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An Unbiased Linear Adaptive Filter with Normalized Coefficients for the Removal of Noise in Electrocardiographic Signals

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ABSTRACT

The authors propose an unbiased linear adaptive filter (ULAF) to eliminate high-frequency random noise in electrocardiographic (ECG) signals. The ULAF does not contain a bias in its summation unit, and the filter coefficients are normalized. During the adaptation process, the normalized coefficients are updated with the steepest-descent algorithm in order to achieve efficient filtering of noisy ECG signals. The authors tested the ULAF with ECG signals recorded from 16 subjects, and compared the performance of the ULAF with that of the least-mean-square (LMS) and recursive-least-squares (RLS) adaptive filters. The filtering performance was quantified in terms of the root-mean-squared error (RMSE), normalized correlation coefficient (NCC), and filtered noise entropy (FNE). A template derived from each ECG signal was used as the reference to compute the measures of filtering performance. The results indicated that the ULAF was able to provided noise-free ECG signals with an average RMSE of 0.0287, which was lower than the second best RMSE (0.0365) obtained with the LMS filter. With respect to waveform fidelity, the proposed ULAF provided the highest average NCC (0.9964) among the three filters studied. In addition, the ULAF effectively removed more noise measured by FNE versus the LMS and RLS filters in most of the ECG signals tested.

Keywords: Adaptive Filters, Artifact Removal, ECG, Noise Reduction, Signal Processing

INTRODUCTION

The electrocardiographic (ECG) signal is the electrical manifestation of the contractile activity of the heart, and is the most commonly used biomedical signal for the detection of arrhythmia

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and diagnosis of cardiovascular diseases (Rangayyan, 2002; Tompkins, 1993). In clinical practice, however, surface recording of the ECG signal (with the frequency range of 0.05-250 Hz), obtained by placing electrodes on the subject's skin, is susceptible to several different types of artifacts. The dominant artifacts in an ambulatory ECG recording include:

- **Baseline wander:** Drift of the baseline is a type of low-frequency (< 0.5 Hz) artifact and usually caused by respiration or movement of the patient.
- **Physiological artifacts:** This type of artifact is mainly induced by muscular contractions. Electrode-motion artifact has a wide frequency range (1-5,000 Hz) and is generally considered to be the most troublesome, because it can mimic the appearance of ectopic beats and cannot be removed easily by simple filters.
- **Random noise:** Random noise could be due to the thermal effect in the instrumentation amplifiers, the recording system, and pickup of ambient electromagnetic signals by cables (Rangayyan, 2002). Random noise usually appears with high frequency; its frequency range depends on the specific source. In real-time clinical monitoring systems used during surgery, electrosurgical noise is a significant obstacle to be overcome.
- **External interference:** Examples of environmental interference are those caused by 50 or 60 Hz power-supply lines, electrode motion, radiation from lights, and radio-frequency emissions from nearby medical devices.

The stage of artifact removal is crucial in ECG monitoring systems, and fundamental for many other ECG processing applications, e.g., beat classification (Afonso, Tompkins, Nguyen, & Luo, 1999; Hu, Palreddy, & Tompkins, 1997), QRS detection (Meyer, Gavela, & Harris, 2006; Hu, Tompkins, Urrusti, & Afonso, 1993), analysis of arrhythmia (Thakor & Zhu, 1991), extraction of the fetal ECG signal from the maternal abdominal ECG (Kanjilal, Palit, & Saha, 1997; Khamene & Negahdaripour, 2000), classification of myocardial ischemia (Silipo & Marchesi, 1998), diagnosis of atrial fibrillation (Yang, Devine, & Macfarlane, 1994), ECG-based sleep apnea detection (Mita, 2007), and ECG signal data compression (Zigel, Cohen, & Katz, 2000; Hamilton, Thomson, & Sandham, 1995). Denoising the inherently nonstationary ECG signals calls for adaptive filters whose impulse response can be automatically adjusted according to the time-varying characteristics of the signal and artifacts.

The fundamental principles of adaptive filtering have been described by Widrow *et al.* (Widrow et al., 1975). The literature shows that many adaptive filtering methods have been effectively applied in diverse practical applications. Mneimneh *et al.* (Mneimneh, Yaz, Johnson, & Povinelli, 2006) utilized an adaptive Kalman filter that could effectively enhance the ECG signal from original recordings corrupted by baseline drift. Sayadi and Shamsollahi (Sayadi & Shamsollahi, 2008) modified the Kalman filter by adding more equations to present the governing equations of the model parameters, in order to implement simultaneously denoising and compression of the ECG. Xue *et al.* (Xue, Hu, & Tompkins, 1992) developed adaptive whitening and matched filters based on artificial neural networks to detect QRS complexes in ECG signals. Thakor and Zhu (Thakor & Zhu, 1991) proposed an adaptive recurrent filter to acquire the impulse response of the normal QRS complex, and then applied it to the detection of arrhythmia in ambulatory ECG recordings. Chen *et al.* (Chen, Chen, & Chan, 2006) incorporated wavelet denoising and moving-average filtering methods to implement noise reduction and real-time QRS detection. Hamilton (Hamilton, 1996) compared adaptive and nonadaptive notch filters for the removal of power-line interference at 60 Hz. Sameni *et al.* (Sameni, Shamsollahi, Jutten, & Clifford, 2007) established a framework to update the nonlinear Bayesian model on a beat-to-beat basis to filter

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