Performance Comparison of Hybrid Empirical Mode Decomposition Based Techniques for Electrocardiogram Denoising

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***Abstract* – The electrocardiogram shows the electrical activity of heart and is used by physicians to inspect the heart condition. Analysis of electrocardiogram becomes difficult if noise is embedded with signal during acquisition. In this paper, a de-noising technique for electrocardiogram signal done based on a combined method of high pass filtering with empirical mode decomposition (EMD) and wavelet de-noising. The major noise present in electrocardiogram signal is baseline wander and powerline interference. The aim of this proposed work is to remove both noises from the noise affected electrocardiogram signal. This work deals with the use of Butterworth high pass filter to de-noise the baseline wander followed by the empirical mode decomposition and wavelet de-noising method to remove powerline interference noise completely. Finally, the signal to noise ratio is calculated for the proposed system. The high pass filtering with EMD de-noising is twice as better than de-noising of electrocardiogram using EMD technique only on an average. The Hybrid method consisting of high pass filtering, EMD with Wavelet which is about 4.5 times better on an average when compared to EMD technique only.**

Keywords - Empirical mode decomposition, Wavelet de-noising, Signal de-noising, Filtering algorithms, Signal reconstruction, Biomedical signal processing.

I. INTRODUCTION

Electrocardiogram shows the electrical activity of the heart during its contraction and expansion. It is one of the important tools used by medical practitioners to examine the pathological condition of the heart. Accurate analysis of electrocardiogram signals becomes difficult if it is corrupted by noise during acquisition. The recorded electrocardiogram signal is often corrupted by different types of noise such as power line noise, baseline noise, motion artifacts etc which may change the characteristics of electrocardiogram signal. Power line noise causes errors by distorting the electrocardiogram signal during the measurement of the QRS complex interval or the QT interval, which are important parameters in diagnosis. The drift of the baseline is usually caused by respiration of the patient. The drift of the baseline with respiration can be represented by a sinusoidal component at the frequency of the respiration added to the electrocardiogram signal. The amplitude and frequency of the sinusoidal component should be variables. The variation could be reproduced by amplitude modulation of electrocardiogram by the sinusoidal component added to the baseline. The baseline wander is a low-frequency noise (below 1 Hz). It is used as a diagnostic parameter for myocardial infarction. Effective removal of the baseline wander is recommended for the measurement of the ST segment with precision and to extract useful information from the signal. Recently, researches from biomedical signal processing have been reported in the literature for electrocardiogram de-noising such as El-Sayed [2] *etal* proposed **g**enetic algorithm and wavelet hybrid scheme based de-noising electrocardiogram. Julien Oster [3] proposed a method based on Bayesian Filtering for de-noising electrocardiogram Rik Vullings[13] proposed a method of adaptive Kalman filter for electrocardiogram signal enhancement . Alireza K. Ziarani [1] proposed a nonlinear adaptive method to remove power line interference noise.

The electrocardiogram data sets are taken from the MIT-BIH Arrhythmia database. These data sets have been frequently used as benchmarks to compare the performance of different noise reduction methods in the literature.

II.THEORETICAL BACKGROUND

A. Empirical Mode Decomposition

The Empirical Mode Decomposition was proposed by Huang *et al*. as a new signal decomposition method for nonlinear and non stationary signals [18]. The EMD decomposes a signal into a collection of oscillatory modes, called Intrinsic Mode Functions (IMFs), which represent fast to slow oscillations in the signal. By applying empirical mode decomposition a signal can be decomposed into a set of mono component functions called Intrinsic Mode Functions (IMFs) (Huang *etal*., 1998). A mono component function indicates an oscillating function close to the most common and basic elementary harmonic function. Therefore, the intrinsic mode functions contain frequencies ranging from the highest to the lowest ones of the signal presented as

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amplitude and frequency modulated (AM-FM) signals, where the AM carries the envelope and the FM is the constant amplitude variation in frequency and calculated using a sifting process. Each IMF can be viewed as a sub band of a signal. Therefore, the EMD can be viewed as sub band signal decomposition. To accomplish this, an intrinsic mode functions must satisfy two conditions.

1) The number of extrema (local maxima and minima) and the number of zero crossings must either equal or differ at most by one.
2) At any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero.

