

Response Letter

Thesis Title: Robust Cardiac Feature Monitoring Based on Millimeter-Wave Radar

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I would like to thank the examiners for their constructive comments and suggestions that help improve the quality of my thesis. The thesis has undergone a thorough revision according to these comments. Please see below my responses. I have carefully followed all constructive comments from the examiners and have highlighted the changes in the revised thesis in [blue](#).

General Suggestions 1:

To strengthen the structure and coherence, a clear mapping between each publication (published or under review) and the corresponding thesis chapters should be provided. This would help the reader understand how each study integrates into the overarching research narrative.

Response:

Thanks for this valuable suggestion. I have highlighted the link between publications and different chapters by attaching the associated chapter at the end of each publication (in the Publication Section). Also, I have added one paragraph to elaborate on the connections between the thesis chapters and journal papers as suggested in another comment. The detailed content for the revision and response will be given in the corresponding comments.

General Suggestions 2:

Fine tune ‘Abstract’ section, i.e., first and second paragraphs.

Response:

Thanks for the question in the later comments, and I have revised the Abstract part by firstly clarifying the relationship between all the challenges and the proposed methods. In addition, I have also corrected the tense issue as mentioned to avoid ambiguity. The detailed content for the revision and response will be given in the corresponding comments.

General Suggestions 2:

Double-check minor typos/grammar/formatting issues, e.g., Title: ‘based on’ -> ‘Based on’ or change ‘based on’ to ‘with’. Page 2, last line: ‘after the design...’ -> ‘with the design’ or ‘through the design’. Page 3, section 1.2: ‘with orders more amplitude...’ -> ‘with an amplitude order of magnitude greater ...’

Response:

Thanks for pointing out all these issues, and I have corrected them in the revised version. Also, I have gone through the thesis and corrected other mistakes:

Section 1.2: multiply → multiple

Section 2.1.2.2: glsmmWave → mmWave

Section 5.4.3.4 capture more dependency → capture more dependencies

Section 6.4.1: tolerant the low-SNR scenarios → tolerate the low-SNR scenarios

Section 6.5.2: yield a bad morphological and peak accuracy → yield poor morphological and peak accuracy

Comment 1 (for Abstract):

The abstract identifies four challenges (a–d), but the methods are classified into three. It would be useful to discuss whether it is worth distinguishing short-term ECG recovery from long-term ECG recovery. Could one method address two challenges simultaneously?

Response:

Thank you for figuring out this ambiguity. In my thesis, each chapter focuses on one challenge. Therefore, challenge (b) corresponds to Chapter 4 for the modelling and realization of short-term ECG recovery, while challenge (c) is overcome in Chapter 5 to realize long-term ECG recovery. In the revised thesis, I have clarified the correspondence between challenges and methods as shown in the Abstract, with the detailed content also listed below.

Based on the challenges above, multiple novel algorithms and deep learning frameworks are proposed: (a) a **cardio-focusing and -tracking (CFT)** algorithm is proposed to iteratively approach the point with a high-SNR radar signal extracted; (b) a deep learning model called

radarODE is designed to realize robust single-cycle ECG recovery; (c) a multi-task learning framework called **radarODE-MTL** is proposed to realize robust long-term ECG recovery; (d) a data augmentation method **Horcrux** and a transfer learning framework **RFcardi** are proposed to jointly decrease the demand for data acquisition. Extensive experiments are performed based on both public and private datasets to show the effectiveness of the proposed algorithms and frameworks. It is believed that this thesis contributes to the general development of the wireless sensing community and brings the future applications of wireless wellness monitoring closer to our daily lives.

Comment 2 (for Abstract):

Line 2: ‘this thesis will focus on...’ -> change to present tense. In additional, the first paragraph focuses on the clarification of general subject area. ‘this thesis will focus...’ seems out of place.

Response:

Thanks for the suggestion. I have rewritten the first paragraphs to avoid the tense issue and also ensure coherence for the abstract section. The detailed revision is shown below.

Wireless sensing empowers numerous emerging industries such as autonomous driving and device-free monitoring. By introducing the contactless sensors such as millimeter-wave (mmWave) radar, a promising and challenging research area is emerging to realize robust and remote vital sign monitoring, enabling contactless monitoring for future in-cabin monitoring, elderly people caregiving and even clinical diagnosis. In recent years, frequency-modulated continuous wave (FMCW) radar with high operating frequency is becoming mainstream in radar front-end design, encouraging the related research to extract fine-grained ECG signals as the golden standard in clinical diagnosis and realize robust monitoring in the presence of real-world noises.

Comment 3 (for Publication):

Clarify more clearly the connections between the thesis chapters and journal papers e.g., in the introduction section.

Response:

Thanks for the comment, and I have updated the content in the Publication section and also added one paragraph to elaborate on the connections between the thesis chapters and journal papers as suggested in another comment. The detailed content for the revision and response will be given in the corresponding comments.

