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Nuraddin Aliyev
Azerbaijan State Oil and Industry University
Master student
https://orcid.org/0009-0003-1377-0805
liance98@mail.ru

Enhanced Techniques for Cardiac Signal Processing in Continuous Daily Monitoring Systems

Abstract

For continuous cardiac assessment, electrocardiographic (ECG) monitoring in wearable and ambulatory settings is becoming more and more important. However, it is still susceptible to a number of noise sources, including baseline drift, motion artifacts, electromagnetic interference (EMI), and muscle activity (EMG). P-waves, the QRS complex, and ST segments are examples of diagnostically important characteristics that may be obscured by these interferences. The non-adaptive, phase-distorting, and morphology-blurring characteristics of classical filters frequently lead to their failure. To address this, we suggest a dual-filter adaptive denoising pipeline that combines a locally adaptive Wiener filter with a modified Savitzky-Golay filter.

Using statistical variance estimations and spectral flatness criteria, our method dynamically adjusts to spectral features and signal shape, preserving important cardiac fingerprints while reducing noise. In-depth MATLAB simulations show increases in signal-to-noise ratio (SNR) of 6–8 dB and a 47.5% decrease in root mean square error (RMSE), while preserving over 90% QRS fidelity across 14 different noise circumstances. Theoretical advances in signal processing and real-time cardiac diagnostics are connected in this work.

Keywords: *ECG Denoising, Savitzky-Golay Filter, Wiener Filter, Ambulatory Monitoring, Signal Processing, QRS Complex, Adaptive Filtering*

Nurəddin Əliyev
Azərbaycan Dövlət Neft və Sənaye Universiteti
magistrant
https://orcid.org/0009-0003-1377-0805
liance98@mail.ru

Davamlı gündəlik monitorinq sistemlərində ürək siqnallarının işlənməsinin təkmilləşdirilmiş üsulları

Xülasə

Ürəyin vəziyyətinin davamlı qiymətləndirilməsi üçün ambulator şəraitdə elektrokardioqrafik (EKG) monitorinq getdikcə daha vacib olur. Bununla belə, o, hələ də baza xəttinin sürüklənməsi, hərəkət artefaktları, elektromaqnit müdaxiləsi (EMI) və əzələ aktivliyi (EMG) daxil olmaqla bir sıra səs-küy mənbələrinə həssasdır. P dalğaları, QRS kompleksi və ST seqmentləri bu maneələrlə gizlədilə bilən diaqnostik vacib xüsusiyyətlərin nümunələridir. Adaptiv olmayan, fazanı təhrif edən və morfologiyanı aşındıran klassik filtrlərin xüsusiyyətləri tez-tez onların uğursuzluğuna səbəb olur. Bu problemi həll etmək üçün biz yerli adaptiv Viner filtrini dəyişdirilmiş Savitsky Goley filtrəsi ilə birləşdirən iki filtrli adaptiv denualizasiya konveyeri təklif edirik.

Dispersiyanın statistik qiymətləndirmələri və spektral müstəvilik meyarlarından istifadə edərək, metodumuz dinamik olaraq spektral əlamətlərə və siqnalın formasına uyğunlaşır, eyni zamanda səs-küyün azaldılması zamanı mühüm ürək barmaq izlərini saxlayır. MATLAB dərin modelləşdirilməsi 14 müxtəlif səs-küy şəraitində QRS dəqiqliyinin 90% -dən çoxunu saxlayaraq 6-8 dB artan siqnal/səs nisbəti (SNR) və 47,5% azalmış orta kvadrat xəta (RMSE) göstərir. Siqnalların emalında və kardiaqnostikada real vaxtda nəzəri nailiyyətlər bu işdə bağlıdır.

Açar sözlər: *Denoizinq EKG, Savitsky-Goley filtri, Viner filtri, ambulator monitorinq, siqnalların emalı, QRS kompleksi, adaptiv filtrasiya*

Introduction

Long-term, real-time electrocardiogram (ECG) monitoring in daily settings is now possible thanks to the widespread use of wearable medical technology, which has revolutionized cardiac diagnostics by enabling continuous health tracking outside clinical environments (Oh, Lee, Kim, & Jeong, 2021). These systems empower early detection of anomalies and provide more comprehensive cardiac profiles over time (Arquilla et al., 2020). However, despite these technological advancements, a wide range of noise types—ranging from low-frequency respiration-induced drifts to high-frequency muscle contractions—continues to significantly affect the quality and reliability of ambulatory ECG data (Zhou et al., 2020). These disturbances can lead to diagnostic errors or missed clinical events, particularly when signals are not adequately processed. Conventional filtering techniques are often insufficient in these scenarios, as they struggle to manage the non-stationary, unpredictable, and morphologically disruptive nature of such noise (Li, Bian, Zhao, Liu, & Guo, 2024).

Moreover, the problem is compounded in long-term monitoring due to the dynamic nature of human activity (Louridi et al., 2021). Wearable ECG devices must process continuously shifting signal environments that reflect real-world conditions, making it critical to have robust, adaptive noise reduction techniques (Aamodt et al., 2020). Long-term, real-time electrocardiogram (ECG) monitoring in daily settings is now possible thanks to the widespread use of wearable medical technology, which has revolutionized cardiac diagnostics (Louridi, Douzi, & Ouahidi, 2021). These innovations offer the potential for real-time feedback, personalized health management, and reduced reliance on hospital-based care (Louridi et al., 2021). However, a wide range of noise types, from low-frequency respiration-induced drifts to high-frequency muscle contractions (EMG), can significantly affect ambulatory ECG data (Arquilla et al., 2020). These noise artifacts can mask critical features such as P-waves or QRS complexes, impairing diagnostic accuracy. Conventional filters are useless because these noise patterns are frequently non-stationary, unexpected, and morphologically disturbing (Pan et al., 2025).