The first condition is necessary for oscillating data to meet the strict conditions needed to calculate the instantaneous frequency that presents the oscillation frequency of a signal at certain point of the time Huang *etal* [18]. It leads to a narrow-band signal. The second condition requires symmetric upper and lower envelopes of an intrinsic mode functions which makes the signal ready for modulation as the intrinsic mode functions component is decomposed from the original data Huang *etal* [18]. It is quite a challenging task to find the envelopes because of the nonlinear and non-stationary nature of the data.

The main idea behind intrinsic mode functions is to separate the data into a slowly varying local mean part and a fast varying symmetric oscillatory part, with the latter part becoming the intrinsic mode functions and the local mean defining a residue. This residue serves as input for further decomposition, with the process being repeated until no more oscillations can be obtained. A sifting process is applied to iteratively separate the different oscillatory riding components of the signal, starting with the fastest and ending with the slowest component. By adding all the IMFs the original signal can be recovered.

Given a signal x (t), the effective algorithm of EMD can be summarized as follows.

1) Identify all extrema of x (t).
2) Interpolate along the point of x(t) identified in the first step, in order to form an upper $e_{max}(t)$ and lower envelope $e_{min}(t)$.
3) Compute the mean

$$m(t)=(e_{min}(t)+e_{max}(t))/2 \qquad (1)$$

4) Extract the detail d(t) = x(t) − m(t).
5) Iterate on the residual m (t).

But practically, the previous procedure has to be refined by a sifting process [19], which amounts to first iterating steps 1 to 4 upon the detail signal *d*(*t*), until this latter can be considered as zero mean according to some stopping criterion. Once this is achieved, the detail is referred to as an IMF, the corresponding residual is computed and step 5 applies. By construction, the number of extrema is decreased when going from one residual to the next, and the whole decomposition is guaranteed to be completed with a finite number of modes. The above procedure to extract the IMF is referred to as the sifting process. The stopping criteria used to terminate the sifting process is the sum of difference (SD)

$$SD = \sum_{t=0}^{T} \left(\frac{|h_{k-1}(t) - h_k|^2}{h_{k-1}^2(t)} \right) \qquad (2)$$

When the sum of difference is smaller than a threshold, the first IMF is obtained, which is written as

$$r_1(t) = x(t) - c_1(t) \qquad (3)$$

Yet the residue $r_1(t)$ still contains some useful information. Hence, the residue should be considered as a new signal and continue applying the above procedure to obtain

$$r_1(t) - c_2(t) = r_2(t),$$
$$\vdots$$
$$r_{N-1}(t) - c_N(t) = r_N(t) \qquad (4)$$

The whole procedure terminates when the residue $r_N(t)$ is either a constant, a monotonic slope, or a function with only one extremum. Combining the equations in (3) and (4) yields the EMD of the original signal.

