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Fractal and EMD based removal of baseline wander and powerline interference from ECG signals

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ABSTRACT

This paper presents novel methods for baseline wander removal and powerline interference removal from electrocardiogram (ECG) signals. Baseline wander and clean ECG have been modeled as 1st and 2nd-order fractional Brownian motion (fBm) processes, respectively. This fractal modeling is utilized to propose projection operator based approach for baseline wander removal. Powerline interference is removed by using a hybrid approach of empirical mode decomposition method (EMD) and wavelet analysis. Simulation results are presented to show the efficacy of both the methods. The proposed methods have been shown to preserve ECG shapes characteristic of heart abnormalities.

1. Introduction

The heart activity of a person is commonly examined using an Electrocardiogram (or ECG) signal. Different leads (or the electrodes) of ECG recording machine are attached to different positions on the human body and recorded by an external device. An ECG signal can be used to measure the rate and abnormality (if present) of heartbeats, to detect disease or damage to the heart, and also to observe the effect of drugs or devices which alter the heart activity. Generally, the amplitude range of a normal ECG signal is 10 μV to 5 mV and the frequency range is 0.05–100 Hz [1]. In recent times, automated ECG analysis has gained immense popularity in the area of telemedicine [2].

An ECG signal represents heartbeat consisting of P wave, QRS complex, T wave, and U wave. The amplitude, duration, and interval between each of these waves help us distinguish between normal and abnormal waveforms. Certain diseases and their identification from an ECG signal are dependent on the characteristics of these waves.

During recording, an ECG signal generally gets corrupted by different types of noises, namely: (1) baseline wander (BW), (2) powerline interference (PI), and (3) physiological artifact (PA). The presence of these noises in an ECG signal makes the detection of abnormality in the heart beat difficult [3]. In this paper, we focus on (a) the modeling of clean ECG signals, (b) modeling of baseline wander noise, and (3) removal of baseline wander noise and powerline interference from ECG signals.

Powerline (AC) interference is a high frequency additive noise of 50 or 60 Hz. It is typically a sinusoidal wave with random phase but constant frequency [4]. This kind of noise comes from the power line to recording machines and is present even if special care is taken in proper grounding, shielding, and design of amplifier [5]. It is generally removed by a fixed or adaptive notch filter [4–7]. However, the requirement of reference signal in an adaptive filter makes its hardware and software implementation difficult [7]. The first intrinsic mode function (IMF) of empirical mode decomposition (EMD) is also used for powerline interference removal. However, in this IMF, R wave component is also present besides powerline interference [5]. This poses difficulty in powerline interference removal because any distortion in the amplitude and frequency of R wave can seriously affect disease diagnosis. Thus, in [5], a modified approach using notch filter on the first IMF is suggested for powerline interference removal.

On the other hand, baseline wander noise is a low frequency artifact frequently present in an ECG signal. The frequency range of this noise is roughly between 0.05 and 0.7 Hz [8]. It is mainly caused by movement of patients due to breathing, coughing, anxiety, stress or pain, and motion of electrodes [9]. Large baseline wander can lead to the following problems: (a) original ECG peak clipping by recording instrument amplifiers resulting in loss of signal, (b) change in the duration and shape of ST segment, and (c) loss of lower amplitude peaks such as P- and T-waves. Thus, during elimination of this noise from an ECG signal, extra care has to be taken to preserve the amplitude of R peak, original ST segment, and P and T wave peaks in the ECG waveform. These attributes are characteristic of ECG signals and are critical for disease diagnosis.

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Failure to preserve these signal-specific attributes during baseline wander removal may lead to either false alarm or miss of heart ailments such as myocardial infarction, ischemia, etc.

A number of methods have been proposed to remove baseline wander noise from ECG signals [1,7–19]. A classical method of baseline wander noise removal is high pass filtering with cut off frequency of 0.7 Hz [10]. However, the spectrum of baseline wander noise and low frequency component of an ECG signal may overlap [11]. In such a case, baseline wander removal using a highpass filter will alter the original clean ECG signal, particularly, the ST segment. Thus, the use of a highpass filter can lead to wrong diagnosis of a disease. The cubic spline method is one of the other methods that are used to estimate baseline wander noise [12]. This method assumes that the PR segment of an ECG signal is well defined and its position is correctly known for normal beats [11]. However, the detection of exact PR segment is often affected by other artifacts such as electrode motion, muscle artifact, etc. present in the signal. Thus, this method does not lead to efficient denoising in the presence of other noises.

Some other techniques commonly used for removing baseline wander noise from the ECG signal are: (a) adaptive filtering [9], (b) moving average filters [13], (c) wavelet approach [14,15], and (d) empirical mode decomposition (EMD) [7,16–19]. Adaptive filtering requires a reference signal for baseline wander removal [7]. In [7], last few IMFs with sufficient baseline wander were used as input signals, while noisy ECG signal was used as the reference signal. Moving average filters are easy to implement but they tend to distort the original signal wherever there is a sudden change in amplitude especially near R peak onset [13]. The process of baseline wander removal using EMD cannot be automated because baseline wander noise may be distributed over a number of intrinsic mode functions (IMFs) [16,18]. A similar problem arises with the wavelet approach where we cannot determine the amount of baseline wander noise present in different levels of detail coefficients [14,18].

