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Contactless Heart Rate Detection Using MM-Wave Radar Systems Advancements

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Abstract*-In recent years, there has been a significant surge in the development of non-contact methods for detecting heart and breathing rates. Various Millimeter-wave (MM-wave) radar systems, operating at different frequency bands like 10 GHz, 24 GHz, 77 GHz, and 122 GHz, have been effectively deployed for this purpose. This paper explores the vital application of contactless systems in the medical field, particularly during disasters and epidemics. These systems are crucial for detecting the heart and breathing rates of individuals trapped under debris, in military operations, long-term vital sign monitoring in hospitals, and aiding the elderly in public spaces. Consequently, our focus is on heart and breathing rate detection using radar systems. This paper highlights the significance of capturing the electrical representation of the heart signal. This approach is known for its trustworthiness and accuracy in identifying various medical conditions. Furthermore, a traditional method based on Fourier transform is presented for heart and respiration rate estimation. This method leverages the direct proportionality between heart and breathing rates and the frequencies of raw radar signals. To estimate the breathing rate, it identifies the maximum peak within the frequency range of 0.15 to 0.4 Hz in the frequency domain and multiplies the corresponding frequency by 60 to obtain the rate per minute. For heart rate estimation, it detects the maximum peak within the frequency range of 0.8 to 2 Hz and calculates the rate per minute accordingly. In addition, a proposal was presented to predict heart rate from contact devices using an old technique, which is autocorrelation using a second-threshold algorithm, based on our understanding of the electrical heartbeat in the time domain.

***Keywords*-Contactless, Heart Rate, Breathing Rate, MM-Wave Radar, Convolution, Medical Monitoring, Fourier Transform.**

I. INTRODUCTION

Electrocardiogram (ECG) signals provide invaluable insights into cardiac activity, with distinct components such as P-wave, QRS complex, T-wave, PR interval, QT interval, and ST segment holding diagnostic significance. Accurate detection of these components is pivotal not only for heart rate analysis but also for the diagnosis of various cardiac diseases. Additionally, this paper delves into the estimation of the respiratory rate, a crucial physiological parameter that can vary with factors like age, exertion, and sleep state. Respiratory rate is typically 12-16 breaths per minute at rest, with a respiration-to-heart rate ratio of approximately 1:4. This paper introduces innovative algorithms for heart rate estimation from ECG signals and electrical heart signal estimation from radar systems, marking a significant advancement in biomedical signal processing. Non-contact heart and breathing rate detection using MM-wave radar systems has gained prominence in recent years. This technology has far-reaching applications, particularly in disaster response, medical monitoring, and public safety. MM-wave radars, operating at various frequency bands, have proven effective in accurately measuring vital signs such as heart rate and breathing rate. This paper delves into the importance of contactless systems in various critical scenarios. Disasters and epidemics demand efficient methods for detecting the vital signs of individuals who may be trapped or require immediate medical attention. In such situations, contactless radar systems can play a pivotal role in locating and monitoring individuals under rubble or in remote locations. Additionally, these systems find utility in military operations, aiding in identifying the presence and number of individuals behind walls or in concealed spaces. In healthcare, contactless radar systems offer a unique advantage. Unlike traditional contact-based devices, they enable long-term monitoring of vital signs without causing discomfort to the patient. This is particularly valuable in hospitals, where continuous monitoring is essential for patient care. Moreover, these systems can be deployed in public spaces to monitor the heart and breathing rates of the elderly, providing timely assistance in case of emergencies. While previous research has primarily focused on heart rate determination, this paper emphasizes the importance of capturing the electrical representation of the heart signal. This electrical representation is not only trustworthy but also offers greater accuracy in diagnosing various medical conditions. A recent study introduces a novel approach that employs deep learning techniques to extract the electrical activity of the heart from radar-based mechanical measurements. This groundbreaking method involves extensive training on electrocardiogram (ECG) data, encompassing different positions and durations. Additionally, this paper presents a traditional method for heart and respiration rate estimation based on Fourier transform. By analyzing the frequency domain of raw radar signals, this method accurately calculates heart and breathing rates, further enhancing the capabilities of contactless radar systems in medical applications. Lately, there have been a wide scope of contributions to create non-contact strategies for heart and breathing rate detection. Different types of MM-wave radars have been deployed and effectively used at different frequency bands such as 10 GHz, 24 GHz, 77 GHz, and 122 GHz. The use of contactless systems in the medical field is important in the event of disasters and epidemics in general. Especially in measuring heart rate and breathing rate using radar systems to detect living people under the rubble or in military raids to know terrorist outposts and their number across walls, as well as in hospitals to measure vital signs over

