Toward Multi-Person Breath Rate Estimation via mmWave Radar

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***Abstract*—The measurement of breath rate (BR) is essential for comprehensive human health monitoring across a wide range of scenarios. Several studies in the literature have explored the estimation of BR using millimeter wave (mmWave) technology. However, these approaches typically focus on a single subject at a time. To enable multi-person estimation, researchers have often relied on data fusion with camera systems or employed specialized hardware configurations. On the contrary, this paper proposes a methodology that employs only one Frequency Modulated Continuous Wave (FMCW) radar to estimate the BR of multiple subjects stationary in the environment. The proposed methodology includes a pre-processing pipeline to refine the radar-captured signals, followed by frequency-domain analysis to distinguish between subjects. Finally, phase variations in the reflected signals caused by chest movements are analyzed to estimate the BR. Advantages and limitations of the approach are discussed on the basis of an experimental campaign.**

***Index Terms*—Breath rate estimation, vital-sign estimation, mmWave radar, multi-person monitoring**

I. Introduction

Monitoring breath rate (BR) is a key factor in assessing an individual's physiological state across various scenarios, including clinical diagnostics, sports performance, and home-based healthcare. Traditionally, BR has been measured using contact-based techniques such as spirometry, chest-worn sensors, facial masks, or nasal cannulas. While these methods are generally precise, they can interfere with natural movement and behavior due to their intrusive design and constraints like battery limitations and dependence on external devices [1], [2].

Advancements in monitoring technologies have increasingly focused on reducing individual's discomfort and enabling unobtrusive tracking of physiological signals. This shift has driven significant progress in the development of contactless sensing approaches, particularly through the use of Radio Frequency (RF) technologies that fill a significant gap in health monitoring practices, providing the capability to measure physiological parameters non-invasively [3]–[5].

In the context of RF-based methods, several studies have explored millimeter wave (mmWave) for vital signs detection in different settings. These approaches make use of Frequency Modulated Continuous Wave (FMCW) radars, such as the AWR1xxx series from Texas Instruments, which typically operate in high-frequency bands (e.g., 77–81 GHz), to detect subtle human body movements, such as those produced by respiration and heartbeat on the chest [6]. The periodic chest displacements caused by these physiological activities induce slight variations in the reflected radar signals, which can be analyzed to estimate BR, and also heart rate (HR).

TABLE I: Characteristics of SOTA approaches for BR estimation through mmWave radar technologies together with the MAE and MAPE.

Ref.	Year	Hardware	MAPE	MAE	# Sbj	Movements
[7]	2016	Dedicated HW	N/A	0.43	2	No
[8]	2022	TI AWR1642	1.33%	N/A	1	No
[9]	2024	TI AWR1642	4.44%	N/A	1	No
[10]	2024	TI AWR1243	26.72%	2.48	1	Yes, freely
[11]	2023	TI AWR1843 + Camera	N/A	0.5	3	Yes, in place

MAE: Mean Absolute Error – **MAPE**: Mean Absolute Percentage Error

Consequently, in the recent past, some approaches have been proposed to perform vital sign estimation through mmWave, the current state-of-the-art (SOTA) is summarized in Table I. In a pioneering work of 2016, Yang *et al.* [7] propose a system that uses 60 GHz mmWave signals for vital sign monitoring. Their setup is composed by two antennas, a transmitter and a receiver, placed at a distance d inside the environment. Thanks to this setup, authors were able to obtain a wide field of view and detailed spatial information, which made them achieve a Mean Absolute Error (MAE) of 0.43. Authors in [8] performed vital sign monitoring of a person sitting on a chair inside an office using FMCW operating at 77 GHz. Furthermore, they introduced a wavelet-based denoise approach to the mmWave data. Sadeghi *et al.* [9] proposed a FMCW radar dataset, with ground truth annotation provided by a Polar H10 chest band. Besides, the authors also provided benchmark results, obtaining a Mean Absolute Percentage Error (MAPE) of 7.33% and 4.44% respectively for HR and BR estimation. In [10], the authors present a methodology to estimate BR of a subject freely moving inside and environment, achieving a MAPE of 26.72%, which correspond, in average, to an error of 2.48 breaths per minute. Wang *et al.* [11] proposed a data fusion-based approach. In particular, they use a Kinect V2 camera to enhance the mmWave estimation, allowing multiple subjects to monitor the environment and achieve promising results.

