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Denoising of ECG signals based on noise reduction algorithms in EMD and wavelet domains

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ABSTRACT

This paper presents a new ECG denoising approach based on noise reduction algorithms in empirical mode decomposition (EMD) and discrete wavelet transform (DWT) domains. Unlike the conventional EMD based ECG denoising approaches that neglect a number of initial intrinsic mode functions (IMFs) containing the QRS complex as well as noise, we propose to perform windowing in the EMD domain in order to reduce the noise from the initial IMFs instead of discarding them completely thus preserving the QRS complex and yielding a relatively cleaner ECG signal. The signal thus obtained is transformed in the DWT domain, where an adaptive soft thresholding based noise reduction algorithm is employed considering the advantageous properties of the DWT compared to that of the EMD in preserving the energy in the presence of noise and in reconstructing the original ECG signal with a better time resolution. Extensive simulations are carried out using the MIT-BIH arrythmia database and the performance of the proposed method is evaluated in terms of several standard metrics. The simulation results show that the proposed method is able to reduce noise from the noisy ECG signals more accurately and consistently in comparison to some of the stateof-the-art methods.

1. Introduction

Among various biological signals, ECG is important to diagnose cardiac arrhythmia. Usually ECG signals are subjected to contamination by various noises. The sources of noise may be either cardiac or extracardiac. Reduction or disappearance of the isoelectric interval, prolonged repolarization and atrial flutter are responsible for cardiac noise, whereas respiration, changes of electrode position, muscle contraction, and power line interference cause extracardiac noise [1,2]. Numerous methods have been reported to denoise ECG signals based on filter banks, principal component analysis (PCA), independent component analysis (ICA), neural networks (NNs), adaptive filtering, empirical mode decomposition (EMD), and wavelet transform [3–10]. The filter bank based denoising process smoothes the P and R amplitude of the ECG signal, and it is more sensitive to different levels of noise [7]. By exploiting PCA or ICA or NNs, a statistical model of the ECG signal and noise is first extracted and then, the in-band noise is removed by discarding the dimensions corresponding to the noise [11–14]. Although PCA, ICA and NNs based schemes are powerful for in-band noise filtering, the statistical model derived therein is not only fairly arbitrary but also extremely sensitive to small changes in either the signal or the noise unless the basis functions are trained on a global set of ECG beat types. In particular, one of the difficulties with the application of ICA is the determination of the order of the independent components (ICs). Thus for further processing, visual inspection is required, which is undesirable in routine clinical ECG analysis [15]. The limitations of the adaptive filtering based ECG denoising lies in the fact that a reference signal has to be additionally recorded together with the ECG [16].

Comparatively, the denoising methods based on EMD and that based on wavelet are found more effective in reducing noise from the ECG signals. Since, ECG signals are relatively weak and may have strong background noises, the thresholding performed in either EMD or wavelet domain alone will result in an inadequate denoising as far as reliable clinical applications are concerned [17]. In an EMD-wavelet based method presented in [17], since the QRS complex of the ECG signal embedded in the first few IMFs consisting of high frequency noise is subject to wavelet thresholding, the thresholding technique cannot distinguish between high frequency noise and the QRS information. This leaves a scope for further noise reduction in ECG by employing a more accurate denoising method.

In this paper, an ECG denoising method employing noise reduction algorithms in EMD and wavelet domains is presented that is capable of overcoming the limitations of the existing methods is presented. In order to preserve the QRS information in the presence of noise, the noisy ECG signal is first enhanced in the EMD domain by a windowing operation. Then, the ECG signal with a relatively reduced noise is transformed in the wavelet domain. Finally,

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an adaptive thresholding scheme is employed to the wavelet coefficients prior to reconstructing a cleaner ECG signal. It has been shown by the simulation results that the proposed method provides a more accurate donoising performance for the ECG signals at different levels of SNR in comparison to some of the state-of-the-art methods.

This paper is organized as follows. The problem of our work is formulated in Section 2, which includes a brief background of the use of EMD and that of wavelet transform in ECG denoising. The proposed ECG denising method based on noise reductions in EMD and wavelet domains is described in Section 3. In Section 4, the simulation results of the proposed denoising method is provided and its performance is compared relative to the other methods. The salient features of the proposed method are highlighted in Section 5 with concluding remarks.

