A Study of Practical Radar-based Nighttime Respiration Monitoring at Home

Yindong Hua*, Zongxing Xie*, and Fan Ye
Department of Electrical and Computer Engineering, Stony Brook University
{yindong.hua, zongxing.xie, fan.ye}@stonybrook.edu

Abstract*—Radar-based solutions support practical and longitudinal respiration monitoring owing to their non-invasive nature. Nighttime respiration monitoring at home provides rich and high-quality data, mostly free of motion disturbances because the user is quasi-stationary during sleep, and 6-8 hours per day rather than tens of minutes, promising for longitudinal studies. However, most existing work was conducted in laboratory environments for short periods, thus the environment, user motions, and postures can differ significantly from those in real homes. To understand how to obtain quality, overnight respiration data in real homes, we conduct a thorough experimental study with 6 participants of various sleep postures over 9 nights in 4 real-home testbeds, each configured with 3–4 sensors around the bed. We first compare the performance among four typical sensor placements around the bed to understand which is the optimal location for high quality data. Then we explore methods to track range bins with high quality signals as occasional user motions change the distance thus signal qualities, and different aspects of amplitude and phase data to further improve the signal quality using metrics of the periodicity-to-noise ratio (PNR) and end-to-end (e2e) accuracy. The experiments demonstrate that the sensor placement is a vital factor, and the bedside is an optimal choice considering both accuracy and ease of deployment (2.65 bpm error at 80 percentile), also consistent among four typical sleep postures. We also observe that, a proper range bin selection method can improve the PNR by 2 dB at 75-percentile, and e2e accuracy by 0.9 bpm at 80-percentile. Both amplitude and phase data have comparable e2e accuracy, while phase is more sensitive to motions thus suitable for nighttime movement detection. Based on these discoveries, we develop a few simple practical guidelines useful for the community to achieve high quality, longitudinal home-based overnight respiration monitoring.

***Index Terms*—Longitudinal Respiration Monitoring, Radar-based Sensing, Sleep Data, Home-based Deployment**

I. Introduction

Continuous and long-time monitoring of respiration plays a key role in predicting and tracking many chronic pulmonary and sleep diseases. Recently radar-based respiration sensing has shown encouraging results, and its non-invasive nature is promising for longitudinal monitoring. However, very few works can be handily applied in real-life scenarios, due to the following gaps between research and practice. Firstly, human subjects are typically required to stay stationary and face the radar [1]–[3] to minimize motion interference and obtain the strongest reflected signal. Maintaining a single posture for a prolonged period of time is strenuous and impractical in real life. Secondly, the majority of research was conducted in controlled laboratory environments [4], [5] — often clean, open space, excluding clutters usually present in real homes and not taking the comfort of human subjects into account. Finally, most works reported their results only from short periods of tens of minutes [6], [7], while overnight monitoring will be 6–8 hours continuously, with occasional wakeups and movements, and changes of postures.

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* Co-primary authors.

To support practical and longitudinal monitoring, the best chances are overnight home-based deployments. The reasons are threefold: 1) people stay stationary for most of sleep time, thus minimizing motion interference for high-quality data; 2) data are collected with the comfort of their own bedroom, minimizing any stress in labs, thus practical for longitudinal real-life monitoring; and 3) the average sleep duration overnight is 6 to 8 hours, which provides sufficient data for long-term observation.

However, to obtain longitudinal, high quality overnight respiration data in real homes, many practical questions must be answered: where are the suitable locations to deploy the sensors; how to track the human body thus suitable range bins under wakeups, movements that change the distance thus signal qualities in bins; and what is the optimal data source between amplitude and phase to demodulate the physiological signal from RF signal for respiration monitoring. While these are critical to data quality and sensing performance, a comprehensive and thorough study in real home overnight monitoring is notably missing.

