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Cardiac Insights On-the-Go: Inexpensive Continuous ECG Monitoring from PPG using Diffusion Models

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Problem statement

- Cardiovascular diseases (CVDs) cause approximately 17.9 million annual deaths, emphasizing the need for accessible and cost-effective cardiac monitoring to prevent them.
- ECG is the gold standard but requires specialized equipment and expertise.
- Continuous ECG is preferred for comprehensive assessment and detecting challenging CVDs like AFib, but reliable continuous ECG is not available in consume-grade wearables for daily use.
- PPG offers non-invasive monitoring in consumer-grade wearables but lacks detailed cardiac information.
- PPG-to-ECG translation combines PPG's convenience with ECG's diagnostic utility, enabling cheap consumer-grade wearables for continuous cardiac monitoring.

Our contributions

- We introduce Region-Disentangled Diffusion Model (RDDM), a novel diffusion model for high-fidelity PPG-to-ECG translation. **To the best of our knowledge, this is the first diffusion model for cross-modal signal-to-signal translation in the bio-signal domain.**
- Our proposed RDDM introduces a novel approach that disentangles the diffusion process into two distinct components. The first component captures the global temporal structure of ECG signals, while the second component is dedicated to capture the fine-grained local details. This enables RDDM to generate high-fidelity ECG and do so in just 10 sampling steps making RDDM highly-efficient.
- To evaluate the quality and utility of the generated ECG signals, we introduce CardioBench, a comprehensive evaluation benchmark comprised of 5 challenging cardiac-related tasks.
- **Our extensive evaluations exhibit that the ECG signals generated by RDDM are significantly better in quality than DDPMs and prior works in both standard quantitative measures and their performance on CardioBench tasks**.

Broader impact

The implications of our work are promising for continuous cardiac monitoring. The ability of RDDM to translate the more basic PPG signals into more comprehensive and informative ECG brings the gold standard of cardiac monitoring closer to the realm of consumer wearables. This represents a significant advancement towards more accessible, cost-effective, and continuous cardiac monitoring, and has the potential for early detection of CVDs. Looking ahead, we aim to extend RDDM to other bio-signal translation tasks, further solidifying its value and impact in the digital health domain.

Proposed method

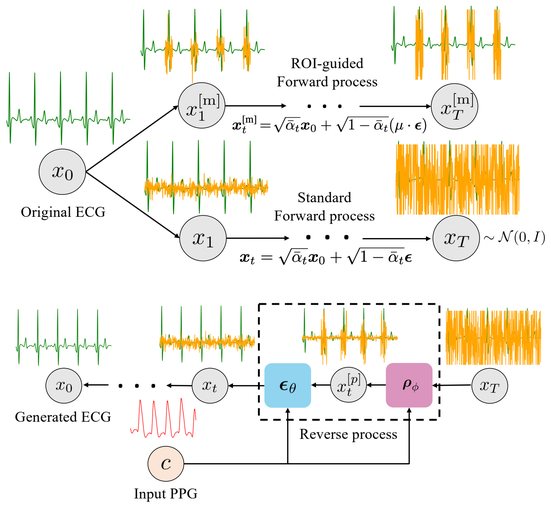

Figure 1: PPG-to-ECG translation with RDDM. **Top:** ROI-guided Forward process selectively adds Gaussian noise to the QRS regions, while standard forward process adds noise uniformly across the ECG. **Bottom:** Our reverse process involves disentangled denoising of the QRS and Non-QRS regions by ϵ_θ and ρ_ϕ respectively.

