The Hong Kong University of Science and Technology (Guangzhou)

Cardio-mmFlow: A Gaussian-Prior-Free Physics-Informed Flow Matching Framework for Electrocardiogram to mmWave Radar Synthesis

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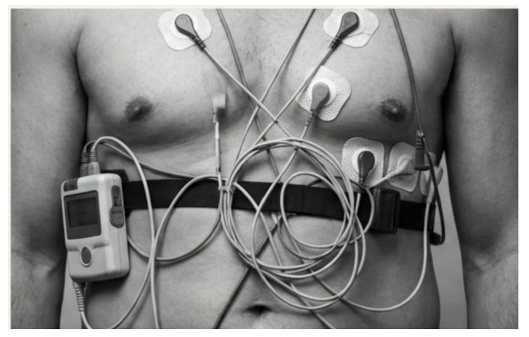
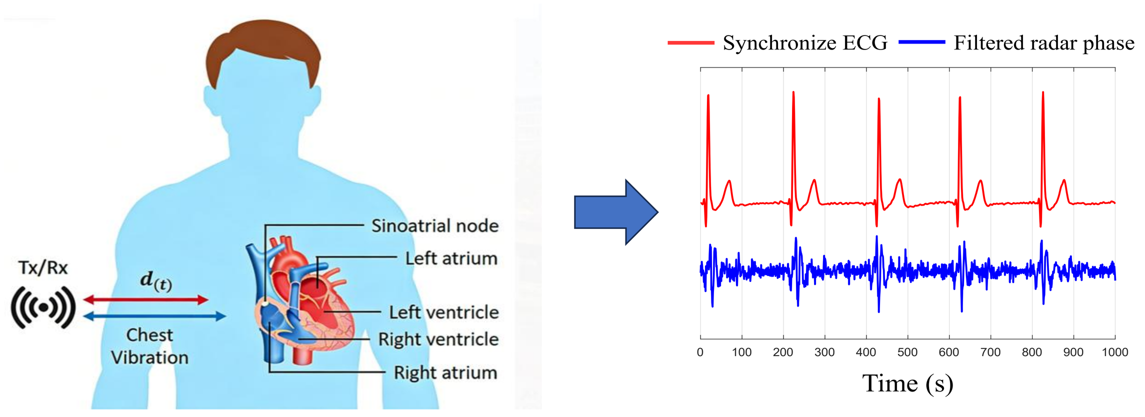
01 Introduction

Background

- Long-term ECG needs to become contactless. Electrodes limit comfort, adherence, and sleep monitoring quality.



- mmWave radar can capture the chest vibration and use Ai model to transform it to ECG.



- Data bottleneck: It is promising, but robust mmWave-to-ECG models need synchronized radar-ECG pairs, which are expensive, privacy-sensitive, and hard to scale.

Motivation

Inspired by recent advances in AI-driven data synthesis, we leverage large-scale public ECG datasets to generate diverse mmWave radar signals, thereby expanding radar-side training data without requiring extensive additional paired recordings.

Key Contributions

a) We propose Cardio-mmFlow, a physics-inspired framework for ECG-to-mmWave synthesis. To our knowledge, it is the first work to synthesize mmWave cardiac waveforms from ECG.
b) We design a Gaussian-prior-free latent flow matching model. It enables direct ECG-to-radar latent transport.
c) We introduce an MSD-inspired FiLM module. It supports subject-aware attenuation modeling with metadata.

Datasets

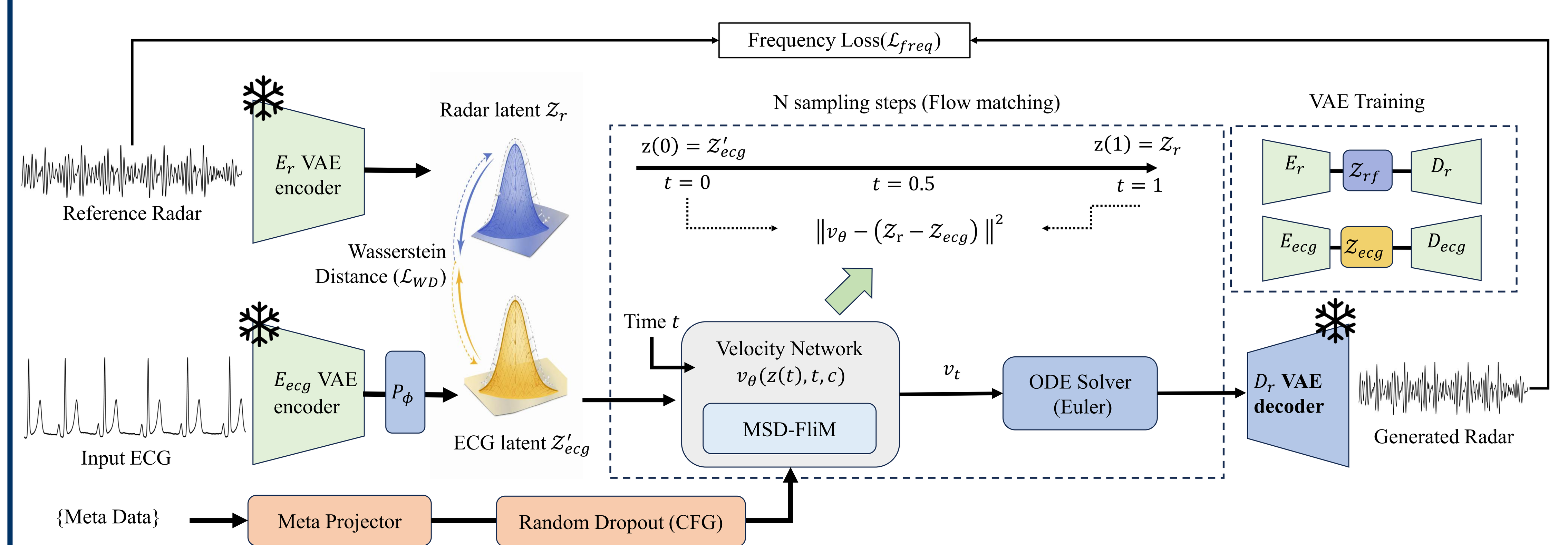
Name	Duration
Clinical radar	~24h
PTB-XL	~61h
Self-collected	~3h
AFib radar (partial)	~10 min

