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Research paper

An efficient ECG denoising methodology using empirical mode decomposition and adaptive switching mean filter

Manas Rakshit*, Susmita Das

Signal Processing & Communication Lab, Department of Electrical Engineering, National Institute of Technology, Rourkela, Odisha, 769008 India

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ABSTRACT

Electrocardiogram (ECG) is a widely employed tool for the analysis of cardiac disorders. A clean ECG is often desired for proper treatment of cardiac ailments. However, in the real scenario, ECG signals are corrupted with various noises during acquisition and transmission. In this article, an efficient ECG denoising methodology using combined empirical mode decomposition (EMD) and adaptive switching mean filter (ASMF) is proposed. The advantages of both EMD and ASMF techniques are exploited to reduce the noises in the ECG signals with minimum distortion. Unlike conventional EMD based techniques, which reject the initial intrinsic mode functions (IMFs) or utilize a window based approach for reducing high-frequency noises, here, a wavelet based soft thresholding scheme is adopted for reduction of high-frequency noises and preservation of QRS complexes. Subsequently, an ASMF operation is performed to enhance the signal quality further. The ECG signals of standard MIT-BIH database are used for the simulation study. Three types of noises in particular white Gaussian noise, Electromyogram (EMG) and power line interference contaminate the test ECG signals. Three standard performance metrics namely output SNR improvement, mean square error, and percentage root mean square difference measure the efficacy of the proposed technique at various signal to noise ratio (SNR). The proposed denoising methodology is compared with other existing ECG denoising approaches. A detail qualitative and quantitative study and analysis indicate that the proposed technique can be used as an effective tool for denoising of ECG signals and hence can serve for better diagnostic in computer-based automated medical system.

1. Introduction

Electrocardiogram (ECG) is commonly utilized for the identification of the cardiovascular diseases. ECG reflects the electrical activities of the cardiac system. Standard morphology of each component of ECG signal conveys numerous clinical information. The actual condition of the heart can be found by extracting the detailed information of each component [1–3]. Due to the rapid growth of population and lack of proper infrastructure, computer-based automated ECG analyzer has become a vital tool for early diagnosis of the cardiac diseases as it does a fast processing also [4]. However, for precise feature extraction of ECG signal, good quality noise free signals are typically desired. In the real scenario, various noises like Gaussian noise, muscle artifacts, power line interference, baseline wander noise contaminate the ECG signal during its acquisition and transmission [5]. Gaussian noise is generated due to signal transmission in poor channel conditions. Muscle artifacts mainly known as Electromyogram (EMG), is a random noise that spreads over the entire frequency range, which is produced due to various muscle activities. Further, the power line noise interferes due to the supply frequency of 50 Hz (or 60 Hz). Baseline wander noise arises due to the patient respiration that fluctuates the baseline from zero potential [6]. Elimination of these noises is an essential task for the proper diagnosis of the cardiac diseases from the signal features. Hence, denoising of ECG signals is very essential and development of computer-based automated ECG denoising technique is an active field of research.

Various researchers have contributed numerous literature to address the development of computer-based automated ECG denoising. These developed techniques are mainly based on finite impulse response (FIR) filter [7,8], adaptive filter [5], neural network [9], principle component analysis (PCA) [10], independent component analysis (ICA) [11], non-local mean (NLM) filter [12],

* Corresponding author.
E-mail addresses: rakshitmanas09@gmail.com (M. Rakshit), sdas@nitrkl.ac.in (S. Das)

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extended Kalman filter (EKF) [13], discrete wavelet transform (DWT) filtering [14–16], empirical mode decomposition (EMD) [17], EMD with DWT [18], adaptive dual threshold filtering [19]. FIR based filtering techniques [7,8] can only remove the noise components those are outside the frequency range of ECG signal. Moreover, this type of methods do not preserve the low-frequency ECG components (P and T waves). Adaptive filter and neural network based systems [5,9] require additional reference signals and training phase, hence not suitable for real-time applications. In PCA and ICA techniques [10,11], the derived statistical model is much sensitive to a small change in the signals or the noises. Moreover, for ICA based approaches, visual inspection of the independent components are crucial which is not feasible for long-term applications. The efficacy of NLM filter [12] depends on the proper selection of parameter bandwidth which can be calculated from the standard deviation of the artifacts. In the practical scenario, the prediction of the standard deviation of artifacts is not possible which leads toward poor performance. EKF [13] based technique involves manual initialization of parameters, which are associated with amplitude, width, and phase of each component of a complete ECG cycle. DWT [14–16] assisted soft and hard thresholding based denoising is popular for filtering of non-stationary signals. The wavelet-based filter cannot preserve the edges properly. Another method based on EMD is quite effective for dealing with the ECG signals. In EMD based technique, the test signals are decomposed into a set of oscillatory components, which are identified as intrinsic mode functions (IMF). The noise components mainly spread over few low orders IMFs. In conventional EMD based technique [20], few low order IMFs are discarded which causes sufficient losses of information in the reconstructed ECG signals. In [17,18], a window is applied to preserve the QRS complexes in the low order IMFs that leaves the noise components in the QRS regions. The adaptive dual threshold filter (ADTF) based technique [19] rejects the initial sub-bands of the wavelet decomposed signal causing significant information loss in the higher frequency region. Moreover, for peak correction, it employs a single amplitude threshold that may fail to detect the peaks correctly for time-varying QRS morphology and abnormal ECG conditions.

