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A comparative analysis of EMD based filtering methods for 50 Hz noise cancellation in ECG signal

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A R T I C L E I N F O

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A B S T R A C T

Electrocardiogram (ECG) is the procedural electrical activity recording of the heart that arises from the heart muscle's electrophysiological pattern. But in clinical atmosphere during acquisition, the ECG signal is corrupted with various types of artifacts. The parting of the preferred signal from noises caused by artifacts such as muscle artifacts, power-line interference, base-line wandering and motion artifacts is a big covenant. Among these noises a power-line interference of 50 Hz frequency is more severe and fluctuate the signals morphological appearances. There are various tools like wavelet transform and empirical mode decomposition (EMD) being used for filtering other than conventional filters. EMD based noise cancellation is a fully signal dependent approach and adaptive in nature that can be used for real-time applications. This paper deliberates the comparative analysis of EMD based filtering methods for noise cancellation in ECG signal under 48–51 Hz of frequency under varying noise amplitudes.

1. Introduction

The noise cancellation in biomedical signal is very influential to distinguish the essential signal features in noise. Wavelet transform (WT) can be a useful tool for non-stationary signal investigation. Wavelet shrinkage concepts developed by Donoho and Johnstone [1] is the new idea in the avenue of denoising. The comparison of empirical wavelet coefficient with a threshold has been performed using designed shrinkage method [2]. In this method if its magnitude is less than a threshold values it is set to zero. Poornachandra and Kumaravel [3,4] developed a subband adaptive shrinkage function for denoising of ECG signals. But the formation of wavelet thresholding trusts on the conjecture that signal magnitudes control the magnitudes of the noise in a wavelet depiction so that wavelet coefficients can be set to zero if their magnitudes are less than a determined threshold [5]. Alternative constraint of wavelet approach is that the basis functions are fixed and thus do not inevitably match all real signals. Empirical mode decomposition (EMD) is a recently familiarized practice and it is used for processing non-linear and non-stationary signals. It has the property of adaptive and signal-dependency [6]. Nimunkar and Tompkins [7] presented a process for 50 Hz interference reduction in ECG signal, this technique is progressed in a way that when SNR is low, the 50 Hz interference gets separated in the first intrinsic mode function (IMF). Blanco-Velasco et al. [8] used the succeeding procedure to denoise the signal: (i) Delineate and separate the QRS complex; (ii) Use proper windowing to preserve the QRS complex; (iii) Use statistical tests to regulate the number of the IMFs contributing to the noise and (iv) Filter the noise by partial reconstruction. Kopsinis and McLaughlin [9] developed an EMD based denoising methods using wavelet thresholding.

2. Empirical mode decomposition

The EMD was familiarized by Huang et al. [6] that helps to decompose adaptively a signal into an assortment of AM–FM components. It is fully a data reliant method and it does not necessitate any basis function a prior. This method is perfectly suitable for signals that vary nonlinearly and are not stationary. By this algorithm it will split the signal into a totality of intrinsic mode functions. A function with equal number of extrema and zero crossings are called IMFs [7,8]. Each IMF is a simple oscillatory approach as a counterpart to the simple harmonic function used in Fourier analysis.

For any signal $x(t)$, the EMD algorithm works as follows:

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1. All the minima and maxima of the signal *x(t)* is to be detected.
2. Interpolate the local maxima of *x(t)* using cubic spline to form an envelope $e_u(t)$. Similarly the envelope connecting the minima is represented as $e_l(t)$.
3. Compute the mean, $m_1(t)$ of the two envelopes: $m_1(t)$ =[$e_u(t)$ + $e_l(t)$]/2.
4. Compute the detail, $h(t)$, by subtracting the mean from the signal, $h(t) = x(t) - m_1(t)$.
5. Replicate the iteration on the residual $m_1(t)$. Carry on until the residual is such that no IMF can be extracted and exemplifies a monotonic function.

