MoViRad: Mobile Vital Radio

ECE598HH: Wireless Networks and Mobile Systems Project

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ABSTRACT

In view of increasing popularity of smart home applications, prior works on wireless sensing and implementation with mobile devices motivated us to explore the possibility of implementing respiration and heart rate monitoring system at using commericial off-the-shelf (COTS) hardware. We present Mobile VitalRadio (MoViRad), which aims to provide an alternative solution in view of many prior works on wireless sensing and monitoring. MoViRad leverages the use of frequency modulated continuous waves (FMCW) to measure minute chest movements, and takes a step further to extract the heart rate on from the measured breathing signal. In this report, we describe the operation of MoViRad, and demonstrates the successful extraction of breathing activity and heart rate.

1. INTRODUCTION

Over the publications of the past few years, we have witnessed on growing interest in wireless localization [1, 5] as well as ubiquitous health monitoring [2, 4]. The advancement in wireless localization technique demonstrates that a resolution of sub-centimeter scale is achievable for indoor localization through wireless sensing, thus further contributing to the implementation of smart home sensing and monitoring applications. Early access to typical health condition indicator such as breathing and heart rate proves critical in evaluating the physical and mental conditions of people. Additionally, it would benefit their medical treatment if said data history was available in case of emergency. However, such task could not be accomplished without dedicated hardwares at the moment (shown in Fig. 1), and the cost of portable medical equipment imposes severe limiting factors in people's access to medical care.

In view of the expensive and bulky equipment setup as well as inadequate availability, we investigate into the prior works on the wireless monitoring system achievable with little hardware overhead. Finding no truly satisfactory results, we present our work: Mobile VitalRadio (MoViRad), which measures physiological signals using only a COTS mobile device. The key features of MoViRad are that the only hardware requirements are a cell phone for acoustic signal transmission and reception as well as a laptop which processes the collected data off-line. The breathing and heart rate measurement is conducted similar to the prior works based on frequency modulated continuous wave (FMCW) [2, 4] such that the minute respiratory movement caused by chest translates into frequency shift in the spectrum, make it possible to be captured given sufficient resolution by applying Fourier

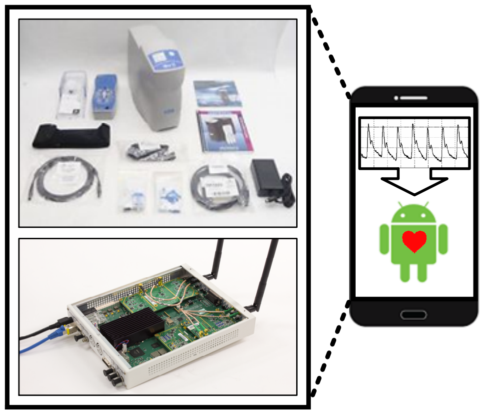

Figure 1: Illustration of hardware overhead observed including portable medical device and USRP required. Our goal is to devise an android app which is capable of monitoring breathing and heart rate.

analysis. Applying the Fast Fourier Transform (FFT) to the received signal after down-conversion, we can perform a coarse search for the breathing signal by locating the peak in the FFT spectrum corresponding to the distance between the cell phone and the user. Higher resolution tracking of the breathing activity is achieved by measuring out the phase of the corresponding peak. Once the breathing signal is obtained, the heart beat is visible as a higher frequency signal riding on top the recovered breathing signal. Consequently, by exploiting use of ballistocardiography (BCG) which refers to body movement that is synchronous with heart beat due to ventricular pump activity, we are able to extract the heart rate information masked on top of the breathing signal by filtering the recovered breathing signal. By taking another FFT on the recovered phase data, we can locate the heart beat by using the method introduced in Vital-Radio [2]. All the measurements are conducted using ultra-sonic waves to ensure that signals transmitted are inaudible to humans during measurements. At the moment, MoViRad operates assuming a pre-knowledge of the location of the user with respect to the cell phone. To integrate the function of locating user of interest would be our future development of MoViRad, alongside providing a real-time streaming of the breathing and heart rate measurements without storing data collected over long time period as required by ApneaApp [4].

