Contactless Respiration Rate Estimation Using MUSIC Algorithm

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Abstract

In some diseases (sleep apnea, sudden infant death syndrome etc.), continuous monitoring of respiration rate of patient at home during sleep is critically important. Nowadays wireless communications signals are widely used in our homes. In this paper, we propose a contactless respiration monitoring system which uses only ambient wireless communications signals to estimate the respiration rate of a person. Laboratory experiments show that the strentgh of the received radio frequency (RF) signals changes due to inhaling/exhaling of a person between the propagation path of the transmitter and the receiver. In this study, a subspace based MUSIC algorithm is proposed to estimate the respiration rate of a person using ambient wireless signals. It is shown in various laboratory experiments, where real data is collected with software defined radios, the MUSIC algorithm can successfully estimate the respiration rate with minimum error compared to the FFT-based Maximum Likelihood Estimation (MLE) approach.

1. Introduction

The respiration (breathing) rate is a vital sign used to monitor a person's illness/medical conditions. Non-normal respiration rate can be a sign of serious diseases. For example, sleep apnea, sudden infant death syndrome (SIDS) and chronic obstructive pulmonary disease (COPD) are some imported ones. In all these diseases, continuously monitoring respiration rate can be life saving. Existing respiration rate estimation methods can be categorized into two groups: contact-based and contactless. In contact-based respiration monitoring, the measuring devices are directly connected to the human body [1]. This method is preferred in clinical environments and the capnometers are commonly used to measure and display the concentration of carbon dioxide in exhaled air. Patients must wear a mask or nasal cannula while using the capnometers. Besides, photoplethysmography (PPG) which makes measurements at the surface of the skin, is used to detect volumetric changes in blood. In non-clinical environment, some wearable sensors based solutions have emerged. For example, microphones are used to collect and analyze the voices that are due to respiration. Besides, accelerometers are used to catch chest and abdomen movements. To monitor respiration rate, pressure sensors based systems are usually used in the form of a smart sleeping mat. In all these systems some special sensing modules are required which limits mobility and comfort of the patients and this is not suitable for long-term and remote patient monitoring.

Contactless respiration monitoring methods have been developed to remove these adverse effects on patients. In contrast to wearable sensors, no measuring device or sensor is connected to the human body in contactless monitoring. Vision-based methods utilize cameras to track the movements of one's chest to measure the exact respiration rate. But, these methods are not suitable for working in low-light sleeping environments and also violate the privacy of users. In recent years, electromagnetic Radio Frequency (RF) signals are started to be considered in order to sense the respiration activity. When RF signals are propagated between the transmitter and receiver, they are affected by chest movements due to respiration over the propagation path. Under this category, Doppler based, ultra-wideband radar-based [2, 3] methods are available. These are known as active radar based methods.

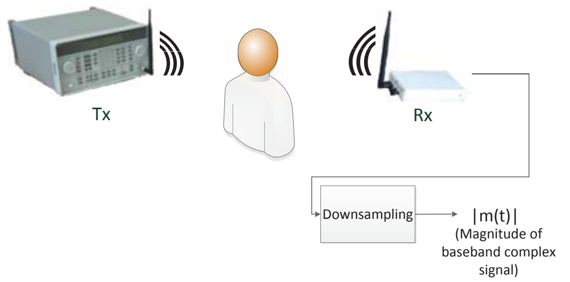

Figure 1. Contactless respiration monitoring setup.

In this study, passive RF based contactless respiration monitoring system with a subspace based rate estimation algorithm is proposed. The proposed method uses wireless communications signals (ambient RF signals) such as phase or frequency modulated signals with constant signal strength as shown in Fig. 1. It is known that RF signals strength at the receiver is changing with the movement of objects which are between the propagation path of the transmitter and receiver. We observed in laboratory that receiver signal strength changes due to inhaling/exhaling of the person which makes it possible to estimate respiration rate. In this study, MUltiple SIgnal Classification (MUSIC) [4] algorithm is firstly applied for respiration rate estimation for the proposed system. The results which are obtained by real measurements are compared with MUSIC and Maximum Likelihood Estimation (MLE) algorithm [5]. It is shown with various cases that the proposed method outperforms the MLE method with a stable and reliable respiration rate estimation results.

