RSS Step Size: 1 dB is not Enough!

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ABSTRACT

A radio transceiver normally provides received signal strength (RSS) quantized with 1 dB or higher step size. Currently, we know of no application which has demonstrated a need for sub-dB RSS estimates. In this paper, we demonstrate the need for, and benefits of, greater resolution in RSS for breathing rate monitoring and gesture recognition. Measuring RSS requires orders of magnitude less bandwidth than measuring OFDM channel state information (CSI) or frequency modulated carrier wave (FMCW) channel delay. We have designed a prototype with an off-the-shelf low-power transceiver and a processor to achieve an RSS estimate with a median error of 0.013 dB. We experimentally verify its performance in non-contact breathing monitoring and gesture recognition. We demonstrate that simply decreasing the step size of RSS lower than 1 dB can enable significant benefits, enabling extremely low bandwidth RF sensing systems. Results indicate that RFIC designers could enable significant gains for RF sensing applications with four more bits of RSS quantization.

CCS Concepts

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

1. INTRODUCTION

Measurements of the received signal from the links in a static deployed wireless network can be used to monitor people in the area of deployment. Measurements of received signal strength (RSS) have been shown to enable "sensorless sensing" [13], device-free localization [14, 4], activity recognition [11], fall detection [8], border monitoring [3], and breathing monitoring [9, 5, 15]. The narrowband transceivers used in these systems enable very low cost RF sensor devices, however, RSS contains no information about signal phase, and measures the channel at the single frequency channel used to send the packet, and is quantized with a step size of 1 dB or higher.

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The RSS on one frequency channel may not show evidence of the event being monitored, e.g., a line crossing or breathing, thus systems have measured multiple channels for reliability. For example, four to sixteen channels are measured in [4, 3, 9, 5], improving performance but increasing bandwidth usage. WiFi channel state information (CSI) measures tens of channels but requires 20-40 MHz RF bandwidth [2, 12]. Note that CSI includes phase per subchannel but random phase changes between packets [12] make it unusable. Ultra wideband impulse response (UWB-IR) or frequency modulated carrier wave (FMCW) transceivers can measure multidimensional complex-valued channel response for RF sensing; requiring 2.5 GHz for UWB-IR in [7] or 1.8 GHz for FMCW in [1]. In comparison, the 2 MHz RF bandwidth of an IEEE 802.15.4-compliant transceiver, or the few 100 kHz RF bandwidth of a TI CC1200 sub-GHz transceiver, is one to four orders of magnitude more efficient in their use of the spectrum per channel measurement. Since RF sensing systems must operate in and occupy the same spectrum as RF communications systems in order to measure the channel, there is a strong need to have systems operate efficiently.

In this paper, we propose a fundamentally different approach. We propose that having a smaller step size in the RSS measurement allows highly reliable RF sensing while using only one narrowband channel. Few low-power transceivers currently provide access to RSS with resolution better than 1 dB as wireless communications systems do not require it. We explore a transceiver that does, the TI CC1200, a sub-GHz transceiver. We demonstrate the capabilities of single-channel RSS measurements as a function of resolution. We argue that the benefits of a few extra bits of RSS are significant in RF sensing applications, particularly as commercial use and thus bandwidth usage of RF sensing increases.

We emphasize in this paper the benefits for non-contact RF-based breathing monitoring. In an otherwise stationary environment, a person's inhalation and exhalation causes a periodic change to the radio channel that can be observed in the RSS signal. For home health care and "quantified self" applications, it would be very useful to be able to track vitals signs regardless of where a person travels within a coverage area. However, the amplitude of the breathing-induced RSS signal varies unpredictably by frequency channel, and is often smaller than 1 dB [9]. In [5], a successful approach was demonstrated in which 1) the channel was sampled at a very high rate and then lowpass filtered to increase the effective resolution of RSS; and 2) RSS measurements were performed on sixteen frequency channels in order to increase the

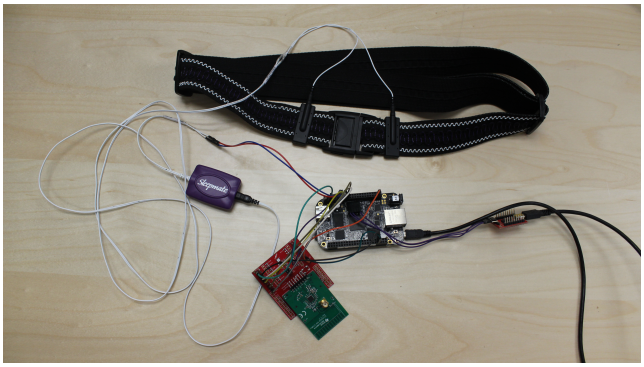

Figure 1: Sub-dB prototype: Beaglebone Black and CC1200 eval module. Ambu RIP band provides ground truth breathing rate.

likelihood that at least one channel would observe a strong breathing-induced signal. The combination of these two effected reliable breathing monitoring with only two devices, compared to the 30 used in [9], but both increase the utilization of the channel. In this paper we show that neither technique is required if better resolution RSS measurements are available. Systems using laboratory-grade instrumentation have been used to measure breathing rate from high resolution RSS at 60 GHz [15], but this paper is the first we are aware of to use an inexpensive wireless transceiver IC, and to explicitly show the benefit of sub-decibel resolution.