The above technique for extracting the IMF is referred to as the *sifting* process. Finally, the EMD of the original signal can be represented as the summation of IMFs and a residue (Eq. (1)):

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

An IMF is a function that satisfies the two following conditions: (a) the number of extrema and the number of zero crossings must either equal or differ at the most by one in whole data set, and (b) the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero at every point.

3. Proposed denoising methods

3.1. EMD based partial reconstruction

The corrupted ECG signal is adaptively decomposed into several intrinsic components called intrinsic mode functions (IMFs) [8]. This filtering mechanism aims at partial reconstructions of the decomposed signal. It is developed based on the approach that most of the significant structures of the signal are concentrated on the lower frequency ones (last IMFs) and decrease towards high-frequency modes (first IMFs). The spectrum on each level illustrate the separation of 50 Hz component in first IMF level and remaining signal components in all other levels. The residue signal at the end of the sifting process has frequency of 0.5 Hz, corresponding to the frequency of baseline wandering. Thus filtering by partial reconstruction of the signal using the IMFs matches to the removal of first IMF level and the residue signal. The reconstruction of enduring signal structures of IMF levels gives a perfect denoised ECG signal. This method does not use any pre or post processing and can be used under any noise levels [10].

3.2. EMD based adaptive filtering technique

The partial reconstruction of signal accomplishes well irrespective of the noisy signal but it has the chance of removal of certain ECG constituents. Thus an adaptive filter is used in the first IMF for the decline of 50 Hz intervention. An adaptive filter is the prospective choice for elimination of 50 Hz power line signal which can regulate its coefficients in according with least mean square algorithm [11,12]. It is an advanced filtering technique that is extensively used due to its less computational complexity. The new weight update equation is given by the Eq. (2).

$$w(n+1) = w(n) + \mu\, e(n)x(n) \tag{2}$$

where $w(n)$ is the weight; $x(n)$ is the input vector of time delayed input values, μ is known as the step size parameter and $e(n)$ is the error signal. $X(n) = [x(n)\ x(n\text{-}1)\ x(n\text{-}2)..\ x(n\text{-}N\text{+}1)]^T$ and $W(n) = [w_0(n)\ w_1(n)\ w_2(n)..\ w_{N-1}(n)]^T$ symbolize the coefficients of the adaptive finite impulse response (FIR) filter tap weight vector at time n.

The construction of two-weight adaptive filtering structure is as shown in Fig. 1. The primary signal is the noisy ECG signal and the reference signal is the 50 Hz noise. The sum of the two weighted versions of the reference signal is then subtracted from the ECG output to produce an error signal. These error signals collected with the weighed inputs are applied to the least mean square (LMS) algorithm, which controls the adjustments applied to the two weights. In this case, the adaptive noise canceller acts as a variable notch filter [13,14].

In this work, the decomposed IMF levels obtained after applying EMD is the primary noisy ECG signal. The resultant is that the 50 Hz interference gets separated in the first IMF level and the remaining levels are free from the interference component. Thus a two-weighted adaptive filtering is performed in IMF1 level. This structure will control the amplitude and phase variation of the signal. Primary signal is taken as $d=x+n$ (signal + noise), IMF1 signal is applied as the reference signal and adaptation is accomplished. The best least-squares approximation of the signal is minimization of mean square error (MSE). Output of adaptive filter $y(n)$ is computed with the eradication of 50 Hz power line interference.

3.3. EMD based adaptive filtering by extracting the interference

In this technique the IMF1 is taken as the reference signal and it is passed to a band pass filter. The range of band pass filter (BPF) is considered as the range of unwanted interference in the original signal. The filtered band of signal is applied as input to the adaptive structure. The phase shifted version of the filtered signal is given as another input to the adaptive filter. Adaptation is performed by feedback of the estimated error signal, $e(n)$. The main advantage of this technique is that no other ECG components get removed rather than only the 50 Hz interference part [15].

4. Results and discussion

In this section, we have discussed the simulation results of the filtering concepts to evaluate our proposed methods. The performance measures are carried out in comparison with some of the state-of-art methods to confirm the proposed study.

