Techno-computing Journal 1(1) 42–51(2025)
https://doi.org/10.71170/tecoj.2025.1.1.42-51
Research Paper

Breath Rate Detection in Single and Multi-User Scenarios Using Wi-Fi Channel State Information

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Abstract

This study presents a signal processing pipeline for non-intrusive breath rate detection in single-user and multiuser scenarios using wireless Channel State Information (CSI). Our approach integrates advanced phase cleaning, Butterworth filtering, and FFT-based feature extraction to accurately estimate respiratory rates in single-user and multi-user scenarios. Experimental results show competitive performance with a Mean Squared Error (MSE) as low as 0.50 BPM in controlled settings. We also discuss the challenges in separating overlapping signals in multi-user environments and propose future work incorporating adaptive filtering and deep learning models for real-time monitoring.

Keywords: Breath Rate Detection, Channel State Information, Butterworth Filter, Phase Cleaning, and FFT

1. Introduction

Non-intrusive respiratory monitoring is critical in modern healthcare, offering a safer and more comfortable alternative to traditional sensor-based methods [1]. In this context, Wi-Fi Channel State Information (CSI) has emerged as a promising signal source, enabling the detection of subtle physiological signals without requiring physical contact [1]. This study introduces a novel dual-feature approach that integrates both amplitude and phase information extracted from CSI. While single-user respiratory monitoring benefits from the periodic nature of CSI signals, multi-user scenarios present a significant challenge due to overlapping respiratory patterns. Our approach effectively separates these overlapping signals, a problem not adequately addressed in previous work. By doing so, we advance state-of-the-art CSI-based monitoring and contribute to developing smart healthcare solutions that align with the interdisciplinary trends in techno-computing and Internet-of-things (IoT) applications.

CSI-based systems are well suited for real-time, scalable healthcare and public safety deployments, as they operate without direct physical contact. In single-user scenarios, respiratory monitoring exploits the inherent periodic changes in CSI amplitude and phase caused by breathing. However, overlapping these periodic signals increases the complexity of accurate breath rate estimation when multiple users are present.

The contributions of this work are summarized as follows:

- Signal Processing Pipeline: We design a robust pipeline incorporating advanced preprocessing techniques, including phase cleaning and Butterworth bandpass filtering, combined with FFT-based feature extraction and reliable peak detection algorithms.
- Theoretical Foundations: Detailed mathematical derivations for the key preprocessing steps are provided, enhancing the proposed method's clarity, interpretability, and reproducibility.
- Comprehensive Evaluation: The proposed approach is rigorously evaluated under single-user and multiuser scenarios using numerical metrics and visual analysis. The results demonstrate their efficacy in accurately estimating breath rates, even in complex multi-user environments.

(Received 12 Dec 2024; revised 03 March 2024; accepted 20 March 2025; first published online 30 April 2025);

Multi-user respiratory monitoring is particularly relevant in real-world settings such as hospital wards, elderly care facilities, and smart homes, where multiple occupants may be present. Traditional sensor-based methods often become cumbersome or intrusive in these environments, reducing user comfort and scalability issues. By leveraging Wi-Fi CSI for non-contact monitoring, our approach aims to improve patient safety and comfort, enabling continuous observation of respiratory health. However, multi-user scenarios inherently introduce signal overlap, making accurate breath rate estimation more challenging. Addressing this overlap problem ensures reliable real-time monitoring across diverse, dynamic indoor environments.

The remainder of the paper is organized as follows: Section II reviews related work, highlighting recent advancements and current challenges in CSI-based respiratory monitoring. Section III describes the dataset and experimental setup. Section IV details the methodology, including preprocessing, feature extraction, and peak detection. Section V presents the results and a detailed evaluation of the proposed approach. Finally, Section VI concludes the paper and discusses future research directions.

2. Related Works

Wi-Fi CSI-based breath rate detection has emerged as a promising non-contact method for respiratory monitoring, particularly in static single-user environments. Early studies have demonstrated that CSI-based techniques can achieve high accuracy. For example, Xu *et al.* [1] employed a combination of peak detection and frequency domain analysis with a lowpass filter, achieving breath rate accuracies better than 0.9 BPM for standing positions and 0.4 BPM for sitting scenarios. Similarly, Yin *et al.* [2] developed a smartphone-integrated system that reliably uses Wi-Fi signals to detect respiration in controlled, single-user settings.

