Pulse Rate Monitoring Using Narrowband Received Signal Strength Measurements

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ABSTRACT

Radio frequency (RF) solutions for human vital sign monitoring have gained importance due to their low device cost and non-contact sensing. However, most systems are quite heavy users of RF spectrum, *e.g.*, transmitting hundreds of WiFi packets per second, which then interferes with wireless communications. In this paper, we present a narrowband RF-based pulse rate monitoring system which uses orders of magnitudes less spectrum and remains low-cost and non-contact. To achieve this, we use received signal strength (RSS) measurements, which then impose challenges due to the very low signal-to-noise ratio and the use of a single-dimensional measurement of the channel. We apply a combination of linear and non-linear filtering, and a new estimator to address these challenges. We report experimental results showing an error of 1.6 beats/min (bpm), similar to the state-of-the-art, but using three orders of magnitude less bandwidth.

CCS CONCEPTS

• **Computer systems organization → Sensor networks**.

KEYWORDS

Device-free, pulse rate estimation, received signal strength, RF sensing.

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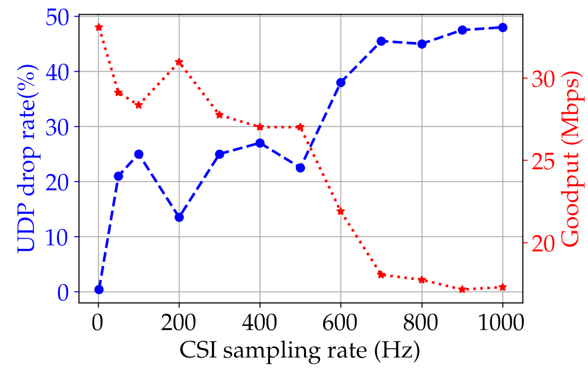

Figure 1: WiFi channel utilization when CSI is measured on the same channel using Atheros CSI tool

1 INTRODUCTION

In the past decade, numerous RF-based sensors have been proposed for non-invasive and unobtrusive vital sign monitoring, most based on channel measurements from WiFi and from radar transceivers. Human motion generally changes the radio channel; even the vibration of skin caused by the pulses of a beating heart can change the radio channel. The change in radio channel measurements due to such skin vibrations is used in non-contact monitoring of pulse rate. However, state-of-the-art RF-based pulse rate monitors are profligate users of scarce RF bandwidth, which ultimately will limit the ability of ubiquitous monitoring systems to coexist with current wireless communication systems. To enable ubiquitous RF vital sign monitoring, *e.g.*, in every room of an assisted living facility or hospital, in the presence of interfering wireless communications systems, efficient bandwidth utilization will be critical.

Existing RF vital sign monitors employ one of various radio channel measurements. Many systems process time-of-flight (TOF), Doppler shift or channel impulse response (CIR) measurements using radar systems [1, 3, 8, 9], or channel state information (CSI) measurements from 802.11n systems [4]. Most of these implementations need a wide RF bandwidth. For instance, radar-based solutions like the frequency-modulated continuous-wave (FMCW) system in [1] require a 1.8 GHz wide bandwidth to estimate breathing and pulse rates. This causes self-interference to other FMCW systems and ultra wideband communications in the same band.

WiFi systems including 802.11n are based on frequent packet transmissions on channels with bandwidth of at least 20 or 40 MHz [4]. WiFi packet transmission rates are as high as 600 samples per second for reliable vital sign monitoring [10]. But we find that

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packet transmission rates at high levels significantly impact co-located WiFi links. In Figure 1, we show the WiFi goodput for a communication link when the same channel is also used to measure CSI measurements on a second link. A CSI sampling rate of 100 Hz reduces goodput by 15%, while a rate of 600 Hz reduces goodput by 33%. Large-scale monitoring of patients throughout a facility, for example, will exacerbate the degradation.

