

WiBreathe: Estimating Respiration Rate Using Wireless Signals in Natural Settings in the Home

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Abstract— Sensing respiration rate has many applications in monitoring various health conditions, such as sleep apnea and chronic obstructive pulmonary disease. In this paper, we present WiBreathe, a wireless, high fidelity and non-invasive breathing monitor that leverages wireless signals at 2.4 GHz to estimate an individual’s respiration rate. Our work extends past approaches of using wireless signals for respiratory monitoring by using only a single transmitter-receiver pair at the same frequency range of commodity Wi-Fi signals to estimate the respiratory rate of an individual. This is done irrespective of whether they are in line of sight or not (e.g., through walls). Furthermore, we demonstrate the capability of WiBreathe in detecting multiple people and by extension, their respiration rates. We evaluate our approach in various natural environments and show that we can track breathing with the accuracy of 1.54 breaths per minute when compared to a clinical respiratory chest band.

Keywords—health sensing, wireless, respiration rate, non-invasive.

I. INTRODUCTION

Continuous, non-invasive, and unobtrusive sensing of various health metrics has the potential to improve an individual’s well being and quality of life. This information not only provides them with timely feedback on their overall physiological condition but also helps detect abnormalities in trends over prolonged periods of time. Of the many health metrics, detecting respiration rate in a home environment has significant impact in determining potential pulmonary exacerbations in advance. In general, respiration rate in particular is used as a physiological measure for tracking diseases in many areas, such as sleep, pulmonology, and cardiology, and can also provide useful insights about the psychological and psychophysiological condition of an individual. In particular, continuous monitoring of respiration rate throughout the night is relevant for diagnosing as well as monitoring sleep apnea; an apnea event is when a patient is not breathing for 10 seconds or longer during sleep [1]. The breathing patterns associated with high stress levels can provide the user relevant information regarding their psychological wellbeing over long periods of time.

In this paper, we present *WiBreathe*, a whole-home respiration rate sensing system that reliably estimates respiration rate in a user’s changing environment. Our system leverages wireless narrowband signals to monitor the breathing of an individual anywhere in a home, even when the person is

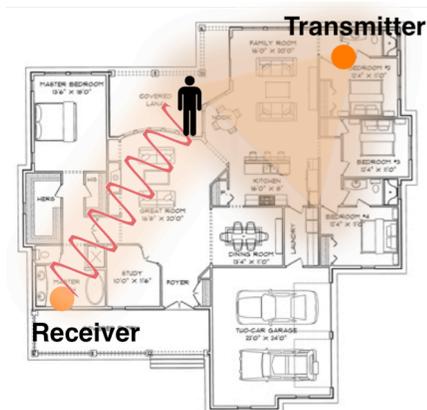


Figure 1: WiBreathe can detect a person’s respiration rate from anywhere in a house without any instrumentation on the body. The system only requires a pair of transmitter and receivers that can be placed anywhere in the house.

behind walls. Specifically, our algorithm clusters and chooses between multiple respiratory rate extraction algorithms, and adapts to a dynamically changing environment. Using a single transmitter-receiver pair (see Figure 1), we show the ability to detect breathing during various activities such as reading, typing at a desk, watching television, and lying down. Given the ubiquity of wireless signals (e.g., Wi-Fi), such an approach can enable true continuous breathing detection throughout the day at various locations in a home, obviating the cost and inconvenience of deploying multiple sensor systems around the home.

We evaluated WiBreathe in a home setting while users performed activities such as reading, typing, or watching a video at multiple locations in Line Of Sight (LOS) and Non-Line of Sight (NLOS) scenarios. The participants were allowed to breathe naturally unlike [9,16] where a fixed respiration rate was maintained using a metronome. We also verify the feasibility of estimating the respiration rates of multiple people present in the same environment using WiBreathe. WiBreathe detects respiratory rate with an average error of 18.4% or 2.16 (breaths per minute) bpm across all conditions in a natural setting. Although clinical devices have not been evaluated in natural settings or when users are performing activities, research has shown that they tend to have similar variability for respiration rate monitoring during sleep[3].

We highlight the following contributions of this paper:

- An approach that enables whole-home breathing detection that works through walls and over large distances using a single transmitter-receiver pair.
- An adaptive algorithms that remains immune to changes in the environment and the user's breathing pattern.
- An evaluation of WiBreathe in a natural setting without asking users to breath to a specific frequency.

II. RELATED WORK

In clinical environments, physicians use invasive methods to monitor the respiration rates of patients. This approach, called Polysomnographic monitoring, involves a Respiration Inductance Plethysmography (RIP) strap and Electrical Impedance Tomography [13]. While these methods provide accurate respiration rate measurement, they can cause considerable discomfort for a person wearing them during sleep and might even be constrictive in certain cases [14].

To enable continuous and accessible respiration rate monitoring in a non-clinical environment, numerous wearable solutions have been proposed [15]. Some of the common methods employ sensors that are implantable or incorporated in wearable bands. The most common sensors used are microphones [4] that pick up acoustic signals due to breathing or accelerometers embedded in wearable fitness trackers [8,10] that pick up mechanical movements due to chest expansion. While these methods enable continuous monitoring they have not been widely adapted due to size, visibility, and forgetfulness of participants. To remove this burden from the user, commercial products and researchers have explored the possibilities of instrumenting the environment instead of the user. The hydraulic bed [7] and Beddit¹ employ force sensors in the bed to monitor respiration rate by detecting changes in pressure when the user is sleeping. The health chair [6] attempts to monitor respiration rate during the day by attaching pressure sensors to a chair. As we can see both these methods do not provide continuous monitoring since the user is constricted to a small sensing area.

An alternative approach, leverages RF signals to enable continuous and unobtrusive sensing. These systems mainly employed for target detection in the early days, [2,11,19] use Ultra-wideband (UWB) radar systems to monitor vitals such as respiration and heart rate. Radio signals with a minimum of 500 MHz bandwidth, are pulsed at nanosecond intervals at the target [12, 21, 22] causing the signals to be reflected at different rates by minute chest movements due to breathing. By extracting the time of arrival (TOA) of these signals, the respiration rate of the target can be inferred. The high penetration and range resolution of these systems however come at a high cost when compared to commercial radio systems. The specialized hardware and array of antennas involving up to 13 transmitting and 8 receiving antennas [20] are not commercially available and are not meant to be deployed in a home for long term sensing.