02 Methods

Insight

Individual differences (e.g., anatomical structure and tissue) can alter the way cardiac-induced vibrations propagate to the skin, resulting characteristics in the measured millimeter-wave signals.

Cardio-mmFlow : VAE + Direct latent flow + MSD inspired FliM + Wasserstein Distance



Training Objectives

VAE Pretraining

$$\mathcal{L}_{\mathrm{VAE}} = \mathbb{E}_{\mathbb{z}\sim\mathbb{q}(\mathbb{z}|\mathbb{x})}[\|x-\hat{x}\|_2^2] + \lambda_{\mathrm{KL}} D_{\mathrm{KL}}\big(q(z|x) \parallel p(z)\big)$$

Latent Flow Matching Training

$$\mathcal{L}_{\mathrm{total}} = \mathcal{L}_{\mathrm{FM}} + \lambda_1\mathcal{L}_{\mathrm{WD}} + \lambda_2\mathcal{L}_{\mathrm{freq}}.$$

$$\mathcal{L}_{\mathrm{FM}} = \mathbb{E}_{((\mathbb{x}_{\mathbb{0}},\mathbb{x}_{\mathbb{1}}),\mathbb{t})}[\|v_\theta(z_t,t,c) - (z_1 - \widetilde{z_0})\|_2^2],$$

$$\mathcal{L}_{\mathrm{WD}} = W_1\big(\widehat{\mathbb{P}_{\widetilde{z_0}}}, \widehat{\mathbb{P}_{z_1}}\big),$$

$$\mathcal{L}_{\mathrm{freq}} = \|S(\widehat{\mathbf{x}_1}) - S(\mathbf{x_1})\|_2^2 + \lambda_p\Big(1-\cos\Big(\mathrm{vec}\big(\Phi(\widehat{\mathbf{x}_1})\big), \mathrm{vec}\big(\Phi(\mathbf{x_1})\big)\Big)\Big)$$

Key notes: ECG latents provide a physiology-grounded starting manifold instead of unstructured Gaussian noise. Meta data controls damping-like attenuation through age, gender, height, weight, and BMI.. We adopt Classifier-Free Guidance (CFG) method which replace condition with none-token randomly.

03 Results and Conclusion

Table 1. Baseline Comparison Radar Synthesis Quality.

Method	Latent-FID ↓	MSE ↓	PSD Sim. ↑	HR-AE (bpm) ↓	#Params (M)
cGAN	15.21	0.036 ± 0.019	0.871 ± 0.085	12.56	10.7M
cVAE	29.31	0.032 ± 0.015	0.823 ± 0.110	16.72	14.4M
DiT	16.79	0.051 ± 0.021	0.905 ± 0.069	12.21	13.7M
RDDM	23.20	0.065 ± 0.196	0.850 ± 0.128	11.27	12.4M
PPGflowECG	18.72	0.029 ± 0.014	0.864 ± 0.107	**6.00**	11.8M
Ours	**14.98**	$\mathbf{0.027 \pm 0.013}$	$\mathbf{0.919 \pm 0.078}$	6.66	11.2M