To answer these questions, we undertake this study in four real homes, each deployed with three or four sensors at different locations around the bed, and data are collected from six volunteers in diverse settings, including nighttime sleep and short periods of various sleep postures. Specifically, we aim to answer concrete questions stemming from our preliminary observations that piqued our curiosity: (1) Periodic pattern data are produced by sensors at different locations. But which one exhibits the highest quality data and demonstrates the best performance? (2) The range bin chosen from the strongest reflection power does not always coincide with the one that exhibits the most pronounced periodic patterns in phase data. How can we continuously identify the optimal range bin with the best quality data under frequent user wakeups, movements during sleep? (3) Both amplitude data and phase data show regular periodicity. How do they compare in contributing to high-quality data, and tasks such as motion detection?

We start by comparing different sensor placements around the bed. We installed 4 sensors on the ceiling, the side wall, underneath the bed, and at the tail of the bed to capture data simultaneously. We use the periodicity-to-noise ratio (PNR) metric [8] to assess the signal quality, and beats per minute (bpm) to measure the error of vital signs estimation against the ground truth. Our preliminary results demonstrate that the sensors on the ceiling and on the side of the bed produce higher accuracy (2.7 and 3.1 bpm error at 80%) than the one under the bed (3.6 bpm error at 80%) and at the tail of the bed (4.2 bpm error at 80%). Then we explore the range bin selection method. We come up with a 2-stage selection strategy — first coarsely anchoring one range bin based on the magnitude data and then selecting a desired bin among adjacent ones around the anchor position. The PNRs are improved by 0.9 db to 2db at 75-percentile for 4 sensors compared to those chosen from a baseline method. The overall accuracy has up to 0.9 bpm improvement at 80-percentile accuracy. Finally we compare the amplitude and phase data in depth. While the amplitude data is easier to locate the area of desired range bin from the range-time heatmap, the phase data is more sensitive to the body movement via the standard deviation distribution. The optimum amplitude data and phase data can produce comparable results of 2.6 bpm error under the optimal sensor location and respective range bin selection methods.

To sum up, we conduct in-depth real-world tests and develop home-based deployment recommendations that produce high-quality data for longitudinal nighttime respiration monitoring.

Our contributions are threefold:

- We build testbeds for sleep respiration monitoring in 4 real homes, each configured with 3–4 RF sensors of different placements, to study the impact of sensor locations and sleep postures in metrics of PNR and e2e accuracy. With data collected from 6 participants over 9 nights, we demonstrate that placing RF sensors on the ceiling or the side of bed gives better and comparable accuracy (2.6 bpm error and 2.65 bpm error at 80 percentile) consistently among four typical sleep postures.
- We identify a set of key components in a generic framework of radar-based respiration monitoring, based on the theoretical signal model of modulating/demodulating vital signs. We extensively evaluate the effectiveness of each component, and demonstrate that a carefully devised range bin selection method can improve the PNR from a baseline by 2 dB at 75-percentile, and e2e accuracy by 0.9 bpm at 80-percentile. We show that vital signals can be extracted from both amplitude and phase of RF with comparable 80-percentile accuracy of 2.6 bpm, while the phase is more sensitive to body movements thus more effective for detecting and excluding motion-distorted data.
- We summarize the discoveries from this study into guidelines for practical longitudinal home-based respiration monitoring: The best place for sensors is on the side of the bed considering both accuracy and fastening efforts. Combined with a lightweight method for proper range bin selection, users can self-administer the installation, thus scaling longitudinal respiration monitoring to many homes without intensive manual configuration efforts from a research team.

II. Primer

In this section, we present theoretical modeling of radar-based respiration sensing, based on which we introduce a generic framework of respiration monitoring.

A. Signal modeling of radar-based respiration sensing

The intuition of radar-based respiration sensing lies in that chest wall displacements due to inhaling and exhaling vary the travel distance of the electromagnetic waves emitted by radar sensors and can be demodulated from the received signal. To digitally process and extract the respiratory signal, the received RF signal is down-converted to the baseband signal $B(\tau)$, and sequentially sampled at discrete time $\tau = nT_f(n = 1, 2, 3...N)$ corresponding to signals reflected from different distances with a sampling interval of T_f, forming a frame along the fast time dimension, expressed as:

$$B(\tau = nT_f) = \alpha(d(\tau))A_s(\tau - \frac{2d(\tau)}{c})e^{-j\frac{4\pi f_c}{c}d(\tau)+\theta}, \quad (1)$$

where α is the scale factor indicating changes in attenuation of received signals due to the varying distance $d(\tau)$ between the radar and the target; $A_s(\tau - \frac{2d(\tau)}{c})$ stands for the delayed version of transmitted radar waveform (e.g., IR-UWB is of Gaussian pulse envelop [9]) reflected by the target at the distance of $d(\tau)$; and θ denotes the initial phase shift with phase noise from the local oscillator.