Some systems use received signal strength (RSS) measurements for monitoring [2]. While most RSS-based systems can not achieve pulse monitoring, the few exceptions require a wideband implementation on expensive platforms such as the universal software radio peripheral (USRP) [11] or laboratory equipment [12].

In this paper, we present pulse rate monitoring capabilities of the RSS measured from commercial-off-the-shelf (COTS) narrowband radio transceivers. To the best of our knowledge, our system is the first pulse rate monitoring system that uses RSS measured from COTS transceivers, and it utilizes the lowest bandwidth of any reported RF-based pulse rate monitor. Past work has demonstrated that the changes induced by a stationary person's inhaling and exhaling provides sufficient impact on the radio channel to be observed in the RSS on a standard WiFi or Zigbee transceiver [2, 4]. However, we have not seen a system capable of estimating the pulse rate of a person purely from the RSS measured on a stationary link. We believe this is because of the multiple challenges that need to be overcome to monitor pulse from the very small changes observed in RSS caused by the vibration of a person's skin due to their pulse:

(1) *Low amplitude signal*: The amplitude of the pulse-induced RSS signal is very small, typically < 0.01 dB, about an order of magnitude lower than the breathing-induced RSS signal.
(2) *Quantization*: Most commercial transceiver ICs quantize RSS to 1 dB or more.
(3) *Noise*: The noise power in the RSS signal is significantly larger than the pulse signal power. In addition, the noise is heavy-tailed, prone to large impulses.
(4) *Non-sinusoidal waveform*: The movement of the skin due to the pulse more closely resembles a repeating impulse rather than a sinusoid, thus standard spectral analysis is suboptimal.

To address these challenges, we first develop a fine-resolution RSS measurement system that uses narrowband transceivers. Our intuition is that RSS is primarily noisy due to quantization; we use a low cost narrowband transceiver and exploit a feature that allows us to obtain raw signal samples so that we can calculate unquantized RSS. Then, while we are unable to use PCA-based denoising like most related wideband monitoring systems because we have a single-dimensional signal, we can still use temporal features to remove noise. We use a combination of Hampel and Butterworth filters to cancel breathing interference and heavy-tailed, high frequency noise. Finally, to address the final challenge, we introduce an estimator to combine the pulse harmonics in the magnitude spectrum to improve estimation performance.

Our experimental results show that accurate pulse rate estimation can be achieved with use of only 11 kHz of the RF spectrum. Initial tests on subjects lying down on a cot result in an average error of 1.6 beats per minute (bpm) across three subjects. These results show that accurate RF based vital sign monitoring can be achieved with inexpensive hardware and with orders of magnitude less bandwidth than reported in related work.

2 METHODS

2.1 Hardware

Our RF sensing hardware is composed of a pair of inexpensive wireless nodes. Each node includes a Beaglebone Green (BBG) platform connected to an RF subsystem via SPI interface. Our custom RF subsystem is designed as a cape for the BBG, and contains a TI CC1200 sub-GHz narrowband radio transceiver, its matching network, and an SMA-connected antenna. The CC1200 can operate at multiple center frequencies, including 169, 434 MHz and 915 MHz ISM bands. The parts for each node cost less than 50 USD, compared to more than 1000 USD for a USRP N200 used in other RF-based vital sign monitoring systems [1, 11]. While this is a proof-of-concept prototype; that the BBG is overkill but made prototyping easier, a purpose-built system would be even less than half of the cost.

2.1.1 *RSS Measurement.*

We adopt a high resolution RSS estimation approach described in [5] using the CC1200 transceiver. In our system, we use two devices with one device transmitting a CW signal at 434 MHz and the other capturing its receiver's complex baseband samples and sending them to the BBG via SPI. We employ the programmable real-time processing unit (PRU) sub-system within BBG for continuous data collection without rate variation.

