ECG denoising using a model-based RL framework

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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.

The project aims to develop a novel approach to ECG denoising by formulating it as a model-based reinforcement learning (RL) problem. At its core, the approach leverages established dynamical models for ECG signals presented in the literature [1, 2].

Just as a robotic arm controller uses a physics-based model of the arm's dynamics to learn optimal control policies, this approach will utilize the mathematical model of ECG generation to learn optimal denoising strategies. Two potential mathematical formulations of the ECG dynamics can be considered:

1. The Cartesian model [1] which describes the ECG dynamics as:

$$\begin{aligned}\dot{x} &= \alpha x - \omega y\\ \dot{y} &= \alpha y + \omega x\\ \dot{z} &= -\sum_{i\in\{P,Q,R,S,T\}} a_i \Delta\theta_i \exp\left(-\frac{\Delta\theta_i^2}{2b_i^2}\right) - (z - z_0)\end{aligned} \quad (1)$$

where (x, y, z) represent the state variables and z corresponds to the ECG signal.

2. The polar coordinate model [2] which offers a simplified representation:

$$\begin{aligned}\dot{r} &= r(1-r)\\ \dot{\theta} &= \omega\\ \dot{z} &= -\sum_{i\in\{P,Q,R,S,T\}} \frac{\alpha_i \omega}{b_i^2} \Delta\theta_i exp(-\frac{\Delta\theta_i^2}{2b_i^2}) - (z - z_0)\end{aligned} \quad (6)$$

where θ represents the phase of cardiac events and z represents the ECG amplitude.

Drawing a parallel to robotic control, where controllers use physics-based models to learn optimal manipulation policies, this approach will utilize these mathematical models of ECG generation to learn optimal denoising strategies. Just as a robotic controller learns to map noisy sensor readings to precise actuator commands, our RL agent will learn to map noisy ECG measurements to clean ECG signals by leveraging the underlying dynamic model.

The key innovation lies in treating the ECG denoising task as a control problem where the RL agent learns to "steer" a noisy ECG signal back to its clean underlying dynamics. The state space will be defined by the three-dimensional system of differential equations from [1,2] model (x, y, z coordinates or r, θ, and z coordinates), where the z-coordinate represents the ECG signal. The action space will consist of correction terms that the agent can apply to the noisy measurements to recover the true signal. The reward function can be designed to minimize the difference between the denoised signal and the expected dynamics described by the model.

The most compelling aspect of this approach is that it incorporates explicit domain knowledge through the dynamical model, unlike pure data-driven approaches. Models in [1, 2] capture key physiological features like the PQRST wave morphology, beat-to-beat variations, and respiratory influences. By using this as the environment model for RL, the denoising agent can learn policies that respect the underlying cardiac dynamics while removing noise. This is analogous to how model-based RL for robotic control leverages physics models to learn physically plausible policies.

A key challenge will be adapting the continuous dynamical model into a suitable format for RL training, potentially requiring discretization or function approximation techniques. Additionally, careful consideration must be given to designing reward signals that promote both noise removal and preservation of clinically relevant features. The project could be evaluated using synthetic data generated from the model with various noise types, as well as real ECG recordings from standard databases.

References

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