This study was carried out within the MICS (Made in Italy – Circular and Sustainable) Extended Partnership and received funding from Next-Generation EU (Italian PNRR – M4 C2, Invest 1.3 – D.D. 1551.11-10-2022, PE00000004). CUP MICS D43C22003120001 - Cascade funding project CollaborICE, and within the PRIN 2022 project "WE.SMOOTH.PD: a WEarable-based System to MOnitor motor functions and levodopa levels for THerapy optimization in Parkinson's Disease" funded by European Union - Next Generation EU, Mission 4 Component 1 CUP 2022EJM345.

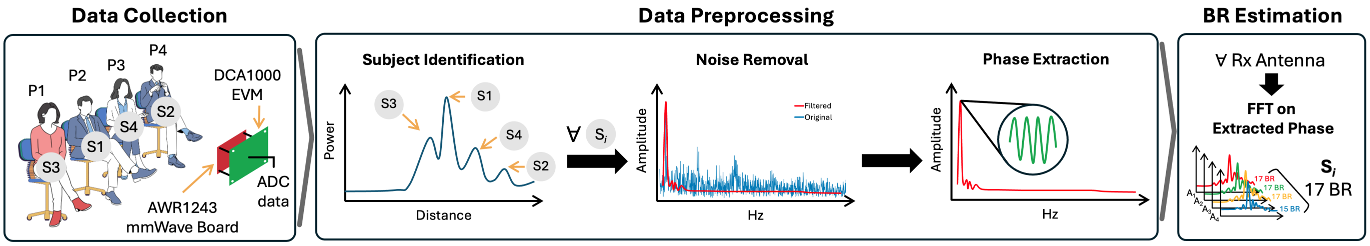

Fig. 1: Methodology Overview

Overall, the previous methodologies, while promising, present some limitations: either the BR estimation is limited to a single subject [8]–[10], or they use a dedicated hardware setup to monitor multiple subjects [7], [11]. Furthermore, using other data sources, such as video streaming, like in [11], can limit the usability and privacy-aware characteristics of the mmWave technology.

To address the previous limitations, this paper introduces a novel mmWave-based technique for estimating the BR of multiple subjects simultaneously present within an environment, without relying on dedicated hardware or data fusion from multiple sources. The proposed methodology operates under the assumption that subjects remain stationary. While this may appear restrictive, it is highly relevant in practical scenarios such as monitoring individuals in senior residences or hospital rooms, particularly during sleep. In particular, the main contributions of our work are:

- A signal processing pipeline capable of identifying and isolating stationary individuals simultaneously present within the radar's field of view. The pipeline incorporates spatial filtering techniques to differentiate also between closely positioned subjects.
- A BR estimation technique based on Fast Fourier Transformation (FFT) spectrum analysis that accurately extracts respiratory frequencies even in the presence of potential cross-subject interference. Our algorithm incorporates adaptive noise suppression and peak validation mechanisms.
- An analysis of the proposed method through experimental validation, comparing our radar-derived estimations against ground truth data collected using Hexoskin Pro Kits [12], a clinically validated wearable respiratory monitoring system.

The remainder of the paper is organized as follows: Section II presents the proposed methodology; Section III discusses the obtained results; and Section IV provides the concluding remarks.

II. Methodology

With reference to Figure 1, this section describes the methodology designed to perform BR estimation of multiple persons inside an environment. The methodology is composed of three main parts: i) data collection, ii) preprocessing pipeline, and iii) BR estimation.

