MULTI-TARGET ESTIMATION OF HEART AND RESPIRATION RATES USING ULTRA WIDEBAND SENSORS

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ABSTRACT

Vital-signs monitoring devices continue to utilize invasive sensing methodologies, ranging from skin surface contact techniques such as the use of electrodes for measuring cardiac signals (ECG test), to more intrusive techniques such as the utilization of a facial mask for measuring gas exchange during respiration. In this paper, we present a wireless radar technique based on ultra-wideband (UWB) technology for non-invasive monitoring of heart and respiration rates. Our technique is based on the detection of chest-cavity motion through the measurement of UWB signal displacements due to this motion. We show that the technique provides accurate results even in the presence of multiple subjects. Specifically, we investigate the two techniques for estimating breathing and heart rates in the presence of multiple subjects: (1) the use of clustering algorithms to isolate the combined position and breathing/heart rate of multiple subjects and (2) the use of MUSIC to accurately estimate only the rates. Results are based on measurements from experiments with multiple subjects in a laboratory setting.

1. INTRODUCTION

Our motivation in using wireless sensing techniques based on UWB technology to detect vital signs has primarily to do with three areas of application: health care, emergency rescue operations, and security.

In medicine and related fields, heart and respiration rates have been monitored for more than a century to aid in the diagnosis of pathological conditions. However, as technology continues to develop, medical devices are becoming more and more complex for medical personnel and sometimes painful to patients. Today, modern heart and respiration rate monitoring devices come in various shapes and sizes; however, these devices can only perform monitoring and diagnostic functions for one patient at a time [1]. Furthermore, as the patient's health condition becomes more critical, the number of configuration setups for monitoring the patient's physiological variables increases, as does the difficulty of managing the patient's data. Acquiring vital signs, such as heart and respiratory rates, using wireless devices will reduce some of these complexities. Likewise, applying the same monitoring idea for multiple patients located within a few meters of each other, and monitoring their vital signs independently, will help reduce the cost of health care by reducing the number of medical devices being used per patient.

The utilization of UWB in health applications was briefly investigated in [2], who studied the advantage of UWB signals' high spatial resolution for capturing reflections caused by significant body motion. Moreover, he illustrated that the coefficient of reflectivity of air-to-dry-skin interface for electromagnetic waves in the range of 300-900 MHz is about 72%. As a result, he showed in a UWB radar setup that the motion of a human body can produce significant changes in the multipath profile. Later, we demonstrated the efficacy of this approach in our own work [3],[4]. UWB-based respiratory monitoring was also examined in [5].

In addition to the potential use of UWB monitoring in healthcare, the same technique can be applied to emergency rescue situations, particularly to the problem of triage when victims are trapped under debris. In such a case the technology described can be used to detect a trapped victim's physical condition and accurately determine their location very quickly. In a similar manner, UWB monitoring can be applied (among many applications) to (1) through-the-wall health and location monitoring of victims in hostage-rescue situations, (2) detection of skiers trapped under snow after an avalanche, (3) vital-signs monitoring for lie-detector tests and (4) athletic performance monitoring [6].

For security applications, UWB monitoring can be applied to aid in the physiological detection of deception (PDD). In order to assess the truthfulness of a person's statements, PDD includes various physiological examinations such as blood pressure, thoracic respiration, brain/neurological signal responses, heart electrical activity, [7], [8], [9], [10], to name a few. We believe that by incorporating UWB monitoring in PDD assessment, examination time and monetary cost could be reduced. Also this can be applied in other applications such as airport security, customs/immigration, and military checkpoints.

The problem of non-invasive detection and estimation of respiration frequency has been previously studied in several contexts, specifically, the use of microwave Doppler radar [11, 12] and the development of motion target algorithms for the detection of respiratory and circulatory movements [13]. However, no specific device or method has been implemented for practical use (to the best of our knowledge) possibly because microwave Doppler radars lack the ability to provide material penetration. On the other hand, one of the main advantages of UWB is the potential to propagate through objects, thereby providing improved coverage and the ability to perform through-the-wall measurements. Thus, our goal is to present a consolidated analysis of easily implemented signal processing algorithms with results that demonstrate the capabilities of UWB monitoring for the detection of respiration and heart rates. In the following we first provide a simple overview of the physical movements to be detected due to heart and respiratory action in Section 2. We then describe the measurement set-up and the mathematical approach for breathing and heart rate estimation in Section 3. Section 4 overviews the measurement results including experiemnts with two and three simultaneous subjects. Section 5 concludes this paper.

