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radarODE: An ODE-Embedded Deep Learning Model for Contactless ECG Reconstruction from mm-Wave Radar

- Part 1 – Background and Problems
- Part 2 – Proposed Signal Model and radarODE Framework
- Part 3 – Results and Evaluations

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Part 1 - Background and Problems

- **Part 1 – Background**
- **Part 2 – Literature Review**

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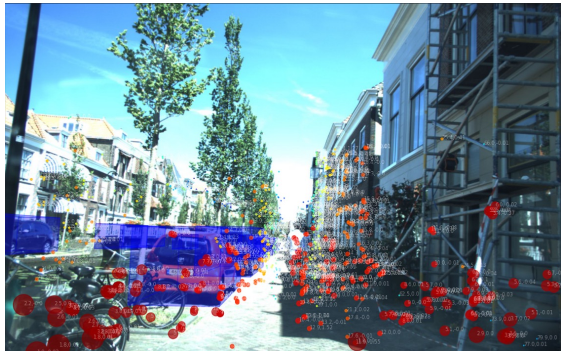
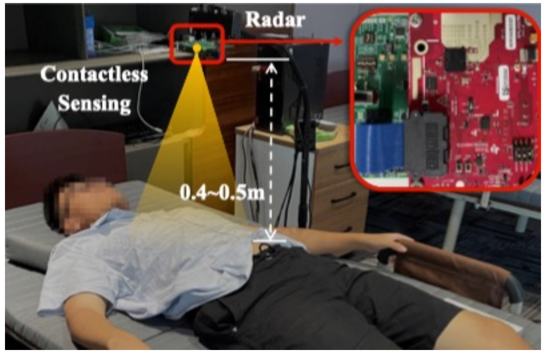
Background - Radar-Based Sensing

Sensors	Cameras	Acoustic Sensors	Wi-Fi Routers	Radars
Pros	1. SOTA. CV algorithms or DL frameworks	1. Directly monitor the heart sound	1. No need for extra devices 2. Unobtrusive	1. Unobtrusive 2. Robustness
Cons	1. Privacy issue 2. Rely on high quality image.	1. Low accuracy 2. Vulnerable to acoustic noise	1. Low accuracy 2. Complex EM environment	1. High cost 2. Immature signal-processing methods

Research Interests

1. Pose estimation
2. Object detection and tracking
3. Vital sign monitoring





Literature Review - Vital Sign Monitoring

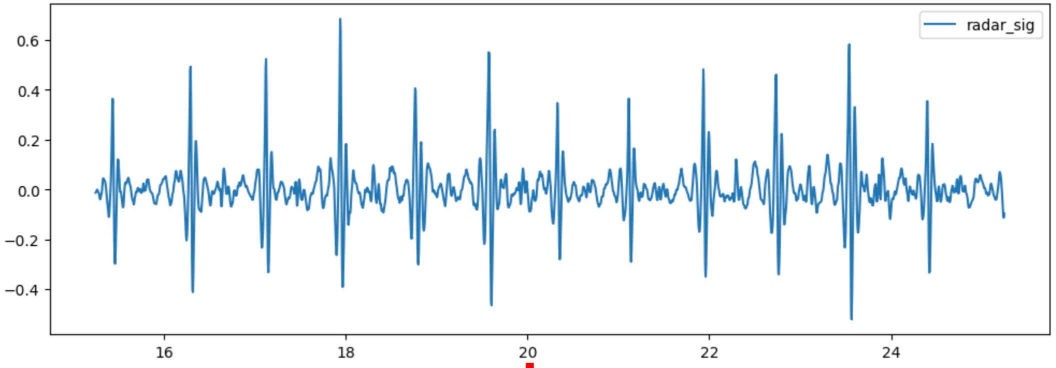
Previous Work

1. First radar-based respiration monitoring in 1975.
2. Improvements on front-end radar designs (e.g., FMCW radar, self-injection-locked radar).
3. Improvements on the advanced algorithms (e.g., HMM, template matching, EMD).

General Obstacles:

My current research interest

1. To extract fine-grained cardiac features (i.e., ECG, SCG)
2. To mitigate the real-world noise (i.e., body movement)
3. To realize multi-person monitoring
4. To enable multi-radar/sensor monitoring



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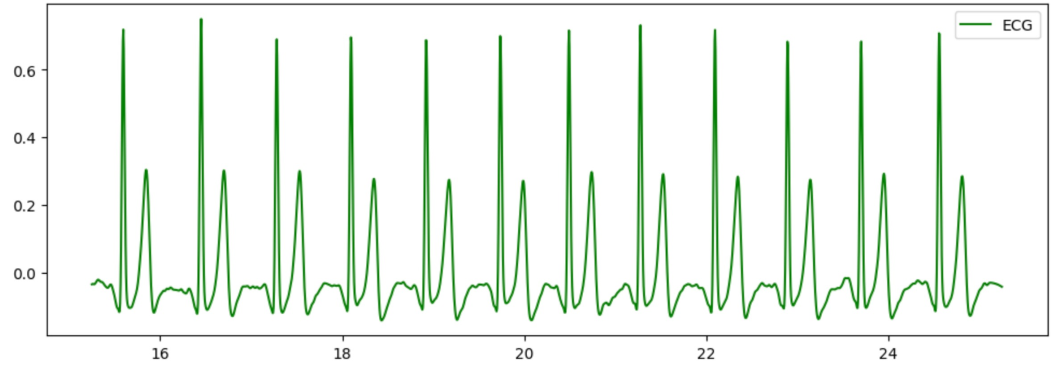
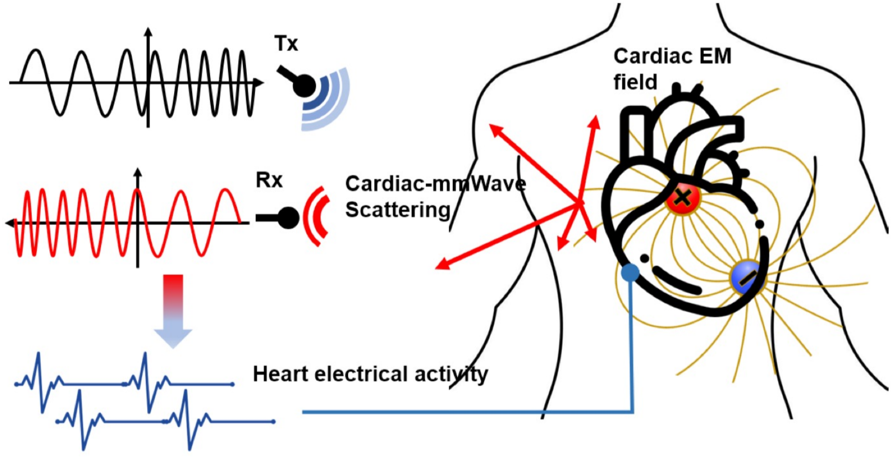


Existing Methods and Limitations

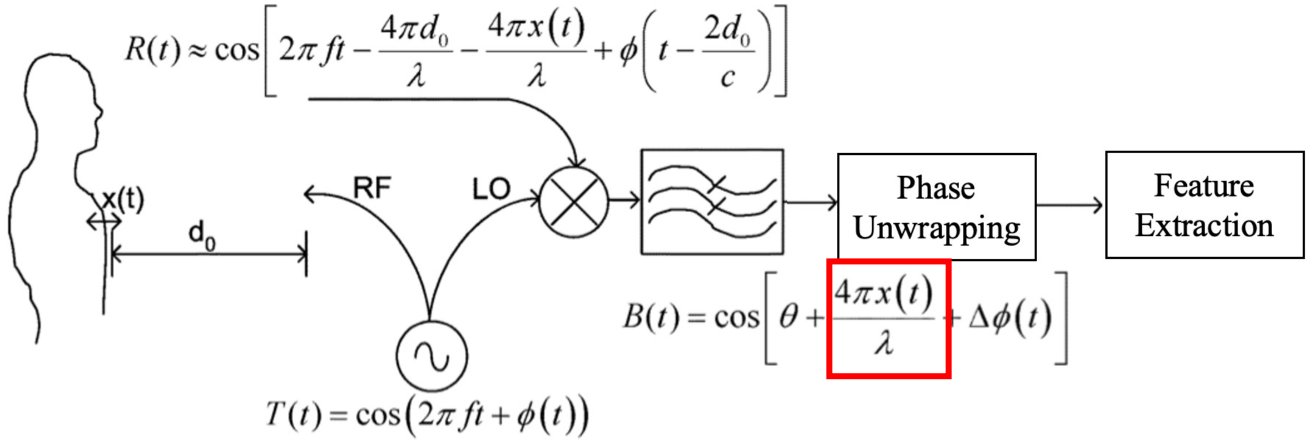
First Category: Sensing the EM field [1]



Limitations:

1. Complex model due to Green Function and biological ionic concentration
2. The solution is hard to be calculated and is vulnerable to changing environment

Second Category: Sensing the vibration from chest region



Limitations:

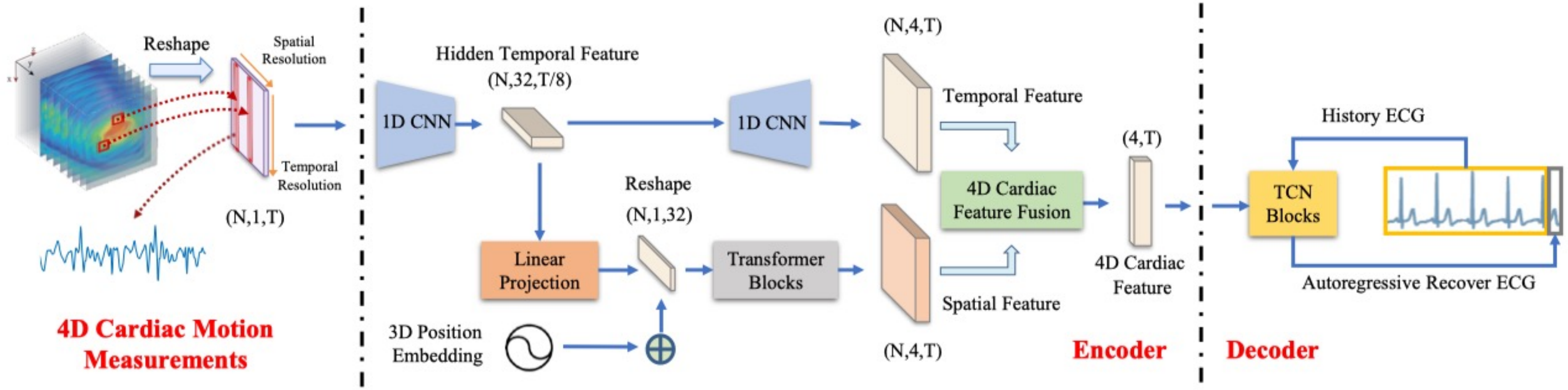
1. Lack of the theoretical model for radar-ECG signal decoupling (from mechanical domain to electrical domain)
2. Rely on purely data-driven methods

[1] C. Xu, H. Li, Z. Li, H. Zhang, A. S. Rathore, X. Chen, K. Wang, M.-c. Huang, and W. Xu, "CardiacWave: A mmWave-based scheme of non-contact and high-definition heart activity computing," Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies (IMWUT), vol. 5, no. 3, pp. 1–26, Sep. 2021.

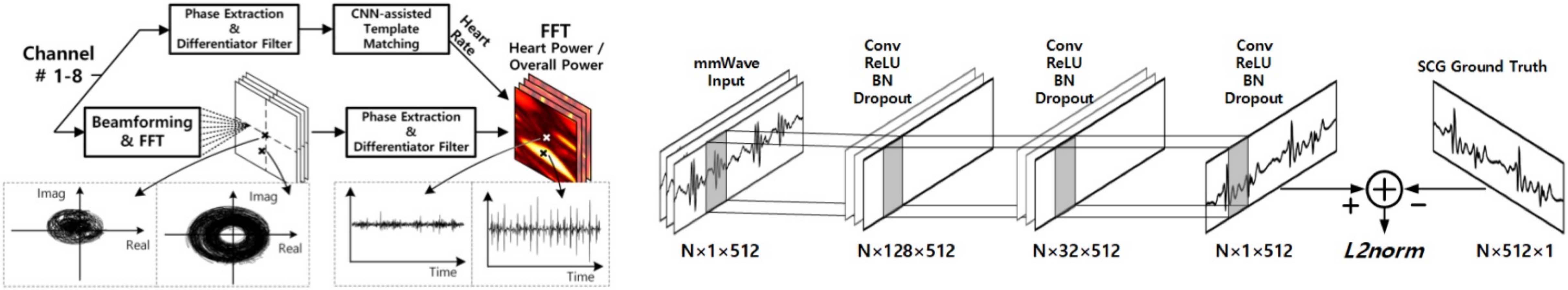
Existing Methods and Limitations

Examples on the methods from the second category:

[2]



[3]



[2] J. Chen, D. Zhang, Z. Wu, F. Zhou, Q. Sun, and Y. Chen, "Contactless electrocardiogram monitoring with millimeter wave radar," IEEE Transactions on Mobile Computing, pp. 1–17, Oct. 2022.
[3] U. Ha, S. Assana, and F. Adib, "Contactless seismocardiography via deep learning radars," in Proceedings of the 26th Annual International Conference on Mobile Computing and Networking (MobiCom), pp. 114, Apr. 2020.

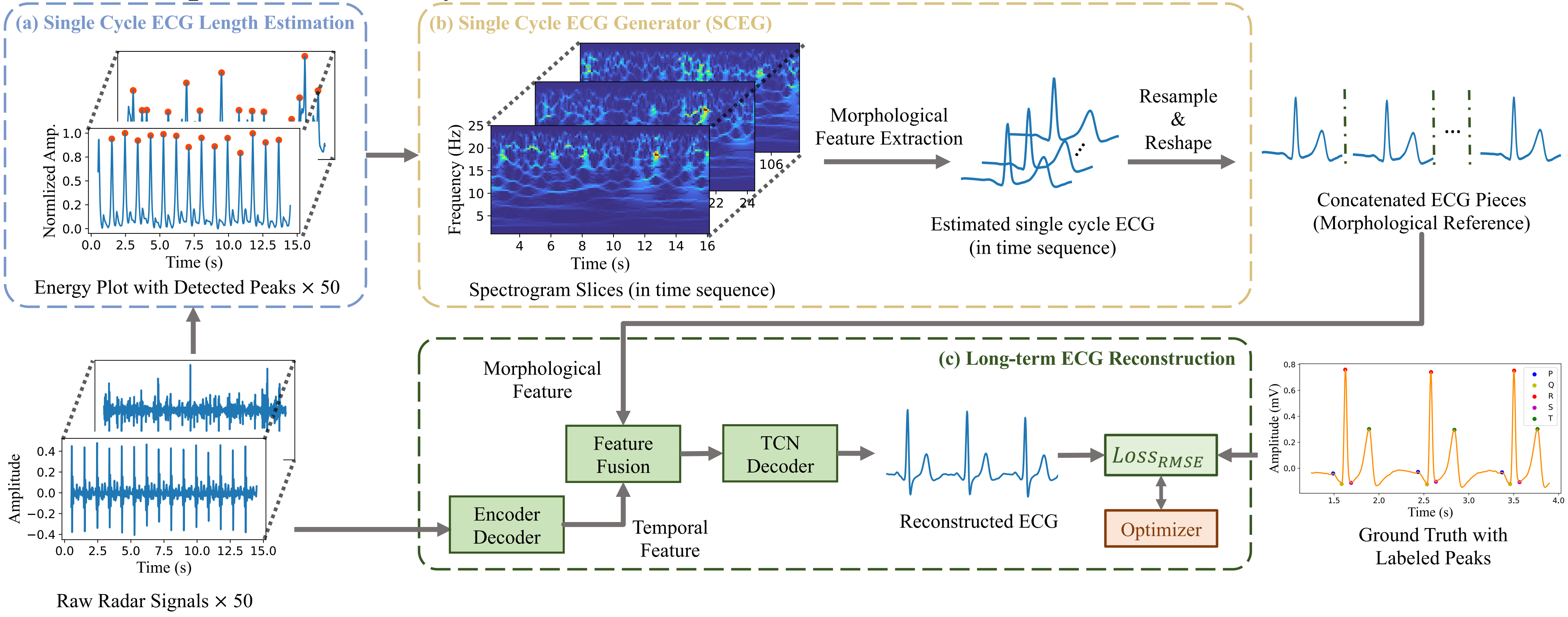
Part 2 – Proposed Signal Model and radar ODE Framework

- Part 1 – Preliminary
- Part 2 – Model for radar signal
- Part 3 – radarODE framework

radarODE: Contributions and Overview

Contributions:

1. Propose the signal model in terms of fine-grained cardiac features.
2. Design an ODE-embedded module SCEG to parameterize the radar signal into sparse representations with morphological meanings.
3. By fusing the extracted morphological and temporal features, the proposed radarODE framework is proven to be robust in the presence of body movement noise and could realize accurate reconstruction of the ECG signal.



Preliminary

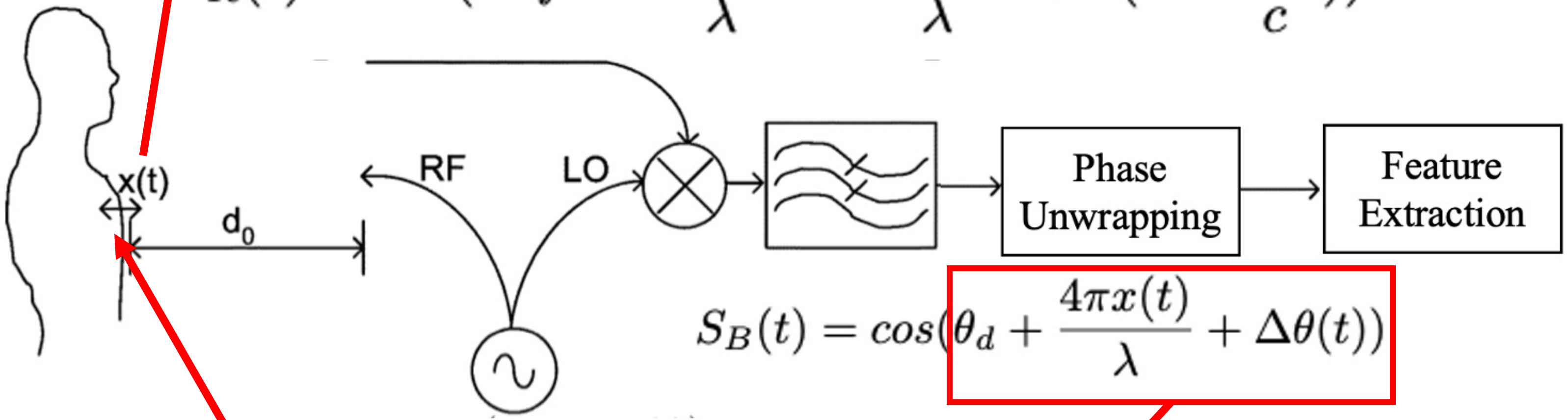
Radar-based Coarse Cardiac (Heartbeat) Monitoring:

$$T_p(t) = \frac{2d(t)}{c}$$

$$d(t) = d_0 + x(t)$$

$$S_R(t) = A_R \cdot \cos(2\pi f(t - T_p(t)) + \theta(t - \boxed{T_p(t)}))$$

$$S_R(t) \approx \cos(2\pi f t - \frac{4\pi d_0}{\lambda} - \frac{4\pi x(t)}{\lambda} + \theta(t - \frac{2d_0}{c}))$$



$$S_B(t) = cos(\boxed{\theta_d + \frac{4\pi x(t)}{\lambda} + \Delta\theta(t))}$$

$$S_T(t) = A_T \cdot \cos(2\pi f t + \theta(t))$$

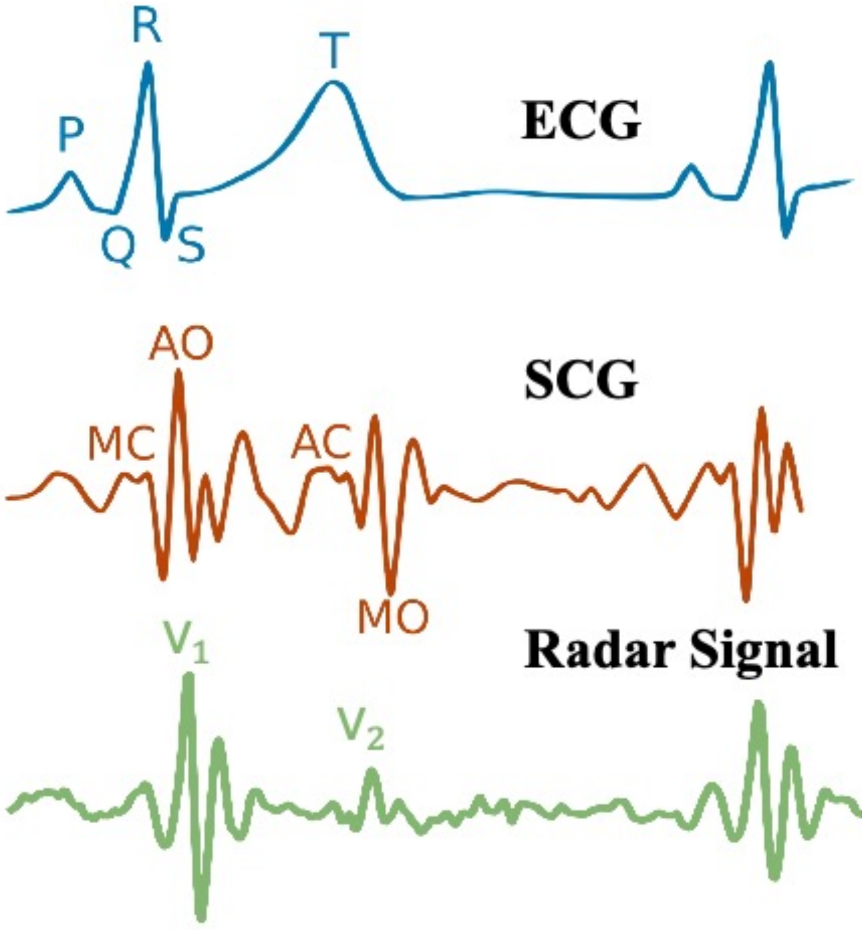
$$\phi(t) = \theta_d + \boxed{\frac{4\pi x(t)}{\lambda}} + \Delta\theta(t)$$

$$\Delta\phi(t) = \frac{4\pi x(t)}{\lambda}$$

Preliminary

Radar-Based Fined-Grained (ECG) Cardiac Monitoring

1. ECG Feature: P-wave, QRS-complex, T-wave for electrical activities of atrial/ ventricular depolarization/repolarization (心房/心室 去极化/复极化).
2. SCG Features: excitation–contraction coupling caused valve (主动脉瓣) opening/closure (AO/AC) and mitral valve (二尖瓣) opening/closure (MO/MC)
3. Radar Feature: Similar with SCG but only with two prominent vibrations v1 and v2 induced by AO and AC.
4. Heart muscle contraction has a pulsatile nature, and the bones/tissues in chest area introduce the extra damping into the pulse [4], [5].



[4] M. Nosrati and N. Tavassolian, "High-accuracy heart rate variability monitoring using Doppler radar based on Gaussian pulse train modeling and FTPR algorithm," IEEE Transactions on Microwave Theory and Techniques, vol. 66, no. 1, pp. 556–567, Jan. 2017.
[5] D. R. Morgan and M. G. Zierdt, "Novel signal processing techniques for doppler radar cardiopulmonary sensing," Signal Processing, vol. 89, no. 1, pp. 45–66, Jan. 2009.

Proposed Signal Model

Proposed Model:

1. The cardiac vibration x(t) can be extracted from the phase variation of the received radar signal as:

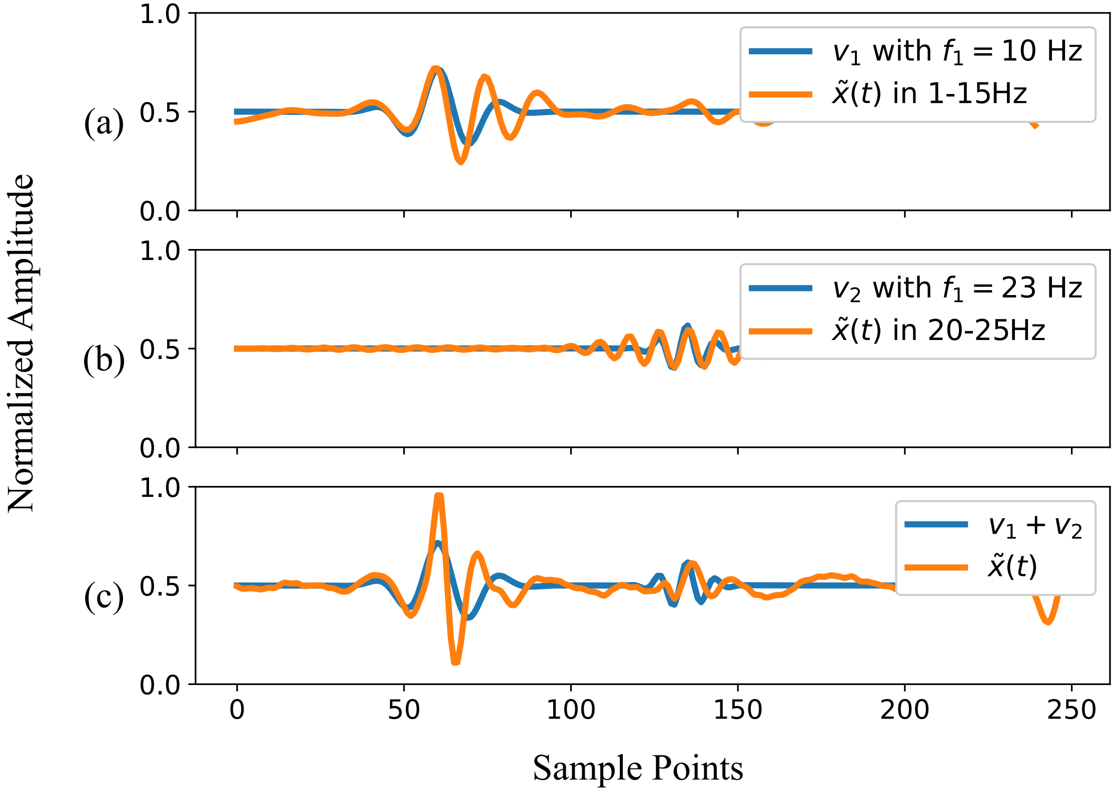
$$\Delta\phi(t) = \frac{4\pi x(t)}{\lambda} \quad \text{with} \quad x(t) = x_c(t) + \cancel{x_r}(t) + x_n(t)$$

2. Based on the previous intuition, we model the $\tilde{x}$(t) as two prominent vibrations and other noises as:

$$\tilde{x}(t) = v_1(t) + v_2(t) + x_n(t)$$

$$v_1 = \mathrm{a}_1 \cos(2\pi f_1 t) \exp\left(-\frac{(t-T_1)^2}{{b_1}^2}\right)$$

$$v_2 = \mathrm{a}_2 \cos(2\pi f_2 t) \exp\left(-\frac{(t-T_2)^2}{{b_1}^2}\right)$$



True Radar signal with Synthesis

a_1, a_2 → amplitude of the vibrations, T_1, T_2 → when the vibrations happen

b_1, b_2 → length/width of the vibration, f_1, f_2 → central frequency of the vibration

Spectrogram

Localization of T_1, T_2 using synchrosqueezed wavelet transform (SST) [6]:

1. Calculate the wavelet transform of $\tilde{x}(t)$:

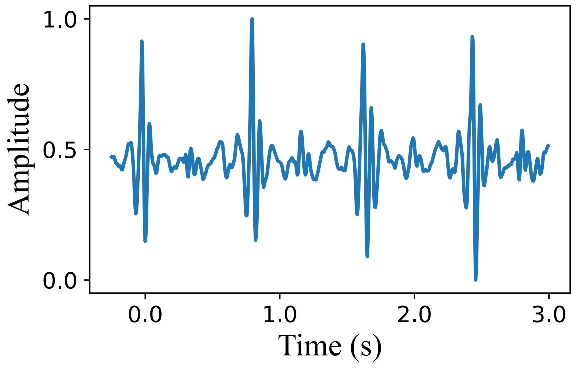
$$W_{\tilde{x}}(a,b) = \int \tilde{x}(t) a^{-1/2} \psi^{*}\left(\frac{t-b}{a}\right) dt$$

