

Article

Contactless ECG Reconstruction from Millimeter-Wave Radar Signals Using a CNN-BiLSTM Network

Mingda Liu ¹, Xiaoyan Zhou ^{2,*}, Bo Ni ², Qida Yu ² and Xinnan Zhao ³¹ Changwang School of Honors, Nanjing University of Information Science and Technology, Nanjing 210044, China; 18306352811@163.com² School of Electronic and Information Engineering, Nanjing University of Information Science and Technology, Nanjing 210044, China³ School of Biological Science and Medical Engineering, Southeast University, Nanjing 211189, China

* Correspondence: 001385@nuist.edu.cn

Abstract

To investigate the feasibility of reconstructing electrocardiogram (ECG) waveforms from non-contact millimeter-wave radar measurements, a radar-based ECG reconstruction method using a CNN-BiLSTM network is presented. A synchronous acquisition platform integrating a millimeter-wave radar and a BIOPAC physiological signal acquisition system was established to collect chest-wall vibration signals and reference ECG signals. A multi-channel cross-correlation-based channel selection and temporal alignment procedure was employed to construct paired radar–ECG samples. The radar chest-wall vibration signals were filtered using an 8–30 Hz band-pass filter and then fed into the CNN-BiLSTM model, while a joint time–frequency loss function was introduced to constrain ECG reconstruction. On the self-built vital sign dataset, the reconstructed ECG achieved a correlation coefficient of 0.5631 with the reference ECG, while the mean absolute errors of heart rate and R–R interval were 1.00 BPM and 10.02 ms, respectively. These results suggest that the reconstructed signals preserve basic heartbeat timing and overall rhythm-related information, although the waveform-level agreement varies among samples and does not yet demonstrate consistent recovery of fine-grained ECG morphology. Evaluation on a public dataset further showed condition-dependent reconstruction performance under Resting, Apnea, and Valsalva conditions. Published MultiRes-LinkNet values were included only as contextual numerical references because the baseline was not reimplemented within the same experimental pipeline. Overall, the results provide preliminary evidence for the feasibility of contactless ECG reconstruction from millimeter-wave radar signals and suggest its potential value for radar-based vital sign monitoring.

Keywords: millimeter-wave radar; electrocardiogram reconstruction; convolutional neural network; bidirectional long short-term memory network; vital sign monitoring



Academic Editors: Deqing Mao, Sen Yuan and Jianping Wang

Received: 12 June 2026

Revised: 15 August 2026

Accepted: 18 August 2026

Published: 20 August 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

Respiration and heart rate are vital signs that reflect the physiological state of the human body, and their long-term, stable monitoring aids in identifying abnormalities, supporting diagnosis, and managing health. Traditional contact-based monitoring devices such as electrocardiograms (ECG) and chest/abdominal respiratory bands offer high measurement accuracy but suffer from discomfort during wear, limited application scenarios, and challenges in long-term continuous monitoring [1,2]. In contrast, non-contact vital sign

monitoring eliminates the need for direct physical contact with the body, offering promising applications in home healthcare, smart medical systems, and sleep monitoring [3].

Among various non-contact sensing techniques, millimeter-wave radar has attracted significant attention due to its high displacement sensitivity, strong environmental adaptability, and favorable privacy protection characteristics [4,5]. Specifically, frequency-modulated continuous wave (FMCW) millimeter-wave radar can simultaneously capture target distance information and subtle chest wall movements, providing a crucial technical foundation for detecting vital signs such as respiration and heartbeat [6,7]. Existing methods for extracting vital signs from radar signals mainly fall into two categories: traditional signal processing approaches and deep learning methods. Conventional techniques typically employ wavelet analysis, autocorrelation computation, multi-channel fusion, and physiological prior modeling to achieve breath suppression, heartbeat separation, and heart rate estimation, achieving notable progress in detecting parameters such as respiratory rate, heart rate, and inter-beat intervals [8–10]. Recently, research has advanced from non-contact ECG monitoring using millimeter-wave radar [11] and low-power heartbeat signal reconstruction [12], to ECG waveform modeling methods based on CNN-LSTM [13], CAE-BiLSTM [14], MultiRes-LinkNet [15], wavelet-neural fuzzy enhanced networks [16], fine-grained heartbeat waveform perception [17], and FMCW radar CNN reconstruction [18].

Related wearable electromagnetic sensing systems offer a complementary route to physiological monitoring. Recent textile microwave sensors have been used for wrist pulse-wave and heart-rate monitoring [19], while flexible microwave metasensors have been developed for sweat-related sensing [20]. Such on-body systems can provide localized sensor–body coupling and compact integration, but require the sensor to be worn on or placed close to the body. In contrast, millimeter-wave radar enables remote measurement without on-body attachment, which may improve comfort in controlled rest or sleep settings; however, it remains sensitive to body motion, posture, environmental clutter, and the indirect mapping from mechanical motion to ECG electrical activity. These modalities should therefore be regarded as complementary rather than directly interchangeable.

However, as research on radar-based ECG reconstruction deepens, related methods have evolved further, incorporating cross-modal dynamic modeling with ODE-based physiological priors [21], robust reconstruction via multi-task learning [22], transfer learning for limited paired samples [23], ECG reconstruction using multi-resolution wavelets and time–frequency constraints [24,25], and robust modeling for multi-lead and cross-posture scenarios [26,27]. Despite these advances, existing methods still face limitations in preserving fine-grained ECG morphological structures, capturing nonlinear mappings from mechanical vibrations to electrical activity, and ensuring stability across different scenarios. Meanwhile, radar and contact-based ECG data are often collected by different devices, differing in sampling rates, activation timing, and channel stability—factors that directly affect temporal synchronization accuracy, thereby influencing the quality of supervised learning samples and model reconstruction performance [28,29]. Therefore, how to improve the stable reconstruction of key ECG waveform structures while maintaining accurate radar–ECG temporal alignment remains a critical challenge in this field.

Generative approaches have also been investigated for radar-based ECG reconstruction. AirECG, for example, uses a cross-domain diffusion framework to model the mapping from millimeter-wave measurements to ECG waveforms [30]. These developments provide important methodological context; however, numerical results reported across studies are not directly comparable when sensing hardware, preprocessing, data partitioning, and training protocols differ.

Beyond radar-based ECG reconstruction, recent intelligent monitoring studies have also investigated learning frameworks for limited labeled data, heterogeneous sensors, and domain shifts. TFDDP employs self-supervised time–frequency dual-domain prediction to learn discriminative representations from limited labeled samples [31]. CSSCL introduces cross-sensor self-contrastive learning to extract consistent representations from heterogeneous sensor measurements under label-scarce conditions [32]. GCDA combines digital-twin-generated samples, graph contrastive learning, and domain adaptation to reduce the discrepancy between simulated and measured data in small-sample monitoring tasks [33]. Although these methods were originally developed for mechanical fault diagnosis rather than radar-based ECG reconstruction, their strategies for self-supervised representation learning, cross-sensor feature alignment, and domain adaptation provide useful methodological references for addressing limited paired radar–ECG data and variations across sensing configurations.

This paper addresses the aforementioned challenges by investigating cross-device temporal alignment, nonlinear mapping between radar-induced mechanical micro-motion signals and ECG electrical activity, and the preservation of key ECG waveform characteristics in contactless ECG reconstruction using millimeter-wave radar. First, a synchronized acquisition platform integrating millimeter-wave radar with the BIOPAC physiological signal recording system is established. A multi-channel cross-correlation-based channel selection method is employed to compensate for cross-device acquisition delays and construct temporally aligned radar–ECG paired samples. However, because the alignment is based on respiratory signals, it cannot completely eliminate the electromechanical delay between ECG electrical activity and radar-detected cardiac mechanical motion. Based on this foundation, a CNN-BiLSTM-based radar ECG reconstruction framework is constructed. The one-dimensional convolutional network extracts local heartbeat-related features from radar-induced chest-wall vibration signals, while the BiLSTM models bidirectional temporal dependencies within the signal segments. Therefore, the current framework is primarily intended for offline reconstruction. Furthermore, a joint time–frequency loss function is adopted to constrain the reconstructed ECG signals in terms of both time-domain amplitude consistency and frequency-domain spectral structure. Experimental results provide preliminary evidence for the feasibility of reconstructing ECG-related waveforms from millimeter-wave radar signals and indicate that the reconstructed signals retain useful information for R-peak detection, heart rate estimation, and R–R interval analysis. Accordingly, the methodological contribution of this study is positioned at the level of task-specific integration and evaluation of cross-device synchronization, radar preprocessing, CNN-BiLSTM reconstruction, and joint time–frequency supervision.