Based on Equ. (1), we can easily find that both the amplitude and phase of the received signal is modulated by the varying distance $d(\tau)$ due to chest wall displacements during exhaling and inhaling, from which we can extract respiration.

B. Generic framework of respiration monitoring

In this section, we identify a set of design components in a pipeline corresponding to a sequence of signal processing steps deriving from the received signal to respiration rate. We show such a pipeline in a generic framework in Figure 1 disregarding their specific algorithms but only indicating respective tasks.

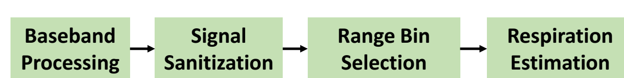
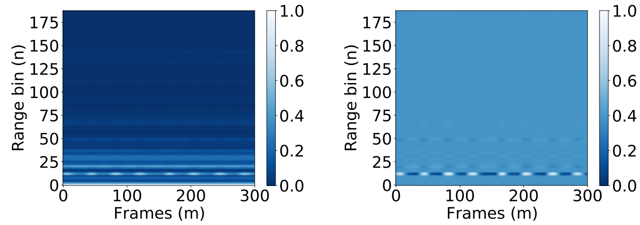


Fig. 1: Block diagram of RR monitoring

To capture periodic variations due to respiration, instead of using a single frame, we stack a sequence of consecutive frames in a sliding window. Such a sliding window of data is presented in a signal matrix R:

$$R(m, n) = B(t = mT_s, \tau = nT_f), \quad (2)$$

where $t = mT_s(m = 1, 2, 3...M)$ is the slow-time dimension to observe periodic patterns, and T_s is the frame interval.



(a) R(m,n)

(b) Z(m,n)

Fig. 2: The heatmap of signal matrix in a time window. The signal's intensity is represented by a pixel's brightness. The target's location is shown by the bins that have high energy over time. The interference from the background causes a number of bins to appear brightness. Only one bar remained after background suppression, which corresponded to the truth location.

The next step is to eliminate interference from cluttered environment and make respiratory signals prominent. One common way to obtain the sanitized signal matrix $Z(m, n)$ is background removal by subtracting the average of accumulated consecutive sliding windows from the current time window:

$$Z(m, n) = R(m, n) - \frac{1}{M}\sum_{i=1}^{M} R(i, n) \tag{3}$$

Figure 2 shows an example comparing the signal matrix before and after background removal.

After signal sanitized, the target is to be located by selecting a proper range bin, from which the respiratory signal can be reliably demodulated. Finally, the respiration rate is estimated based on periodic variations.

III. Methodologies

In this section, we describe methodologies of finding proper home-based schemes for nighttime sleep respiration monitoring thus high-quality longitudinal data collection. We first study home-based overnight sensor deployment, where we specifically use IR-UWB radar sensors in this experimental study; then we examine the signal processing pipeline of radar-based respiration monitoring.

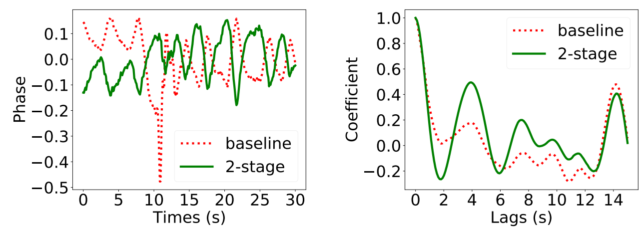
A. *Home-based overnight sensor deployment*

To find the optimal sensor placement, we build real-home testbeds with sensors deployed in four typical bed-region locations following the existing work: on the ceiling [6], [10], [11], on the side and tail of the bed [12], [13], and beneath the bed on the floor [14]. In addition to comparing performance from different sensor placements, we also compare performance in four representative sleep postures: on left/right side, one back and on stomach. The primary metric to evaluate the difference is the e2e performance. We also compare the periodicity-to-noise ratio (PNR) in the frequency domain introduced in our previous work to indicate the probability of a signal being detected [8]. A large PNR indicates the periodicity of the vital signal is strong in the time domain and can be easily detected in the frequency domain.