2. Related Works

In general, Wi-Fi and radio signals are used for human activity detection and monitoring in some studies. In these studies, different signal parameters such as Received Signal Strength (RSS), Channel State Information (CSI) are used. RSS and CSI give some information how an RF signal propagate from the TX(s) to the RX(s) and reveals the combined effect of, for instance, scattering, fading, and power decay with distance [6]. CSI involves both subcarrier phase and amplitude information. On the other hand, RSS only gives amplitude information. It is also possible to collect the complex raw signal samples with a Software Defined Radio (SDR) platform. In this case, it is possible to get high resolution/rate over the propagation path.

In this study, SDR platform based system is proposed. The proposed SDR platform based approach can be applied to any RF signals, on the other hand, CSI and RSS based approaches can only be applied to some specific signals (Wi-Fi signals). Since SDR platform does not have any limitation about frequency selection, bandwidth and transmission mode, the current system can be applicable to any kind of signals.

In [5], they have utilized RSS measurements taken from many links in a deployed twenty-device wireless network. In order to estimate the respiration rate, maximum likelihood estimation have been used. They showed that 30 seconds of data is sufficient to frequency estimation, within 0.07 to 0.42 breaths per minute (bpm) RMS error. They also showed that the using directional antennas improves the system performance. In [6], they proposed a new respiratory monitoring system using off-the-shelf Wi-Fi devices. They utilized CSI data to overcome hard conditions like change of sleeping positions, sleep apnea. They computed the Fast Fourier Transform (FFT) of the amplitude of signal segments and the location of the peaks of the FFT in each segment gave the respiration rate of the breathing person. In [7], they used RSS measurements of a single COTS TX-RX pair. They achieved mean absolute error of 0.12 bpm. They also used maximum likelihood estimation to estimate respiration rate. They proposed to hinder the effect of external motions. Therefore, the Hidden Markov Model (HMM) was used to identify the motion interference. In [8], they utilized a radar technique called as Frequency Modulated Continuous Wave (FMCW) to monitor the respiratory. They proposed a method that respiration frequency can be accurately measured by performing a linear regression on the phase of the complex time-domain signal. They filtered the output of the FFT and kept only the peak and its two adjacent samples. Then, they have implemented inverse FFT. The phase of the obtained complex time-domain signal will be linear and its slope gave the respiratory frequency (rate). In [9], two USRP were used one for the transmitting and one for the receiving the wireless signal at 2.4 GHz. They proposed four different algorithms to estimate the respiration rate, which are zero-crossing, FFT maximum selection, linear predictive coding, least squares harmonic analysis. Then a final algorithm dynamically combines and selects the results from all four algorithms.

3. Respiration Rate (RR) Estimation System

3.1. Impact of Moving Objects' Movements to RF Signals Propagation

It is observed in the laboratory that the RF signal amplitude changes due to the inhaling/exhaling of the person which is on the propagation path as shown in Fig. 2. The person sitting on the chair in Fig. 2, holds his breath (after exhalation) between the 22^{nd} and 35^{th} seconds. Then he continues to breathing until 43^{rd} second. Afterwards, he holds his breath again (after inhalation) between the 43^{rd} and 55^{th} seconds. Fig. 3 shows the received baseband signals power level in SDR platform for the above scenario. The received RF signal's amplitude level changes with inhaling/exhaling of the person and this causes a periodicity on the received signal due to the respiratory movements. Even though the received signal is affected by the ambient noise, it preserves its periodic structure. The respiration monitoring methods estimate the respiration rate taking advantage of periodicity of the received signal.

Figure 2. Experimental setup in laboratory.