The main work of this study is summarized as follows:

- (1) A synchronized acquisition framework combining millimeter-wave radar with the BIOPAC physiological signal system is established. A multi-channel respiratory cross-correlation method is used for radar-channel selection and compensation of cross-device acquisition delays, providing temporally aligned radar–ECG paired samples while acknowledging the possible presence of residual electromechanical delay.
- (2) A radar ECG reconstruction framework integrating 1D convolutional layers and BiLSTM is implemented to combine local heartbeat-related feature extraction with bidirectional temporal modeling and learn the nonlinear relationship between radar-induced chest-wall vibrations and ECG waveforms. Because the BiLSTM uses both past and future information, the current framework is designed for offline reconstruction.
- (3) A joint time–frequency loss function combining time-domain amplitude errors with STFT-based frequency-domain discrepancies is incorporated into the reconstruction framework to constrain the output waveform from complementary domains. The ef-

fectiveness of the integrated framework is evaluated as a whole, while the independent contributions of its individual components require further ablation studies.

- (4) The integrated framework is evaluated on both a self-built radar–ECG vital sign dataset and a public dataset using waveform reconstruction metrics and R-peak-derived rhythm parameters. The results demonstrate the feasibility of the proposed pipeline for stationary monitoring and its potential utility for estimating basic cardiac rhythm parameters, while providing a basis for future evaluation of finer ECG morphological details and broader cross-subject performance.

2. Materials and Methods

2.1. Radar–ECG Synchronous Acquisition and Data Preprocessing

To achieve supervised learning-based reconstruction of ECG waveforms from millimeter-wave radar signals, this study first establishes a synchronized acquisition platform comprising a millimeter-wave radar and a BIOPAC multi-channel physiological monitor, simultaneously capturing radar signals related to chest wall vibrations, respiratory signals, and reference ECG signals. Subsequently, by extracting chest wall vibration signals, performing cross-device time synchronization, and preprocessing the ECG reference signals, temporally aligned radar–ECG paired samples are constructed [28,29]. This dataset not only provides input signals and supervisory labels for the subsequent CNN–BiLSTM model but also offers a unified data foundation for model training and performance evaluation. Based on this, frequency band selection is further applied to the radar-derived chest wall vibration signals, which are then fed into the CNN–BiLSTM model for ECG reconstruction. The overall data construction and reconstruction process is illustrated in Figure 1.

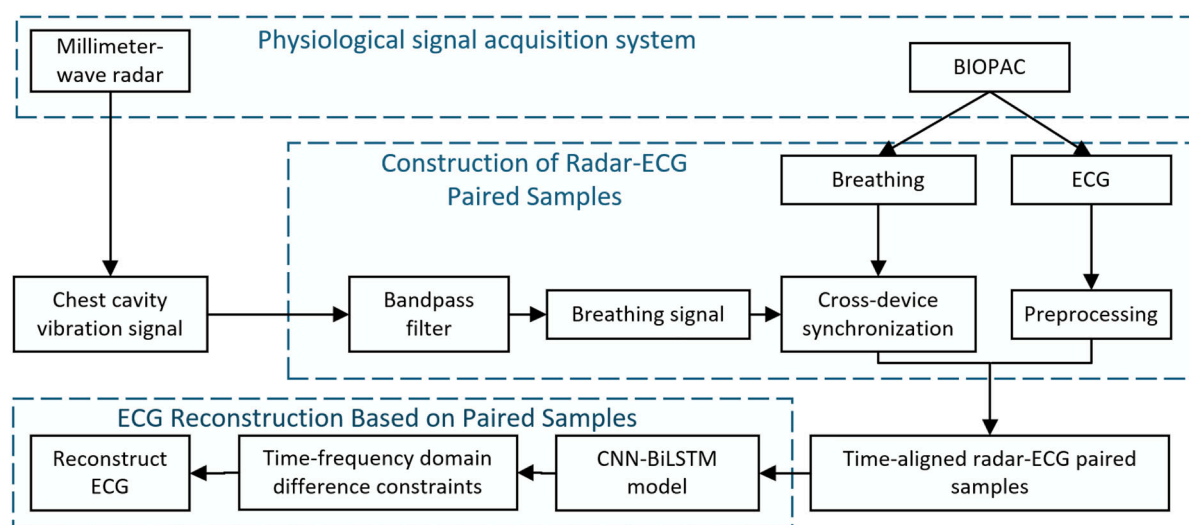
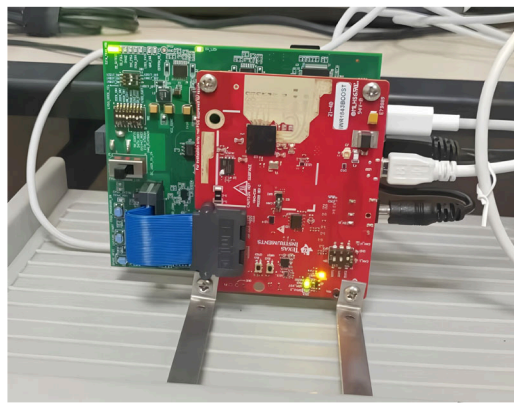


Figure 1. Flowchart of Chest Wall Vibration Signal Extraction and Time Synchronization.

2.1.1. Experimental System and Data Acquisition

A synchronous data acquisition platform, as illustrated in Figure 2, was established based on a millimeter-wave radar and contact-based physiological monitoring devices. On the radar side, a Texas Instruments IWR1843BOOST frequency-modulated continuous-wave (FMCW) millimeter-wave radar evaluation board and a DCA1000EVM data capture card (both from Texas Instruments Incorporated, Dallas, TX, USA) were employed. Operating in the 77–81 GHz frequency band, the radar integrates three transmit and four receive antennas, enabling non-contact acquisition of subtle chest wall vibration signals. In this study, the radar was configured in a single-transmit, four-receive mode. The main radar parameters are summarized in Table 1.



(a)



(b)

Figure 2. Physiological signal acquisition equipment: (a) millimeter-wave radar equipment; (b) BIOPAC equipment.

Table 1. Parameters related to radar systems.

Parameter Name	Parameter Value
ADC Sampling Points	256
Starting Frequency f_c	77 GHz
Sweep Slope S	89.993 MHz/ μ s
Sweep Period T_c	40 μ s
Bandwidth	3.59 GHz
Frame Period	4 ms
Number of Chirps per Frame	1
Transmit Antenna	Tx0
Receive Antenna	Rx0, Rx1, Rx2, Rx3

To obtain the physiological reference signals, an MP150 multi-channel physiological signal acquisition system equipped with a BioNomadix BN-RSPEC wireless module, a BN-RESP-XDCR respiratory transducer, and a BN-EL30-LEAD3 lead set (BIOPAC Systems, Inc., Goleta, CA, USA) was used to synchronously record respiratory and ECG signals at a sampling rate of 2000 Hz. Disposable electrodes were used for ECG recording. The acquired signals were transmitted wirelessly from the BioNomadix transmitter to the receiver, transferred through the MP150 unit to a computer, and displayed in real time using AcqKnowledge software. During data acquisition, the subjects remained seated and as still as possible, with their chests facing the radar at a distance of approximately 0.5 m. This synchronized acquisition platform simultaneously acquired the radar-derived chest-wall vibration signal, respiratory reference signal, and ECG reference signal, providing the data required for subsequent temporal alignment, sample construction, and model training.

2.1.2. Extraction of Chest Wall Vibration Signals and Time Synchronization

Range-domain processing was first performed on the raw intermediate-frequency (IF) echo signals acquired from the four receive channels of the millimeter-wave radar. Let $x_i[p, n]$ denote the fast-time ADC samples of the i -th receive channel within the n -th chirp, where p and n represent the fast-time and slow-time indices, respectively. A fast Fourier transform (FFT) was applied along the fast-time dimension to obtain the range profile:

$$X_i[r, n] = \text{FFT}_p\{x_i[p, n]\} \quad (1)$$

where r denotes the range bin index. Since the subject's chest was located directly in front of the radar and produced a strong reflection, the range bin with the maximum accumulated

magnitude over slow time within a predefined range interval was selected as the target bin, denoted as r_0 .

