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Research paper

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

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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],

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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. | $C_{1_{ECG}}[n]$<br>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.