A. Data Collection Setup

Our data collection setup employes the Texas Instruments (TI) AWR1243BOOST mmWave board for capturing radar signals. This board interfaces with the DCA1000EVM data capture adapter, enabling real-time streaming of ADC data to a host computer system. We managed the entire data acquisition process through TI's mmWave Studio software package, which allows for the configuration of capture parameters. We configured the system with two transmitting antennas and four receiving antennas to optimize respiratory movement detection, exploiting an enhanced Signal-to-Noise Ratio (SNR) and wider angular resolution. The measurement rate was set at 25 Hz, meaning it collects 25 frames per second, to adequately sample breath-related motion. Each frame is composed of 99 chirps that capture 374 analog-to-digital (ADC) samples. In practice, each frame collected from the mmWave board can be represented by a 3D matrix where the first dimension corresponds to the number of chirps, the second represents the number of ADC samples, and the last denotes the number of antennas. A chirp refers to a frequency-modulated signal whose frequency increases over time during a fixed time interval, known as the chirp duration. The mmWave radar continuously transmits a sequence of chirps and listens to the reflected signals from objects within its sensing environment. The transmitted signal can be modeled as a linearly increasing frequency sweep, covering a bandwidth of 4 GHz, which enables fine range resolution. When the transmitted chirp hits a moving or stationary object, the signal is reflected back with a delay proportional to the subject/object's distance. Additionally, if the object moves (e.g., due to breathing-induced chest motion), the reflected signal experiences a phase shift and a small frequency offset due to the Doppler effect. By analyzing time delay and frequency shift across successive chirps, it is possible to estimate both the range and the motion characteristics of the target. Therefore, each collected chirp contains spatial and temporal information crucial for detecting respiratory movements.

B. Preprocessing Pipeline

To estimate the BR of multiple subjects from the FMCW, the collected data flow through the following preprocessing pipeline.

1) Data Preparation: From the ADC samples collected by the AWR1243BOOST, we organized the radar data into a 4D tensor with the following dimensions: (frames × chirps × ADC samples × antennas). Then, we applied the proposed methodology using a time windowing approach, with window sizes of, for example, 30, 60, or 120 seconds. Each window contains a fixed number of frames, determined by the window duration. For example, a 30-second window at a sampling rate of 25 Hz contains 750 frames (30 s $\times$ 25 Hz). To reduce data complexity while retaining meaningful temporal information, we applied a temporal aggregation technique. Specifically, for each frame, we grouped the ADC samples (third dimension) into clusters—where each cluster represents the full set of samples from a single chirp—and averaged the rows within each cluster. In this context, a "row" refers to a single time sample from the ADC. Therefore, each cluster includes all ADC samples from a frame, and the number of rows per cluster equals the number of ADC samples. This averaging process reduces the data dimensionality but preserves the temporal structure of the radar signal, which is essential for analyzing motion patterns such as breathing. The aggregation, as well as the steps reported in the following of this section, were applied separately to the data from each receiving antenna.

2) Subject Identification: As reported above, FMCW radars transmit chirps, i.e., continuous signals whose frequency increases linearly over time. When these signals reflect off an element (either persons or objects) and return to the radar, there is a time delay between the transmitted and received signals. This delay results in a frequency difference, called the *beat frequency*, which is directly proportional to the element's distance. The Range FFT is applied to the Intermediate Frequency (IF) signal obtained after mixing the received signal with the transmitted signal. This process transforms the time-domain signal into the frequency domain. The spectral elements that demonstrate significantly higher amplitude values, which are graphically visualized as peaks relative to the surrounding frequency bins, correspond to distinct physical element present in the environment. The corresponding peak will always appear at the same index if an element is static. Using this logic, we can remove peaks corresponding to static elements by subtracting consecutive frames. As a result, we have a tensor containing peaks that show only the moving elements, i.e., the chests of the subjects stationary present in the environment.