At this range bin, the complex slow-time sequence was extracted for each receive channel:

$$s_i[n] = X_i[r_0, n] = I_i[n] + jQ_i[n], \quad i = 1, 2, 3, 4 \quad (2)$$

where $I_i[n]$ and $Q_i[n]$ are the in-phase and quadrature components, respectively, and j is the imaginary unit. As shown in (2), $s_i[n]$ represents the complex echo sequence of the target bin across successive chirps. Its amplitude and phase vary with the subtle displacement of the chest wall, thereby containing respiration- and heartbeat-induced vital sign information [5–7].

To suppress DC offset caused by static clutter, antenna coupling, and hardware leakage, which may shift the complex trajectory away from the origin and degrade phase stability, DC offset removal was performed using a sliding average subtraction method:

$$\tilde{s}_i[n] = s_i[n] - \frac{1}{L} \sum_{k=n-L+1}^n s_i[k] \quad (3)$$

where $\tilde{s}_i[n]$ denotes the DC-corrected complex signal and L is the sliding window length. In the implementation, the sliding average length L was set to 250 samples, corresponding to 1.0 s at the radar slow-time sampling rate of 250 Hz.

The wrapped phase was then extracted from the real and imaginary parts:

$$\theta_i[n] = \arctan \left(\frac{\text{Im}(\tilde{s}_i[n])}{\text{Re}(\tilde{s}_i[n])} \right) \quad (4)$$

where $\theta_i[n]$ is the wrapped phase sequence of the i -th channel. Since the phase obtained by arctangent is confined within $(-\pi, \pi]$, discontinuities may occur. Therefore, phase unwrapping was applied to obtain the continuous phase sequence:

$$\phi_i[n] = \theta_i[n] + 2k\pi, \quad k \in \mathbb{Z} \quad (5)$$

where $\phi_i[n]$ denotes the unwrapped phase, which reflects the temporal variation in chest wall displacement. Phase unwrapping reconstructs the continuous phase from the wrapped representation by compensating for 2π discontinuities.

The extracted chest wall vibration signal contains both respiration- and heartbeat-induced displacement components. The respiration component, characterized by larger amplitude and higher stability, was used for channel quality evaluation and cross-device temporal synchronization, while the heartbeat-related component was used as the input for subsequent ECG reconstruction.

To perform cross-device temporal alignment, the chest-wall vibration signal extracted from each radar receive channel was processed using a third-order Butterworth band-pass filter with a passband of 0.1–0.6 Hz to obtain the radar-derived respiratory signal. Forward–backward filtering was employed to avoid additional phase distortion. After the BIOPAC respiratory signal was resampled to 250 Hz and matched in length with the radar-derived respiratory signal, the normalized cross-correlation was evaluated over a delay range of -3 to 3 s, corresponding to ± 750 samples:

$$\rho_i(\tau) = \frac{\sum_n (r_i[n] - \mu_{r_i})(b[n + \tau] - \mu_b)}{\sigma_{r_i} \sigma_b} \quad (6)$$

where μ_r and μ_b denote the mean values of the radar-derived and BIOPAC respiratory signals, respectively; σ_r and σ_b denote their corresponding standard deviations; and τ represents the candidate relative time delay within the predefined search range.

The optimal channel was selected based on the maximum cross-correlation peak:

$$k = \operatorname{argmax}_i \left(\max_{\tau} \rho_i(\tau) \right) \quad (7)$$

and the corresponding optimal delay was obtained as:

$$\tau^* = \operatorname{argmax}_{\tau} \rho_k(\tau) \quad (8)$$

The chest wall vibration signal from channel k was selected for subsequent analysis and model input, and τ^* was used as the temporal compensation between radar and BIOPAC signals, thereby completing optimal channel selection and cross-device temporal synchronization. A comparison of radar-derived and BIOPAC respiration signals before and after synchronization is shown in Figure 3.

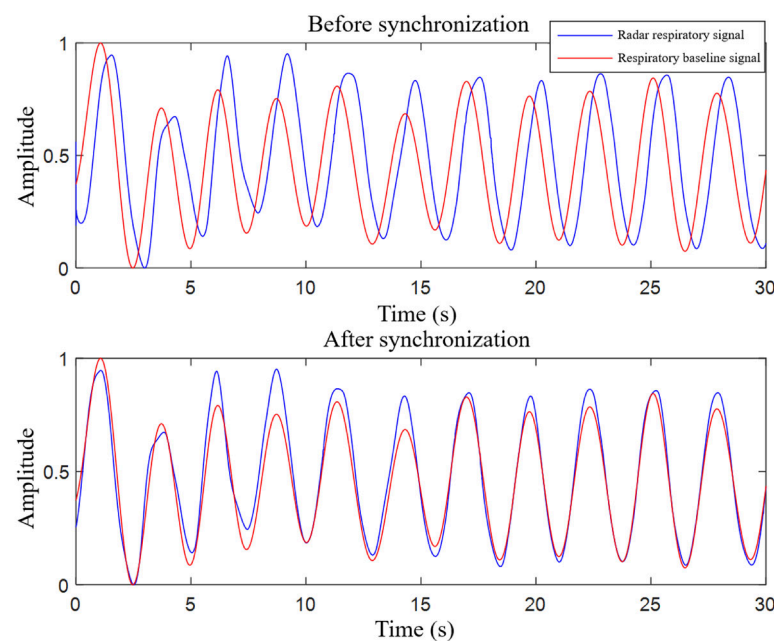


Figure 3. Comparison of radar respiratory signals before and after synchronization with BIOPAC respiratory signals.

2.1.3. Preprocessing of ECG Reference Signal and Sample Construction

After optimal channel selection and cross-device temporal compensation, the ECG signal acquired by the BIOPAC system was preprocessed to construct the reference ECG labels. The raw ECG signal was first resampled from 2000 Hz to 250 Hz. A second-order IIR notch filter centered at 50 Hz was then applied using forward–backward filtering to suppress power-line interference, followed by a second-order Butterworth band-pass filter with cutoff frequencies of 0.5 and 40 Hz to attenuate baseline drift and high-frequency noise. The resulting signal was used as the preprocessed reference ECG signal $\hat{e}[n]$.

On the unified time axis, the compensated radar-derived chest-wall vibration signal $x[n]$ and the reference ECG signal $\hat{e}[n]$ were segmented using a fixed-length sliding window to construct paired samples for supervised learning:

$$\begin{aligned} X_m &= [x[mH], x[mH + 1], \dots, x[mH + N - 1]] \\ Y_m &= [\hat{e}[mH], \hat{e}[mH + 1], \dots, \hat{e}[mH + N - 1]] \end{aligned} \quad (9)$$

where X_m denotes the m -th radar input sample, Y_m denotes the corresponding ECG label, N is the window length, and H is the sliding step size. In this study, paired samples were constructed using a sliding window with a length of 2048 points and an overlap ratio of 50%. Because partitioning was performed after segmentation with 50% overlap, overlapping windows originating from the same recording could be assigned to different subsets. This setting increases the number of available samples while allowing each window to cover multiple complete cardiac cycles.

After segmentation, the paired radar–ECG windows obtained from all recordings were pooled while preserving the correspondence between each radar input and its ECG label. The subsequent dataset partition was performed randomly at the window level using a fixed random seed.

It should be noted that the respiration signal was used only for cross-device temporal synchronization and was not involved in constructing the subsequent reconstruction targets. The preprocessed ECG signal was used as the supervised label for model training and as the reference for performance evaluation. Through the above processing steps, a time-aligned radar–ECG paired dataset with reliable labels was obtained, providing the data basis for subsequent model training and experimental evaluation.

2.2. CNN-BiLSTM-Based Radar ECG Reconstruction Method

2.2.1. Input Signal Representation and Preprocessing

Based on the paired radar–ECG samples constructed in Section 2.1, the synchronized radar-derived chest-wall vibration signal was used as the model input, while the reference ECG signal at the corresponding time was used as the supervised label. Because the chest-wall vibration signal contains both respiratory and heartbeat-related components, a fourth-order Butterworth band-pass filter with cutoff frequencies of 8 and 30 Hz was applied using forward–backward filtering before window segmentation. This processing attenuated low-frequency respiratory interference and high-frequency noise while emphasizing the faster mechanical components associated with cardiac activity [13,14]. The filtered signal was subsequently used as the input to the reconstruction network, as illustrated in Figure 4.