In this article, the effectiveness of EMD and adaptive switching mean filter (ASMF) are considered together for developing an efficient ECG denoising technique. ASMF is a widely used image-denoising tool for reduction of noises in the images. Unlike the above-mentioned EMD based techniques, here, wavelet soft thresholding based denoising is the applied to initial three IMFs. This approach effectively reduces the noise components in QRS regions and enhances the QRS complexes. Subsequently, an ASMF technique is utilized to decrease the effect of noises in the low-frequency region of the ECG signals and to improve the signal quality further. Due to the ASMF operation, peaks of the ECG signals are attenuated slightly. Hence, a peak correction process assisted with R-peaks position information is employed to preserve these peaks. To verify the efficacy of the presented ECG denoising methodology, test ECG signals of MIT-BIH arrhythmia database are utilized [21]. Three noises namely white Gaussian noise, EMG noise and power line interference at various signal to noise ratio (SNR) are considered with the ECG signals to generate noisy signals. Standard performance metrics like output SNR improvement (SNR_{imp}), mean square error (MSE) and percentage root mean square difference (PRD) are employed. The presented denoising scheme is compared with the existing techniques in order to prove its efficacy.

The outline of the article is presented as follows. In Section 2, a brief description of proposed denoising methodology is presented. The detailed illustration of result and discussion of the presented work are explained in Section 3. Finally, a conclusive remark on this work has been drawn in Section 4.

2. Proposed ECG denoising methodology

The outline of the ASMF based ECG denoising approach is demonstrated in Fig. 1. A detail discussion on every step is given below.

2.1. Empirical mode decomposition (EMD) of ECG

EMD is one of the efficient processing tools in the field of modern signal processing. In EMD, the test signal is decomposed into a set of oscillatory functions, known as intrinsic mode function (IMF) [22,23]. The basis functions of EMD are completely driven from the test data itself, which makes it efficient for processing of non-linear and non-stationary signals. Each IMF signifies the oscillatory characteristics of the signal [24,25]. The initial IMFs convey the high-frequency information, and higher order IMFs express the low-frequency information. Each IMF should follow a set of criteria [6].

1. The total extreme points and zero crossings in each IMF should be equal or at most differ by one.
2. There should be symmetricity in each IMF with respect to zero local mean.

The procedure of extracting IMFs from the test signal is known as "Sifting" process. The algorithm of the sifting process is presented as follows.

Input: Test signal (Raw ECG signal) $X_{ECG}[n]$
Output: Corresponding IMFs $C_{ECG}[n]$

1.	Find the extreme points in both directions in the test ECG signal $X_{ECG}[n]$.
2.	Connect upper extreme points using cubic spline interpolation to get the upper extreme envelope $e_h[n]$.
3.	Similarly, by connecting the lower points get the lower extreme envelope $e_l[n]$.
4.	Find the mean envelope $m[n]$ by $m[n]=((e_h[n]+e_l[n])/2)$
5.	Get $d_1[n]$ by subtracting mean envelope from $X_{ECG}[n]$.
6.	If $d_1[n]$ follows the criteria of IMF, then it is the first IMF $C_{1_{ECG}}[n]$, else $d_1[n]$ is considered as the data of the sifting process and repeat the steps from (1) to (5). Thus a new function $d_{11}[n]$ is obtained. This process will be repeated until either, $d_{1k}[n]$ follows the criteria of IMF or, certain termination condition (generally standard deviation criteria) is met.
7.	$C_{1_{ECG}}[n]$ After getting the first IMF, we will subtract it from XECG[n] to get
8.	The entire steps from (1) to (7) is repeated until $r_i[n]$ becomes a monotonic function which is defined as the residue signal.

Let consider a test ECG signal $X_{\mathrm{ECG}}[\mathrm{n}]$ is decomposed into total $L-1$ number of IMFs and a residue signal then, it can be expressed as

$$X_{ECG}[n] = \sum_{l=1}^{L-1} C_{l_{ECG}}[n] + r_L[n] \tag{1}$$

A typical noisy ECG signal and its IMFs are presented in Fig. 2. Here, the noisy ECG signal is decomposed into six IMFs (IMF1 to IMF6) and a residue signal. From IMF1 to residue signal, a decreasing nature of oscillation is noticed. The lower order IMFs (IMF1–IMF3) contain high-frequency signal information (QRS complex) and noises are mainly spread over these IMFs. In conventional EMD based ECG denoising method [20], to reduce the noises, these lower order IMFs are rejected. However, in this process, some high-frequency information of the signal is also excluded. In [17,18] techniques to avoid the effect of rejecting lower order IMFs, some window based practice is adopted. Here, the first three IMFs are summed and to preserve the QRS complexes, a window is applied.

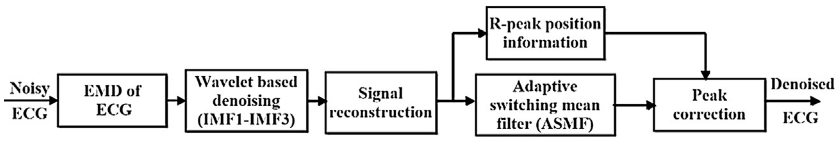

Fig. 1. Outline of the proposed ECG denoising technique.

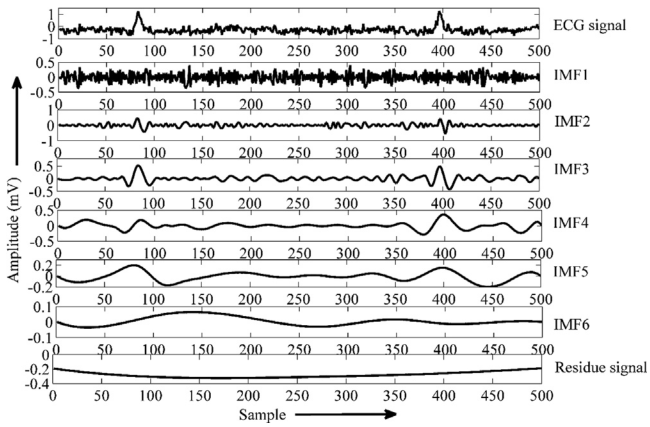

Fig. 2. Noisy ECG signal and the IMFs after EMD operation.

Hence, the noises which are in the region of QRS complexes are ignored. Moreover, in the presence of noises, for time varying QRS morphologies and abnormal ECG beat, the selection of appropriate window length is quite problematic. In order to reduce the effect of noise in higher IMFs and to preserve the QRS complexes, a new approach is proposed in this work.