We also address the impact of sub-dB RSS resolution on gesture recognition. When the distance between the person and the transmitter or receiver is large, the magnitude of the disruption in the RSS is small. If RSS is quantized to 1 dB, the disruption either may not be measured at all, or the spectral features calculated from the quantized RSS may be too noisy. One solution for power-based gesture recognition is to use analog circuitry [6], avoiding the quantization problem altogether. We suggest an alternate approach, and show the ability to see gesture patterns in RSS when the person is several feet from either the transmitter or receiver.

2. SUB-DB RSS MEASUREMENT

To measure RSS with step size less than 1 dB, we build a prototype system from off-the-shelf components, shown in Fig. 1, which we refer to as the *sub-dB RSS measurement system*. Our prototype uses a TI CC1200EMK-420-470 evaluation module board connected to a Beaglebone Black (BBB). The CC1200 is a transceiver able operate at 169 MHz, 434 MHz, or 900 MHz. Our evaluation board was populated with a 420 – 470 MHz matching network. We use a TI EM Adapter BoosterPack to bridge the CC1200 board to the BBB.

The CC1200 datasheet states that 12 bits of RSS (equivalently, 1/16 dB step size) is available, but this is misleading. Our empirical study shows that the least significant 4 bits do not change with sub-dB changes in the received power. Instead, the four LSBs only change when there is a change in the AGC gain stage, that is, the gain stage correction factor may have 12 bits resolution. However, the RSS on the CC1200 effectively has 1 dB quantization steps.

As the CC1200's native RSS would not provide the desired resolution, our sub-dB system relies on another feature of the radio, the IQ sample feature. The CC1200 exports three registers for the magnitude and two registers for the angle of each sample immediately after the CORDIC algorithm. We denote the nth sample as s_n. The sampling period is determined by the channel bandwidth setting. In our case, a new magnitude $|s_n|$ comes through the 7 MHz SPI bus every 22.2 μs, a sample rate of 45.044 kHz. The data is meaningless if the sample is read out while the buffer is being written with another sample. Thus, we check the CC1200 `MAGN_VALID` signal, which rises in order to indicate the availability of the new measurement.

Due to the preemptive architecture of the Linux OS, we cannot use the BBB's main processor to capture the IQ samples from the radio at a precise regular interval. However, the BBB comes with two real-time co-processors, the programmable real-time processing unit (PRU) sub-system. Our application configures the radio, starts magnitude data collection on the PRU, and writes it into shared memory. The main processor calculates the sum of the squared magnitude $P = \frac{1}{N}\sum_{n=1}^{N}|s_n|^2$. The RSS (in dBm) is then $c + 10\log_{10} P$. The value of constant c is calculated via a calibration experiment in which P is computed while a known signal power is input by cable to the receiver. With $N = 100$ and the time required for configuration and computation, our system has an RSS sample rate of 348 Hz.

2.1 RSS Evaluation

We validate sub-dB by analyzing its performance with respect to an input signal with known magnitude function. We generated a signal with a National Instruments vector signal generator in which a 434 MHz carrier wave is modulated to have amplitude that varies as a triangular wave with a period of 1 second and a modulation index of 0.9. This signal, shown in Fig. 2, is input to the CC1200 receiver directly via cable connection so that we know exactly what signal is received.

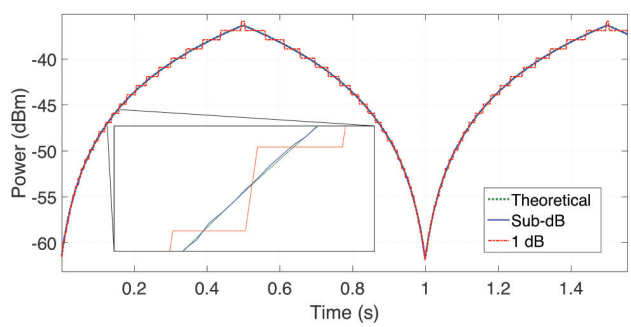

Figure 2: Power (dBm) of triangle wave signal input to the CC1200 (···), measured by proposed system (——), and if quantized to 1 dB (- - - -).

We then plot the RSS calculated by sub-dB in Fig. 2, which shows that the two almost perfectly overlap. If the RSS is quantized to 1 dB, there would be larger differences, as shown in Fig. 3. Errors from sub-dB are less than 0.06 dB except for when the received power is lowest, perhaps because the SINR is lowest. The CDF of error for sub-dB shows a median error of 0.013 dB for our system, vs. 0.25 dB for when RSS has a 1 dB step size, a 19x difference.