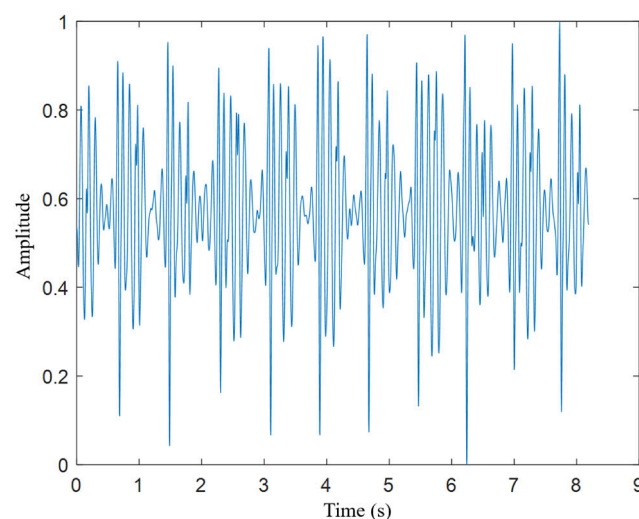


Figure 4. Schematic illustration of the radar-derived heartbeat activity signal after 8–30 Hz band-pass filtering.

To balance the integrity of temporal features and computational efficiency, a sliding window was used to segment the radar signal and the synchronized ECG signal. The window length was set to 2048 points with an overlap ratio of 50%, corresponding to a step size of 1024 points. At a sampling rate of 250 Hz, each window corresponds to

approximately 8.2 s of data, covering multiple complete cardiac cycles. This enables the model to learn both local waveform details and cross-cycle temporal dependencies [15].

After segmentation, each radar input window and its corresponding ECG label were normalized separately. Z-score standardization was first applied to each sequence to obtain zero mean and unit variance. The standardized sequences were then linearly scaled to the range [0, 1] using their respective minimum and maximum values. The normalized radar windows and ECG labels were used directly as the network inputs and supervised targets, respectively, thereby matching the output range of the Sigmoid activation function.

2.2.2. CNN-BiLSTM Network Architecture

The proposed CNN-BiLSTM network structure in this paper is shown in Figure 5. The overall structure consists of an encoder, a decoder, a BiLSTM, and a temporal regression output module, achieving end-to-end reconstruction from one-dimensional radar time series signals to the corresponding ECG waveforms. The network input is a single-channel radar sequence of length 2048, and the output is the single-channel ECG reconstruction result of the corresponding length [16]. In the figure, the tensor dimensions are represented in the form of “number of channels $\times$ sequence length”.

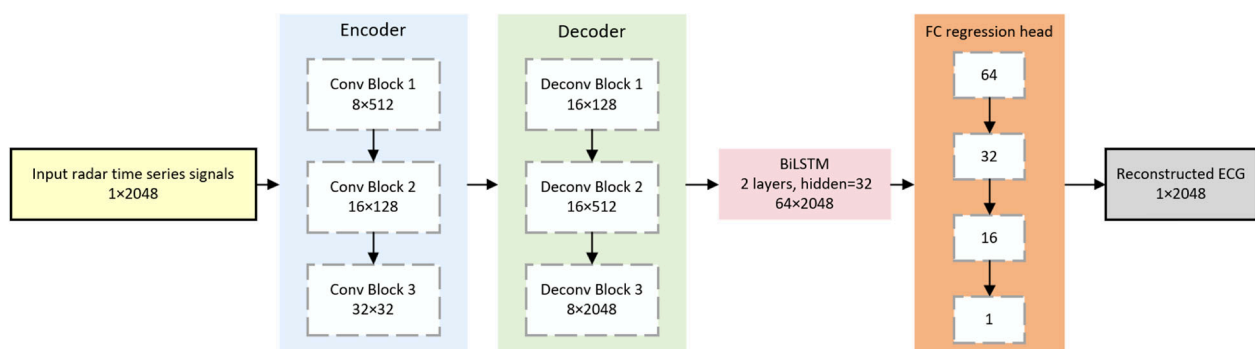


Figure 5. Schematic architecture of the CNN-BiLSTM network for radar-based ECG reconstruction.

The encoder adopts a three-level one-dimensional convolution structure to extract local temporal patterns in the radar signal layer by layer, in order to learn short-term features related to cardiac mechanical activity. The three-level convolution modules map the input sequence to feature representations of 8×512 , 16×128 , and 32×32 respectively, thereby gradually compressing the time length while enhancing the feature channel expression ability. Each convolution module consists of one-dimensional convolution, batch normalization, and ReLU activation function, which are used to improve training stability and nonlinear feature expression ability.

Considering that the ECG waveform not only depends on local morphological features but is also closely related to the temporal evolution between multiple adjacent moments, this paper introduces two layers of BiLSTM after the decoder to further model the restored temporal features. The input feature dimension of BiLSTM is 8, and the hidden layer dimension is set to 32. If the bidirectional structure is enabled, the forward and backward hidden states are concatenated in the feature dimension to obtain a bidirectional temporal feature output of 64×2048 . In PyTorch, when `bidirectional = True`, the LSTM output will include the concatenation of forward and reverse hidden states, so the output feature dimension of a BiLSTM with a hidden dimension of 32 is $2 \times 32 = 64$.

Finally, a three-layer fully connected regression output module is adopted to map the output features of the BiLSTM at each time point. The 64-dimensional features at each time point are sequentially mapped to 32-dimensional, 16-dimensional, and 1-dimensional ECG amplitudes. The fully connected layer essentially performs an affine transformation on the

input features, and its output dimension is determined by out_features. Therefore, this module accomplishes the nonlinear regression from high-dimensional time series features to a single-channel ECG waveform, ultimately generating a reconstructed ECG sequence of length 2048. To suppress overfitting, the network introduces a dropout mechanism in the BiLSTM and fully connected layers.

2.2.3. Design of the Joint Time–Frequency Loss Function

Radar-based ECG reconstruction is essentially a continuous temporal waveform regression problem. Its objective is not only to recover the overall amplitude variation trend of the signal, but also to preserve key morphological structures in the ECG as much as possible, such as the R wave and QRS complex. The mean squared error (MSE) can constrain the point-wise deviation between the predicted waveform and the ground-truth waveform from the time-domain perspective, and is therefore commonly used as a basic loss function for waveform regression tasks. However, when only MSE is used for optimization, the model tends to learn a smoothed solution in the sense of the overall mean. This may weaken sharp peak structures and average out local details in the reconstructed results, thereby degrading the recovery quality of the R-wave peaks, QRS morphology, and high-frequency features [34,35].

To alleviate the smoothing tendency associated with the use of MSE alone, this study incorporated an STFT-based frequency-domain loss in addition to the time-domain MSE loss [36], thereby forming a joint time–frequency loss function. The STFT-based term complements the point-wise time-domain constraint by measuring differences between the local magnitude spectra of the reconstructed and reference ECG signals.

Let the ground-truth ECG signal be $y[n]$, and the model-predicted output be $\hat{y}[n]$. The time-domain MSE loss is defined as:

$$L_{\text{MSE}} = \frac{1}{N} \sum_{n=1}^N (y[n] - \hat{y}[n])^2 \quad (10)$$

where N denotes the length of a single sample sequence.

For a discrete signal $x[n]$, its short-time Fourier transform is expressed as:

$$X[m, k] = \sum_{n=0}^{N-1} x[n] w[n - mH] e^{-j2\pi kn/N} \quad (11)$$

where $w[\cdot]$ is the window function, N is the window length, H is the frame shift, and m and k represent the time frame index and the frequency index, respectively. Based on this, the average L1 distance between the amplitude spectra of the true ECG and the reconstructed ECG in the STFT frequency domain is defined as the frequency domain loss:

$$L_{\text{STFT}} = \frac{1}{MK} \sum_{m=1}^M \sum_{k=1}^K \left| |X_{\text{true}}[m, k]| - |X_{\text{pred}}[m, k]| \right| \quad (12)$$

where M and K represent the number of time frames and frequency points, respectively, and X_{true} and $X_{\text{pred}}[m, k]$ denote the STFT results of the ground-truth ECG and reconstructed ECG, respectively.