B. *Signal processing pipeline*

1) Range bin selection: While it is critical to select a proper range bin for reliable vital signs extraction from the target, no conclusive statement has been made on how to select the optimal range bin. We aim to explore and fine-tune the range bin selection specifically for reliable nighttime respiration monitoring, and compare with a baseline defined as taking the range bin with the maximum variance of the magnitude in the range-time heatmap Z(m, n) from Equ. (3) following the existing work [11], [15].

Although the range bin can be roughly identified based on the amplitude data, the phase data inside those adjacent range bins all exhibit periodic patterns. Despite that, the range bin in which the phase data exhibits the most periodic pattern is not necessarily the same as the one from the baseline approach, as is illustrated in Figure 3 by contrasting the first peak of the auto-correlation coefficients of the phase data from two bins.



(a) phase

(b) auto-correlation

Fig. 3: The range bin from our proposed 2-stage method is different from the one selected by baseline approach. 2-stage procedure picks up the range-bin shown a more periodical phase proved by a higher first peak of auto-correlation coefficient.

We detail the fine-tuned 2-stage method, which combines the magnitude and the phase together to decide the range bin: (1) First roughly locates the range bin from the baseline method (by searching the maximum variance of the magnitude in the range-time heatmap (Z(m, n)). We take the range-bin as an anchor. (2) Then, we calculate the auto-correlation coefficients of the adjacent 7 bins near the anchor bin and pick up the desired bin which has the highest first peak of auto-correlation coefficient. The bigger the coefficient is, the more periodical the phase data shows.

2) Data sources of respiration extraction: According to Equ. (1), both the amplitude and phase of the received signal are modulated by chest wall displacements and can be used for respiration extract. While existing methods individually use either amplitude or phase to extract the respiration [13], [16], [17], a thorough understanding is missing about which one is preferable. We apply head-to-head comparison with both data sources — amplitude and phase for respiration sensing.

IV. Experiments

In this section, we introduce the experiment setup and then evaluate the performance of the experiments.

A. *Experiment Setup*

The testbed was illustrated in Figure 4. We installed four sensors in each participant's bedroom. One was placed on the

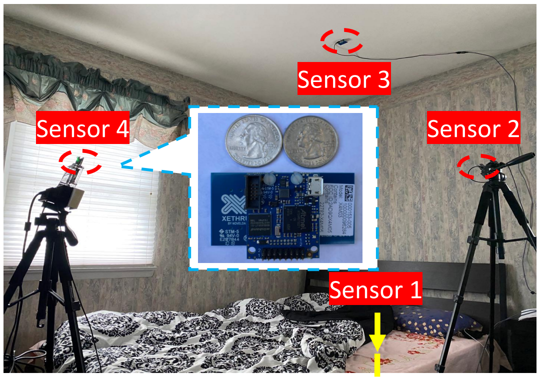


Fig. 4: Experimental setup in a real home. 4 sensors collect data simultaneously (Due to view limitation, we only indicate that Sensor 1 is under the bed on the floor, but not depicted in the diagram).

floor beneath the bed (named Sensor 1, cannot be displayed due to view restriction), one was placed on the side of the bed, one was affixed to the ceiling, and the final sensor was placed on the bed's tail. We follow the implementation of an existing work [18] to build our testbeds. Specifically, we collect data with the deployment of IR-UWB (X4-XeThru) sensors [19], which are coin-size, not intrusive to the built environment; use an existing respiration estimator [18] for respiration data collection; and use Masimo [20], an FDA-approved vital signs sensor, for ground truth.

