

Smart Homes that Monitor Breathing and Heart Rate

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ABSTRACT

The evolution of ubiquitous sensing technologies has led to intelligent environments that can monitor and react to our daily activities, such as adapting our heating and cooling systems, responding to our gestures, and monitoring our elderly. In this paper, we ask whether it is possible for smart environments to monitor our vital signs remotely, without instrumenting our bodies. We introduce Vital-Radio, a wireless sensing technology that monitors breathing and heart rate without body contact. Vital-Radio exploits the fact that wireless signals are affected by motion in the environment, including chest movements due to inhaling and exhaling and skin vibrations due to heartbeats. We describe the operation of Vital-Radio and demonstrate through a user study that it can track users' breathing and heart rates with a median accuracy of 99%, even when users are 8 meters away from the device, or in a different room. Furthermore, it can monitor the vital signs of multiple people simultaneously. We envision that Vital-Radio can enable smart homes that monitor people's vital signs without body instrumentation, and actively contribute to their inhabitants' well-being.

Author Keywords Wireless; Vital Signs; Breathing; Smart Homes; Seeing Through Walls; Well-being

Categories and Subject Descriptors H.5.2. Information Interfaces and Presentation: User Interfaces - Input devices and strategies. C.2.2. Network Architecture and Design: Wireless Communication.

INTRODUCTION

The past few years have witnessed a surge of interest in ubiquitous health monitoring [22, 25]. Today, we see smart homes that continuously monitor temperature and air quality and use this information to improve the comfort of their inhabitants [46, 32]. As health-monitoring technologies advance further, we envision that future smart homes would not only monitor our environment, but also monitor our vital signals, like breathing and heartbeats. They may use this information to enhance our health-awareness, answering questions like "Do my breathing and heart rates reflect a healthy lifestyle?" They may also help address some of our concerns by answering questions like "Does my child breathe normally during sleep?" or "Does my elderly parent experience irregular

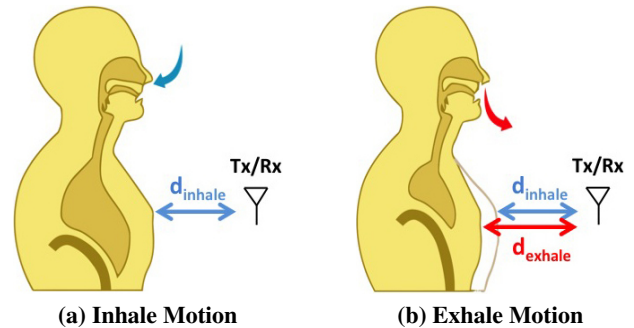


Figure 1—Chest Motion Changes the Signal Reflection Time. (a) shows that when the person inhales, his chest expands and becomes closer to the antenna, hence decreasing the time it takes the signal to reflect back to the device. (b) shows that when the person exhales, his chest contracts and moves away from the antenna, hence the distance between the chest and the antenna increases, causing an increase in the reflection time.

heartbeats?" Furthermore, if non-intrusive in-home continuous monitoring of breathing and heartbeats existed, it would enable healthcare professionals to study how these signals correlate with our stress level and evolve with time and age, which could have a major impact on our healthcare system.

Unfortunately, typical technologies for tracking vital signals require body contact, and most of them are intrusive. Specifically, today's breath monitoring sensors are inconvenient: they require the person to attach a nasal probe [19], wear a chest band [43], or lie on a special mattress [3]. Some heart-rate monitoring technologies are equally cumbersome since they require their users to wear a chest strap [18], or place a pulse oximeter on their finger [21]. The more comfortable technologies such as wristbands do not capture breathing and have lower accuracy for heart rate monitoring [12]. Additionally, there is a section of the population for whom wearable sensors are undesirable. For example, the elderly typically feel encumbered or ashamed by wearable devices [20, 37], and those with dementia may forget to wear them. Children may remove them and lose them, and infants may develop skin irritation from wearable sensors [40].

In this paper, we ask whether it's possible for smart homes to monitor our vital signs remotely – i.e., without requiring any physical contact with our bodies. While past research has investigated the feasibility of sensing breathing and heart rate without direct contact with the body [17, 16, 15, 34, 27, 48, 14], the proposed methods are more appropriate for controlled settings but unsuitable for smart homes: They fail in the presence of multiple users or extraneous motion. They typically require the user to lie still on a bed facing the device. Furthermore, they are accurate only when they are within close proximity to the user's chest.

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We introduce Vital-Radio, a new input device for tracking breathing and heartbeats without physical contact with the person’s body. Vital-Radio works correctly in the presence of multiple users in the environment and can track the vital signs of the present users simultaneously. Also, Vital-Radio does not require the user to face the device or be aware of its presence. In fact, the user can be sleeping, watching TV, typing on her laptop, or checking her phone. Furthermore, Vital-Radio can accurately track a user’s breathing and heart rate even if she is 8 meters away from the device, or in a different room.

Vital-Radio works by using wireless signals to monitor the minute movements due to inhaling, exhaling, and heartbeats. Specifically, it transmits a low-power wireless signal and measures the time it takes for the signal to reflect back to the device. The reflection time depends on the distance of the reflector to the device, and changes as the reflector moves. Fig. 1 illustrates the impact of breathing on the signal’s reflection time. When the person inhales, his chest expands and moves forward, reducing the reflection time. In contrast, when the person exhales, his chest contracts moving away from the device, hence increasing the reflection time. Generally, even when the person is not directly facing our device, the wireless signal traverses his body and his vital signs cause periodic changes in the signal’s reflection time. Vital-Radio measures these changes and analyzes them to extract breathing and heartbeats.