2. THE PHYSIOLOGY BASICS

The heart is located in the ventral lower part of the mediastium, and is partially juxtaposed in the diaphragm. Since the heart lies adjacent to the lungs, it alters its position with the movement of the diaphragm, the rib-cage and the lungs [14]. The rhythmic nature of the heart action is due to the generation and conduction of excitation signals originating at the sinoatrial node (SA node) located in the right atrial wall. After atrial contraction, the signals travel from the SA node down through conduction pathways that terminate in the walls of the ventricles causing major muscle contraction. This phenomenon represents the heart's electrical activity [15], [16], which can be recorded by an electrocardiogram (ECG). The ECG consists of placing electrodes on the chest, arms, and legs and recording the heart's electrical activity, which is represented by the P, QRS complex, and T waveforms. The heart rate is then measured by amplifying the ECG signal and measuring either the average or instantaneous time interval between two successive R peaks. Thus, by converting the R wave into a pulse of fixed amplitude and duration, and then determining the current average from these pulses, the heart rate is typically computed. By contrast in the approach investigated here, we use the physical displacement of the heart as measured by a sequence of UWB pulses in order to estimate heart rate.

The mechanics of breathing consist of the movement of the diaphragm and associated muscles, the rib-cage and associated musculature and the characteristics of the lungs themselves. The muscular action controls breathing and it causes the volume of the lungs to increase and decrease in order to regulate the content of carbon dioxide in the arterial blood [17]. Currently, there are various methods used to assess the function of each breathing mechanism component, however no single device can accurately evaluate the overall performance of breathing [1]. Some common methods used for breathing detection are: (1) the displacement method, which consists of wearing a chest wrap with adhesive sensors attached to it, (2) the thermistor method, which requires a facial mask for measuring respiration heat, (3) the impedance pneumography test, which attaches electrodes on the surface of the skin and measures chest movement, and (4) the CO_2 method, which consists of a continuous measurement of expired air and the utilization of infrared rays [14]. From the described methods, we observe that these are relatively invasive techniques, leading us to believe that UWB monitoring can be a solution for assessing respiration rate non-invasively, provided that the accuracy is similar to existing techniques.

3. MEASUREMENT SETUP

The basic measurement setup is shown in Figure 1. In our experiments we used TEM horn antennas for transmitting and receiving, which we placed one meter apart from each other and a meter away from the subject. Note that the subject can be facing the antennas directly or be located behind an obstruction such as a wall. The transmit antenna is connected to a pulser with a Pulse-Repetition Frequency (PRF) of 100 kHz which generates pulses with a width of 300 picoseconds. The pulser also triggers a digital oscilloscope (Tektronix TDS694C real-time scope) that is connected to the receive antenna. The oscilloscope averages $N_a = 100$ received multipath profiles to improve the signal-to-noise-ratio (SNR) and stores the averaged waveforms. The time-resolution δ_τ for measuring the received waveforms is 25 picoseconds where each recorded profile is $\tau_{max} = 50$ ns long. This implies that each waveform comprises $N_s = \frac{\tau_{max}}{\delta_\tau} = 2000$ sample points.

The time-axis along each received waveform is termed "fast-time" and denoted by τ, which is typically on the order of picoseconds, whereas the time-axis of all recorded waveforms is termed "slow-time" and denoted by t, which is the total monitoring time in seconds [3]. The time interval between each successive received (or averaged) waveform is $T_s = 0.1$ seconds and the total monitoring time is $T_{meas} = 70$ seconds thus, the number of recorded waveforms is $N_w = \frac{T_{meas}}{T_s} = 700$. Furthermore, the sampling frequency in slow-time is defined as $F_s = \frac{1}{T_s} = 10$Hz and the sampling frequency in fast-time is $R = \frac{1}{\delta_\tau} = 40$ GHz.