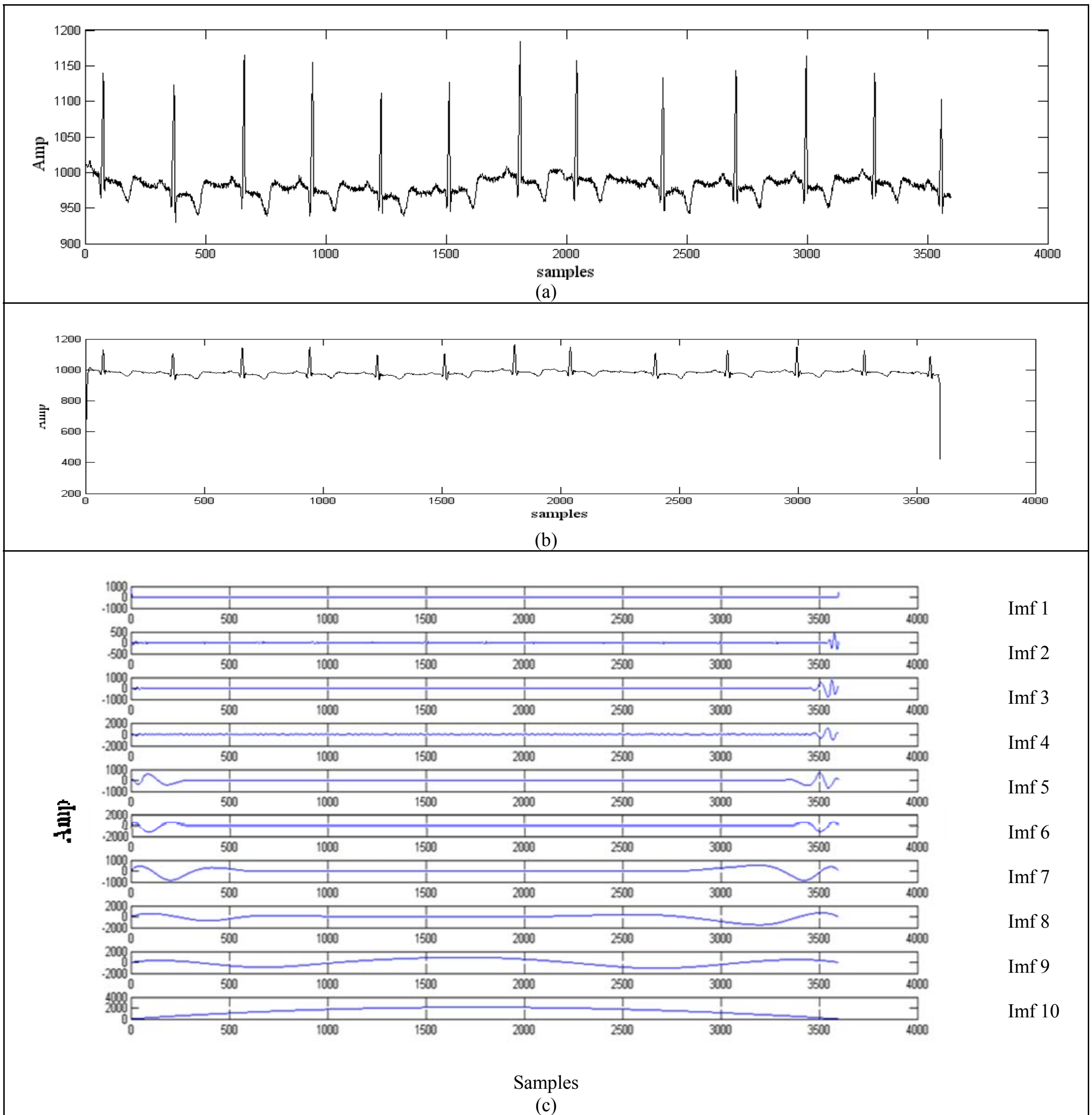

Figure 1: (a) Input Electrocardiogram 100.m recorded signal; (b) EMD based denoised output of Electrocardiogram 100.m recorded signal; (c) Intrinsic mode function of 100.m electrocardiogram signal

$$x(t) = \sum_{n=1}^{N} c_n(t) + r_N(t) \qquad (5)$$

The result of the EMD produces N IMFs and a residue signal. For convenience, the $c_n(t)$ is referred as the n th-order IMF. By this convention, lower-order IMFs capture fast oscillation modes while higher-order IMFs typically represent slow oscillation modes. In the interpretation is done for EMD on a time-scale analysis method, lower-order IMFs and higher-order IMFs correspond to the fine and coarse scales, respectively High-frequency de-noising by the EMD is carried out by partial signal reconstruction, which is based on the fact that noise components lie in the first several IMFs. Noise encountered in ECG applications is usually located in the high-frequency band. Hence, the IMFs corresponding to those noises are removed and then construction of the original signal is obtained by summing up the remaining IMFs to obtain de-noised signal. But, yet the process noise is not completely removed.

B. *Baseline Wander:*

The baseline wander in electrocardiogram is usually caused by respiration of the patient. Baseline wander could mask certain important characteristics in the ECG wave which makes wave detection and signal classification difficult. The variation could be reproduced by amplitude modulation of electrocardiogram by the sinusoidal component added to the baseline.

In order to remove base line wander Butterworth high pass filtering is used. The cutoff frequency of high pass filter is experimentally set to be 0.5 Hz, which achieves best removal of baseline noise in electrocardiogram. After applying Empirical mode decomposition to the input signal which is record no 100.m electrocardiogram signal power line noise is removed but baseline noise is not completely removed completely. In order to overcome the problem, high pass filtering method is done before performing empirical mode decomposition.