Revision for the Publication Section**Journal paper:**

1. Yuanyuan Zhang, Rui Yang, Yutao Yue, Eng Gee Lim, Zidong Wang, “An Overview of Algorithms for Contactless Cardiac Feature Extraction from Radar Signals: Advances and Challenges”, *IEEE Transactions on Instrumentation and Measurement*, Jul. 2023. ([Chapter 2](#))
2. Yuanyuan Zhang, Runwei Guan, Lingxiao Li, Rui Yang, Yutao Yue, Eng Gee Lim, “radarODE: An ODE-Embedded Deep Learning Model for Contactless ECG Reconstruction from Millimeter-Wave Radar”, *IEEE Transactions on Mobile Computing*, Apr. 2025. ([Chapter 4](#))
3. Yuanyuan Zhang, Rui Yang, Yutao Yue, Eng Gee Lim, “radarODE-MTL: A Multi-Task Learning Framework with Eccentric Gradient Alignment for Robust Radar-Based ECG Reconstruction”, *IEEE Transactions on Instrumentation and Measurement*, Apr. 2025. ([Chapter 5](#))

Conference paper:

1. Yuanyuan Zhang, Sijie Xiong, Rui Yang, Eng Gee Lim, Yutao Yue, “Recover from Horcrux: A Spectrogram Augmentation Method for Cardiac Feature Monitoring from Radar Signal Components”, in *2025 47th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC2025)*, Jul. 2025. ([Chapter 6](#))

Under Review:

1. Yuanyuan Zhang, Haocheng Zhao, Sijie Xiong, Rui Yang, Eng Gee Lim, Yutao Yue, “From High-SNR Radar Signal to ECG: A Transfer Learning Model with Cardio-Focusing Algorithm for Scenarios with Limited Data”, *IEEE Transactions on Mobile Computing*. (Under Major Revision) ([Chapter 3](#))

Revision for the Introduction Section (Section 1.4)

All the main chapters are associated with the published or under review publications and are modified from the corresponding manuscripts. In detail, Chapter 2 is based on the review paper published in the IEEE Transactions on Instrumentation and Measurement (TIM) named “An Overview of Algorithms for Contactless Cardiac Feature Extraction From Radar Signals: Advances and Challenges”. Chapter 3 focuses on the efficient high-SNR radar signal collection and is modified from the under-reviewed paper submitted to IEEE Transactions on Mobile Computing (TMC) named “From High-SNR Radar Signal to ECG: A Transfer Learning Model with Cardio-Focusing Algorithm for Scenarios with Limited Data”. Chapter 4 and 5 are for single-cycle and long-term radar-based ECG recovery, and the contents are based on two publications in TMC and TIM, named “radarODE: An ODE-Embedded Deep Learning Model for Contactless ECG Reconstruction from Millimeter-Wave Radar” and “radarODE-MTL: A Multi-Task Learning Framework with Eccentric Gradient Alignment for Robust Radar-Based ECG Reconstruction”, respectively. Lastly, Chapter 6 contains the methods for alleviating data scarcity based on the content in the conference paper (EMBC2025) named “Recover from Horcrux: A Spectrogram Augmentation Method for Cardiac Feature Monitoring from Radar Signal Components”.

Comment 4 (for Contents):

Section structure may be expanded to cover more subsubsection information for clarity.

Response:

Thanks for pointing out this issue, and I have added the depth of the content table to show the “subsubsection”.

Comment 5 (for Chapter 1):

In Section 1.3, the challenge is phrased as “Efficient High-SNR Signal Acquisition.” It may be intended as “Inefficient High-SNR Signal Acquisition,” to better reflect that acquiring high-quality signals remains a challenge. The phrasing of the other challenge statements should also be clarified.

Response:

Thank you for pointing out this ambiguity, and I have changed the title for all the challenges as:

[Section 1.3.1: Inefficient High-SNR Signal Acquisition](#)

[Section 1.3.2: Non-robust Single-cycle ECG Recovery](#)

[Section 1.3.3: Non-robust Long-term ECG Recovery](#)

[Section 1.3.4: Dependency on Massive Data](#)

Comment 6 (for Chapter 1):

Clarification is needed on the intended meaning of the term ECG recovery. Does it refer to: denoising the ECG signal to enhance SNR, discovering or decoding ECG patterns such as heart rate; or as you might phrase it: “ECG recovery refers to the estimation of ECG equivalent signals from radar data, either through denoising or signal reconstruction, enabling cardiac feature extraction without direct skin contact”?

Response:

Thanks for this instructive comment. I have clarified the exact meaning of ECG recovery in this thesis in Section 1.3 as shown below.