We asked 6 volunteers (3 females, 3 males, ranging in age from 19 to 31) to contribute data from 4 bedrooms. 3 people provide the controlled dataset, with each session lasting between 30 and 40 minutes and encompassing 4 postures (on the left side, on the right side, on the back, and on the stomach). And the others offer actual nine-night sleep data(1–4 nights per person).

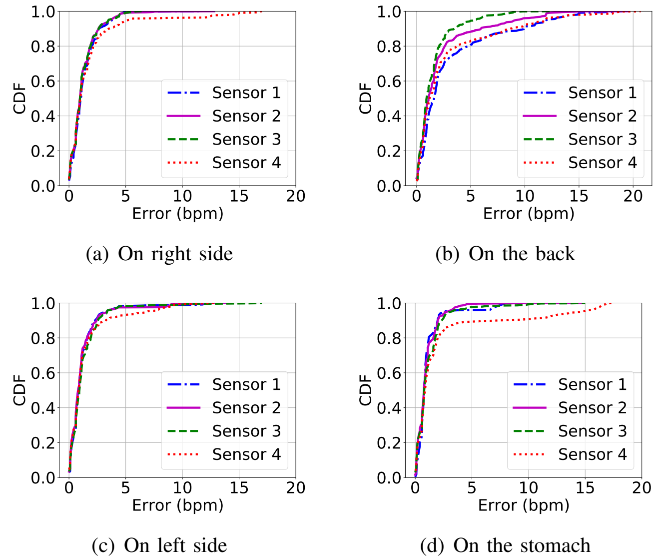
B. Home-based overnight sensor deployment

We assess the e2e performance of 4 sensors to figure out where we can get the highest quality data. We locate the rang-bin using the baseline method and use the phase data as the input for the respiration calculation. First, we analyze the performance of the sensors in 4 representative postures. The results are depicted in Figure 5. At the 80th percentile, sensors 2 and 3 exhibit a higher consistent accuracy of 2–2.5 bpm error across a variety of positions. The outcomes expose that different sensors have varying performances, while the same sensor maintains consistent performance over a variety of postures. We thus infer that the location of the sensor is a key role to impact the performance and those two sensors should be the best candidates for nighttime data collection.

Then we test the sensors on all the data. Figure 6 proves our reasoning that the sensor 2 and sensor 3 have better performance. Their errors are 2.7 bpm and 3.1 bpm respectively at 80 percentile. This phenomenon can be attributed to the fact that these two sensors have high PNRs (-4.5 dB).

C. Micro benchmarks

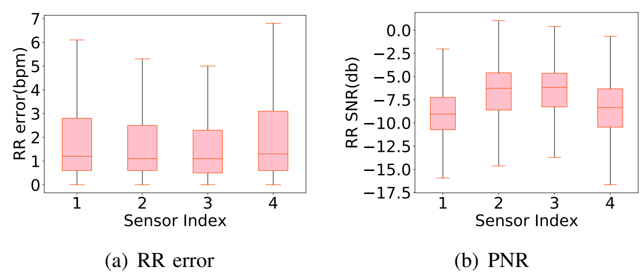
1) Range bin selection: We first examine the distributions of range bins selected by the baseline method and the proposed 2-stage approach as shown in Figure 7.



(a) On right side (b) On the back

(c) On left side (d) On the stomach

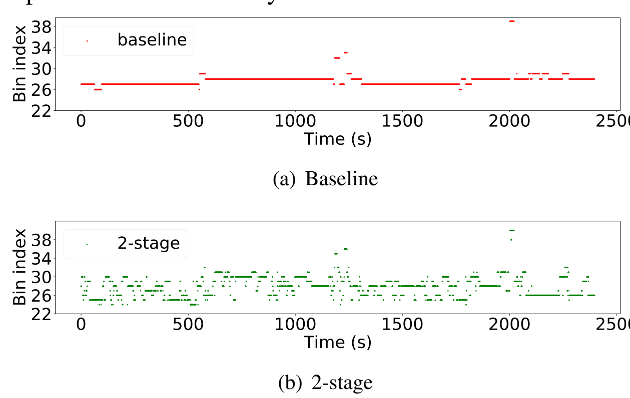
Fig. 5: The performances of sensors on 4 postures. Sensor 2 and 3 display stable and high performance.