In order to make wireless breathing detection cost-effective and easy to deploy, Patwari *et al.* have used ZigBee transceivers, based on the IEEE 802.15.4 protocol and Microwave sensors [16]. ZigBee transceivers, most commonly used for wireless sensor networking, employ low quality analog electronics and quantizers for communication. While these transceivers are easy to deploy and are commercially available, they require the aggregate RSSI (Received Signal Strength Indication) of over twenty TX/RX links to reliably estimate the respiration rate of an individual [16]. While further work has been done by Kaltiokallio *et al.* to extract breathing with very low error over a single TX/RX link [9], the user is still limited to a space of about 2 meters in-between the antennas. Similarly, microwave sensors used in the frequency range of 2.42 GHz detect the I and Q components of the backscattered field due to breathing when placed directly above the user's chest at a distance of 1m [5]. We were inspired by this work to develop a solution that would provide continuous, nearly whole-home coverage and operate through walls. In addition, we also evaluate the approach in a natural environment with actual breathing fluctuations.

III. THE WIBREATHE SYSTEM

WiBreathe leverages 2.4 GHz wireless signals to detect the respiration rate of a person located anywhere in a home. To do so, the user places a transmitter-receiver pair at any location in the house without any calibration. Ideally, the transmitter and receiver are placed in the two corners of the room to provide full coverage (see Figure 6).

A. Theory of Operation

The two phases of breathing: inspiration and expiration involve the intercostal muscles and the diaphragm. The expansion and contraction of these muscles cause a corresponding increase and decrease in the lung volume and by extension, displacement of the chest and abdomen. When wireless signals propagate in a medium, apart from the direct path between the transmitter and the receiver, the signal reflects off various objects in the environment. The human body, when present in the path of signal propagation, acts as a reflector. The minute chest and abdomen movements amplitude-modulate the wireless signal before it reaches the receiver. WiBreathe captures these signal variations and deduces the respiratory rate from the periodicity of the amplitude modulation. In particular, our system employs an envelope detection algorithm to extract the breathing frequency from the 2.4 GHz wireless signals.

B. Hardware

We used two Ettus USRP (Universal Software Radio Peripheral) N210 to prototype the WiBreathe system as it allows access to a high performance FPGA that can be used to generate a continuous signal at 2.4 GHz. One USRP was configured as a transmitter and another as a receiver. In our work, we chose the XCVR2450 RF transceiver frontend that operates in the 2.4 GHz to 5.9 GHz range. The USRP generates the continuous signal with a center frequency of 2.4 GHz over a narrow bandwidth of 20 MHz similar to a single sub-channel of an Orthogonal Frequency Domain Multiplexing (OFDM) wireless signal. The transmit power is set to 15 dBm. In addition, LP0965 directional antennas with a

¹ Beddit: Sleep tracker and Wellness Coach

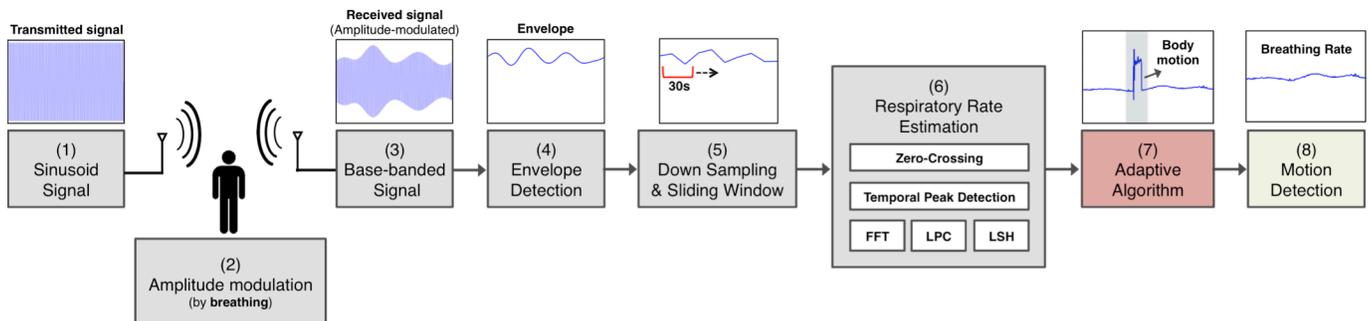


Figure 2: Signal processing for the breathing detection algorithm. After demodulating and detecting the modulation envelope, a 30-second sliding window is applied to compute the average breathing rate for each window using all five sub-algorithms (Step 6). These breathing rate estimates are input into an adaptive algorithm that selects the best estimate (Step 7). The harmonic fit from the LSH estimator is then used to classify windows containing body motion, which are ignored (Step 8).

gain of 6 dBi and antenna factor of 32 at 2.4 GHz are used to enhance the signal strength. In the following sections, we refer to the USRPs along with the directional antennas as access points (AP).

C. System and Implementation Details

Figure 2 shows the data flow diagram of the WiBreathe system. We transmit a continuous sinusoid from the USRP transmitter at 2.4 GHz (Fig 2, step 1). Breathing alters the magnitude of reflected signal inducing an amplitude modulation on the transmitted wireless signal. (Fig 2, step 2). This amplitude-modulated signal can be mathematically modeled as:

$$u(t) = A_c m(t) \cos(2\pi f_c t) \quad (1)$$

where A_c and f_c are the amplitude and frequency of the 2.4 GHz carrier signal, respectively, and $m(t)$ is the breathing signal acting as modulator upon the carrier.

At the receiving end, the access point first demodulates the 2.4 GHz amplitude-modulated signal down to baseband and samples it at a rate of 32 KHz (Fig 2, step 3). The transmitted sinusoid is then narrow-band filtered and demodulated by taking the magnitude of a single DFT bin over overlapping windows across the entire signal, generating an envelope of the received signal (Fig 2, step 4). This rejects all spectral energy not centered around the transmitted sinusoid, keeping all data within 23 Hz of the carrier frequency. Since the respiration rate of a human usually does not exceed 1 Hz, we further down sample and filter the signal to restrict the frequency domain to contain only the relevant spectral energy (i.e., 0.2 - 1.0 Hz). We simultaneously reject high frequency noise as well as the strong DC component present in all recorded signals through this bandpass filtering. (Fig 2, step 5).