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long periods of time, unlike contact devices that tire the patient during the measurement process, which takes a long period of time, as well as in public places to measure heart and breathing rates for the elderly and provide assistance in time of distress (in case of falling on the ground). Therefore, the focus was on measuring heart rate and breathing rate using radar systems. Previous researchers pointed out at the beginning of their launch the determination of the heart rate due to its importance in identifying and diagnosing the patient case. However, the determination of the electrical representation of the heart signal itself is more trustworthy and more accurate in identifying diseases in general as known in medical books that concern the study of the heart. A recent study indicated the extraction of the electrical activity of the heart from the mechanical activity measured from radar using deep learning (DL) technique. The DL training was made on thirty-five ECG cases to measure the electrical signal of the heart for ten hours for five different positions of the sample members to teach the neural network to extract the electrical signal using domain transformation from mechanical to electrical. This module consists of an encoder-decoder based network architecture to solve this domain transformation problem using RF radar signal mapping to ECG as introduced in [1]. This paper presents novel algorithms for the concurrent estimation of heart rate from an ECG signal and electrical heart signal from mechanical heart activity using radar systems. Accurate cardiac parameter estimation is fundamental for both heart rate analysis and the diagnosis of various cardiac conditions. Furthermore, the estimation of respiratory rate, a vital physiological metric, is discussed. The proposed heart rate estimation algorithm is applied to electrical signals obtained from a contact medical sensor, while the electrical heart signal estimation algorithm is applied to received RF radar signals representing mechanical heart activity. The technical details in [2], equipment specifications, and experimental setup are comprehensively documented. The radar signals are acquired using 24.25 GHz and 10.525 GHz Doppler radars, and simultaneous data collection of ECG and respiratory belt signals is achieved through a contact instrument (BIOPAC, BN-REPEC). The analog signals are digitized using an ADC (USB-6003, National Instruments) with a sampling frequency of 1000 Hz and recorded using the LabVIEW data acquisition software.

II. DEFINITION AND MEASUREMENT OF THE VITAL SIGNS METHODS

Heartbeat, breathing rate, temperature, and blood pressure are all vital signs that represent important physiological functions to examine the human degree of physical functioning. The researchers seek to increase the aforementioned vital parameters to include oxygen saturation, degree of consciousness, weight, and height [3, 4].

The medical conditions that must be considered while measuring an ECG signal, how to place the ECG probes on the patient's chest and limbs, types of leads, and direct and indirect measuring methods are presented in [4]. It is necessary to know the composition of the heartbeat of a healthy body as well as the amplitude and interval of time taken for each part of the heartbeat of a healthy body as shown in Fig. 1.

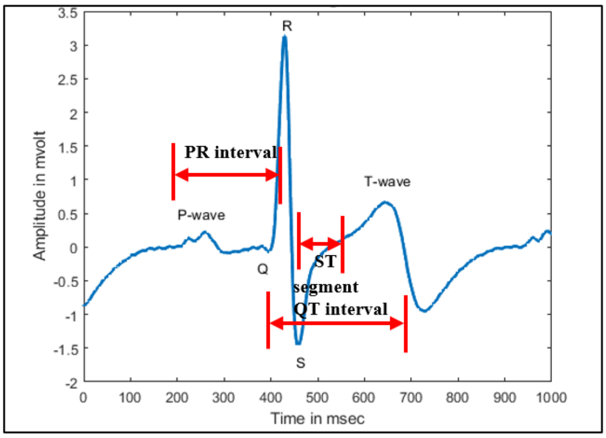

Fig. 1 ECG signal.

An ECG signal consists of P-QRS-T components which are having specified magnitude and intervals as follows [4]:

1- P-wave: wave represents electrical activation, called depolarization, of the atrial muscle and it is a positive wave having an amplitude of 0.11 mV.

2- QRS complex: represents the impulse spreading throughout the ventricles resulting in ventricular contraction and duration less than or equal to 0.12 seconds, that has an amplitude greater than 0.5 mV in at least one standard lead.

3- T-wave: return (repolarization) of the ventricular muscle to its resting electrical state.

4-PR interval: electrical impulse to spread from the atria to the ventricles through the atrioventricular node and normally between 0.12 and 0.20 seconds.