2.2. Wavelet based denoising (IMF1–IMF3)

The lower order IMFs (IMF1–IMF3) contain high-frequency artifacts as well as QRS complexes [18]. To remove the noises from these IMFs, a wavelet soft thresholding based denoising technique is applied. In, this method, the signal is divided into a set of approximation and detail coefficients. As detail coefficients contain the high-frequency information, these coefficients are thresholded according to some predefined rule. Then, by applying the inverse wavelet transform, the filtered signal is extracted from the updated coefficients. The approximation coefficients contain most of the energy of the signal. Hence, these coefficients are excluded in the threshold operation [26]. Let, $C_{ECG}[n]$ is the noisy IMF and $\overline{C}_{ECG}[n]$denotes the wavelet denoised IMF then,

$$\overline{C}_{ECG}[n] = Thr\left[C_{ECG}[n]\ ,\ \varepsilon\right] \tag{2}$$

Where Thr defines the thresholding operator and ε is the threshold value.

In this work, each IMF is decomposed into two levels by employing Symlet wavelet of order 7 (*Sym7*). Symlet family wavelets are much popular for signal denoising because of their energy concentration at low frequency [27]. The threshold value is calculated according to Eq. (3), which is adopted from [28].

$$\varepsilon = \sigma\sqrt{2\log N} \tag{3}$$

Where, σ and N denote the standard deviation and the length of the detail wavelet coefficients at a particular level. Soft thresholding technique is employed in this work. The expression of soft thresholding is presented below

$$\overline{dw}_i[l] = \begin{cases} |dw_i[l]| - \varepsilon_l & |dw_i[l]| \geq \varepsilon_l \\ \text{beginDispEQchecked6pt]}0 & |dw_i[l]| < \varepsilon_l \end{cases} \tag{4}$$

Where, $dw_i[l]$ and $\overline{dw}_i[l]$ are the original and thresholded detail coefficients of level l.

2.3. Signal reconstruction

In this stage, the processed signal is restored by the adding the denoised IMFs with the remaining IMFs and the residue signal.

$$X^e_{ECG}[n] = \sum_{l=1}^{3}\overline{C}_{l_{ECG}}[n] + \sum_{l=4}^{L-1}C_{l_{ECG}}[n] + r_L[n] \tag{5}$$

2.4. R-peak position information

The locations of R-peaks in the ECG signal are extracted in this stage. This information will be helpful for correction of peaks after ASMF operation. Here, by employing any standard R-peak detection algorithm, the positions of R-peaks are extracted. In this work, standard Pan-Tompkins method [29] for QRS detection is utilized. This R-peak detection technique is well accepted and efficient for real-time applications.

2.5. Adaptive switching mean filter (ASMF)

After EMD based denoising, some noises still exist in the reconstructed signal. These noises are clearly visible in the low time varying components of the ECG signal i.e. the region between QRS complexes. Hence, an adaptive switching mean filtering (ASMF) approach is applied for further enhancement of signal quality. ASMF is an efficient image filtering tool which is employed for removing the impulse noises from images [30]. The basic principle of ASMF is that there should be a similarity in the neighborhood samples of a signal. In this method, a particular length of window is taken, and at each iteration, the center of the window is placed on a test ECG sample. Now, a threshold value is estimated by calculating the standard deviation of the windowed region. If the difference between test ECG sample and the mean value of the windowed area is beyond the threshold limit, then it is considered as a corrupted sample, and its value is updated according to the mean value. The mathematical expression of the ASMF operation is demonstrated below.

$$\overline{X}_i = \begin{cases} m_i & if\,|X^e_i - m_i| \geq \alpha \times \sigma_i \\ \text{beginDispEQchecked6pt]}X^e_i & else \end{cases} \tag{6}$$

Where X^e_i and $\overline{X}_i$ are the input and processed ECG samples of ASMF operation, m_i and σ_i are the mean and standard deviation of the windowed region. Here, α is a threshold selecting parameter, which determines the limit of the threshold value. The value of α varies in between 0–1. In this work, the value α is empirically taken 0.1 and a window of length 9 samples is chosen. The improvement of the signal quality after ASMF operation can be visualized in Fig. 3.

2.6. Peak correction

The R-peaks in the ECG signals are attenuated due to ASMF operation. These peaks carry vital medical information. Hence, the recovery of these peaks is much essential. In this step, by utiliz-

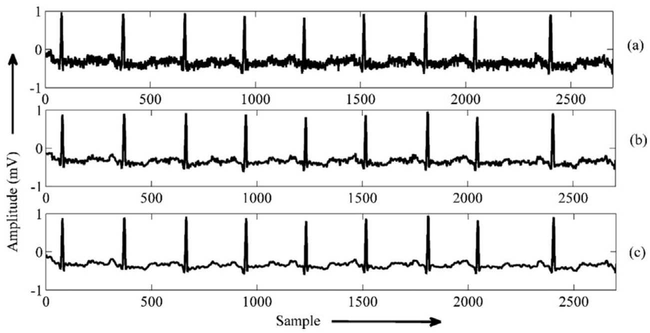

Fig. 3. Signal quality improvement by ASMF operation (a) Noisy ECG signal (b) EMD based denoised signal (c) Final denoised signal.

ing the position information of R-peaks, the peaks are corrected according to the following algorithm.

$X^{a}_{ECG}[n]$Input: ASMF processed signal and EMD based denoised signal $X_{ECG}[n]$	Output: Peak corrected signal	
1.	Get R-peak sample position n_R	
2.	For $n = n_R - 10 : n_R + 10$	
	$X'_{ECG}[n] = X^{e}_{ECG}[n]$	
3.	$X'_{ECG}[n] = X^{a}_{ECG}[n]$	Otherwise

3. Result and discussions

The efficacy of the proposed work is evaluated using standard MIT-BIH arrhythmia database [21]. This database consists a total 48 ECG records of a duration 30 min each. Like the existing literature, in this work, the ECG records named as 100m, 101m, 103m, 105m, 115m, 200m, 215m, and 230 m have been used for simulation purpose. These signals contain time-varying QRS morphology, both normal and abnormal ECG beats.