(a) RR error (b) PNR

Fig. 6: Sensor 2 and Sensor 3 indicate higher accuracy due to their better PNRs.

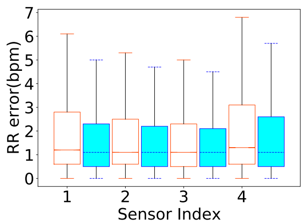
We observed that the devised method always selected the range bin deviated from the baseline solution which indicated that the range bin showing the most periodical pattern in the phase data is not consistent with the one selected by the amplitude data for 85%. We further inspect the PNR and e2e performance which are displayed in Figure 8. It illustrates the 2-stage range bin selection can improve performance from a baseline up by 2 dB of 75-percentile PNR and by 0.9 bpm of 80-percentile e2e accuracy.



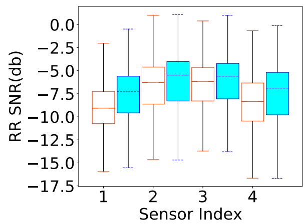
(a) Baseline

(b) 2-stage

Fig. 7: The range bins differ for 85% of samples between selected from the baseline method and our fine-tuned method. Each sample stands for one second.



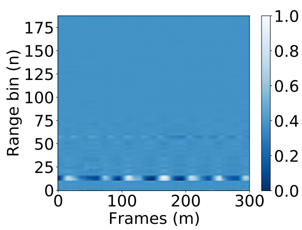
(a) RR error



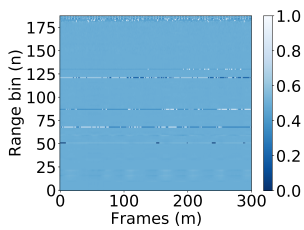
(b) PNR

Fig. 8: Our proposed range bin selection method (blue color) improves the PNR and e2e performances compared to the baseline solution (white color).

2) Signal Source Comparison: Figure 2 shows how background-subtracted amplitude data can be utilized to determine the target location. We are wondering if phase data can serve the same purpose. Using the same background suppression technique and time window, we construct two heatmaps displayed in Figure 9. Phase data, however, could not be a candidate to directly locate the range bin since it has multiple interference bright bars which obscure the true location.



(a) Amplitude



(b) Phase

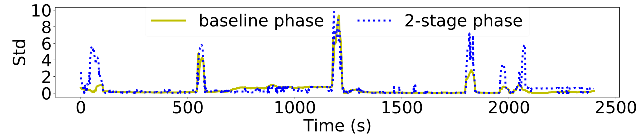
Fig. 9: Signal matrix heat-maps of amplitude data and phase data within a 30 senconds time window. The range bin of ground truth is around bin 15 which can be reflected from the amplitude data heat-map but can not be distinguished from the phase data heat-map.

Figure 10 shows the distribution of the standard deviation in a controlled short-term dataset. Individuals are examined in a total of four distinct postures, with a posture change occurring roughly every 10 minutes. While the occurrence of peaks in the phase data indicates the moments of posture change, such correlations do not exist in amplitude data. This observation implies that the phase of RF signals is indicative for removing body motion and generating higher-quality data.

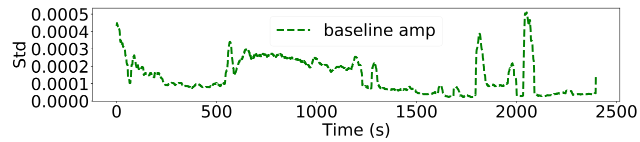
We further examine the e2e performance by using the two signal sources with their ideal range bin selection methods, amplitude data with baseline range bin selection and phase data with 2-stage range bin selection, as input for the RR estimator. The outcomes are displayed in Figure 11. We prove that vital signals can be extracted from both amplitude and phase data with comparable 80-percentile accuracy of 2.6 bpm. Nevertheless, the phase is more sensitive to body movements thus more effective for detecting and excluding motion-distorted data.