Algorithm 1: RDDM Training

repeat
  $\mathbf{x}_0 \sim q(\mathbf{x}_0)$;
  $t \sim \text{Uniform}(\{1, \dots, T\})$
  $\boldsymbol{\epsilon} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$
  Apply ROI mask: $\boldsymbol{\epsilon}^{[\text{m}]} = (\mu \cdot \boldsymbol{\epsilon})$
  Compute $x_t = \sqrt{\bar{\alpha}_t}\boldsymbol{x}_0 + \sqrt{1-\bar{\alpha}_t}\boldsymbol{\epsilon}$
  Estimate $x_t^{[\text{p}]} = \rho_\phi(x_t, c, t)$
  Compute $x_t^{[\text{m}]} = \sqrt{\bar{\alpha}_t}\boldsymbol{x}_0 + \sqrt{1-\bar{\alpha}_t}\boldsymbol{\epsilon}^{[\text{m}]}$
  Calculate gradient as
  $\nabla_{\theta,\phi}\left(\lambda_1 \left\|\boldsymbol{\epsilon}^{[\text{m}]} - \boldsymbol{\epsilon}_\theta(x_t^{[\text{m}]}, c, t)\right\|^2 + \lambda_2 \left\|x_t^{[\text{m}]} - x_t^{[\text{p}]}\right\|^2\right)$
until converged

The loss term $|(\mu \cdot \boldsymbol{\epsilon}) - \boldsymbol{\epsilon}_\theta(x_t^{[\text{m}]}, c, t)|^2$ encourages $\boldsymbol{\epsilon}_\theta$ to estimate noise that, when subtracted from the signal, refines and enhances the morphology of the ROIs. This is achieved by minimizing the difference between the noise generated by $\boldsymbol{\epsilon}_\theta$ and the ROI-specific noise $(\rho \cdot \boldsymbol{\epsilon})$ in the original data distribution. Therefore, **the role of $\boldsymbol{\epsilon}_\theta$ is to learn the fine-grained details of the ROI.** Next, the loss term $|x_t^{[\text{m}]} - \rho_\phi(x_t, c, t)|^2$ encourages ρ_ϕ to minimize the discrepancy between $x_t^{[\text{m}]}$ and the signal recovered by $\rho_\phi(x_t, c, t)$. Consequently, the function ρ_ϕ learns to denoise the non-ROI parts of the ECG signal, which implicitly involves learning 'where' to place the QRS complexes. **This results in ρ_ϕ capturing the temporal dynamics of the ECG signal**. This disentanglement makes RDDM particularly suitable for PPG-to-ECG translation, which requires capturing both the spatial and temporal characteristics of ECG signals.

Generated ECG waveforms

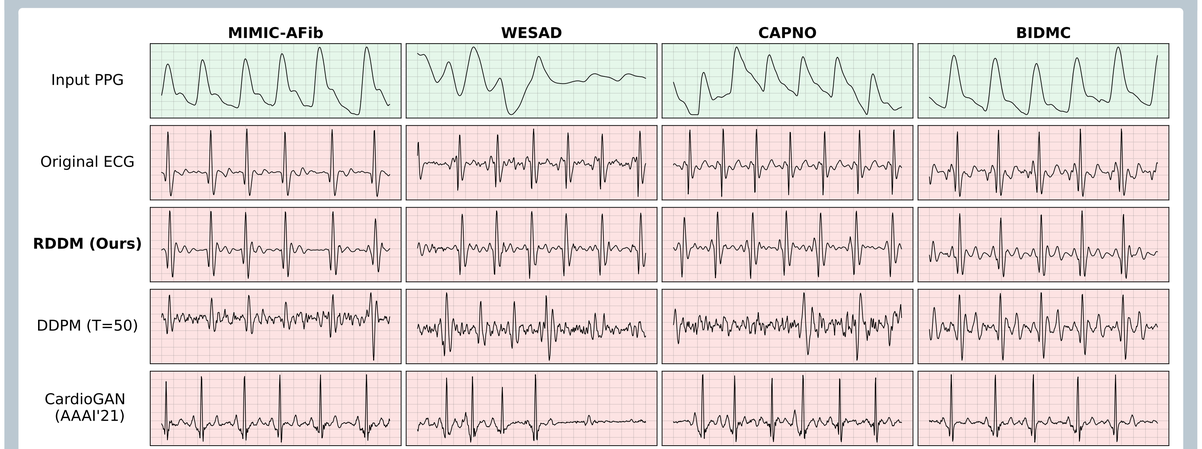

Figure 2: Qualitative comparison on generated ECG using varying nature of input PPG. RDDM consistently generates ECG that closely resembles the original ECG, even when the input PPG is noisy (e.g., WESAD), unlike CardioGAN and DDPM.