A key feature of Vital-Radio is its ability to monitor the vital signs of multiple people and operate robustly without requiring the users to lie still. The main challenge in delivering this feature is that any motion in the environment can affect the wireless signal and hence interferes with tracking breathing or heartbeats. Past work addresses this challenge by requiring that only one person be present in front of the device and that the person remains still. In contrast, Vital-Radio recognizes that one can address this problem by building on recent technologies that localize users using wireless signals [6]. Specifically, Vital-Radio first localizes each user in the environment, then zooms in on the signal reflected from each user and analyzes variations in his reflection to extract his breathing and heart rate. By isolating a user’s reflection, Vital-Radio also eliminates other sources of interference including noise or extraneous motion in the environment, which may otherwise mask the minute variations due to the user’s vital signs. This enables Vital-Radio to monitor multiple users’ breathing and heart rates, and to operate at distances up to 8 m from the user or even from behind a wall.

We built a real-time prototype of Vital-Radio and validated its capabilities by conducting experiments with 14 subjects. For baselines, we use FDA-approved breathing and heart rate monitors; these include chest straps for monitoring the inhale-exhale motion and pulse oximeters placed on the subject’s finger to monitor their heart rate. In our benchmark evaluation, we ask the users to wear the baseline monitors, while Vital-Radio monitors them remotely without any body contact. We compare the output of Vital-Radio with the ground truth from the FDA-approved baselines, demonstrating that

Vital-Radio accurately tracks breathing patterns and heartbeats. Over more than 200 two-minute experiments, our results show that:

- Vital-Radio can accurately track a person’s breathing and heart rate without body contact, even when the user is up to 8 meters away from the device, or behind a wall.
- Vital-Radio’s median accuracy for breathing is 99.3% (error of 0.09 breath/minute) and for heart rate is 98.5% (0.95 beat/minute) when the person is 1 m away from the device. The accuracy decreases to 98.7% (error of 0.15 breath/minute) and 98.3% (1.1 beat/minute) when the person is 8 m away from the device.
- In an area that spans $8\text{ m} \times 5\text{ m}$, Vital-Radio can monitor the vital signs of up to three individuals with the same accuracy as for one person.

We also perform activity-focused experiments to explore Vital-Radio’s monitoring capabilities. Specifically, we demonstrate that Vital-Radio can accurately measure users’ breathing and heart rates while they are typing on their computer or using their cell phones. We also demonstrate that Vital-Radio can track sharp changes in vital signs. Specifically, we perform experiments where users are asked to exercise, and show how Vital-Radio accurately tracks the change in breathing and heart rates after exercising.

We believe Vital-Radio takes a significant step toward enabling smart homes that allow people to monitor their vital signals, and that its capabilities can have a significant impact on our health awareness and our health-care system.

RELATED WORK

The desire for non-contact monitoring of vital signs has occupied researchers since the late 70’s [29]. Early work presented a proof of concept that the wireless signal is affected by movements of the chest. In these experiments, the person lies still on a bed and the sensor is placed only 3 cm away from the apex of the heart. The results are qualitative with no evaluation of accuracy.

Subsequently, military research explored the potential of building radars that can detect human presence through walls or under rubble by relying on the fact that breathing impacts wireless signals [42, 47, 26, 45]. Specifically, because wireless signals traverse obstacles, they could be used to sense the chest movements of a trapped victim through rubble or enable SWAT teams to sense movement from behind an obstacle and avoid being ambushed. However, since these systems target the military, they typically transmit at excessive power and use military-reserved spectrum bands [47, 45], which is not feasible for consumer devices. More importantly, this line of work generally focused on the detection of users by sensing motion due to their vital signs rather than estimating or monitoring the vital signs themselves.

Recently, the mounting interest in technologies for well-being has led researchers to investigate non-contact methods for analyzing vital signs. Current research on this topic can be divided into two areas: vision-based techniques and wireless systems. Specifically, advances in image processing allowed researchers to amplify visual patterns in video feeds (such as color changes due to blood flow) to detect breathing and heart

rate [8, 44]; however, such video-based techniques require the user to face the camera and do not work when he/she turns around or is outside the camera’s field of view.

Similarly, advances in wireless transmission systems and signal processing have enabled researchers to detect and analyze human vital signs. Past proposals use one of the following techniques: Doppler radar [17, 16, 15], WiFi [34, 27], or ultra-wideband radar [48, 14, 7]. The key challenge in using wireless signals to extract vital signs is that any motion in the environment affects the signal. Since breathing and heartbeats are minute movements, they can be easily masked by interference from any other source of movement in the environment. Furthermore, the presence of multiple users – even if none of them moves – prevents these systems from operating correctly since the wireless signal will be affected by the combination of their vital signs, making it hard to disentangle the vital signs of each individual. Past proposals deal with this problem by ensuring that there is only one source of motion in the environment: namely, the vital signs of the monitored individual. Hence, their experimental setup has one person, who typically lies still in close proximity to the device [17, 16, 15, 34, 27, 48, 14, 7, 4].

In contrast to these past systems, Vital-Radio has an intrinsic mechanism that enables it to separate different sources of motion in the environment. To do so, Vital-Radio builds on state-of-the-art wireless localization techniques [6], which can identify the distance between the device and different moving objects. Vital-Radio, however, uses these methods to disentangle the incoming signals based on distance, rather than estimate the actual location. This allows it to separate signals reflected off different bodies and body parts. It then analyzes their motion independently to estimate the breathing and heart rate of potentially multiple individuals.

CONTEXT AND SCOPE

We envision that Vital-Radio can be deployed in a smart home to monitor its inhabitants’ breathing and heart rates, without body instrumentation. The device can monitor multiple users’ vital signs simultaneously, even if some of them are occluded from the device by a wall or a piece of furniture. A single device can monitor users’ vital signs at distances up to 8 meters, and hence may be used to cover a studio or a small apartment. One can cover a larger home by deploying multiple Vital-Radio devices in the environment.

Vital-Radio’s algorithms run continuously, separating signals from different users, then analyzing the signal from each user independently to measure his/her vital signs. However, when a user walks (or performs a large body motion), the chest motion is mainly impacted by the walk and no longer representative of the breathing and heart rate.¹ At home, there are typically sufficient intervals when a user is quasi-static; these include scenarios where the user is watching TV, typing on a

¹The vast majority of vital signs monitors, including chest bands that monitor breathing and pulse oximeters that monitor heart rate, cannot provide accurate estimates when the user walks or moves a major limb [35, 28, 11]. To prevent such motion from causing errors in its vital-signs estimates, Vital-Radio automatically detects periods during which the user is quasi-static and computes estimates only during such intervals.