4.1. Specification details of input

In this simulation study, we used simulated ECG signals and MIT–BIH arrhythmia database for analyzing and denoising ECG signals. The synthetic ECG signals are achieved using the ecgsyn software which is downloaded from physionet, and Table 1 shows the specifications considered in this study.

The ECG signal is degraded by 50 Hz and it is sampled at 360 Hz for the study purpose. The corrupted ECG signal is further decomposed into diverse IMFs and one residue. Fig. 2 shows only the first five IMF levels (IMF1-5). The spectrum plots obtained from the first four IMF levels are shown in Fig. 3, from which the power line interference can be clearly observed.

4.2. Performance evaluation and comparison

The performance of the proposed technique is assessed by associating it with the wavelet technique of filtering like soft and hard thresholding methods. The simulations were carried out in MATLAB2015b® environment and the assessments were implemented both qualitatively and quantitatively.

4.2.1. Qualitative evaluation

First, the performance of the proposed denoising algorithm was compared qualitatively by visual assessment. Fig. 4 shows the denoised signal obtained from the three proposed methods such as partial reconstruction, adaptive filtering and adaptive filtering by extracting the interference. A band pass filter is placed in the path of noisy signal to exactly separate only the noisy component. The band of frequency is chosen as 48 – 51 Hz. It is to be revealed that the pattern of the

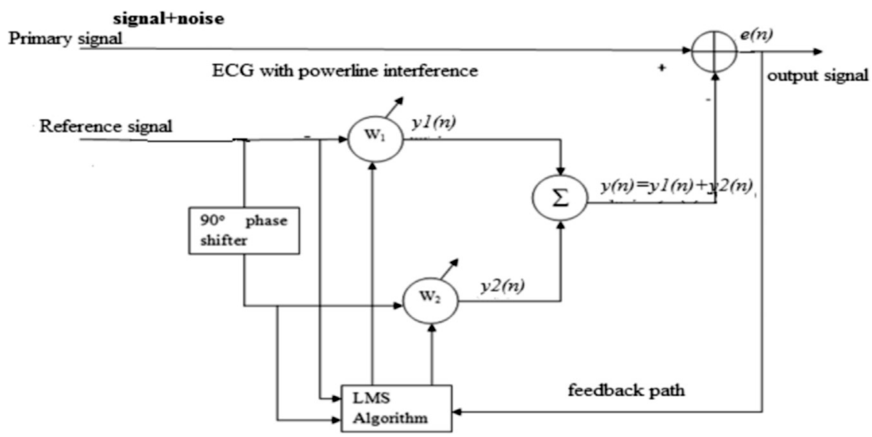

Fig. 1. Typical block diagram of two-weight adaptive filtering structure.

Table 1
Specification considered for processing the ECG signal.

Parameter	Symbol	Value Chosen
ECG sampling frequency	sfecg	360 Hz
Approximate number of heart beats	N	256
Additive uniformly distributed measurement noise	Anoise	0 mV
Mean heart rate	HR_{mean}	60 beats/minute
Standard deviation of heart rate	HR_{SD}	1 beat/ minute

denoised ECG signal resulting from the proposed method resembles the original ECG signal more and seems flatter in comparison to the signal obtained from the wavelet method.

4.2.2. Quantitative evaluation

Now, the performance of proposed methods was compared quantitatively with respect to the other methods based on the following metrics. The performance of the denoised signal is analyzed using the metrics like signal to noise ratio (SNR), percentage root mean-square difference (PRD), improved signal to noise ratio (SNR_{imp}), root mean square (RMS) error and peak signal to noise ratio (PSNR) to study the quality of the reconstructed signal. The SNR is the ratio of recovered signal power to noise power. The RMS error is the difference between RMS value of input signal and RMS value of the recovered signal. PSNR is a parameter that indicates the quality of the recovered signal.