3) Noise Removal: We perform an average on the ADC samples of the chirps belonging to the same frame to remove hardware and environmental noise, such that we can better recognize the moving entities according to their respective peaks. Then, the peaks that exceed a predetermined threshold are retained, and their indices are monitored to track the movement of the chest.

Since the chest movement is composed of inspiration and expiration phases, continuously shifting for one to the other, the distance between the chest and the radar behaves like a continuous function, thus each breath of a subject results in a cluster of closely spaced peaks. Among those, we select only the index associated with the highest peak as a representative of the cluster.

4) Phase Extraction: Using the information gathered in Section II-B3, we extract the phase information from the raw data tensor for each detected individual. At this point, we perform phase unwrapping and phase differentiation for each individual. Phase unwrapping ensures a continuous phase representation by eliminating artificial discontinuities, while phase differentiation extracts the instantaneous frequency variations, making it possible to isolate relevant physiological signals with greater accuracy [13], [14]. We then implement a band-pass filtering operation with cutoff frequencies specifically calibrated to encompass the standard human respiratory frequency spectrum, from 0.16 to 0.50 Hz, corresponding to 10-30 breaths per minute.

C. Breath Rate Estimation

The final stage in our processing pipeline is the estimation of BR for each detected subject. We perform frequency domain analysis on the extracted phase signal using the FFT. This transformation converts the time-domain respiratory oscillations into the frequency domain, where respiratory patterns appear as distinct spectral peaks. The respiratory rate is identified as the dominant frequency component in the expected physiological range for human breathing (e.g., 0.25 Hz corresponds to 15 breaths per minute). To enhance robustness against noise and movement artifacts, we leverage our multi-antenna configuration. The BR estimation process is performed independently for each of the four antennas in our radar array, resulting in four separate respiratory rate estimations $(\mathrm{BR}_1, \mathrm{BR}_2, \mathrm{BR}_3, \mathrm{BR}_4)$ for each detected subject. We then employ a consensus mechanism to determine the final breathing rate BR_f as follows:

$$\mathrm{BR}_f = \mathrm{mode}(\mathrm{BR}_1, \mathrm{BR}_2, \mathrm{BR}_3, \mathrm{BR}_4) \tag{1}$$

This approach selects the most frequently occurring breathing rate estimate across all antennas. In cases of a tie (when two different rates occur with equal frequency), we select the median value to minimize the impact of outlier measurements.

III. Experimental Results

To evaluate the proposed approach we first collected data as outlined in Section II-A, through the TI AWR1243BOOST radar operating at 77-81 Hz. For all experiments, we used the following settings: two transmitting antennas, four receiving antennas, 374 samples per chirp, 99 chirp loops, a measurement rate of 25 Hz, an ADC sample rate of 3×10^6 and a chirp slope of 3.013×10^{13}.

During the recording, multiple subjects were present in the environment, in particular, sitting in different positions facing the mmWave board. The data collection involved 4 volunteers (3 males, 1 female), breathing normally. Considering the fact that the subjects' bodies should not overlap, we chose to position them diagonally, as shown in Figure 1. All the subjects were free from respiratory, cardiac, or any other diseases that may alter the normal breathing. Each recording we performed lasts two minutes.

We collected ground truth data for breath rate using Hexoskin Pro Kit [12], which is a wearable system designed for continuous monitoring of physiological parameters. This shirt integrates Respiratory Inductance Plethysmography (RIP) bands positioned around the chest and abdomen, which detect thoracic and abdominal movements associated with breathing cycles.

TABLE II: MAPE and MAE in breath rate estimation, at varying of the number of subjects and the window size.

