

Regular Article

Non-contact Beat-to-Beat Pulse Interval Estimation from Radial Artery Micro-Movements Using mmWave Radar

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Abstract– This study presents a novel contactless method for beat-to-beat pulse interval estimation using 24 GHz millimeter-wave radar detection of radial artery surface motion. The proposed system employs Doppler effect principles to detect physiological micro-movements, incorporating comprehensive signal processing including band-pass filtering (0.7-3 Hz), baseline wander removal, and advanced nonlinear denoising algorithms. An adaptive peak-finding algorithm extracts inter-beat intervals (IBI) from processed radar signals. Validation was performed against simultaneous electrocardiogram (ECG) recordings in 15 healthy subjects during 60-second measurement sessions. Results demonstrated excellent agreement with reference ECG measurements, achieving a high Pearson correlation coefficient of $r = 0.991$, mean absolute error of 11.8 ms, and root mean square error of 16.93 ms. Bland-Altman analysis revealed 95% limits of agreement within ± 33.15 ms. The mmWave radar approach provides a highly accurate, contactless alternative for cardiovascular monitoring, offering enhanced patient comfort and suitability for long-term health assessment applications while maintaining clinical accuracy comparable to traditional methods.

Keywords– mmWave radar, contactless monitoring, inter-beat interval, pulse wave detection, cardiovascular assessment, Doppler effect, signal processing

1 INTRODUCTION

Continuous monitoring of cardiovascular status plays an important role in assessing overall health. Therefore, building a long-term cardiovascular monitoring system is essential [1, 2]. Pulse waves contain valuable information about cardiovascular health status. When blood circulates through blood vessels, changes in arterial elasticity lead to variations in pulse waveform at different measurement locations [3]. Thus, pulse waves can be used as a key indicator for assessing cardiovascular health status [4].

Accurate detection of pulse peak timing at peripheral sites plays a crucial role in many clinical medical applications and biomedical research. From a cardiovascular diagnostic perspective, this parameter provides important information about the pumping efficiency of the left ventricle and the functional status of the peripheral circulatory system [5]. Variations in pulse transit time from the heart to peripheral sites can reflect changes in arterial wall stiffness, arterial pressure, and vascular compliance, thereby supporting early detection of cardiovascular diseases such as atherosclerosis or hypertension [6]. Furthermore, pulse rate variability analysis, an important indicator in assessing autonomic nervous system activity and predicting cardiovascular risk, requires high accuracy in determining the time intervals between consecutive pulse peaks. From a technological

and applied research perspective, the development of personal health monitoring devices and remote medical monitoring systems increasingly demands high reliability of pulse peak detection algorithms. The ability to accurately process pulse peak timing also serves as the foundation for developing machine learning and artificial intelligence models in predicting and analyzing cardiovascular health status [7].

The initial pulse wave monitoring technique involved invasive assessment, where a catheter was inserted within an arterial vessel to continuously track pulse wave signals. From the start of the previous century, to address numerous drawbacks of invasive sensors [8], numerous non-invasive methods and devices have been proposed to acquire pulse wave signals.

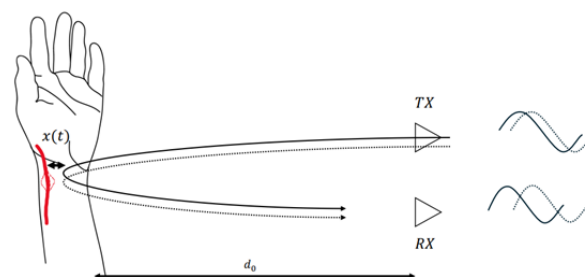


Figure 1. CW radar principle for detecting physiological micro-movements at the radial artery through the Doppler effect.

Among these, the tonometry method using pressure sensors can deliver precise pulse wave assessments, but susceptibility to movement and reliance on practitioner expertise render it less appropriate for clinical screening uses. Furthermore, various additional contact techniques have appeared in recent years, including photoplethysmography (PPG) sensors [9], microelectromechanical systems (MEMS) sensors [10], and combinations of cardiopulmonary function charts, electrocardiograms (ECG), and impedance cardiography (ICG) sensors [11]. Nevertheless, these techniques all necessitate direct contact with the patient's skin, which can cause discomfort and pressure, especially for vulnerable populations such as newborns, elderly people, and patients with dementia. Moreover, factors such as contact pressure and body fluids (such as sweat) can reduce the accuracy of contact measurements [12]. Furthermore, contact sensors may require fixation to ensure monitoring, reducing patient quality of life and affecting their compliance in sensor usage [13].