For accurate representation of each recorded waveform $r(t,\tau)$ by its time sampled $r(nT,\tau)$, two conditions must be met: (1) the waveform $r(t,\tau)$ must be band-limited, that is, its frequency spectrum must be limited by some maximum frequency, say f_{max}, and (2) the sampling rate f_s must be chosen to be at least twice the maximum frequency f_{max}. Thus by the Nyquist rate, the minimum sampling rate allowed is $f_s = 2f_{max}$. Applying these concepts in environments where patient monitoring is necessary, where the respiration frequency is normally lower than 30 breaths per minute (0.5 Hz) and the heart rate less than 120 beats per minute (2 Hz), the calculated slow-time sampling frequency F_s satisfies these two conditions.

3.1 Mathematical Analysis

Let us assume that the transmitter and receiver are respectively located at coordinate vectors $\mathbf{x}_t$ and $\mathbf{x}_r$. Further, we assume that the nominal location of the air-skin interface of the chest cavity of the subject is $\mathbf{x}_l$. Therefore, the multipath component arriving at the receiver after reflection at the chest cavity of the subject travels a nominal distance

$$d_0 = \|\mathbf{x}_l - \mathbf{x}_t\| + \|\mathbf{x}_r - \mathbf{x}_l\| \tag{1}$$

However, due to respiration, the chest cavity expands and contracts periodically (under normal conditions), and the distance traveled by the corresponding multipath component $d_l(t)$ also varies periodically about the nominal distance:

$$d_l(t) = d_0 + g(t) \tag{2}$$

Assuming that the change in tidal volume and the displacement of the chest cavity is a sinusoidal function of time, and

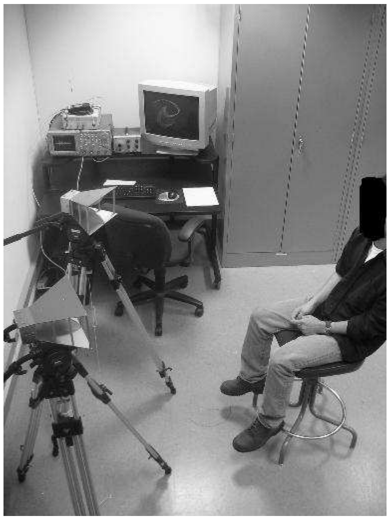

Figure 1: Measurement Setup

the distance traveled by the corresponding multipath component also varies periodically about the nominal distance with a period dependent on the respiration rate f_b:

$$d_l(t) = d_0 + g(t) = d_0 + \Delta_d \sin 2\pi f_b t \tag{3}$$

where Δ_d represents the maximum deviation in the distance traveled by the relevant multipath component. With the assumption that the environment (besides the subject) is *static*, this movement is manifested in a time-varying channel impulse response $h(t,\tau)$:

$$h(t,\tau) = \underbrace{\sum_i \alpha_i \delta(\tau - \tau_i)}_{\textit{static channel}} + \underbrace{\alpha_b \delta(\tau - \tau_b(t))}_{\textit{respiratory variations}}, \tag{4}$$

where t and τ denote the fast and slow times respectively. Note that the direct coupling between the antennas was observed to be the strongest and earliest-arriving multipath component. In the above equation $\tau_b(t)$, termed the "breathing signal" is given by

$$\tau_b(t) = \frac{d_l(t)}{c} = \frac{d_0 + \Delta_d \sin 2\pi f_b t}{c} = \tau_0 + \tau_d \sin 2\pi f_b t \tag{5}$$

where c is the speed of light in air. Neglecting pulse-distortion and other non-linear effects, the signal measured by the receive antenna can be written as the convolution of the transmit pulse and the channel impulse response. Ignoring noise, the received signal measured at slow-time t can be written as:

$$\begin{aligned} r(t,\tau) &= p(t) \star h(t,\tau) \\ &= \sum_i \alpha_i p(\tau - \tau_i) + \alpha_b p(\tau - \tau_b(t)) \end{aligned} \tag{6}$$

Therefore, we are measuring the received waveforms at discrete instants in slow time $t = mT_s$, $(m = 1, 2, \cdots, N_w)$

$$r(mT_s, \tau) = \sum_i \alpha_i p(\tau - \tau_i) + \alpha_b p(\tau - \tau_b(mT_s)).$$

We store N_w discrete-time sequences resulting from the sampling of the received signals which can be expressed as

$$r[m,n] = \sum_i \alpha_i p(n\delta_\tau - \tau_i) + \alpha_b p(n\delta_\tau - \tau_b(mT_s)) \tag{7}$$

These values are stored in a $(N_w \times N_s)$ matrix $\mathbf{R} = \{r[m,n]\}$, $1 \leq m \leq N_w$, $1 \leq n \leq N_s$. A row of the matrix $\mathbf{R}$, denoted by $\mathbf{r}_i$, $1 \leq i \leq N_w$ represents the samples corresponding to the ith received waveform.