2. Calculate the candidate instantaneous frequency as:

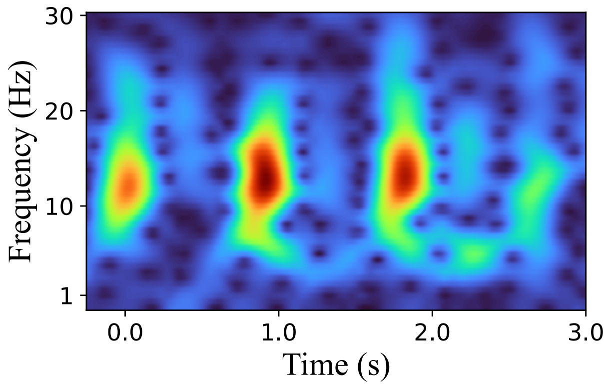
$$f_{\tilde{x}}(a,b) = -2\pi i \left(W_{\tilde{x}}(a,b)\right)^{-1} \frac{\partial W_{\tilde{x}}(a,b)}{\partial b}$$

3. Concentrate the energy along the candidate instantaneous frequency:

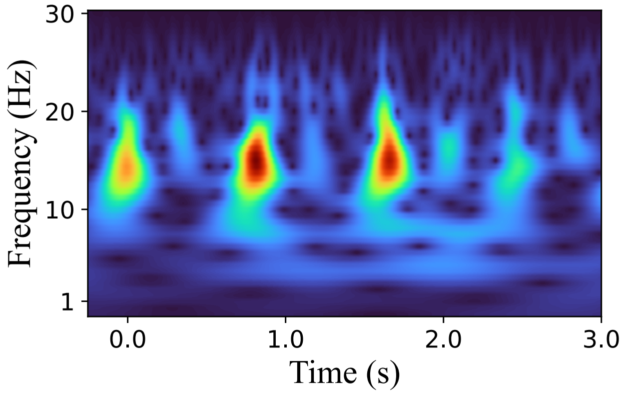
$$T_{\tilde{x}}(2\pi f, b) = \int_{A(b)} W_{\tilde{x}}(a,b) a^{-3/2} \delta\left(2\pi f_{\tilde{x}}(a,b) - 2\pi f\right) df$$



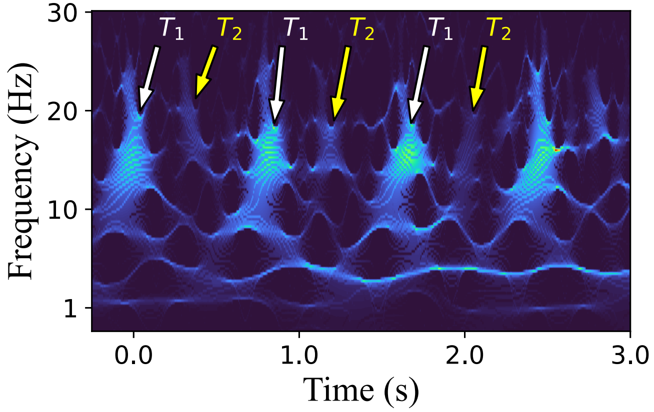
Radar Signal $\tilde{x}(t)$



STFT



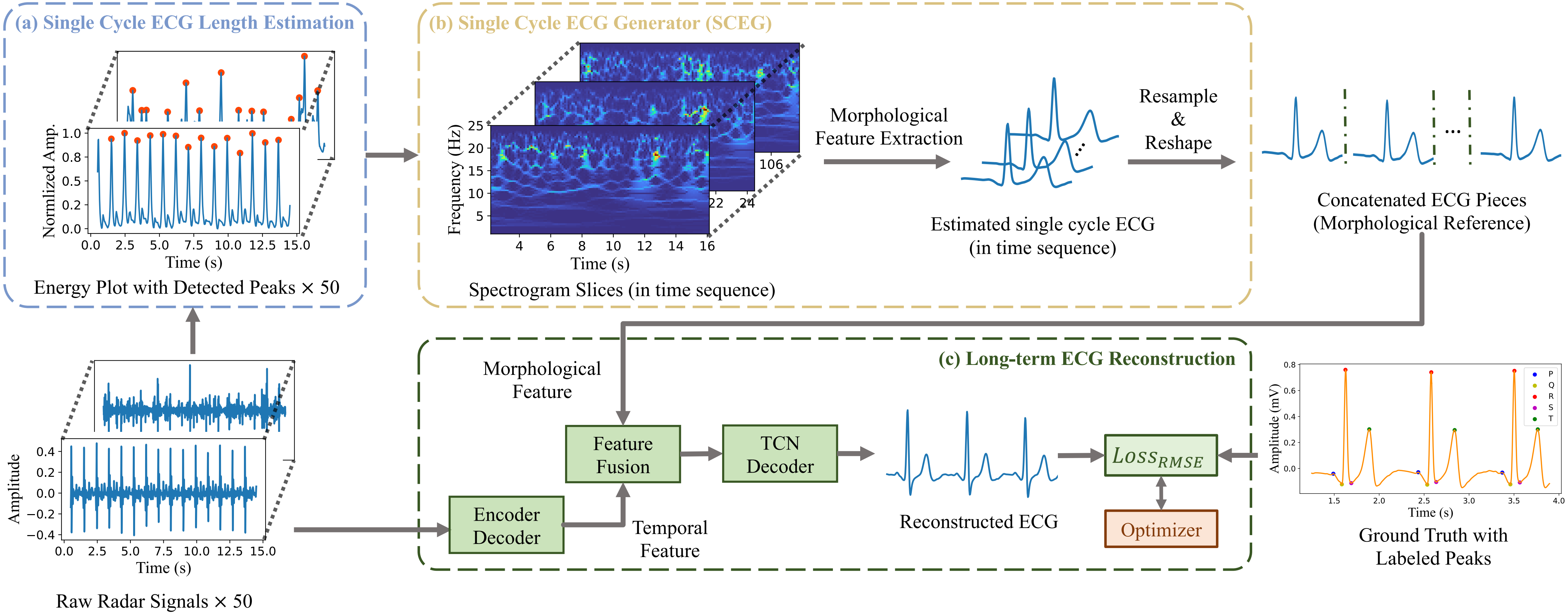
CWT



SST

[6] I. Daubechies, J. Lu, and H.-T. Wu, "Synchrosqueezed wavelet transforms: An empirical mode decomposition-like tool," Applied and computational harmonic analysis, vol. 30, no. 2, pp. 243–261, Aug. 2011.

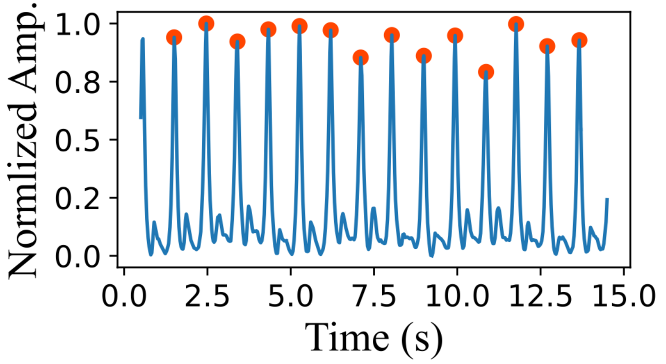
radarODE: Overview



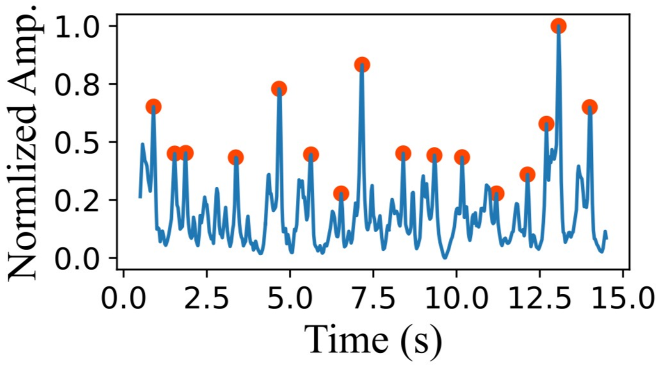
radarODE Framework

Single Cycle ECG Length Estimation:

Energy plot from SST using peak detection algo. for ECG



High SNR with correct peaks



Low SNR with wrong peaks

Proposed to eliminate the wrong PPI

Algorithm 1 PPI Estimation

Input: $\tilde{X}_I = \{\tilde{x}_1, \tilde{x}_2, \ldots, \tilde{x}_i\}$ with $i \in I = \{1, 2, \ldots, 50\}$
Segments Length L_{seg} and Step Length L_{step}
Output: Estimated PPI with length L
INITIALIZATION:
- Let $\tilde{X}_I^S = \{\tilde{X}_I^1, \tilde{X}_I^2, \ldots, \tilde{X}_I^s\}$ be an ordered list of the segments sliced from $\tilde{X}_I$ with length L_{seg} and step L_{step}, where $s \in S = \left\{1, 2, \ldots, \frac{L - L_{seg}}{L_{step}}\right\}$.
- Let $PPI \leftarrow \emptyset$

MAIN ITERATION:
for each segment $\tilde{X}_I^s \in \tilde{X}_I^S$ **do**
- Let $PPI_I \leftarrow \emptyset$ to save the candidate PPI obtained from each segment.