On the other hand, based on the Doppler phase modulation effect, radar can detect subtle physiological movements without attaching electrodes or wearable sensors to the body, enabling contactless vital sign monitoring [14, 15]. By transmitting electromagnetic waves and analyzing the phase variations of the reflected signal, radar captures micro-displacements of the skin surface caused by pulse waves propagating through peripheral blood vessels. These pulse-induced vibrations introduce measurable phase shifts, allowing non-invasive pulse detection. In particular, millimeter-wave (mmWave) radar provides high sensitivity to small displacements due to its short wavelength, making it suitable for peripheral pulse monitoring. Compared with conventional contact-based methods, radar-based approaches improve user comfort and offer greater flexibility for long-term cardiovascular monitoring. Given the clinical importance of accurate peripheral pulse wave peak estimation and the advantages of radar as a contactless sensing modality, this study proposes a non-linear algorithm for estimating pulse wave rhythm using radar signals measured at the wrist over the radial artery. The performance of wrist pulse peak detection is evaluated by comparing inter-beat intervals (IBIs) estimated from radar signals with reference IBIs extracted from ECG.

The remainder of this paper is organized as follows: Section II describes the IBI estimation method based on radar signals measured at the wrist position. Section III presents and discusses the results of the proposed method. Finally, conclusions are presented in Section IV.

2 PROPOSED METHOD

2.1 Radar Principles in Pulse Signal Acquisition

Continuous-wave (CW) millimeter-wave radar enables contactless detection of arterial micro-displacement through phase modulation of reflected electromagnetic waves. In this study, a 24 GHz Doppler

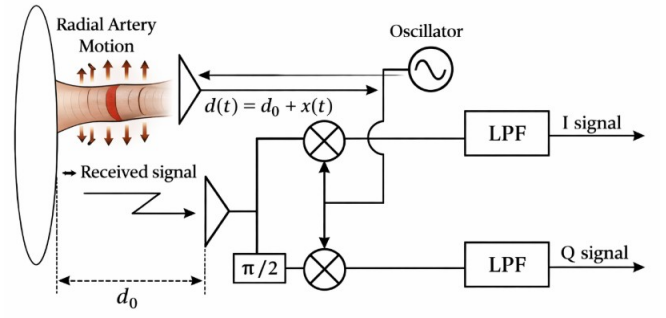


Figure 2. Continuous-wave radar architecture for non-contact pulse sensing at the radial artery.

radar is directed toward the radial artery at the wrist to sense subtle skin surface motion induced by pulse wave propagation, as shown in Figure 1.

The transmitted signal is modeled as

$$s_{TX}(t) = A \cos(2\pi f_c t), \quad (1)$$

where f_c denotes the carrier frequency and A is the signal amplitude. The corresponding wavelength is

$$\lambda = \frac{c}{f_c}, \quad (2)$$

which is approximately 12.4 mm at 24 GHz.

If the nominal radar-to-skin distance is d_0 and the pulse-induced surface displacement is $x(t)$, the instantaneous propagation distance becomes

$$d(t) = d_0 + x(t). \quad (3)$$

The received signal can therefore be expressed as

$$s_{RX}(t) = A_r \cos\left(2\pi f_c t - \frac{4\pi}{\lambda} d(t)\right), \quad (4)$$

where A_r is the reflected signal amplitude. This expression indicates that physiological motion is encoded in the phase term of the received wave.

