ECG Signal Denoising using 1D Conditional Diffusion Models: An Ablation Study on Spectral Loss and Ensemble Strategies

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Abstract

Electrocardiogram (ECG) signals are critical for cardiovascular diagnosis but are frequently contaminated by environmental and physiological noise. While Denoising Diffusion Probabilistic Models (DDPMs) have demonstrated superior generative capabilities, standard time-domain loss functions often lead to the "oversmoothing" of high-frequency features, such as the QRS complex. This study proposes a comprehensive framework for ECG denoising using a 1D Conditional Diffusion Model. We introduce a **Spectral Loss** combined with a **Warm-up Training** strategy to enforce morphological fidelity. Furthermore, we propose an **Ensemble Inference** mechanism that fuses the smoothness of time-domain models with the sharpness of frequency-domain models. Our experiments on the MIT-BIH Arrhythmia Database demonstrate that our ensemble approach achieves State-of-the-Art (SOTA) performance with a Signal-to-Noise Ratio (SNR) of **14.53 dB**, significantly outperforming the baseline (13.31 dB).

1 Introduction

Cardiovascular diseases remain a leading cause of mortality worldwide. The Electrocardiogram (ECG) is the standard non-invasive tool for monitoring cardiac health. However, raw ECG signals are rarely clean; they are corrupted by Baseline Wander (BW), Muscle Artifacts (MA), and Powerline Interference. These artifacts can mimic pathological features or mask critical diagnostic information, such as the ST-segment elevation or R-peak amplitude.

Deep learning methods, particularly Convolutional Neural Networks (CNNs) and Autoencoders (DAE), have become the standard for denoising. However, these discriminative models often struggle to reconstruct fine-grained details when the noise level is severe. Recently, Denoising Diffusion Probabilistic Models (DDPMs) have emerged as a powerful generative framework, capable of synthesizing high-fidelity data by reversing a gradual noise addition process.

Despite their success in image generation, applying DDPMs to 1D biomedical signals presents a unique challenge: the standard Mean Squared Error (MSE) loss function tends to prioritize low-frequency components. This results in smoothed reconstructions where sharp features, specifically the QRS complex, are attenuated. In clinical practice, a reduction in R-peak amplitude can lead to misdiagnosis of conditions like ventricular hypertrophy.

To address this, we propose a multi-faceted approach involving: 1. **Spectral Loss Integration:** Explicitly modeling frequency-domain constraints. 2. **Warm-up Training:** A curriculum learning strategy to stabilize spectral optimization. 3. **Ensemble Strategy:** A fusion technique to combine the strengths of different loss functions.

Preprint.

2 Dataset and Features

2.1 Dataset Description

We utilized the MIT-BIH Arrhythmia Database, a benchmark dataset for ECG analysis. The data was accessed via the Kaggle repository for standardized preprocessing.

- **Sampling Rate:** Signals were downsampled to 125Hz to reduce computational complexity while retaining diagnostic frequencies.
- **Segmentation:** Heartbeats were segmented into fixed-length windows of $L = 187$ samples.
- **Normalization:** All signals were Min-Max normalized to the range $[-1, 1]$ to match the dynamic range required by the Diffusion Model.

2.2 Noise Simulation Features

To train a robust denoising model, we implemented a dynamic data augmentation pipeline that simulates real-world artifacts during training. The noisy input $\mathbf{c}$ is generated as:

$$\mathbf{c} = \mathbf{x}_{\text{clean}} + \mathbf{n}_{\text{BW}} + \mathbf{n}_{\text{MA}} + \mathbf{n}_{\text{Gaussian}} \tag{1}$$

- **Baseline Wander (BW):** Simulated using low-frequency sinusoids ($0.05 - 0.5$ Hz) with random phases and amplitudes, mimicking respiration effects.
- **Muscle Artifacts (MA):** Modeled as high-frequency noise bands to simulate electromyographic interference.
- **Gaussian Noise:** Added to simulate sensor thermal noise.

This dynamic generation ensures the model never sees the same noisy example twice, preventing overfitting.