The rest of the report is organized as follows. First, we discuss the two prior wireless sensing networks of which our project build upon in Section 2. Section 3 presents the implementation of MoViRad, starting by an explanation of FMCW method followed by a discussion of the hardware synchronization and how to extract the breathing from the phase of desired FFT peak. Section 4 presents the experimental data we have obtained, demonstrating the proper operation of MoViRad measuring up to two patients at different distances. Finally, Section 5 summarizes our project and discusses about aspects to be considered to further improve the functionality of MoViRad.

2. RELATED WORKS

MoViRad is implemented based on the prior publications investigating into wireless localization utilizing a radar technique: FMCW, or frequency modulated continuous wave [1, 2, 4]. Specifically, VitalRadio discusses the selection of frequency bands to sweep for the transmitted signal, and provides a clear guidance in terms of the trade-off between minimum distance detectable and sweeping bandwidth [2]. Operating at RF frequency band from 5.46GHz to 7.25GHz, VitalRadio is implemented using software defined radio (USRP). We want to avoid additional hardware overhead as in ApneaApp [4], which essentially converts the smart phone into a sonar system and transmits ultra-sonic waves in the form of FMCW signal to detect the movement of the chest. It is also worth mentioning that ApneaApp did not demonstrate the extraction of heart rate, motivating us to think of the possibility of duplicate the functionality of VitalRadio using acoustic medium. Finally, ApneaApp is not available yet as the developing team held it from publication in process of acquiring FDA approvals. As a result, we proposed to explore and implement MoViRad as an open-source mobile application which monitors and measures the breathing and heart rate.

3. MOVIRAD OVERVIEW

This section presents an overview regarding the implementation of MoViRad. Specifically, we first present a review of the theoretical background for FMCW and how one maps the frequency shift to an absolute distance. Then, we will addresses the sampling frequency offset issue observed between transmitter and receiver.

3.1 FMCW Spectrum: Peak for Coarse Estimate

In order to extract the breathing signal, we need to detect the minute chest movement, which is typically on the order of centimeters. Adequate accuracy is possible based on the recent advancement for indoor wireless localization using FMCW technique. As shown in Fig. 2, an FMCW is created and transmitted using as a sinusoidal wave whose frequency is modulated to change linearly with respect to time.

Denoting the transmitted signal as $TX(t)$, and the FMCW transmits signals with frequency varying between $f_{\min}$ and $f_{\max}$ within a period of T_S, we have

$$TX(t) = e^{j2\pi(\frac{k}{2}(t^2+f_{min}t))} \tag{1}$$

where k denotes the carrier modulation frequency in the FMCW signal. It is defined as:

$$k = \frac{\Delta f}{\Delta t} = \frac{f_{\max} - f_{\min}}{T_S} \tag{2}$$

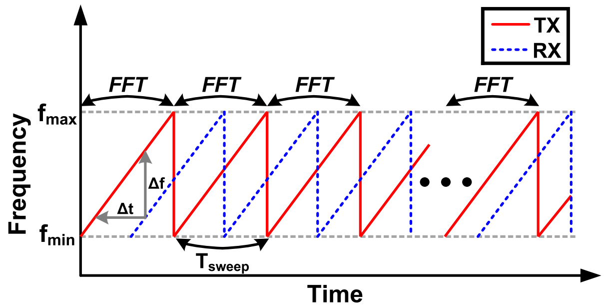

Figure 2: FMCW operation. The transmitted signal frequency changes linearly with respect to time across the sweeping bandwidth. As a result, the reflected signal $RX(t)$ will simply be a time-delayed version of the $TX(t)$.