[In the context of this thesis, radar-based ECG recovery¹ refers to the estimation of ECG equivalent signals from radar measurements through the nonlinear mapping/reconstruction from cardiac mechanical activities \(radar\) to electrical activities \(ECG\), enabling cardiac feature extraction without direct skin contact.](#)

¹[In this thesis, ECG recovery, ECG generation and ECG reconstruction refer to the same meaning.](#)

Comment 7 (for Chapter 1):

Please elaborate on the role of deep learning in noise handling. If radar sensing can denoise ECG over short-term windows with defined frequency, why is it less effective over long-term

recordings? Is this due to signal misalignment? If so, what types of misalignments were considered (e.g., subject movement, sensor disconnection)?

Response:

Thank you for raising this question, but I think there is a slight misunderstanding about the process of radar collection and robust ECG recovery. Firstly, the radar sensing technique cannot denoise the ECG signal, because the measured radar signals only have the cardiac mechanical features similar to seismocardiography (SCG). In Chapter 3, the proposed method (CFT) can ensure an efficient data collection, especially for scenarios with posture changes. However, this method cannot resist extensive body movement (e.g., during the changing of posture).

In this case, the heavily distorted radar signals do not contain any useful information for the deep-learning-based ECG recovery, causing a meaningless result (as indicated in Chapters 4 and 5). Therefore, I proposed radarODE and radarODE-MTL to separately improve the noise robustness in terms of single-cycle and long-term ECG recovery, because the previous work all considered the radar-based ECG recovery as a whole process and could not intervene in the learning process to improve robustness.

For the different effectiveness of single-cycle and long-term ECG recovery, the key obstacle is the inaccurate PPI estimation, and that is why I use the cycle length decoder in the MTL paradigm for the PPI estimation in Chapter 5 to solve the misalignment issue. In the revised thesis, I have enhanced the explanation mentioned above in Section 1.4 to avoid ambiguity, and the detailed content is also shown below.

- Chapter 3 proposes a cardio-focusing and -tracking (CFT) algorithm based on derivative-free optimization (DFO) to find the cardio-focused (CF) point by iteratively evaluating the potential points in a discontinuous objective space, with a universal signal template designed to adaptively assess the signal SNR as costs. The collected radar signals ideally contain ample cardiac mechanical features (e.g., as in SCG signal) to ensure a reasonable recovery of the ECG signal in later chapters.
- Chapter 5 investigates the noise robustness in radar-based ECG recovery against constant or abrupt noise by modeling the cardiac domain transformation as three tasks. Then, an end-to-end multi-task learning (MTL) framework named radarODE-MTL is accordingly proposed to realize these tasks and leverage adjacent cardiac cycles to compensate for the

distorted one. Together with Chapter 4, long-term radar-based ECG recovery is modeled into different expandable stages with mathematical restrictions to resist strong noises, and the robust single-cycle ECG pieces can also be precisely assembled without the misalignment issue.

Comment 8 (for Chapter 1):

After defining each challenge (research gap), a separate paragraph should link each to a corresponding research question (RQ) to make the gap-question alignment explicit. For example: RQ1: How can radar sensing reconstruct ECG signals using [specific methods] to address [specific challenge]?

Response:

Thanks for the suggestion, and I agree with you that specifying the research question will help the understanding of the aims of the thesis. In the revised thesis, I have added the research questions at the end of each challenge in Section 1.3, with the detailed content shown below.

Research question 1: How to precisely locate and track the cardiac location based on space search during data collection to efficiently extract high-SNR radar signal.

Research question 2: How to design the signal model that considers fine-grained cardiac features within a single cardiac cycle and design a robust single-cycle ECG generation module against abrupt noises.

Research question 3: How to model and generate the noise-robust long-term ECG recovery from radar signal by assembling and aligning the single-cycle ECG pieces.

Research question 4: How to reduce the dependency on large-scale datasets and develop appropriate transfer learning or data augmentation methods to alleviate data scarcity, especially for the deployment in new scenarios with limited data.

Comment 9 (for Chapter 1):

Add appropriate citations for 1.3.3

Response:

Thanks for the suggestion. Since all the previous studies did not separately use the concept of single-cycle or long-term ECG recovery, the reference paper added for Section 1.3.3 will be very similar to those for Section 1.3.2. To better clarify the difference, I have revised the content in Section 1.3.3 to explain the necessity of deconstructing the ECG recovery process into fine stages, with the detailed content also shown below.

After the modeling and recovery of single-cycle ECG pieces, a follow-up issue is to model and realize the robust long-term ECG recovery. The previous studies all consider the transformation as an entire process without any explanation or control and cannot resist even mild noises [1, 50, 55–57]. Although the model for the domain transformation between single-cycle radar/ECG pairs has been proposed in [2], the long-term ECG recovery might be misaligned with ground truth due to inaccurate peak-to-peak interval (PPI) estimation, deteriorating the recovery quality even if the morphological features are well-recovered.

Research question 3: How to model and generate the noise-robust long-term ECG recovery from radar signal by assembling and aligning the single-cycle ECG pieces.