Recent research has also explored CSI-based respiration analysis for person identification. Wang *et al.* [3] presented a pipeline that combines FFT, spectral filtering, Iterative Dynamic Programming (IDP), and a Markov Chain Model to analyze respiratory patterns for people counting and recognition, achieving accuracies of 86% and 85.78%, respectively. However, transitioning from single user to multi-user environments introduces significant challenges due to overlapping respiratory signals. To address these complexities, several studies have proposed advanced signal processing methods. Zhang *et al.* [4] developed novel techniques using LoRabased sensing and beamforming to increase signal strength and effectively separate breath patterns of multiple users, reporting an average accuracy of 98.1% in environments involving five subjects.

Other works have explicitly focused on multi-user scenarios. Wan *et al.* [5] developed a CSI amplitude sensing system that leverages OFDM and FFT to track respiratory patterns in multi-user moving scenarios, achieving an accuracy of less than 1 BPM. Xiong *et al.* [6] further explored using SIMO radar combined with adaptive digital beamforming for multitarget respiration detection, demonstrating improved accuracy in environments with multiple users. In addition, Guan *et al.* [7] employed beamforming with density-based spatial clustering to isolate individual breath patterns in crowded spaces, achieving 97.04% accuracy, while Gao *et al.* [8] used a dynamic adaptive matching algorithm in a three-user scenario to reach 97.5% accuracy.

Beyond breath rate detection, CSI-based methods have shown potential in broader health-related applications. Guo *et al.* [9] explored the use of respiratory patterns for biometric authentication, achieving 97.5% accuracy with a weighted minimum distance-dynamic time warping (WMD-DTW) algorithm, thereby highlighting the broader applicability of CSI in secure and reliable identity verification. Despite the impressive results achieved in single-user and multi-user settings, the literature indicates that accurately detecting respiratory signals in multi-user environments remains challenging. Existing approaches—such as clustering, adaptive matching, beamforming, and multiple sensing modalities—often require substantial computational resources and may not generalize well across diverse settings. In contrast, our work introduces a simplified yet robust pipeline that leverages amplitude and phase features to address these inherent challenges. Overall, the reviewed literature establishes a strong foundation for CSI-based respiratory monitoring while underscoring the need for improved methods to efficiently separate overlapping signals in multiuser contexts.

3. Methodology

The methodology consists of several key stages, including data preprocessing, feature extraction, peak detection, and evaluation, as illustrated in Figure 1.

2.1 Dataset Overview

The dataset comprises CSI samples collected in an office environment under controlled (constant breath rate) and varied (changing breath rate) conditions. Experiments include single-user and two-user scenarios with different breath rate patterns [10]:

- Controlled Mode: Users maintain a constant breathing rate throughout the experiment.
- Varied Mode: Participants alter breathing rates by increasing breathing frequency between 12 and 24 breaths per minute.

Data was collected with an Intel AX200 WiFi device operating at a central frequency of 5.57 GHz and a sampling rate of 100 Hz, a total of 245 subcarriers. The ground truth is obtained with an Open Signals device, which provides breath rates per minute (BPM) at one-second intervals. Table I provides an overview of the data set.

***Table 1**: Summary of the Dataset*

Experiment No	Scenario	Breth Mode	Breath Rate (BPM)
1	One Person	Controlled	12
2	One Person	Controlled	15
3	Two People	Controlled	15, 20
4	Two People	Varied	12–24

Following the guidelines and specifications of ACI 211.4R–93 [16] sixteen series of high-performance steel fibre-reinforced concrete (HP-SFRC) mixes were formulated, and the mixture proportions used in this investigation are listed in Table 2. Each mix had water to binder ratio (w/b) and a fibre volume fraction (Vf) of 0.5, 1.0, or 1.5% by volume of concrete. Additionally, a superplasticizer with a dosage range of 1.75 to 2.5% by weight of binder was added to the mixes. To evaluate the performance of the HP-SFRC mixes. three cylinders 150 diameters × 300 mm height and three prisms 100 × 100 ×500 mm was produced for each mix and cured at 27 ± 2 ◦C in water.