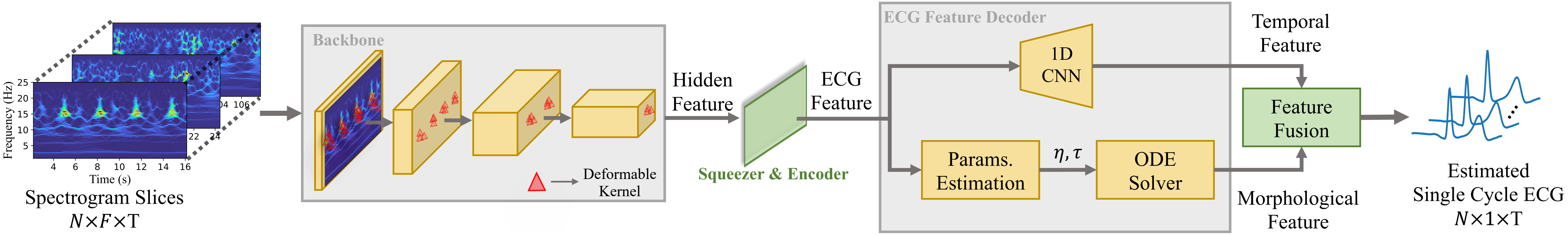
  for each $\tilde{x}_i^s \in \tilde{X}_I^s$ **do**
  1) Apply biopeaks on $\tilde{x}_I^s$ to get candidate peaks P
  2) Get PPI for the current radar signal i using differentiation as $PPI_i \leftarrow diff(P)$
  3) Update $PPI_I \leftarrow PPI_I \cup PPI_i$
- Calculate the probability density function $\hat{f}(p)$ using KDE as in (17).
- Determine the final PPI for current segment and update the set as $PPI \leftarrow PPI \cup \arg\min_p \hat{f}(p)$.

  end for

end for
Resample the PPI to length L

radarODE Framework

Single Cycle ECG Generator (SCEG):



The ODE model describes a 3D trajectory denoted by (x, y, z) [6]

$$\frac{dx}{dt} = \alpha(x,y)x - \omega y$$

$$\frac{dy}{dt} = \alpha(x,y)y + \omega x$$

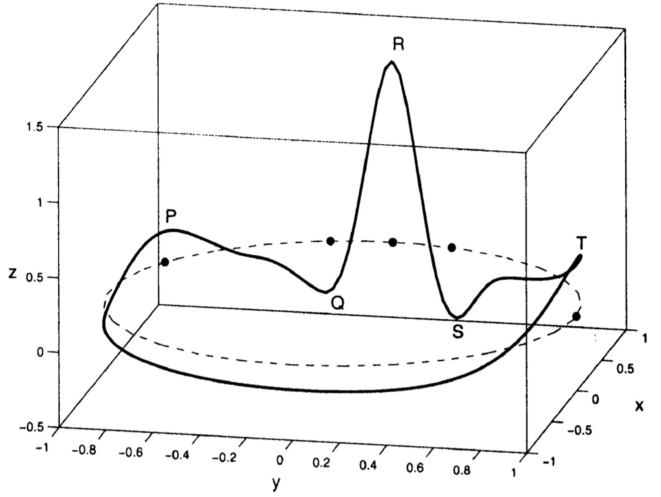
$$\frac{dz}{dt} = -\sum_{e_f \in \mathcal{F}} a_{e_f} \Delta\theta_{e_f}(x,y) e^{-\Delta\theta_{e_f}(x,y)^2 / 2b_{e_f}^2} - z$$

$$\alpha(x,y) = 1 - \sqrt{x^2 + y^2}$$

$$\Delta\theta_{e_f}(x,y) = \left(\theta(x,y) - \theta_{e_f}\right) \mod 2\pi$$

$$\theta(x,y) = \operatorname{atan2}(y,x)) \in [-\pi, \pi]$$

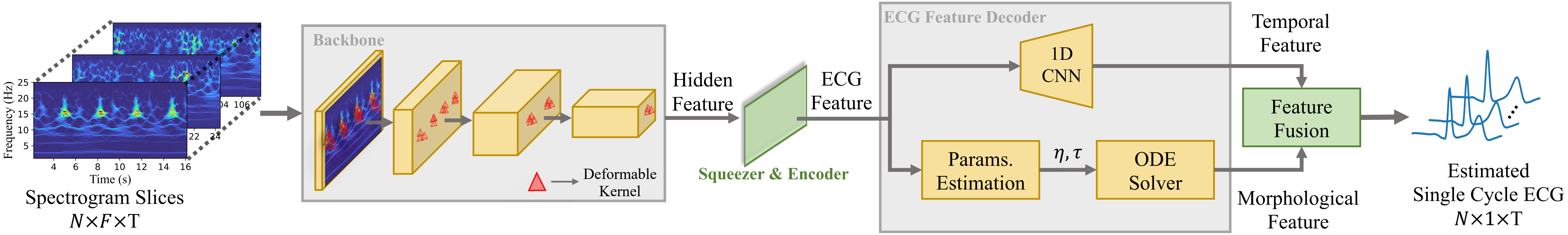
$$e_f \in \mathcal{F} = \{e_P, e_Q, e_R, e_S, e_T\}$$



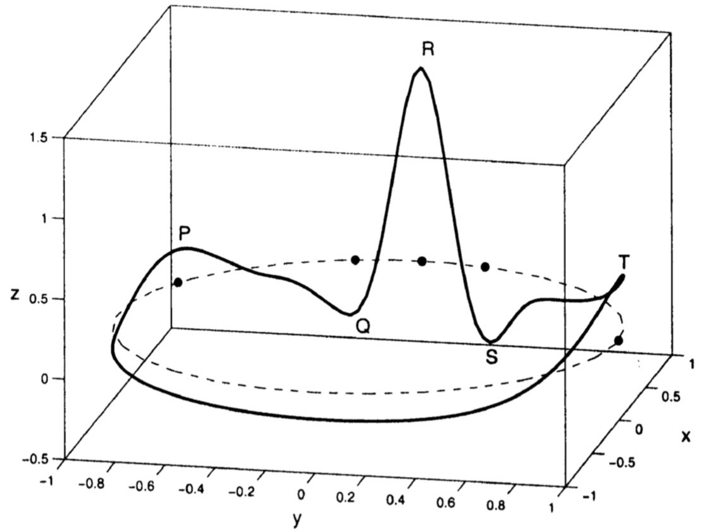
[6] P. E. McSharry, G. D. Clifford, L. Tarassenko, and L. A. Smith, "A dynamical model for generating synthetic electrocardiogram signals," IEEE transactions on biomedical engineering, vol. 50, no. 3, pp. 289–294, Mar. 2003.

radarODE Framework

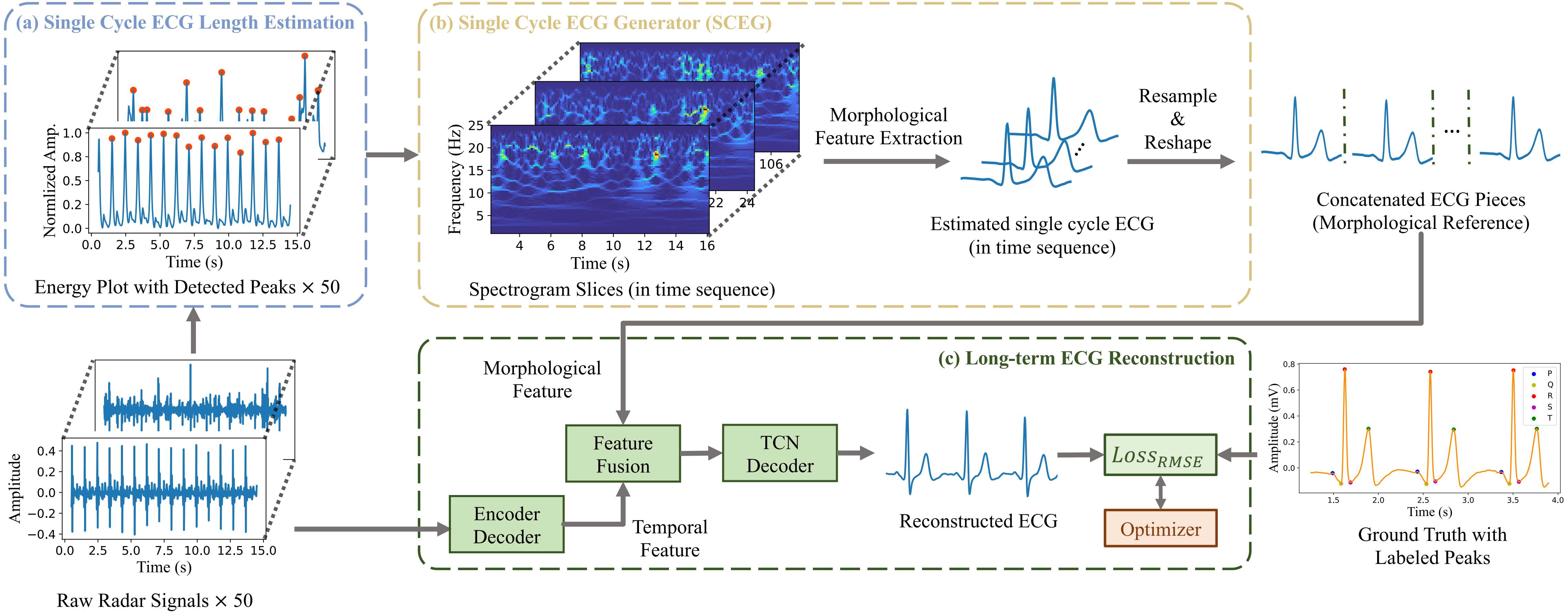
Single Cycle ECG Generator (SCEG):