Comment 10 (for Chapter 2):

Section 2.1 could be better linked to the challenges/research questions in Chapter 1.

Response:

Thanks for pointing out this problem. Considering that the next comment also asks for rearranging Section 2.1 and 2.2 to fit the narrative of research challenges, I decided to rewrite the whole chapter following two stages claimed in the challenges (Section 1.3): (a) radar signal collection and pre-processing to increase SNR; (b) cardiac feature extraction using advanced algorithms or deep learning. The content for the whole chapter will not be pasted in this response letter, and only the structure of the revised Chapter 2 is provided as shown below.

Chapter 2 Background and Literature Review

Section 2.1 Radar Signal Collection and Pre-processing – This section is mainly related to the first challenge/research question to collect high-SNR radar signals for future cardiac feature extraction.

[Section 2.2 Advanced Algorithms for Cardiac Feature Extraction](#) – This section reviews the relevant methods for cardiac feature extraction with the pros/cons provided. Also, the deep learning method is focused on, as it is the only way to generate ECG recovery, and the rest of the challenges/research questions are associated with this part to deal with the issues related to deep learning.

Comment 11 (for Chapter 2):

Section 2.2 (literature review) would benefit from division into 3 –4 subsections, each reviewing current solutions relevant to one research question, and summarising the gaps that remain. Relevant background (currently in 2.1) could be integrated to focus on identifying research gaps.

Response:

Thank you for raising this question about the arrangement of the literature review part. As I have responded to the previous comment, I have rearranged the whole Chapter 2 to fit the challenges/research questions.

Specifically, Section 2.1 describes the background information and the literature review for the radar signal collection and highlights the necessity of designing an appropriate method for obtaining high-SNR radar signals (Research question (RQ) 1).

Then, Section 2.2 mainly focuses on the methods for extracting cardiac features from the radar signal. Considering that only deep learning methods can generate ECG recovery while most studies before 2020 are about the signal processing methods (e.g., spectrum-based method, signal decomposition), Section 2.2 reviews the methods not only for the ECG recovery. In addition, the RQ2, 3 and 4 are all the methods used for extracting different cardiac features (i.e., RQ1 for single-cycle ECG features, RQ2 for long-term ECG features and RQ3 for coarse cardiac features using self-supervised learning). Therefore, Section 2.2 introduces the concept of radar-based ECG recovery and the necessity of solving RQ2-4.

Comment 12 (for Chapter 2):

Regarding the use of the term “Evaluations”, I assume this refers to evaluation metrics or processes for assessing current methods. However, from the text it sometimes reads as personal reflections or opinions; this should be clarified.

Response:

Thanks for pointing out this ambiguity, and I have rephrased the “Evaluations” as “Strengths and Weaknesses” as the purpose of these paragraphs in the review paper is for the evaluations of pros and cons of different methods for cardiac feature extraction.

Comment 13 (for Chapter 2):

Section 2.2: organise the key metrics of different methods into a table for better clarity.

Response:

Thanks for this comment. As discussed in the viva session, I have summarized the content about the strength and weakness of different methods into one table in Section 2.2, and the detailed content is also shown below.

This section provides a thorough review of the popular methods for radar-based cardiac features extraction with the corresponding pros and cons shown in Table 2.1.

Table 2.1: Strengths and weaknesses of cardiac feature extraction algorithms

Category	Advantage	Disadvantage
Spectrum-based Methods	1. Have low algorithm complexity 2. Can be implemented directly on the hardware 3. Good real-time performance	1. Hardly detect the abrupt HRV 2. Easily affected by noise
Periodicity-based Methods	1. Can identify individual heartbeat 2. Can realize cardiac event segmentation 3. Naturally immune to non-periodic noise	1. Require prior-knowledge 2. Hardly detect rarely happened cardiac events 3. Require calibration for new participants
Blind Source Separation Methods	1. No need for prior knowledge 2. Can perform non-linear or non-stationary signal decomposition	1. Require a careful selection of the parameters and the resultant decomposed signals 2. May insufficiently or over decompose the mixed signals
Deep Learning Methods	1. Can reconstruct the fine-grained cardiac features (e.g., ECG waveform) 2. Can leverage long term dependency in estimation 3. Can potentially resist different kinds of noises	1. Require massive data for training 2. Rely on full-featured dataset with numerous scenarios for good performance 3. Use large deep learning model and cannot be implemented on lightweight devices

Comment 14 (for Chapter 2):

Page 22, last paragraph: ‘infer on’ -> ‘infer from’

Response:

Thanks for the correction, and I have changed it in the revised thesis.

Comment 15 (for Chapter 3):

Figure 3.1: The caption does not explain the meaning of the orange and blue lines. Why does the time axis start at 46 seconds?

