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

M. Suchetha[a,*], N. Kumaravel[b], M. Jagannath[a], Saravana Kumar Jaganathan[c]

[a] School of Electronics Engineering VIT University Chennai, India
[b] Department of Electronics and Communication Engineering College of Engineering Guindy Anna University Chennai, India
[c] Faculty of Biosciences and Medical Engineering, Universiti Teknologi Malaysia, Skudai 81310, Malaysia

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ABSTRACT

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:

* Corresponding author.
E-mail addresses: suchetha_mt@yahoo.com (M. Suchetha), kumaravel_n@annauniv.edu (N. Kumaravel), jagan.faith@gmail.com (M. Jagannath), saravana@utm.my (S.K. Jaganathan).

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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. $X(n) = [x(n)\ x(n-1)\ x(n-2)..\ x(n-N+1)]^T$ 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