Respiration Monitoring using a Wireless Network with Space and Frequency Diversities

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***Abstract*—Non-invasive respiration monitoring of a person has many human-centric applications. In this paper, we use received signal strength indicator (RSSI) from a wireless network to perform non-contact respiration rate monitoring. We develop a low-cost monitoring system that uses multiple commercial-off-the-shelf (COTS) radios operating on multiple frequency channels. We propose a maximum likelihood estimator (MLE) to estimate respiration rate from RSSI on multiple links and multiple channels. Our experimental results show that the system is more robust to user orientations and postures. The system is over 40% more accurate than previous systems for eight human subject experiments.**

***Index Terms*—Low power wireless, sensing, signal processing**

I. Introduction

Respiration monitoring is an important topic in human-centric applications such as patient monitoring, elder care, and smart facilities. Researchers have been studying various respiration sensing methods, such as airflow sensing, blood gas measurement, movement, volume and tissue composition detection [1]. As wireless devices become more pervasive, a wireless network provides a low-cost way of monitoring human activities such as respiration. In this paper, we study respiration rate monitoring using received signal strength indicator (RSSI) measurements, which are widely available in standard wireless devices.

Recent studies [2], [3] have proposed to use RSSI measurements from wireless devices to estimate a person's respiration rate. However, these systems are not robust to the person's orientations and postures, due to the coarse granularity of the RSSI measurements and also the multipath effects. That is, if a person changes her posture or orientation, the performance of these systems may degrade significantly. In this paper, we propose to improve the robustness of RSSI-based respiration rate monitoring by 1) using a wireless network with wireless nodes deployed at different locations, and 2) using pairwise RSSI on multiple frequency channels.

First, we propose to use a wireless network so that we can use RSSI from multiple links instead of a single link as in [2]. We can see the importance of multiple links from Fig. 1. The RSSI time series from Link 6 has the same signal pattern as the spirometer data, which is recorded as the ground truth of a person's respiration rate. However, Link 3 does not show any periodic changes caused by the respiration motion. Their different sensitivities to motion should be due to the relative locations of the links with respect to the person, and the multipath effects of the environment (the positions of Link 3, Link 6 and the person is shown in Fig. 3). To make a system more robust to changes of user location, orientation and posture, we propose a maximum likelihood estimator to include RSSI from multiple nodes and multiple antennas. That is, we take advantage of the space diversity to mitigate the multipath effects.

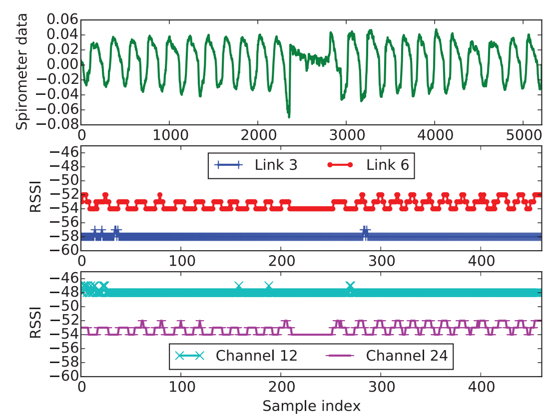

Fig. 1. Spirometer (as ground truth) and RSSI time series from multiple links and channels.

Second, we use RSSI from multiple frequency channels. From Fig. 1, we see that for the same physical link between a transmitter and a receiver, two frequency channels show different sensitivities to the respiration motion. While the RSSI on one channel (Channel 12) does not show much effect from the respiration motion, RSSI on another channel (Channel 24) shows clear periodic changes due to respiration. Note that the person holds her breath for a short time period in the middle of the test, which is clearly shown as flat in the RSSI time series on Channel 24. Since the radio wavelengths are different on different channels, the multipath effects can be very different on multiple channels, even for the same link and person locations. Thus, we use a time division multiple access (TDMA) network protocol to collect RSSI from multiple channels to improve system robustness.

In sum, we aim to improve the robustness of wireless respiration rate monitoring by using frequency and space

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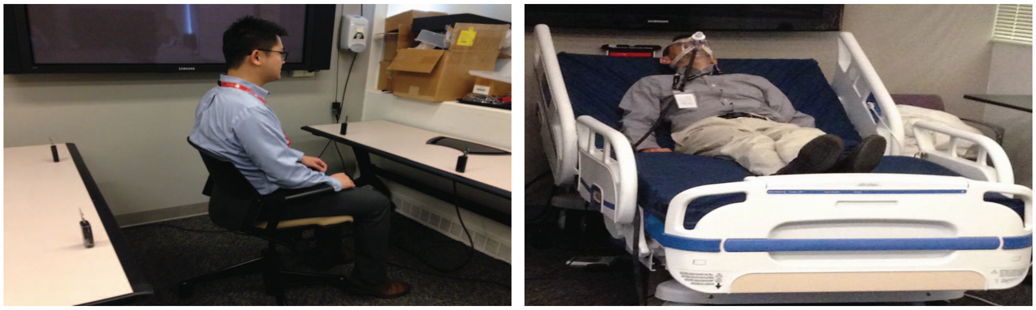

