Reinforcement Learning for Dynamic Filter Design: Application to ECG Baseline Wander Removal

Masoud Nateghi[1]

[1] Department of Biomedical Informatics, Emory University, USA

E-mail: masoud.nateghi@emory.edu

Background

Electrocardiogram (ECG) is a vital diagnostic tool that provides critical insights into cardiac health by recording the electrical activity of the heart. However, the acquisition of clean ECG signals is often challenged by various types of noise, including power line interference, muscle artifacts, baseline wander, and motion artifacts, which can mask important diagnostic features and potentially lead to misdiagnosis. This makes ECG denoising a crucial preprocessing step in both clinical settings and remote health monitoring systems. Effective denoising techniques help preserve the morphological characteristics of key ECG components like P waves, QRS complexes, and T waves while removing unwanted noise, enabling healthcare providers to make more accurate diagnoses of cardiac conditions.

Baseline wander (Figure 1) is one of the most significant sources of noise in ECG recordings, primarily caused by patient respiration, body movements, and poor electrode contact. Its removal is crucial for accurate ECG interpretation since baseline drift can mask subtle but clinically significant ECG features and complicate both manual analysis and automated detection algorithms. However, removing baseline wander presents a challenging trade-off: while baseline wander typically occupies the very low frequency spectrum (usually below 0.5 Hz), it partially overlaps with some clinically important low-frequency ECG components. Conventional approaches using fixed low-pass or high-pass filters can inadvertently distort critical diagnostic

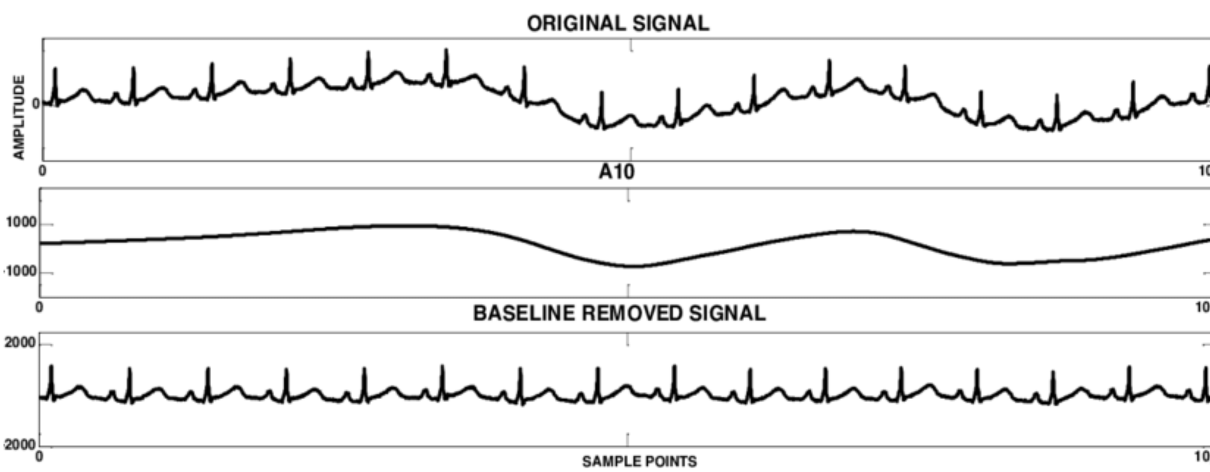

Figure 1: From top to bottom: ECG signal contaminated by baseline wander, baseline wander signal, and the denoised ECG signal [1].

features of the ECG, particularly the ST segment and QT interval, which contain valuable low-frequency components. This is especially problematic because these intervals are vital markers for various cardiac conditions - ST segment changes can indicate myocardial ischemia or infarction, while QT interval abnormalities may signal increased risk of life-threatening arrhythmias. Therefore, we propose an RL-based adaptive filtering approach that can dynamically adjust its cutoff frequency based on the specific characteristics of different ECG segments appears essential. Such an approach would provide more precise baseline wander removal while preserving the integrity of crucial low-frequency diagnostic features in the ECG signal.

Problem Formulation

The ECG denoising problem can be formulated as a reinforcement learning task with the following components:

Environment and States: The cardiac system serves as our environment, which we observe through ECG recordings. These recordings contain both the cardiac electrical activity (the signal of interest) and various noise components, particularly baseline wander. The observable states are the raw ECG measurements, which can be represented as:

$$x(t) = s(t) + b(t)$$

where s(t) is the clean ECG signal and b(t) is the baseline wander component.

RL Agent Design: The agent is implemented as an adaptive 1-parameter low-pass filter with tunable parameter which is formulated as follows:

$$H(z, \alpha) = \frac{1 - \alpha}{1 - \alpha z^{-1}}$$

This parameter, particularly the cutoff frequency (f_c), is learned and refined through multiple episodes of interaction with the environment. At the end of training phase, the agent learns to select the optimal filter parameter that best separate the baseline wander from the physiological ECG components for each segment of the ECG signal adaptively. Since we did not assume any explicit model for the environment, **a model-free algorithm will be employed for the training process of the agent which is suitable for continuous action space.**

Action: The action space consists of the filtering operation with the selected parameters. When the agent selects a particular cutoff frequency, the filtering process produces two estimates:

$$\hat{b}(t) = LPF(x(t), f_c)$$

$$\hat{s}(t) = x(t) - \hat{b}(t)$$

Reward: The reward function is designed based on a periodicity measure using the Rayleigh quotient. For a given signal $y(t)$ this measure can be defined as below [2, 3]:

$$\epsilon(y(t),\tau) = \frac{E_t\{y(t)y(t+\tau)\}}{E_t\{y(t)^2\}}$$

Where τ is the period of the estimate which can be estimated by peak detection and RR-interval.

This approach leverages the fundamental difference between the quasi-periodic nature of the ECG signal and the aperiodic characteristics of baseline wander.

Therefore, the reward can be formulated as:

$$R = \frac{\epsilon(\hat{s}(t),\tau)}{\epsilon\big(\hat{b}(t),\tau\big)}$$

This ratio should be maximized, as we expect high periodicity in the clean ECG signal (numerator) and low periodicity in the baseline wander component (denominator). This reward structure guides the agent to find filter parameters that optimally separate the periodic ECG components from the aperiodic baseline drift while preserving critical low-frequency features in segments like the ST interval and QT segment.

Experiments and Benchmarks

To validate our proposed reinforcement learning-based adaptive filtering approach, we will conduct comprehensive experiments using the PTB-XL dataset [4]. PTB-XL is one of the largest publicly available electrocardiogram datasets, containing 21,799 clinical 12-lead ECG records from 18,869 patients. This dataset is particularly suitable for our study as it includes ECGs of varying quality and contains detailed annotations of ECG characteristics and diagnostic findings.

Alternative RL agents

While our initial approach employs a simple one-parameter low-pass filter as the RL agent, we can explore more sophisticated filtering structures that could potentially enhance baseline wander removal performance. These alternatives include second-order low-pass filters where the RL agent learns to optimize multiple filter coefficients simultaneously, auto-regressive (AR) filters with fixed coefficients allowing for more complex frequency responses, and time-varying AR filters that can adapt their coefficients based on local signal characteristics. Each of these structures offers different degrees of flexibility in shaping the filter's frequency response, potentially leading to more effective baseline wander removal while preserving critical ECG features. The increased complexity of these filters expands the action space of the RL agent, requiring more sophisticated learning strategies but potentially yielding superior results.

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