Ultimately, this paper adopts the following joint time–frequency loss function to optimize the network:

$$L = \alpha L_{\text{MSE}} + \beta L_{\text{STFT}} \quad (13)$$

where α and β are the weights assigned to the time-domain and frequency-domain loss terms, respectively. In this study, $\alpha = 1$ and $\beta = 0.5$. The magnitude spectra used in

the STFT loss were calculated using a 64-point rectangular window with a frame shift of 16 samples, and normalized spectral magnitudes were used for loss calculation. The MSE term constrains point-wise amplitude deviations, whereas the STFT term constrains differences in local spectral structure. The joint loss therefore provides complementary time- and frequency-domain constraints intended to support the preservation of waveform amplitude and local spectral characteristics.

2.3. Datasets and Experimental Setup

The experimental setup and sensor configuration are shown in Figure 6. The experiment was conducted using a self-built millimeter-wave radar–BIOPAC synchronized data acquisition platform. The radar side consisted of a TI IWR1843BOOST FMCW millimeter-wave radar development board and a DCA1000EVM data acquisition card (Texas Instruments Incorporated, Dallas, TX, USA), which were used to capture micro-motion signals from the human chest wall. The contact-based reference system employed a BIOPAC MP150 multi-channel physiological signal acquisition system (BIOPAC Systems, Inc., Goleta, CA, USA) to simultaneously record respiratory signals and three-lead ECG signals, with the BIOPAC system set to an initial sampling rate of 2000 Hz. During the experiment, participants remained seated with their chests facing the radar transmit and receive antennas, positioned approximately 0.5 m away from the radar. Each participant wore a respiratory belt and three-lead ECG electrodes. Data collection began by first activating the BIOPAC system to record respiration and ECG signals; after about 6 s, the millimeter-wave radar was triggered to initiate data acquisition, enabling preliminary time alignment between the two devices. Subsequently, each trial collected continuous data for at least 120 s, during which participants were required to remain still and avoid significant body movements. In total, 35 valid datasets were obtained from four subjects, with a combined duration exceeding one hour. The four-subject cohort was used to verify the feasibility of the synchronized radar–ECG acquisition and reconstruction pipeline under controlled stationary conditions. Broader participant coverage may be considered in subsequent evaluations. After radar–ECG time synchronization, ECG preprocessing, extraction of 8–30 Hz radar heartbeat activity signals, and sliding window segmentation, 1015 paired radar–ECG samples were constructed. Using a fixed random seed, the pooled windowed samples were randomly partitioned at the window level into training, validation, and test sets at an approximate ratio of 70%, 15%, and 15%, respectively. The partition was not performed according to subject or trial identity. Model training and testing were performed on a computational platform equipped with an Intel Core i5-11400H CPU, 16 GB RAM, and an NVIDIA GeForce RTX 3050 Ti Laptop GPU. The software environment included Python 3.8, CUDA 11.3, cuDNN 8.2.0, and PyTorch 1.10.1.

To further validate the model’s ECG reconstruction capability under different physiological conditions, this study also conducts supplementary experiments using a publicly available radar vital signs dataset. This dataset includes simultaneously collected radar signals and contact-based ECG reference signals, covering various physiological states such as resting (Resting), apnea (Apnea), and Valsalva maneuver (Valsalva). The Resting, Apnea, and Valsalva scenarios were processed and evaluated separately. For each scenario, the same preprocessing, overlapping-window segmentation, and fixed-seed window-level partitioning strategy used for the self-built dataset was applied. The number of subjects, samples, and the distribution of training, validation, and test sets across each dataset are shown in Table 2.

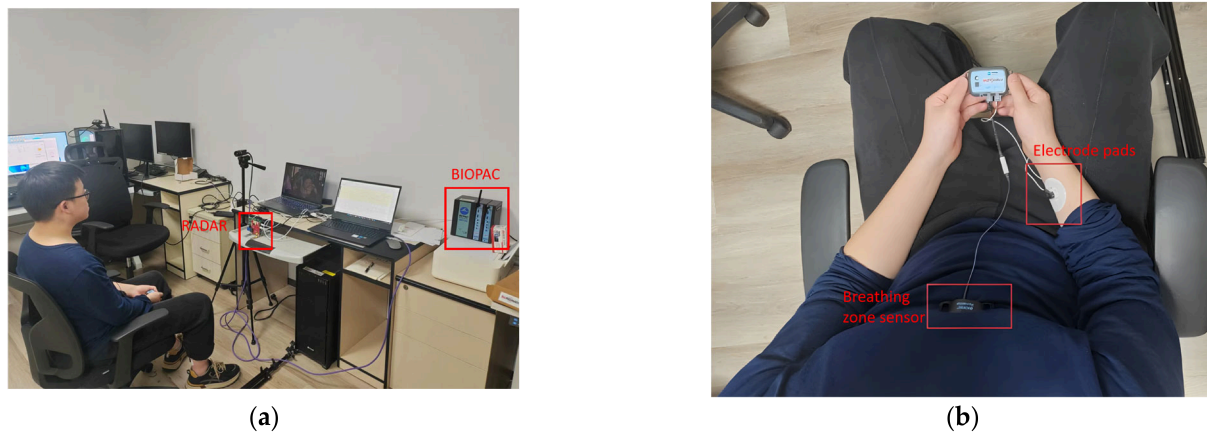


Figure 6. Experimental scene and sensor configuration: (a) experimental setup; (b) respiratory and ECG monitoring devices.

Table 2. Number of subjects and window-level sample partition for each dataset.

Dataset	Number of Subjects	Number of Samples	Training Set	Validation Set	Test Set
Vital Signs Dataset	4	1015	711	152	152
Resting	30	4609	3227	691	691
Apnea	24	1061	743	159	159
Valsalva	27	6791	4753	1019	1019

The model training employs the Adam optimizer with an initial learning rate of 0.001, a batch size of 32, 50 training epochs, and an L2 weight decay coefficient of 1×10^{-5} . During the training process, the joint time–frequency loss function defined by Equation (13) is used as the optimization objective. For the STFT loss calculation, a 64-point fast Fourier transform is adopted with a frame shift of 16 points. The experiments are implemented based on the Python and PyTorch framework. The model parameters corresponding to the lowest validation set loss are selected as the final model, and the performance is evaluated on the test set.

To comprehensively evaluate the performance of the reconstructed ECG, this paper adopts Mean Absolute Error (MAE), Mean Squared Error (MSE), Correlation Coefficient (CC), and Relative Root Mean Squared Error (RRMSE) as waveform reconstruction evaluation metrics. All waveform-level metrics were calculated directly from the normalized ECG sequences in the range [0, 1], without inverse transformation to the original ECG voltage scale. Additionally, based on the R-peak detection results of the reconstructed ECG, the average R-R interval, average heart rate, standard deviation of heart rate, and the root mean square of successive R-R interval differences (RMSSD) are further calculated to assess the model's effectiveness in restoring the electrocardiographic rhythm and estimating downstream physiological parameters.

3. Results

Before analyzing the reconstruction results of the test set, the training process of the model is evaluated first. As shown in Figure 7, as the number of training rounds increases, the losses of both the training set and the validation set gradually decrease and tend to stabilize, and their changing trends are basically consistent, without any obvious separation. These results indicate that the model achieved stable numerical convergence under the adopted window-level partitioning setting.

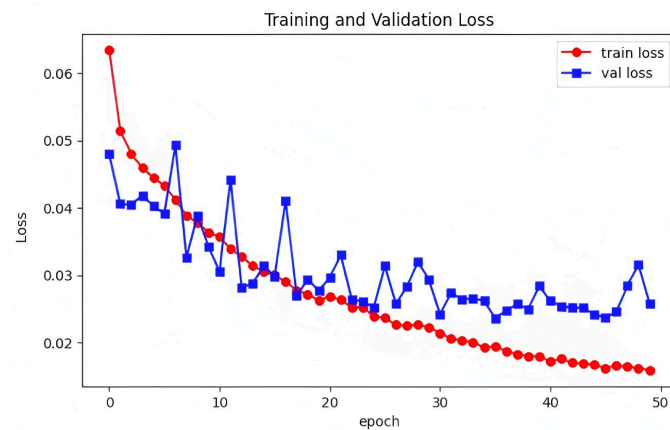


Figure 7. Training and validation loss curves of the CNN-BiLSTM model.

The reconstruction results of typical test samples are shown in Figure 8. The representative test samples exhibit general consistency with the reference ECG in overall cardiac rhythm and the locations of major R peaks, while minor discrepancies remain in local morphological features and waveform amplitude.