Feature Fusion		
Feature Multiply	–	$(N, 1, 200)$
Stack	–	$(N, 1, 4, 200)$
Conv2d Block	$(1, 16, (5, 5), (1, 2))$	$(N, 16, 2, 98)$
Conv2d Block	$(16, 32, (3, 3), (1, 2))$	$(N, 32, 2, 48)$
Conv2d Block	$(32, 64, (3, 3), (2, 2))$	$(N, 64, 1, 23)$
Transconv1d Block	$(64, 32, 5, 2)$	$(N, 32, 52)$
Transconv1d Block	$(32, 16, 5, 2)$	$(N, 16, 106)$
Transconv1d Block	$(16, 8, 3, 2)$	$(N, 8, 10, 211)$
Transconv1d	$(8, 4, 6, 1)$	$(N, 4, 206)$
Transconv1d	$(4, 2, 5, 1)$	$(N, 2, 202)$
Transconv1d	$(2, 1, 3, 1)$	$(N, 1, 200)$



Long-Term ECG Reconstruction

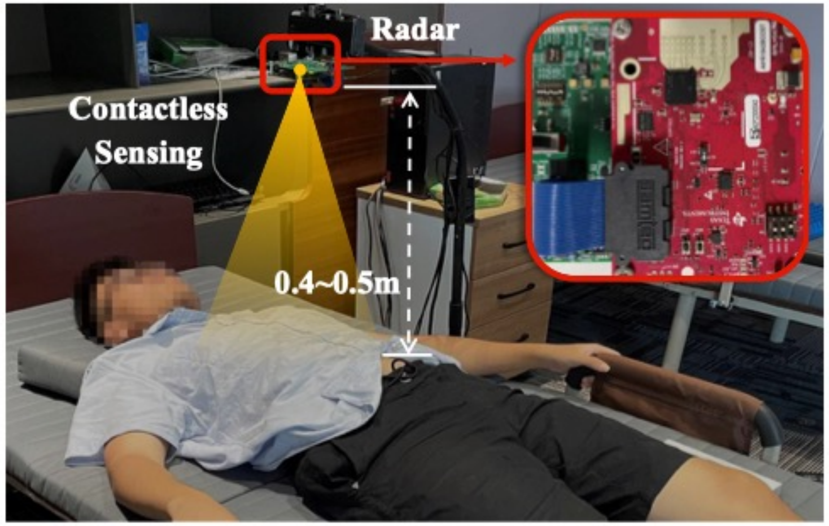


Part 3 – Results and Evaluation

- **Part 1 – Dataset Introduction**
- **Part 2 – Results of PPI**
- **Part 3 – Result of SCEG**
- **Part 4 – Overall Performance**

Dataset Introduction

1. Collected by TI AWR-1843
2. 91 trials for 11 subjects (half size of the real dataset using in [2])
3. Each trials last for 3 minutes for normal breath (NB), irregular breath (IB), sleep (SP) and post exercise (PE)
4. NB: 43 trials, IB: 18 trials, SP: 18 trials, PE: 12 trails
5. Pre-processed by differentiator, dynamic time wrapping and clustering to remove respiration noise.

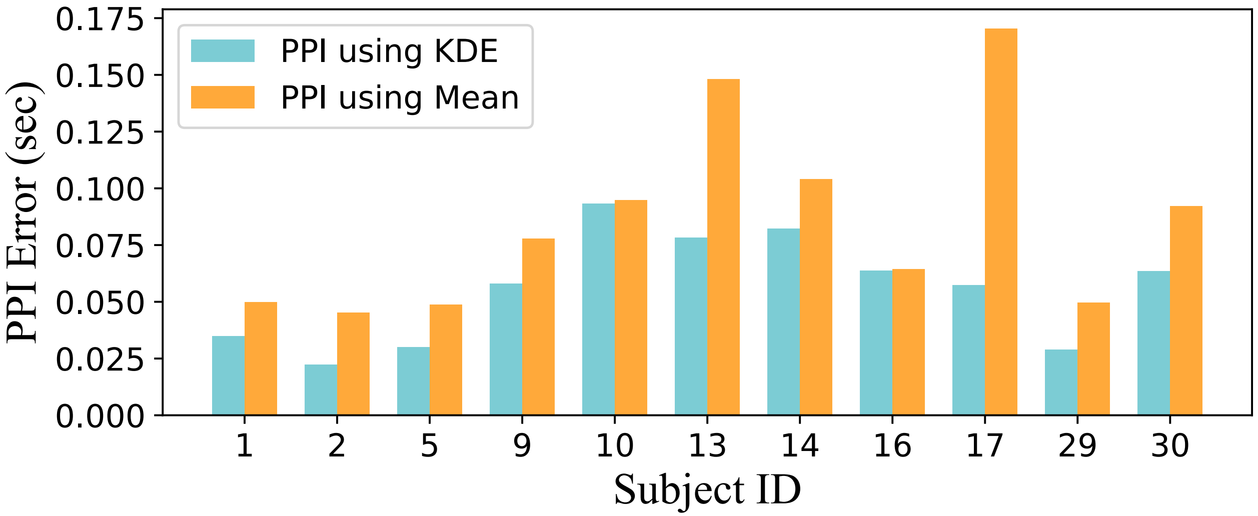


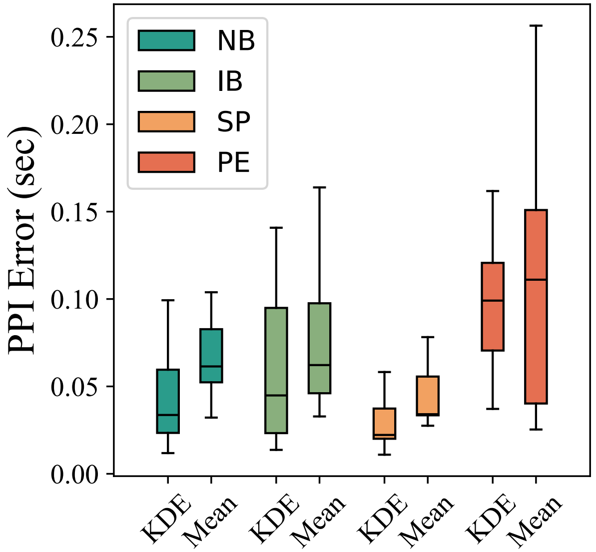
Parameter	Value
Start frequency	77GHz
Frequency slope	65MHz/μs
Idle time	10μs
Ramp end time	60μs
Sample points	256
Sample rate	5MHz
Frame periodicity	5ms

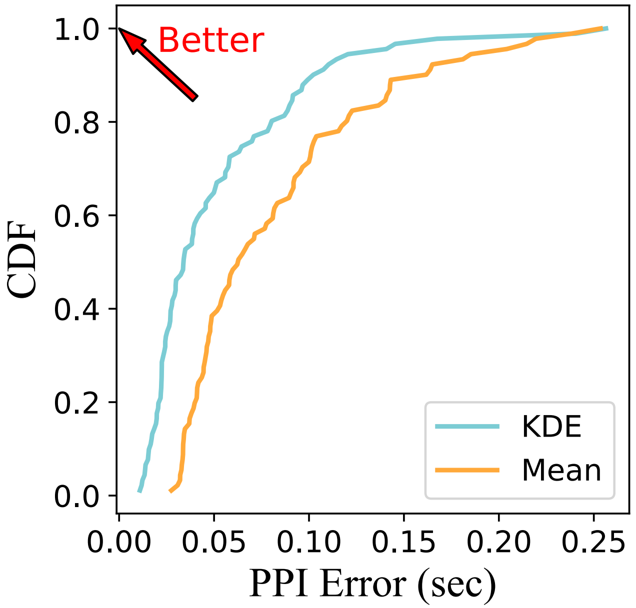
Radar Setting

[2] J. Chen, D. Zhang, Z. Wu, F. Zhou, Q. Sun, and Y. Chen, "Contactless electrocardiogram monitoring with millimeter wave radar," IEEE Transactions on Mobile Computing, pp. 1–17, Oct. 2022.

Result for PPI Estimation



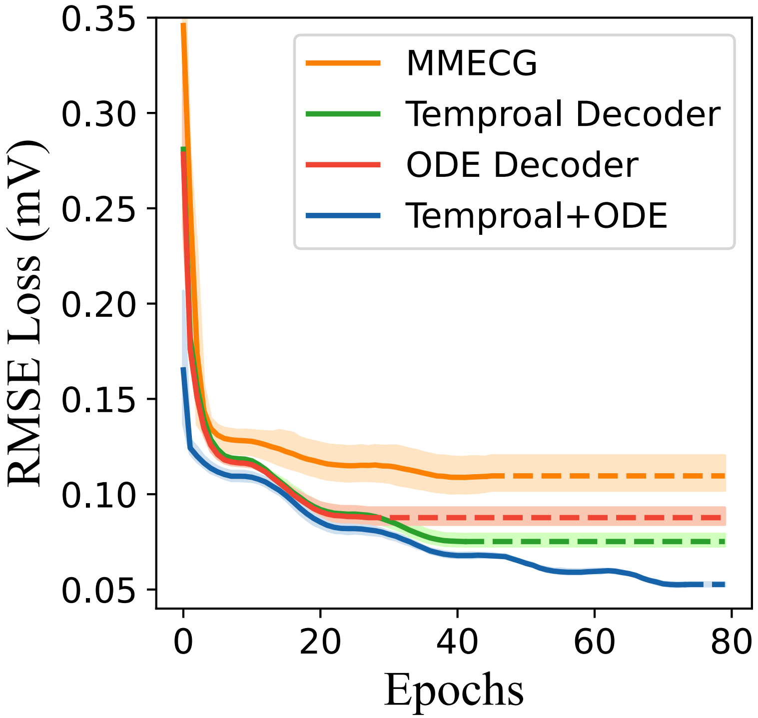




Result for SCEG

COMPARISON WITH BENCHMARK AND ABLATION STUDY ABOUT TEMPORAL DECODER AND ODE DECODER (WITHOUT RESAMPLING)