At this point, the down sampled signal is similar to a carrier signal amplitude-modulated in the range of 0.2 to 0.5 Hz, (i.e., the human's normal breathing frequency) [14], and we can begin frequency estimation.

To estimate the frequency of the breathing signal, we divide the signal into 30s sliding windows, with 97% overlap between them (Fig 2, step 5). Each window is then analyzed

with multiple frequency estimation algorithms including (1) Zero-crossing detection, (2) Fourier transform maximum selection (FFT), (3) Linear Predictive Coding (LPC) and (4) Least-Squares Harmonic analysis (LSH) (Fig 2, step 6).

Zero-crossing detection attempts to directly estimate the frequency of a periodic signal by measuring the number of negative-to-positive transitions of a time waveform in a given time window. Temporal peak detection similarly measures the number of local maxima/minima of a time waveform in a given time window. Both of these methods work well in the absence of noise; however as noise increases, it is to be expected that their performance will suffer.

Fourier transform maximum selection (hereafter denoted as the FFT method) takes the DFT of a given time window, and simply selects the frequency with the largest component. This method was employed by [9] in a highly controlled setting and has shown promising results.

Linear Predictive Coding (LPC) analyzes a given time window by learning the linear relationship of samples in that window via a least-squares estimation method. This algorithm was first introduced by O'Shaughnessy, D. [18] and has found wide applications in fields such as speech processing. The linear relationship found through LPC represents a filter that estimates power spectral density of the signal, and therefore using the result of LPC analysis allows us to estimate the location of the dominant spectral shape in the signal being analyzed. Furthermore, this algorithm is not quantized in its accuracy as compared to methods such as zero-crossing, temporal peak detection, or the FFT method. In all these previous cases, the output value is quantized by either the temporal sampling rate, or the Fourier bin size; however LPC is capable of yielding frequency values with sub-bin resolution.

Least-Squares Harmonic analysis (LSH), proposed by Qin, L. [17], takes advantage of the fact that the breathing signal is not perfectly sinusoidal, but is still roughly periodic. Periodic non-sinusoidal signals create harmonics at integer multiples of the fundamental frequency, and LSH uses this fact to gain better results in situations with high noise. It does this by using the Goertzel algorithm to analyze spectral energy at specific, harmonically related frequencies, and chooses the fundamental

frequency whose harmonics have the greatest total energy. The Goertzel algorithm uses a filter to determine the energy in a narrow band of frequency similarly to the DFT, but with an arbitrary frequency resolution, which we have chosen to be 0.001Hz between 0.1 and 0.7Hz. This addresses the quantization issues mentioned above, and exploits the fact that breathing signals have at least a second harmonic with significant energy above the noise floor. This allows LSH to gain sub-bin resolution similar to LPC, and aids the estimator in the presence of noise, because the extra energy in the second harmonic effectively increases the signal power.

These four algorithms each take advantage of different features of the breathing signal, performing very differently depending on factors such as the subject's breathing pattern, the ambient noise level and the orientation of the subject relative to the transmitter and receiver. In Figure 3, we show two received breathing waveforms, showing a variety of signal characteristics. On the top, the waveform displays a large amount of high frequency energy due to a combination of user motion and noise. This high frequency energy causes the zero-crossing and LPC to severely overestimate the breathing rate resulting in an comparatively high error percentage of 51% and 67% respectively, whereas the Least-Squares Harmonic analysis and FFT estimator are able to accurately locate the

base harmonic of the breathing signal, and give a closer approximation with 21% and 31% error rate respectively. Conversely, on the bottom is shown a situation in which the signal is particularly non-sinusoidal due to shallow breathing, and therefore lacks a strong single dominant frequency, preventing FFT and LSH estimators from accurately determining the breathing rate. The LPC and ZC methods on the other hand are better equipped to estimate the central frequency component in a large group of frequencies of similar magnitudes when spectral energy due to noise is not an issue, and therefore are able to perform with an error rate of 7% and 15%, as opposed to FFT and LSH estimators which result in 21% and 26% error rate respectively.

Our analysis shows that no single method is able to perform adequately across all situations since different factors induce varying frequencies close to the actual respiration rate. To address this, we have created an adaptive algorithm that dynamically combines and selects results from all four algorithms presented (Fig 2, step 7). Initially, the algorithm determines the mean of two closest frequency estimates between all the four algorithms. Once we have at least 5 past estimates, the adaptive algorithm then takes the results from all sub-algorithms for the current window and selects the result closest to the median of the last five frequency estimates. All the four individual estimation techniques estimate a new value every 0.9 seconds, therefore using the past 5 estimates is a reasonable choice since the respiration rate does not change drastically over 4.5 seconds. Furthermore it assumes that at least two of the four sub-algorithms are able to estimate the respiration rate with moderate accuracy in any scenario. This way, our system is able to select the best sub-algorithm such that the frequency estimate does not vary dramatically over short time periods, a phenomenon which plagues all of these five frequency estimation methods and results in large spikes in error rate. Combining the results across multiple algorithms to adaptively choose the best estimate, allows this algorithm to outperform any single algorithm by avoiding these large deviations from the true respiration rate.

One exception to this algorithm is in the case where the second harmonic of the breathing signal is stronger than the fundamental frequency. This causes all frequency estimation methods except LSH to track the second harmonic rather than the fundamental, due to the spectral and temporal domination of that second harmonic. This harmonic structure arises when the participant's breathing is particularly non-sinusoidal. One example of this is when the inspiration duration is significantly longer than the expiration, causing the time waveform to skew and in turn, the frequency representation of the signal to have stronger harmonic components. This phenomenon, although rare, does cause a significant error in calculations when present, and as such we have explicitly removed the one instance where it occurred from our analysis corpus.

In periods of time where participants shift position or make any but the smallest body movements, our adaptive algorithm is able to recognize such motion segments and remove them from the analysis. These motion segments contain significant non-breathing energy and may not be used for respiration rate detection. To segment this, we inspect the residual error from the harmonic fit for each sliding window (as described in [17]).