Three simulated noises namely white Gaussian noise, Electromyogram (EMG) noise and power line interference at different SNR levels (0 decibels (dB), 5 dB, 10 dB, 15 dB, and 20 dB) are added to the signals. EMG noise is simulated by generating random noises as presented in [31]. Power line interference is simulated by producing a sinusoidal signal of frequency 50 Hz as presented in [19]. The performance of the proposed work is compared with existing ECG denoising techniques namely FIR filter [8], wavelet soft thresholding based filter (DWT) [16], EMD with DWT technique [18], EKF [13], DWT with ADTF technique [19]. The effectiveness of the presented work has been evaluated in both qualitative and quantitative analysis. All the simulations are carried out using MATLAB software environment.

3.1. Qualitative analysis

In this subsection, a qualitative performance analysis of the proposed technique through visual inspection is carried out. Fig. 4 presents the denoised ECG records 103m, which is corrupted by white Gaussian noise at SNR level 10 dB.

The figure demonstrates that the ASMF based approach has the better proficiency to extract the ECG signal from a noisy record with less distortion. The method also preserves the morphological characteristics of the processed signal which contain significant clinical information.

Fig. 5 presents the denoising proficiency of the proposed technique for an ECG signal which is corrupted with EMG noise. Here, ECG record 100 m is contaminated by EMG noise at SNR level 5 dB. The figure illustrates that the technique efficiently rejects EMG noise from the signal and preserves the details.

ECG record 215 m is contaminated by the power line interference at SNR level 10 dB. Fig. 6 presents a qualitative analysis of the

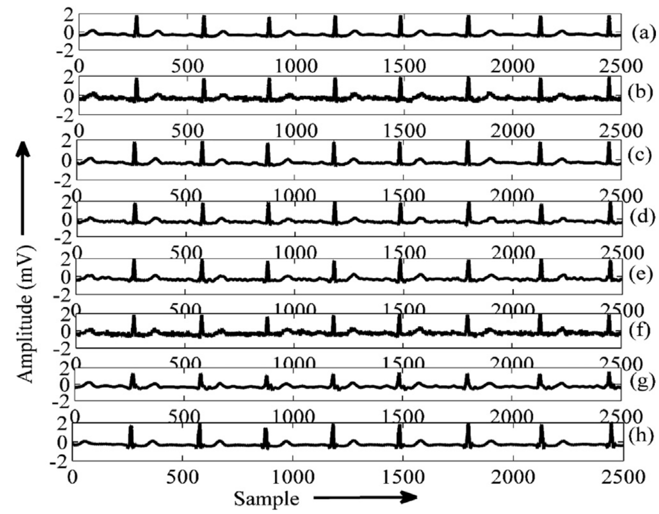

Fig. 4. Denoised ECG signal 103 m corrupted with white Gaussian noise at input SNR 10 dB (a) Original ECG (b) Corrupted signal (c–h) Filtered signals using presented work, DWT + ADTF, EMD + DWT, FIR, DWT, EKF.

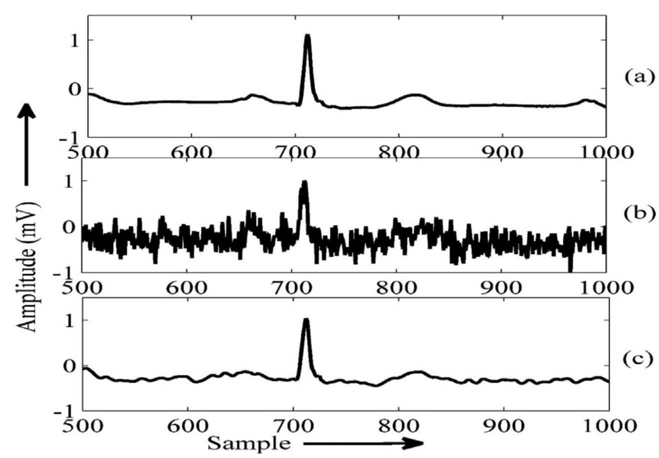

Fig. 5. Denoising of EMG noise corrupted ECG signal (a) Original ECG record 100 m (b) EMG infected signal (c) Recovered ECG signal.

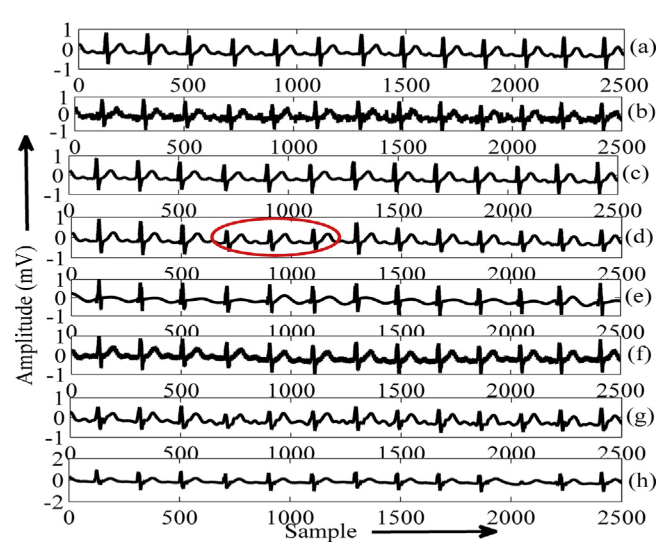

Fig. 6. Correction of power line interference infected ECG signal at SNR level 10 dB (a) Original ECG record 215 m (b) Corrupted signal (c–h) Filtered signals using presented work, DWT + ADTF, EMD + DWT, FIR, DWT, EKF.

estimated signals through various methodologies. A visual inspection of the figure reveals that the proposed ASMF based technique can efficiently remove the effects of power line interference and maintains all the characteristic details of the ECG signals. The ADTF [19] and EKF [13] based approaches fail to preserve the R-peaks of the ECG signals. For ADTF based technique, this phenomenon is highlighted by a red color circle in the subfigure (d).