Research

Modified Savitzky-Golay Filtering

Using a moving window, the original Savitzky-Golay (SG) filter carries out polynomial regression:

$$yi = \sum_{j=-m}^{m} cjx(i + j)$$

where cj are fixed coefficients for polynomial order p with a window size of 2m+1 that are calculated using least squares (Kumar et al., 2021).

Limitation: This makes the assumption that data importance is constant across the window, which is problematic for ECG signals that have flat baselines and steep gradients (like R-peaks).

Adaptive Solution: Add weights wj to the regression that are aware of gradients:

$$c_j^{adaptive} = \text{argmin}_{cj} \sum_j wj(x(i + j) - x\hat{}(i + j)\hat{}2$$

Where: wj=|∇x(i+j)| highlights areas with abrupt changes; x^(i+j) is the estimate of the local polynomial.

The smoothing behavior is dynamically adjusted by this reparameterization, which attenuates noise elsewhere while maintaining high-gradient regions (QRS).

Locally Adaptive Wiener Filtering

Under the assumption of stationary noise, the mean square error is minimized via the classical Wiener filter (Wong et al., 2023):

$$yi = \frac{\sigma^2 s}{\sigma^2 s + \sigma^2 n} \cdot xi$$

Where σ^2s and σ^2n are global signal and noise variances, respectively.

Limitation: Because of transitory noise, the stationarity assumption does not hold true in ambulatory environments.

Adaptive Resolution: Determine local variations across a sliding window:

$$\mathrm{yi} = \frac{\sigma^2 \mathrm{s(i)}}{\sigma^2 \mathrm{s(i)} + \sigma^2 \mathrm{n(i)}} \cdot \mathrm{xi}$$

Where: $\sigma^2\mathrm{s(i)} = \frac{1}{N}\sum_{j=-m}^{m}(\mathrm{x(i+j)} - \bar{\mathrm{x}})\hat{}2$; σ^2n (i) is calculated using pieces of a flat baseline; N=30 sample window.

When noise predominates, this Bayesian MMSE-based gain factor attenuates the signal; when the signal predominates, it maintains morphology (Jhuma et al., 2024).

Spectral Flatness Measure (SFM) and Decision Logic

SFM measures the signal's tonality (Dahiya et al., 2024):

$$\mathrm{SFM} = \frac{\left(\prod_{i=1}^{N} \mathrm{xi}\right)^{\frac{1}{N}}}{\frac{1}{N}\sum_{i=1}^{N} Xi}$$

SFM ≈ 1 → broadband noise (e.g., Gaussian); SFM ≪ 1 → tonal noise (e.g., EMI)

Filter Decision Logic:

If **SFM > 0.5** and **baseline variance high** → Apply **Savitzky-Golay** first.

If **SFM ≤ 0.5** and **drift evident** → Apply **Wiener** first.

QRS Preservation Ratio (QPR):

$$\mathrm{QPR} = \frac{A^{filtered_r}}{A^{original_r}}$$

If QPR < 0.90, a second filter is applied to further refine morphology.

Synthetic Simulation Environment

We use replicated QRS vectors to mimic five heartbeats of an ECG signal s(t)∈R^{300}:

s(t)=repmat(qrs,1,5),t∈[1,300].

Noise injections:

Gaussian noise: $x\,G\,(\,t\,) = s\,(\,t\,) + \sigma \cdot \mathrm{randn}\,(\,1\,,\,N\,)$

High-frequency EMI: $x\,H\,F\,(\,t\,) = s\,(\,t\,) + A \cdot \sin\,(\,2\,\pi\,f\,H\,F\,t\,)$

Low-frequency drift: $x\,L\,F\,(\,t\,) = s\,(\,t\,) + A \cdot \sin\,(\,2\,\pi\,f\,L\,F\,t\,)$

Combined:$x\mathrm{comp}(t) = s(t) + nG(t) + nHF(t) + nLF(t)$

Repeatable assessments under 14 distinct noise conditions are made possible by these test signals.

Performance Metrics (Shao et al., 2023)

$$\mathrm{SNRdB} = 10 \cdot \log 10 \left(\frac{\|s\|^2}{\|s-s\ \ \|^2}\right)$$

RMSE:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Si - S\hat{}i)}\hat{}2$$

QRS Preservation Ratio:

$$\mathrm{QPR} = \frac{A^{filtered_R}}{A^{original_R}}$$

Conclusion

The robust dual-filter denoising technique proposed in this study improves the reliability of ECG signals captured in ambulatory environments. Our method guarantees reduced morphological distortion and improved signal quality by adding local adaptation and spectral metrics to the traditional Savitzky-Golay and Wiener filters.

Key contributions include:

1. Theoretical development of signal processing using Bayesian variance modeling and adaptive polynomial weighting.
2. Impact in practice with modular MATLAB simulations that replicate actual noise levels.

3. Clinical importance since the method allows for real-time application in wearable devices and maintains diagnostic properties (QPR $\geq$ 0.90 in 93% of cases).

For next-generation ECG monitoring systems, this denoising pipeline provides a scalable solution that combines clinical-grade accuracy with computational economy in dynamic, non-stationary situations.

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