2.2 Data Preprocessing

CSI Data Pre-processing is essential to enhance signal clarity and suppress noise, improving the signal-to-noise ratio (SNR) in detecting respiratory patterns. Our approach incorporates the following preprocessing techniques:

1) Phase Cleaning: The CSI phase often contains noise and discontinuities due to wrapping effects, which can obscure respiratory patterns. To address this, a phase cleaning method inspired by WiDance [11] is implemented. This method unwraps the phase, removing distortions and offsets, thereby preserving respiratory-related periodic patterns. The cleaning process uses the formula:

$$\textit{Sanitized Phase} = \textit{Unwrapped Phase} - (a \cdot t + b) \tag{1}$$

Where:

$$a = \frac{\text{Phase}\,[-1] - \text{Phase}\,[0]}{2\pi F}, \quad b = \frac{\Sigma\text{Phase}}{F} \tag{2}$$

Here:

- a: Represents the linear trend across the phase values.
- b: Stand for the average phase offset across all samples.
- t: Represents the time index for each sample.
- F: Denotes the number of phase samples.

This equation adjusts the phase values by subtracting the linear trend ($a \cdot t$) and the offset (b), resulting in a clean phase signal.

Figure 1 illustrates the impact of phase cleaning. The raw phase shows significant fluctuations and discontinuities, while the sanitized phase exhibits a smoother trajectory, highlighting the underlying periodic patterns.

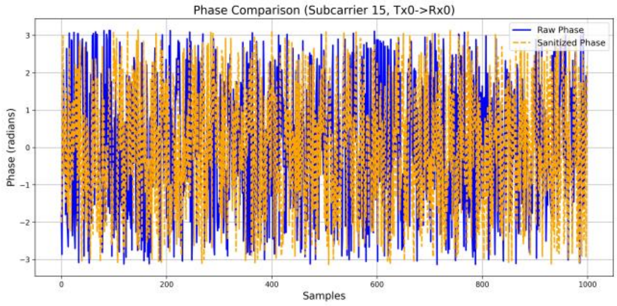

Figure 1: *Comparison of Raw CSI Phase and Sanitized CSI Phase for Subcarrier 15 (Tx0-Rx0).*

2) *Butterworth Bandpass Filter:* We employ a first-order Butterworth Bandpass filter to isolate the breathing frequency range, retaining frequencies between 0.1 Hz and 0.5 Hz. These frequencies correspond to breathing rates between 6 and 30 breaths per minute (BPM). The Butterworth filter is particularly effective for this task due to its flat frequency response in the passband, ensuring minimal distortion of respiratory signals while suppressing irrelevant noise.

The normalized cutoff frequencies f_{low}, and f_{high} are calculated as:

$$f_{\text{low}} = \frac{2 \cdot 0.1}{f_s}, \quad f_{\text{high}} = \frac{2 \cdot 0.5}{f_s} \tag{3}$$

The CSI data's sampling frequency is $f_s = 100$ Hz. Then, a first-order Butterworth filter is defined with the transfer function $H(s)$:

$$H(s) = \frac{b_0}{s + a_1} \tag{4}$$

Here, b_0 and a_1 are the coefficients derived by the cutoff frequencies. The filtered signal, $x\hat{}(t)$, is obtained by filtering the CSI amplitude $x(t)$ via the filter defined above as:

$$x\hat{}(t) = H(s) * x(t) \tag{5}$$

where $*$ denotes convolution. The result of such a filtering operation increases periodic breathing-related patterns while eliminating high-frequency noise and unrelated low-frequency components.

Figure 2 shows the result of applying the Butterworth bandpass filter to the CSI amplitude. The top panel presents the raw amplitude data, which contains a lot of noise and overlapping frequencies. The bottom panel presents the processed amplitude after filtering, where the periodic respiratory signal can now be seen.

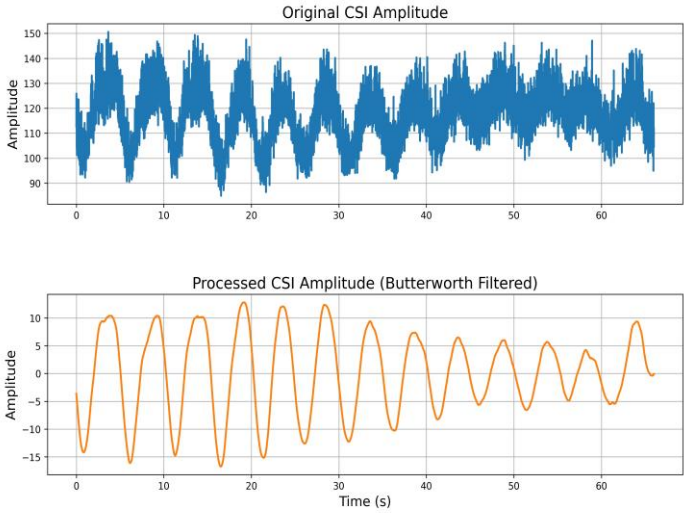

Figure 2. *Comparison of Original CSI Amplitude (Top) and Butterworth Filtered CSI Amplitude (Bottom).*