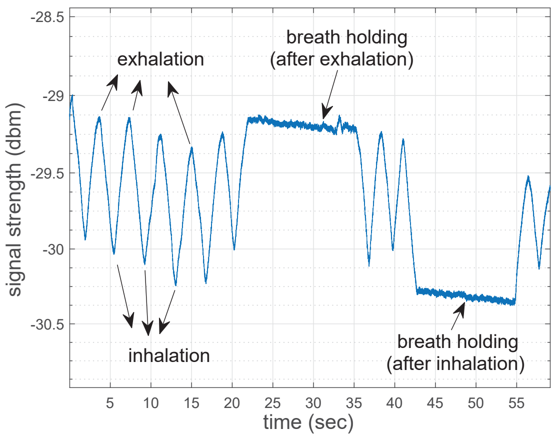

Figure 3. The effect of the exhalation, inhalation and breath holding to the received signal.

3.2. Experimental Setup

In our work, the HP 8647A signal generator is used to generate a continuous wave signal at 900 MHz as the transmitter. Ettus USRP B210 software defined radio is configured as a receiver. USRP (Universal Software Radio Peripheral) is an SDR platform developed by Ettus Research. The experimental setup established for the measurements is shown in Fig. 2. A 900 MHz carrier signal with constant amplitude is generated from the transmitter. The power of transmitted signal is adjusted as

-10 dbm. VERT900 omni-directional vertical antenna with 3 dBi gain is used as an antenna in both transmitter and receiver.

3.3. Measurement Model

Transmission path between the transmitter and receiver is shown in Fig. 1. It is assumed that the transmitted signal is a phase or frequency modulated signal with a constant peak amplitude which is a reasonable assumption for wireless communication signals. In this case, the averaged received signal strength should be constant during communications. On the other hand, the respiration of a person on the propagation path of the signal (as shown in Fig. 1 and Fig. 2) will change the amplitude level of the received signal which is also observed in literature [5, 6]. If there is no movement between transmitter and receiver, the received signal's averaged amplitude should be,

$$r(t) = |m(t)| = \mu + w(t) \tag{1}$$

where μ is the mean of received signal, w is assumed additive zero-mean noise signal. If a breathing person exists in the environment, the magnitude of the baseband complex signal can be modelled as follows,

$$r(t) = \mu + x(t) + w(t) \tag{2}$$

$$x(t) = A_c cos(2\pi f_R t + \phi) \tag{3}$$

A_c, f_R, ϕ are the amplitude, respiration frequency (rate) and phase, respectively. Since respiration requires a periodic action in the form of inhaling and exhaling the cosine model in (3) is suitable to model respiration. Then the respiration rate estimation is the frequency estimation (f_R) of the baseband received signal.

4. Respiration Rate (RR) Estimation

In order to make the respiration rate estimation algorithm properly with real measurements, some pre-processing steps are required. In this section, the basic pre-processing steps such as Outlier Removal, DC Removal and Downsampling are briefly summarized.

4.1. Pre-Processing Steps

4.1.1. Outlier Removal

In some cases, deviations that are not induced by respiratory movements are observed on the received signal. This deviations are called as outliers. In Fig. 4, the outliers can be seen that near 8, 10, 38, 46, 55 and 59 sec. If this signal is used as input to the respiration rate estimation system, the results will be incorrect. So, the outliers must be eliminated. For this purpose, the well known Hampel identifier is used [10]. Hampel identifier calculates the median (μ) and standard deviation (σ) of the samples in the measurement window. Then, it determines an upper and lower bound using μ and σ. Upper and lower bounds are set to $\mu + 3\sigma$ and $\mu - 3\sigma$, respectively. A new sample which is out of these bounds is qualified as outlier. The outliers are detected and removed from the original signal as seen from the Fig. 4.

4.1.2. Downsampling

The received signal is sampled by the USRP at 1200 Hz. Since the respiration rate is below 1 Hz, high sampling rate makes difficult to distinguish the respiration signal in the frequency spectrum. Moreover, high sampling rate increases the computational cost. Due to these reasons, the received signal is downsampled without distorting its waveform and periodic form. After downsampling, the sampling rate of the received signal is reduced to 1 Hz.

