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Empirical mode decomposition based filtering techniques for power line interference reduction in electrocardiogram using various adaptive structures and subtraction methods

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A B S T R A C T

Electrocardiogram (ECG) is a vital sign monitoring measurement of the cardiac activity. One of the main problems in biomedical signals like electrocardiogram is the separation of the desired signal from noises caused by power line interference, muscle artifacts, baseline wandering and electrode artifacts. Different types of digital filters are used to separate signal components from unwanted frequency ranges. Adaptive filter is one of the primary methods to filter, because it does not need the signal statistic characteristics. In contrast with Fourier analysis and wavelet methods, a new technique called EMD, a fully data-driven technique is used. It is an adaptive method well suited to analyze biomedical signals. This paper foregrounds an empirical mode decomposition based two-weight adaptive filter structure to eliminate the power line interference in ECG signals. This paper proposes four possible methods and each have less computational complexity compared to other methods. These methods of filtering are fully a signal-dependent approach with adaptive nature, and hence it is best suited for denoising applications. Compared to other proposed methods, EMD based direct subtraction method gives better SNR irrespective of the level of noises.

1. Introduction

The electrocardiogram (ECG) is a graphical representation of the functionality of human heart and is an important tool used for diagnosis of cardiac abnormalities. In clinical environment during acquisition, the ECG signal gets added to various types of artifacts. The predominant artifacts present in the ECG include: Power-line Interference and Baseline Wander. This artifact strongly affects the ST segment, degrades the signal quality, frequency resolution, and produces large amplitude signals in ECG that can resemble P–Q–R–S–T waveforms. Consequently, these factors mask small features that are important for clinical monitoring and diagnosis of heart failure. Annulment of these artifacts in ECG signals is an important factor for better diagnosis. The extraction of high-resolution ECG signals from recordings which are perturbed by noise is an important issue. The goal of ECG signal denoising is to separate the wanted signal components from the unwanted artifacts, so as to present an ECG that facilitates easy and accurate interpretation.

Traditional noise reduction method is based on standard filtering, either by low pass filter or high pass filter. A low pass filter removes high frequency noise, while a high pass filter removes low frequencies, such as baseline wander and respiration interference. However, these ideal filters will remove the desired signal component within the band of noise since both signal and noise display an overlapping spectrum. Another conventional method to remove power line interference is to use a notch filter, which is tuned to the frequency of interference. The problem with finite impulse response (FIR) notch filter is that the notch has a relatively large bandwidth, which attenuates the needed signal components within the bandwidth [1,2].

The advanced signal processing methods applied on the studies of ECG noise reduction is nonlinear filter bank [3], independent component analysis [4], adaptive filtering [5,6] and wavelet transforms [7]. Adaptive filtering is a powerful signal detection technique. The least mean square (LMS) algorithm introduced by Widrow and Hoff (1959) is one of the most widely used algorithms in adaptive filtering due to its simplicity and ease of computation [8]. The concept of wavelet transform was proposed by the geophysicist Morlet in analysis and processing geophysical data in France in 1984. An advantage of wavelet transform is that the windows vary, and it has an infinite set of possible basis functions.

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Donoho and Johnstone (1994) have developed hard and soft shrinkage functions [9,10]. In the case of soft shrinkage the insignificant empirical wavelet coefficients are set to zero if it lies between the ranges of thresholds and shrink the coefficients to zero in a linear fashion. In case of hard shrinkage the insignificant empirical wavelet coefficients are vanished if it lies between the threshold ranges and the remaining coefficients are used to represent the signal. Poornachandra and Kumaravel (2005) developed a subband adaptive shrinkage function for denoising of ECG signals [11,12]. The shrinkage function is incorporated at the vicinity of power line frequency by selecting the proper subband level. But the concept of wavelet thresholding relies on the assumption that signal magnitudes dominate the magnitudes of the noise in a wavelet representation so that wavelet coefficients can be set to zero if their magnitudes are less than a predetermined threshold [12]. Another limitation of wavelet approach is that the basis functions are fixed and, thus, do not necessarily match all real signals.