3.2. Quantitative analysis

A quantitative performance analysis of the described technique is presented in this section. Three performance metrics namely output SNR improvement (SNR_{imp}), mean square error (MSE), and percentage root mean square difference (PRD) are considered for evaluation. SNR_{imp}, MSE and $PRD$are commonly used as performance parameters in the study of ECG denoising [18,19]. Signal to noise ratio (SNR) is the standard metric to quantify the quality of a signal from the energy perspective. SNR defines the signal energy with respect to the energy of the associated noise. SNR_{imp} denotes the improvement of SNR value of a signal by the filtering process. As the objective of this study to denoise the ECG signals, SNR improvement is a relevant performance metric to quantify the efficacy of the filter to reduce the effect of background noise. MSE tracks the accuracy of the filtering technique to estimate the original signal. It defines the energy of the error signal in the filtering process. Hence, lower value of MSE denotes better estimation of the original signal and better preservation of signal details. Each component of ECG signal conveys numerous clinical information. A highly distorted ECG is quite irrelevant for medical applications. Hence, to measure the efficiency of the filtering techniques in terms of preserving relevant medical information during signal extraction, PRD is employed as a performance metric. A lower PRD value defines the better preservation of physiological information in the processed ECG signal. Here, for each ECG record at each input SNR level, total 100 simulations are carried out, and the mean value of these results are considered. The performance parameters can be expressed as follows.

$$SNR_{imp}[dB] = 10\log_{10}\frac{\sum_{n=1}^{N}(X_{ECG}[n]-Y_{ECG}[n])^2}{\sum_{n=1}^{N}\left(X'_{ECG}[n]-Y_{ECG}[n]\right)^2} \tag{7}$$

$$MSE = \frac{1}{N}\sum_{n=1}^{N}\left(Y_{ECG}[n]-X'_{ECG}[n]\right)^2 \tag{8}$$

$$PRD = \sqrt{\frac{\sum_{n=1}^{N}\left(Y_{ECG}[n]-X'_{ECG}[n]\right)^2}{\sum_{n=1}^{N}Y_{ECG}^2[n]}} \times 100 \tag{9}$$

Here, $Y_{ECG}[n]$ denotes the original ECG, $X_{ECG}[n]$ defines the corrupted signal, $X'_{ECG}[n]$ signifies the denoised ECG signal, and N is the length of the ECG signal.

Fig. 7 represents the output $SNR_{imp}$of the denoised ECG signals considering white Gaussian noise at input SNR 0 dB to 20 dB. The figure demonstrates that at each input SNR level the SNR_{imp} of the proposed algorithm is higher than the other methods.

The improvement of SNR in case of EMG noise corrupted ECG signals has been presented in Table 1. It illustrates that the ASMF based methodology attains a better SNR_{imp} than other techniques around the entire input SNR level. With increasing of input SNR level, the SNR_{imp} reduces. However, it is superior to the others.

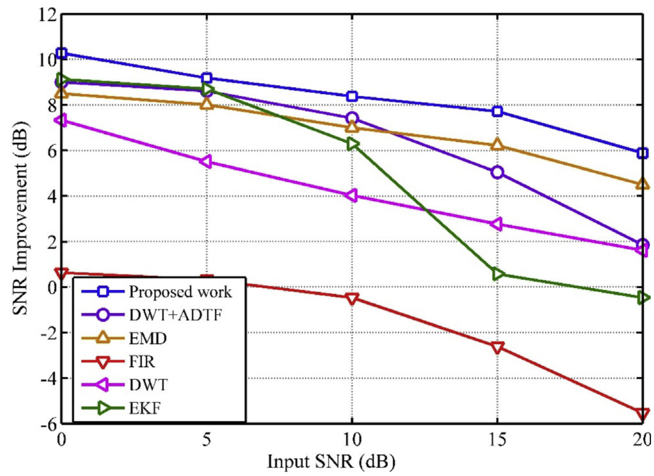

Fig. 7. SNR improvement of the denoised signals for white Gaussian noise.

Table 1
SNR improvement of the output ECG signals in case of EMG noise.

Technique	Input SNR (dB)				
	0	5	10	15	20
Proposed work	9.2980	9.1351	8.7879	8.0516	5.6733
DWT + ADTF	9.0000	8.6518	7.5980	5.1815	1.8318
EMD	8.2000	7.5312	7.0021	6.1038	4.0000
FIR	0.6478	0.3448	−0.4767	−2.3368	−5.4874
DWT	7.4590	5.4974	4.1377	2.7421	1.6184
EKF	8.0888	8.53870	5.8616	2.7893	−0.6739

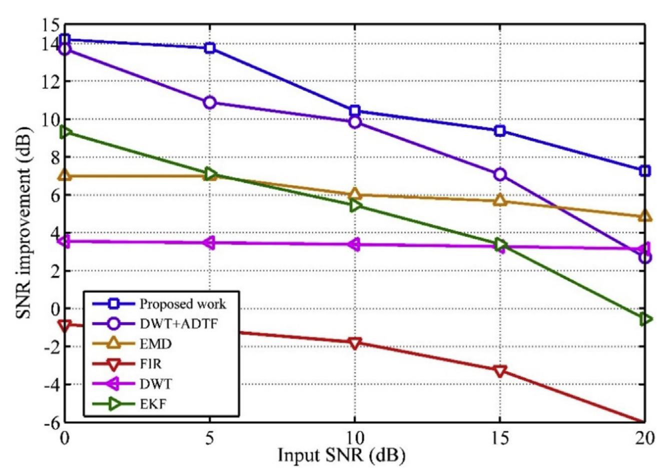

Fig. 8. SNR improvement results of the filtered signals for power line interference.