Response:

Thanks for the questions. I have added the legends for the orange and blue lines with the explanation in the main text. The blue radar signals represent the radar measurements with high and low SNR, which can be revealed by identifying the prominent peaks corresponding to the peaks of the orange ECG ground truth. In addition, I use the actual time axis in each data trial throughout my thesis. Therefore, this illustration represents the radar and ECG measurement starting from 46 seconds in that record. The revised part is in Section 3.1, with the detailed content also listed below.

Although, it is natural to think the high-SNR radar signal can be searched in a constrained space by optimization, there is no appropriate method to assess the signal SNR in terms of cardiac features contained, and the objective space is actually highly discontinuous because the adjacent points may reveal totally different SNR as shown in Figure 3.1(a) and 3.1(b), with high-SNR radar signal shown prominent peaks aligning with ECG peaks but not vice versa.

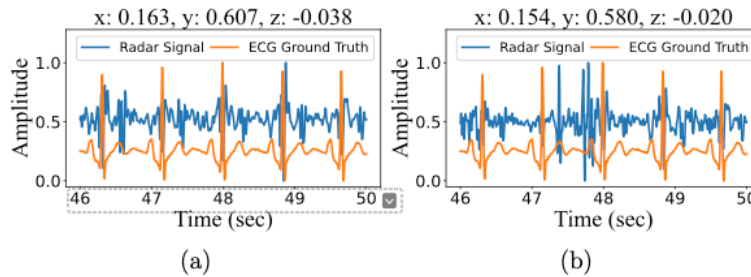


Figure 3.1: Challenges for high-SNR signal collection: (a) and (b) Radar signals with high and low SNR for adjacent points with a distance of 0.03m. The ECG ground truth is plotted to help the identification of the prominent peaks.

Comment 16 (for Chapter 3):

Figure 3.2: How is the boundary defined between high-SNR and low-SNR signals? What deep learning model architecture and training approach was used?

Response:

Thank you for pointing out this issue. As we discussed during viva, there is no explicit boundary for high- and low-SNR signals, and this chapter also did not use “high” or “low” to filter out the bad signal. Therefore, Figure 3.1 only shows these two types of signals to intuitively indicate the difference between them. In the revised thesis, I have added the annotation for this ambiguity in Section 3.2.1, with the detailed content also shown below.

The rough location acts as the initial state for the CFT algorithm, and the points within a constrained space will be evaluated to find the red CF point with high SNR while ignoring the space where only low-SNR signals² can be extracted from, as shown in Figure 3.2(b).

²There is no boundary for distinguishing high or low signals, because explicit values will be used as the accurate estimation of SNR instead of the vague binary classification.

For the second question, I directly used the same deep learning model and training approach as in Chapter 5 (i.e., radarODE-MTL as published in [60]). I have added the corresponding reference for the used deep learning model in Section 3.3.2.2, and the training process will be elaborated in the next response. The detailed revised content is also listed below.

The deep learning model adopts the same backbone, encoder and decoder structure with the same hyperparameters as used in our previous open-sourced work [60] coded in PyTorch and trained on NVIDIA RTX 4090 (24GB). The total training epoch is set to 100 with a batch size of 8, and each experiment is repeated five times to ensure statistical significance. All the results show the statistical significance with P values much smaller than 0.05, hence, they are not shown in the tables or figures for conciseness. The dataset is split based on a 5-fold cross-validation training strategy, with the trials from 1 fixed subject for testing and the other 4 subjects alternatively selected for training or validation, ensuring to make use of all the possible trials while not involving the testing data in the training phase.

Comment 17 (for Chapter 3):

Table 3.2: How were the training and testing datasets separated? Was the same procedure applied to all algorithms? How many runs were conducted? Was statistical significance assessed (e.g., $p < 0.05$)?

Response:

Thank you for these questions. For the short answers to these questions: (a) The training, validation, and testing set is separated according to 5-fold cross-validation. (b) Yes, the same procedure is applied for all the content related to deep learning training/testing. (c) For the testing of the deep learning model, all the experiments are repeated five times. (d) The designed deep learning models in this thesis are not super complex with high uncertainty. According to my observation, all the results have negligible deviations compared with the improvement achieved. I will explain all the answers in the following parts.

Q1: How were the training and testing datasets separated?

The dataset is divided based on subjects, with the trials for one subject for testing, one for validation and the rest of the dataset for training. During the training stage for each subject, the testing data (from one subject) will never be involved in training and is only used for the final evaluation of the well-trained deep learning model. In addition, I also applied 5-fold cross-validation as a popular technique to make the most of all the trials in the training set.

Q2: Was the same procedure applied to all algorithms?

Yes, I employed the same procedure for all the deep learning training/testing throughout this thesis.

Q3: How many runs were conducted?

All the experiments are repeated five times to avoid uncertainty.

Q4: Was statistical significance assessed (e.g., $p < 0.05$)?