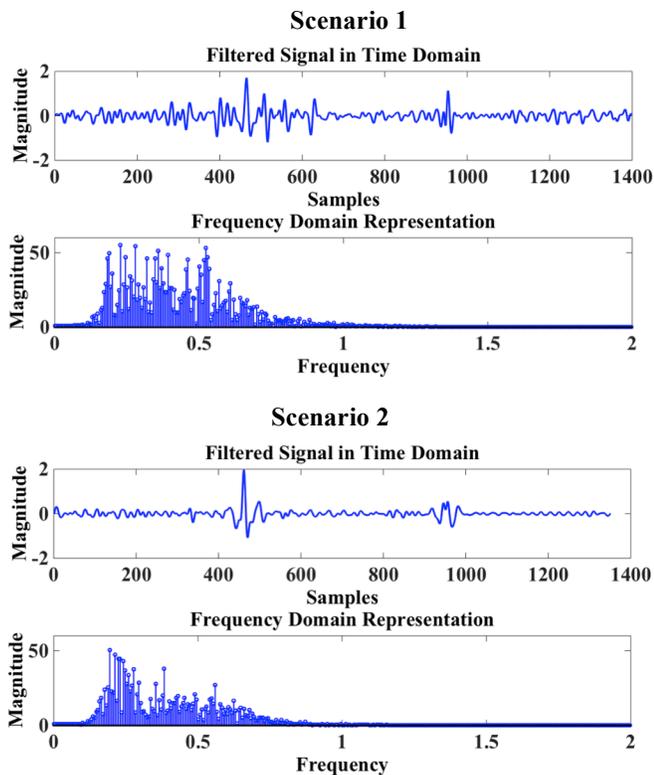


Figure 3: Breathing waveform for two different scenarios with time and frequency domain representations. (Scenario 1) Significant high frequency energy due to activity and signal attenuation, reducing the performance of zero crossing and LPC. (Scenario 2) Non-sinusoidal breathing pattern lacking a dominant frequency causing increased error rate in FFT and LSH estimators.

This residual error is thresholded to denote windows as either clean or noisy, and all noisy windows are removed from analysis. This segmentation of data rejects sections of data that would introduce spurious frequency content that is independent of respiration rate. This motion detection can be further applied to other applications such as sleep quality monitoring.

IV. EVALUATION AND RESULTS

We evaluated the performance of WiBreathe in four different conditions and compare the performance against the individual techniques mentioned in the *System and Implementation Details* section. Apart from the four techniques used in WiBreathe, we also evaluate the results from another common technique Peak detection, used mainly for breathing detection in wearable or contact breathing detection. For all the experiments, participants wore a Vernier respiration-monitoring band around their abdomen to capture the ground truth respiration rate. The strap is similar to a brachial blood pressure cuff and consists of a bladder that is filled with air. Since the outward and inward abdomen movements cause changes in the air pressure, a differential air pressure sensor is used to convert the varying air pressure to a voltage ranging from 0 to 5V. The analog voltage was then recorded using a data acquisition unit.

We conducted experiments in two settings. The first set of experiments was done in a controlled lab environment and the second set of experiments was performed in participant's homes in a natural setting.

A. Controlled Setting

To explicitly evaluate the trade off between increased SNR and coverage of the directional antennas we conducted a controlled study with 3 participants in an office space. Participants were asked to sit at various positions with respect to the transmitter receiver pair and their breathing rate was recorded for a period of 3 minutes in each position.

1) *Distance*: Participants were asked to sit at 5 different positions with an altitude of 0.9m, 1.5m, 2.1m, 2.7m, 3.3m, 4.3 m as shown in Fig. 4(left). Fig. 5(right) shows the error rate for all the individual algorithms as well as WiBreathe's combination algorithm when the participant sat at various distances from the transmitter-receiver pair. From the figure,

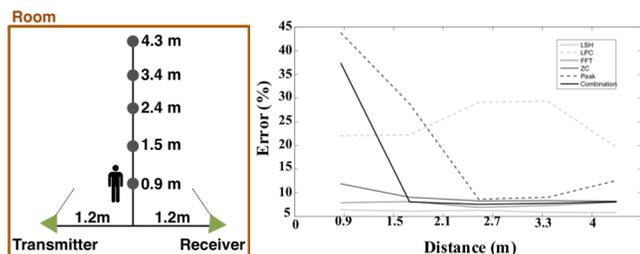


Figure 4: Experimental test-bed for Study 1: Line-Of-Sight. (Left) Data was collected at 5 locations (marked as grey points) of different distances. (Right) Error percentage (%) for Study 1: Line-Of-Sight (various distances) of four estimation techniques and Combined (WiBreathe) algorithm.

we can notice a general trend in error rate for all the algorithms: the error increases considerably when the participant sits closer to the transmitter-receiver pair (i.e., less than 1.5 m). The reduced performance when the user is too close to the antennae results from the directionality of the antennas. As the directional antennas used in the experiment have a radiation pattern similar to that of a cone radiating outwards, the intensity of the signal is higher along the main-lobe while slightly attenuated along the side lobes. Therefore, the positions located in the range of the main-lobe (i.e. 1.75m ~ 4.3m) yield a low error rate while in the positions that fall out of range of the main lobe have higher error rates. In case of the Combination algorithm, this variability in error percentage due to distance is reduced and the performance of the system stabilizes. The fact that the Combination algorithm performs better even when close to the antennae suggests that WiBreathe is able to counter the variability of signal strengths and a user's positions. It can be used reliably in most locations and is less prone to dead-zones.

2) *Orientation*: To study the effect of orientation of the individual with respect to the antennas on the respiration rate in a controlled environment, we recorded data at three different positions as shown in Fig. 5 (left). We can observe slightly increased error percentage in frequency estimation for individual algorithms in case of off-center orientations. When the angle of incidence is equal to the angle of reflection (e.g.. 33°), there is total internal reflection like conditions for the signal, making the error rate comparatively lower. As the user moves away from the point of optimal reflection, the intensity of the reflected signal decreases resulting in decreased signal to noise ratio. This leads to higher error rates. However, by adaptively choosing the best estimates from the five algorithms, we are able to resolve this problem and make the system more reliable with change in position. Our approach has an average error of 9.8% when the user is at the center and 7.1% when the user is off-center, as compared to 7.5% and 15.25%, respectively, without using WiBreathe's combination of algorithms.