2.3 Feature Extraction

FFT is applied to the preprocessed signals to identify the dominant respiratory frequency. The FFT is defined as:

$$X(f) = \sum_{n=0}^{N-1} x(n) e^{-j2\pi fn/N} \tag{6}$$

where $x(n)$ denotes the time-domain signal in time, N *is* the total number of samples, and f represents the frequency bin.

The FFT shows the strength of the frequency components in the signal, which is used to find the principal frequency corresponding to the breathing rate. Figure 3 shows the selected amplitude component of subcarrier 15 for the link Tx1-Rx0 and its corresponding FFT result, illustrating how the dominant frequency component corresponds to the respiratory frequency. Figure 4 presents the selected phase component, highlighting its variation over time and capturing additional nuances of the respiratory signal.

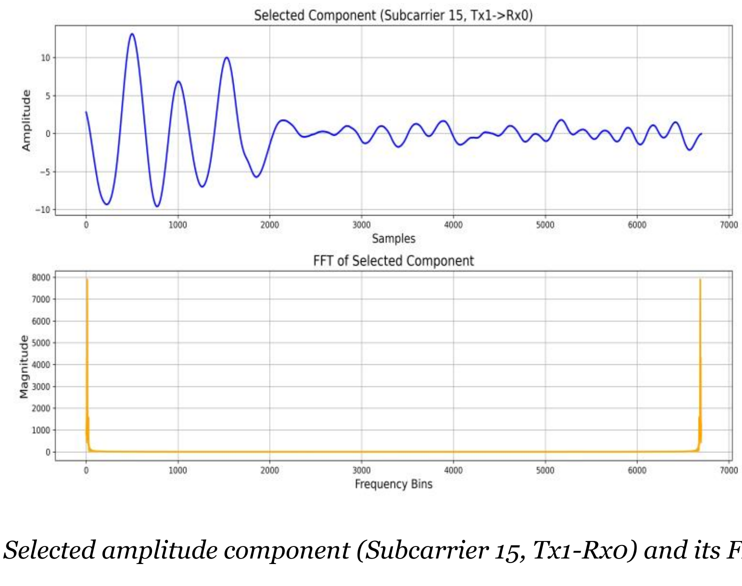

Figure 3: *Selected amplitude component (Subcarrier 15, Tx1-Rx0) and its FFT result.*

2.4 Breath Rate Detection

The Fast Fourier Transform (FFT) converts the filtered signal to the frequency domain to capture periodic components associated with breathing. For a signal $x(t)$ sampled at $f_s = 100$ Hz, the FFT is computed as:

$$X(f) = \sum_{n=0}^{N-1} x(n) e^{-j2\pi fn/N} \tag{7}$$

Where N is the number of samples. The peak in $|X(f)|$ within the breathing range identifies the primary respiratory frequency. The detected peak corresponds to the dominant frequency, then converted to breaths per minute (BPM).

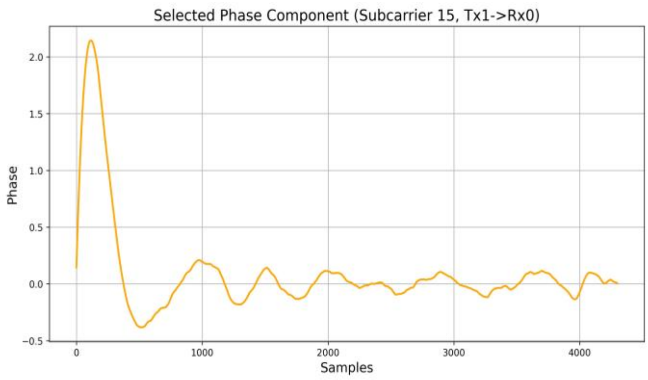

Figure 4: *Selected phase component (Subcarrier 15, Tx1-Rx0) highlighting time-domain variations.*

Peak detection is relatively straightforward for single-user scenarios, as only one dominant frequency exists. We investigated the amplitude and phase components for the two-user cases to find the peaks representing the two users' breathing characteristics. The separation is accomplished by isolating the signals of individual users using the phase information.