5- QT interval: normally less than or equal to 0.44 seconds.

6- ST segment: the period when the ventricles are completely activated normally greater than 0.5 m sec.

7- Sometimes a small positive (U wave) may be seen following the T wave (is absent in Fig. 1). This wave represents the last remnants of ventricular repolarization.

Accurate QRS detection is not only important for heart rate analysis but also for diagnosing other cardiac diseases [5,6]. For determination of the respiratory rate, the rate of an adult at rest should be 12-16 times per minute and the ratio of respiration to heart rate is about 1:4. Respiration rates can vary in different states of wakefulness and sleep. Respiration (number of breaths per minute) depends on a number of factors, including the age of the individual and the degree of exertion. Fig. 2 shows the pattern (or rhythm) of breathing and the way the chest moves in different cases [6].

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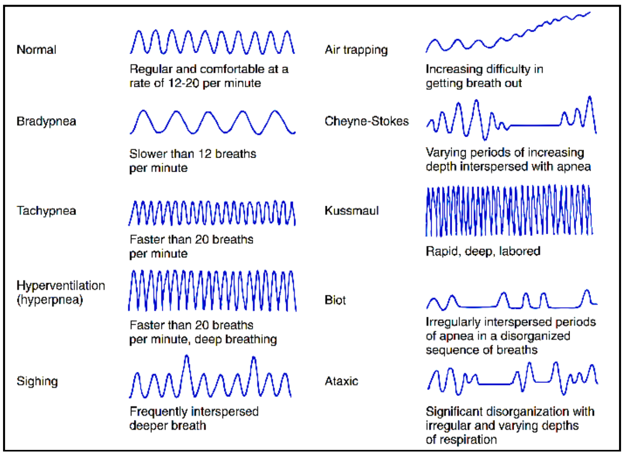

Fig. 2 Patterns of respiration. The x-axis indicates the relative rates of these patterns. The y-axis indicates the relative depth of respiration [6].

In this paper, new algorithms are introduced for heart rate estimation from an ECG signal and electrical heart signal estimation from mechanical activity of the heart using radar systems. The proposed heart rate estimation algorithm is applied on a heart electrical signal from a contact medical sensor. While the proposed electrical heart signal estimation algorithm is applied on a received RF radar signal that represents the mechanical activity of the heart. The utilized published data and technical details of the devices and the experimental setup are presented in [2]. The heart rate estimation algorithm proposed in this study is designed to operate on electrical signals acquired from a contact medical sensor. Simultaneously, an electrical heart signal estimation algorithm is applied to radar signals received from radar systems. The experimental setup utilized for data collection is meticulously detailed, featuring the use of 24.25 GHz and 10.525 GHz Doppler radars for radar signal acquisition. Additionally, concurrent recording of ECG and respiratory belt signals is facilitated by a contact instrument (BIOPAC, BN-REPEC). The analog signals are subjected to digitization via an ADC (USB-6003, National Instruments) operating at a sampling frequency of 1000 Hz. Data capture and storage are orchestrated using the LabVIEW data acquisition software, ensuring precision and fidelity in the recorded signals. In [7], a traditional method to extract heart and respiration rates based on the fact that their rates are directly proportional to the frequencies of the raw radar signal has been introduced. Therefore, their rate can be found using the conversion from the time domain to the frequency domain (based on Fourier transform). To estimate the breathing rate, it determines the maximum peak in the frequency domain within the frequency band (0. 15 - 0.4 Hz) and multiplying its corresponding frequency by 60 to find the rate per minute. And for heart rate estimation, it determines the maximum peak within the frequency range (0.8 to 2 Hz) and multiplying its corresponding frequency by 60 to find the rate per minute as shown in Fig. 3.