2. Problem formulation

2.1. Empirical mode decomposition

EMD is intuitive and adaptive, with basic functions derived fully from the data. The computation of EMD does not require any previously known value of the signal [18]. The key task here is to identify the intrinsic oscillatory modes by their characteristic time scales in the signal empirically, and accordingly, decompose the signal into intrinsic mode functions (IMFs) [19]. As a result, EMD is especially applicable for nonlinear and non-stationary signals, such as ECG. A function is considered to be an IMF if it satisfies two conditions; first, In the whole data set, the number of local extrema and that of zero crossings must be equal to each other or different by at most one and second, at any point, the mean value of the envelope defined by the local maxima and that defined by the local minima should be zero. The systematic way to decompose the data into IMFs, known as the "sifting" process, is described as follows:

i. All the local maxima of the data are determined and joined by cubic spline line as the upper envelope.
ii. All the local minima of the data are found and connected by cubic spline line as the lower envelope.
iii. In the first sifting process, the mean m_1 of the upper and lower envelops is first determined, and then, subtracted from the original data $x[n]$ to obtain the first component $h_1[n]$ as:

$$h_1[n] = x[n] - m_1. \tag{1}$$

If $h_1[n]$ satisfies the conditions to be an IMF as mentioned above, it is considered as the first IMF $c_1[n]$.

iv. If $h_1[n]$ dissatisfies the conditions to be an IMF, it is treated as the data in the second sifting process, where steps i, ii and iii are repeated on $h_1[n]$ to derive the second component $h_2[n]$ as:

$$h_2[n] = h_1[n] - m_2, \tag{2}$$

where m_2 is the mean value determined from $h_1[n]$. With a view to determine $c_1[n]$ from $h_2[n]$, the conditions to be satisfied to be an IMF is checked for $h_2[n]$. If $h_2[n]$ does not satisfy the conditions, a standard difference (SD) is calculated from the two consecutive sifting results, namely $h_{i-1}[n]$ and $h_i[n]$ as:

$$\mathrm{SD} = \sum_{n=0}^{N} \frac{|h_{i-1}[n] - h_i[n]|^2}{h_{i-1}^2[n]}. \tag{3}$$

When the value of SD resides within a predefined range, the sifting process is terminated, and $h_i[n]$ is considered to be the first IMF and termed as $c_1[n]$. Here, (i) and $(i-1)$ are index terms indicating two consecutive sifting processes.

v. Once $c_1[n]$ is obtained, it is then subtracted from the original data to get a residue $r_1[n]$:

$$r_1[n] = x[n] - c_1[n]. \tag{4}$$

The residue $r_1[n]$ is treated as a new signal, and sifting process as described above is carried out on $r_1[n]$ to obtain the next residue signal $r_2[n]$. Therefore, the residue signal thus obtained can be expressed in general as:

$$r_j[n] = r_{j-1}[n] - c_j[n]. \tag{5}$$

If $r_j[n]$ becomes a constant or monotonic function, the process of decomposing the signal into IMFs is terminated.

To this end, for an L level decomposition, the original signal $x[n]$ can be expressed as:

$$x[n] = \sum_{i=1}^{L-1} c_i[n] + r_L[n]. \tag{6}$$

In (6), $x[n]$ is represented as the sum of the decomposed IMFs and the resulting residue $r_L[n]$.

The basic principle of using EMD in ECG signal denoising is to decompose the noisy signal into the IMFs as shown in Fig. 1. Since some IMFs contain useful signal information and others carry signal plus noise, the selection of proper number of IMFs is an important factor in ECG denoising by EMD. Numerous approaches have been proposed to identify whether a specific IMF contains useful information or noise [20]. Conventionally, a number of initial IMFs assumed to contain noise are discarded in the process of denoising thus causing distortion in the reconstructed ECG signal, particularly, in the QRS complex as shown in Fig. 2. It is observed from Fig. 1 that the first IMF $c_1[n]$ contains mostly high frequency noise. The second and third IMFs ($c_2[n]$ and $c_3[n]$), in general, contain not only the high frequency noise, but also the components of the QRS complex. The rest of the IMFs mainly carry useful information about the ECG signal. With a view to remove noise, discarding the first IMF as is done in the conventional EMD method may still retain considerable noise and removing the first two IMFs may result in a heavy distortion in the R waves of the denoised signal. Therefore, in the EMD domain, the method of thresholding the initial IMFs as performed via removing them is not effective enough for ECG denoising.

2.2. Discrete wavelet transform

In wavelet transform, a signal is analyzed and expressed as a linear combination of the sum of the product of the wavelet coefficients and mother wavelet. A family of the mother wavelet is available [21] having the energy spectrum concentrated around the low frequencies like the ECG signal as well as better resembling the QRS complex of the ECG signal. Therefore, for the analysis of an ECG signal $x[n]$ at different scales, wavelet transform (DWT) is used in practice. In discrete wavelet transform (DWT), for analyzing both the low and high frequency components in $x[n]$, it is passed through a series of low-pass and high-pass filters with different cut-off frequencies. This process results in a set of approximate (c_a) and detail (c_d) DWT coefficients, respectively. The DWT hierarchy of a 2 level signal analysis and reconstruction/synthesis is shown in Fig. 3, where down arrow and up arrow represent down-sampling and up-sampling the DWT coefficients, respectively. The filtering operations in DWT result in a change in the signal resolution [22], whereas sub sampling (down sampling/up sampling) causes change of the scale. Thus, DWT decomposes the signal into approximate and detail information thereby helping in analyzing it at different frequency bands with different resolutions.