In order to obtain the relative distance measurement, we record the received signal $RX(t)$, which will contain both the near-field $TX(t)$ signal as well as the reflected signal to the received signal (RX). Since the transmitted signal frequency changes linearly with time, reflected signal will be a time-delayed replica of the TX-signal, and the time required for the propagation would be linearly translated as a frequency shift. In the presence of multiple paths in wireless transmission, without loss of generality, the received signal RX could be described as a linear combination of multiple $TX(t)$ each with their own delay.

$$RX(t) = \sum_i A_i e^{j2\pi(\frac{k}{2}((t-\tau_i)^2 + f_{\min}(t-\tau_i)))} \tag{3}$$

where τ_i is the delay caused by ith path. Specifically, to properly measure the received frequency shifts, we multiply RX with TX to perform down-conversion, then apply a low-pass filter to the product and obtain the RX signal as:

$$LPF\{RX(t) \cdot TX(t)\} = \sum_i A_i e^{j2\pi(k\tau_i t + f_{min}\tau_i)} \tag{4}$$

The time-delay τ_i is now observed as a peak in the low-frequency spectrum, and we can back-calculate the relative distance from the measured path delay τ_i as:

$$D = \frac{c \cdot \tau_i}{2} = \frac{c}{2} \cdot \frac{\Delta f}{k} \tag{5}$$

where c denotes the propagation velocity of the carrier; in our case, $c = 340\text{m/s}$, which is the speed of sound at room temperature. Notice that after down-conversion, the spectrum located at carrier frequency would now reside at DC. In other words, Δf directly measures the absolute distance between the object under test and the cell phone. Given that wireless reflections add up linearly over the medium, multiple objects could be identified simultaneously at different locations as indicated in Fig. 3.

3.2 FMCW Spectrum: Phase for Fine Estimate

As shown in the section above, the spectrum only leads us to a coarse estimate regarding the corresponding frequency range. As with all short-time Fourier transforms, there is an inherent trade-off between frequency resolution and time resolution. Due to the time length of FFT, which was pri-

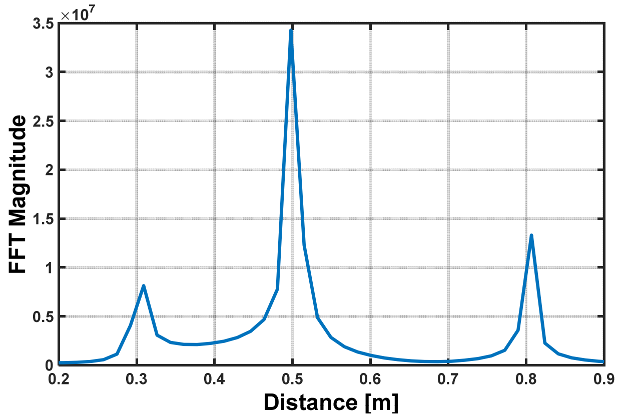

Figure 3: Spectrum of the simulated down-conversion of $RX(t)$. We emulate reflections at 30cm, 50cm and 80cm and we are able to recover the location of all three with one FFT.

marily limited by hardware, the resolution of the distance estimate could be calculated as:

$$D_{min} = \frac{c}{2} \cdot \frac{\Delta f_{\min}}{k} \tag{6}$$

The FFT is typically applied to one frame of such FMCW transmission, as the discontinuities between FMCW frames are accentuated by the hardware platform. Given this, the minimum frequency shift that we are able to identify is equal the bin spacing of the resulting FFT, which can be calculated as:

$$\Delta f_{min} = \frac{1}{T_S} \tag{7}$$

Hence, Eq.(6) translates to a distance resolution of:

$$D_{min}(t) = \frac{c}{2} \cdot \frac{1/T_S}{k} = \frac{c}{2 \times F_S} \tag{8}$$

