0) is set as a reference point. P_0 is a partial sum that deviates from the zero mark. Since the ECG signal average value is usually non-zero it is rejected in favour of P_1 whose partial sum gives a zero value. The terminating IMF K, whose partial sum gives a zero value, is regarded as the noise rank. Filtering the IMFs beyond K could result in significant distortion to useful components of the ECG signal.

In a situation where the mean value of the signal bearing IMFs gives a value close to zero, the noise rank was set between 1 and 5. This was because the power-line interference rarely spread beyond the fifth IMF. To avoid distortion however, the first IMF was filtered, then the second and progressively until the fifth IMF.

3.3. Denoising the IMFs

Infinite Impulse Response (IIR) notch filter was used to remove the power line interference. The filter was designed with the transition bandwidth, $\Delta f \;\; 4Hz$ and the centre frequency, $f_0 \;\; 50Hz$ using pole-zero placement method. The sampling frequency $f_s \;\; 360Hz$ was used, the radius, r, of pole is determined by

$$r \approx 1 - \frac{\Delta f \pi}{f_s} \tag{8}$$

The pole location θ_0 is determined by:

$$\theta_0 = \frac{2\pi f_0}{f_s} \tag{9}$$

The output of the notch filter, filtering from the first IMF is represented as $P_1(t) + P_2(t) \ldots\ldots. P_n(t)$

The general sum of the output of the notch filter is given as $\sum_{i=1}^{K} P_i(t)$

To remove the noise the output of the filter is subtracted from the summation of the IMFs.

$$\hat{x}_p(t) = \sum_{i=1}^{N} c_i(t) + r_n - \sum_{i=1}^{K} P_i(t) \tag{10}$$

where, $\hat{x}_p(t)$ is the recovered signal after power-line interference removal

$\sum_{i=1}^{N} C_i(t)$ is the sum of IMFs

r_n is the residue component

$\sum_{i=1}^{K} P_i(t)$ output of the IIR notch filter.

Thus to filter the power-line noise the first few IMFs containing the noise were first filtered, the output of the filter was then subtracted from the original corrupted ECG signal.

3.4. Design of Lowpass Filter Bank for BW Filtering

The last few IMFs contain the baseline wander. To remove this noise, a bank of lowpass filters was designed.

$$h_i(t),\ i = 1, 2 \ldots g \tag{11}$$

Then filter the IMFs starting from the residue r_n by these filters. The outputs $m_i(t)$ of these filters are:

$$\begin{aligned} m_1(t) &= h_1(t) * r_n, \\ m_2(t) &= h_2(t) * c_N(t) \\ &\vdots \\ m_g(t) &= h_g(t) * c_{N-g}(t) \end{aligned} \tag{12}$$

Set the cut-off frequency of the first lowpass filter $h_1(t)$ to be f_o. The cut-off frequency of the kth filter is set as

$$f_k = \frac{f_o}{T^{k-1}} \tag{13}$$

Equation 13 ensures the cut-off frequency reduces as the rank of the IMF reduces, since fewer baseline wander components are present in the IMFs. The filter treats each IMF separately. The value T which should be greater than one is a frequency folding number.

3.5. Ranking the Baseline Wander

The output $m_i(t)$ extracts the BW component in each IMF. Therefore, it can be used to determine the BW rank G. The variance of each $m_i(t)$ is determined as

$$Var\{m_i(t)\} = \frac{1}{L-1}\sum_{t=0}^{L-1}\left[m_i(t) - \mu m_i\right]^2 \tag{14}$$

where μm_i is the mean value of $m_i(t)$. Starting from the last IMF, we choose G such that

$$Var\{m_{G+1}(t)\} < \sigma \tag{15}$$

and

$$Var\{m_G(t)\} \geq \sigma \tag{16}$$

where σ is a threshold value.