In order to extract respiration frequency information from this data, we first eliminate "background clutter", i.e., all signal components derived from other objects that are not related to respiration motion. If we assume that the propagation environment is static, and the only motion present is that of the subject's chest-cavity, then the background clutter consists of multipath corresponding to stationary scatterers in the multipath environment. Since we would like to separate moving scatterers from stationary scatterers, we apply a "motion-filter" to the received signals so that the stationary components are removed. In order to accomplish this, we first average all the received waveforms (rows) in the matrix $\mathbf{R}$ and then subtract this metric from each individual row in the matrix. The averaging of all rows captures all the "constant" features across slow-time and subtracting this from each row results in a set of signals due to the changes in the multipath profile(i.e. the variation due to the motion of scatters). For further detailed mathematical analysis of the motion-filtered data, the reader should refer to [3]. Following the motion filter step, we compute the energy content of all filtered waveforms and identify the fast-time bin indices where the most significant energy is contained. In order to determine the respiration and heart rate frequencies we further process the matrix $\mathbf{R}$ using two techniques: (1) cluster identification using a k-means classifier and (2) frequency estimation using MUSIC. However, before this step the data must be filtered based on the vital sign being monitored. Specifically, when estimating breathing rate, the data must be low-pass filtered below 1Hz. For heart-rate data, a band-pass filter is applied between 1-2Hz.

3.2 Frequency Estimation Analysis

In the clustering technique, after computing the indices where the most significant energy is contained, we compute the Discrete Fourier Transform (DFT) along slow-time at each fast-time bin index and find the respective maximum frequency values. This provides a maximum likelihood estimate of the breathing rate assuming sinusoidal breathing variation. The resulting frequencies and position (i.e., bin) values are placed in a new matrix, which is then feed into the k-means classifier for frequency/position cluster classification. The k-means classifier partitions the matrix into k clusters (in the case of two-person monitoring, k=2) and computes the mean for each vector column in the matrix. The resulting means are labeled centroids and these form the center of the each cluster. The iterative classifier algorithm minimizes the sum of distances over all clusters using the squared Euclidian distances of all frequencies to their respective centroids. As a result, the clustering algorithm allows the combined estimation of the position and frequency.

Our second approach allows for estimation of frequency only. In this approach we proceed by using the significant energy bin indices to construct a slow-time matrix containing only the significant motion. The resulting slow-time matrix is of size m-by-n, where m (i.e. # of rows) is the length of indices where most of the motion energy is contained and n (i.e. # of columns) is the length of averaged recorded waveforms. The data matrix is used to estimate the temporal correlation matrix of the received data. We then apply the MUtiple SIgnal Classification method (MUSIC) technique [20] to the correlation matrix to determine the heart or breathing frequencies of each subject. Results for both estimation techniques are given in the following section.

4. RESULTS

A summary of two experiments for breathing rate analysis is displayed in Table 1. Specifically, the table displays the directly measured breathing rates (the number of breaths divided by the monitoring time T_{meas}) and the estimated frequencies, which are calculated using either the clustering technique based on the k-means classifier (shown in Figures 2 and 3) or the technique based on MUSIC (shown in Figures 4 and 5). The two experiments had two or three subjects situated as shown in the top illustrations of Figure fig:allscenarios.

In the clustering estimation technique, we identified the most populated clusters each of which correspond to the respiration frequency of one subject. This can be seen graphically in Figure 2 and Figure 3 for the cases of monitoring two and three persons respectively. Note that the subjects are located within 0.5 meters of each other. Similarly in the frequency estimation based on MUSIC, we can clearly distinguish the presence of multiple peaks as shown in Figure 4 for the case of two subjects and Figure 5 for the case of three subjects. These peaks can be identified as the individual breathing rate estimates. The estimates, which are summarized in Table 1, are shown to be fairly accurate with errors ranging from 2% to as high as 15%.