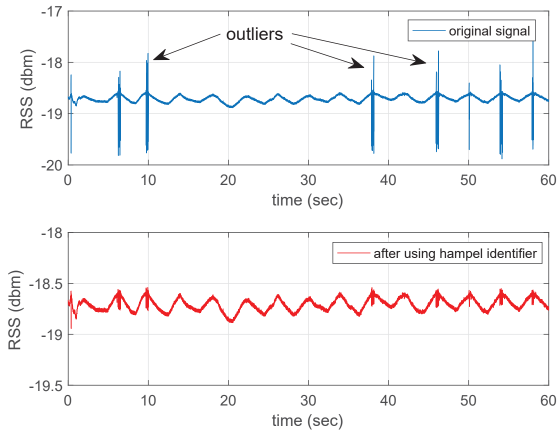

Figure 4. (*Top*) The original signal with outliers. (*Bottom*) The signal whose outliers are removed using Hampel identifier.

4.1.3. DC Removal

When the spectral analysis is carried out, it is seen that the first component of the signal in frequency domain contains high energy. This DC component that is the average value of the signal in frequency domain suppresses the other frequency components. Besides, DC component does not contain any information about the respiration. For removing the DC component from signal, the average value is subtracted from entire signal. After DC removal process, the component at 0 Hz is removed from the frequency spectrum of the signal.

$$y(t) = r(t) - \mu \tag{4}$$

where μ is the average amplitude of the received signal and $y(t)$ is the output of the DC removal system.

4.2. MUSIC Algorithm

In this part, we consider the estimation of the respiration rate using Multiple Signal Classification (MUSIC) algorithm which is a subspace based estimation method [4]. MUSIC algorithm is commonly used to estimate the direction of arrival of signals. MUSIC is a super-resolution technique and since it works by separating signal and noise subspace and estimates the frequency more accurate than sample windowed FFT based methods.

Firstly, the covariance matrix model is introduced. A notation that will often be used in the following is:

$$\mathbf{a}(f) = [1 \;\; e^{-j2\pi f} ... \; e^{-j(m-1)2\pi f}]^T \qquad (m \times 1)$$

$$\mathbf{A} = [\mathbf{a}(f_1) \;\; ... \;\; \mathbf{a}(f_n)] \qquad (m \times n) \tag{5}$$

where m is a positive integer which is number of samples in the sequence. n is the number of unknown sinusoidal component. It is assumed that n is known. If we collect m samples in a vector as,

$$\tilde{\mathbf{y}}(t) = \begin{bmatrix} y(t) \\ y(t-1) \\ \vdots \\ y(t-m+1) \end{bmatrix} = \mathbf{A}\tilde{x}(t) + \tilde{\mathbf{w}}(t) \tag{6}$$

The covariance matrix of $\tilde{\mathbf{y}}(t)$ is defined as,

$$\mathbf{R} = E\{\tilde{\mathbf{y}}(t)\tilde{\mathbf{y}}^*(t)\} \tag{7}$$

MUSIC is derived from the covariance model in (7) with $m > n$. The eigenvalues of $\mathbf{R}$ matrix are obtained as $\lambda_1 \geq \lambda_2 \geq ... \geq \lambda_m$ and $\{s_1, ..., s_n\}$ is a set of orthonormal eigenvectors corresponding to $\{\lambda_1, ..., \lambda_n\}$ and $\{g_1, ..., g_{m-n}\}$ are the orthonormal eigenvectors associated with $\{\lambda_{n+1}, ..., \lambda_m\}$. The eigenvectors of $\mathbf{R}$ can be divided into two subsets as signal and noise eigenvectors as shown in the following,

$$\mathbf{S} = [\mathbf{s}_1, ..., \mathbf{s}_n]_{(m \times n)}, \qquad \mathbf{G} = [\mathbf{g}_1, ..., \mathbf{g}_{m-n}]_{(m \times (m-n))} \tag{8}$$

where $\mathbf{S}$ and $\mathbf{G}$ denote signal and noise eigenvectors, respectively. The noise subspace $\mathbf{G}$ is orthogonal to Vandermonde matrix $\mathbf{A}$ which is defined as,

$$\mathbf{A}^*\mathbf{G} = \mathbf{0} \tag{9}$$

where $\mathbf{A}$ is a function of the frequencies $\{f_l\}_{l=1}^{n}$. The columns of $\mathbf{G}$ belong to the null space of $\mathbf{A}$ as shown in (9). The MUSIC algorithm is defined in two steps as follows,