Table 4. Ablation Studies Results

Metric	Initialization Strategy		Modulation Layer			Loss Components		Guidance Strategy	
	Latent	Noise	MSD-FiLM	MLP-FiLM	AdaLN + crossAttn	w/o $\mathcal{L}_{\mathrm{freq}}$	w/o $\mathcal{L}_{\mathrm{WD}}$	w/ CFG	w/o CFG
MSE ↓	$\mathbf{0.027}_{\pm 0.013}$	$0.031_{\pm 0.014}$	$0.027_{\pm 0.013}$	$0.032_{\pm 0.014}$	$\mathbf{0.026}_{\pm 0.014}$	$0.029_{\pm 0.014}$	$0.035_{\pm 0.015}$	$\mathbf{0.027}_{\pm 0.013}$	$0.029_{\pm 0.015}$
HR-AE ↓	**6.66**	12.95	**6.66**	11.39	7.58	8.75	9.96	**6.66**	8.82
PSD Sim ↑	$\mathbf{0.919}_{\pm 0.078}$	$0.807_{\pm 0.100}$	$\mathbf{0.919}_{\pm 0.078}$	$0.825_{\pm 0.112}$	$0.819_{\pm 0.082}$	$0.879_{\pm 0.098}$	$0.846_{\pm 0.103}$	$\mathbf{0.919}_{\pm 0.078}$	$0.919_{\pm 0.068}$
Latent-FID ↓	**14.98**	24.55	**14.98**	18.273	24.93	18.09	24.64	**14.98**	18.11

Table 2. mmWave to ECG results under the Zero-shot protocol.

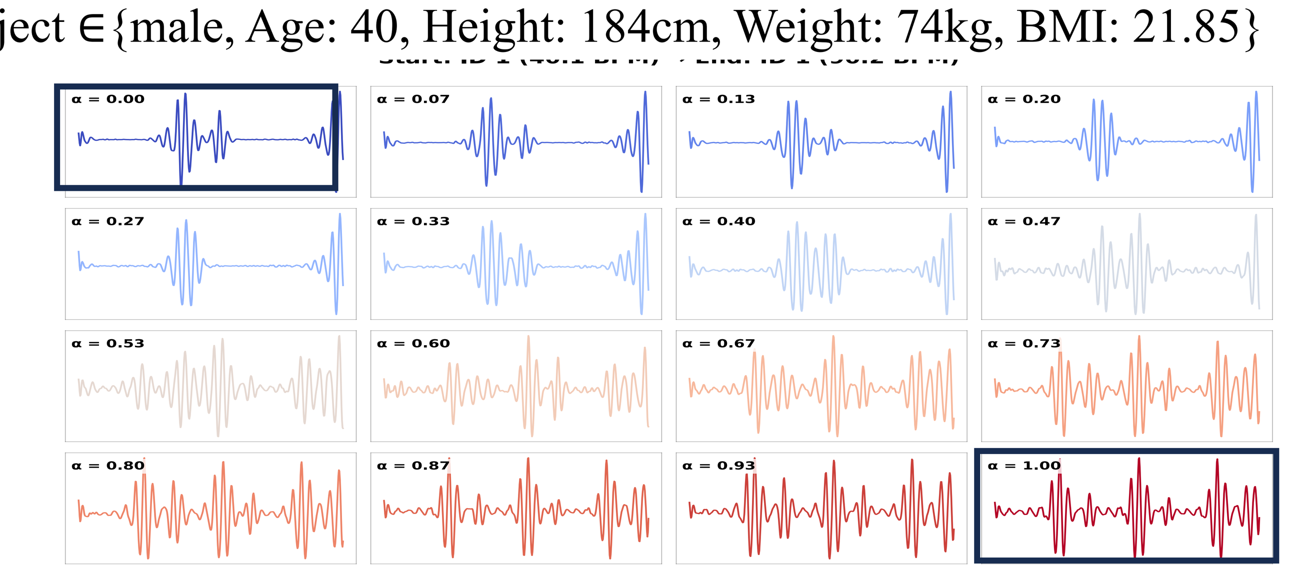
Method	RMSE ↓	PCC ↑	RR Err. (ms) ↓
cGAN	0.13 ± 0.03	0.71 ± 0.07	11.92 ± 3.53
cVAE	0.17 ± 0.03	0.51 ± 0.15	15.37 ± 7.45
DiT	0.12 ± 0.03	0.74 ± 0.08	9.17 ± 4.98
RDDM	0.19 ± 0.04	0.57 ± 0.15	16.01 ± 6.30
PPGflowECG	0.13 ± 0.02	0.69 ± 0.06	9.28 ± 4.67
Our	$\mathbf{0.11 \pm 0.02}$	$\mathbf{0.79 \pm 0.06}$	$\mathbf{8.13 \pm 3.94}$

Table 3. Downstream AFib classification performance

Metric ↑	Mean ± Std
Recall	0.87 ± 0.039
Precision	0.62 ± 0.046
F1-Score	0.72 ± 0.038
Accuracy	0.68 ± 0.040
AUC-ROC	0.72 ± 0.043

Input ECG Sample | Time domain *Gen vs. Ref* | Freq domain *Gen vs. Ref*

Linear interpolation in latent space from *Heart rate 58.5* to *90.1 bpm* with subject ∈{male, Age: 40, Height: 184cm, Weight: 74kg, BMI: 21.85}



04 Takeaways

Cardio-mmFlow is a framework that synthesizes contactless mmWave radar from ECG templates to overcome data scarcity and generalization in contactless ECG sensing.

- **Cross Model Mapping:** Integrates Gaussian prior-free latent flow matching with an MSD-FiLM to capture subject-specific signal propagation.
- **Scalable Complementary Resource:** Serves as an expandable asset for model training and benchmarking, significantly reducing reliance on extensive real-world recordings.