The performance comparison of SNR_{imp} for the power line interference affected signals is summarized in Fig. 8. The figure demonstrates that the proposed ASMF based ECG denoising method outperforms the existing methods in removing power line interference.

Mean square error (MSE) is one of the significant performance metrics to evaluate the efficacy of a denoised algorithm. It defines the proficiency of the algorithm to estimate the original signal. Small MSE level indicates better recovery of the original signal. Fig. 9 presents the MSE of the denoised ECG at different input SNR level. These signals are corrupted with white Gaussian noise at various SNR levels.

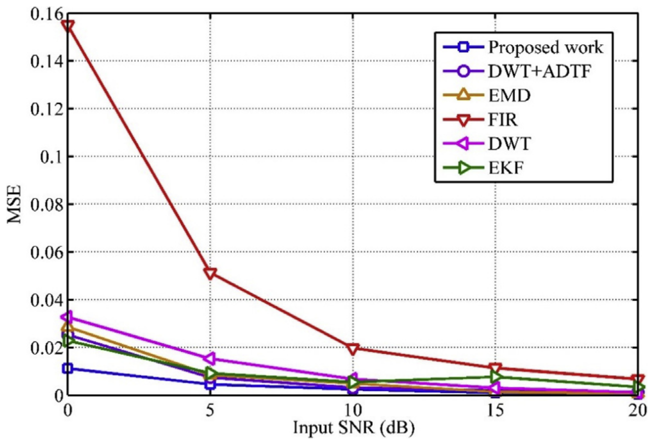

Fig. 9. *MSE* of the denoised signals using various denoising methods for white Gaussian noise.

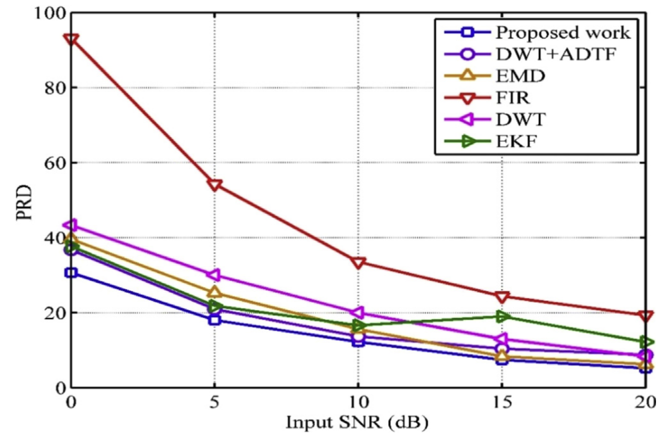

Fig. 11. *PRD* comparison of the denoised signals for white Gaussian noise.

Table 2
Comparison of *MSE* of filtered signals for EMG noise.

Technique	Input SNR (dB)				
	0	5	10	15	20
Proposed work	0.02022	0.00655	0.00232	0.00088	0.00050
DWT + ADTF	0.02364	0.00716	0.00281	0.00177	0.00134
EMD	0.02647	0.00896	0.00478	0.00125	0.00084
FIR	0.15001	0.05093	0.01914	0.00980	0.00662
DWT	0.03109	0.01487	0.00627	0.00284	0.00116
EKF	0.03115	0.01056	0.00704	0.00530	0.00425

Table 3
PRD comparison table for enhanced signals for EMG noise.

Technique	Input SNR (dB)				
	0	**5**	**10**	**15**	**20**
Proposed work	34.3190	18.9527	11.5257	7.1224	5.3033
DWT + ADTF	37.7140	20.8500	13.3889	10.2319	8.7831
EMD	40.1254	26.5745	16.8745	9.5864	7.6850
FIR	92.9268	54.1514	33.5602	23.5305	19.1760
DWT	42.6498	30.0412	19.7296	13.0159	8.3313
EKF	41.3647	22.1110	17.5171	14.9936	13.0636

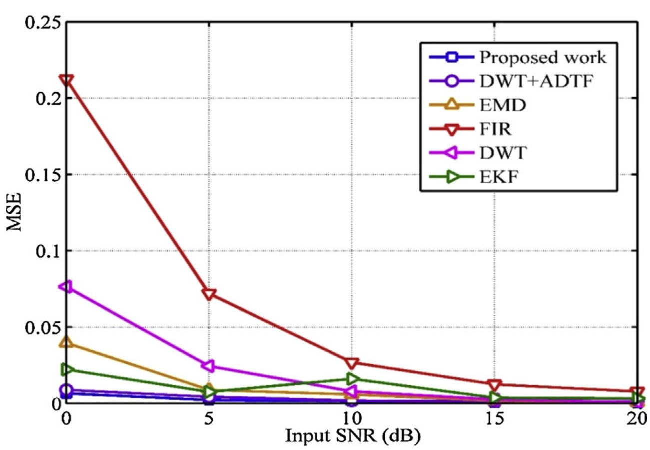

Fig. 10. *MSE* comparison of denoised signal using different approaches for power line interference.

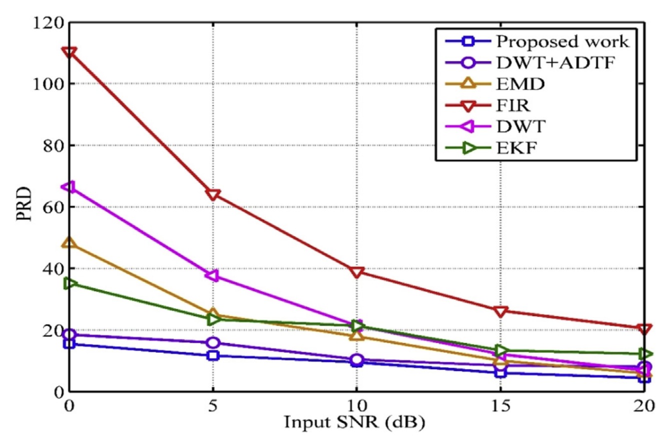

Fig. 12. *PRD* comparison of the processed signals for power line noise.