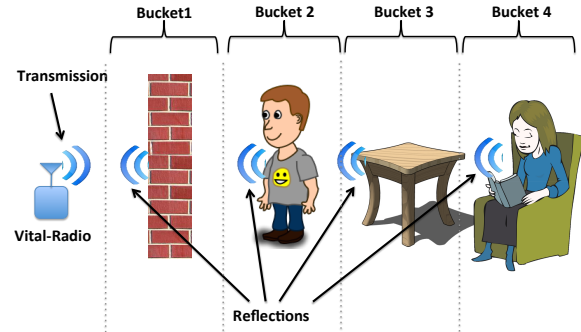


Figure 2—Separating Reflectors into Different Buckets. Vital-Radio uses a radar technique called FMCW to separate the reflections arriving from objects into different buckets depending on the distance between these objects and the device.

laptop, reading a newspaper, or sleeping. Vital-Radio can use all of these intervals to monitor a user’s vital signs, and track how they vary throughout the day.

THEORY OF OPERATION

Vital-Radio transmits a low power wireless signal and measures the time it takes its signal to travel to the human body and reflect back to its antennas. Knowing that wireless signals travel at the speed of light, we can use the reflection time to compute the distance from the device to the human body. This distance varies slightly and periodically as the user inhales and exhales and his heart beats. Vital-Radio captures these minute changes in distance and uses them to extract the user’s vital signs.

However, natural environments have a large number of reflectors, such as walls and furniture as well as multiple users whose bodies all reflect the wireless signal. To address these issues, Vital-Radio’s operation consists of three steps:

1. Isolate reflections from different users and eliminate reflections off furniture and static objects.
2. For each user, identify the signal variations that are due to breathing and heartbeats, and separate them from variations due to body or limb motion.
3. Analyze signal variations to extract breathing and heart rates.

In what follows, we describe how these steps enable us to monitor users’ vital signs using Vital-Radio.

Step 1: Isolate Reflections from Different Users and Eliminate Reflections off Furniture and Walls

To understand the operation of Vital-Radio, let us consider the scenario in Fig. 2, where the device is placed behind the wall of a room that has two humans and a table. When Vital-Radio transmits a wireless signal, part of that signal reflects off the wall; the other part traverses the wall, reflects off the humans and the table inside the room, and then traverses the wall back to the device.

To isolate signals reflected off different objects, Vital-Radio uses a radar technique called FMCW (Frequency Modulated Carrier Waves). We refer the reader to [6] for a detailed description of how FMCW works. A key property of FMCW that we exploit in this paper is that it enables separating the reflections from different objects into buckets based on their

reflection times. Since wireless signals travel at the speed of light, signals reflected off objects at different distances would fall into different buckets.

However, in contrast to past work on localization, which uses FMCW to sense the amount of power arriving from different distances to localize the users, Vital-Radio uses the FMCW technique as a filter –i.e., it uses it to isolate the reflected signals arriving from different distances in the environment into different buckets, before it proceeds to analyze the signals in each of these buckets to extract the vital signs (step 2 below).

Our implementation of FMCW follows the system in [6], where the resolution of FMCW buckets is about 8 cm. This has two implications:

- Reflections from two objects that are separated by at least 8 cm would fall into different buckets. Hence, two users that are few feet apart would naturally fall into different buckets. For example, in Fig. 2, the wall, Bob, the table, and Alice are at different distances from our device, and hence FMCW isolates the signals reflected from each of these entities into different buckets, allowing us to focus on each of them separately.
- Using FMCW as a filter also allows us to isolate some of the limb motion from chest movements due to breathing and heartbeats. For example, the signal reflected off the user’s feet will be in a different bucket from that reflected off the user’s chest. Thus, having the user move his feet (in place) does not interfere with Vital-Radio’s ability to extract the breathing and heart rate.

After bucketing the reflections based on the reflector’s distance, Vital-Radio eliminates reflections off static objects like walls and furniture. Specifically, since static objects don’t move, their reflections don’t change over time, and hence can be eliminated by subtracting consecutive time measurements.

At the end of this step, Vital-Radio would have eliminated all signal reflections from static objects (e.g., walls and furniture), and is left with reflections off moving objects separated into buckets.²

Step 2: Identifying Reflections Involving Breathing and Heart Rate

After Vital-Radio isolates reflections from different moving users into separate buckets, it proceeds by analyzing each of these buckets to identify breathing and heart rate. For example, in Fig. 2, we would like to identify whether the user in bucket 2 is quasi-static and his motion is dominated by his vital signs, or whether he is walking around or moving a limb.

To do that, Vital-Radio zooms in on the signal reflection which it isolated in the corresponding bucket. This wireless reflection is a wave; the phase of the wave is related to the distance traveled by the signal as follows [39]:

$$\phi(t) = 2\pi \frac{d(t)}{\lambda}, \quad (1)$$

²While unlikely, it is possible that multiple users are at the same distance from the device and hence fall into the same bucket. To deal with such cases, one may deploy multiple devices so that if two users are at the same distance with respect to one device, they are at different distances with respect to another device.

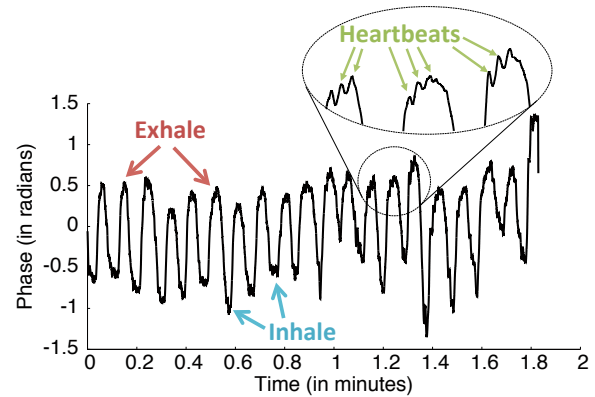


Figure 3—Phase variation due to vital signs. The figure shows the variations in phase due to breathing and heartbeats, where peaks and valleys in the phase correspond to exhale and inhale motions respectively; also, zooming in on the signal allows us to observe the heartbeats modulated on top of the breathing motion.

where λ is the wavelength of the transmitted signal, and $d(t)$ is the traveled distance from the device to the reflector and back to the device. The above equation shows that one can identify variations in $d(t)$ due to inhaling, exhaling, and heartbeats, by measuring the resulting variations in the phase of the reflected signal.