Framework	Backbone	Encoder	Decoder	Fusion Method	RMSE (mV)	Correlation
MMECG [33]	Conv1d + Transformer		Transconv1d + TCN	Multiplication	0.091	87.9%
SCEG	DeformConv2d	Conv1d	Initial + Temporal	-	0.086	89.4%
			Initial + ODE	-	0.092	85.5%
			Initial + Temporal + ODE	Multiplication + Stack + Conv2d	**0.077**	**92.6%**

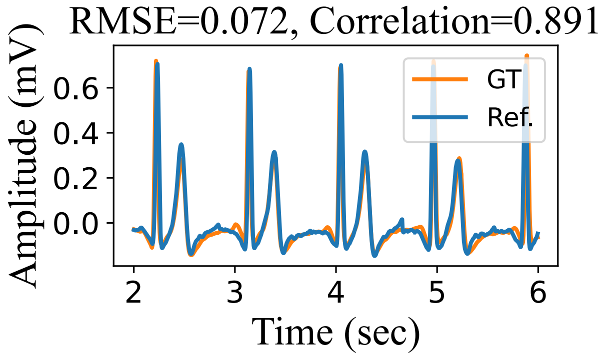


Training Process

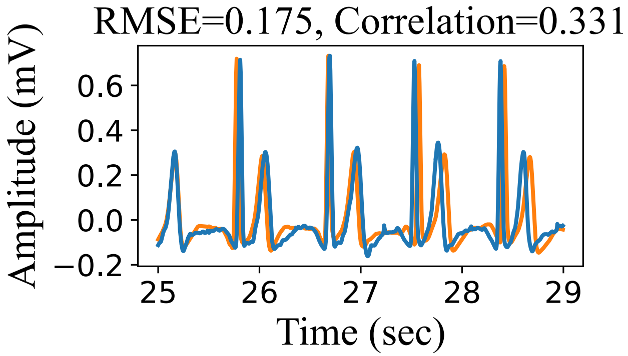
Resample based on PPI

&

Concatenate



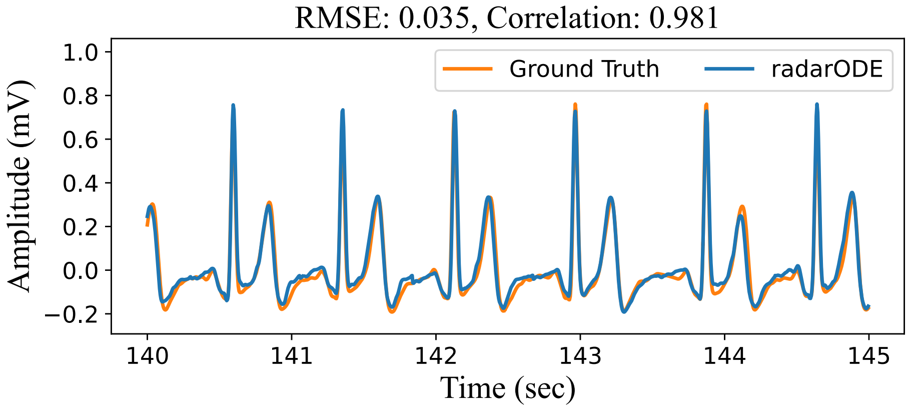
Good Morphological Reference

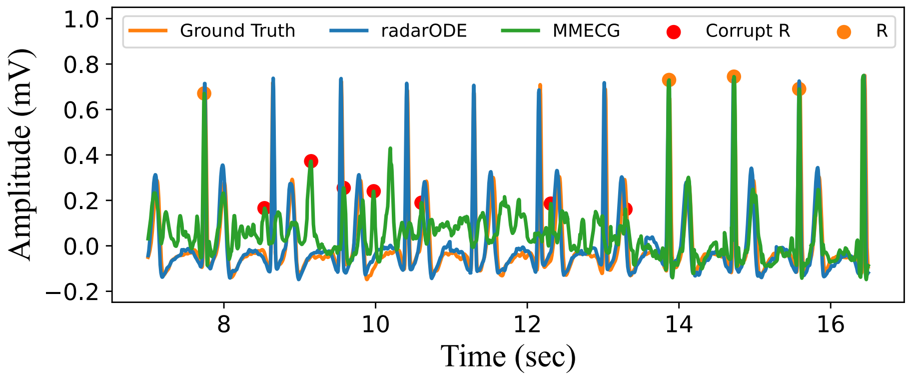


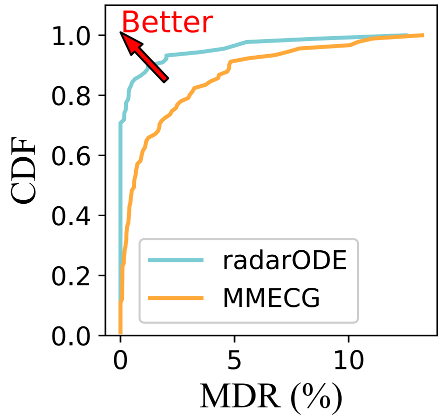
Poor Morphological Reference

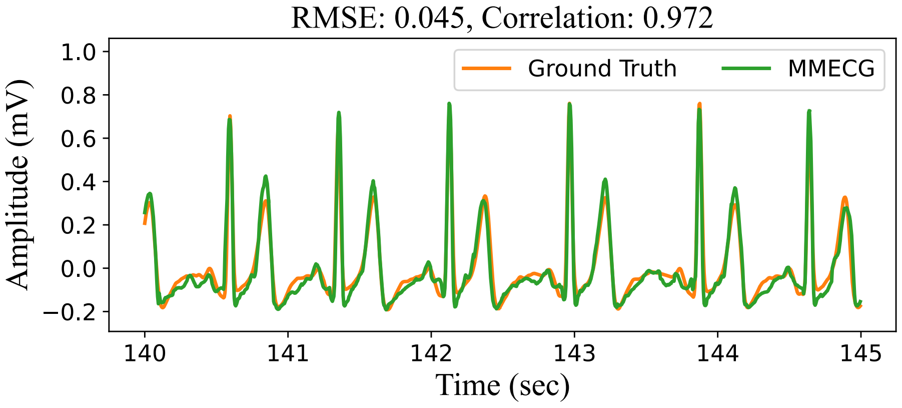
Result for Long-Term Reconstruction

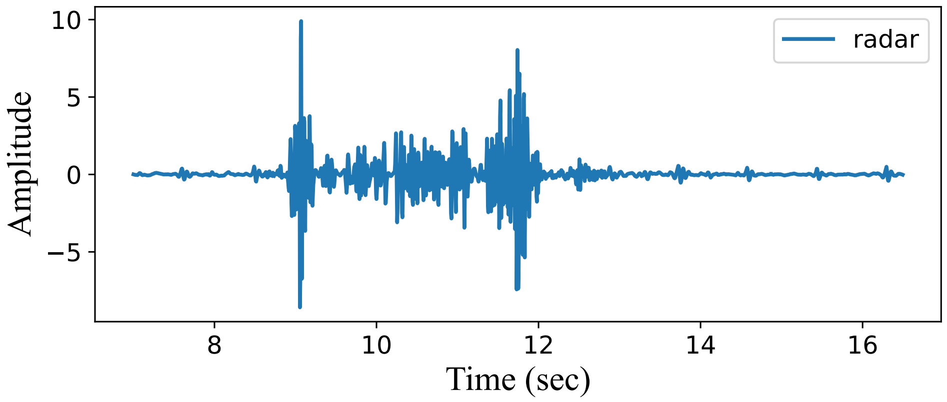
Missed Detection Rate (MDR)