III. PROPOSED METHOD

A. High pass filtering

In the proposed method both Butterworth high pass filter and wavelet de-noising is used to remove both baseline wander and power line noise completely. Steps followed in hybrid technique are as follows:

Step-1 The electrocardiogram signals from the MIT Arrhythmia database with both power line and baseline noise is given as input

Step-2 Set a sampling frequency =360Hz and cut-off frequency= 0.5Hz for the Butterworth high pass filtering to achieve best result of removing baseline wander noise.
Step-3 Apply EMD based de-noising to remove power line noise.

After applying high pass filter with empirical mode decomposition, baseline noise and power line noise is removed. The high pass filtering with EMD in comparison with the EMD based de-noising for the electrocardiogram signal and it gives an improved signal to noise ratio as shown in Table I.

TABLE I: SNR COMPARISON OF EMD AND HPF & EMD

ECG Record No	SNR(dB) for EMD	SNR(dB) for High pass filter and EMD
100	4.3502	9.6263
103	5.4178	6.6076
113	7.1286	8.1421
114	4.1228	10.196
121	4.0814	23.536
201	4.088	9.9091

In order to improve quality of the signal, wavelet de-noising method is performed on the proposed method. By applying wavelet, the signal quality and signal to noise ratio can be enhanced. The proposed method is carried on ECG records 100,103,113,114,121 and 201 from the MIT arrhythmia database. The above records were chosen as they contain both power line and baseline noise.

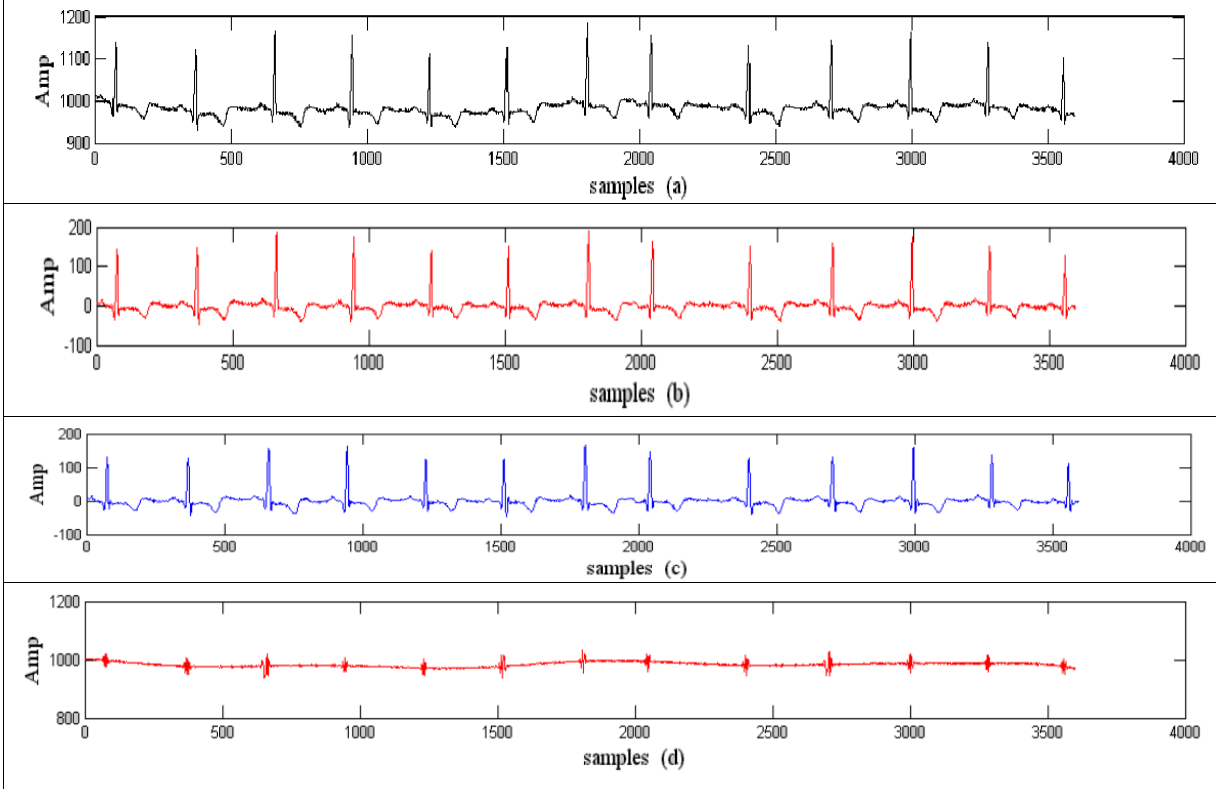

Figure 2: (a) Input electrocardiogram signal; (b) Denoised ECG signal using Butterworth high pass filter;
(c) Denoised ECG by giving the output of HPF to EMD (d) Noise obtained after applying high pass filtering and EMD.