To illustrate how the phase varies with vital signs, let us consider the example in Fig. 1, where a user sits facing the device. When the person inhales, his chest expands and gets closer to the device; and when he exhales, his chest contracts and gets further away from the device. Because the phase and the distance to a reflector are linearly related, Vital-Radio can track a person’s breathing. Fig. 3 shows the phase of the captured reflection as a function of time. Specifically, a peak in the phase corresponds to an exhale (highest distance from the device), and a valley in the phase corresponds to an inhale (smallest distance from the device). We note that our implementation uses a wavelength λ around 4.5 cm. According to the above equation, sub-centimeter variations in the chest distance due to breathing cause sub-radian variations in the phase, which is what we observe in the figure.

Similarly, a person’s heartbeats cause minute movements of different parts of his body. Specifically, the physiological phenomenon that allows Vital-Radio to extract heart rate from signal reflections is ballistocardiography (BCG). BCG refers to movements of the body synchronous with the heartbeat due to ventricular pump activity [36]. Past work has documented BCG jitters from the head, torso, buttock, etc. [5, 8]. Periodic jitters cause periodic variations in the wireless signal allowing us to capture the heart rate. These movements translate to smaller fluctuations on top of the breathing motion in the wireless reflection as we can see from local peaks in Fig. 3. Note that the periodicity of breathing and heartbeats is independent of the user’s orientation. For example, if the user has his back to the device, the valleys become peaks and vice versa, but the same periodicity persists.

Still, an important question to answer is: what happens when a person moves around or moves a limb, and how can Vital-Radio distinguish such motions from breathing and heart-

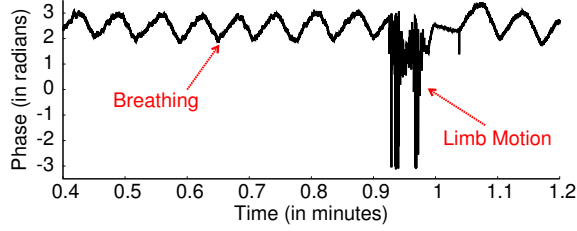


Figure 4—Limb motion affects vital sign monitoring. The figure shows the subject breathing until right before the 1 minute mark where he waves his hand. The device eliminates time intervals when such motion happens.

beats? To help answer this question, we show in Fig. 4 a scenario where the user waves his hand before the one minute mark resulting in aperiodic phase variations of the signal.

To deal with such scenarios, Vital-Radio exploits that motion due to vital signs is periodic, while body or limb motion is aperiodic. It uses this property to identify intervals of time where a user’s whole body moves or where she performs large limb movements and discards them so that they do not create errors in estimating vital signs. To achieve this, Vital-Radio operates on time windows (30 seconds in our implementation). For each window, it measures the periodicity of the signal. If the periodicity is above a threshold, it determines that the dominant motion is breathing and heart rate; otherwise, it discards the window. A typical approach to measure a signal’s periodicity is evaluating the sharpness of its *Fourier transform* (or FFT) [10]. Hence, we perform an FFT on each window, choose the FFT’s peak frequency, and determine whether the peak’s value is sufficiently higher than the average power in the remaining frequencies.³

This metric allows us to maintain intervals where a user does not perform large limb movements, including scenarios where the user types on her laptop or checks her phone. This is because, while these movements are indeed aperiodic, they do not mask the breathing or the heart rate since their power does not overwhelm the repetitive movements due to our vital signs.⁴ Additionally, in some of these scenarios, the user’s hands are stretched out to the laptop and away from his chest as he is typing. As a result, the major part of his typing motion falls into a separate FMCW bucket than the user’s chest. Naturally, because the human body is connected, hand movements would still result in muscle stretches and minor shoulder jitters that are close to the user’s chest; however, because such movements are weak and aperiodic, they are diluted at the output of the FFT. In contrast, periodic movements due to vital signs are enforced in the FFT operation, which results in maintaining intervals of such quasi-static scenarios.

The above steps allow us to filter out extraneous motion and focus on time windows where the dominant motion for each user is the breathing and heart rate. In the following section, we show how Vital-Radio extracts breathing and heart rate from these intervals.

³In our implementation, we choose this peak to be at least $5\times$ above the average power of the remaining frequencies.

⁴Mathematically, these signals would appear as “white noise” in low frequencies, and are filtered out in Step 3 of Vital-Radio’s operation.

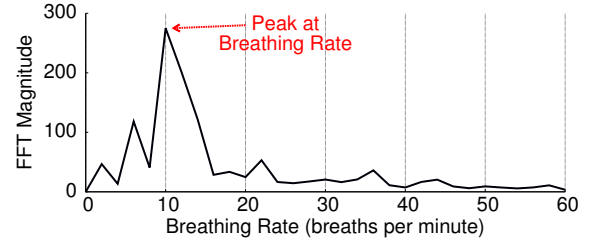


Figure 5—Output of Fourier Transform for Breathing. The figure shows the output of the FFT performed on the phase of the signal of Fig. 3. The FFT exhibits a peak around 10 breaths/minute, providing a coarse estimate of the breathing rate.

Step 3: Extracting Breathing and Heart Rate

Breathing Rate Extraction

Because breathing is a periodic motion, we can extract the frequency (rate) of breathing by performing a Fourier transform (an FFT). The peak at the output of the FFT will correspond to the dominant frequency, which in our case is the breathing rate. Specifically, we perform an FFT of the phase signal in Fig. 3 over a 30 second window and plot the output in Fig. 5. The peak of this signal gives us an initial estimate of the person’s breathing rate.