In this paper, new methods are proposed for powerline interference and baseline wander noise removal from ECG signals. First, powerline interference is removed from noisy ECG signals (ECG signals corrupted by baseline wander and powerline interference). Noisy ECG is decomposed using EMD and the first IMF is processed using wavelet approach for powerline interference removal. Thus, we obtain ECG signal corrupted with only baseline wander noise. Next, statistical modeling of baseline wander noise and clean ECG signals is done. This modeling is used to propose projection operator based approach for the removal of baseline wander noise.

The paper is organized into eight sections. Section 2 presents a brief review on empirical mode decomposition (EMD) and the theory of projection operator. Section 3 informs about the database (or source) of ECG signals, powerline interference, and baseline wander noise used in this paper. Clean ECG and the noise recordings are modeled in Section 4. The proposed methods for powerline interference removal and baseline wander removal are presented in Section 5. Section 6 discusses the complete proposed denoising algorithm. Simulation results and comparison with other existing methods are presented in Section 7. In the end, conclusions are presented in Section 8.

1.1. Notations

We use lowercase bold letters and uppercase bold letters to represent vectors and matrices, respectively. The scalar variables are represented by lowercase italicized letters. In addition, $\mathrm{E}(\cdot)$ denotes the expectation operator.

2. Preliminaries

2.1. Empirical mode decomposition

Empirical mode decomposition (EMD) is an adaptive data driven approach that decomposes any nonlinear and non-stationary signal (like biomedical signals) into amplitude and frequency modulated (AM–FM) components called intrinsic mode functions (IMFs) [19,20]. Thus, a given signal $x(t)$ can be represented using IMFs as below:

$$x(t) = \sum_{n=1}^{N} c_n(t) + r_N(t) \tag{1}$$

where N=total number of IMFs, $c_n(t)$ for $n=1,\ldots,N$ are the IMFs, and $r_N(t)$ is the residual (or the last) IMF. These IMFs can be used for spectral analysis because as the IMF index increases, frequency of IMF decreases. EMD can also be used for subband filtering where the IMFs are adaptive or signal dependent [21]. Currently, this method is being applied to various applications including biomedical, seismic, geological, financial data analysis, etc. [20]. For the complete algorithm, readers may refer to [20,21].

2.2. Theory of projection operator

Consider a two-dimensional ($M=2$) vector space X_{vs}, spanned by basis vectors $\mathbf{x}_1$ and $\mathbf{x}_2$. Given a vector $\mathbf{y}$ belonging to the vector space W_{vs} of dimension $N=3$, the aim is to project $\mathbf{y}$ onto the space X_{vs} such that

$$\mathbf{y} = \hat{\mathbf{y}} + \mathbf{e} \tag{2}$$

where X_{vs} is the projection space for W_{vs} with $\dim(X_{vs}) < \dim(W_{vs})$, $\hat{\mathbf{y}}$is the estimate of $\mathbf{y}$ that lies in the space X_{vs}, and $\mathbf{e}$ is the estimation error. The squared length of vector $\mathbf{e}$ (or the energy of the signal characterized by $\mathbf{e}$) is minimum when $\mathbf{e}$ is perpendicular to the space X_{vs} [22]. This is also called as the orthogonal projection of vector $\mathbf{y}$ onto the space X_{vs} [22]. From (2), we can write

$$\mathbf{e} = \mathbf{y} - \hat{\mathbf{y}} \tag{3}$$

Since $\mathbf{e}$ is orthogonal to space X_{vs}, the inner product of $\mathbf{e}$ with all the basis vectors of X_{vs} will be zero, i.e.,

$$\langle \mathbf{x}_k, \mathbf{e} \rangle = \mathbf{x}_k^T \mathbf{e} = 0 \quad \text{for} \quad 1 \le k \le M \tag{4}$$

where $\mathbf{x}_k$'s are the basis vectors spanning the space X_{vs}.

Or

$$\mathbf{X}^T \mathbf{e} = 0. \tag{5}$$

The estimate $\hat{\mathbf{y}}$ (refer to Fig. 1) can be written as

$$\hat{\mathbf{y}} = \mathbf{Xc} = \sum_{k=1}^{M} c_k \mathbf{x}_k \tag{6}$$

where $\mathbf{X}$ contains the basis vectors of X_{vs} and c_k's are constants.

On substituting (3) and (6) in (4), we obtain

$$\langle \mathbf{x}_k, \mathbf{e} \rangle = \mathbf{x}_k^T (\mathbf{y} - \mathbf{Xc}) = 0 \quad \text{for} \quad 1 \le k \le M \tag{7}$$

Or,

$$\mathbf{X}^T (\mathbf{y} - \mathbf{Xc}) = 0 \tag{8a}$$

$$\Rightarrow \mathbf{X}^T \mathbf{y} = \mathbf{X}^T \mathbf{Xc} \tag{8b}$$

$$\Rightarrow \mathbf{c} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y} \tag{9}$$

On using (6) and (9), we obtain

$$\begin{aligned} \hat{\mathbf{y}} &= \mathbf{Xc} \\ &= \mathbf{X}(\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y} \\ &= \mathbf{Py} \end{aligned} \tag{10}$$