Adaptive denoising of ECG using EMD, EEMD and CEEMDAN signal processing techniques

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Abstract. Using adaptive signal processing techniques denoising of ECG signal is performed which is obtained from physionet database. In this paper, the baseline wandering noise is removed using different adaptive techniques such as Empirical Mode Decomposition (EMD), Ensemble Empirical Mode Decomposition (EEMD) and Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN). All these algorithms are effectively used to decompose the noisy ECG signal into different Intrinsic Mode Functions (IMFs) and further these IMFs are filtered using low pass filtering method to extract the low frequency baseline component. The high frequency noise present in the reconstructed signal is reduced by further decomposing into IMFs using all the three methods. These IMFs are soft thresholded to remove the high frequency noise. The results obtained from the CEEMDAN outperform EMD and EEMD in extracting signal from noise. Further, distinct parameters such as skewness, crest factor, RMS value and kurtosis are estimated for the reconstructed signal to analyse their behaviour.

1. Introduction

The ECG signals in health care are of extreme importance because of the amount of crucial information contained in them. ECG is basically an electrical signal extracted from the body directly using physiological sensors or electrodes as shown in Figure 1. ECG signals are very low frequency signals typically lying between 0.05 Hz to 100 Hz [1]. Most valuable information in the ECG signal is observed in the ultra-low frequency band limited to 45 Hz. The ECG signals recorded using the sensors attached to the body can easily be corrupted by the surrounding noises produced either by muscle movements or due to sensor’s poor performance [2]. The kind of noise which is of main concern in ECG signal analysis is the Baseline Wander (BW). There are various sources which lead to the generation of BW which can either be device based like sensitivity of sensor probes connected to body or due to the body movement during breathing. BW is characterized as a low frequency artifact which makes difficult to identify ST segments of ECG signal [3].

ECG signal is a non-stationary signal where the noise and signal spectra are overlapped. In order to analyse this kind of signal, a nonlinear tool such as EMD algorithm can be employed. This is a method of decomposing a signal into Intrinsic Mode Functions (IMFs) [4]. These IMFs are characterised as zero mean AM and FM signals. In this paper the baseline drift that is present in the corrupted ECG signal is removed using adaptive techniques such as EMD, EEMD and CEEMDAN. This baseline record is obtained from MIT-BIH Noise Stress Test database and is added with the record ‘103’ ECG signal of MIT-BIH arrhythmia database. The parameters such as RMS value, kurtosis, Crest factor and skewness are evaluated for the reconstructed signals using all the three methods. The overall paper is divided into
seven sections. Section II involves detailed discussion about EMD, section 3 and 4 describes about EEMD and CEEMDAN respectively. Section V discusses the approaches used in extraction of baseline component and high frequency noise removal using low filtering and soft threshold function methods. The simulation studies are presented in Section VI followed by conclusion in section VII.

![Figure 1. Typical sensors/electrodes placed at different locations on the body to extract ECG signals.](image)

2. **Empirical Mode Decomposition (EMD)**

The unique property of EMD is its independency on basis function which makes it a fully data driven method and most suitable for ECG signals which are nonlinear and nonstationary. In EMD method, a given signal \( x(t) \) is decomposed into a set of IMFs which represents an oscillatory and zero mean functions. This method of extracting IMFs is known as sifting [5]. Given a signal \( x(t) \), the first job is to figure out upper and lower envelopes by just observing maxima and minima utilising any interpolation method. The mean \( m(t) \) calculated from these envelopes is used to extract the temporal oscillations \( h(t) \). If the average value of \( h(t) \) is zero then it is termed as first IMF \( c_1(t) \).

\[
h(t)=x(t)-m(t) \tag{1}
\]

The first residue \( r_1(t) \) is given by

\[
r(t)=x(t)-c_1(t) \tag{2}
\]

These steps are repeated to extract the remaining IMFs \( c_i(t) \) for \( i = 2, \ldots, N \). This method of decomposition is repeated until we get a residual function \( r(t) \) which is either a monotonic function or a constant value [6]. The signal \( x(t) \) decomposed using EMD is given by.

\[
x(t)=\sum_{i=1}^{N} c_n(t)+r_N(t) \tag{3}
\]

where \( c_n(t) \) represents an \( n \)th IMF and \( r_N(t) \) is a residue which is monotonic function with one extremum function. In general the lower order IMFs extracts high frequency components of signal and higher order modes capture the slow variations.