- **Step-1**: Compute the sample covariance matrix

$$\hat{\mathbf{R}} = \frac{1}{N}\sum_{t=m}^{N} \tilde{\mathbf{y}}(t)\tilde{\mathbf{y}}^*(t) \tag{10}$$

  and its eigendecomposition. $\hat{\mathbf{S}}$ and $\hat{\mathbf{G}}$ are the signal and noise eigenvectors obtained from $\hat{\mathbf{R}}$ matrix.

- **Step-2**: Determine respiration frequency estimates as the locations of the n highest peaks of the estimation function

$$\hat{\mathbf{P}}_{music}(f) = \frac{1}{\mathbf{a}^*(f)\hat{\mathbf{G}}\hat{\mathbf{G}}^*\mathbf{a}(f)} \tag{11}$$

In this study, since there is a single patient, the number of sinusoidal signals is assumed to be one ($n = 1$). It is also possible to monitor multiple patients ($n > 1$) with MUSIC algorithm.

4.3. Maximum Likelihood Estimation (MLE)

In [5], MLE of the respiration rate is given as an extension of the classical sinusoid parameter estimation problem. In [5], a respiration rate estimator is proposed which calculates the power spectral density (PSD) using the most recent N samples, estimates the respiration rate as the frequency at the maximum of the PSD. It is a good approximation of the MLE of frequency $\hat{f}_R$ is given by,

$$\hat{f}_R = \underset{f_{min} \leq f \leq f_{max}}{\operatorname{argmax}} \left| \sum_{i=1}^{N} y(i) e^{-j2\pi f T_s i} \right|^2 \tag{12}$$

where T_s is sampling period. This approximation works unless the normalized frequency, fT_s, is very close to 0 or 1/2.

5. Experimental Results

In this part, we design some experiments in laboratory in order to observe the performance of the respiration monitoring system. The measurements were taken for 10 minutes at the position where the participants were sitting on the chair between the receiver and the transmitter antenna as shown in Fig. 2. The distance between the transmitter and the receiver is specified as 2 meters. Our proposed MUSIC based method and FFT-based MLE method in [5] are compared for the different window durations and cases.

In Fig. 5, spectrum estimations of MUSIC algorithm and the MLE based power spectral density (PSD) algorithm are compared. The number of samples (window durations) are selected as $T = 40$ sec for these two algorithm. In this simulation, actual respiration rate is 15 bpm (0.25 Hz). In Fig. 5, the highest peaks of the both spectrums show the respiration rate correctly. It can be seen that MUSIC spectrum has a narrow peak with a higher amplitude.

In Fig. 6, the actual respiration rate was 12 bpm (0.2 Hz) and differently window duration is selected as 10 seconds instead of 40 seconds. In this case, it is shown in figure that the resolution of FFT-based method is quite low, on the other hand MUSIC algorithm has a narrow peak with high gain. In the case of low signal to noise ratio the MUSIC algorithm will be more accurate and robust. Besides, in multiple person case, FFT-based method can not distinguishes different frequencies due to its low resolution.

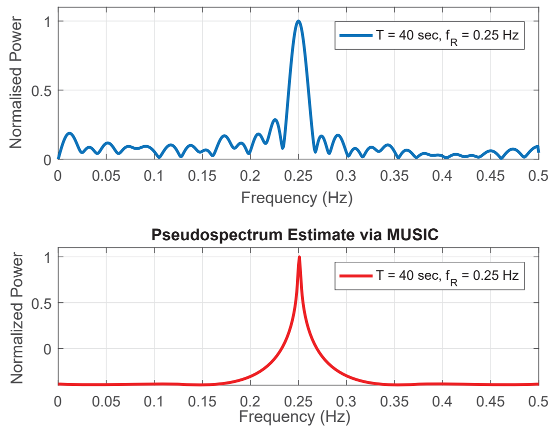

Figure 5. (*Top*) The power spectrum of the FFT-based MLE method. (*Bottom*) Psedospectrum estimation using MUSIC algorithm. In both cases, window duration $T = 40$ sec and actual respiration rate $f_R = 0.25$ Hz (15 bpm).