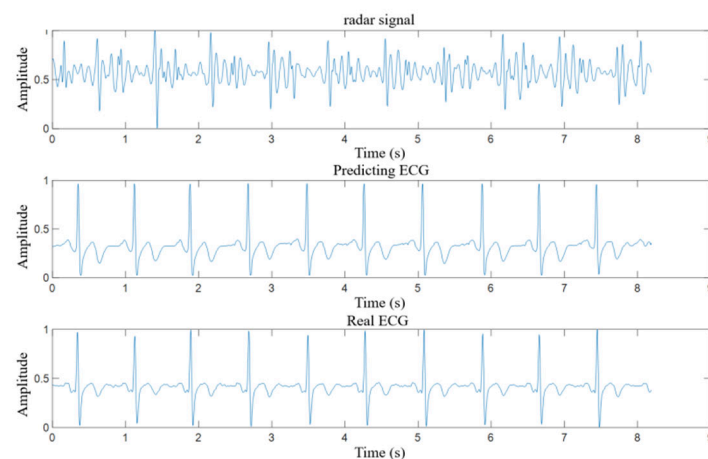


Figure 8. Comparison of radar signals, reconstructed ECG and real ECG.

For contextual comparison, the published MultiRes-LinkNet results reported in Ref. [15] for the same three physiological scenarios were included. These values were taken directly from the literature rather than obtained through reimplementing and are therefore used as a numerical reference under the evaluated conditions.

4. Discussion

The quantitative evaluation results are presented in Table 3. On the self-built vital sign dataset, the model achieved an MAE of 0.0555 ± 0.026 , an MSE of 0.0126 ± 0.007 , a CC of 0.5631 ± 0.287 , and an RRMSE of 0.3162 ± 0.101 . These results indicate that the reconstructed signals preserve overall waveform correspondence and heartbeat rhythm information. The moderate mean CC and its relatively large standard deviation also suggest that reconstruction consistency varies among samples and can be further improved.

The observed performance variation may be associated with individual differences in chest-wall mechanical characteristics, radar signal quality, residual motion or respiratory interference, and local temporal deviations between ECG electrical activity and radar-detected mechanical motion. In particular, respiratory cross-correlation mainly compensates for

cross-device acquisition delays, whereas subject-dependent cardiac electromechanical delay may still influence local waveform correspondence.

The present evaluation used a fixed-seed random partition of the pooled windowed samples after signal segmentation. Accordingly, the reported metrics characterize the performance of the proposed framework under the mixed-subject and mixed-recording window-level protocol adopted in this study. Subject-disjoint and trial-disjoint protocols may be incorporated in future studies to further evaluate transfer across participants and recording sessions.

Table 3. Test results on different datasets (The MultiRes-LinkNet results were taken from Ref. [15]).

Model	Dataset	MAE±STD	MSE±STD	CC±STD	RRMSE±STD
CNN-BiLSTM	Vital signs dataset	0.0555 ± 0.026	0.0126 ± 0.007	0.5631 ± 0.287	0.3162 ± 0.101
	Resting	0.0382 ± 0.021	0.0051 ± 0.006	0.8923 ± 0.101	0.2637 ± 0.108
	Apnea	0.0783 ± 0.044	0.0161 ± 0.013	0.6919 ± 0.203	0.4928 ± 0.208
	Valsalva	0.0468 ± 0.032	0.0074 ± 0.010	0.8387 ± 0.194	0.2990 ± 0.161
MultiRes-LinkNet [15]	Resting	0.1325 ± 0.07	0.0306 ± 0.02	0.6609 ± 0.19	0.4368 ± 0.22
	Apnea	0.1447 ± 0.06	0.0347 ± 0.02	0.5533 ± 0.18	0.4769 ± 0.20
	Valsalva	0.1498 ± 0.07	0.0367 ± 0.03	0.5753 ± 0.21	0.4639 ± 0.18

All data in the self-built dataset were collected under a static seated condition without active body movement, while the public dataset contains stationary recordings under different physiological maneuvers, including Resting, Apnea, and Valsalva. The present study focuses on stationary monitoring scenarios, such as sleep-related monitoring and sedentary health assessment, in which large body movements are generally absent. Under substantial movement or frequent posture changes, motion-induced radar components may dominate the subtle mechanical signals associated with cardiac activity. Addressing such dynamic scenarios requires dedicated motion-suppression strategies and is beyond the scope of the present stationary-monitoring study.

To provide a broader performance context, the proposed framework was compared with the published MultiRes-LinkNet results reported in Ref. [15] for the same three public-dataset conditions. Under Resting, Apnea, and Valsalva, the present framework achieved CC values of 0.8923, 0.6919, and 0.8387, respectively, compared with 0.6609, 0.5533, and 0.5753 reported for MultiRes-LinkNet. The corresponding MAE values of the present framework were 0.0382, 0.0783, and 0.0468, respectively, whereas the published reference values were 0.1325, 0.1447, and 0.1498. These results show consistently higher CC and lower MAE values across the evaluated physiological conditions. Because the MultiRes-LinkNet values were obtained from the original publication rather than through reimplementation within an identical experimental pipeline, the comparison is presented as a cross-study performance reference rather than a strictly controlled head-to-head evaluation.

To further evaluate the preservation of cardiac rhythm information, R-peak detection was performed on both the reference and reconstructed ECG signals. Based on the detected peaks, the average R–R interval, average heart rate, heart rate standard deviation, and RMSSD were calculated.

As shown in Table 4, on the self-built dataset, the mean absolute errors of heart rate and R–R interval were 1.00 BPM and 10.02 ms, respectively, while the mean relative error of heart rate was 1.30%. On the public dataset, the mean absolute R–R interval errors under Resting, Apnea, and Valsalva were 3.54 ms, 8.45 ms, and 4.09 ms, respectively. The corresponding mean absolute heart-rate errors were 0.23 BPM, 0.01 BPM, and 0.34 BPM, with relative errors of 0.37%, 0.01%, and 0.55%, respectively. These low errors indicate

that the reconstructed ECG effectively preserves dominant heartbeat timing under the evaluated stationary conditions and supports accurate estimation of average heart rate and mean R–R interval.

Table 4. Reconstruction of ECG R-peak detection and downstream rhythm parameter error results.

Dataset/Scenario	Average Absolute Error of R-R Interval (ms)	Average Absolute Error of Heart Rate (BPM)	Average Relative Error of Heart Rate (%)	Relative Error of Heart Rate Standard Deviation (%)	Relative Error of RMSSD (%)
Vital signs dataset	10.02	1.00	1.30	38.55	113.74
Resting	3.54	0.23	0.37	1.97	3.99
Apnea	8.45	0.01	0.01	38.94	116.03
Valsalva	4.09	0.34	0.55	8.70	21.37

Waveform-level metrics and R-peak-derived rhythm parameters characterize complementary aspects of ECG reconstruction. Average heart rate and mean R–R interval are primarily determined by the timing of dominant R peaks, whereas waveform-level CC is additionally affected by amplitude differences, local temporal deviations, and detailed morphological variations. Therefore, the low errors in average heart rate and mean R–R interval demonstrate that the framework effectively captures fundamental heartbeat timing, while the waveform-level results provide a more stringent assessment of local reconstruction details.

Table 4 further shows that RMSSD is more sensitive to local R-peak localization errors and short-term beat-to-beat variations than average heart rate and mean R–R interval. The comparatively higher RMSSD errors on the self-built dataset and under Apnea reflect the greater sensitivity of this parameter to small local timing deviations. At the same time, the low errors in average heart rate and mean R–R interval confirm that the framework accurately captures the dominant cardiac rhythm. Overall, the proposed framework demonstrates practical potential for R-peak detection, average heart-rate estimation, and mean R–R interval analysis, while further refinement of local R-peak localization may extend its capability for short-term beat-to-beat variability assessment.

The present study was designed to evaluate the feasibility of radar-based ECG reconstruction for stationary contactless vital-sign monitoring, with emphasis on normalized waveform similarity, R-peak detection, average heart rate, and R–R interval estimation. These endpoints directly reflect the principal monitoring functions targeted by the proposed framework. A detailed diagnostic evaluation of ECG morphology, including P waves, QRS duration, ST-segment characteristics, QT intervals, and arrhythmia-related abnormalities, was not part of the current study design. Future studies incorporating expert-annotated clinical ECG data may extend the evaluation from fundamental rhythm monitoring to more detailed morphological and clinical applications.