The following metrics are used for the comparison (Eqs. 3–6):

$$\mathrm{SNR}(\mathrm{dB}) = 20\log\left[\frac{x(n)}{x(n) - d(n)}\right] \tag{3}$$

$$\mathrm{MSE} = \frac{1}{N}\sum_{n=1}^{N}(x(n) - \hat{x}(n))^2 \tag{4}$$

$$\mathrm{PRD} = \sqrt{\frac{\sum_{n=1}^{N}(x(n) - \hat{x}(n))^2}{\sum_{i=1}^{N}x^2(n)}}\ X\ 100 \tag{5}$$

$$SNR_{imp}(\mathrm{dB}) = 10\log_{10}\frac{\sum_{n=1}^{N}|y(n) - x(n)|^2}{\sum_{n=1}^{N}|\hat{x}(n) - x(n)|^2} \tag{6}$$

where $x(n)$ is the original signal and $\hat{x}(n)$ is the recovered signal.

The novelty of this paper is that the amplitude variation and frequency variation in a real time environment is considered. Practically the noise varies within in the range of 48–51 Hz. The sifting process has two effects: (i) Elimination of riding waves and (ii) Smoothening of uneven amplitudes. To guarantee that the IMF components will retain enough physical sense of both amplitudes and frequency modulations, it is necessary for the sifting process to stop. This is accomplished by limiting the use of standard deviation (SD) computed from the two consecutive sifting results. Usually SD is between 0.2 and 0.3. In our experimentation we have considered the

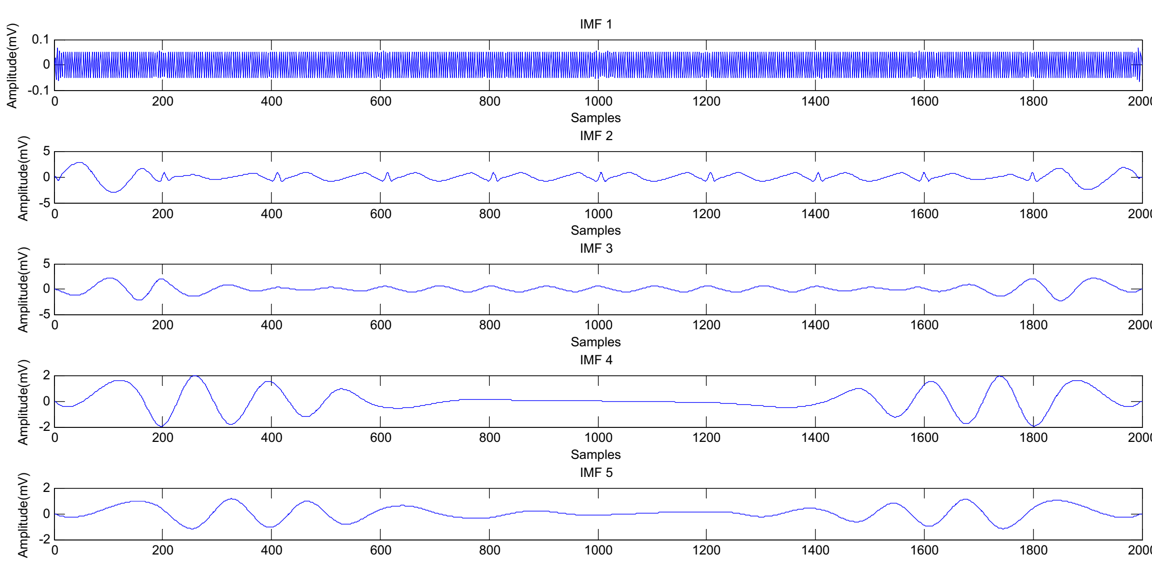

Fig. 2. Empirical mode decomposition of a noisy ECG and its intrinsic mode function levels (IMF1-5).