Fig. 7 shows the performance comparison of the proposed MUSIC based method and the FFT-based MLE method [5]. The Root-Mean-Square-Error (RMSE) of the two methods are shown for different window durations. The window is shifted along the 10 minutes data with 5 seconds intervals for all window durations. It can be seen in the figure, error rates decrease with the increasing of window duration. However, selection of the long window duration reveals some disadvantages. We take the samples from the received signal for a duration T before estimating the respiration rate. So, window duration T is important because it determines the waiting time. Moreover, the long

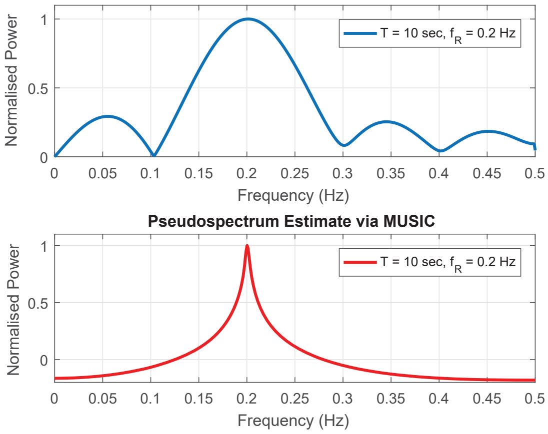

Figure 6. (*Top*) The power spectrum of the FFT-based MLE method. (*Bottom*) Pseudospectrum estimation using MUSIC algorithm. In both cases, window duration $T = 10$ sec and actual respiration rate $f_R = 0.2$ Hz (12 bpm).

window duration causes to miss sudden changes in respiration rate. The proposed MUSIC based method outperforms the FFT-based MLE method for all window durations. As seen from the figure, while the RMSE of the proposed method is lower than 0.2 bpm for all window durations $T \geq 30$ s, the FFT-based method reaches this rate for window durations approximately $T \geq 40$ s. Especially for short window duration ($T < 30$ s), the performance of our proposed method is quite better than the FFT-based MLE method. This is important for the respiration monitoring system requiring low latency.

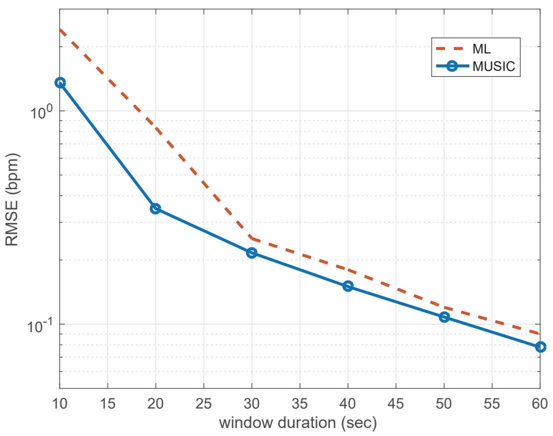

Figure 7. The RMSE of our proposed MUSIC based method and FFT-based MLE method [5] for different window durations.

6. Conclusion

In this paper, the contactless respiration monitoring system which uses subspace based rate estimation algorithm is presented. The respiration of a person on the propagation path of the signal between the transmitter and receiver causes changes in the received signal strength. These changes in the received signal strength are leveraged to estimate the respiration rate of a person. In laboratory, we designed some experiments and we used real measurements to show the performance of the proposed respiration rate estimation method. The proposed system uses complex raw data collected with SDR platform which does not any limitation about frequency selection, bandwidth, etc. The subspace based MUSIC algorithm is firstly applied for respiration monitoring system using wireless communications signals. It is shown with several experiments that the proposed method can estimate the respiration rate of a person with 0.2 bpm RMS error. It is also shown that the proposed method outperforms the MLE method. The performance of the MUSIC algorithm that provides more accurate estimates with low signal strength and limited number of samples is shown through real measurements.

7. References

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