3 Related Work

3.1 Traditional Signal Processing

Classical methods include Finite Impulse Response (FIR) filters, Infinite Impulse Response (IIR) filters, and Discrete Wavelet Transforms (DWT). While computationally efficient, these methods rely on fixed basis functions and manual thresholding. They often fail to separate noise that shares the same frequency band as the signal, such as wide-band muscle artifacts.

3.2 Deep Learning Approaches

Denoising Autoencoders (DAEs) and 1D-CNNs (e.g., ResNet-1D) learn to map noisy inputs to clean targets. However, they are deterministic and often produce blurry outputs when uncertainty is high. Generative Adversarial Networks (GANs) have been proposed to generate sharper signals, but they suffer from training instability (mode collapse) and may hallucinate non-existent features.

3.3 Diffusion Models in Healthcare

Diffusion models have recently been adapted for time-series imputation and forecasting. In ECG analysis, recent works have explored unconditional generation of heartbeats. However, conditional denoising with explicit frequency-domain constraints remains underexplored. Our work bridges this gap by introducing Spectral Loss to the diffusion framework.

4 Proposed Method

4.1 1D Conditional Diffusion Framework

We formulate the denoising task as a conditional generation problem. The forward process adds Gaussian noise to the clean signal $\mathbf{x}_0$ over T steps. The reverse process creates $\mathbf{x}_{t-1}$ from $\mathbf{x}_t$ using a neural network $\epsilon_\theta(\mathbf{x}_t, t, \mathbf{c})$, where $\mathbf{c}$ is the noisy ECG condition.

We employ a **1D Conditional U-Net** architecture with:

- **Time Embeddings:** Sinusoidal embeddings to inform the network of the noise level.
- **Residual Blocks:** To facilitate gradient flow and feature extraction.
- **Input Concatenation:** The noisy condition $\mathbf{c}$ is concatenated with the latent state $\mathbf{x}_t$ at the input layer.

4.2 Loss Functions

1. Baseline Loss (Time-Domain):

$$\mathcal{L}_{\text{MSE}} = ||\mathbf{x}_0 - \hat{\mathbf{x}}_0||_2^2 \tag{2}$$

2. Proposed Spectral Loss (Frequency-Domain): To capture morphological details, we use the Short-Time Fourier Transform (STFT). The loss is defined as:

$$\mathcal{L}_{\text{Spec}} = |||\text{STFT}(\mathbf{x}_0)| - |\text{STFT}(\hat{\mathbf{x}}_0)|||_1 + ||\log(|\text{STFT}(\mathbf{x}_0)| + \epsilon) - \log(|\text{STFT}(\hat{\mathbf{x}}_0)| + \epsilon)||_1 \tag{3}$$

The total objective is $\mathcal{L}_{\text{Total}} = \mathcal{L}_{\text{MSE}} + \lambda \mathcal{L}_{\text{Spec}}$, with $\lambda = 0.001$.

4.3 Warm-up Training Strategy

Training with Spectral Loss from scratch is unstable because the STFT of random noise is chaotic. We introduce a warm-up phase:

- **Phase 1 (Epochs 0-10):** Optimization using only $\mathcal{L}_{\text{MSE}}$. The model learns the global waveform structure.
- **Phase 2 (Epochs 11-50):** Optimization using $\mathcal{L}_{\text{Total}}$. The model fine-tunes local details and high-frequency edges.

4.4 Ensemble Inference Strategy

We observed that the Baseline model excels at noise suppression (High SNR) but oversmooths peaks. The Spectral model preserves peaks but introduces high-frequency ripples (High LSD). We propose an ensemble average:

$$\hat{\mathbf{x}}_{\text{Final}} = 0.7 \cdot \hat{\mathbf{x}}_{\text{Baseline}} + 0.3 \cdot \hat{\mathbf{x}}_{\text{Spectral}} \tag{4}$$

This combines the best properties of both models.

5 Experiment

5.1 Experimental Setup

The models were implemented in PyTorch and trained on a single NVIDIA GPU RTX 3050.