After quadrature demodulation and low-pass filtering, the baseband in-phase and quadrature components [16] are obtained as

$$I(t) = B \cos\left(\frac{4\pi}{\lambda} x(t) + \phi_0\right), \quad (5)$$

$$Q(t) = B \sin\left(\frac{4\pi}{\lambda} x(t) + \phi_0\right), \quad (6)$$

where B represents the baseband amplitude and ϕ_0 is a constant phase offset determined by the initial distance. These two orthogonal components form the complex representation

$$z(t) = I(t) + jQ(t) = B \exp\left\{j\left(\frac{4\pi}{\lambda} x(t) + \phi_0\right)\right\}. \quad (7)$$

The instantaneous phase is given by

$$\theta(t) = \tan^{-1}\left(\frac{Q(t)}{I(t)}\right), \quad (8)$$

which yields a linear relationship between displace-

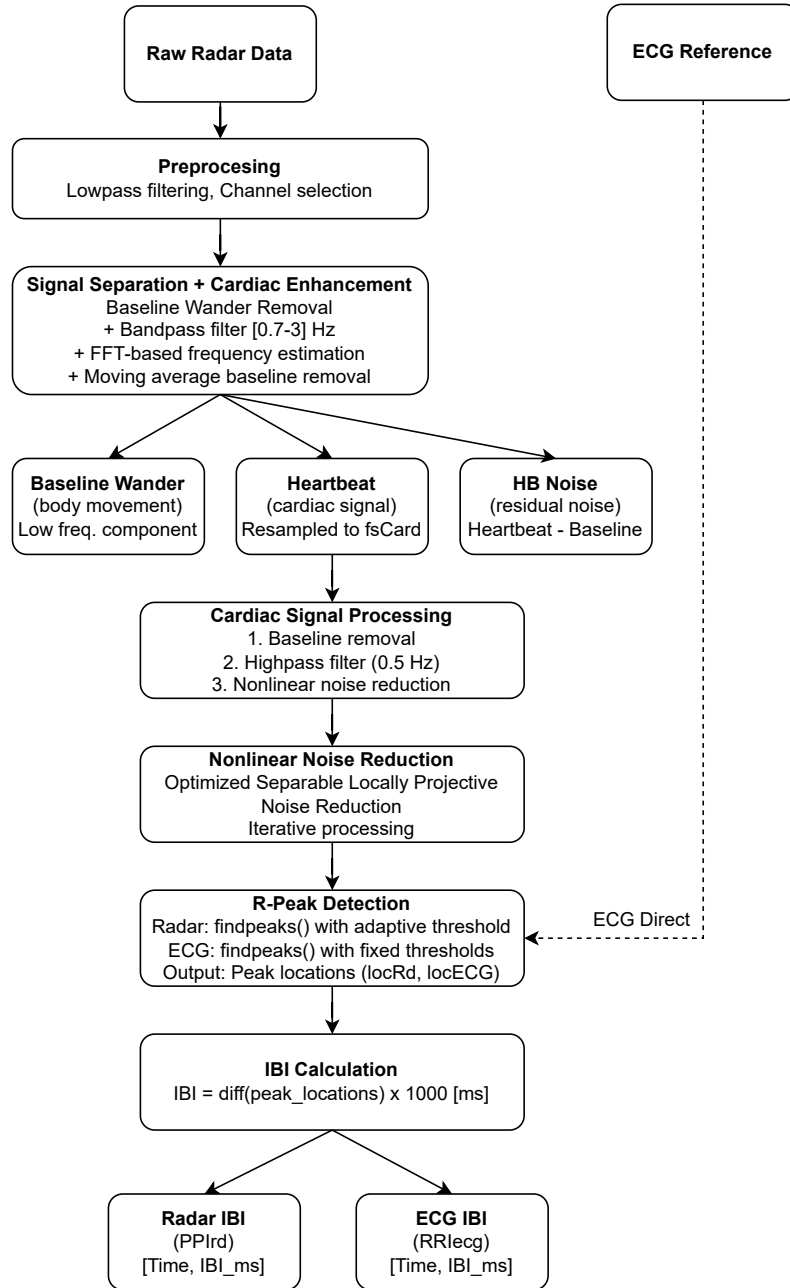


Figure 3. Diagram of proposed method.

ment and phase

$$x(t) = \frac{\lambda}{4\pi} \theta(t). \quad (9)$$

For radial artery monitoring, the displacement amplitude is much smaller than half of the wavelength

$$x(t) \ll \frac{\lambda}{2}. \quad (10)$$

Under this small-displacement condition, the phase excursion remains within a limited angular range and the baseband oscillation frequency directly corresponds to the physiological pulse frequency. Each cardiac cycle therefore produces one quasi-periodic fluctuation in the demodulated radar signal, enabling beat-to-beat timing extraction without phase unwrapping.