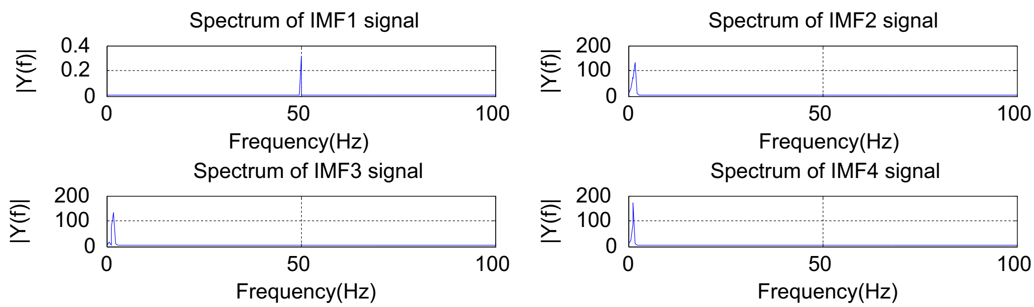

Fig. 3. Spectrum of IMF1-4.

noise amplitude variation as 5%, 10%, 15%, 20% and 30%. A detailed study has been carried out and the performance measures are calculated at each noise level and frequency varying ranges. A SNR variation of 43–45 dB is obtained at 10% and 20% noise variation at various frequencies in partial reconstruction method. There is a corresponding variation in MSE also and a very low value of 0.0035 is obtained at 10% noise with a frequency of 49.5 Hz. Performance comparison of Adaptive filtering technique for various frequencies is tabulated in Table 2. A noise level at 10%, 20% and 30% are considered at various noise frequency values. In this technique the SNR value is ranging from 40 dB to 42 dB. A MSE value of 0.003 is obtained at 49.5 Hz frequency. But some of the signal components are also destroyed in this adaptive filtering method. Next experimentation is carried out by band pass filtering the noise signal with a band pass filter in the IMF1. This band of IMF1 is given as input to adaptive filter. The performance of this method of filtering is better comapred to other-proposed techniques. A SNR of 45 dB is achieved with minimum mean square error. This adaptation result in undisturbed ECG signal components and removal of undisired noise components.

The proposed methods yield the smallest MSE with better quality (Tables 2–4). Compared to wavelet method EMD based denoising gives improved SNR irrespective of the noise levels. Tables 2–4 presents the comparison of different denoising methods in terms of SNR and MSE. This method gives higher SNR value when noise level is low and decreases gradually as noise level increases. SNR improvement of more than 20 dB is obtained using the proposed method. The main advantage is its simplicity in implementation and better accuracy even though the level of noise is varying. It can be applicable to any denoising applications even with very low frequency range. The simulation is carried out on ECG signal for noise level from 0% to