However, simply taking the peak of the FFT does not provide an accurate estimate of breathing rate. Specifically, the frequency resolution of an FFT is $1/\text{window size}$. For a window size of 30 seconds, the resolution of our breath rate estimate is $\approx 0.033\text{Hz}$, i.e., 2 breaths/minute. Note that a larger window size provides better resolution, but is less capable of tracking changes in breathing rate. To obtain a more precise measurement, we exploit a well-known property in signal processing which states that: if the signal contains a single dominant frequency, then that frequency can be accurately measured by performing a linear regression on the phase of the complex time-domain signal [33]. Hence, we perform an additional optimization step, whereby we filter the output of the FFT, keeping only the peak and its two adjacent bins; this filtering allows us to eliminate noise caused by extraneous and non-periodic movements. Then, we perform an inverse FFT to obtain a complex time-domain signal $s'(t)$. The phase of $s'(t)$ will be linear and its slope will correspond to the breathing frequency, i.e., the breathing rate. Mathematically, we can compute an accurate estimate of the breathing rate (in terms of breaths per minute) from the following equation:

$$\text{Estimate} = 60 \times \frac{\text{slope}\{\angle s'(t)\}}{2\pi}, \quad (2)$$

where the factor of 60 transforms this frequency from Hz (i.e., $1/\text{second}$) to breaths/minute.

Heart Rate Extraction

Similar to breathing, the heartbeat signal is periodic, and is modulated on top of the breathing signal, as shown in Fig. 3. However, the breathing signal is orders of magnitude stronger than the heartbeat. This leads to a classical problem in FFT’s, where a strong signal at a given frequency leaks into other frequencies (i.e., leaks into nearby bins at the output of the FFT) and could mask a weaker signal at a nearby frequency.

To mitigate this leakage, we filter the frequency domain signal around [40-200] beats per minute; this allows us to filter

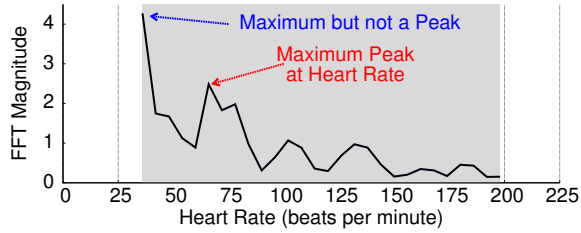


Figure 6—Output of Fourier Transform for Heart Rate. The figure shows the output of the FFT after applying a hanning window and filtering between [40-200] beats/minute. The highest peak (i.e., “local maximum”) provides a coarse estimate of the heart rate.

out breathing, which is typically between 8 and 16 breaths per minute [41]⁵ as well as high frequency noise (which is higher than 200 beats per minute).

We plot the output of this obtained frequency domain signal in Fig. 6, and pick the maximum *peak* of this output as the frequency that corresponds to the heart rate. Note that we do not simply pick the *absolute* maximum of the FFT, because this absolute maximum is typically the first bin after filtering (i.e., around 40 beats/minute), and is due to the leakage from the breathing. In contrast, in this example, the peak occurs at 66 beats/minute.

Similar to breathing, simply taking the peak of the FFT leads to poor resolution. To obtain a more precise estimate of the heart rate, we take an inverse FFT of the signal in the FFT bin corresponding to the heart rate peak and the two adjacent FFT bins. We then regress on the phase of this signal using equation 2. After this regression step, the obtained heart rate is 66.7 beats/minute, whereas the ground truth heart rate obtained from a pulse oximeter is around 66.5 beats/minute.

Finally, we note that for computing heart rate, we use an FFT window of 10 seconds only. This window is long enough to capture the periodicity of heartbeats but it is short enough to quickly react to an increase/decrease in heart rate. Also note that the FFT is computed over overlapping windows that are shifted by 30ms, hence providing a new estimate every 30ms.

IMPLEMENTATION

Our implementation consists of the following components:

Hardware: We reproduced a state-of-the-art FMCW radio designed by past work on wireless localization [6]. The device generates a signal that sweeps from 5.46 GHz to 7.25 GHz every 2.5 milliseconds, transmitting sub-mW power. These parameters are chosen in [6] such that the transmission system is compliant with FCC regulations for consumer electronics.

The FMCW radio connects to a computer over Ethernet. The received signal is sampled (digitized) and transmitted over the Ethernet to the computer for real-time processing.

Software: We implement the signal processing algorithms described in the previous sections in C++. The code runs in realtime, plotting on the screen the breathing and heart rate as function of time and at the same time logs them to a file. The code operates on shifted overlapping FFT windows and

⁵In fact, this filtering allows us to filter out the breathing signal and its first harmonic.

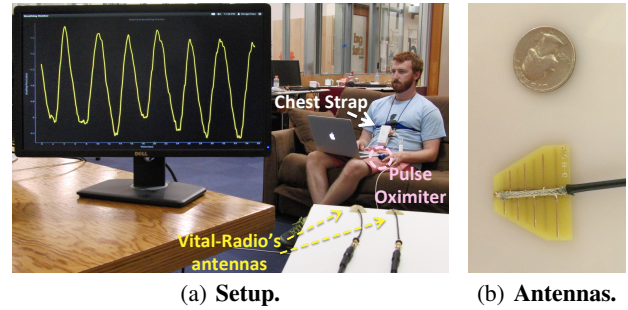


Figure 7—Experimental Setup. (a) shows a user sitting about 2.5m away from Vital-Radio’s antennas; the user also wears a chest strap and a pulse oximeter, which are connected to the Alice PDx for obtaining ground truth measurements. (b) shows one of Vital-Radio’s antennas placed next to a quarter.

generates new estimates every 30ms. The output also shows user motion –i.e., the code tags every 30ms window to show whether the user is quasi-static or performing a major motion.

EXPERIMENTAL EVALUATION

Participants: To evaluate the performance of Vital-Radio we recruited 14 participants (3 females). These participants were between 21 and 55 years old ($\mu = 31.4$), weighed between 52 and 95 kg ($\mu = 78.3$), and were between 164 and 187 cm tall ($\mu = 175$). During the experiments, the subjects wore their daily attire, including shirts, T-shirts, hoodies, and jackets with different fabric materials.