The input window contains 2048 samples, corresponding to approximately 8.2 s at a sampling rate of 250 Hz and covering multiple cardiac cycles. This configuration enables the CNN-BiLSTM network to combine local heartbeat-related feature extraction with bidirectional temporal modeling over a sufficiently long observation interval. The current implementation is optimized for offline waveform reconstruction and is suitable for retrospective analysis and periodic stationary monitoring. Dedicated measurements of model size, inference latency, memory consumption, and edge-hardware performance were not the primary focus of the present study. Future engineering work will evaluate computational profiling and lightweight adaptation to further explore real-time and edge-oriented deployment.

5. Conclusions

This study investigated a contactless ECG reconstruction framework integrating millimeter-wave radar, radar–BIOPAC synchronized acquisition and preprocessing, a CNN-BiLSTM network, and a joint time–frequency loss function. Multi-channel respiratory cross-correlation was employed for radar-channel selection and cross-device temporal alignment. The CNN-BiLSTM network combined local heartbeat-related feature extraction with bidirectional temporal modeling, while the joint loss constrained waveform differences in both the time and frequency domains. The current implementation is primarily designed for offline waveform reconstruction.

On the self-built vital sign dataset, the reconstructed ECG achieved a CC of 0.5631 ± 0.287 , while the mean absolute errors of heart rate and R–R interval were 1.00 BPM and 10.02 ms, respectively. These results indicate that the proposed framework captures useful waveform correspondence and fundamental heartbeat timing information under the targeted stationary-monitoring setting. Evaluation on the public dataset further demonstrated condition-dependent reconstruction performance under Resting, Apnea, and Valsalva. Compared with the published MultiRes-LinkNet results, the proposed framework achieved consistently higher CC and lower MAE values across the three evaluated conditions, providing supportive evidence of its competitive reconstruction performance. The published values are used as a cross-study numerical reference because the two methods were not evaluated within an identical experimental pipeline.

Overall, the results support the feasibility and application potential of reconstructing ECG-related waveforms and fundamental cardiac rhythm information from millimeter-wave radar signals in stationary monitoring scenarios. The proposed framework provides a non-contact solution for applications in which continuous monitoring and reduced dependence on wearable sensors are desirable, such as sleep-related monitoring and sedentary health assessment. Building on the current results, future work will expand the number and diversity of participants and recordings, adopt subject-disjoint and trial-disjoint evaluation protocols, further refine local waveform reconstruction and R-peak localization, and explore dedicated motion-suppression strategies for broader monitoring scenarios. Additional clinical annotation and computational profiling may further extend the framework toward detailed morphological analysis and lightweight deployment.

Author Contributions: Conceptualization, M.L., X.Z. (Xiaoyan Zhou) and X.Z. (Xinnan Zhao); methodology, M.L. and X.Z. (Xinnan Zhao); software, M.L.; validation, M.L. and X.Z. (Xinnan Zhao); formal analysis, M.L. and X.Z. (Xinnan Zhao); investigation, X.Z. (Xinnan Zhao) and M.L.; resources, X.Z. (Xiaoyan Zhou), Q.Y. and X.Z. (Xinnan Zhao); data curation, X.Z. (Xinnan Zhao) and M.L.; writing—original draft preparation, M.L.; writing—review and editing, B.N., X.Z. (Xiaoyan Zhou) and Q.Y.; visualization, M.L. and X.Z. (Xinnan Zhao); supervision, X.Z. (Xiaoyan Zhou), B.N. and Q.Y.; project administration, X.Z. (Xiaoyan Zhou) and Q.Y.; funding acquisition, X.Z. (Xiaoyan Zhou) and Q.Y. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The self-built radar–ECG vital sign dataset generated and analyzed during the current study is not publicly available because it contains physiological signals collected from human participants and is subject to privacy and ethical restrictions. The data are available from the corresponding author upon reasonable request and subject to institutional approval, ethical review, and participant-consent restrictions. The public radar vital-sign dataset used for supplementary validation is openly available from Schellenberger et al. [28] at <https://doi.org/10.6084/m9.figshare.12186516>.

Acknowledgments: The authors would like to acknowledge Nanjing University of Information Science and Technology for its institutional support during this study. The authors are also grateful to Southeast University for providing ECG experimental equipment and related experimental support.

Conflicts of Interest: The authors declare no conflicts of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

References

1. Serhani, M.A.; El Kassabi, H.T.; Ismail, H.; Navaz, A.N. ECG Monitoring Systems: Review, Architecture, Processes, and Key Challenges. *Sensors* **2020**, *20*, 1796. [\[CrossRef\]](#) [\[PubMed\]](#)
2. Zhang, B.B.; Zhang, D.; Li, Y.; Lu, Z.; Chen, J.; Wang, H.; Zhou, F.; Pu, Y.; Hu, Y.; Ma, L.K.; et al. Monitoring Long-Term Cardiac Activity with Contactless Radio Frequency Signals. *Nat. Commun.* **2024**, *15*, 10598. [\[CrossRef\]](#) [\[PubMed\]](#)
3. Turppa, E.; Kortelainen, J.M.; Antropov, O.; Kiuru, T. Vital Sign Monitoring Using FMCW Radar in Various Sleeping Scenarios. *Sensors* **2020**, *20*, 6505. [\[CrossRef\]](#) [\[PubMed\]](#)
4. Peng, Z.; Li, C. Portable Microwave Radar Systems for Short-Range Localization and Life Tracking: A Review. *Sensors* **2019**, *19*, 1136. [\[CrossRef\]](#) [\[PubMed\]](#)
5. Fang, Z.; Jian, P.; Zhang, H.; Yao, Y.; Geng, F.; Liu, C.; Yan, B.; Wang, P.; Du, L.; Chen, X. Review of Noncontact Medical and Health Monitoring Technologies Based on FMCW Radar. *J. Radars* **2022**, *11*, 499–516. (In Chinese) [\[CrossRef\]](#)
6. Hao, Z.; Gao, Y.; Tang, Y.; Wang, Y.; Fan, K.; Li, F. FMCW-Based Contactless Heart Rate Monitoring. *Sci. Rep.* **2025**, *15*, 2616. [\[CrossRef\]](#) [\[PubMed\]](#)
7. Ren, W.; Cao, J.; Yi, H.; Hou, K.; Hu, M.; Wang, J.; Qi, F. Noncontact Multipoint Vital Sign Monitoring with mmWave MIMO Radar. *IEEE Trans. Microw. Theory Tech.* **2025**, *73*, 4176–4190. [\[CrossRef\]](#)
8. Liu, L.; Zhang, S.; Xiao, W. Noncontact Vital Signs Detection Using Joint Wavelet Analysis and Autocorrelation Computation. *Chin. J. Eng.* **2021**, *43*, 1206–1214. (In Chinese) [\[CrossRef\]](#)
9. Qu, L.; Liu, S.; Yang, T.; Sun, Y. Life Signal Extraction Based on Multi-Channel Frequency Modulated Continuous Wave Radar. *J. Electron. Inf. Technol.* **2022**, *44*, 1318–1326. (In Chinese) [\[CrossRef\]](#)
10. Zhang, B.; Jiang, B.; Zheng, R.; Zhang, X.; Li, J.; Xu, Q. Pi-ViMo: Physiology-Inspired Robust Vital Sign Monitoring Using mmWave Radars. *ACM Trans. Internet Things* **2023**, *4*, 15. [\[CrossRef\]](#)
11. Chen, J.; Zhang, D.; Wu, Z.; Zhou, F.; Sun, Q.; Chen, Y. Contactless Electrocardiogram Monitoring with Millimeter Wave Radar. *IEEE Trans. Mob. Comput.* **2024**, *23*, 270–285. [\[CrossRef\]](#)
12. Wang, H.; Du, F.; Zhu, H.; Zhang, Z.; Wang, Y.; Cao, Q.; Zhu, X. HeRe: Heartbeat Signal Reconstruction for Low-Power Millimeter-Wave Radar Based on Deep Learning. *IEEE Trans. Instrum. Meas.* **2023**, *72*, 4004515. [\[CrossRef\]](#)
13. Yamamoto, K.; Hiromatsu, R.; Ohtsuki, T. ECG Signal Reconstruction via Doppler Sensor by Hybrid Deep Learning Model with CNN and LSTM. *IEEE Access* **2020**, *8*, 130551–130560. [\[CrossRef\]](#)
14. Luo, J.; Zhang, Y.; Dai, X.; Fu, D.; Liu, K. Non-Contact ECG Reconstruction Algorithm Based on Millimeter Wave Radar. *Telecommun. Sci.* **2024**, *40*, 50–65. (In Chinese) [\[CrossRef\]](#)
15. Chowdhury, F.A.; Hosain, M.K.; Islam, M.S.B.; Hossain, M.S.; Basak, P.; Mahmud, S.; Murugappan, M.; Chowdhury, M.E.H. ECG Waveform Generation from Radar Signals: A Deep Learning Perspective. *Comput. Biol. Med.* **2024**, *176*, 108555. [\[CrossRef\]](#) [\[PubMed\]](#)
16. Kim, T.-W.; Kwak, K.-C. End-to-End Electrocardiogram Signal Transformation from Continuous-Wave Radar Signal Using Deep Learning Model with Maximum-Overlap Discrete Wavelet Transform and Adaptive Neuro-Fuzzy Network Layers. *Appl. Sci.* **2024**, *14*, 8730. [\[CrossRef\]](#)
17. Zhang, S.; Zheng, T.; Chen, Z.; Luo, J. Can We Obtain Fine-Grained Heartbeat Waveform via Contact-Free RF-Sensing? In *Proceedings of the IEEE INFOCOM 2022—IEEE Conference on Computer Communications, London, UK, 2–5 May 2022*; IEEE: Piscataway, NJ, USA, 2022; pp. 1759–1768. [\[CrossRef\]](#)
18. Toda, D.; Anzai, R.; Ichige, K.; Saito, R.; Ueki, D. ECG Signal Reconstruction Using FMCW Radar and Convolutional Neural Network. In *Proceedings of the 20th International Symposium on Communications and Information Technologies, Tottori, Japan, 19–22 October 2021*; IEEE: Piscataway, NJ, USA, 2021; pp. 176–181. [\[CrossRef\]](#)
19. Karami-Horestani, A.; Moradi, B.; Paredes, F.; Martín, F. Wearable Textile Microwave Sensor for Wrist Pulse Wave and Heart Rate Monitoring. *IEEE Sens. J.* **2026**, *26*, 17014–17021. [\[CrossRef\]](#)
20. Wang, S.; Shen, Y.; Zheng, Y. Coplanar Hybridization of Half-Mode Magnetic Plasmonic Skyrmions: Realization and Application in a Flexible Wearable Microwave Sweat Metasensor. *IEEE Trans. Microw. Theory Tech.* **2025**, *73*, 9415–9428. [\[CrossRef\]](#)
21. Zhang, Y.; Guan, R.; Li, L.; Yang, R.; Yue, Y.; Lim, E.G. radarODE: An ODE-Embedded Deep Learning Model for Contactless ECG Reconstruction from Millimeter-Wave Radar. *IEEE Trans. Mob. Comput.* **2025**, *24*, 9806–9821. [\[CrossRef\]](#)

