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ScienceDirect

Medical Engineering & Physics 31 (2009) 17–26

Medical Engineering & Physics

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Filtering electrocardiographic signals using an unbiased and normalized adaptive noise reduction system

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Received 4 December 2007; received in revised form 25 March 2008; accepted 28 March 2008

Abstract

We present a novel unbiased and normalized adaptive noise reduction (UNANR) system to suppress random noise in electrocardiographic (ECG) signals. The system contains procedures for the removal of baseline wander with a two-stage moving-average filter, comb filtering of power-line interference with an infinite impulse response (IIR) comb filter, an additive white noise generator to test the system's performance in terms of signal-to-noise ratio (SNR), and the UNANR model that is used to estimate the noise which is subtracted from the contaminated ECG signals. The UNANR model does not contain a bias unit, and the coefficients are adaptively updated by using the steepest-descent algorithm. The corresponding adaptation process is designed to minimize the instantaneous error between the estimated signal power and the desired noise-free signal power. The benchmark MIT-BIH arrhythmia database was used to evaluate the performance of the UNANR system with different levels of input noise. The results of adaptive filtering and a study on convergence of the UNANR learning rate demonstrate that the adaptive noise-reduction system that includes the UNANR model can effectively eliminate random noise in ambulatory ECG recordings, leading to a higher SNR improvement than that with the same system using the popular least-mean-square (LMS) filter. The SNR improvement provided by the proposed UNANR system was higher than that provided by the system with the LMS filter, with the input SNR in the range of 5–20 dB over the 48 ambulatory ECG recordings tested.
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Keywords: ECG; Noise reduction; Adaptive filters; Artifact removal; Biomedical signal analysis; Signal processing

1. Introduction

The electrocardiographic (ECG) signal is the electrical representation of the heart's activity. Computerized ECG analysis is widely used as a reliable technique for the diagnosis of cardiovascular diseases, and the ECG signal is the most commonly used biomedical signal in clinical practice [16,20]. However, ambulatory ECG recordings obtained by placing electrodes on the subject's chest are inevitably contaminated by several different types of artifacts. Commonly encountered artifacts include baseline wander, power-line interference, physiological signals generated by other organs of the body or induced by muscular contractions related to breathing, and high-frequency random noise.

The removal of artifacts in ECG signals is an essential procedure prior to further diagnostic analysis in many clinical applications, e.g., detection of QRS complexes [10,13], classification of ectopic beats [1,9], analysis of asymptomatic arrhythmia [19], extraction of the fetal ECG signal from the maternal abdominal ECG [11,12], diagnosis of myocardial ischemia [18], diagnosis of atrial fibrillation [27], and ECG data compression [5,28].

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doi:10.1016/j.medengphy.2008.03.004

The extraction of high-resolution ECG signals from recordings contaminated with background noise is an important issue to investigate [4]. The goal for ECG signal enhancement is to separate the valid signal components from the undesired artifacts, so as to present an ECG that facilitates easy and accurate interpretation [2]. Despite the publication of several previous studies in the literature [3,6,14,17,19,23–25], there are still a number of clinical applications that lack effective signal processing tools for efficient and reliable implementation of methods for the filtering and analysis of ECG signals.

In recent years, adaptive filtering has become one of the effective and popular approaches for the processing and analysis of the ECG and other biomedical signals [16]. The fundamental principles of adaptive filtering for noise cancellation were described by Widrow et al. [21]. For stationary signals, the Wiener filter is the optimal linear filtering technique in the minimum mean-squared error (MMSE) sense [8]. Unfortunately, the Wiener filter cannot provide good results when filtering a noisy ECG signal, due to the nonstationary nature of the cardiac signal as well as the noise. The literature contains many alternative adaptive filtering methods that have been used in several practical applications. Xue et al. [26] developed adaptive whitening and matched filters based on artificial neural networks to detect QRS complexes in ECG signals. Thakor and Zhu [19] proposed an adaptive recurrent filter to acquire the impulse response of normal QRS complexes, and then applied it for arrhythmia detection in ambulatory ECG recordings. Hamilton [6] compared adaptive and nonadaptive notch filters for the reduction of power-line interference at 60 Hz. Sameni et al. [17] established a framework of nonlinear Bayesian filtering for ECG noise cancellation.

Although the advantages of adaptive filters for ECG analysis are widely accepted, many such algorithms require detailed study of the features of a given ECG signal, e.g., segmentation of P-QRS-T waves [23], windowing of QRS complexes [17], delineation of artifacts [3], or filter-band reconstruction [2]. These methods consume a significant amount of time for modeling, and are not flexible for application from one patient or condition to another. In this paper, we present a novel unbiased and normalized adaptive noise reduction (UNANR) system for the efficient cancellation of high-frequency random noise in ambulatory ECG recordings.

The remaining parts of this paper are organized as follows. Section 2 provides a description of the adaptive noise-reduction system and the adaptation algorithm of the UNANR model. Section 3 presents the experimental results obtained with 48 noisy ambulatory ECG recordings using the proposed UNANR system, in comparison with those of the prevailing least-mean-square (LMS) filter. Section 4 presents an analysis of the convergence behavior of the UNANR learning rate parameter, and also a discussion on the effects on system performance caused by different values of the learning rate. Section 5 concludes our investigation and presents potential applications with the proposed UNANR system.

2. The unbiased and normalized adaptive noise reduction system

An overview of the proposed UNANR system is provided in Fig. 1. The system contains procedures for signal processing that include a two-stage moving-average filter for the removal of baseline wander, and an infinite impulse response (IIR) comb filter for the removal of periodic power-line interference, which are different in relation to our previous work [24]. A noise generator is placed before the UNANR model in the system, because the focus of the present study is on the reduction of random noise in noisy ambulatory ECG recordings. The details of the aforementioned procedures, together with the adaptation process of the UNANR model, are presented in the following subsections.

2.1. Baseline wander removal with a moving-average filter

In the moving-average filter [4], the first- and second-stage averaging window lengths are set to be 1/3 and 2/3 of the length of the input signal in samples, respectively. This filter is used to extract the baseline drift and place the output signal on the isoelectric line of the ECG recording.

2.2. Comb filtering with an IIR comb filter

The transfer function of the IIR comb filter with the coefficients specified to 4-decimal-digit word length[1] is

$$H(z) = 0.9502 \frac{1 - z^{-6}}{1 + z^{-1} - 0.9004z^{-6}}. \quad (1)$$

The quality factor (Q factor) parameter of the IIR comb filter, q, is defined as the ratio of the frequency to be removed, f_0, to the filter's bandwidth, bw, i.e., $q = (2\pi f_0)/\mathrm{bw}$. The order of the IIR comb filter is determined by the ratio f_s/f_0, in which f_s represents the sampling rate of the ECG recordings. For the ECG recordings sampled at 360 Hz, which were studied in our experiments in Section 3, the IIR comb filter with an order of $360/60 = 6$ and a Q factor $q = 30$ provides the frequency response as shown in Fig. 2, which presents a comb filter with rejection bands around 60, 120, and 180 Hz. The zeros and poles of the IIR comb filter are displayed in Fig. 3. Because the order of the IIR comb filter is low, the regions of the zeros and poles appear to be close by, but they do not overlap one another. The impulse response of the IIR comb filter is shown in Fig. 4, from which we can observe

[1] We tested the effect of the coefficients represented using 4, 8, and 16 decimal digits on the IIR comb filter, and found the magnitude and phase responses of the filter to be stable in the finite-word-length implementation.

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