In the same manner, the two methods were applied to heart rate estimation as shown in Figures 7,8, 9, and 10. The results are summarized in Table tab:results2 and the exact measurement scenarios are depicted in the lower part of Figure fig:allscenarios. The accuracy is slighlty worse than the breathing rate estimation due to the lower signal-to-noise ratio of the heart reflections. Nonetheless, the estimated rates are well within 10% of the measured heart rates.

Table 1: **Measured and Estimated Respiration Frequencies**

Exp. #	Person #	Dist. to Rx (m)	Directly measured Freq. (Hz)	Cluster estimated Freq. (Hz)	MUSIC estimated Freq. (Hz)
1	1	1.25	0.31	0.30	0.30
	2	1.52	0.28	0.26	0.28
2	1	1.25	0.35	0.30	0.29
	2	1.03	0.22	0.23	0.24
	3	1.68	0.43	0.42	0.42

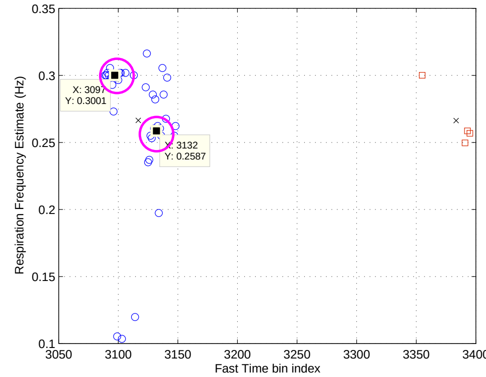

Figure 2: Respiration frequency estimation for two-person using clustering method.

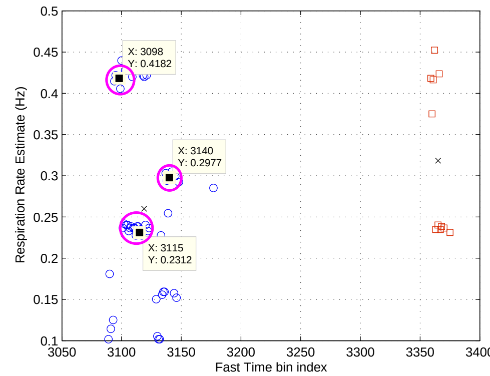

Figure 3: Respiration frequency estimation for three-person using clustering method.

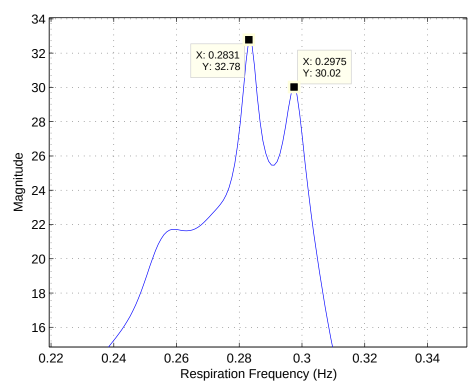

Figure 4: Respiration frequency estimation for two-person using MUSIC method.

5. CONCLUSIONS

In this paper we have presented a UWB-based monitoring technique for non-invasive detection of respiratory and heart rates for multiple subjects located within a few meters of each other. A framework for the analysis as well as the development of signal processing techniques was described.

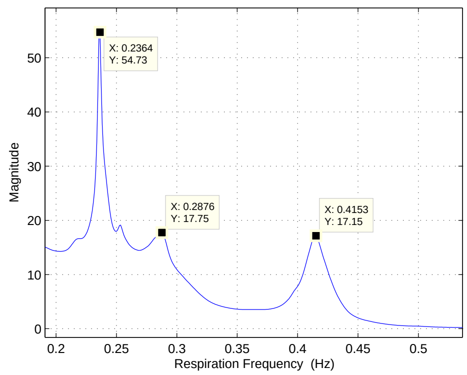

Figure 5: Respiration frequency estimation for three-person using MUSIC method.