22. Zhang, Y.; Yang, R.; Yue, Y.; Lim, E.G. radarODE-MTL: A Multi-Task Learning Framework with Eccentric Gradient Alignment for Robust Radar-Based ECG Reconstruction. *IEEE Trans. Instrum. Meas.* **2025**, *74*, 4008315. [\[CrossRef\]](#)
23. Zhang, Y.; Zhao, H.; Xiong, S.; Yang, R.; Lim, E.G.; Yue, Y. From High-SNR Radar Signal to ECG: A Transfer Learning Model with Cardio-Focusing Algorithm for Scenarios with Limited Data. *IEEE Trans. Mob. Comput.* **2026**, *25*, 4520–4534. [\[CrossRef\]](#)
24. Liu, K.-C.; Peng, S.-Y.; Tsao, Y.; Liu, C.-Y.; Chen, Z.-A.; Han Han, Z.; Chen, W.-C.; Hsieh, P.-Q.; Li, Y.-J.; Hsu, Y.-J.; et al. A Cross-Modal Autoencoder for Contactless Electrocardiography Monitoring Using Frequency-Modulated Continuous Wave Radar. *IEEE Sens. J.* **2024**, *24*, 41462–41473. [\[CrossRef\]](#)
25. Xu, D.; Xu, Y.; Xu, K.; Hu, Z.; Xing, M.; Gini, F.; Greco, M.S. WaveGRU-Net: Robust Non-Contact ECG Reconstruction via MIMO Millimeter-Wave Radar and Multi-Scale Semantic Analysis. *Signal Process.* **2025**, *237*, 110108. [\[CrossRef\]](#)
26. Lu, Z.; Chen, J.; Zhang, D.; Wang, H.; Huang, P.; Zhou, F.; Hu, Y.; Sun, Q.; Gao, M. Contactless 12-Lead Electrocardiogram via Deep Computational Radar. *npj Biomed. Innov.* **2026**, *3*, 6. [\[CrossRef\]](#) [\[PubMed\]](#)
27. Liu, Z.; He, S.; Liang, F.; Huang, C.; Zhong, S.; Wu, K. mmJEPa-ECG: Cross-Posture Robust Contactless Electrocardiogram Monitoring via Millimeter Wave Radar Sensing. *Proc. AAAI Conf. Artif. Intell.* **2026**, *40*, 38962–38970. [\[CrossRef\]](#)
28. Schellenberger, S.; Shi, K.; Steigleder, T.; Malessa, A.; Michler, F.; Hameyer, L.; Neumann, N.; Lurz, F.; Weigel, R.; Ostgathe, C.; et al. A Dataset of Clinically Recorded Radar Vital Signs with Synchronised Reference Sensor Signals. *Sci. Data* **2020**, *7*, 291. [\[CrossRef\]](#) [\[PubMed\]](#)
29. Shi, K.; Schellenberger, S.; Will, C.; Steigleder, T.; Michler, F.; Fuchs, J.; Weigel, R.; Ostgathe, C. A Dataset of Radar-Recorded Heart Sounds and Vital Signs Including Synchronised Reference Sensor Signals. *Sci. Data* **2020**, *7*, 50. [\[CrossRef\]](#) [\[PubMed\]](#)
30. Zhao, L.; Lyu, R.; Lei, H.; Lin, Q.; Zhou, A.; Ma, H.; Wang, J.; Meng, X.; Shao, C.; Tang, Y.; et al. AirECG: Contactless Electrocardiogram for Cardiac Disease Monitoring via mmWave Sensing and Cross-Domain Diffusion Model. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* **2024**, *8*, 1–27. [\[CrossRef\]](#)
31. Xu, Y.; He, D.; Sun, H.; Jin, Z.; Zhao, M. Self-supervised learning for train bearing fault diagnosis based on time–frequency dual domain prediction. *Struct. Health Monit.* **2026**, advance online publication. [\[CrossRef\]](#)
32. Xu, Y.; He, D.; Luo, X.; Sun, H. CSSCL: A cross-sensor self-contrastive learning for nondestructive fault detection of heavy locomotive motors in label-scarce scenarios. *Nondestruct. Test. Eval.* **2026**, advance online publication. [\[CrossRef\]](#)
33. Dai, C.; He, D.; Jin, Z.; Zhang, X.; Chen, G.; Wu, J.; Zhao, J.; Xu, Y. Digital twin-assisted graph contrastive domain adaptation for small-sample bearing fault diagnosis. *Struct. Health Monit.* **2026**, advance online publication. [\[CrossRef\]](#)
34. Joung, C.; Kim, M.; Paik, T.; Kong, S.-H.; Oh, S.-Y.; Jeon, W.; Jeon, J.-H.; Hong, J.-S.; Kim, W.-J.; Kook, W.; et al. Deep Learning-Based ECG Segmentation for Delineation of Diverse Arrhythmias. *PLoS ONE* **2024**, *19*, e0303178. [\[CrossRef\]](#) [\[PubMed\]](#)
35. Pan, J.; Tompkins, W.J. A Real-Time QRS Detection Algorithm. *IEEE Trans. Biomed. Eng.* **1985**, *BME-32*, 230–236. [\[CrossRef\]](#) [\[PubMed\]](#)
36. Takaki, S.; Nakashika, T.; Wang, X.; Yamagishi, J. STFT Spectral Loss for Training a Neural Speech Waveform Model. *arXiv* **2018**, arXiv:1810.11945. [\[CrossRef\]](#)

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.