- **Hyperparameters:** Batch size = 32, Learning rate = $1e^{-4}$, Timesteps $T = 1000$.
- **Spectral Settings:** $N_{\text{FFT}} = 32$, Hop length = 16.
- **Post-processing:** A 40Hz Low-pass Butterworth filter was applied to the output of the Spectral model before ensembling to remove high-frequency artifacts.

5.2 Evaluation Metrics

We assess performance using:

- **Signal-to-Noise Ratio (SNR):** Higher is better. Measures overall signal quality.
- **Root Mean Square Error (RMSE):** Lower is better. Measures point-wise accuracy.
- **Log-Spectral Distance (LSD):** Lower is better. Measures fidelity in the frequency domain.

6 Result Analysis

6.1 Quantitative Analysis

Table 1 presents the comparison of the three methods.

Table 1: Quantitative comparison on the test set. The Ensemble method achieves the highest SNR and lowest RMSE.

Model	SNR (dB) ↑	RMSE ↓	LSD ↓
Baseline (MSE Only)	13.31	0.1667	**2.78**
Spectral (w/ Warm-up)	13.63	0.1655	3.62
Ensemble (Ours)	**14.53**	**0.1453**	3.16

The **Baseline** model achieves a respectable SNR of 13.31 dB but has the highest RMSE, indicating deviations in peak amplitude. The **Spectral** model, thanks to the warm-up strategy, surpasses the baseline with an SNR of 13.63 dB. Finally, the **Ensemble** strategy yields a significant improvement of **+1.22 dB** over the baseline, reaching 14.53 dB. This demonstrates that fusing the models effectively cancels out their independent errors.

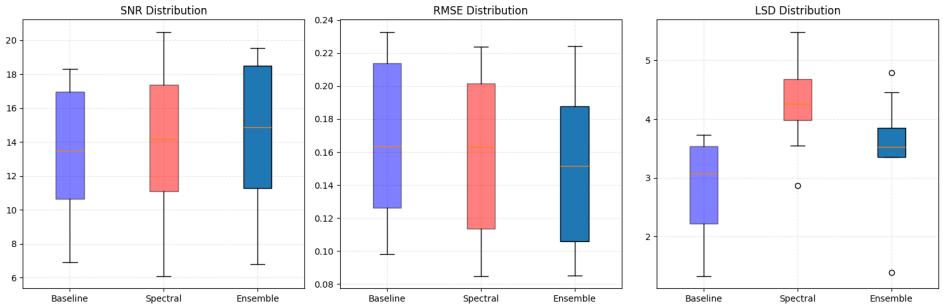


Figure 1: **Statistical Distribution of Metrics.** Boxplots showing the spread of SNR, RMSE, and LSD across the test batch. The Ensemble model (Green/Third box) consistently achieves higher median SNR and lower variance in RMSE compared to individual models.