Table 2: **Measured and Estimated Heart Frequencies**

Exp. #	Person #	Dist. to Rx (m)	Directly measured Freq. (Hz)	Cluster estimated Freq. (Hz)	MUSIC estimated Freq. (Hz)
1	1	1.80	1.20	1.25	1.24
	2	2.00	1.07	1.18	1.00
2	1	1.56	1.20	1.12	1.20
	2	1.20	1.27	1.21	1.33
	3	2.25	1.33	1.28	1.38

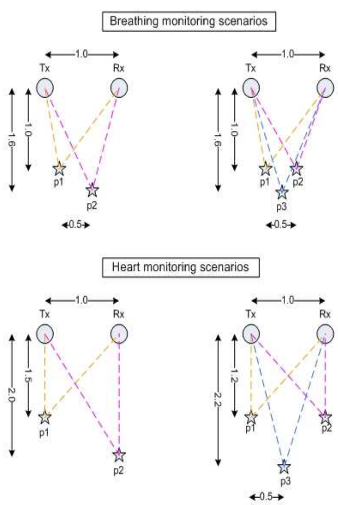

Figure 6: Scenario setups for two-person and three-person monitoring

Also, it was demonstrated via measurements in a laboratory setting, that the respiration and heart rates can be accurately estimated using this concept in various scenarios using two different techniques. Furthermore, we have previously shown that the monitoring of respiration rate can be performed through walls and therefore the same concept can be applied to multi-target monitoring for non-invasive detection.

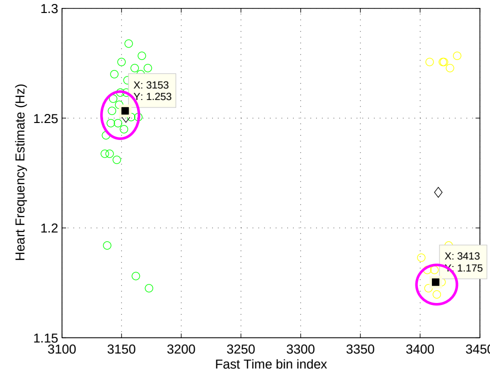

Figure 7: Heart frequency estimation for a two-person scenario using the clustering method

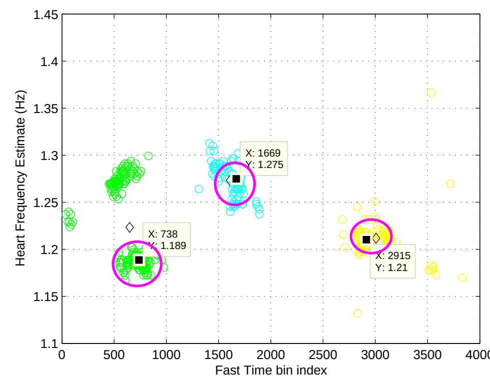

Figure 8: Heart frequency estimation for a three-person scenario using the clustering method

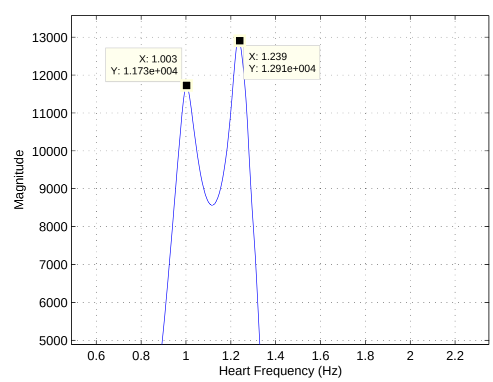

Figure 9: Heart frequency estimation for a two-person scenario using MUSIC

Future challenges include the detection of irregular breathing and heart patterns and increasing the accuracy with a limited measurement duration.

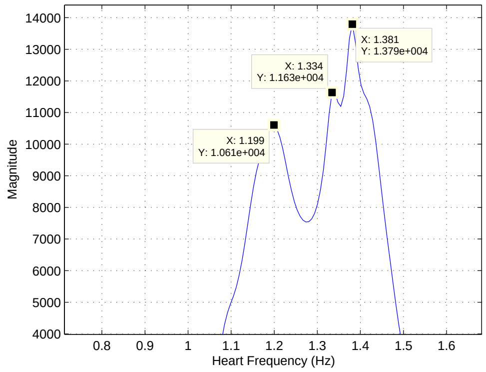

Figure 10: Heart frequency estimation for a three-person scenario using MUSIC

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