(a) Exp 1.1 (b) Exp 2.1

Fig. 2. Pictures of two sets of experiments (Experiment 1: sitting in chair scenario, Experiment 2: lying on bed scenario).

diversities with low-cost COTS wireless nodes. We propose a maximum likelihood estimator using RSSI from multiple nodes measured at multiple channels in Section II. We present our human subject experiments at different environments and experimental results in Section III. We discuss related work in Section IV, and we conclude in Section V.

II. Method and System

A. Method

We formulate an MLE algorithm using RSSI from multiple frequency channels and multiple links (including multiple antennas). We use $s_{c,l,t}$ to denote RSSI measured from link l on channel c at time t. To capture the periodic changes of RSSI due to respiration, we calculate the RSSI change by removing the averaged RSSI during a time window $t = [0, 1, \cdots, m]$:

$$y_{c,l,t} = s_{c,l,t} - \bar{s}_{c,l,t} \tag{1}$$

where m is the length of the window, and $\bar{s}_{c,l,t} = \frac{1}{m}\sum_{i=0}^{m-1} s_{c,l,t-i}$ is the sample average during this time period.

For a static wireless network with N radio nodes, we have $L = N(N-1)/2$ bidirectional links operating on C frequency channels. Suppose RSSI can be modeled as a periodic signal due to respiration motion, we propose to use the maximum likelihood estimator (MLE) to estimate the respiration rate [4]:

$$\hat{f} = \underset{f_{min} \le f \le f_{max}}{\arg\max} \sum_{l=1}^{L}\sum_{c=1}^{C}\left|\sum_{t=i-m+1}^{i} y_{c,l,t} e^{-j2\pi f T_s t}\right|^2, \tag{2}$$

where i is the current time index, $j = \sqrt{-1}$, m is the window length, and T_s is the sampling period. Note that if each node has M antennas, then we have $L = N(N-1)M^2/2$ bidirectional links. That is, our MLE formulation is a general solution to include both space and frequency diversities.

The above MLE solution is essentially an estimate of the maximum frequency of the power spectral density (PSD) of the RSSI time series. Here we assume the respiration rate remains the same when RSSI is measured from L links and C channels. Thus, the sampling rate of the system needs to be at least twice as high as the respiration rate. We discuss our prototype system and sampling rate next.

B. Testbed System

We choose TI CC2531 USB dongle [5], which operates at 2.4 GHz industrial, scientific and medical (ISM) band, as our wireless node. We use a basestation and a time division multiple access (TDMA) network protocol [6] to collect RSSI from multiple nodes operating on multiple channels. The network protocol allows users to choose the number of nodes and the number of channels according to their applications. In this work, we program four nodes operating on IEEE 802.15.4 Channel 11 to 26. Thus, we have six bidirectional links and 16 channels.

In the protocol, time is divided into three groups: round, cycle and slot. A slot is the smallest time group during which a node is broadcasting on a particular frequency channel while the other nodes are listening the broadcast and measuring the RSSI between themselves and the broadcasting node. After one node finishes broadcasting, the next one takes over, and a cycle is the time that all nodes broadcasts once on a single frequency channel. After a cycle, nodes will start operating on the next channel. When all channels are gone through, a round is complete.

The sampling rate of RSSI from all six links of the network is 53 Hz on a particular channel, which is two orders of magnitude greater than the typical adult respiration rate (12 to 20 breath per minute (BPM)). If we use all 16 channels, the system sampling rate is 3.3 Hz, which is still an order of magnitude greater than ordinary human respiration rate.

III. Experiments and Results

A. Experiments

We perform human subject experiments at typical indoor environments. Our experiments include two common scenarios: a person sitting in a chair and lying on a bed. We call the first scenario Experiment 1, and the second scenario Experiment 2. For Experiment 1, four wireless nodes powered by battery packs are placed on desks, as shown in Fig. 2a. The person sits in a chair and faces different directions in different tests. For Experiment 2, four nodes are attached to the bed frames, as shown in Fig. 2b. The LOS of Link 1 passes through the chest of the person, while the LOS of Link 6 passes through the person's legs. The person held different postures

TABLE I
EXPERIMENT DESCRIPTION.