3) *Metronome*: A generally accepted approach to collect ground truth breathing data in the research community is using

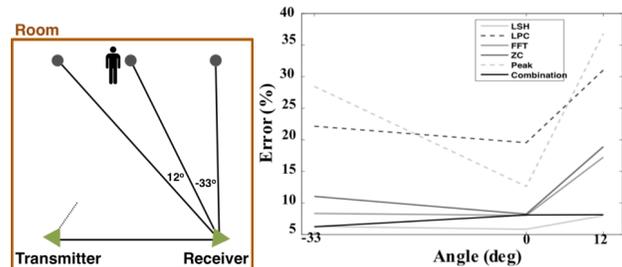


Figure 5: Experimental test-bed for Study 2: Line-Of-Sight. (Left) Data was collected at 3 spots with various orientations (incident angles of 12° , 0° and -33°) relative the receiver. (Right) Error percentage (%) for Study 2: Line-Of-Sight (various orientation), of four estimation techniques and Combined (WiBreathe) algorithm.

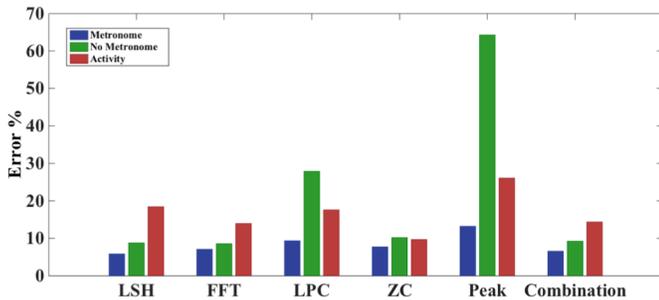


Figure 6: Performance of WiBreathe: participants breathing with the metronome versus participants breathing without metronome (i.e., they are allowed to breathe freely at any breathing frequency).

a metronome [9,16]. However, breathing to a metronome forces the user to breathe artificially and does not capture the variability in an individual’s normal respiration rate. We wanted to demonstrate the challenges that with using just a metronome and why we believe evaluating these approaches in more natural settings is necessary. We believe that the performance of all respiration analysis systems should be measured without the metronome as well, otherwise there is a chance that the algorithms may over-fit to the artificial respiration patterns established by a metronome.

It can be observed from Figure 6 that in a controlled setting with no body movements, the error percentage overall is least when the participant is breathing to a metronome, slightly higher when no activity is performed and almost double the error rate of metronome when the participant is performing an activity.

The intuition behind this trend can be explained when we observe the time and frequency domain plots in Figure 7. Data was collected at a single position where a participant breathed to a metronome at first and then breathed naturally while performing an activity. In both cases the time domain signal is fairly clean without ambient noise or disruptions due to body movements. However, in the frequency domain we can observe that there is only one clear dominant frequency (equal to that of the metronome) when the participant breathes to a metronome whereas there is significant energy from 0.2Hz to 0.4Hz when the participant breathes naturally. This is representative of the subtle and gradual variations in breathing frequency when the participant is in a natural setting and signifies the importance of evaluating a respiratory rate estimation technique in a natural setting.

B. Natural Setting

In order to evaluate how well WiBreathe works in a natural setting, experiments were conducted across 4 homes varying in square footage from 600 sq. ft. to 2000 sq. ft. with 6 unique participants, ranging from 23 to 40 years old (3 female). Since each home had a different floor plan, we have generalized the representation of the test bed across all 6 homes in Figure 8. Each home had at least 6 LOS and 2 NLOS scenarios. Prior scientific literature and our controlled experiments have both suggested that a number of factors could affect the

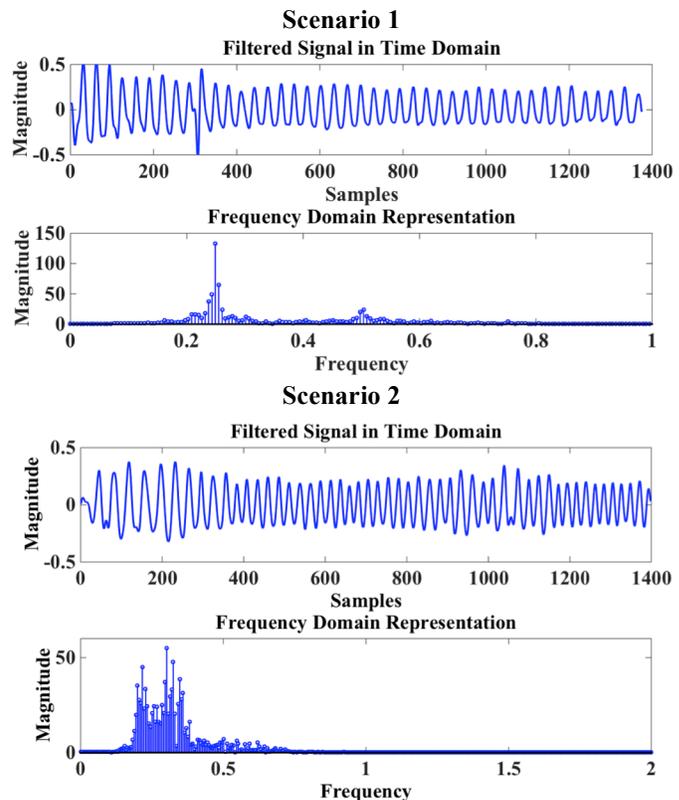


Figure 7: Breathing waveform for two different scenarios with time and frequency domain representations. (Scenario 1) Breathing to a metronome resulting in single dominant frequency estimate. (Scenario 2) Unconstrained breathing while performing an activity resulting in variations in breathing frequency.

performance of a wireless sensing system in an environment. Of those, the most relevant and crucial ones are: 1) Environmental factors such as distance and orientation of the user from the antennas and 2) Subject variations such as movement, posture and activity of the user. To test the performance of WiBreathe across these factors, we collected data for each participant at multiple locations while they performed different activities. The users were asked to sit at different positions in a room where the antennas were placed in two corners as shown in Figure 8. The extracted breathing signal from WiBreathe and the ground truth was captured for a period of 3 minutes in each position.