Evaluation on CardioBench

To test the utility of the generated ECG in analyzing cardiac activity, e.g., detecting CVDs, we introduce CardioBench. CardioBench is designed as a comprehensive and challenging benchmark aimed at evaluating the generated ECG signals, with a focus on their ability to facilitate the detection of a range of heart conditions. **ECG signals generated with our proposed RDDM demonstrate state-of-the-art performance on CardioBench.**

AFib detection

AFib detection in synthetic ECG demands accurate generation of non-periodic irregular rhythms, absent P waves, variable ventricular rates, possible fibrillatory waves, and temporally compressed QRS complexes.

Test modality	Classifier	Acc.(↑)	F1(↑)
Orig. ECG (Upper bound)	VGG-13	0.73	0.74
Orig. PPG	(Aliamiri and Shen 2018)*	0.61	0.55
Orig. PPG	(Shen et al. 2019)*	0.51	0.47
Gen. ECG (DDPM (T = 50))	VGG-13	0.43	0.60
Gen. ECG (RDDM (ours))	**VGG-13**	**0.65**	**0.71**

Diabetes detection

Diabetes detection from synthetic ECG involves accurate capture of the anomalies in the ECG signals induced by the disease, such as prolonged QT intervals, alterations in the QRS complex, and changes in the ST-T segment.

Test modality	Classifier	Acc.(↑)	F1(↑)
Orig. PPG	(Avram et al. 2020)*	0.65	0.44
Gen. ECG (Performer) + Orig. PPG	(Lan 2023)**	0.76	-
Gen. ECG (DDPM (T=50))	VGG-11	0.47	0.43
Gen. ECG (RDDM (ours))	**VGG-11**	**0.80**	**0.52**

Blood Pressure (BP) estimation

Estimation of BP from synthetic ECG requires an accurate representation of ECG-derived features like heart rate, P wave, QRS duration, and QT interval, all of which correlate with blood pressure levels.

Test modality	Estimator	MAE-SBP(↓)	MAE-DBP(↓)
Orig. PPG + Orig. ECG (Upper bound)	UNet	3.31	0.75
Orig. PPG	(Ibtehaz et al. 2022)	5.73	3.45
Orig. PPG	(Vardhan et al. 2021)	5.16	2.89
Orig. PPG + Gen. ECG (DDPM (T = 50))	UNet	5.95	**0.63**
Orig. PPG + Gen. ECG (RDDM (ours))	**UNet**	**2.48**	1.20

Stress and Affect detection

Stress and affect classification using generated ECG requires an accurate representation of nuanced changes in heart rate variability, sympathetic-parasympathetic balance, and emotional state-induced ECG patterns.

Test modality	Classifier	Acc.(↑)	F1(↑)
Orig. ECG (Upper bound)	(Behinaein et al. 2021)	0.75	0.68
Orig. PPG	(Schmidt et al. 2018)	0.65	0.57
Orig. PPG	(Lisowska, Wilk, and Peleg 2021)	0.58	-
Gen. ECG (DDPM (T = 50))	(Behinaein et al. 2021)	0.65	0.58
Gen. ECG (RDDM (ours))	**(Behinaein et al. 2021)**	**0.71**	**0.64**

Heart rate estimation

Accurate Heart rate (HR) estimation from synthetic ECG depends on the presence of R-peaks at the correct temporal locations with consistent RR intervals. Therefore, HR estimation is used to evaluate the temporal fidelity of generative models.

Dataset	Method	Test modality	MAE (↓)
DALIA	(Schäck et al. 2017)	Orig. PPG	20.5
	(Reiss et al. 2019)	Orig. PPG	11.1
	(Wójcikowski and Pankiewicz 2020)	Orig. PPG	6.77
	(Song, Nam, and Kim 2021)	Orig. PPG	6.02
	(Sarkar and Etemad 2021)	Gen. ECG	8.30
	DDPM (T = 50)	Gen. ECG	5.66
	RDDM (ours)	**Gen. ECG**	**4.49**
WESAD	(Schäck et al. 2017)	Orig. PPG	19.90
	(Reiss et al. 2019)	Orig. PPG	9.50
	(Sarkar and Etemad 2021)	Gen. ECG	8.60
	DDPM (T = 50)	Gen. ECG	4.67
	RDDM (ours)	**Gen. ECG**	**1.40**