# Sbj	# Exp	30 sec window		60 sec window		120 sec window	
		MAPE	*MAE*	*MAPE*	*MAE*	*MAPE*	*MAE*
1	8	4.6%	0.83	2.4%	0.44	2.9%	0.55
2	7	5.7%	0.96	6.4%	1.07	2.9%	0.53
3	8	3.9%	0.70	3.1%	0.56	4.5%	0.81
4	4	4.8%	0.75	6.5%	1.03	2.1%	0.34
Average		4.7%	0.79	4.6%	0.77	3.3%	0.59

A. Analysis of the Results

To evaluate the proposed methodology, we estimated the BR varying the number of subjects sitting in the room and using different time window sizes to find the best configuration. Table II reports the achieved results in terms of estimation accuracy. The first column indicates the number of subjects simultaneously sitting in the room, while the second column shows the number of experiments conducted under the corresponding setup. The remaining columns present the MAPE and MAE values for three different window sizes: 30, 60, and 120 seconds, respectively. The MAE and MAPE are defined as follows:

$$\text{MAPE} = 100\frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \qquad \text{MAE} = \frac{1}{n}\sum_{t=1}^{n}|A_t - F_t|$$

where A_t is the ground truth value, F_t is the estimated value, and n is the number of observations.

The results demonstrate that window size has a significant impact on the estimation of the BR. Short windows (e.g., 30 seconds) make it more challenging to capture complete respiratory cycles for frequency analysis, resulting in higher MAE and MAPE values. In our experiments, since subjects maintained a constant respiratory rhythm during data collection, the optimal window size was found to be 120 seconds, yielding an average MAPE of 3.3% and an average MAE of 0.59. However, one could argue that longer windows may smooth out short-term variations by averaging different BR values, potentially reducing estimation accuracy when the subject experiences sudden changes in breathing rate. While this aspect warrants further investigation, such abrupt changes are relatively infrequent within the population. On the other side, the results obtained using 30 and 60-second time windows are getting worse, respectively scoring a MAPE of 4.6% and 4.7% and a MAE of 0.77 and 0.79. With very short time windows (e.g., 15 seconds, not reported in the table), the algorithm often failed to detect significant peaks, resulting in highly inaccurate BR estimations. We faced some variability in optimal window sizes for different subject counts, particularly evident in the 3-subject scenario. However, there is not a specific trend on accuracy degradation on the BR estimation error when several people are present simultaneously in the monitored environment.

Compared to state of the art methods exploiting TI AWRxxx devices (see Table I), the approach proposed in this paper achieves a comparable MAE and MAPE while simultaneously monitoring more subjects (up to 4). Optimal performance was obtained, in particular, when monitoring 4 subjects concurrently, achieving a MAE of 0.34 and MAPE of 2.1%.

B. Limitations and Future Work

The proposed approach presents some limitations related to the position of individuals involved and their movements. Specifically, it was not possible to accurately estimate the breathing rate of subjects who were not facing the mmWave board. In such cases, chest movements produced minimal phase variation, rendering respiratory detection ineffective. For similar reasons, the board must be positioned at chest height to maximize sensitivity to respiratory motion. Moreover, since the algorithm differentiates subjects based on their distance from the board, individuals must be placed at distinct and sufficiently spaced positions to prevent signal interference caused by adjacent chest movements. This issue was particularly evident during measurements involving three subjects, where the central individual consistently showed the highest estimation error due to interference from neighboring movements. Another limitation is the requirement for subjects to remain still, as any body movement introduces significant noise and degrades the quality of the collected data.

While these limitations may affect the general applicability of mmWave technology for BR estimation in dynamic or uncontrolled environments, there are specific scenarios where these constraints are naturally satisfied. For instance, in hospital rooms, sleep laboratories, or elderly-care facilities, individuals often remain relatively stationary for extended periods and can be positioned in a controlled manner with respect to the mmWave board. These environments also allow for proper sensor alignment at chest level, minimize motion artifacts, and reduce the likelihood of interference from nearby individuals. As such, they represent ideal use cases where the proposed approach can be effectively applied.

Future work will focus on improving robustness in less controlled environments, enhancing subject identification in crowded settings, and incorporating motion compensation techniques to extend applicability to a broader range of real-world scenarios.