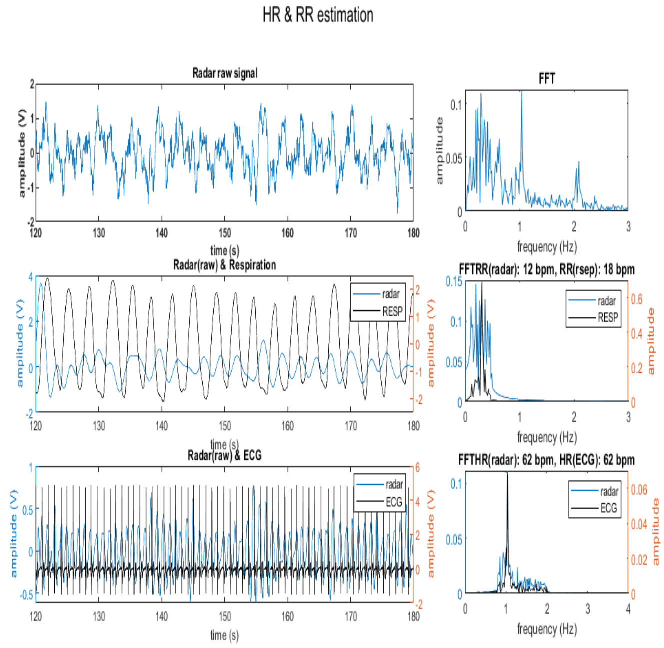

Fig. 3 Heart and breathing rates estimation using FFT based method [2, 7].

III. PROPOSED ALGORITHM FOR DETECTION OF HEART RATE FROM ECG SIGNAL.

One of the first to use the autocorrelation method in time domain and Fast Fourier Transform (FFT) method in frequency domain to find the heart rate using radar was [7]. This article indicated that autocorrelation method expresses the time difference of a recurring function for a group of peaks whenever the result of the function has a maximum with the delay of autocorrelation function in the time period between 0.6 seconds to 1.33 seconds. This period is very important to determine min and max lag of integration factor of autocorrelation function. It is inversely proportional to the heart rate and was applied in its article to a radar signal after passing a band pass filter within frequency range of heat rate, whether respiratory rate or heart rate and autocorrelation is given by

$$y[n] = x[n] * x[n] = \sum_{k=1}^{N-n} x(k)x(n+k) \qquad (1)$$

where, $min\_lag \le n \le max\_lag$, N: length of data is taken for 1 second equal to 1000 samples.

Min lag equal to (Fs/f_{h_e}) Corresponding to end frequency of heart $f_{h\_e} = 2\,Hz$ at a sampling frequency of 1000 Hz and max lag equal to (Fs/f_{h_s}). Corresponding to start frequency of heart $f_{h\_s} = 0.8\,Hz$ at a sampling frequency of 1000 Hz but max lag equal to 1000 for one second for because of limited length of data in one second (one second data equal to 1000 samples).

The index of vector $y[n]$ stores in vector $I_{1\times K}$ is defined as difference between two excessive heartbeats in msec and length of vector $I_{1\times K}$ determine of number of QRS complex in ECG signal, then it is taken sliding window by 0.8 sec (800 samples) Because the medically recognized average, A full heartbeat takes about 0.8 seconds.

Threshold_1 can be determined by finding minimum R-R wave of QRS wave and taken auto-correlation, then find max

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value that value equal to threshold_1 because two QRS in one second and can be determined by normalized ECG signal reference and take autocorrelation and chosen the peak and denormalization the peak.

Threshold_2 equal to minimum peak at long R-R interval medically accepted.

The equation to determine heart rate form R-R interval by auto correlation is given by [7]

$$Heart\ Rate = 60 * (1.0)/\left(\frac{Max\_Index\_lag}{samplingFreq\_Hz}\right) \qquad (2)$$

Fig. 5 shows the results of the proposed algorithm in Fig. 4 and compared with R-R interval between heartbeats from ECG signal a long time and also detection heart rate every R-R interval point is computed by equation 2 versus time axis as shown in Fig. 6. by calculating the following equation 3 to get the mean value of the heart rate per minute that accumulated R-R interval with time that point to heartbeat and apply it to the heart signal as shown in Fig. 7. Although there was an error in Fig. 6 for calculating the period between R-R wave which led to an error in calculating the heart rate, when calculating the cumulative heart rate then the final peak improved. It's shown the result of the heart rate after rounding the result to the nearest whole number as shown in the Fig. 8, taking the correct value of the heart rate, ignoring the fraction, and displaying the results as shown in the Fig. 9.

$$\begin{cases} Time[z] = \sum_{z=1}^{K} \frac{I[z]}{1000} \\ Heart\ rate\ [z] = z \,/ \left(\frac{Time[z]}{60}\right) \end{cases} \quad where\ 1 \leq z \leq k \qquad (3)$$