3.6. Correcting the BW

The BW is hidden in the last several IMFs; the number of IMFs that contains the BW is referred to as the baseline wander rank G. The output of the Lowpass filter bank is sum together, the sum represent the baseline wander present in the ECG signal. To get the clean ECG signal this output is subtracted from the sum of the IMFs. The signal with BW is $x(t)$. After performing the EMD, we obtain all the IMFs

$$x(t) = \sum_{i=1}^{N} c_i(t) + r_n \tag{17}$$

Denoting the BW rank as G. Once the BW rank G is determined, the outputs of all the filters are synthesized to form the estimate.

$$\hat{m}(t) = \sum_{i=1}^{G} m_i(t) \tag{18}$$

Finally, removing the BW yields the reconstructed signal

$$\hat{x}_b(t) = \sum_{i=1}^{N} c_i(t) + r_n - \sum_{i=1}^{G} m_i(t) \tag{19}$$

3.7 The Enhancement Method

To clean the signal of both the baseline wander and power line interference, the method used can be summarised in the following equation:

$$\hat{x}(t) = \sum_{i=1}^{N} c_i(t) + r_n - \sum_{i=1}^{G} m_i(t) - \sum_{i=1}^{K} P_i(t) \tag{20}$$

Where:

$\sum_{l=1}^{N} c_i(t) + r_n$ represent the IMFs,

$\sum_{l=1}^{G} m_i(t)$ the BW component and

$\sum_{l=1}^{K} P_i(t)$ the noise component from IIR filter.

3.8 Performance Matric

Power line interference was added to the original clean signal to yield 5dB, 10dB, and 15dB SNR. The following MIT-BIH data: 100.dat, 103.dat, 105.dat, 113dat and 115.dat were used for the analysis. The technique is quantified using Signal Error Ratio (SER) in dB.

The SER can be represented as the following:

$$SER = \frac{\sum_{t=0}^{L-1} x(t)^2}{\sum_{t=0}^{L-1} n(t)^2} \tag{21}$$

where $x(t)$ is the signal and $n(t)$ is the noise.

4. Results and Discussion

Figure 5a,b,c show the original signal 103.dat from the MIT-BIH database, the corrupted signal and the recovered signal respectively. The result of the test on signal 100.dat from MIT-BIH database is shown in Figure 6a,b,c. It is clear from the result shown that the proposed method performs well in denoising ECG signals corrupted with both BW and power line noise.

Table 1.0 shows the comparison of the proposed method with Wavelet Transform (WT), and Empirical Mode Decomposition with Spectral flatness (EMDF). The results show a better SER for the method at different SNR.

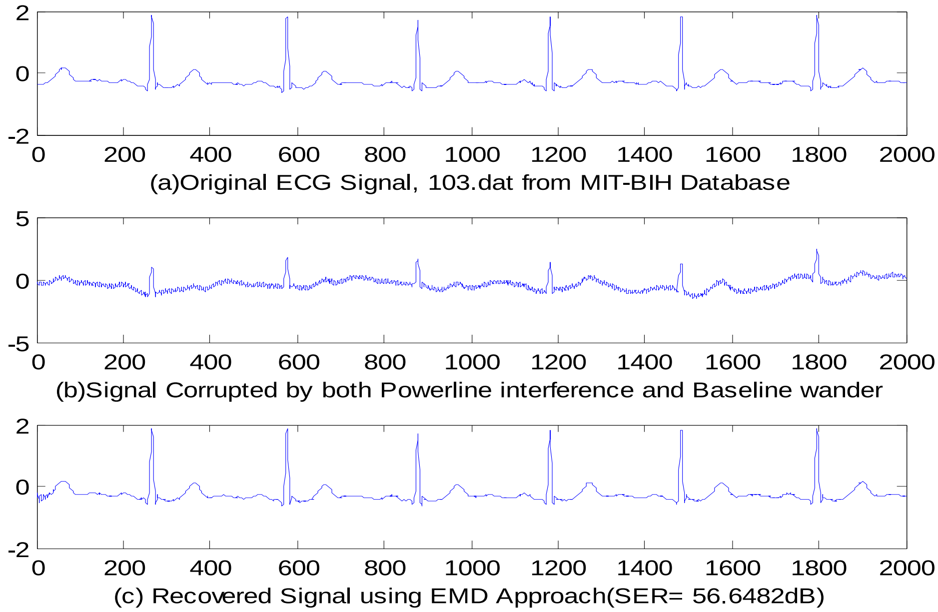

Figure:5: (a) Original ECG 103.dat, (b) Corrupted ECG, and (c) Recovered ECG.