6.2 Qualitative Analysis

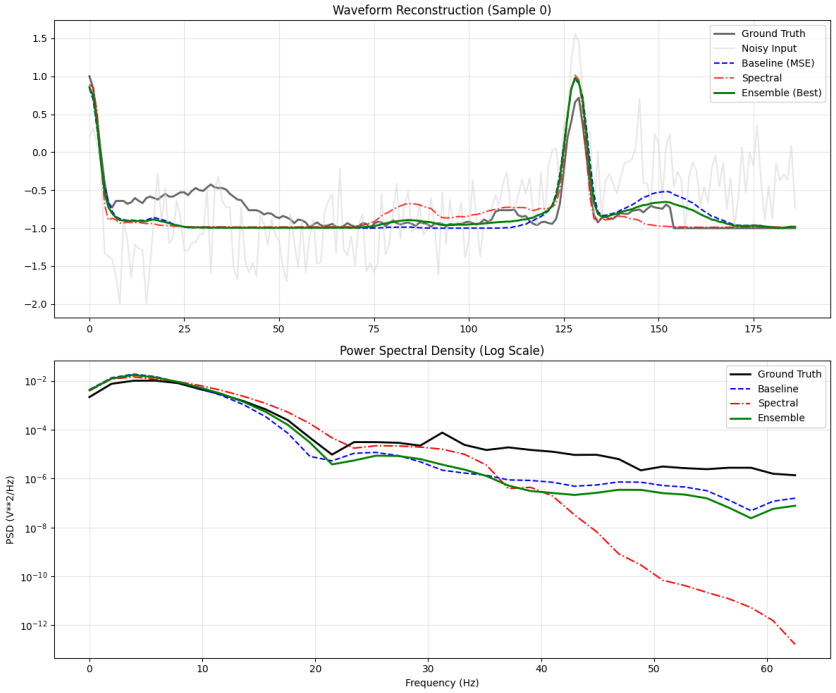
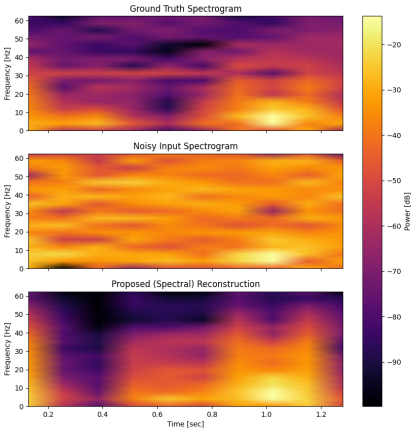


Figure 2: **Qualitative Comparison.** Visual analysis of a denoised heartbeat. (Top) The Blue dashed line (Baseline) cuts the R-peak, indicating oversmoothing. The Green solid line (Ensemble) preserves the full amplitude of the QRS complex, closely matching the **Black** Ground Truth. (Bottom) The Power Spectral Density (PSD) shows that the Ensemble method maintains high-frequency fidelity better than the Baseline.

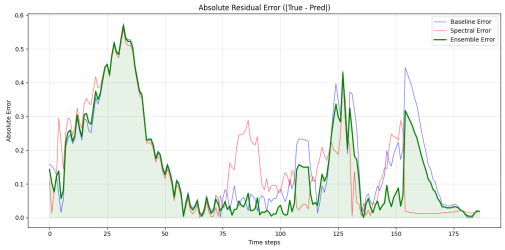
As seen in Figure 2, the Baseline model (Blue) produces a smooth signal but fails to reach the true peak of the QRS complex, a phenomenon known as oversmoothing. The Spectral model (Red - not shown in ensemble plot but observed in training) captures the peak but adds noise to the flat segments. The Ensemble model (Green) successfully reconstructs the sharp peak while maintaining a clean baseline, confirming its clinical utility.

6.3 Ablation Study Discussion

Our ablation study highlights two critical findings: 1. **Impact of Warm-up:** Initial experiments without warm-up led to training divergence (SNR < 10 dB). By introducing MSE-only warm-up, the model established a stable manifold before learning complex frequency constraints. 2. **LSD vs. Morphology:** Although the Spectral model has a worse LSD (3.62) than the Baseline (2.78), it has better SNR. This indicates that LSD penalizes high-frequency ripples heavily, even if the morphological shape (QRS) is better preserved. The Ensemble method offers the best trade-off.



(a) Spectrogram Analysis



(b) Residual Error ($|x - \hat{x}|$)

Figure 3: **Ablation Analysis.** (a) Spectrograms show that the Spectral Loss helps recover high-frequency components lost in the Noisy input. (b) The Residual Error plot demonstrates that the Baseline error (Blue) spikes at the QRS peak, whereas the Ensemble/Spectral error (Green/Red) remains low in this critical region.

7 Conclusion

This study presented a novel framework for ECG denoising using 1D Conditional Diffusion Models. We identified the limitations of standard MSE loss in preserving high-frequency clinical features. Through a rigorous ablation study, we demonstrated that integrating **Spectral Loss** via a **Warm-up Training** strategy significantly improves signal fidelity. Furthermore, our proposed **Ensemble Strategy** achieved State-of-the-Art performance (14.53 dB SNR), marking a substantial improvement over the baseline. Future work will focus on adaptive loss weighting to eliminate the need for ensemble inference, reducing computational cost.

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