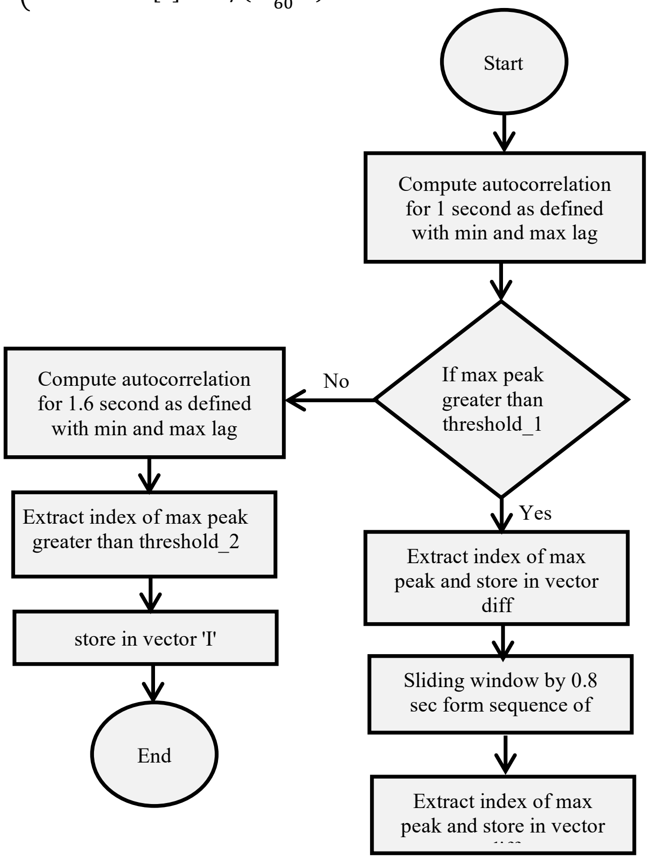

Fig. 4 Block diagram for detection R-R interval and heart rate

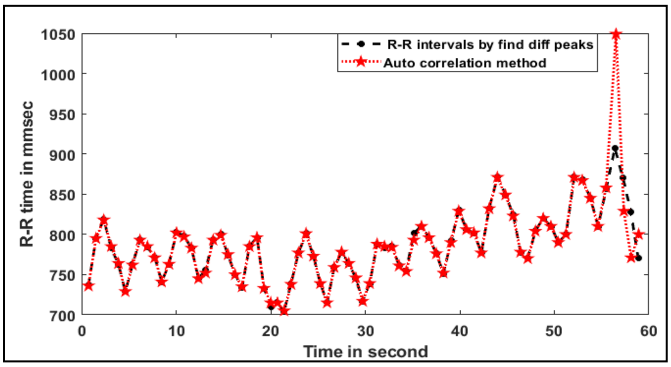

Fig. 5 Simulation result for the proposed algorithm to compute R-R interval

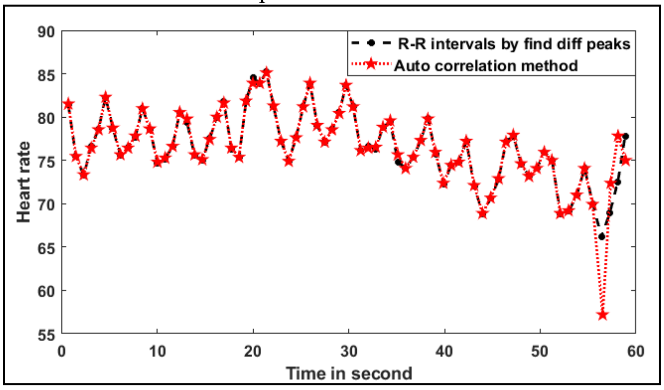

Fig. 6 Simulation result of the proposed algorithm for heart rate detection from ECG signal

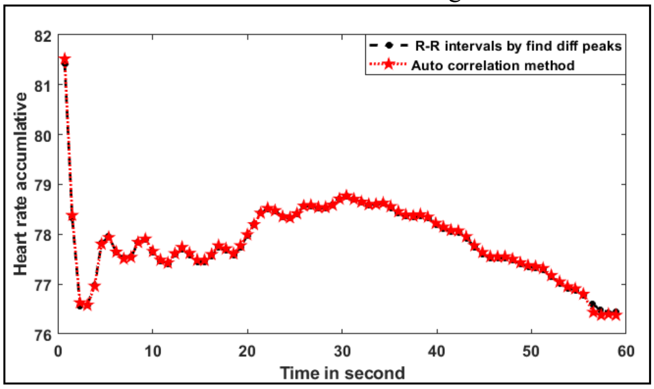

Fig. 7 Simulation result for the proposed auto correlation method heart rate accumulative with time