Figure 5 presents a single-user peak detection, whereas Figures 6 and 7 illustrate peak detection for two users. In these latter figures, the dominant frequency for each user is isolated using different features, effectively underlining the separation of overlapping signals.

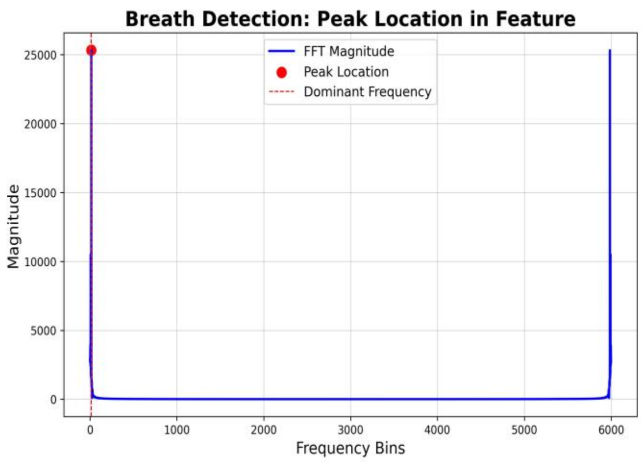

Figure 5: *Peak detection for a single user showing the dominant frequency in the FFT magnitude spectrum.*

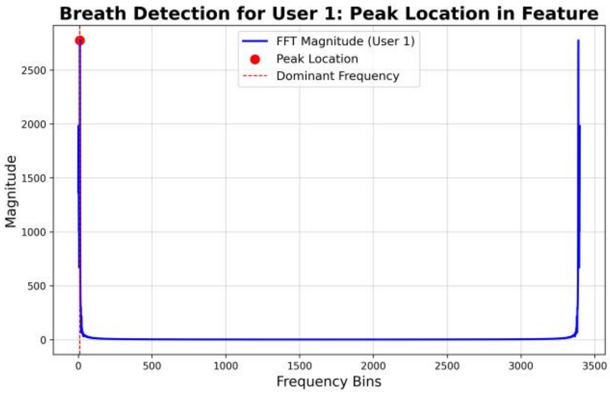

Figure 6: *User 1: Peak detection in the FFT amplitude feature.*

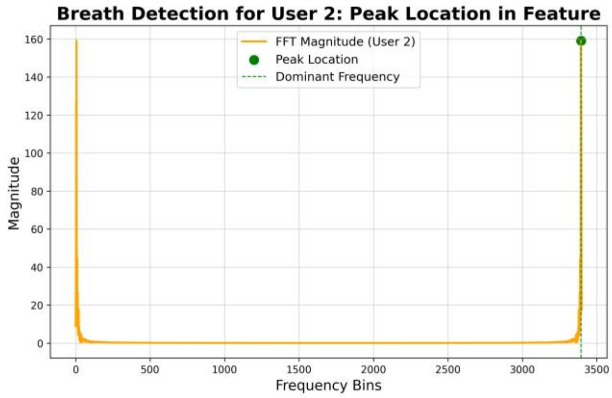

Figure 7: *User 2: Peak detection in the FFT phase feature.*

2.5 Parameter Sensitivity Analysis

To validate the chosen parameters for our pipeline, we conducted a preliminary sensitivity study on the Butterworth filter order and cutoff frequencies. Specifically, we tested filter orders ranging from 1 to 3, and cutoff frequency ranges slightly broader (0.05–0.6 Hz) and narrower (0.15–0.45 Hz) than our default setting (0.1–0.5 Hz). The results indicated that:

- Filter Order: Increasing the filter order beyond 1 yielded marginal improvement in noise suppression but introduced phase distortions, complicating multi-user signal separation.
- Cutoff Frequencies: Deviating from the 0.1–0.5 Hz band led to under- or over-filtering relevant respiratory frequencies, increasing the mean error by approximately 0.2–0.3 BPM.

Therefore, our chosen first-order Butterworth filter with a 0.1–0.5 Hz passband balanced effective noise suppression and minimal signal distortion. Similarly, we tested various thresholds for unwrapping for phase cleaning and found that the current setting best preserved the subtle respiratory patterns while mitigating phase discontinuities.