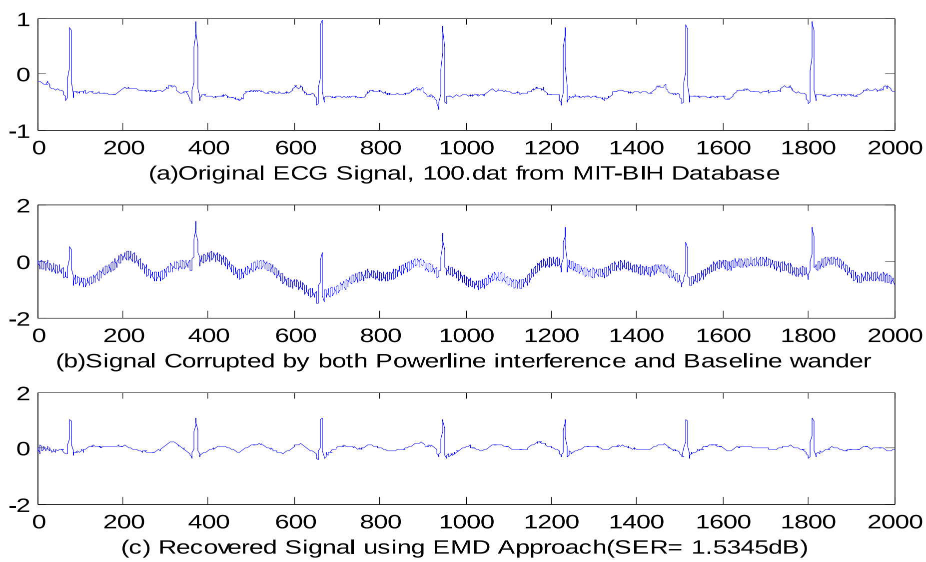

Figure 6: (a) Original ECG 100.dat, (b) Corrupted ECG, and (c) Recovered ECG.

Table 1: Comparisons of ECG Enhancement Methods.

	5 (dB)			10 (dB)			15 (dB)		
	WT	EMDF	EMD	WT	EMDF	EMD	WT	EMDF	EMD
Data	SER	SER	SER	SER	SER	SER	SER	SER	SER
100.dat	8.1000	9.5000	10.0005	11.4600	14.3500	14.2985	15.1100	18.6700	17.7279
103.dat	8.5500	9.8800	10.1553	12.0200	14.8900	15.1113	15.9500	17.5600	18.8729
105.dat	9.1000	10.0110	10.2409	12.5600	14.6200	14.9731	16.1200	18.5200	19.3086
115.dat	9.4500	10.2200	10.2557	13.0900	14.5900	14.9344	16.7600	17.6100	19.6588
Average	8.8000	9.9028	**10.1630**	12.2825	14.6125	**14.8293**	15.9850	18,0900	**18.8921**

A plot of SER against SNR for a set of data used is shown in Figure 7.0. signal to error ratio appreciate as SNR increases giving a direct relationship as expected.