According to my observation during the training and testing for all the deep learning models designed in this thesis, the results are very stable with negligible deviation compared with the improvement achieved. For the statistical analysis, I do consider the popular T-test as shown in Chapter 5, but the calculated P values are much less than 0.05, as shown in Table 5.1

pasted below. The same small P values can also be found in Table 5.2-5.4. Therefore, I did not annotate the P values for other results as they are all close to 0.

Table 5.1: Comparison of different optimization strategies on radar-based ECG recovery

Methods \ Tasks	ECG Shape Recovery			Cycle Length Estimation	ECG Anchor Estimation		$\Delta m\%$ \uparrow	P Value ($\times 10^{-2}$)
	RMSE (mV) \downarrow	PCC \uparrow	R^2 \uparrow	PPI Error (ms) \downarrow	Timing Error (ms) \downarrow	MDR \downarrow		
Single-task baseline	0.106	86.6%	0.81	9.6	7.5	6.67%	0.00 \pm 1.43	-
Loss Balancing Methods								
Equal Weight	0.125	79.7%	0.63	8.0	9.7	5.51%	-1.78 \pm 2.16	9.26
UW [230]	0.066	88.5%	0.85	11.2	5.5	6.44%	4.04 \pm 3.79	2.43
GLS [229]	0.087	87.3%	0.81	14.1	6.7	4.32%	-5.89 \pm 2.02	0.02
DWA [228]	0.133	80.7%	0.79	8.3	6.4	5.33%	6.45 \pm 3.71	0.20
STCH [227]	0.070	88.0%	<u>0.86</u>	13.9	5.5	3.28%	2.90 \pm 3.21	5.12
Gradient Balancing Methods								
CAGrad [226]	0.107	84.2%	0.79	10.2	6.2	3.98%	6.84 \pm 2.12	0.01
IMTL [225]	0.088	<u>89.4%</u>	<u>0.86</u>	9.3	<u>6.0</u>	6.22%	8.43 \pm 1.39	0.00
MoCo [224]	0.179	61.0%	0.66	8.7	6.8	4.27%	-2.32 \pm 1.37	1.16
Aligned-MTL [223]	0.092	87.9%	0.84	10.0	6.9	3.52%	10.14 \pm 1.11	0.00
EGA ($T = 0.1$)	0.119	79.0%	0.72	10.6	6.8	<u>3.34%</u>	2.83 \pm 0.98	0.19
EGA ($T = 0.5$)	<u>0.082</u>	89.6%	0.87	9.9	6.3	4.19%	<u>11.55\pm1.44</u>	0.00
EGA ($T = 1.0$)	0.085	87.4%	0.85	8.5	7.2	4.31%	13.37\pm1.36	0.00
EGA ($T = 1.5$)	0.105	82.9%	0.78	<u>8.1</u>	6.3	5.13%	10.94 \pm 1.30	0.00
EGA ($T = 2.0$)	0.091	86.3%	0.84	9.2	7.3	4.01%	10.43 \pm 0.95	0.00
Bold and underline represent the best and the second best results, respectively.								

Bold and underline represent the best and the second best results, respectively.

I have revised the related part in the thesis in Section 3.3.2.2, with the detailed content listed below.

The deep learning model adopts the same backbone, encoder and decoder structure with the same hyperparameters as used in our previous open-sourced work [60] coded in PyTorch and trained on NVIDIA RTX 4090 (24GB). The total training epoch is set to 100 with a batch size of 8, and each experiment is repeated five times to ensure statistical significance. All the results show the statistical significance with P values much smaller than 0.05, hence, they are not shown in the tables or figures for conciseness. The dataset is split based on a 5-fold cross-validation training strategy, with the trials from 1 fixed subject for testing and the other 4 subjects alternatively selected for training or validation, ensuring to make use of all the possible trials while not involving the testing data in the training phase.

Comment 18 (for Chapter 3):

Provide more details on the radar hardware setting/specifications of the MIMO radar and deployment considerations (e.g., the optimal transmission power and subject distance).

Response:

Thank you for the suggestions. As we discussed during the viva, I have added the necessary radar settings (e.g., Tx/Rx gain and power) as shown in the revised Table 3.1. Also, the detailed ECG collection setting is shown in the revised Figure 3.6. In addition, the distance between radar and human body varies from 0.5-1.2m. I have revised the thesis in Section 3.3.1, with the detailed content also listed below.

The subjects are asked to sit casually and are allowed to change postures during data collection, and each data trial lasts for 1 minute. The distance between radar and human body varies from 0.5-1.2m, and a longer distance causes the decrease of signal SNR with a smaller portion of the space points containing useful cardiac features.

TI-AWR 1843 radar with 2 Tx and 4 Rx is used for data collection with 8 virtual antenna channels created [77], and the radar configurations are listed in Table 3.1 with the name provided in TI mmWave-Studio interface. The signal will be sampled at 200Hz, and only a band-pass filter from 0.5 to 50Hz and a differentiator are used for removing respiration noise because the radar signal extracted from CF points already has high SNR. Lastly, the ECG ground truth is collected using TI ADS1292 with AC coupling and integrated right-leg drive (RLD) amplifier to remove potential baseline drift or power-line noise, as shown in Figure 3.6. The related ECG processing (e.g., smoothing and peak finding) is realized by NeuroKit2 python package [201] after the collection.