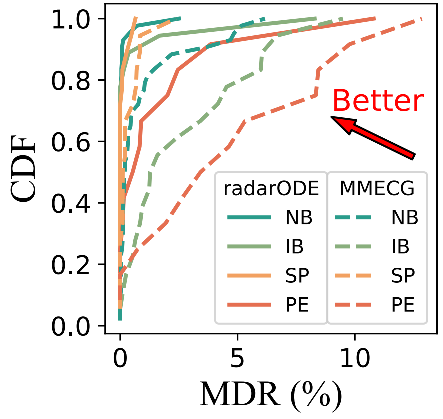






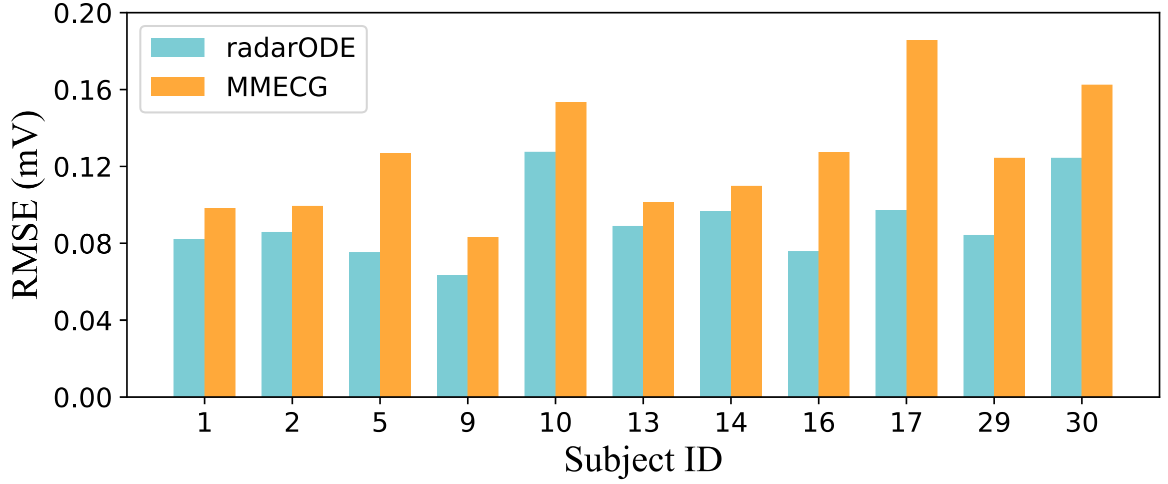


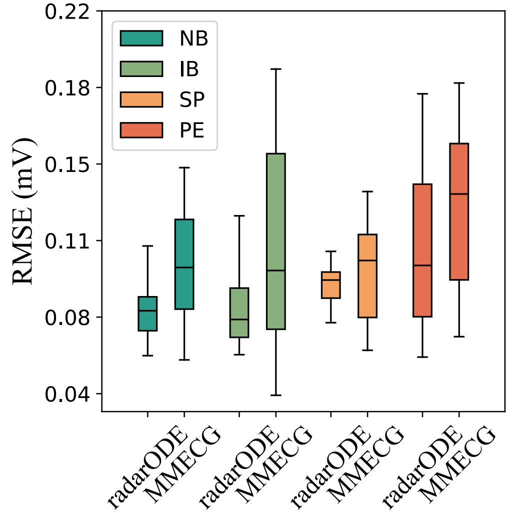


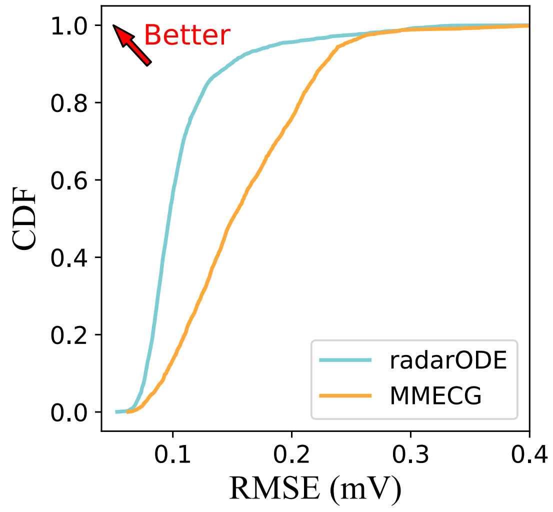


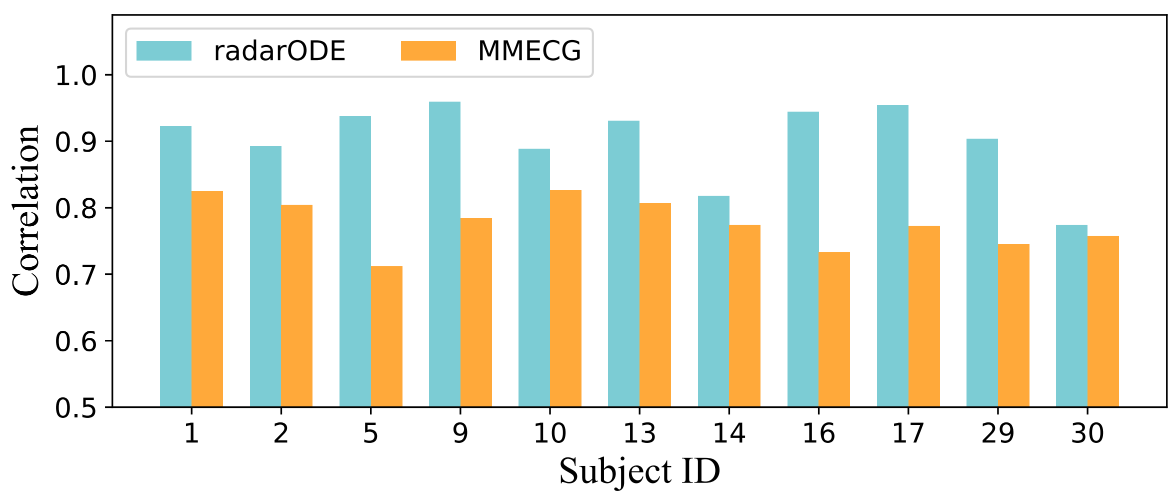
Result for Long-Term Reconstruction

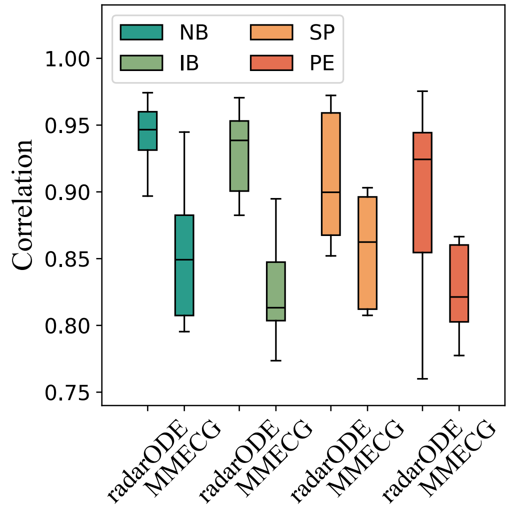
Morphological Accuracy

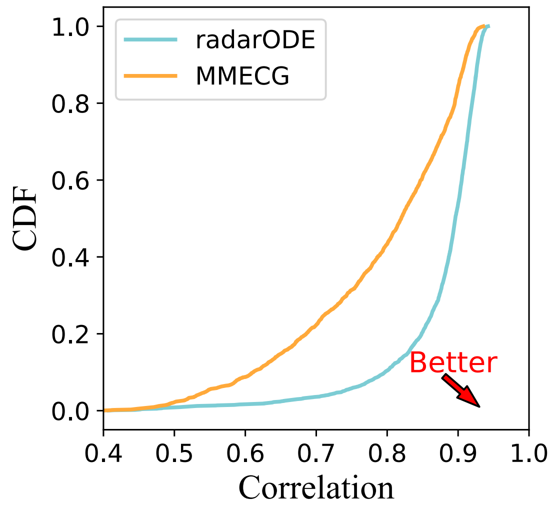






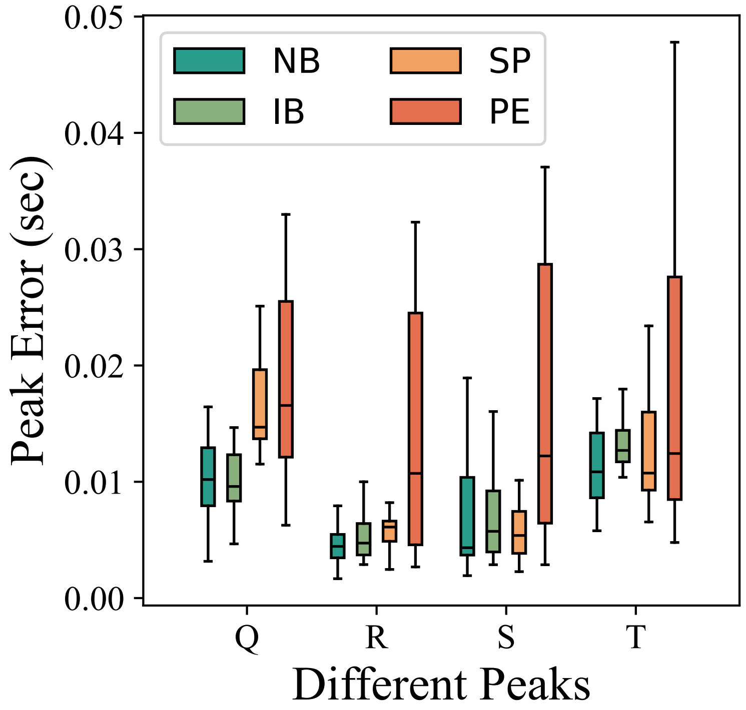


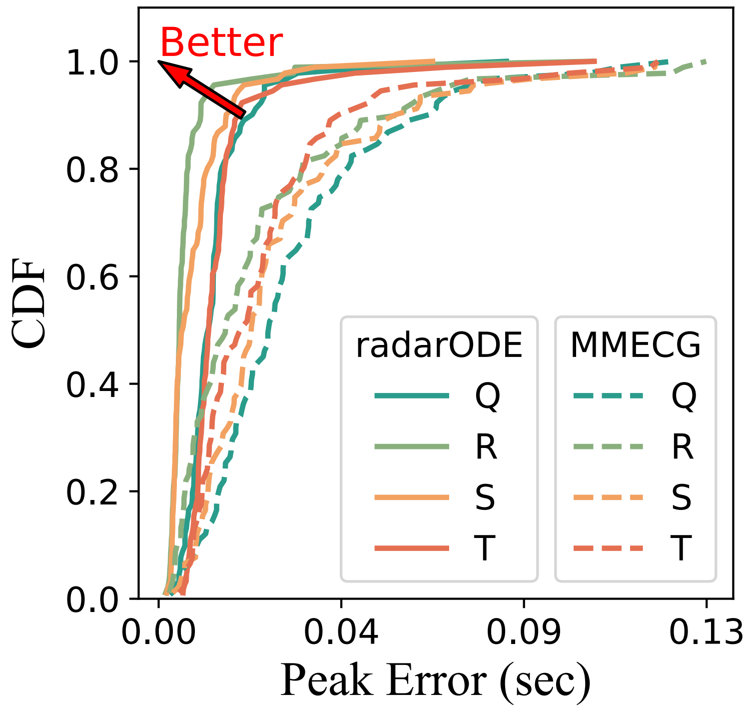




Result for Long-Term Reconstruction

Fine-Grained Cardiac Events Reconstruction





Q&A

Thanks for your time!