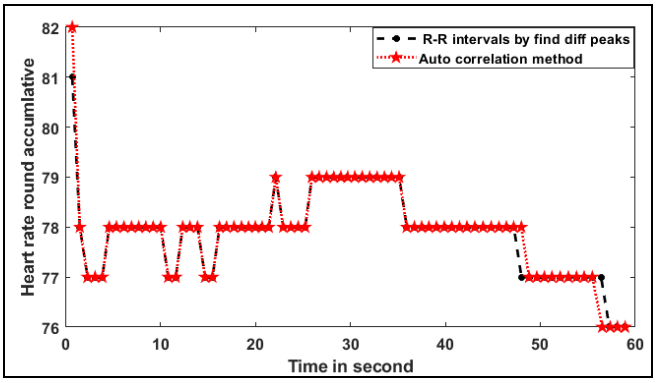

Fig. 8 Simulation result for the proposed auto correlation method heart rate round accumulative with time

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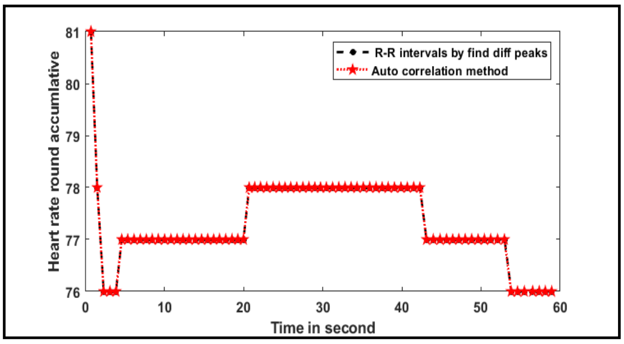

Fig. 9 Simulation result for the proposed auto correlation method heart rate floor accumulative with time

An evaluation metrics is taken to determine the error value using the proposed algorithm pointing to equations 3-5 and the resulted is listed in Table 1 and Table 2.

Table 1 Results of the heart rate in different method. The data length is 60 seconds in this table for each experiment.

subject	*Number of R peaks in reference ECG signal*	*TP*	*FN*	*Error (%)*
1	76	76	0	0
2	72	72	0	0
3	69	69	0	0
4	84	84	0	0
5	66	66	0	0

$$Error = \frac{TP-FN}{Number\ of\ R\ peaks} \quad (3)$$

TP (True Positive), FN (False Negative) compared with the heart rate of R-peaks of ECG reference Signal. TP denotes the place where the ECG reference Signal indicates heart rate, and the algorithm detects it with heart rate. Secondly, FN represents the component that was detected in the of ECG reference signal with heart rate but not in the algorithm with heart rate.

The Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) for all five subjects who participated in the experiments, and it's listed in Table 2 that are compared with their related reference method can be expressed by[8].

$$\text{MAE} = \frac{\sum_{i=1}^{n}|y_i - x_i|}{n} = \frac{\sum_{i=1}^{n} e_i}{n} \quad (4)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - x_i)^2} \quad (5)$$

y_i is represent R-R interval by proposed algorithm, x_i is represent R-R interval by different peaks R-R by conventional method.

Table 1 Results of different errors for R-R interval in seconds for ECG signal.

subject	MAE	RMSE
1	0.0043	$3.4801*10^{-4}$
2	0.0078	0.0015
3	0.0116	0.0011
4	0.0011	$9*10^{-6}$
5	0.0580	0.0070
Average error	0.01656	0.0019914

IV. CONCLUSION

This paper showcases the advancements in contactless heart and breathing rate detection using MM-wave radar systems. These systems hold immense potential in disaster response, medical monitoring, and public safety. The combination of deep learning techniques and traditional Fourier transform methods offers accurate and reliable results, making contactless radar systems a valuable tool in healthcare and emergency scenarios. This research opens avenues for further developments in non-contact vital sign monitoring. This paper lays the foundation for a comprehensive approach to cardiac parameter estimation and respiratory rate assessment through the fusion of ECG signals and radar-based techniques. The novel algorithms introduced here promise to enhance the accuracy and efficacy of heart rate analysis and facilitate the extraction of electrical heart signals from radar-generated mechanical heart activity data. The rigorous documentation of equipment specifications, experimental setup, and data acquisition methodologies provides a robust framework for further research in the domain of biomedical signal processing.

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Conflicts of Interest: The author declares that there is no conflict of interest.

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