B. Wavelet Based ECG Denoising:

In wavelet based de-noising, a signal is decomposed to a certain level using Discrete Wavelet Transform (DWT), a set of wavelet coefficients is correlated to the high frequency sub bands while the other wavelet coefficients are correlated to low frequency sub bands. Matlab Wavelet Toolbox is used for calculating the DWT to decompose the signal into wavelet coefficients and then to reconstruct the signal using inverse discrete wavelet transform (IDWT). The application of wavelet noise suppression requires the selection of different parameters: Wavelet basis function, the thresholding type, thresholding selection rule, decomposition level, and a noise scaling option.

The first step in producing a wavelet de-noising is to choose a wavelet basis function to be used in signal decomposition. Different types of wavelet (orthogonal and bi orthogonal) are available in Matlab toolbox. The selection of a suitable level depends on the signal. Often the chosen level is based on a desired low-pass cutoff frequency. The high frequency sub bands contain the details in the data set. If these details are small, they might be removed without substantially affecting the main features of the data set.

Therefore, by setting the wavelet coefficients corresponding to these small details as zero, the noise is removed. This becomes the basic concept behind thresholding. Applying the IDWT on the results may lead to reconstruction with essential signal characteristics and less noise [6, 7]. Two types of thresholding functions are which are often used are hard thresholding and soft thresholding [5].

Wavelet de-noising scheme can be summarized as follows:

Step-1 The output of the proposed method is given as a input to the wavelet de-noising method.

Step-2 Set the proper wavelet thresholding de-noising parameter ranges for electrocardiogram signal.

Step-3 Perform a 1-Dimensional discrete wavelet transform for the noisy electrocardiogram signal to get all the wavelet coefficients

Step-4 Threshold the noisy coefficients in electrocardiogram signal with the optimal thresholds, and obtain the modified new electrocardiogram components after the reconstruction of the signal.

IV. RESULTS AND DISCUSSIONS

To calculate the filtration efficiency of the proposed technique, several real world datasets were downloaded from the MIT-BIH database. Each of the electrocardiogram records has the following specifications: signal length is 3600 samples; sampling rate is 360 Hz with 11 bits per sample of resolution. These data sets have been frequently used as benchmarks to compare the performance of different noise reduction methods in the literature. Simulations for several different cases carried out to evaluate the performance of the proposed hybrid technique based method.

A noisy signal s(t)=x(t)+n(t) is processed to obtain an enhanced reconstructed version $\hat{x}$. The corrupted signal s(t) consists of an clean signal x(t), which is free of noise, and a noise component realization n(t) .Three groups of experiments are presented.

The first simulation experiment is performed over electrocardiogram with power line noise and baseline noise by using EMD. Drawback of the first experiment is that it removes only the power line noise and does not remove the baseline noise. Second experiment is performed over the same data set which removes both the power line and the baseline wander noise using hybrid technique of Butterworth high pass filtering and EMD de-noising. Third experiment is the hybrid method comprising of adding wavelet de-noising method added to the combined technique of HPF and EMD for improving signal quality and SNR. Every record considered here consists of two lead recordings sampled at 360 Hz with 11 bits per sample of resolution.

The quantitative evaluation is assessed by the signal-to noise ratio (SNR)

$$\mathrm{SNR} = \frac{\sum_{t=0}^{L-1} x^2(t)}{\sum_{t=0}^{L-1}[x(t) - \hat{x}(t)]^2} \qquad (1)$$

where x (t) is the original clean signal and $\hat{x}(t)$ is the reconstructed signal.

The Figure 3 shows the result of combination of high pass, EMD, and wavelet. The Daubechies wavelet transform is used as it allows perfect and simple reconstruction of the original signal [5].