V. Related Work

Researchers have shown a considerable deal of interest in radar-based vital sign detection, which shows great promise

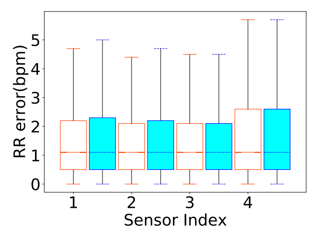


(a) Phase data

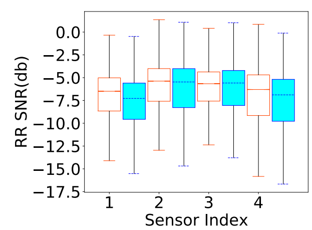


(b) Amplitude data

Fig. 10: The standard deviation distributions on a controlled short term dataset. While the values of the amplitude data coming from the baseline range bin selection (baseline amp) is very small, the standard deviations of phase data deriving from both range bin tracking methods emerge high peaks. The peaks indicate the moments of body posture change.



(a) RR error



(b) PNR

Fig. 11: Both the amplitude data (white box) and phase data (blue box) yield identical results, indicating that both are comparably effective for extracting respiration.

[13], [21], [22]. The tendency of reported accomplishments are based on immobile participants in ideal laboratory circumstances [23], [24], and short-term collected data [6], [7]. However, they are not realistic conditions for long-term monitoring in real-life. We concentrated on home-based sleep scenario monitoring that can give longitudinal and high-quality data for practical monitoring.

While researchers have collected sleep datasets from a variety of sensor locations, including on the ceiling, [6], [10], [11], on the side wall [12], [13], and under the floor [14], there is a dearth of evidence demonstrating the ideal site for obtaining high-quality data. In addition, another factor about tracking the target in the real-life interference-rich environment impacts the signal quality as well. The majority of previous studies employ reflection power-based methods [11], [15]. Nevertheless, the range bin corresponding to the strongest reflection does not always provide the most apparent vital signs patterns in phase data. Moreover, the signal source for demodulating physiological signal is also a potential factor to impact the RR performance. Existing works extract the respiratory rate either by leveraging the amplitude information or by utilizing the phase data from the received radar signal reflected from the body [13], [16], [17]. Unfortunately, there is insufficient discussion over the appropriate approach. We conduct a thorough experimental study to answer practical problems regarding home-based deployment towards reliable nighttime monitoring. We first analyze the performance of four typical bed-region sensor placements to determine the ideal site for obtaining high-quality data. We then investigate range bin tracking algorithms and various amplitude data and phase data characteristics to further improve the signal quality.

VI. Discussion

In this work, IR-UWB sensors are used to demonstrate the key settings for in-home monitoring of respiration. The pipeline of respiration detection is also applicable to other RF technologies, such as Frequency-Modulated Continuous Wave (FMCW) radar or WiFi, without sacrificing generality. In the our nighttime respiration data collected with IR-UWB sensors, we observe that the intermittent involuntary body motion accounts for the majority of respiration detection errors. With further analysis, we find that the standard deviation of phase data is sensitive for motion detection. In the future, we will use phase data to detect body motions for improved quality of the collected data. Last but not least, we build our respiration monitoring pipeline with classical signal processing algorithm to achieve interpretability of the whole design space. To further improve the robustness and accuracy of respiration monitoring, we will investigate machine learning methods [25] for RF sensing in future work.

VII. Conclusion

In this paper, we focus on finding suitable configurations for practical radar-based nighttime respiration monitoring at home. We conduct comparisons among four typical sensor locations and find the best sensor placement is on the side of the bed considering both accuracy (2.65 bpm error) and installation efforts. Along this process, we further discovery that the range bin tracking is a key factor to the accuracy when extracting the respiration from the phase, and a customized range bin selection method improves 80-percentile accuracy by 0.9 bmp. Besides, we show that amplitude and phase of RF data have distinct attributes that should be treated and leveraged separately, while both data sources can produce comparable e2e accuracy for the respiration estimation: the amplitude data is easier to locate the rough range of the target and the phase data is more sensitive to the body movement. These practical discoveries pave the way for the communities to develop robust algorithms and achieve high quality data for long-term sleep monitoring with a lightweight method.

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