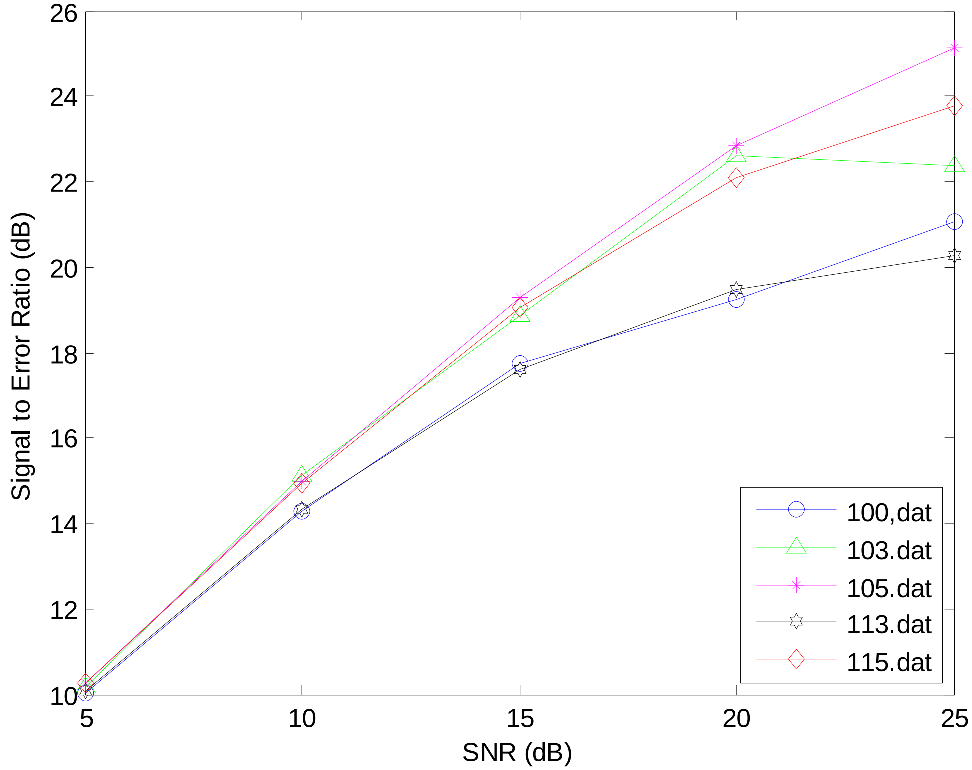

Figure 7: Plot of SER against SNR

5. Conclusion

An EMD based method for removing the baseline wander and power line interference from ECG signal has been developed in this paper. Automatic detection of noisy IMFs is done using Statistical method. The noisy IMFs and those containing baseline wander are filtered and the outputs of the filters are then removed from the sum of the IMFs to obtain the denoised ECG signal. The proposed technique is evaluated on 5dB, 10dB and 15dB SNR where the power line noise and BW noise are artificially added with original signal. Performance of the proposed method shows better SNR performance compared to Wavelet Transform based technique which is usually used as an ECG signal noise removal technique. The proposed method will also find application in some biomedical engineering application including automated detection of venous bubbles, classification of normal and hypoxia ECG.

6. References

Manpreet K., Birmohan S. and Seema. (2011)' Comparisons of Different Approaches for Removal of Baseline Wander from ECG Signal' *2nd International Conference and workshop on Emerging Trends in Technology (ICWET) 2011 Proceedings published by International Journal of Computer Applications.)*

Chinchkhede, K.D, Govind, S.Y., Hirekhan S.R., and Solanke, D.R. (2011) "On the Implementation of FIR Filter with various Windows for Enhancement of ECG signal" International Journal of Engineering Science and Technology, vol. 3, no. 3, pp.2031-2040.

Urszula M. K, (2005) 'Mining of an electrocardiogram', XXI Autumn Meeting of Polish Information Processing Society, conference proceedings. Wroclaw University of Technology, Institute of Applied Information Wroclaw, Poland. 169-175.

Christov, I. I. and Daskalov, I. K., (1999) "Filtering of electromyogram artifacts from the electrocardiogram," *Med. Eng. Phys.*, vol. 21, 731–736.

Mneimneh M.A, (2006) An adaptive Kalman filter for removing baseline wandering in ECG signals, computers in cardiology, ISSN 0278-6547, 253-256.

Van Alste, J. A and Schilder, T. S. (1985) Removal of Base-Line Wander and Power-Line Interference from the ECG by an Efficient FIR Filter with a Reduced Number of taps, IEEE transactions on biomedical engineering, vol. bme-32, no. 12.

Vineet K. M., (2010) 'Baseline Wander Estimation for ECG Characterization'. An unpublished master thesis submitted to electronic instrumentation and control Department Thapar University Patiala -147004.

Zhi-Dong Z and Yu-Quan C, (2006) A new method for removal of Baseline Wander and Power line interference in ECG signals, Proceedings of the fifth international conference on machine learning and cybernetics,

Pan N, Vai M, Mai P.U and Pun S.H, (2007) Accurate removal of Baseline Wander in ECG using Empirical Mode decomposition, Proceedings of NFSI and ICFBI, Hangzhou, China. 1-4244-0949.

Rato, R.T., Ortigueira, M.D., Batista, A.G., (2008) On the HHT, its problems, and some solutions, Mechanical Systems and Signal Processing 22 pp. 1374–1394.

Boudraa, A.O., Cexus, J.C. and. Saidi, Z (2005) EMD-Based Signal Noise Reduction, World Academy of Science, Engineering and Technology 2 pp. 96-99.

Blanco-Velasco, M, Weng, B Barner, K.E (2006) A New ECG Enhancement Algorithm for Stress ECG Tests, Computers in Cardiology, pp. 917−920.

Karagiannis, A and. Constantinou, Ph (2010) On the Processing Of White Gaussian Noise Biomedical Signals With The Empirical Mode Decomposition, Analysis of Biomedical Signals and Images, pp. 439-446.

Wu, Z. and Huang, N. E. (2004) A study of the characteristics of white noise using the empirical mode decomposition method, *Proc. Roy. Soc. London 460A*, pp. 1597- 1611.

MIT-BIH (Massachusetts Institute of Technology- Beth Israel Hospital) Arrhythmia Database (online) available at http://phsionet.org/physiobank/database/mitbd.