The displacement sensitivity is governed by the factor $4\pi/\lambda$. At 24 GHz, sub-millimeter arterial motion induces a measurable phase variation that can be recovered after appropriate filtering and noise suppression. Consequently, the radar system functions as a non-contact displacement sensor that converts arterial wall vibration into a phase-modulated signal suitable for inter-beat interval estimation.

2.2 Pulse Wave Peak Estimation Method

The pulse wave peak estimation (IBI) method is illustrated in Figure 3. The detailed description of the method is presented below.

The radar and ECG signals were synchronously acquired at 1000 Hz and a 60 s steady segment was

analyzed. The radar I and Q channels were low-pass filtered at 10 Hz, while ECG was low-pass filtered at 30 Hz. The cardiac channel was selected based on the standard deviation (Equation (11)) of the band-pass-filtered radar channels (0.7–3 Hz).

$$\text{Std} = \sqrt{\frac{1}{N_{\text{sum}}} \sum_{i=1}^{N_{\text{sum}}} (x_i - \mu)^2}, \quad (11)$$

where N_{sum} is the length of the signal and $\mu = \frac{1}{N_{\text{sum}}} \sum_{i=1}^{N_{\text{sum}}} x_i$; in the present implementation, the channel with higher standard deviation was used in experiments.

After that, the radar signal was processed by a nonlinear signal separation framework. A signal-scale parameter was first estimated adaptively using a high-pass FIR filter and median amplitude statistics over 1.5 s windows. Baseline/respiration was then estimated using moving-average smoothing, with the averaging length determined from FFT-based heart-frequency estimation. The raw cardiac component was obtained by subtracting the estimated baseline and then high-pass filtering at 0.5 Hz. Nonlinear denoising was subsequently performed using an optimized separable locally projective noise reduction (OSLPNR) algorithm [17].

Given the preprocessed radar signal $x(i)$, delay-coordinate embedding is first performed to reconstruct the state space as

$$x_i = [x(i), x(i + \tau), \dots, x(i + (m - 1)\tau)], \quad (12)$$

where m denotes the embedding dimension and τ is the time delay. For each state vector, a local neighborhood is identified using an adaptive radius and a minimum number of neighbors constraint. If the number of neighbors is insufficient, the search radius is progressively increased until the neighborhood size criterion is satisfied. Within each neighborhood, a local mean vector is computed, and the neighborhood data are centered accordingly. A weighted covariance matrix is then constructed, incorporating endpoint weighting to reduce boundary effects in the delay vectors. Eigenvalue decomposition is applied to this covariance matrix to separate signal and noise subspaces. The components associated with the smallest eigenvalues are interpreted as noise, and the signal is denoised by projecting the state vectors away from this noise subspace. The resulting correction is mapped back to the time domain, and the procedure is applied iteratively to progressively refine the signal. In this study, two iterations are performed for the cardiac component, with parameters including embedding dimension $m = 50$, minimum number of neighbors $k_0 = 60$, endpoint weight 2000, and adaptive neighborhood radius ε_0 derived from the signal scale estimate. The algorithm reconstructs delay vectors, searches local neighbors in state space, estimates the local covariance structure, and removes components associated with the smallest local eigenvalues, thereby suppressing noise while preserving beat-to-beat timing.

The use of OSLPNR is especially suitable in this setting because the radar-derived cardiac component is nonlinear and low-amplitude. Simple linear smoothing may reduce noise but can also distort the timing and sharpness of pulse peaks. In contrast, locally projective denoising attempts to preserve the intrinsic local trajectory of the signal in state space, which helps maintain beat location while reducing stochastic perturbations. This is precisely why OSLPNR was used before derivative-based peak enhancement. After denoising, the cardiac signal was further enhanced by band-pass filtering and a derivative operator, and pulse peaks were detected by an adaptive *findpeaks* procedure in which the minimum peak distance was determined from the FFT-estimated dominant cardiac frequency.

After OSLPNR denoising, the cardiac component was passed through an additional band-pass filtering stage and then through a derivative operator to sharpen pulse peaks before detection. Peak detection was performed using MATLAB *findpeaks*(). For radar, the minimum peak distance was set adaptively from the dominant frequency estimated in the 0.7–3 Hz band, as equation (13)

$$d_{\min} = \frac{0.8}{f_{\text{dom}}}, \quad (13)$$

where f_{dom} is the dominant frequency estimated by FFT.