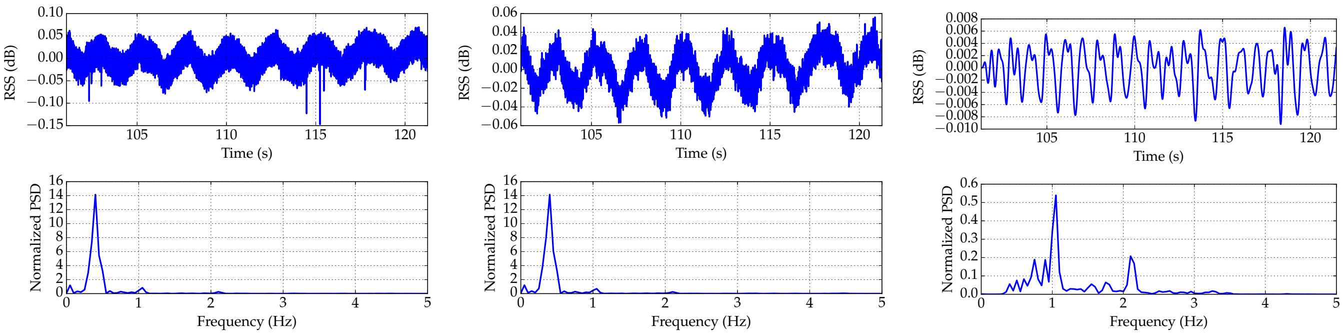
The CC1200 radio transceiver is configured to use a 11.26 kHz channel in the 434 MHz ISM band. The transceiver allows reading the 17-bit magnitude and 10-bit angle of each complex baseband sample received by the CC1200. The PRU subsystem on the BBG is programmed to collect every new sample via SPI bus at a rate of 45 kHz and store the samples in the shared memory space. Concurrently, the main program running on Linux on the main processor reads data from the shared memory, and adds timestamps. Each RSS estimate, $r(t)$, is computed from 100 samples of the 17-bit magnitude by summing the squared magnitude [5]. This process reduces the average sampling rate to 449 Hz, which is more than sufficient for pulse rate estimation.

2.2 Algorithms

In this subsection, we describe how we apply methods to filter the noise and interfering signals, and we present a novel spectral domain method to estimate the pulse rate despite the non-sinusoidal nature of the signal.

For pulse rate estimation, we consider a human subject lying or sitting between a pair of wireless nodes. Any larger motion of the body would cause very large changes in the RSS that would prevent isolating the pulse-induced signal. However, humans are stationary at many points during the day and night, and monitoring resting pulse rate may have application in home health monitoring, fitness tracking, and sleep monitoring. A person would not need to remember to wear or turn on a pulse rate monitor, as non-contact RF sensors could be embedded in the environment and simply monitor pulse rate whenever a person was present and stationary.

Fig. 2a shows an RSS signal recorded from a seated subject. Breathing patterns are visible in the power measured at the receiver — we can see about eight cycles with peak-to-peak amplitude of about 0.1 dB over 20 seconds, which corresponds to a breathing rate of 24 breaths per minute. Without any other signal processing, however, it is impossible to identify the pulse signal. In addition to



(a) Raw RSS and PSD **(b) Hampel-filtered RSS and PSD** **(c) Butterworth-filtered RSS and PSD**

Figure 2: RSS before and after denoising using Hampel and Butterworth bandpass filters for a person lying down.

the breathing-induced signal, the RSS measurements are corrupted by noise that appears to be additive and Gaussian, as well as impulsive, heavy-tailed noise that sends the measured RSS significantly lower or higher for one or two samples.

2.2.1 RSS Denoising. We apply denoising techniques to be able to remove the effects of noise and corrupting signals and extract the pulse-induced signal. To replace outliers due to heavy-tailed noise, we implement a Hampel filter, a generalized median filter with more flexibility in parameter tuning [7]. Fig. 2b shows the output of the Hampel filter for the raw data in Fig. 2a. The Hampel filter can be seen to remove outliers from the raw RSS data, but to keep low-frequency interfering signals, including a strong breathing-induced signal. Hence, a fourth order Butterworth bandpass filter (BPF) is applied to cancel out additive Gaussian noise, respiration harmonics, and other low-frequency interference. The lower and higher cut-off frequencies of the BPF are set to 0.8 Hz and 5.0 Hz, respectively. The PSD of the resulting signal, shown in Fig. 2c, is dominated by the harmonics of the pulse signal.