1) *Distance and Orientation:* The directional antennas used in our experiments (see III B. *Hardware*) were placed in locations that maximize the sensing coverage of users’ daily activities such as reading, watching tv, or typing. At each position, we examined the effect of distance and orientation between the user and the antennas. The six positions varied in distance from 1.5 m to 6 m across 4 homes.

Figure 9 shows the error rate for all of the individual algorithms as well as WiBreathe’s combination algorithm when the participant sat at various positions with respect to the antennas. Our approach presents an average error of 1.92

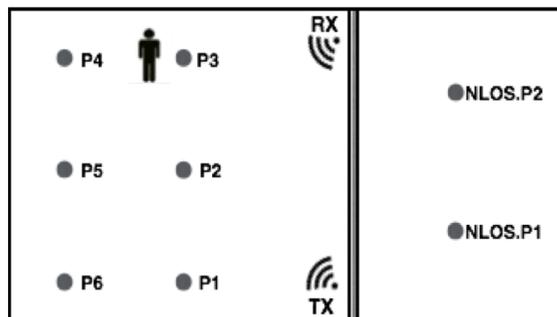


Figure 8: Test Bed for WiBreathe: participants breathing at various LOS and NLOS positions in homes while performing an activity.

breaths per minute (bpm) across all 6 positions. We can also observe that the variability in error rate is higher for all other individual algorithms compared to WiBreathe across the six positions. The observation that the WiBreathe algorithm performs better across all positions suggests that WiBreathe is able to counter the variability of signal strengths and user orientations by adaptively choosing the best estimate from the individual algorithms. It can be used reliably in most locations and is less prone to dead-zones instead of using any of the other single techniques.

2) *Activity*: We also evaluated the performance of WiBreathe when we factor in motion and probable changes in posture when users perform everyday activities. The users were engaged in four different activities, in decreasing order of intensity of motion: typing, reading, watching a video, and lying down. In order to simulate sporadic body movements while performing these activities, like stretching, adjusting their posture, *etc.*, we instructed the users to move at timed intervals. This served as ground truth since we could determine when the algorithm ignored segments from motion and not due to addition of noise by other environmental factors.

While it is expected that activities such as typing would have a higher error rate due to increased motion, Figure 10 shows that across the three activities where the participant is

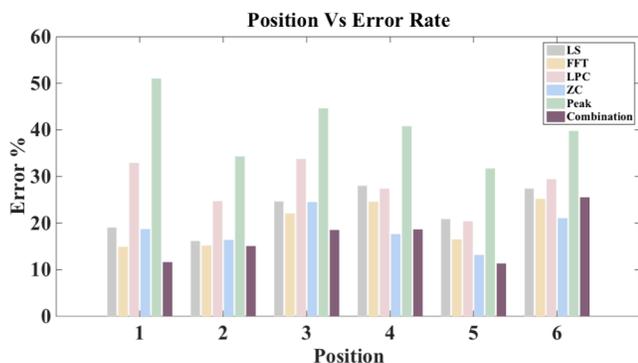


Figure 9: Error percentage (%) for Study 1: Line-Of-Sight (various distances) of five estimation techniques and our approach: LSH, FFT, Zero Crossing, Peak Detection and Combination.

sitting, reading has a slightly higher error rate. Amongst the various factors that contribute to error, we have observed that the participant's posture (sitting straight versus slouching), induce much more noise in the signal compared to finger and hand movements. This effect is further shown by the fact that the error is least, 0.96 bpm, when the participant is lying down.

The improved performance of WiBreathe's combined approach compared to individual algorithms across all activities in the presence of motion suggests that WiBreathe has the potential to be used in natural settings where users move around and change posture from time to time.

3) *Through the wall*: Most natural settings will have multiple walls therefore non-line-of-sight breathing detection is highly desirable. We evaluated the performance of WiBreathe when the user was positioned behind a wall (Figure 8 NLOS.P1 and NLOS.P2) and performed a randomly selected activity, each, from the aforementioned activities. It was observed during data-collection that large metal objects behind a wall such as a refrigerators, computer monitors or large furniture significantly attenuated the signal. We can observe from Fig. 11 that while using LPC and Zero Crossing techniques resulted slightly higher error rates, LSH performs fairly well in NLOS scenario, hence WiBreathe's combination algorithm is able to counter the effects of low SNR caused by attenuation by adaptively choosing the best estimate for any given scenario.

C. Breathing Pattern Detection

Our detailed discussions with medical professionals informed us that for most medical applications, the detecting changes in a user's breathing pattern and respiration rate are far more important than determining respiration rate when users are engaged in motion. For example significant variance in respiration rate of an individual or repetitive shallow breaths can point towards respiratory distress or dyspnea. Detection of time periods where there is no breathing signal or discontinuities in the breathing signal point to apnea and arousal events during a sleep cycle which helps in diagnosis of sleep apnea. This means a system that adapts to sudden variations in breathing rates can be equally or even more useful

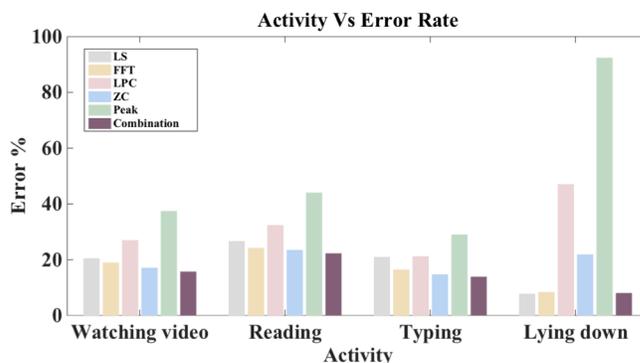


Figure 10: Error percentage (%) for Study 1: Line-Of-Sight (various orientation), of five estimation techniques and our approach: LSH, FFT, Zero Crossing, Peak Detection and Combination.