Figure 3.6: Indoor scenarios for synchronous radar and ECG collection.

Table 3.1: Parameters for data collection interface

Parameter	Value	Parameter	Value
Start Frequency	77GHz	Frequency Slope	65MHz/ μ s
Idle Time	10 μ s	Tx Start Time	1 μ s
ADC Start Time	6 μ s	ADC Samples	256
Sample Rate	5000kbps	Ramp End Time	60 μ s
Start/End Chirp Tx	0/2	No. of Chirp Loops	2
No. of Frames	12000	Frame Periodicity	5ms
Tx Gain (G_T)	10 dBi	Rx Gain (G_R)	30 dBi
Tx power (P_T)	12 dBm	Noise Figure (NF)	15 dB
Wavelength (λ)	3.9 mm	Bandwidth (B)	3.8 GHz

Comment 19 (for Chapter 4):

Figure 4.1: Could you clarify the differences between ECG Generation, ECG Recovery, and ECG Reconstruction? Why is long-term ECG considered here rather than in Chapter 5?

Response:

Thanks for pointing out this ambiguity. Based on our discussion during viva, I have clarified that there is no difference between ECG Generation, ECG Recovery, and ECG Reconstruction in Section 1.3 as shown below.

¹In this thesis, ECG recovery, ECG generation and ECG reconstruction refer to the same meaning.

Also, based on our discussion, the long-term ECG recovery module in Chapter 4 is for the consistency of the work done in Chapter 5, and also could provide a benchmark for the radarODE-MTL designed in Chapter 5.

Comment 20 (for Chapter 4):

Move the title of Fig. 4.17 to the caption for formatting consistency.

Response:

Thanks for the suggestion, and I have revised the figure as shown below.

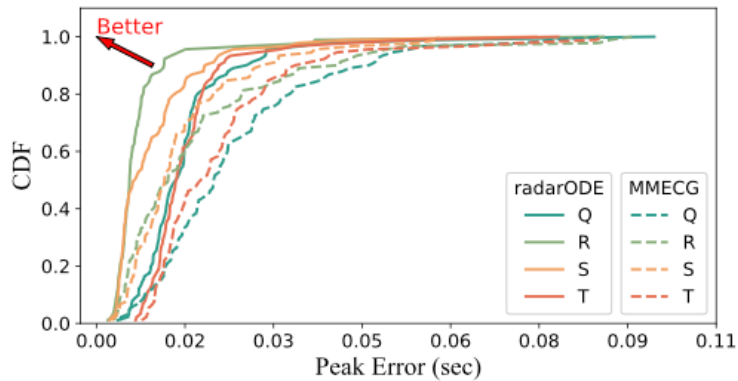


Figure 4.17: CDF of the overall timing error, with overall improvement for each peak as: Q: 4%, R: 15%, S: 5%, T: 9%.

Comment 21 (for Chapter 5):

Figure 5.2: How long does it take to perform single-cycle ECG recovery? How about long-term ECG recovery? For the module named “Cycle Length Decoder”, How does this address inaccurate PPI estimation? Is it due to predicting the cycle length itself, or related to classifying different cycles across varying ECG patterns?

Response:

Thanks for raising these questions, and I will answer them one by one.

How long does it take to perform single-cycle ECG recovery? How about long-term ECG recovery?

The time consumed for single-cycle and long-term ECG recovery should be very similar, because the complexity analysis shows that the major parameters in the model are for the backbone part, which is the same for both processes. The exact time consumed is shown in Table 5.5 added in Section 5.4.5, with the detailed content also shown below.

Table 5.5 presents a detailed complexity comparison of three frameworks considering the parameter count (Params.), floating point operations (FLOPs), multiply accumulate operations (MACs), and training time per epoch. The parameter count reflects the total number of parameters in each model, and FLOPs and MACs quantify the computational costs [216]. As shown in Table 5.5, the complexities of ODE-based methods are higher than those of MMECG due to the different input data types, with radarODE and radarODE-MTL using spectrogram input and MMECG processing 1D radar signals. In addition, the majority of the parameters (59%) and FLOPs (95%) for radarODE-MTL are for the backbone stage for spectrogram processing, and an important future work is to squeeze the backbone size with reduced input spectrograms.

Compared with the gaps in model size, the training times per epoch for three frameworks are closer, because the MMECG is trained on arbitrary radar/ECG segments with a step length of 0.15 sec [1], while the ODE-based frameworks are based on single cardiac cycles. In this case, the MMECG needs to traverse 48k samples while radarODE-MTL only has 19k samples, indicating that many samples for MMECG training are homogeneous and cannot contribute to dataset diversity and may increase the risk of overfitting.