Simultaneous ECG peak detection is performed using the same *findpeaks* function, but with fixed amplitude thresholds optimized for the more stable characteristics of ECG signals. This parallel processing approach allows direct comparison of cardiac timing between radar and reference ECG results. The algorithm output consists of precise temporal locations of detected peaks (designated as locRd for radar, locECG for ECG), represented as sample indices relative to the acquisition time axis.

IBI values are calculated from peak locations through time difference analysis between consecutive peaks. Inter-beat intervals are computed as the time difference between two successive peaks, multiplied by 1000 to express results in milliseconds. This process is performed independently for both radar signals (producing IBIRD value series) and reference ECG signals (producing IBIECG series). The final results include time-stamped IBI value series for both measurement modalities, thereby supporting comprehensive heart rate variability (HRV) analysis and validation of radar measurement accuracy against the gold standard ECG. Inter-beat intervals were computed independently for radar and ECG signals as the time difference between consecutive detected peaks. Because IBI is defined as a relative interval within each modality, a constant time offset between ECG and radar signals does not affect the interval values. Therefore, IBIs from radar and ECG were paired in chronological order for quantitative comparison. Although a delay exists between ECG R-peaks and radar-derived peaks due to electromechanical coupling, signal propagation, and processing latency, this delay does not influence the accuracy of IBI estimation.

2.3 Experiment

In this study, a 24 GHz Doppler radar model NJR4262J manufactured by New Japan Radio Co., Ltd. was used, with transmission frequencies ranging from 24.05 to 24.25 GHz and a sampling frequency of 1000 Hz. The analog-to-digital (A/D) converter used was the USB-6001 model supplied by National Instruments, supporting 8 analog input channels. The electrocardiogram (ECG) device used as reference was BIOPAC ECG100C, employing a 3-electrode method. The test subjects were 7 healthy students from the University of Electronics and Communications, with a mean age of 23.4 ± 0.9 years and 8 healthy subjects including students and lecturers from Le Quy Don Technical University, with the age in range of 22 to 50 year-old. The subjects were fitted with ECG electrodes, seated on chairs, and data were collected for 60 seconds by directing the radar toward the radial artery location. Data collection was performed using National Instruments' LabVIEW software, while data analysis was conducted using MathWorks' MATLAB.

To minimize the effects of vibration, only the experimenter and the subject were allowed in the laboratory. The measurement subject was first asked to sit on a chair, then ECG electrodes were attached to the chest. Subsequently, the arm was placed on a table with a support fixture as illustrated in Figure 4. This fixture helps stabilize the arm and thin the skin layer in the radial artery region to increase measurement accuracy. The experimenter identified the location with the greatest oscillation of the skin surface at the radial artery by palpation, then marked it and adjusted the radar to point toward that location. Data collection then began, consisting of 60 seconds of normal breathing. This study was approved by the Ethics Committee of the University of Electro-Communications and the Ethics Committee of Le Quy Don Technical University.

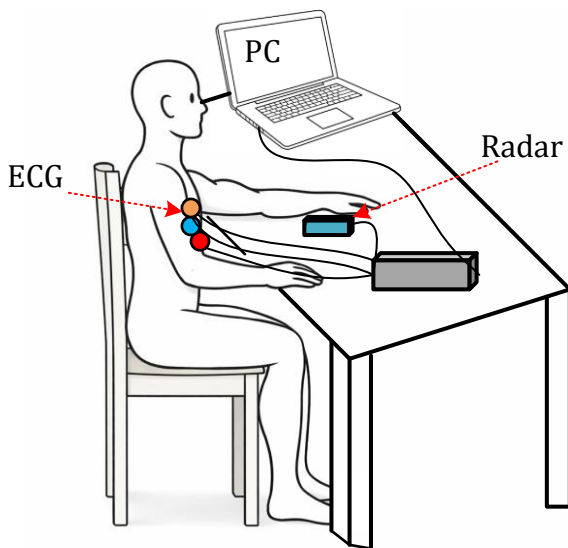


Figure 4. Experimental setup and radial artery region positioning during measurement.