The figure illustrates that *MSE* of the denoised signal by the proposed technique is less than the other methods. This implies the superiority of the ASMF based technique to recover the original signal from a noisy environment.

The *MSE* comparison various ECG denoising techniques in the case of EMG noise is summarized in Table 2. It is observed that ASMF based ECG denoising method attains lower *MSE* than the existing methods for all SNR levels.

Fig. 10 demonstrates *MSE* comparison of denoised ECG signals using different approaches for power line interference.

Percentage root mean square difference (*PRD*) is another quantitative analysis parameter, which determines the degree of distortion occurs in the denoised signal. It defines the noise reduction ability of the filtering method without losing any critical information. For lower distortion and better recovery of the original signal, the *PRD* value should be small. A performance comparison of *PRD* value for white Gaussian noise is presented in Fig. 11. The proposed technique shows lower *PRD* value for all input SNR levels, which suggests the better preservation of clinical information in the filtered signal with low distortion.

The *PRD* value comparison of recovered signals in case of EMG noise is summarized in Table 3. The proposed technique achieves less *PRD* value for each input SNR level, which suggests its proficiency for reduction of EMG noise in the ECG signals.

Fig. 12 presents a graphical comparison of *PRD* values of the processed ECG signals where the test signals are corrupted by power line interference. The figure illustrates that the proposed method get lower *PRD* value than the other techniques at each input SNR level. This affirms that the ASMF based methodology outperforms the existing techniques to remove power line interference in the ECG signals.

Now, a detailed analysis on the output SNR_{imp} of all denoising techniques for different ECG signals of MIT-BIH database is presented. Here, white Gaussian noise at SNR level 5 dB is added to the

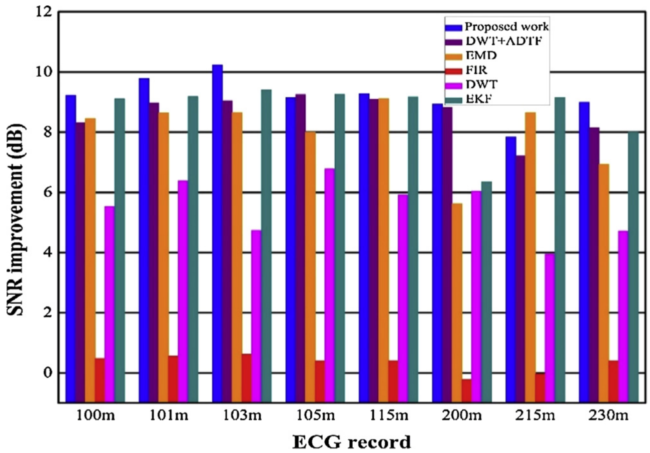

Fig. 13. Comparison of SNR improvement of different ECG signals using various approaches for white Gaussian noise.

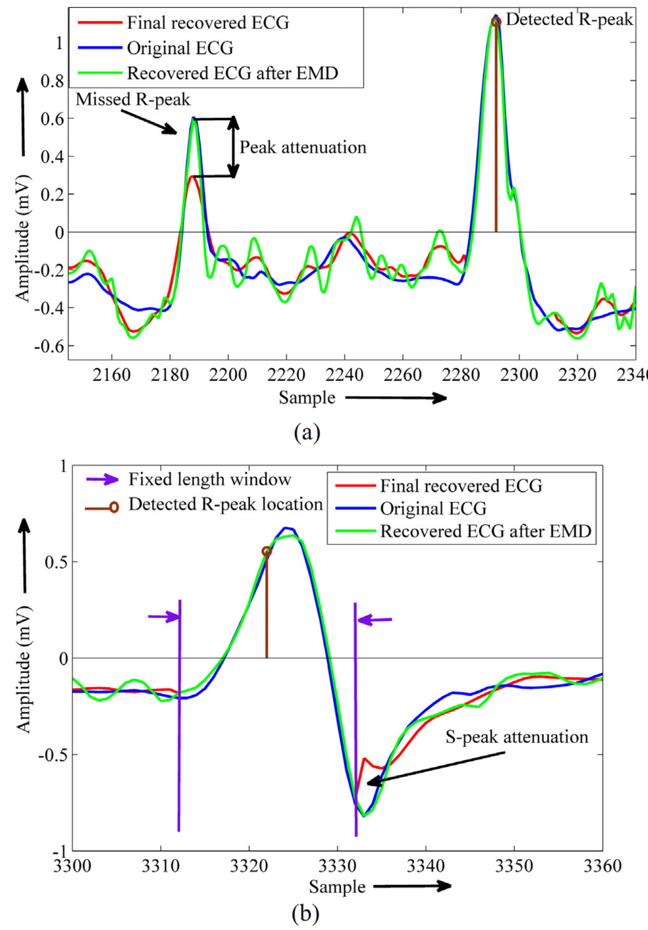

Fig. 14. Peak recovery error for ECG records (a) 105 m (b) 215 m.

original ECG signals. Fig. 13 presents SNR_{imp} of each denoised ECG record using various approaches.