Ground Truth: To determine Vital-Radio’s accuracy, we compare its output against the Alice PDx [1], an FDA approved device for monitoring breathing and heart rate. The Alice PDx is equipped with a chest band and a pulse oximeter. The chest band is strapped around each subject’s chest to monitor breathing, and the pulse oximeter is placed on his/her finger to monitor heart rate during the experiment.

Experimental Environment: We perform our experiments in a standard office building; the interior walls are standard double dry walls supported by metal frames with sheet rock on top. The evaluation environment contains office furniture including desks, chairs, couches, and computers.

Throughout the experiments, Vital-Radio’s antennas are placed on a table, about 3 feet above the ground as shown in Fig. 7. The user sits at some distance from these antennas and wears the Alice PDx’s chest band and pulse oximeter to obtain the ground truth measurements as shown in the figure. In our evaluation, we vary the distance and orientation of the user with respect to Vital-Radio to determine its accuracy in different scenarios as we show in the next section.

Core Experiment: Accuracy Versus Distance

We would like to validate Vital-Radio’s ability to monitor a subject’s breathing and heart rate at different distances from our device. In this experiment, we place the device in the corner of a large room, whose floor plan is shown in Fig. 8. The device’s antennas are pointed toward the center of the room to ensure that they capture motion inside that room. We ask the subject to sit on a chair at marked locations whose distances range from 1 m to 8 m away from the device. In each experi-

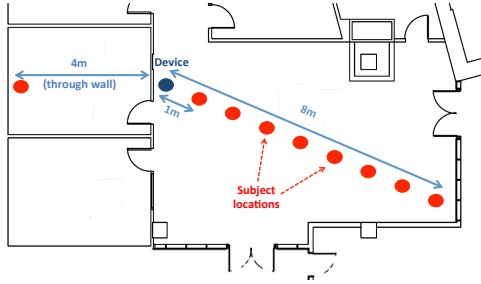


Figure 8—Testbed. The figure shows a layout of our experimental setup, marking the location of Vital-Radio in navy blue, and the different locations where our monitored subjects sat down in red.

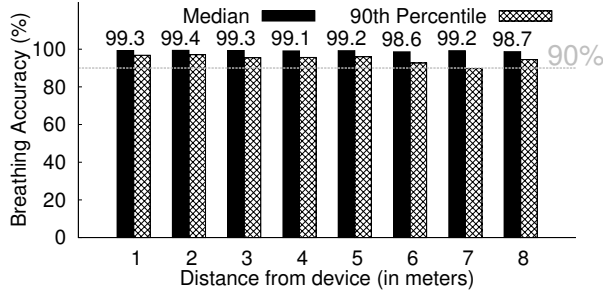


Figure 9—Breathing Accuracy vs Distance. The figure shows Vital-Radio’s breathing accuracy versus its distance to the subject.

ment, the subject sits on a chair facing Vital-Radio’s antennas and wears the Alice PDx, as shown in Fig. 7.

We run a total of 112 experiments, where we ask each of the 14 subjects to sit at the marked locations from 1m to 8 m.⁶ Each experiment lasts for two minutes, during which the user sits facing the device in each of these locations. We extract the breathing and heart rate in real-time using Vital-Radio and log these vital signs using the AlicePDx. During each two minute experiment, Vital-Radio outputs a vital sign estimate every 30 milliseconds, leading to a total of 448,000 measurements across all experiments and all locations.

Based on the ground truth measurements using the Alice PDx, the subjects’ breathing rates range from 5 to 23 breaths/minute, while their heart rates vary from 53 to 115 beats/minute. These rates span the range of adult breathing and heart rates [41, 31].⁷

Breathing Rate Accuracy

We compare the output of Vital-Radio with that of the Alice PDx, and plot the median and 90th percentile accuracy of breathing as a function of distance from 1 to 8 meters in Fig. 9. The figure shows that our median accuracy is 99.3% at 1 m and remains as high as 98.7% at 8 m from the device. It also shows that our 90th percentile accuracy is higher than 90% across all these distances.

⁶We limit the experiments to distances of 8 m because the localization accuracy of FMCW-based systems for consumer applications drops beyond this range [6].

⁷We note that one of our subject has a significantly high heart rate of 115 beats/minute. We confirmed with the subject that this value, which was measured with the Alice PDx, is compatible with his medical records. Also one of our subjects has a low breathing rate of 5 breaths/minute, as measured by the Alice PDx. This subject practices yoga on a daily basis.

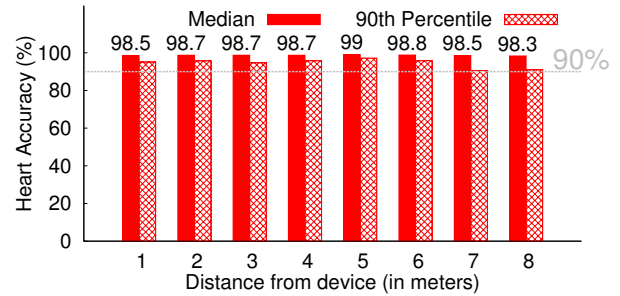


Figure 10—Heart Rate Accuracy vs Distance. The figure shows Vital-Radio’s heart rate accuracy versus its distance to the subject.

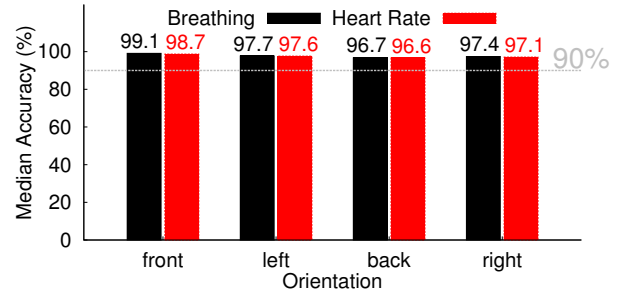


Figure 11—Accuracy versus Orientation. The figure shows Vital-Radio’s median accuracy for breathing and heart rate for a user sitting 4 m from the device and facing different directions.