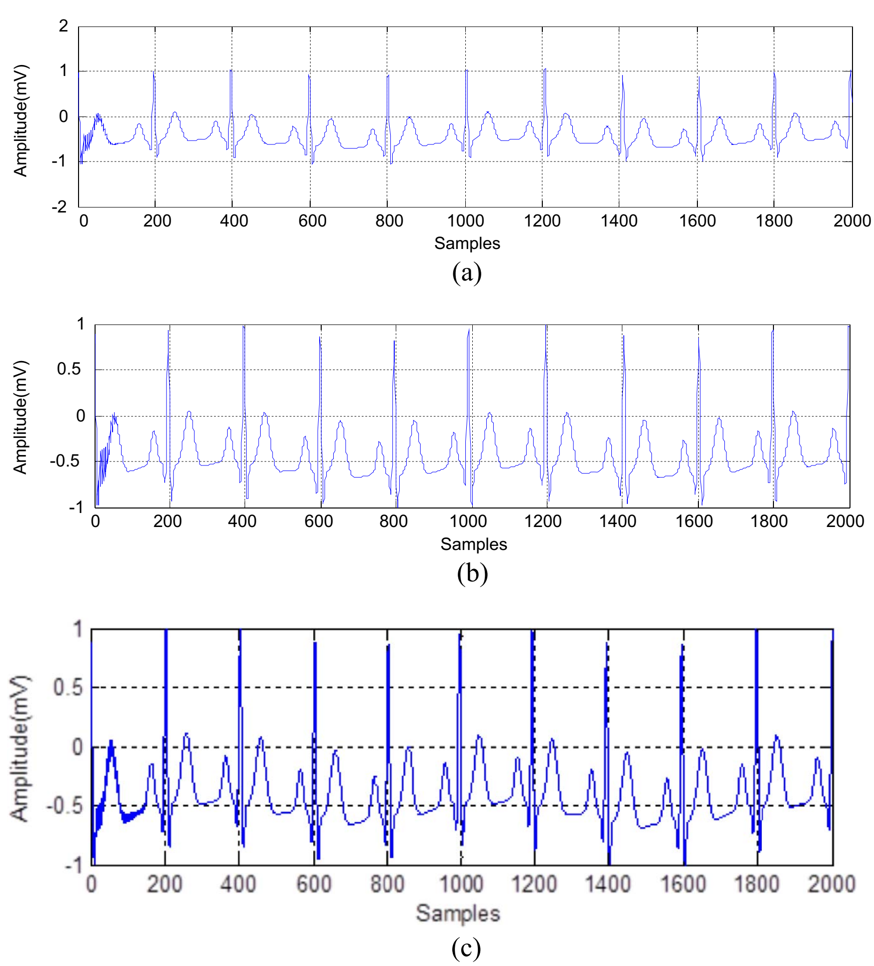

Fig. 4. Denoised ECG signal obtained from three methods: (a) EMD based partial reconstruction, (b) EMD based adaptive filtering and (c) EMD based adaptive filtering by extracting the interference.

Table 2
Performance comparison of EMD based partial reconstruction technique for various frequencies and amplitudes of noise level.

Noise Frequency (Hz)	5% Noise Level					10% Noise Level					20% Noise Level				
	SNR	MSE	SNR_{imp}	PRD	PSNR	SNR	MSE	SNR_{imp}	PRD	PSNR	SNR	MSE	SNR_{imp}	PRD	PSNR
48	44.8155	0.0078	21.6313	0.0033	21.0514	43.2281	0.0067	22.0312	0.0033	21.0414	37.5461	0.0866	26.6476	0.0176	10.627
48.5	43.5073	0.0106	20.3428	0.0045	19.7629	43.5607	0.0076	20.3460	0.0045	19.7239	38.3413	0.0708	27.5183	0.0147	11.4977
49	45.3903	0.0071	22.0547	0.0029	21.4748	44.3669	0.0071	22.3205	0.0029	21.8248	38.9566	0.0638	27.9749	0.0127	11.9543
49.5	44.1251	0.0134	20.9242	0.0056	20.7619	43.9211	0.0034	20.5642	0.0056	20.6519	38.4189	0.0711	27.5043	0.0144	11.4837
50	45.9066	0.0058	22.9162	0.0026	22.3363	44.9230	0.0058	22.4462	0.0026	22.3234	38.2412	0.0738	27.3404	0.015	11.3198
50.5	45.9355	0.0061	22.7075	0.0025	22.1275	45.6781	0.0067	22.3475	0.0025	22.5235	37.4728	0.0789	27.0508	0.0179	11.0302
51	44.7818	0.0078	21.6458	0.0033	21.0659	43.7801	0.0075	21.6458	0.0033	21.2159	38.9128	0.0679	27.105	0.0145	11.5304

Table 3
Performance comparison of adaptive filtering technique for various frequencies and amplitudes of noise level.