Noise reduction is an imperative task for automated processing of ECG signal. The aim of this study is to bring together the advantages of EMD and ASMF operation to reduce the noise in ECG signal with less distortion. The data driven adaptability of EMD process efficiently decomposes the signal into the IMFs with the variation of oscillation. The energy compaction property of wavelet denoising approach allows eliminating the effect of noises in the lower order IMFs. Finally, the utilization of ASMF operation followed by the peak restoration technique provides a better recovery of original ECG signal with less distortion. Three types of noise at different SNR levels are added to the original ECG records for simulation study. Figs. 4–6 describe the qualitative analysis of the recovered signals for various type of noises. A close observation of the above figures demonstrates that the quality of the recovered signals by the proposed scheme is much better that the other signals. The processed signals properly contain the local features, which express numerous clinical information. For the quantitative analysis, three performance metrics SNR_{imp}, MSE and PRD are used. It is observed from Figs. 7–8 that the SNR_{imp} of denoised signal quality by the proposed technique is larger than the others existing methods if Gaussian noise and powerline interference are considered. At high input SNR (20 dB), the ASMF based technique attains an improvement of SNR value more than 6 dB, which reveals the superiority of the technique in improving the signal quality by reducing the noise energy. Table 1 illustrates the efficacy of the described method for removing EMG noise. The higher value of SNR improvement (9.29 dB) at lower SNR level (0 dB), justifies the proficiency of the proposed scheme in high noise condition. Figs. 9–10 and Table 2 present the effectiveness of the ASMF based technique in terms of MSE. At each input SNR level (0 dB – 20 dB), the MSE of the presented methodology is less than the other methods which suggest that the ASMF based approach can estimate the original ECG signal with less error. This also validates the proficiency of the AMSF based approach in order to estimate the original ECG for each scenario. PRD value determines the quality of the processed signal in term of clinical applications. Figs. 11–12 show that the proposed technique obtains less PRD value than the other methods for Gaussian noise and powerline interference. This phenomenon suggests the superiority of the proposed ASMF based technique for restoring details clinical information in the filtered signal. Table 3 presents that the ASMF based method shows a lower PRD value at each input SNR level for EMG noise. At input SNR of 20 dB, the PRD value is 5.3033, which suggests that the filtered ECG signal is a "good quality" signal for medical application [32]. To the end, the qualitative and quantitative analysis conclude the advantages of proposed technique in reducing the noise in ECG signal with less distortion.

In Fig. 13, for ECG record 105m, the proposed scheme shows nearly equal SNR improvement at input SNR of 5 dB. The predominant features of this original signal are high-frequency noises and artifacts [21]. In this study, for obtaining the information regarding the R-peaks, Pan-Tompkins method [29] is applied. This R-peak detection technique uses amplitude threshold value for detection of QRS complexes. Due to rapid change of amplitude level in the ECG record, some of the R-peaks cannot be detected properly by Pan-Tompkins method. Hence, in such scenario, the peaks could not be recovered properly, which causes reduction of overall SNR_{imp}. This phenomenon can be visualized in Fig. 14(a). However, the problem in detection of peaks can be overcome by employing advanced R-peaks detection techniques such as [33]. The ECG record 215 m of MIT-BIH database contains wide QRS complexes. After ASMF operation, the peaks of QRS complexes are attenuated and hence, a peak restoration operation is employed to recover these peaks. In peak restoration operation, a window of fixed size ± 10 with respect to the position of R-peak is empirically chosen to recover the ECG samples. Due to wide QRS complex morphology, some S-peaks are located outside the range of the window. Hence, these peaks cannot be recovered properly, which degrades the overall improvement of output SNR. Therefore, the proposed scheme shows a less improvement of SNR for such signal. This problem can be solved by selecting an adaptive length window by getting the knowledge of the duration of QRS complex in "R-peak position identification information" stage. Fig. 14(b) shows the effect of fixed window in peak recovery for the ECG record 215 m. However, for most of the ECG records, the proposed work shows better performance response than the existing techniques. In this study, the experimental ECG signals contain time-varying QRS morphologies, normal and abnormal ECG beats. ADTF based technique rejects the detail information of initial two levels of wavelet decomposition, hence some high-frequency QRS complex information is missed and overall SNR improvement is reduced. ECG records 200 m and 230 m contains time-varying morphologies of QRS complexes. The proposed ASMF based technique managed to retain its SNR improvement ability for these signals. However, the EMD [18] and EKF [13] based technique fail to estimate the morphologies QRS complexes correctly. Hence, these approaches show a relatively weak response to these signals. At high input SNR 20 dB, though all the existing methods reduce the effect of noises, but due to over-smoothing of signals, the local details of the signal are attenuated. Hence, at high input SNR, the improvement of SNR for these methods are less. However, the proposed ASMF based approach manages to retain the signal details properly. Hence, the overall improvement of SNR is quite high. At input SNR 20 dB, the proposed scheme attains an average SNR improvement of 6.5 dB which is quite high than the existing techniques. The qualitative and quantitative analysis suggest that the proposed ASMF based technique presents a better ECG denoising response than the existing techniques, when signals are corrupted by white Gaussian noise, EMG noise, and power line interference.

4. Conclusions

In this article, an efficient combined ECG denoising methodology using EMD and ASMF is proposed. The main aim of this work is to incorporate the advantages of both EMD and ASMF in reducing the noises present in ECG signals. In conventional EMD based ECG denoising techniques, rejection of initial IMFs or window-based approach is employed for reduction of high-frequency noises. However, these approaches either harm the high-frequency details of ECG signals or ignore the noises in QRS complex region. Unlike, conventional EMD based methods, here, a wavelet based soft thresholding technique is applied for rejection of high-frequency noises and preservation of QRS complexes. Then, an ASMF operation is employed for enhancing the signal quality by further removing of artifacts. So combining these two scheme yield better ECG denoising.

The standard MIT-BIH database ECG signals are used for simulation study analysis. Three general noises specifically white Gaussian noise, EMG noise, and power line interference are added with the test signals at various input SNR levels. Three performance parameters: SNR_{imp}, MSE and PRD are considered for evaluating the efficacy of the proposed methodology. The efficiency of the presented technique is compared with ADTF [19], EMD with DWT [18], FIR [8], DWT [16], and EKF [13] based ECG denoising approaches. It is observed from simulation study and detail analysis that the proposed ASMF based ECG denoising method outperforms the existing techniques. An in-depth inspection of the qualitative and quantitative analysis suggests that the presented ASMF based technique can be used as a standard tool for reduction of noises in the pathological ECG signals. This advanced technique will be beneficial for future computer-based automated diagnostic systems.

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