Heart Rate Accuracy

We plot the median and 90th percentile accuracy of heart rate as a function of distance from 1 to 8 meters in Fig. 10. The figure shows that our median accuracy is 98.5% at 1 meter and drops to 98.3% at 8 meters from the device. It also shows that our 90th percentile accuracy remains higher than 90%, even with the subject is 8 m away from the device.

Accuracy in Various Scenarios

Accuracy versus Orientation

To validate that Vital-Radio operates correctly even when subjects do not directly face the device, we run experiments where we ask our subjects to orient themselves in different directions with respect to the device. Specifically, we ask each subject to sit at the 4 m distance from Vital-Radio and we run experiments in four different orientations: subject faces the device, subject has his back to the device, and the subject is facing left or right (perpendicular) to the device.

We plot the median accuracies for breathing and heart rate for these four different orientations in Fig. 11. The figure shows that, indeed, when the user faces the device, the median accuracy of breathing and heart rate is highest (99.1% and 98.7% respectively). However, this accuracy only slightly drops by at most 3% across all the different orientations. Note that the device can detect chest motion even when that motion is perpendicular. This is because when one inhales, his chest expands in all directions, and Vital-Radio can detect a chest side expansion though it is minute.⁸

Next, we validate that Vital-Radio does not require the user to be along a straight line facing the antenna. Specifically, we

⁸Such expansion is no smaller than variations due to heartbeats.

place the antennas at the center of the room, and ask users to sit at a distance of 4 m from the antennas and at angles ranging from -90° to $+90^\circ$ with respect to the pointing direction of the antennas. We perform 20 one-minute experiments with different subjects at different angles. The results show that Vital-Radio can capture the user’s vital signs as long as she is at an angle between -75° and $+75^\circ$ with respect to the antenna’s pointing direction. Specifically, the median accuracy is above 98% when the user is on a straight line with respect to the antenna, and decreases to 96% at the far edge (i.e., $\pm 75^\circ$).⁹

Through-Wall Accuracy

In order to test the ability of Vital-Radio to measure user’s vital signs even when they are in a different room, we run a set of through-wall experiments where the device is placed in a different room than our subjects. Specifically, we use the experimental setup in Fig. 8. The device is kept in the larger room, while the subject sits in an adjacent room behind a wall. The subject faces the device and is about 4 m from it.

Across all experiments, our median accuracies are 99.2% and 90.1% respectively for breathing and heart rate. These results indicate that the breathing rate remains almost the same both in the presence and absence of the wall (at the same distance of 4 m). However, the median heart rate accuracy drops due to the fact that the wall attenuates the heart rate signal significantly (which was already a very minute signal), hence, reducing our signal-to-noise ratio. Still, the heart rate accuracy remains around 90% even in such through-wall scenarios.

Multi-User Accuracy

We are interested in evaluating Vital-Radio’s accuracy for multi-user vital sign monitoring. Hence, we perform controlled experiments, where we ask three of our users to sit on a chair at the 2 m, 4 m, and 6 m marks in Fig. 8. In each experiment, Vital-Radio determines that there are 3 users, each at his respective distance from the device, and outputs the vital signs of each; however, the baseline (AlicePDx) can only monitor a single user at any point in time. Hence, to evaluate accuracy, we first connect the baseline to the first user and compare its output to the output of VitalRadio for the user at that distance and for that moment. Then, we move the baseline to the remaining users in succession.

We run 20 experiments with different sets of subjects and plot the accuracies in Fig. 12. The figure shows that Vital-Radio’s breathing and heart rate monitoring accuracy is around 98% for all three users. Note also that the median accuracy of the nearest user is higher than that of the further two users because of the increase in distance between these users and the device. These results verify that Vital-Radio can monitor multiple users’ vital signs, and that its monitoring accuracy for multiple users is the same as that for a single user.

Next, we would like to confirm that Vital-Radio can accurately capture the vital signs of a quasi-static user while other users are moving in the environment. In principle, Vital-Radio should still operate correctly since FMCW separates reflections from different users based on their distance to the

⁹This result is expected since Vital-Radio uses log-periodic antennas whose directionality is around 150° .

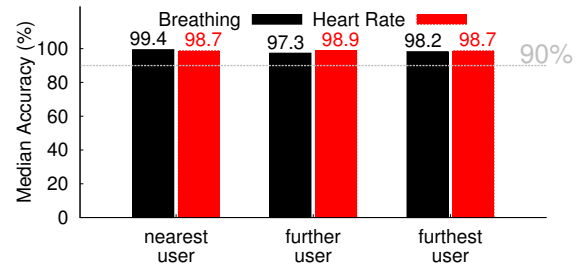


Figure 12—Multi-User Accuracy. The figure shows Vital-Radio’s median accuracy in monitoring the vital signs of 3 users simultaneously. The users are sitting at 2 m, 4 m, and 6 m from the device.

device. Hence, we run experiments where we ask one of our subjects to sit on a chair at the 3 m mark in Fig. 8 while asking another subject to walk around in the room. Over 20 experiments with different subjects, the median accuracy of breathing and heart rate remains above 98% for the monitored user as long as the moving user is at a distance of at least 1.5 m away from him. This accuracy drops below 75% when the moving user gets closer than 1 m to the monitored person. This is because when the two users are closer than 1 m, the reflections off their bodies interfere with each other, preventing Vital-Radio from isolating the signal variations due to the monitored user’s vital signs.

Activity-Focused Experiments

Daily In-Place Activities

We would like to evaluate Vital-Radio’s accuracy in monitoring users as they perform in-place day-to-day activities, such as typing on their laptops, watching TV, or sleeping. Thus, we divided the subjects into two groups: one interacting with their laptops and another interacting with their smartphones. In each experiment, we ask the subject to sit at 4 m from the device and naturally use his/her phone or laptop. Each experiment lasts for 5 minutes; the user reports at the end the activities he/she performed with their laptop or phone. The reports show that the users performed various tasks ranging from checking and responding to their emails to reading news on the web or logging on to Facebook or Instagram. Some users were texting using their phones and one user worked on a problem set on his laptop.