where $F_S = f_{\max} - f_{\min}$ is the selected frequency bandwidth of the FMCW carrier. Eq.(8) indicates that the distance resolution only depends on the sweeping bandwidth. For example, with FMCW chirp signal sweeps between 18kHz to 20kHz, the minimum distance that could be identified is calculated to be 8.5cm, which could not sense the small variation of chest movement. Therefore, we seek to extract the phase of the corresponding FFT peak as a fine estimate of the location [2]. As shown in Eq.(4), the FFT of the down-converted signal has a phase expression that also changes periodically with time at frequency of $k \cdot \tau_i$. This information can be extracted based on the coarse estimate from the peak location. As a result, we focus on the frequency bin of interest, and monitors the phase variation across time.

However, due to limited FFT resolution, it is unlikely that our frequency will fall at the bin chosen. It is instead more likely that the frequency will fall between two bins, creating significant skirting in FFT spectrum. Additionally, there will be a constant frequency offset f_{offset}, defined as:

$$f_{\text{offset}} = |f_{\text{true}} - f_{\text{bin}}| \tag{9}$$

Measuring the phase now has two components: the integral of f_{offset} as well as the recovered movement signals. Assuming the user is static relative to bin spacing during operation, the f_{offset} will accumulate linearly. Applying a linear regression to the obtained phase data, we can estimate and calibrate for f_{offset} and can obtain fine estimate of the chest movement.

Since the phase wraps every 2π, with linear regression applied to the unwrapped phase, it leads us to the desired breathing signal. Once the breathing signal is extracted, the heart beat would show itself as a small periodic ripple on top the breathing signal. Consequently, we would apply FFT on the breathing signal, and identify the heart rate. Typically, the breathing signal has much higher power in the resulting FFT spectrum and the leakage may create another peak. Therefore, we will not report this peak due to breathing signal leakage at lower frequency, but we search for the strongest peak after bandpass filtering around valid heartbeat frequencies.

3.3 MoViRad Implementation Challenges

The first part of the section discusses about the background theory necessary to understand the operation of MoViRad. In the practical implementation, we have run into a few issues that we believe are worth mentioning: (1) filtering of the chirp signal, and (2) sampling frequency offset (SFO).

- *FMCW transmission signal is filtered before practical transmission.* The selected sweeping bandwidth in our implementation is from 18kHz to 20kHz, and it shows the form of a saw-tooth shape. In theory, this frequency band falls into the ultra-sonic region for typical adult hearing, yet the hardware creates audible clicking at the discontinuity between the two consecutive frames. In order to alleviate the audible noise due to cell phone's hardware limitation, a triangular filter is applied which zero-forces the chirp signal at the discontinuity. While the audible noise does get removed, the filtering causes another practical issue in the implementation (as shown in Fig. 4): it directly reduces the usable sweeping bandwidth of the FMCW transmission, therefore degrading the distance resolution achievable (following the calculation of Eq.(8)).

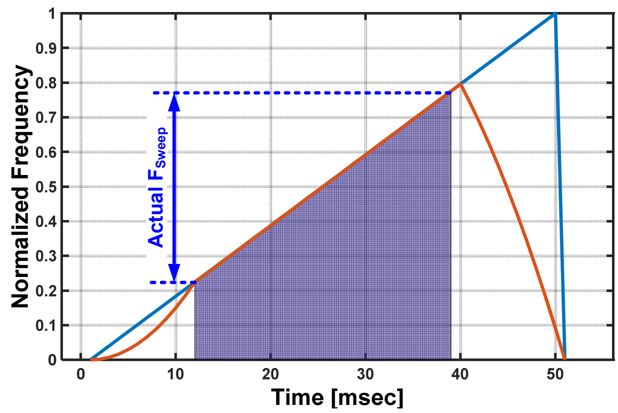

Figure 4: Exaggerated illustration of the effect of filtering on the FMCW transmitted signal. In our implementation, we left about 1% of T_S at the two discontinuities.