Experiment	Description
Exp. 1.1	face Link 1 in chair, breathe non-stop for two minutes
Exp. 1.2	face Link 6, hold breath for ten seconds
Exp. 1.3	face Link 2, hold breath for ten seconds
Exp. 1.4	face Link 1, hold breath for ten seconds
Exp. 2.1	face upward on bed, breathe non-stop for two minutes
Exp. 2.2	face left, hold breath for ten seconds
Exp. 2.3	face right, hold breath for ten seconds
Exp. 2.4	face upward, hold breath for ten seconds

in different tests. For each test, we ask the human subjects to wear disposable masks so that we record their respiration rates using a spirometer as the ground truth. For some tests, we ask the participant to hold breath for a short time period in the middle of the test. The description of all eight tests is listed in Table I.

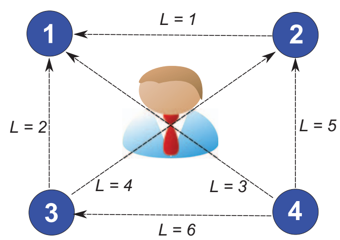

Fig. 3. Experiment layout for Exp 1.2 (person facing Link 6).

Considering human subjects may not breathe constantly during a two-minute test, we define the following validation metric to measure the accuracy of the system. We first calculate the ground truth respiration rate by averaging four detected breaths from the spirometer data. Then, we find the corresponding time windows for the RSSI time series. For each time window, we calculate the respiration rate from RSSI data, and compare it with the ground truth rate. Finally, we calculate the mean absolute error in BPM as:

$$\epsilon = 60\frac{1}{R}\sum_{r=1}^{R}|\hat{f}(r) - \bar{f}|, \quad (3)$$

where R is the number of time windows, and $\bar{f}$ is the ground truth calculated from the spirometer data - the averaged rate from four breaths.

B. Experimental Results

Once we have the validation metric, we run our MLE algorithm to find the peak location of the power spectral density, as our estimate. Then we use (3) to calculate ϵ for all experiments. One PSD example is shown in Fig. 4.

Now we first compare the performance of our multi-link multi-channel system with the single-channel system. For the single-channel system, we use RSSI collected from all six links but only one channel. We list the absolute errors from the single-channel system together with our system in Table II (Channels 11, 15, 20 and 26 are shown as examples). Also listed are the averaged errors across all eight tests and the

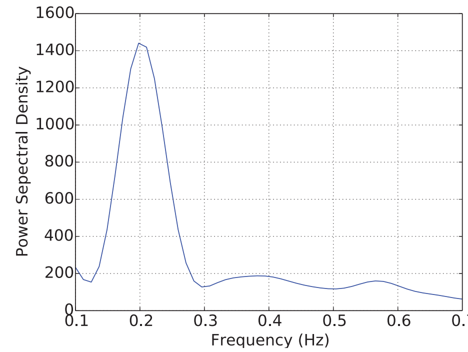

Fig. 4. Power spectral density (PSD) of the RSSI time series (peak location 0.2 Hz is our respiration rate estimate).

improvement from our system. We see that the absolute errors of the single-channel system are much higher than our system in general. For Exp. 1.1, the absolute errors from the single-channel system are all above one BPM, while our system has an error of only 0.36 BPM. We also see that a particular channel can achieve better performance than our system. (Note that we do not find any particular channel that achieves the best performance across all tests.) For example in Exp. 2.1, if Channel 11 is used, the error is 0.37 BPM, slightly better than the 0.6 BPM from our system. However, the errors from our system are all below one BPM, and if we average over all tests, our system outperforms the single-channel system by over 60%.

TABLE II
COMPARISON WITH SINGLE CHANNEL SYSTEM (ABSOLUTE ERROR ϵ IN BPM).

Channel	11	15	20	26	all
Exp. 1.1	1.44	2.96	3.69	2.37	0.36
Exp. 1.2	1.23	2.02	3.09	1.04	0.39
Exp. 1.3	4.66	2.37	3.07	1.14	0.38
Exp. 1.4	1.20	1.42	2.16	2.97	0.88
Exp. 2.1	0.37	3.82	0.93	0.49	0.60
Exp. 2.2	1.57	7.43	0.39	0.22	0.89
Exp. 2.3	1.41	0.52	0.82	5.80	0.49
Exp. 2.4	2.35	3.00	0.84	0.64	0.54
Average	1.78	2.94	1.87	1.83	0.57
Improvement	68.0%	80.6%	69.5%	68.9%	N/A

TABLE III
COMPARISON WITH SINGLE LINK SYSTEM (ABSOLUTE ERROR ϵ IN BPM).