3 RESULTS

Figure 5 illustrates the raw signals obtained from the radar sensor (blue) and ECG (red). The initial raw radar signal shows the presence of multiple frequency components, including both noise and physiological signals. After processing and signal separation, the cardiac component is isolated from background noise and body movement artifacts. The simultaneously acquired reference ECG signal shows clear QRS complexes, serving as the gold standard for evaluating the accuracy of the proposed method. The peak detection process is illustrated in detail in Figure 6. The peaks detected from the radar signal (marked with blue dots) demonstrate high correlation with the R-peaks of the ECG (marked with red dots). The adaptive peak detection algorithm successfully identifies the precise timing of cardiac cycles accurately.

Figures 7 and 8 present detailed comparisons between IBI values estimated from radar (Beat-to-Beat interval) and reference IBI values from ECG (RR interval) within a 60-second time window. Figure 7 shows the connected IBI values as direct results from the estimation method, while Figure 8 displays the resampled IBI plot with smoother IBI points. The plots show time series of both IBI measurements, demonstrating close tracking between radar estimates and ECG reference. The correlation analysis presented in the Bland-Altman plot (Figure 9) shows a high level of agreement between the radar and ECG methods, with a standard deviation of 33.15 ms. The 95% limits of agreement fall within the range of -33.1 ms to +33.2 ms, indicating good consistency between the two measurement methods. Comprehensive statistical results from data of 15 subjects are presented in Figures 10 and 11. Figure 10 displays the distribution of Pearson correlation coefficients between radar IBI and ECG IBI, with a mean value

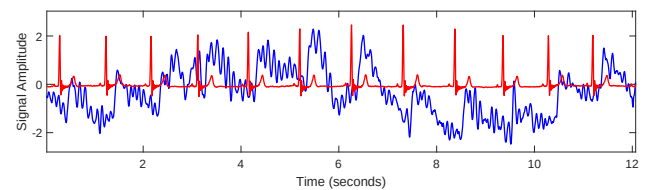


Figure 5. Raw signals obtained from radar sensor (blue) and simultaneous ECG recording (red) showing multiple frequency components before signal processing.

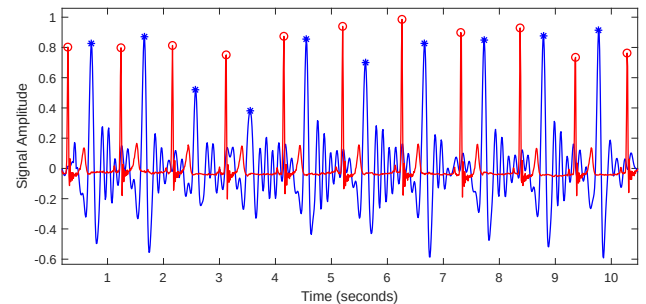


Figure 6. Peak detection results showing radar-detected peaks (blue dots) and ECG R-peaks (red dots) demonstrating high correlation between the two methods.

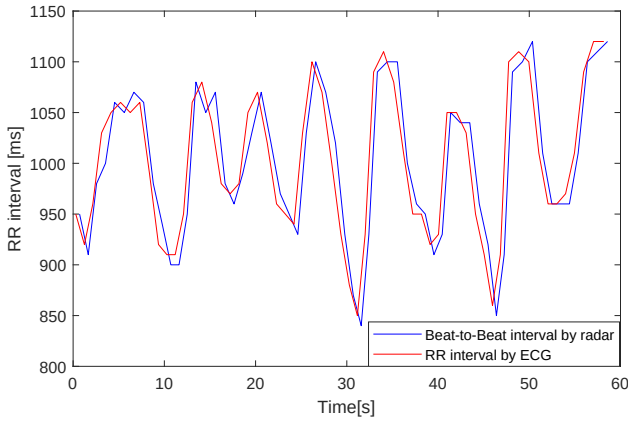


Figure 7. Direct comparison of IBI values estimated from radar (Beat-to-Beat interval) versus reference ECG IBI values (RR interval) over 60-second time window.