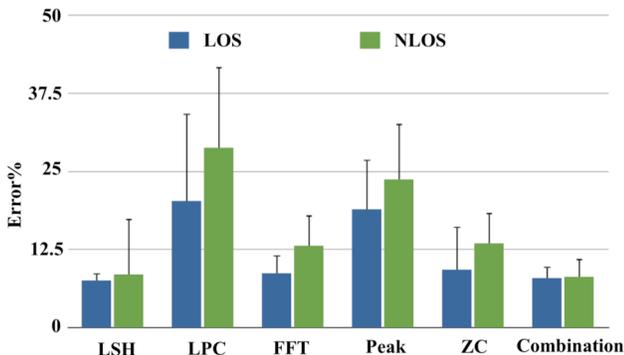


Figure 11: Performance of WiBreathe: the transmitter-receiver pair deployed in the same room with the participant versus the transmitter-receiver pair deployed behind the wall.

than the earlier systems. Therefore we investigated how WiBreathe performs if a user’s breathing pattern changes considerably over a short duration of time.

Figure 12 (top) shows the received signal versus the ground truth in a situation where the user is initially breathing slowly, then suddenly increases their respiration rate. This period of rapid breathing is then followed by a period of no breathing, then a short time of deep slow breaths followed by a few fast and slow breaths. The performance of various algorithms and WiBreathe’s combined algorithm can be seen in Figure 12 (bottom). Although WiBreathe rejects sudden changes in frequency in a short window, when multiple algorithms show consensus it is able to get a closer estimate across the entire time frame resulting in reduced average error rate.

V. DISCUSSION AND FUTURE WORK

From our results, we observe that some algorithms have high resilience to distance and orientation such as zero crossing and FFT with an average error percentage of 18.5% and 19.6% respectively while some adapt better in the presence of noise due to activity such as FFT and LS estimator with error percentages of 16.8% and 18.8% respectively. Overall there is no single algorithm that works the best in all situations. Given these results, we designed WiBreathe to adapt to the natural variations in breathing frequency as well as changes in the environment. Our approach combines the estimates from an ensemble of four different techniques and adapts dynamically over a different scenarios to enable continuous respiration rate monitoring over long periods of time.

One limitation of WiBreathe is poor respiratory rate estimation in cases where three of the four algorithms give an incorrect frequency estimate (as mentioned in *System and Implementation details*). Also, large body movements cause severe disruptions in the signal strength. While the present algorithm, as well as current literature for contactless breathing detection, are unable to provide a frequency estimation at these instances, addressing this issue will allow users to track their breathing while performing physical activities such as walking or running. We will leave this as the future work. Nonetheless, we believe there is significant value in being able to track an individual’s breathing not just while sleeping, but also while

they are stationary, for example, they are working on a desk, or watching a movie, *etc.*

Given that our preliminary experimentation suggests that WiBreathe’s respiration rate estimation technique is reliable under various conditions, we believe the next step is to apply similar signal processing and frequency estimation techniques presented here to actual Wi-Fi signals. This would make the system truly ubiquitous and allow a Wi-Fi router to receive RF signals from any single Wi-Fi transmitting device (Access point, cellphone, laptop, smart TV, *etc.*) for respiratory rate estimation. The directional antennas used for WiBreathe provide significant gain and directionality and aid in breathing pattern detection. However, omnidirectional antennas used in commercial routers may not be able to provide such high gain. We are currently working on extracting raw signals from the encoded Wi-Fi packets and testing the feasibility of breathing rate detection. The adaptation of the current algorithm to an actual Wi-Fi router is being explored further.

Our experiments point to the fact that postures play a critical role in reliable breathing frequency estimation. For instance, we noticed that some subjects crouched in the sofa during our data collection. This body posture results in relatively small chest movements and slightly degrades the system accuracy. While it places a limitation on the current system, we can leverage this phenomenon in scenarios where providing feedback and correcting the posture of a user may be beneficial *e.g.*, to prevent ergonomic injuries while users are engaged in long periods of sedentary activities.

In order to verify the feasibility of using WiBreathe to detect the respiration rates of multiple individuals present in the same room, we conducted a preliminary study with two

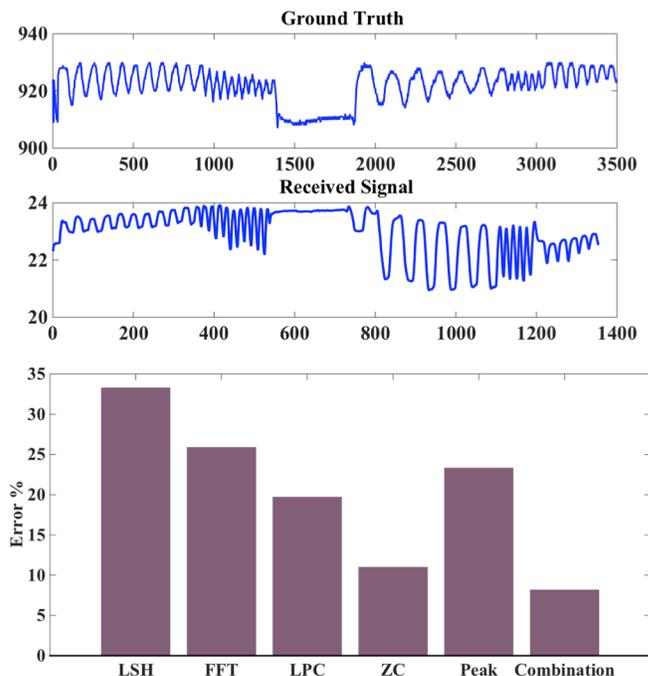


Figure 12: (Top) Breathing pattern detection in reflected raw received signal. (Bottom) Performance of various algorithms for drastic changes in breathing rate.

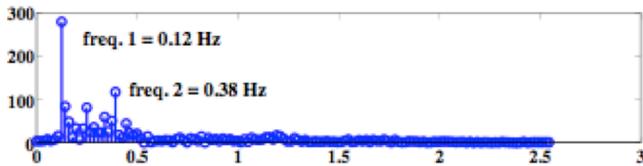


Figure 13: Detection of the presence of two individuals in the same space.

users. The participants were asked to breathe to a metronome at set frequencies. Figure 13 shows the FFT plots with the estimated frequencies of the two individuals. The relative position of the users and the breathing patterns causes one of the frequencies to be dominant. By implementing a simple notch filter we can filter the dominant frequency and the second person's frequency can be then estimated. We see that for multiple users the sub-algorithms can reliably detect respiration rate with an error of 1.54 bpm.