Noise Frequency (Hz)	10% Noise Level					20% Noise Level					30% Noise Level				
	SNR	MSE	SNR_{imp}	PRD	PSNR	SNR	MSE	SNR_{imp}	PRD	PSNR	SNR	MSE	SNR_{imp}	PRD	PSNR
48	40.4256	0.0052	17.7423	0.0091	22.863	40.5422	0.0053	29.6654	0.0088	22.6636	41.2489	0.0045	24.3405	0.0075	23.303
48.5	41.7055	0.0044	18.4739	0.0067	23.4122	40.3267	0.0059	29.2362	0.0091	22.9635	42.0683	0.0033	25.6795	0.0062	24.7857
49	41.5545	0.0043	18.537	0.007	23.5309	40.324	0.0063	28.9461	0.0093	21.9695	42.0432	0.004	24.9031	0.0062	23.9891
49.5	41.8083	0.004	18.8744	0.0066	24.0012	40.0582	0.006	29.1667	0.0099	22.0205	41.6678	0.0037	25.1832	0.0068	24.2894
50	41.635	0.0042	18.6762	0.0069	23.7818	40.1747	0.0063	28.909	0.0096	21.6493	42.3254	0.0035	25.4144	0.0059	24.5148
50.5	41.3526	0.0044	18.4569	0.0073	23.1461	40.5456	0.0056	29.4369	0.0088	22.2902	42.0776	0.0034	25.5477	0.0062	24.5579
51	40.3185	0.0051	17.8223	0.0093	22.9429	40.5046	0.0031	32.0224	0.0089	25.0878	42.3925	0.0032	25.8034	0.0058	24.8775

Table 4
Performance comparison of adaptive filtering technique with band pass filter for various frequencies and amplitudes of noise level.

Noise Frequency (Hz)	5% Noise Level					10% Noise Level					20% Noise Level				
	SNR	MSE	SNR_{imp}	PRD	PSNR	SNR	MSE	SNR_{imp}	PRD	PSNR	SNR	MSE	SNR_{imp}	PRD	PSNR
48	45.5978	0.0046	22.7672	0.0028	27.8599	43.8304	0.0068	27.1184	0.0041	26.2063	42.309	0.0093	31.7921	0.0059	24.8716
48.5	45.9834	0.0039	23.4709	0.0025	28.4201	43.0844	0.0065	26.1446	0.0049	25.169	40.2041	0.0165	29.2972	0.0095	22.1917
49	45.9531	0.0048	22.6192	0.0025	27.6503	43.9429	0.0064	27.4064	0.004	26.5065	40.2542	0.1049	29.7374	0.0094	22.8169
49.5	45.7422	0.0046	22.7709	0.0027	27.76	44.0139	0.0067	27.1858	0.004	26.292	39.6445	0.0203	28.3938	0.0109	21.4256
50	45.4664	0.0048	22.6321	0.0028	27.3525	44.591	0.0054	28.1005	0.0035	27.164	40.2274	0.0154	29.6099	0.0095	22.6893
50.5	45.4839	0.0047	22.6917	0.0028	27.6446	44.4186	0.0053	28.1825	0.0029	27.2887	39.5504	0.0172	29.1115	0.0111	21.9745
51	45.7118	0.0044	22.9558	0.0027	27.7937	44.5194	0.0061	27.6398	0.0035	26.7399	40.4367	0.0156	29.5359	0.009	22.4243

100% of signal magnitude. The discussion on the results obtained from simulation was broadly classified into lower, medium and high noise levels. In minimum level, the noise range was less than 5% of signal magnitude, for medium it was 5–20% of signal magnitude and for high noise level it was greater than 20% of signal magnitude. Up to 20% noise level range was considered as the practical noise level range was considered as the practical noise level acquired at pre-amplifier stage of any good instrumentation. The noise level more than 20% was considered as deliberate noise case, which was a non-practical condition.

5. Conclusion

This study has made to clearly summarize the enlargement of EMD based filtering techniques. The novel techniques presented reveal an enhanced performance associated to wavelet denoising in the cases where the signal SNR is low and there is no restriction that signal magnitude should be higher than the noisy signal. These techniques follow the property of signal dependency and are adaptive. The experimental results demonstrated that EMD can be employed as an effective tool for denoising. These recovered signals provided high correlation values between the original and processed ECG signal and thereby yielded good visual quality.

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