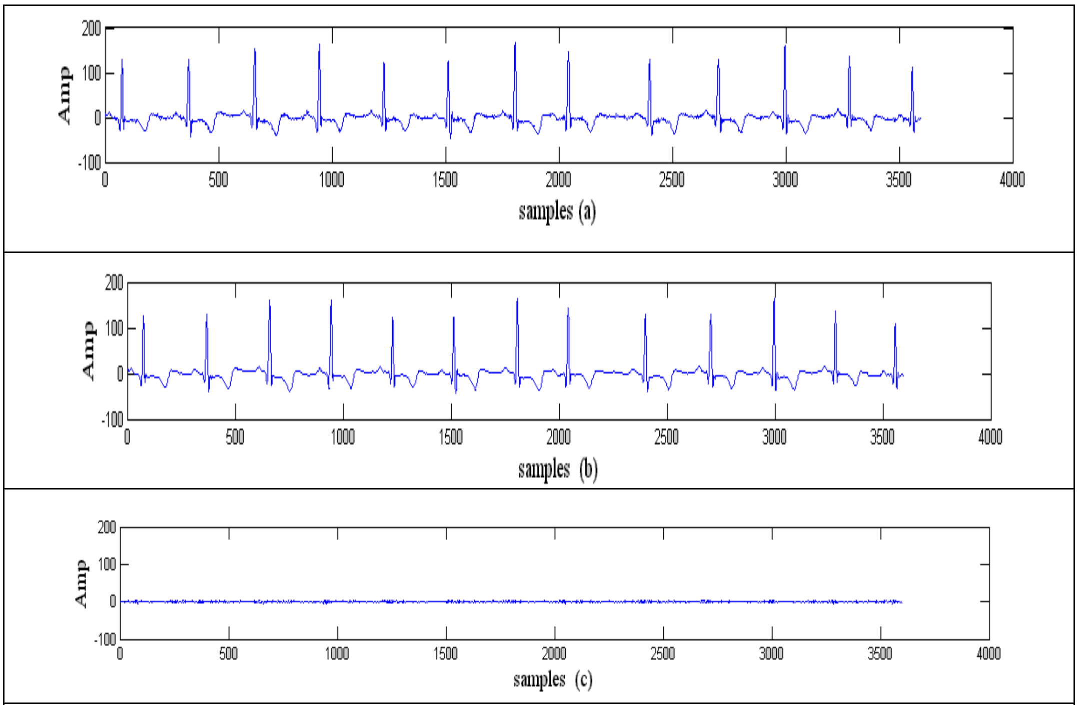

Figure 3: (a) Proposed method (HPF+EMD); (b) Output after applying wavelet denoising method to the HPF, EMD method; (c) Noise obtained after applying HPF,EMD and wavelet denoising .

Even though hard thresholding is the simplest method to use in comparison with soft thresholding, soft thresholding can produce better results than hard thresholding, as hard thresholding may cause discontinuities in the signals. The SNR of the hybrid technique with simple wavelet de-noising using daubechies families shows improved signal to noise ratio in proposed method. The performance analysis of all the discussed methods is shown in a Table II.

TABLE.II SNR COMPARISON OF THE THREE METHODOLOGIES ADOPTED

ECG Record No	EMD SNR(dB)	HPF+EMD SNR(dB)	HPF+EMD+WAVELET (Db3) SNR(dB)
100	4.3502	9.6263	23.4
103	5.4178	6.6076	25.0
113	7.1286	8.1421	29.1
114	4.1228	10.196	30.9
121	4.0814	23.536	25.6
201	4.088	9.9091	27.4

V. CONCLUSION

A hybrid de-noising technique for electrocardiogram signals is proposed based on the combination of Butterworth high pass filtering, EMD de-noising and wavelet de-noising method. This technique is used to remove both baseline wander and power line noise. Selection of wavelet de-noising is critical to remove baseline wander noise elimination process for the electrocardiogram signal. Efficient selection of cut-off frequency of high pass filter is necessary to remove baseline noise completely. This proposed technique achieves a best quality of electrocardiogram signal. It could be concluded that, the noise reduction of a signal depends on the optimum value of the level of decomposition, suitable forms of wavelet family and the thresholding techniques. The empirical mode decomposition and high pass filter based de-noising is twice better than de-noising using EMD alone on an average. The Hybrid method consisting of High pass filter, EMD and Wavelet (Db3) is about 4.5 times better on an average in comparison to using Empirical mode decomposition alone. Hence, in future this approach can be used in devices for real time monitoring of electrocardiogram.

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