3. **Ensemble Empirical Mode Decomposition (EEMD)**

The EMD method suffers from the problem of mode mixing where two different IMFs can represent the oscillations from a certain time scale. This mode mixing can be eliminated by employing Ensemble mode decomposition. In EEMD, a series of white noise is added to signal during each trial and the signal is decomposed using EMD [7, 8]. This process is repeated for an ensemble number of trials where a different amount of white noise is added to the signal to obtain the IMF component. The final IMF component is the mean of the IMFs obtained during the ensemble number of trials [9, 10]. The number of IMF components obtained from EEMD is influenced by the number of trials involved in the process. This makes EEMD computationally complex.
\[ c_j = \frac{1}{N} \sum_{i=1}^{N} c_{ij}(t) \]  

(4)

where \( c_{ij} \) is the extracted IMFs obtained during each iteration.

4. Complete Ensemble Mode Decomposition with Adaptive noise

In EEMD method there will be residual noise present in the recovered signal. This is due to the fact of various possibilities of signal combined with additive white Gaussian noise. The \( j \)th mode extracted from EMD process can be represented by \( E_j(.) \) and \( n_i(t) \) be the random signal with mean of zero and variance of unity value [11]. In CEEMD, the first intrinsic mode \( IMF_1(t) \) is average IMF obtained by applying EMD on the signal \( x(t) + \beta_0 w^i(t) \). After computing the first IMF, residual component \( r_1(t) \) is found by subtracting the signal \( x(t) \) with \( IMF_1(t) \).

The second IMF is found by obtaining the first IMF of \( N \) decompositions of

\[ r_1(t) + \beta_1 n_1 \left( w^i(t) \right) \text{ for } i=1,2,3,...,N \]  

(5)

This procedure is followed to extract the remaining IMFs of CEEMD by the first mode of EMD. For each of these realizations the residue is calculated. The \( k \)th residue \( r_k(t) \) is calculated from the expression with \( K \) representing the number of modes.

\[ r_k(t) = r_{k-1}(t) - IMF_{k-1} \text{ for } k=2,3,...,K \]  

(6)

The various possible combinations of signal-to-noise ratio are chosen at each stage of decomposition by the parameter \( \beta_k \). It is advised in CEEMDAN to choose large amplitude noise for signals containing low frequency components. It is also observed that the number of modes obtained here is lesser compared with EEMD [12].

5. Baseline Wander removal using multiband filtering approach

The ECG signal containing baseline (BW) and high frequency noise components is decomposed into IMFs using EMD, EEMD and CEEMDAN methods. Each of the IMFs contains noise as well as essential part of the ECG signal. According to observation made, there is inverse relationship between the IMFs order and frequency component, higher the order of IMFs lower is the frequency component present in it and vice versa. The residual part which is obtained from the decomposition cannot be regarded as BW since it has to violate the properties of IMF. Hence it is required to extract the low frequency noise components from each of the IMFs starting from the residue or last IMF up to the lower order IMFs. The higher order contains both the baseline wander as well as the essential part of the signal. Hence the elimination of higher order modes is not preferred. The bank of low pass filters with different cut off frequencies is applied to the higher order IMFs and the baseline wander is extracted from the filtered signals. This type of filtering is done from last IMF. Let us consider the signal \( x(t) \) containing the BW when decomposed using the EMD contains the residue as the last IMF can be represented by

\[ x(t) = \sum_{i=0}^{N+1} c_i(t) \]  

(7)

Now starting from the last IMF a set of low pass filters are designed with impulse responses \( h_i(t) \) \( \text{ for } i=1,2,...,Q \) are used to filter out the baseline wander. Here \( Q \) is referred to an order of the BW. This is determined when the variance of filtered IMFs \( h_i(t) \) is less than threshold (\( \xi < 10 \)). The filter outputs are given by

\[ b_i(t) = h_i(t) * c_{N+i+2} \text{ for } i=1,2,...,Q \]  

(8)
The cut off frequency of the filters $h_i(t)$ are chosen by selecting a fixed frequency folding number $M = 20$ for EMD and $M = 10$ for EEMD and CEEMDAN starting from the last IMF or residue to the first [3].

$$\omega_k = \frac{\omega_0}{M^{k-1}}$$

(9)

Here $\omega_0$ is selected as $0.8$. The estimated baseline wander $\hat{b}_i(t)$ is obtained as

$$\hat{b}_i(t) = \sum_{j=1}^{Q_i} b_j(t)$$

(10)

The reconstructed signal $\hat{x}(t)$ obtained by removing the baseline wander from the corrupted ECG is represented by

$$\hat{x}(t) = x(t) - \hat{b}_i(t)$$

(11)

This method of filtering performed to extract the BW from the IMFs of EMD is again repeated for EEMD and CEEMDAN decomposition methods. The reconstructed signal contains the high frequency variations which can be removed by again decomposing the signal into IMFs by using EMD method. These IMFs are soft thresholded by using a global thresholding function defined for all the modes [13]. The threshold value for each of the mode is obtained by calculating the energies $E_i$ of all modes and knowing the length of the signal $n$.