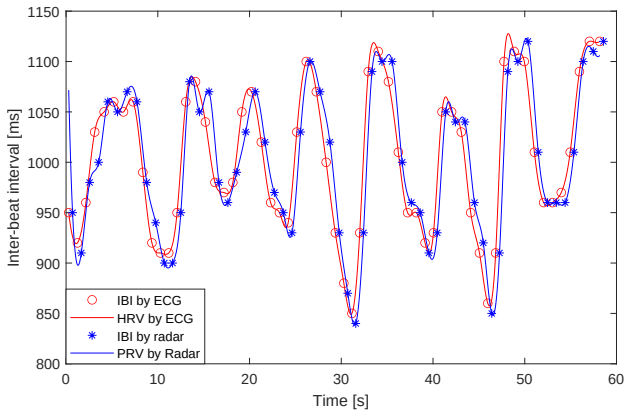


Figure 8. Resampled IBI comparison plot with smoothed data points showing temporal tracking between radar estimates and ECG reference measurements.

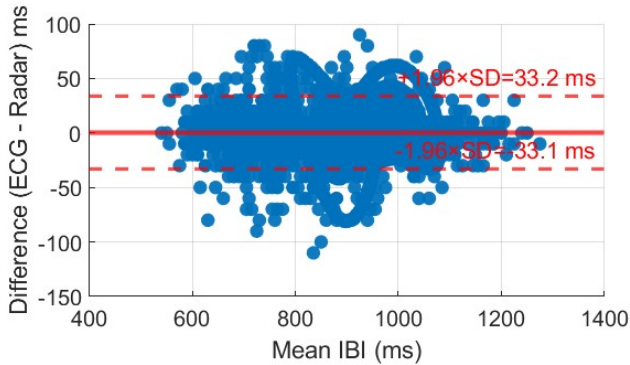


Figure 9. Bland-Altman plot demonstrating agreement between radar and ECG methods with 95% limits of agreement.

of $r = 0.991$, showing high correlation levels. All cases achieved correlation coefficients above 0.86, with 88% of cases having $r > 0.95$. Figure 11 shows the distribution of estimated IBI and reference IBI, where the plot reveals the deviation of calculated IBIs and their distribution. The distribution of estimated IBI shows consistent allocation and agreement with reference IBI. Table I summarizes the main performance metrics of the system. Mean absolute error (MAE) analysis shows an average MAE of 11.8 ms. Approximately 80% of cases had $MAE < 18$ ms, and all cases had

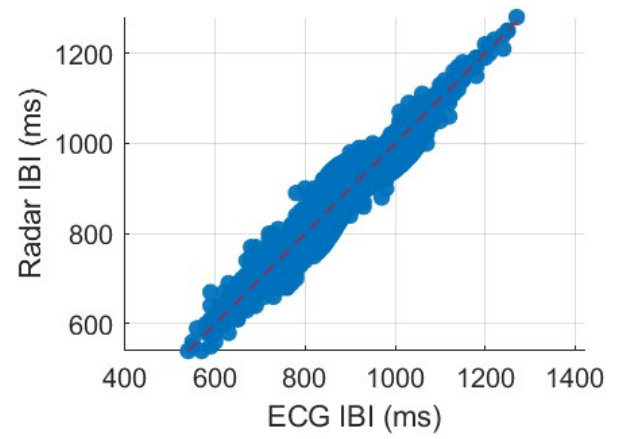


Figure 10. Distribution of Pearson correlation coefficients between radar IBI and ECG IBI across 15 subjects.

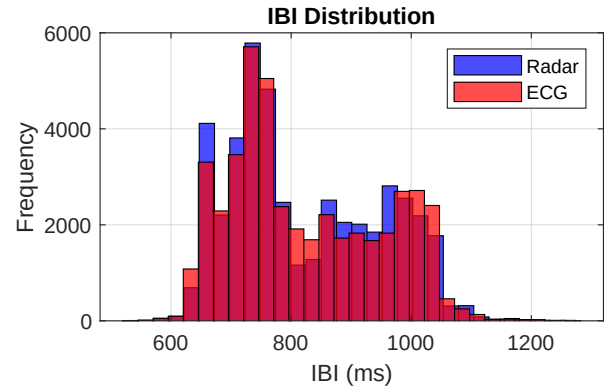


Figure 11. Distribution of estimated IBI versus reference IBI values showing consistency and agreement between radar-derived and ECG-derived measurements.

$MAE < 100$ ms. The mean error was 11.8 ms, RMSE was 16.93 ms, and the correlation coefficient reached 0.991 compared to reference ECG IBI.