Table 5.5: Complexity Comparison Across Deep Learning Frameworks

Framework		Params. (M)	FLOPs (G)	MACs (G)	Time/Epoch (min)
MMECG [1]		0.67	0.59	0.30	3.25
radarODE [2]		6.04	2.45	1.23	4.51
radarODE- MTL	Backbone	4.81	2.37	1.18	-
	Encoder	0.72	0.05	0.03	-
	Decoder	2.59	0.07	0.03	-
	All	8.12	2.50	1.23	4.85

For the module named “Cycle Length Decoder”, How does this address inaccurate PPI estimation? Is it due to predicting the cycle length itself, or related to classifying different cycles across varying ECG patterns?

In Chapter 4, PPI estimation is realized using the algorithm by identifying the peaks of heartbeats, while radarODE-MTL uses the deep learning decoder to estimate the cycle length (which is equivalent to the peak-to-peak interval). The deep learning model does not only rely on the current peak/cardiac cycle, but also extracts useful information from the adjacent cycles. Therefore, the accuracy of PPI can be improved, especially when the current cycle is contaminated while the adjacent cycles have good SNR. I have added the explanation in Section 5.4.3.5, and the detailed content is also listed below.

Different from other frameworks with equal length of input and output, radarODE-MTL adopts a 4-sec segment to reconstruct the ECG piece for one cardiac cycle, and the radar signal from adjacent cardiac cycles also contributes to the recovery of the current ECG piece. Therefore, the peak accuracy can be compensated from the adjacent cardiac cycles with less noise distortion.

Comment 22 (for Chapter 5):

Page 77, first paragraph: ‘well-recovery’ -> ‘well-recovered’; ‘a optimization’ -> ‘an optimization’

Response:

Thanks for figuring out these typos, and I have corrected them in the revised thesis.

Comment 23 (for Chapter 6):

How are “limited labelled data” conditions defined (e.g., 40%, 60%)? How does this differ from the original dataset distribution?

Response:

Thanks for the questions. As we discussed during the viva, I just randomly discarded the samples in the dataset to reduce the input data scale. Therefore, the data will have an increasing variance component, making the model less stable and more prone to overfitting. The revised part is in Section 6.4.2.3, with the detailed content also listed below.

As a data augmentation technique, Horcrux is tested with different scales of dataset with the overall performance $\Delta m\%$ shown in Figure 6.5. The samples in the dataset are randomly dropped, and the rest of the dataset will have an increasing variance component, making the model less stable and more prone to overfitting.

Comment 24 (for Chapter 6):

Shorten the Chapter title or use smaller font size to avoid misalignment/overlapping in the page header.

Response:

Thanks for pointing out this issue, and I have fixed this problem.

Comment 25 (for Chapter 7):

The conclusions should re-emphasize the provided answers to the research questions/objectives set in chapter 1/2.

Response:

Thanks for the suggestion, and I have revised Section 7.1 to highlight the value of my research, and the detailed content is shown below.

- Chapter 3 overcomes the inaccurate localization of the human chest region (Research question 1) and explores methods for efficiently collecting high-SNR radar signals that

contain rich cardiac features. A novel **CFT** algorithm is designed to dynamically identify points with optimal SNR and track the cardiac location as subjects change postures.

- Chapter 4 aims to bridge the gap to realize a robust transformation from the mechanical domain to the electrical domain (Research question 2) by proposing the signal model with fine-grained features considered. Furthermore, a deep learning framework, **radarODE**, is designed with morphological prior embedding as ODEs to provide faithful single-cycle ECG recoveries even under strong noise.
- Chapter 5 is based on the robust single-cycle ECG generator designed in the previous chapter and further investigates the long-term ECG recovery under noises or ECG misalignment (Research question 3). The realization of ECG recovery is appropriately deconstructed into three sub-tasks with an MTL framework called **radarODE-MTL** designed to generate the long-term ECG signal. Additionally, a novel optimization strategy named EGA is presented to optimize all tasks simultaneously, effectively avoiding issues such as stalling or negative transfer.
- Chapter 6 tries to alleviate the data scarcity for DNN training (Research question 5), because radar-based ECG reconstruction is highly reliant on data-driven approaches. Firstly, a data augmentation method called **HorcruX** is proposed to expand the diversity of the limited training dataset without distorting the key features. Secondly, a transfer learning framework called **RFcardi** is designed by leveraging an appropriate pre-text task (i.e., SSR), enabling an effective learning of the latent representations from radar signals to assist the final ECG recovery task.

Comment 26 (for Chapter 7):

Page 134, line 4: ‘car vibrations’ -> ‘platform vibrations’; ‘enable a realistic radar ECG measurement’ -> ‘enable realistic radar-based ECG monitoring’

Response:

Thanks for pointing out these issues, and I have corrected them in the revised thesis.