- *Sampling frequency offset (SFO).* We ran into the SFO at our initial use case: using the cell phone as the transmitter and using the laptop as the receiver. Since the sources are separated and not synchronized, there will be a non-zero delay between the two recordings. In order to match up the TX and RX frames, we first compute a cross-correlation between TX and RX signals to figure out the necessary delay before doing the down-conversion. As shown in Fig. 5, the sampling frequency offset between the cell phone and the laptop makes it difficult to distinguish the correct delay value corresponding FMCW in the RX.

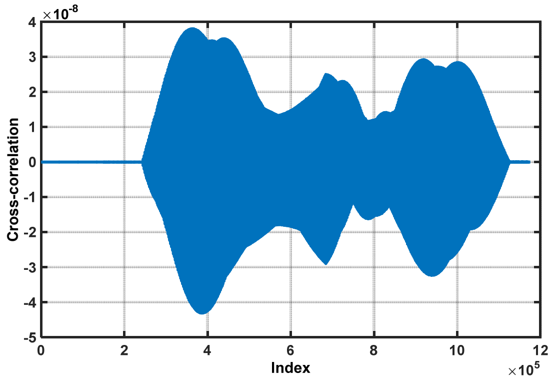

Figure 5: Illustration of the SFO problem if TX and RX are processed using different hardwares..

In view of this problem, we implement an Android application that is responsible for both sending and recording the FMCW signal. With this test setup, the SFO issue is resolved, and we could easily align the TX and RX signal by processing the collected audio data offline in our laptop. The correlation results between TX and RX is presented in Fig. 6 (a), when only cell phone is used for data collection. Zooming into the maximum correlation point in Fig. 6 (b), we see that the peaks correspond to FMCW frame delays, which are multiples of T_S. Furthermore, we could observe the effect of multi-path as small peaks are found near each peak. We believe that running the correlation is necessary to correctly align the sent and received frames so that we could properly apply FFT across each frame of the FMCW signal.

4. EXPERIMENTAL MEASUREMENTS

4.1 Implementation

Our implementation consists of the following components:

- *Hardware:* The main hardware requirement is an Android phone. In our implementation, a Motorola Droid Turbo is used which is equipped with speaker with a bandwidth of at least 20kHz and a microphone that samples audio signal at rate of 44.1kSa/s.

- *Software:* An Android application, MoViRad, is implemented to conduct the FMCW transmission and recording simultaneously using the cell phone. As shown in Fig. 7, one chooses the FMCW chirp signal generated, with or without filtering applied. Then we hit "START RECORD" followed by "PLAY" to ensure that all the FMCW frames are recorded throughout the experiment duration.