Table I
PERFORMANCE METRICS SUMMARY

Metric	Mean Value
Correlation coefficient (r)	0.991
MAE (ms)	11.8
RMSE (ms)	16.93
MRE (%)	1.39

4 DISCUSSION AND CONCLUSION

This study demonstrates the feasibility of using 24 GHz millimeter-wave radar for contactless beat-to-beat pulse interval estimation at the radial artery, achieving excellent correlation with ECG reference ($r = 0.991$) and low measurement errors ($MAE = 11.8$ ms, $RMSE = 16.93$ ms). The proposed signal processing approach effectively isolates cardiac components from complex radar signals, enabling precise pulse peak detection through adaptive algorithms. The results are comparable to those of previous studies [18–20], which reported RMSE values of 22.07 ms, 33.94 ms and 28.8 ms, respectively.

Accurate pulse peak detection at the radial artery holds significant clinical importance beyond basic heart rate monitoring. The precise timing of pulse wave arrival at peripheral sites enables calculation of pulse transit time, a key parameter for non-invasive blood pressure estimation and arterial stiffness assessment. Furthermore, the high-resolution inter-beat interval measurements support comprehensive pulse rate variability analysis, which is crucial for cardiovascular risk stratification and autonomic nervous system evaluation. The ability to continuously monitor pulse wave characteristics at the wrist provides valuable insights into peripheral circulation status and early detection of cardiovascular pathologies such as atherosclerosis and hypertension.

The contactless solution of mmWave radar technology addresses critical limitations of traditional monitoring methods, offering enhanced patient comfort and compliance while eliminating contact pressure artifacts. This capability is particularly valuable for vulnerable populations and long-term monitoring applications where conventional electrode-based systems are impractical. It should be noted that the number of participants in the present study is relatively limited, and therefore the results cannot yet support strong statistical conclusions regarding physiological differences among demographic groups. Nevertheless, during the experimental observations, we noticed an interesting tendency: participants who were lecturers around the age of 50 tended to exhibit relatively lower inter-beat intervals, which corresponds to a higher number of heartbeats per minute. Although this observation requires validation with a larger cohort, it may suggest potential age-related or occupational physiological characteristics that deserve further investigation.

In addition, the pairing between radar-derived inter-beat intervals (IBIs) and ECG-derived RR intervals was performed under the assumption of consistent beat-to-beat correspondence following preprocessing and peak detection. However, in practical scenarios, missed peaks or beat mismatches may still occur due to noise, motion artifacts, or imperfect detection, potentially introducing bias into the reported error metrics. Although these effects were mitigated through adaptive peak detection and nonlinear denoising, the present work does not explicitly incorporate a dedicated mechanism for robust beat alignment or mismatch correction. Addressing this limitation constitutes an important direction for future research. In particular, we plan to integrate machine learning-based sequence alignment models capable of learning temporal correspondence between radar and ECG signals in a data-driven manner. Architectures with feedforward pathways and temporal memory mechanisms will be explored to preserve learned representations of valid cardiac cycles while handling missing or spurious peaks. Such models are expected to implicitly correct misalignments, interpolate missing beats, and suppress outliers, thereby improving the robustness and reliability of inter-beat interval estimation, especially under real-world conditions with increased signal variability.

This study represents an initial step within a longer-term research project aimed at developing reliable contactless cardiovascular monitoring techniques using mmWave radar. In the next phase of the project, we plan to conduct measurements on a significantly larger number of participants, covering a wider age range and a broader spectrum of health conditions. Such expanded datasets will enable more comprehensive statistical analyses and help generalize the findings of this work. Furthermore, to support the research community working in related fields, we intend to publicly release the collected measurement datasets. Making these datasets openly available will facilitate reproducibility, comparative studies, and the development of improved signal processing and physiological modeling approaches for radar-based cardiovascular monitoring. Overall, the results establish mmWave radar as a promising foundation for next-generation contactless cardiovascular monitoring systems with broad clinical and research applications.

DECLARATIONS

All authors declare that they have no conflict of interest.

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wearable and contactless sensing technologies, vital sign monitoring, machine learning, embedded systems for healthcare applications, and biomedical signal analysis and processing.

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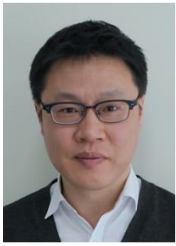
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