2.2.2 Pulse Rate Estimation. Once the undesired signals are filtered from the raw RSS, a resulting pulse rate can be estimated from the PSD using our estimation algorithm. Since a normal adult human resting pulse rate falls in the range between f_{min} = 0.84 Hz and f_{max} = 1.67 Hz [6], the pulse rate is estimated by locating the peak value of PSD in the frequency band. However, pulse energy is distributed along harmonics of the fundamental frequency of the pulse signal. Pulse detection is enhanced by superimposing the first two harmonic bands corresponding to cardiac frequency band. The pulse rate is determined by finding the peak frequency in the resulting superimposed PSD.

The pulse rate estimation algorithm starts by initializing a buffer to store the incoming RSS samples continuously. At every second, mean-subtracted RSS data in the buffer is denoised using both Hampel and Butterworth bandpass filters. Then, the PSD $s_r(f)$ of the resulting data is computed using the FFT. To improve pulse detection, we superimpose the PSD in resting cardiac frequency band (i.e. f_{min} to f_{max}) upon the PSD in its second harmonic band (i.e., $2f_{min}$ to $2f_{max}$). The estimated pulse rate corresponds to the frequency at which the maximum value of the sum of PSDs is obtained. To avoid inaccurate pulse rate estimation as a result of random body motion, pulse rate is estimated only when the peak value of the PSD is below a certain threshold as disturbance in the RSS data due to motion artifacts usually provide higher peak value of the PSD compared to the value obtained for pulse-induced signal.

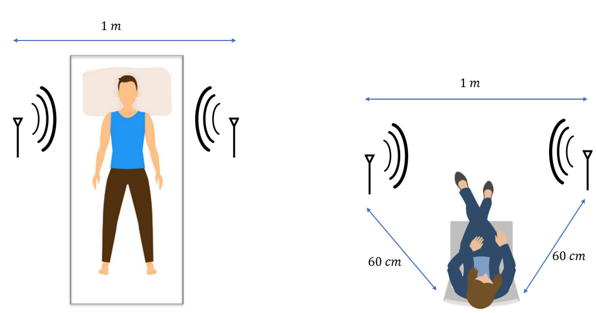
$$\hat{f} = \arg\max_{f} \left(s_r(f) + s_r(2f) \downarrow_2 \right), \quad f \in (0.84, 1.67)$$

3 EXPERIMENT

To evaluate our system for real time pulse rate monitoring, we test three different subjects and two different environments. All subjects are healthy adults in the age between 24 to 29 years old.

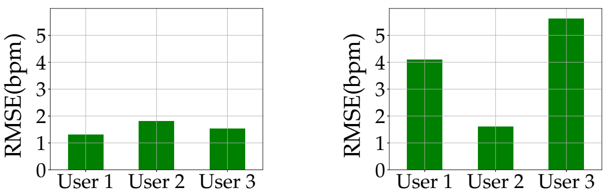
The two environments are: 1) a research laboratory, and 2) a conference room. Both are occupied with their typical furnishings, including chairs, desks, and equipment. Both rooms have an approximate area of 56 m^2, and only a single user is present in the room during each experiment. Fig. 3a shows the setup for experiments when the subject lies down. A cot elevates the person 15 cm above the floor, and the two directional antennas are set at 30 cm from the ground, separated by 1 m from each other, and directed at the chest of the subject. In another setup, a subject sits in a chair 50 cm above the ground. In this case, each antenna is 60 cm away from the chest of the subject, 1 m away from the other antenna, and 1 m above the ground as shown in Fig. 3b. The receiver node of our system is connected to a laptop that processes the RSS data, and outputs pulse rate estimates in real-time.