$$\tau_i = 0.5 \sqrt{E_i 2 \ln(n)}$$

(12)

The energy $\hat{E}_i$ is calculated according to the relation

$$\hat{E}_i = \frac{E_i}{0.719^{2019^i}} \text{ for } i=2,3,\ldots,N$$

(13)

$E_i$ is the energy of the first mode given by

$$E_1 = \frac{\text{median of first IMF}}{0.6745}$$

(14)

The noisy IMFs $c_{ni}(t)$ are thresholded using the expression

$$\hat{c}_i(t) = \begin{cases} c_{ni}(t) - \tau_i & \text{if } c_{ni}(t) \geq \tau_i \\ 0 & \text{if } |c_{ni}(t)| < \tau_i \\ c_{ni}(t) + \tau_i & \text{if } c_{ni}(t) \leq -\tau_i \end{cases}$$

(15)

The reconstructed signal $\hat{x}_R(t)$ will now be free from high frequency variations and is given by:

$$\hat{x}_R(t) = \sum_{i=1}^{N} \hat{c}_i(t) + r_N(t)$$

(16)
6. Simulation Results
The baseline noise is obtained from the MIT-BIT Noise Stress Database. This recording of 3600 samples for a length of 10 sec is added to a clean ECG signal recording 103 of MIT-BIH Arrhythmia Database. The sampling rate of the signals obtained from the database is 360 samples/sec. This is the noisy ECG signal which contains the baseline drift as shown in Figure 2. The qualitative analysis is performed on this corrupted signal to eliminate the baseline drift [14]. This signal is decomposed into IMFs by using EMD, EEMD and CEEMDAN methods as shown in Figure 3, Figure 4 and Figure 5. After decomposing the signal into IMFs, they are low pass filtered to extract the baseline component from each mode. The reconstructed signal is obtained by removing this baseline from the corrupted ECG for EMD, EEMD and CEEMDAN methods is given in Figure 6. The baseline at the input is compared with the baselines extracted from all the method is shown in Figure 7. This reconstructed signal contains the high frequency noises which are reduced by using soft threshold technique. The reconstructed signal is further decomposed into IMFs using EMD, EEMD and CEEMDAN methods. The threshold value for each IMF is determined by calculating its energy as given in equation (12). Each IMF is applied to the threshold function according to equation (15). The reconstructed signal is obtained by adding the IMFs obtained after the application of threshold function. This represents smoother version of the ECG with less high frequency variations is shown in Figure 8. The statistical parameters such as kurtosis, crest factor, skewness and RMS values are calculated for the clean ECG signal to analyse their behaviour, as shown in Table 1.

Kurtosis:

\[
\hat{\gamma}_4 = (N-1) \frac{\sum_{n=1}^{N} x^4(n)}{(\sum_{n=1}^{N} x^2(n))^2}
\]  

(17)

Crest Factor:

\[
CF = \frac{x_{\text{PEAK}}}{x_{\text{RMS}}}
\]

(18)

Skewness:

\[
g_1 = \frac{\sum_{n=1}^{N} (x(n)-\bar{x}(n))^2}{\sigma^3}/N
\]

(19)

RMS value:

\[
\text{RMS} = \sqrt{\frac{1}{N} \sum_{n=1}^{N} [x(n)]^2}
\]

(20)
**Figure 2.** ECG signal record 103 from MIT-BIH database corrupted with baseline wander (BW)

**Figure 3.** ECG signal decomposed using EMD method
**Figure 4.** ECG signal decomposed using EEMD method

**Figure 5.** ECG signal decomposed using CEEMDAN method
Figure 6. ECG signal baseline corrected using IMFs of all the three methods

Figure 7. Baseline Wander obtained using EMD, EEMD and CEEMDAN methods
Figur 8. Denoised ECG signal obtained using threshold technique

Table1. Comparison of statistical parameters of reconstructed signal obtained using EMD, EEMD and CEEMDAN Methods

| Sl. No. | M | Method | Kurtosis | RMS value | Crest Factor | Skewness |
|--------|---|--------|----------|-----------|--------------|----------|
| 1      | 20| EMD    | 17.1023  | 0.1559    | 6.2344       | 3.2414   |
| 2      | 10| EEMD   | 18.9856  | 0.1740    | 6.9824       | 3.3594   |
| 3      | 10| CEEMDAN| 20.5177  | 0.1740    | 7.0475       | 3.6722   |

7. Conclusion
Denoising of ECG signal is performed by using adaptive signal processing methods such as EMD, EEMD and CEEMDAN. The clean ECG signal so obtained is further analyzed based on distinct parameters like skewness, kurtosis, RMS value and crest factor. For CEEMDAN method, higher statistical values are obtained for the reconstructed signal as compared with EMD and EEMD.

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