IV. Conclusions

Exploiting FMCW radar, this paper presents an approach to estimate the breath rate of up to four people simultaneously sitting in an environment. We tested the proposed methodology across different settings, achieving in average, for the most challenging case of 4 simultaneous subjects, a MAPE of 2.1%, with a deviation from ground truth of only 0.34 breaths, by considering an observation time window of 120 seconds.

References

[1] T. Hussain, S. Ullah, R. Fernández-García, and I. Gil, "Wearable sensors for respiration monitoring: A review," *Sensors*, vol. 23, no. 17, p. 7518, 2023.

[2] H. C. Bidsorkhi, N. Faramarzi, B. Ali, L. R. Ballam, A. G. D'Aloia, A. Tamburrano, and M. S. Sarto, "Wearable graphene-based smart face mask for real-time human respiration monitoring," *Materials & Design*, vol. 230, p. 111970, 2023.

[3] A. M. M. L. C. C. A. C. X. W. O. S. D. B. J. M. B. L. Le Ngu Nguyen, Praneeth Susarla, "Monitoring long-term cardiac activity with contactless radio frequency signals," *Information Fusion*, vol. 110, no. 1, pp. 1–18, 2024.

[4] P. Susarla, A. Mukherjee, M. L. Cañellas, C. Á. Casado, X. Wu, O. Silvén, D. B. Jayagopi, M. B. López *et al.*, "Non-contact multimodal indoor human monitoring systems: A survey," *Information Fusion*, vol. 110, p. 102457, 2024.

[5] A. Singh, S. U. Rehman, S. Yongchareon, and P. H. J. Chong, "Multi-resident non-contact vital sign monitoring using radar: A review," *IEEE Sensors Journal*, vol. 21, no. 4, pp. 4061–4084, 2020.

[6] J. Gong, X. Zhang, K. Lin, J. Ren, Y. Zhang, and W. Qiu, "Rf vital sign sensing under free body movement," *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, vol. 5, no. 3, pp. 1–22, 2021.

[7] Z. Yang, P. H. Pathak, Y. Zeng, X. Liran, and P. Mohapatra, "Monitoring vital signs using millimeter wave," in *Proceedings of the 17th ACM international symposium on mobile ad hoc networking and computing*, 2016, pp. 211–220.

[8] M. Xiang, W. Ren, W. Li, Z. Xue, and X. Jiang, "High-precision vital signs monitoring method using a fmcw millimeter-wave sensor," *MDPI Sensors*, vol. 22, no. 19, p. 7543, 2022.

[9] E. Sadeghi, K. Skurule, A. Chiumento, and P. Havinga, "Comprehensive mm-wave fmcw radar dataset for vital sign monitoring: Embracing extreme physiological scenarios," *arXiv preprint arXiv:2405.12659*, 2024.

[10] C. Turetta, M. Varasteh, S. Kolozali, and G. Pravadelli, "Leveraging mmwave for contactless breath rate estimation of moving subjects," in *2024 IEEE International Conference on Digital Health (ICDH)*, 2024, pp. 33–39.

[11] Y. Wang, Z. Wang, J. A. Zhang, H. Zhang, and M. Xu, "Vital sign monitoring in dynamic environment via mmwave radar and camera fusion," *IEEE Transactions on Mobile Computing*, vol. 23, no. 5, pp. 4163–4180, 2023.

[12] Hexoskin, "Hexoskin Pro Kit," https://hexoskin.com/products/hexoskin-pro-kit-mens, 2025, accessed: 2025-04-29.

[13] Y. Chen, J. Yuan, and J. Tang, "A high precision vital signs detection method based on millimeter wave radar," *Scientific Reports*, vol. 14, no. 1, p. 25535, 2024.

[14] B. Zhang, B. Jiang, R. Zheng, X. Zhang, J. Li, and Q. Xu, "Pi-vimo: Physiology-inspired robust vital sign monitoring using mmwave radars," *ACM Trans. Internet Things*, vol. 4, no. 2, May 2023. [Online]. Available: https://doi.org/10.1145/3589347