To record the ground truth, we capture pulse rate measurements using a pulse oximeter physically attached to the subject's finger. We use Respironics Philips NM3 with pulse oximeter which is also connected to the same laptop. For this evaluation, we run each experiment for five minutes.



(a) Lying on a cot **(b) Sitting on a chair**

Figure 3: Experiment setup for pulse rate monitoring.



(a) RMSE: Lying on a cot **(b) RMSE: Sitting on a chair**

Figure 4: Pulse rate RMSE for different subjects

4 RESULTS

We evaluate the performance of pulse rate estimation in two different setups. The first setup involves a test in a conference room of size approximately 7 $m \times 8$ m in which the subject sits on a chair, and the directional antennas separated by 1 m are set across their shoulders. Fig. 4b shows the root mean squared error (RMSE) of pulse rate estimates for each user. In Fig. 4a, we show the RMSE for lab setup where a subject lying on their back on a cot 15 cm above the ground. We observe that the RMSE for the second setup yields an RMSE of 1.57 bpm compared to 3.67 bpm for sitting users in the first setup. It may be that the geometry for monitoring pulse via RF is better in the setup with the cot than with the chair. This may also be that it is more difficult to be genuinely still while seated vs. when lying down. However, the RMSE for lying users is still comparable with the median error of ~2 bpm obtained using wideband WiFi CSI measurements [4].

Fig. 5 quantifies the ability of the system to track the changes in pulse rate over time. Our algorithm is able to estimate the pulse rate for users who have different pulse rates, in the 67-73 bpm range for user sitting on a chair and in the 56-64 bpm range for user lying on a cot. Also, the pulse rate shown in Fig. 5 typically tracks the increases and decreases in pulse rate observed over the course of tens of seconds for the person. However, there are short periods during which the pulse rate estimate jumps very high or very low. Further investigation will be required to track other motions of a person to determine if the jumps are caused by larger motion of their body, or if there is another cause. Further work could also investigate tracking methods that could avoid the large jumps in the pulse rate data.

Given the 69 cm wavelength at the center frequency in use (434 MHz), and the fact that pulse rate-induced skin vibrations may move the skin on the order of mm, it is quite surprising to be able to observe a person's pulse rate in the measured RSS. However, the results indicate that RSS-based pulse rate monitoring is possible with 20 s of data, that it can track pulse rate variations over time, and that it can stay within 1.6 bpm RMSE of the rate measured by a clinical-grade pulse oximeter.

5 CONCLUSION

In this paper, we present an RF-based pulse rate monitoring system using two low-cost single carrier radio transceivers which operate using 11 kHz of RF bandwidth. We develop a method to estimate a person's pulse rate from single-channel RSS measurements. We test our RSS-based pulse rate estimation, and show that it attains an RMSE of 1.6 bpm across three lying subjects. Our low-cost RF-based vital sign monitoring system performs as well as reported results from several state-of-the-art systems while using three orders of magnitude less bandwidth. Without reducing the very high bandwidth utilization of the state-of-the-art RF sensing systems, we believe that it will be very difficult to realize ubiquitous RF sensing as envisioned by many in the research area. We believe our results provide an important proof-of-concept to show that low-cost and low-bandwidth sensing is possible and may be an enabler for ubiquitous RF sensing.

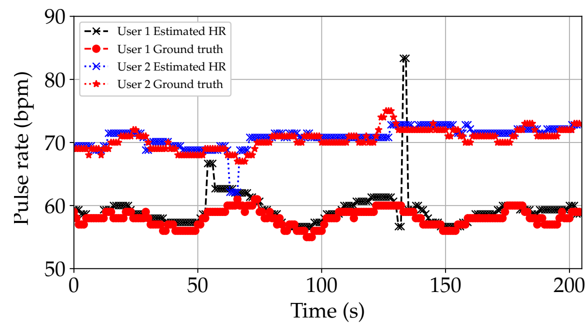


Figure 5: Estimated pulse rate vs ground truth over time. User 1 is lying on a cot, User 2 sitting on a chair.

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