Empirical mode decomposition (EMD) is a recently introduced technique and it is also used for processing non-linear and non-stationary signals in addition to stationary signals [13]. EMD has the property of adaptive and signal-dependency, making this technique well suited for biomedical signal analysis. It is proposed as a preprocessing stage to efficiently compute the instantaneous frequency through the Hilbert transforms [14,15], however, it can be applied independently also. It is discussed in the literature that EMD behaves as a “wavelet-like” dyadic filter bank for Gaussian noise [16,17]. It is an iterative algorithm that computes the maximum and minimum extreme. The major advantage of the EMD is that the basis functions are derived from the signal itself. Thus the analysis is adaptive in contrast to the traditional methods where the basis functions are fixed. The EMD is based on the sequential extraction of energy associated with various intrinsic time scales of the signal, starting from finer temporal scales (high-frequency modes) to coarser ones (low-frequency modes). Thus according to this decomposition any signal can be represented as the sum of intrinsic mode functions (IMFs) and a residue [18,19]. An IMF is defined as a function with equal number of extreme and zero crossings with its envelopes, as defined by all the local maxima and minima. The filtering of noises in arrhythmia signals using ensemble empirical mode decomposition algorithm is proposed in the paper [20]. The principle of the EEMD is to add white noise into the signal with many trials. The noise in each trial is different and the added noise can be canceled out on average. Thus, as more and more trials are added to the ensemble, the residual part is the signal. But these types of filtering further disturb the morphology of ECG signal due to different trials in addition of white noise. A robust power line suppression system based on an extended version of kalman filter and an improved version of EMD is used to attenuate the QRS complex of ECG signal [21].

This work discusses various possible EMD based adaptive filtering techniques and subtraction techniques for denoising the contaminated ECG signal. The decomposed IMF levels will separate the frequency components present in the noisy ECG signal. The 50 Hz complex sinusoidal interference is separated in the first IMF level, so a two-weight adaptive filter is used in the first level to remove the interference. The different possible ways of using the adaptive filter and subtraction techniques are discussed in detail in Section 3. This approach does not need the thresholding of signal levels like wavelet thresholding. It is also not necessary that the signal amplitude be higher than the noise amplitude. This makes the techniques applicable to any kind of noisy nature of the signal. The present approach of filtering is fully a data-dependent and an adaptive method.

This paper is organized as follows: Section 2 discusses basics of empirical mode decomposition and adaptive filtering; Section 3 studies the theme of the paper and the proposed model; and Section 4 examines the results of the MATLAB simulation.

2. Introduction to empirical mode decomposition and adaptive filtering

2.1. Empirical mode decomposition

The EMD was recently proposed by Huang et al. [13] as a tool to adaptively decompose a signal into a collection of AM–FM components. Other data analysis methods, like Fourier and wavelet-based methods require pre-defined basis functions to represent a signal. The EMD is fully a data based mechanism that does not require any *a priori* known basis. It is especially well suited for analysis of biomedical signals. The goal of empirical mode decomposition is to represent a signal as an expansion of adaptively defined basis functions with well-defined frequency localization levels. It will decompose the input signal into a sum of IMFs. To decompose a signal $x(t)$, the EMD algorithm works as follows:

(1) Identify all maxima and minima of the signal $x(t)$.
(2) Connect all the local maxima of the signal $x(t)$ by a cubic spline to form the upper envelope, represented as $e_u(t)$. Similarly, connect all the local minima to form the lower envelope, $e_l(t)$.
(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) Repeat the iteration on the residual $m_1(t)$, steps (3) and (4). Continue until the residual is such that no IMF can be extracted and represents a monotonic function.

The above procedure to extract the IMF is referred to as the *sifting* process. Finally, the EMD of the original signal can be represented as the sum of IMFs and a residue

$$x(t) = \sum_{i=1}^{N} c_i(t) + r(t) \tag{1}$$

where $c_i(t)$ is the sum of IMF levels and $r(t)$ is the resultant residue. An IMF is a function that satisfies the two following conditions: (a) the number of extreme and the number of zero crossings must either equal or differ at most by one, 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. The detailed procedure for empirical mode decomposition is shown in Fig. 1.

2.2. Two-weight adaptive filter

An adaptive filter is the natural choice for removal of power line interference which can adjust its coefficients according to certain algorithm. Widrow and Hoff et al. (1959) introduced the least mean square (LMS) algorithm and are widely used in adaptive filtering algorithms. It is more powerful and simple in computation. The main aim of an adaptive filter is to calculate the difference between the desired signal and the adaptive filter output, $e(n)$. This error signal is feedback into the adaptive filter and its coefficients are changed algorithmically in order to minimize a function of this difference, known as the cost function [8]. When the adaptive filter output is equal to the desired signal, the error signal goes to zero. Thus with each iteration of the LMS algorithm, the filter tap weights of the adaptive filter are updated according to the weight update equation:

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu e(n)\mathbf{x}(n) \tag{2}$$