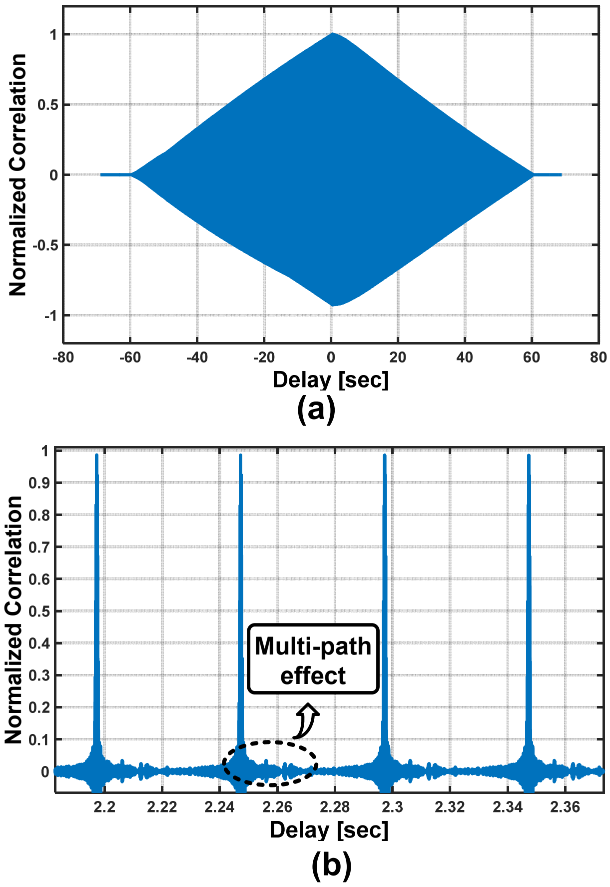

Figure 6: (a) Cross-correlation between the TX and RX signals, which are sent and recorded using only cell phone. (b) Zooming in near the correlation peak.

The collected data is currently processed off-line using MATLAB. First, we compute the cross-correlation between generated FMCW signal and received audio signal. As explained in Section 3.3, we need the correlation results to confidently align the first frame of RX to the first frame of TX as no extra delay needs to be applied. Then, we would use the MATLAB to apply an FFT on the received signal and extract the desired breathing and heart rate information.

4.2 Experimental Evaluation

Shown in Fig. 8 is the setup of our experiment on evaluation of the MoViRad performance. We use a tripod to hold the cell phone instead of having the phone held in hand to eliminate any direct disturbance on the receiver. Additionally, the tripod helps us to avoid any problems with near-field reflections overpowering the microphone. We adjust the holding position of the phone so that the phone's speaker and microphone point at the participant's chest. The experiment is conducted in a relatively open space indoor (basement of Coordinated Science Laboratory) to mitigate possible interference from multipath. During the measurements,

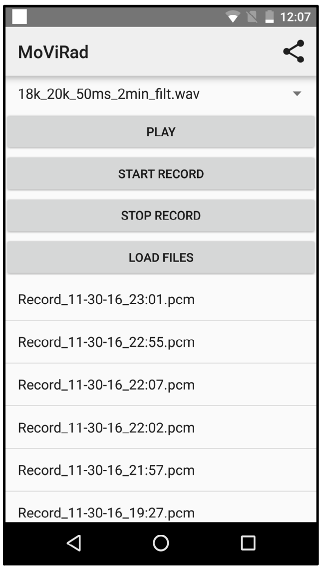

Figure 7: Interface of MoViRad application.

participants are wearing daily T-shirts and jeans with different fabric materials.

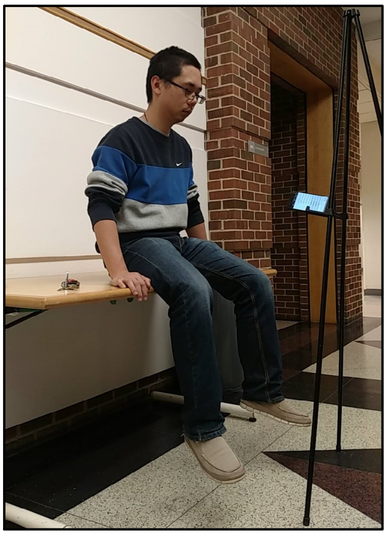

Figure 8: Experimental setup.

In order to characterize the performance, our extracted results are compared with ground-truth. In terms of breathing counts, we use the number reported by the participant. For the heart rate, the measurement from Pulse Oximeter is cited as the reference. During the experiment, participant is wearing the oximeter on his index finger (not shown in Fig. 8).

The evaluation of MoViRad is presented from two perspective. First, the accuracy of the breathing and heart rate is shown across distance. In this case, the participant stands at 30, 50, and 70 inches away from the tripod and we measure the breathing and heart rate. As shown in Fig. 9, the breathing rate accuracy is measured to maintain at least 87.8% with standard deviation of 1.3%. On the other hand, the heart rate is measured with an accuracy of at least 92.8% with standard deviation of 6.5%.