Throughout the experiments where our subjects used their phones, the median accuracies for breathing and heart rate were 99.4% and 98.9% respectively. These accuracies slightly dropped to 99.3% and 98.7% when our subjects were using their laptops. This minor drop in accuracy is expected because using a laptop typically involves slightly larger movements than using a phone, leading to a slight reduction in Vital-Radio’s accuracy. Note, however, that these accuracies are almost the same as those when subjects were sitting still at the same distance with respect to our antenna. Hence, Vital-Radio was able to monitor users’ breathing and heart rate as they perform day-to-day activities that do not require them to move around their apartments.

Exercising and Health-Awareness

Heart rate recovery – which corresponds to how fast a person’s heart rate decreases after exercising – is an important metric for determining how healthy a person’s heart is. Specifically, a stronger heart has a fast heart rate recovery, and

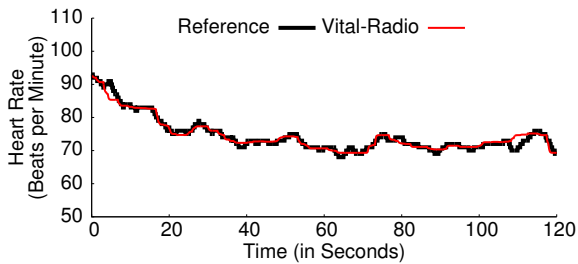


Figure 13—Tracking Heart Rate after Exercising. The figure shows how Vital-Radio can accurately and in real-time track a user’s heart rate as it decreases after exercising.

that recovery rate is a predictor of mortality [13, 24]. Hence, an important way in which Vital-Radio may contribute to a smart home inhabitants’ well-being is by accurately measuring the heart rate after users exercise.

To evaluate this capability, we evaluate the accuracy of Vital-Radio’s real-time vital sign monitoring after asking our subjects to exercise. Specifically, each of the subjects jumps rope for 2 minutes then sits down on a chair, 4 m away from the device, and breathes normally. During these experiments, we also ask our subjects to wear the Alice PDx chest band and oximeter to obtain ground truth measurements for their vital signs. While both Vital-Radio and Alice PDx cannot accurately measure heart rate during the excessive motion of jumping, they can both measure the vital signs when a user sits down after exercising.

Fig. 13 overlays the heart rate estimated by Vital-Radio (in red) on top of the the ground-truth heart rate of a subject as monitored by the pulse oximeter (in black), throughout a two-minute period after the subject stops exercising. The figure shows that Vital-Radio can effectively track the variations in the heart rate. Note that, throughout this two-minute period, there’s a downward trend in the heart rate (from about 93 beats/minute to around 70 beats/minute), which is expected since the subject is in a resting state after exercising. Also, note that throughout this period, the heart rate varies continuously about that trend, and that both the ground truth and Vital-Radio are able to capture these variations.

Across the experiments with multiple subjects, Vital-Radio’s median accuracy in measuring breathing and heart rate is 99.4% and 99% respectively, and the 90th percentile is 91.7% and 96.8%. These figures are similar to the accuracy achieved in our previous experiments, where subjects were fully rested, indicating that Vital-Radio can indeed capture our vital signs and track them accurately even as they vary.

LIMITATIONS

In this section, we elaborate on the limitations of Vital-Radio:

1. *Minimum Separation between Users:* Vital-Radio uses FMCW to separate reflections from different users before extracting the per-user vitals. For ideal point reflectors, FMCW can separate reflections from two objects if they are at least $C/2B$ apart [6], where B is the bandwidth and C is the speed of light. For Vital-Radio, this translates to a theoretical minimum separation of 8 cm. However, because

a human is not a point reflector, our experiments show that a separation of 1–2 m is needed for high accuracy.

2. *Monitoring Range:* Since Vital-Radio is a wireless system, it requires a minimum signal-to-noise ratio (SNR) to extract the signal from the noise, and this SNR bounds its range and accuracy. Specifically, the maximum distance at which Vital-Radio detects users is 8m. This is because the SNR drops with user distance from the device.
3. *Quasi-static Requirement:* Our implementation measures the vital signs only for quasi-static users (e.g., typing, watching TV). This is because signal variations due to full body motion would otherwise overwhelm the small variations due to vital signs, and prevent Vital-Radio from capturing the minute movements.
4. *Non-human Motion:* Vital-Radio uses FMCW to separate reflections from different objects in space; hence, it can separate the reflection of various moving objects (e.g., humans, fans, pets). It then analyzes the reflections of each moving object to detect breathing. Since the periodicity of breathing is much lower than fans, the device never confuses a fan as a human. Even if the device confuses a fan for a human, it will not affect the vital signs of the real humans since their signals are separated from the fans by FMCW. However, it may still identify the presence of a pet and output its breathing and heart rate assuming it is another user in the environment.

CONCLUSION AND FUTURE OPPORTUNITIES

The HCI community has significant literature on the use of physiological sensing for various applications [38, 30, 9, 23]. In particular, HCI researchers have used physiological sensing to *evaluate user experience* including emotional reactions, stress levels, cognitive performance, and user engagement. But, a key concern with past sensors (e.g., oximeters, EEG, FNIRs, GSR) is that they require direct contact with the user’s body, and hence may affect a user’s response. In contrast, Vital-Radio doesn’t require users to be aware of its presence, and hence doesn’t interfere with user experience.

Additionally, Vital-Radio enables *new interface and interaction capabilities*. For example, it may be incorporated into user interfaces to adapt to a user without requiring him to wear sensors. Also, it can enable environments to adapt the music or lighting by sensing the user’s vital signs and inferring his mood. Further, a user walking up to a Vital-Radio-enabled kiosk in an unfamiliar location (such as an airport) might receive customized assistance based on his stress level.

Beyond these applications, we believe that Vital-Radio can impact a wide array of areas in HCI including quantified self, smart homes, elderly care, personal health and well-being, and mobile emotional sensing.¹⁰

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¹⁰While we built our radio for flexible development/control, FMCW radios are available on the market [2] and can be used for the above applications once augmented with our algorithm in software.

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