4. Results Evaluation

4.1 Single-User Breath Rate Detection

In a single-user controlled breathing scenario, the preprocessing by Butterworth filtering and FFT successfully estimated the breath rate to be 15 BPM, with an MSE of 0.50 BPM. The following figure compares the estimated and actual breath rates and visualizes them in Figure 8, showing the high accuracy of the employed detection method.

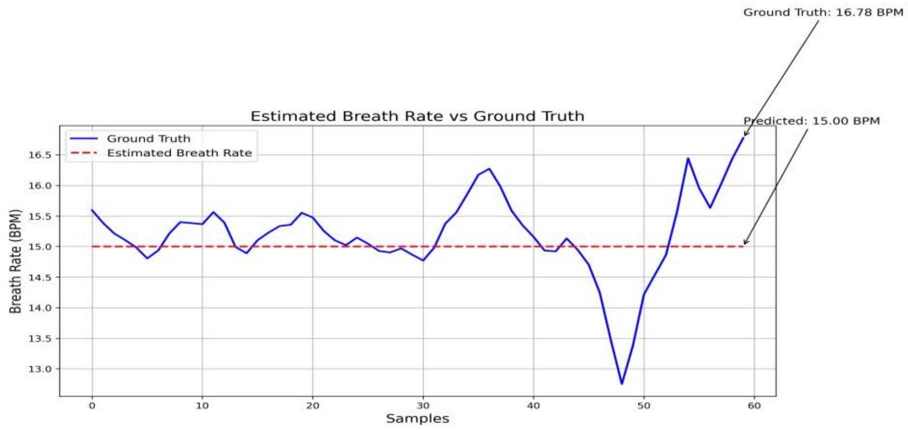

Figure 8: *A comparison between estimated and actual breath rates in the case of a single user. The annotations point to the final estimated rate of 15.0 BPM with the ground truth rate of 16.78 BPM.*

4.2 Multi-User Breath Rate Detection

Amplitude and phase features were used to separate overlapping respiratory signals for the multi-user breathing scenarios. The preprocessing and peak detection stages identified the breath rates for Users 1 and 2 as 16.42 BPM and 21.61 BPM, respectively, with MSE values of 1.45 and 5.34 BPM. Figure 9 compares users estimated and ground-truth breath rates. While the amplitude-based detection for User 1 achieved high accuracy, challenges in phase-based detection for User 2 are discussed, emphasizing the need for enhanced phase-cleaning methods in future work.

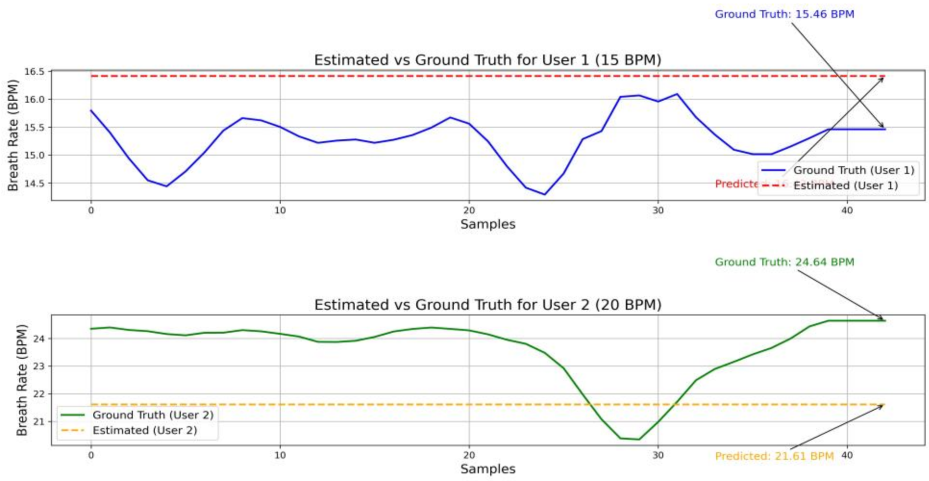

Figure 9: *Comparison of estimated and ground truth breath rates for the two-user scenario. The top plot represents User 1 (15 BPM), while the bottom represents User 2 (20 BPM). Annotations highlight the estimated and ground truth rates for both users.*

5. Limitations and Future Directions

5.1 Limitations

Although our breath rate detection pipeline demonstrates robust performance in both single-user and multi-user scenarios, several factors contribute to residual errors:

- Motion Artifacts: Even minor body movements, such as arm gestures or posture shifts, can introduce additional fluctuations in CSI signals, leading to higher estimation errors.