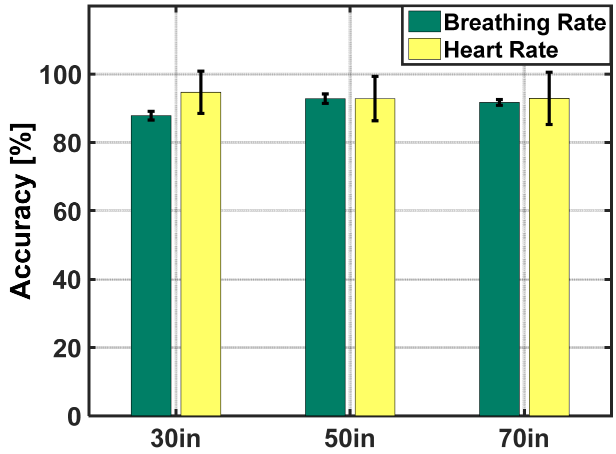

Figure 9: The accuracy of breathing and heart rate measurement versus distance of the participant relative to the phone.

Next, we investigate into the effect of the participant's orientation relative to the receiver. In this case, we measure and extract breathing and heart rate when the participant stands facing towards as well as sideways with respect to the cell phone. As shown in Fig. 9, the breathing rate accuracy is measured to maintain at least 88% with standard deviation of 1.3%. On the other hand, the heart rate is measured with an accuracy of at least 92% with standard deviation of 5.4%.

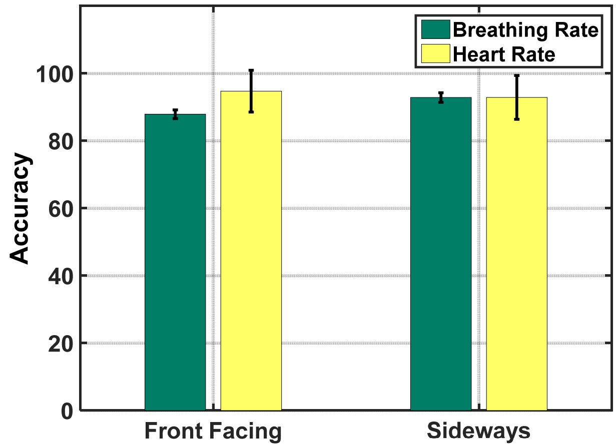

Figure 10: The accuracy of breathing and heart rate measurement versus the orientation of the participant relative to the phone.

Overall, consistent performance of breathing and heart rate measurement is observed for MoViRad. One problem associated with the accuracy measurement of the breathing rate is that the ground truth relies on the reported count based on the participant. However, due to their ultra-sonic nature, we do not exactly know the starting and ending of the ultra-sonic FMCW signal so that there may be some rounding error for the one-minute duration of the recording.

5. CONCLUSIONS

This project report summarizes our implementation of MoViRad, a mobile application that is capable of monitoring breathing and heart rate at no additional hardware cost. At the moment, all the data processing are conducted off-line using MATLAB. Additionally, our data processing assumes the approximate location of the user a priori in order to extract the breathing and heartbeat signals. Accuracy rates of over 90% are shown for heartbeat detection, and over 85% for breathing using COTS hardware.

For future work, we encourage readers to investigate "real-time" processing of the data collected. We note due to the low frequency of breathing, what would otherwise be considered severe latency is acceptable. Furthermore, based on previous work done using distributed FMCW [3], we believe it is possible to integrate the functionality such that MoViRad is able to detect the user location, even if the user is moving. This would require more careful analysis of the phase extraction methodology, as a simple linear analysis fails when the user moves between FFT bins. Lastly, we note that many phones have multiple microphones in order to mitigate background noise during phone and video calls. If the distance between the microphones is known, static objects could be calibrated out similar to a MIMO interface. This would significantly reduce the amount of noise in the FFT spectrum due to skirting caused by near-field signals, which should in turn lead to higher accuracies.

6. ACKNOWLEDGMENTS

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