While frequencies of two people breathing in the same environment can currently be estimated given certain preconditions, a more useful application of the system would be the ability to track the respiration rate of a single person in the presence of multiple people. This would be helpful in the case of tracking the respiration rate of one person when two people are sleeping side by side on a bed. We plan to implement this by beamforming by leveraging MIMO systems available in modern routers to estimate the Angle of Arrival of two signals using Multiple Signal Classification.

VI. CONCLUSION

In this work, we present a non-invasive breathing monitor system that requires no instrumentation on the human body. Using a single pair of transmitter and receiver, our system is able to monitor the respiratory rate of an individual located anywhere in the house. Our algorithm takes the results adaptively from five different sub-algorithms, making the system robust in a dynamically changing environment. We evaluated the system in both a lab-controlled and real home environment. The results show an average error rate of 2.16 bpm in a natural setting across our 6 participants, which is comparable to a clinical breathing monitor. As health sensing becomes more commonplace, WiBreathe enables whole-home, continuously respiratory rate monitoring, obviating the need for any wearables on body.

REFERENCES

- [1] American Academy of Sleep medicine. The International of Classification of Sleep Disorders (ICSD) 2001.
- [2] Boric-Lubecke, O.; Awater, G.; and Lubecke, V., Wireless lan pc card sensing of vital signs. In *Wireless Communication Technology*, 2003.
- [3] Clifton D.; Douglas J.G; Addison P.S.; Watson J.N., Measurement Of Respiratory Rate From the Photoplethysmogram In Chest Clinic Patients, *Journal of Clinical Monitoring and Computing*, 2007, pp. 1387-1307.
- [4] Corbishley P.; Rodriguez-Villegas E., Breathing Detection: Towards a Miniaturized, Wearable, Battery-Operated Monitoring System. *IEEE Trans. Biomed. Engineering* 2008 pp55(1):196-204.
- [5] Dei D.; Grazzini G.; Luzi G.; Pieraccini M.; Atzeni C.; Boncinelli S.; Camiciottoli G.; Castellani W.; Marsili M.; Dico J.L., Non-Contact Detection of Breathing Using a Microwave Sensor, *Molecular Diversity Preservation International (MDPI)*. 2009.
- [6] Griffiths E.; Saponas T.S.; Brush A.J.B., Health Chair: Implicitly Sensing Heart and Respiratory Rate, *UbiComp 2014*.
- [7] Heise D.; Skubic M., Monitoring Pulse and Respiration with a Non-Invasive Hydraulic Bed Sensor, *32nd Annual International Conference of the IEEE EMBS*. 2010.
- [8] Hung P.D.; Bonnet S.; Guillemaud R.; Castelli e.; Yen P.T.N., Estimation Of Respiratory Waveform Using an Accelerometer, *Biomedical Imaging: From Nano to Macro, 2008. ISBI 2008. 5th IEEE International Symposium on*, pp 1493 – 1496.
- [9] Kaltiokallio, O.; Yigitler, H.; Jantti, R., Catch a Breath: Non-invasive Respiration Rate Monitoring via Wireless Communication. *CoRR abs/1307.0084* (2013).
- [10] Kawamoto K.; Tanaka T.; Kuriyama H., Your Activity Tracker Knows When You Quit Smoking, *UbiComp 2014*.
- [11] Kilic, Y.; Wymeersch, H.; Meijerink, A.; Bentum, M.J.; Scanlon, W.G., Device-Free Person Detection and Ranging in UWB Networks, *Selected Topics in Signal Processing, IEEE Journal of*, vol.8, no.1, pp.43,54, Feb. 2014.
- [12] Li, C.; Xiao, Y.; Lin, J. A 5 GHz double-sideband radar sensor chip in 0.18mm CMOS for noncontact vital signs detection. *IEEE Microwave Wireless Components Lett.*, vol. 18, no. 7, pp.494-496 2008.
- [13] Marco B.; Núria C.; Teresa F.; Mercedes G.; Daniel A.; Pere J. R.; Pere C., Measuring Breathing Pattern in Patients With Chronic Obstructive Pulmonary Disease by Electrical Impedance Tomography, *Archivos de Bronconeumologia* 2009.
- [14] Noah, J. A.; Boliek, C.; Lam, T.; Yang, J. F., Breathing Frequency Changes at the Onset of Stepping in Human, *Journal of Neurophysiology* 2008, Published 1 March pp.1224-1234.
- [15] Pantelopoulos, A.; Bourbakis N. G., A Survey on Wearable Sensor-Based Systems for Health Monitoring and Prognosis. *IEEE Transactions on Systems, Man, and Cybernetics* 2010, 1–12.
- [16] Patwari, N.; Wilson, J.; Anathanarayanan P.R.S.; Ksera K.S. and Westenskow D, Monitoring Breathing via Signal Strength in Wireless Networks. *CoRR abs/1109.3898* (2011).
- [17] Qin, L.; Atlas, L. Time-Variant Least Squares Harmonic Modeling. Acoustics, Speech, and Signal Processing, Proceedings. (ICASSP '03). 2003 IEEE International Conference on , vol.2, no., pp.II,41-4 vol.2.
- [18] O'Shaughnessy, D., "Linear predictive coding," *Potentials, IEEE*, vol.7, no.1, pp.29,32, Feb. 1988.
- [19] Singh, S.; Liang, Q.; Chen, D.; and Sheng, Li, Sense Through Wall Human Detection Using UWB Radar. *EURASIP Journal on Wireless Communications and Networking*, 2011.
- [20] T.S. Ralston, G.L. Charvat, and J.E. Peabody, Real-time Through-wall Imaging Using an Ultrawideband Multiple-Input Multiple Output (MIMO) Phased Array Radar System, *Proceedings of IEEE International Symposium on Phased Array Systems and Technology*, 12–15 October 2010, pp. 551–558.
- [21] Xiao, Y.; Li, C.; Lin, J., A portable Non-contact Heartbeat and Respiration Monitoring System Using 5 GHz radar, *IEEE Journal Sensors*. 2007, pp.1042-1043.
- [22] Xiao, Y.; Lin, J.; Boric-Lubecke, O.; Lubecke, V.M. Frequency-Tuning Technique For Remote Detection of Heartbeat and Respiration Using Low-Power Double-Sideband Transmission in the Kaband. *IEEE Trans. Microwave Theory Tech*. 2006, pp.2023-2032.