Link	1	2	3	4	5	all
Exp. 1.1	0.36	11.36	0.39	0.30	7.27	0.36
Exp. 1.2	4.09	0.57	0.57	0.57	7.05	0.39
Exp. 1.3	3.47	0.51	0.52	1.15	1.53	0.38
Exp. 1.4	1.25	1.62	1.15	0.52	1.74	0.88
Exp. 2.1	2.82	8.35	3.65	0.55	2.07	0.60
Exp. 2.2	2.97	1.96	0.91	2.79	10.17	0.89
Exp. 2.3	0.82	0.61	0.86	1.10	0.54	0.49
Exp. 2.4	0.54	5.20	0.40	0.69	5.17	0.54
Average	1.92	3.77	1.06	0.96	4.44	0.57
Improvement	70.3%	84.9%	46.2%	40.6%	87.2%	N/A

We also compare the performance of our system with the

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single-link system with all 16 channels. We use one of the six links for the single-link system, and list the errors in Table III. We see that the performance of the single-link system highly varies depending on which link it uses. For example, the absolute error is 0.55 BPM if Link 4 is used in Exp. 2.1. If Link 2 is used, the absolute error becomes 8.35 BPM. We also average the errors over all eight tests for the single-link system. We see Links 3 and 4 achieve better overall performance than the other links. The average errors are 1.06 BPM for Link 3, and 0.96 BPM for Link 4. From Fig. 3, we see that Links 3 and 4 are the diagonal links that cross the monitoring area, while the other links are peripheral links. Intuitively, if a link passes through the human body, the RSSI from that link would be more sensitive to the respiration motion than links far away from the human body. Note that the average error from our system is only 0.57 BPM, 40.6% more accurate than the best of the single-link system.

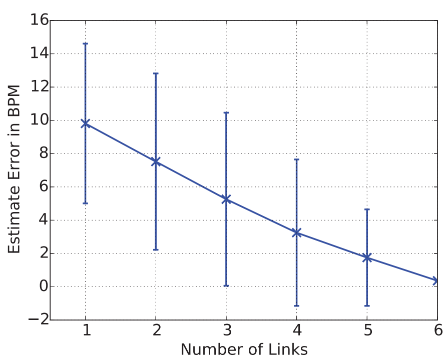

Fig. 5. Estimate error vs. number of links.

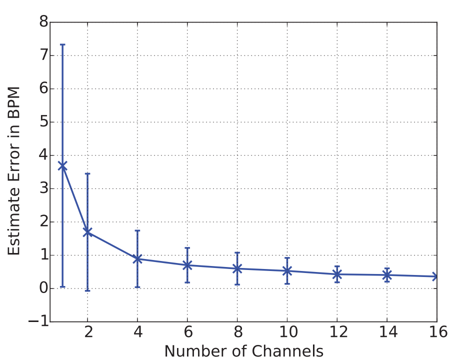

Fig. 6. Estimate error vs. number of Channels.

Finally, we investigate the effects of the number of links and channels on the system performance. We first use all channels and test the effect of the number of links, and then we use all links and see how the number of channels affect the performance. Take Exp. 1.1 as one example, the plot of the estimate error vs. the number of links is shown in Fig. 5, and the plot of the estimate error vs. the number of channels is shown in Fig. 6. Note that for the same number of links and channels, we test different combinations of links and channels, and run our MLE algorithm a thousand times to calculate an average error and the standard deviation of the errors (shown as error bars in Fig 5 and Fig. 6). We see that the average errors are above two BPM if the number of links is less than five, even if we use all 16 channels. However, if we use all six links, we only need four channels to decrease the average error to one BPM. More channels above ten have diminishing returns.

IV. Related Work

One way of monitoring respiration rate is measuring the inspiratory airflow, such as a spirometer. The problem is that users may feel uncomfortable wearing a mouthpiece or facemask. As a non-invasive way of monitoring respiration rate, the Doppler radar has been extensively studied to detect motion due to respiration. For example, researchers at General Electric have developed an unobtrusive Doppler radar system that can measure a person's respiration rate and even heart-beat rate [7]. The Doppler radar system is modified from a commercial Doppler motion sensor and is low-cost. However, it is difficult to detect respiration motion, if the motion is perpendicular to the radar pulse direction. Recent studies [2], [3] show that the inhalation and exhalation of respiration cause periodic changes on the RSSI from wireless communication devices. However, they are also sensitive to user orientations and postures. We build upon their work, and use RSSI on multiple frequency channels and multiple communication links to robustly estimate the respiration rate of a person with different orientations and postures.

V. Conclusion

We develop a low-cost wireless network system using COTS radios to monitor a person's respiration rate. We propose an MLE solution that uses RSSI measurements from multiple channels and multiple links. Our proposed method and system is more robust to user posture and orientation changes. Our experiments show that it is on average over 40% more accurate than previous systems.

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