- Interference from Other Devices: Other wireless networks or IoT devices can degrade signal quality, especially in the 5 GHz band, resulting in inconsistent CSI readings.
- Channel Variability: Changes in environmental conditions (e.g., temperature, furniture rearrangement) may alter channel characteristics, requiring periodic recalibration of the pipeline.

In multi-user contexts, the phase-based detection method occasionally fails to isolate distinct respiratory patterns when users are positioned too closely. These limitations suggest that further improvements in phase cleaning or more advanced beamforming might be necessary to handle users who are spaced closely. Future work will address these issues by incorporating adaptive filtering and deeper neural architectures that can better separate overlapping signals.

5.2 Future Direction

The Butterworth filter consistently achieves accurate breath rate detection in single-user scenarios. However, phase-based detection in multi-user cases introduces variability, as seen in the elevated MSE for User 2. Building upon the current findings, this study identifies several opportunities for improving Wi-Fi CSI-based respiratory monitoring:

1) Enhancing Model Architectures: Various research studies have used BiLSTM and achieved reasonable results. However, its limitations in capturing global contextual relationships and computational efficiency motivate the exploration of advanced architecture:

- Attention Mechanisms: Integrate self-attention or Transformer-based models to capture long-range dependencies in CSI sequences. Hybrid BiLSTM-Attention models could further enhance accuracy.
- Graph Neural Networks (GNNs): Represent the relationships between antennas, subcarriers, and time by graphs so that GNNs can extract structural and temporal features.
- Hybrid CNN-LSTM Models: Researchers can use CNNs as spatial feature extractors with LSTMs or even Transformers for temporal processing.

2) Integrating Advanced Preprocessing Techniques: Preprocessing techniques significantly impact detection performance. Future efforts will be explored:

- Noise Reduction: Apply denoising autoencoders or wavelet transform-based filtering for improved noise suppression.
- Augmentation Techniques: Future Studies can utilize generative models such as CsiGAN to expand the dataset with diverse and robust samples.
- Feature Extraction: Beyond FFT, future research will explore Short-Time Fourier Transform (STFT), Wavelet Transform, and Empirical Mode Decomposition (EMD) to extract features better.

3) Addressing Multi-User Challenges: Extending the dataset and methods to dynamic, multi-user environments will improve real-world applicability:

- Multi-User Separation: Implement algorithms like Source Separation and Beamforming to isolate overlapping respiratory signals.
- Dynamic Scenarios: To evaluate robustness, test the system under dynamic environments, including moving objects and varying noise levels.

4) Leveraging Explainability and Interpretability: Healthcare applications require transparent models. Future work will:

- Use SHAP (SHapley Additive exPlanations) and LIME to identify the most influential features.
- Visualize attention maps in Transformer-based models to provide insights into feature importance.

5) Incorporating Edge AI and Real-Time Processing: To enable real-time applications:

- Develop lightweight models optimized for edge devices using TensorFlow Lite or ONNX.
- Investigate model compression techniques like pruning and quantization.

4. Conclusion

This paper presented a comprehensive signal processing pipeline for Wi-Fi CSI-based breath rate detection, demonstrating effectiveness in single-user and multi-user contexts. By combining amplitude and phase information, we achieved an MSE as low as 0.50 BPM in controlled, single-user settings and addressed the complexities of overlapping signals in multi-user scenarios. In addition to validating our approach with real-world data, we identified limitations arising from motion artifacts, interference, and environmental changes. Our analysis indicates that more adaptive filtering strategies and advanced learning architectures could enhance performance. Looking ahead, we plan to integrate transformer-based models for improved feature extraction and incorporate explainable AI tools, such as SHAP, to elucidate which CSI features most strongly influence detection accuracy. Ultimately, our goal is to deliver a robust, low-cost solution that enables continuous respiratory monitoring in healthcare and smart-home environments, paving the way for more personalized and proactive health management.

Competing Interests: The authors declare no competing interests.

Data Availability Statement: The supported data and codes associated with this researcher are available upon request from the corresponding author.

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