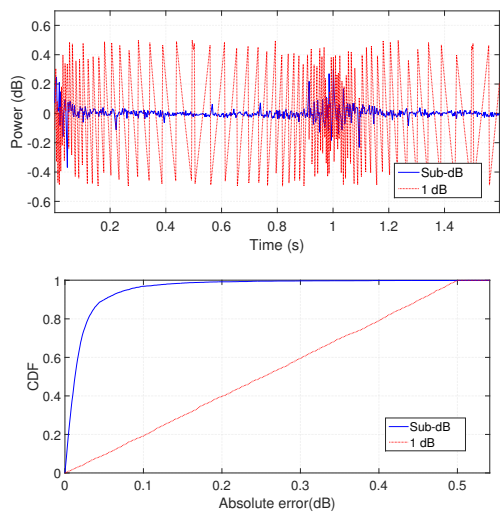

Figure 3: RSS error of sub-dB system (——) vs. RSS quantized to 1 dB (——), (a) over time, and (b) CDF.

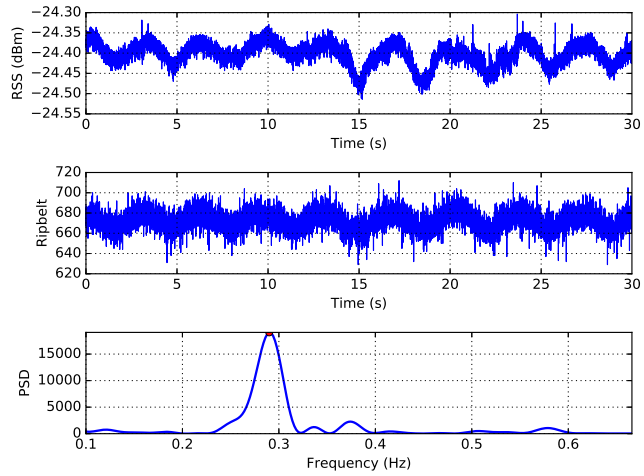

Figure 4: (Top) Breathing-induced RSS changes compared to (Middle) RIP belt measurements. (Bottom) PSD of filtered RSS w/ rate estimate (•).

3. BREATHING MONITORING

In this section, we evaluate the performance of a breathing rate estimator using measurements from the sub-dB prototype system.

3.1 Experiments

We conducted experiments with three different subjects and three different positions. The subject lies on a cot 15 cm above the ground. The antennas are also 15 cm above the ground and 60 cm away from either 1) each shoulder of the subject, or 2) from the head and feet of the subject. All of the above described experiments were done in a office of size 8.4 m × 6.7 m, cluttered with desks, computers, monitors, and lab equipment. For ground truth, the subject wears an Ambu RIPmate inductance belt around his abdomen. We have included experiments with both controlled and uncontrolled breathing as well. In controlled breathing, the subject is required to breath in and out with a metronome at a fixed rate. Since breathing tends to be heavier when the subject is conscious about his breathing, we include multiple uncontrolled breathing experiments to avoid that bias.

Figure 4 shows a 30 seconds window of the RSS, showing periodic variations very similar to the RIP belt, with peak-to-peak difference of 0.1 dB. With RSS quantized to 1 dB, there is little chance that the changes would be observed. In the power-spectral density (PSD) of the sub-dB RSS, however, we can distinctively observe a peak at 0.244 Hz (14.64 bpm). This is only 0.12 bpm different from the peak of the PSD of the RIP belt voltage signal.

3.2 Evaluation of Breathing Monitoring

During real-time operation, an application using RSS could operate on the 348 Hz stream of floating-point RSS data. However, for evaluation, it is critical to know how well the system would work with more efficient settings of sample rate and quantization step size. For example, if an 7.25 Hz RSS sample rate is sufficient, we could save energy and reduce channel utilization by using the transceivers only 1/48 of the time. A key question to be answered is the required RSS step size, or equivalently, the number of bits of RSS. We study both quantitatively via the following procedure.

Each floating-point RSS value and its timestamp from the sub-dB system is saved to file for post-processing. The post-processing algorithm operates as shown in Fig. 5. We downsample by P to evaluate the performance had we sampled less often, and quantize to Q bits to simulate the performance had the RSS been quantized to a particular step size. Here, $Q = 8$ is defined as a step size of 1 dB, as many RFICs use $Q = 8$ to provide 1 dB step size. Each additional bit cuts the step size by half. Filtering is used for two reasons: 1) a DC-removal filter removes the mean so that we look only at the changes in RSS; and 2) as in [5], a lowpass filter provides a means to approximate a higher resolution quantizer when oversampling — we include it for comparison purposes. We then downsample by $M = 144/P$ so that the rate of 2.4 Hz is used in the breathing rate algorithm, regardless of P. This ensures a constant computational complexity for the discrete Fourier transform (DFT). We use a window of the most recent 30 seconds of data as input to the DFT. The breathing rate estimate is the frequency with the maximum amplitude of the DFT (equivalently, the PSD).

Many medical monitors count the cycles in the signal to estimate breathing rate. We implemented a version we call *count breaths* (CB), which counts zero crossings over the same 30 s window. However, by counting only whole numbers of breaths, CB quantizes the breathing rate estimate, and thus introduces quantization error of its own.

3.3 Experimental Results

We provide a comparison of RSS-based and RIP belt-based breathing rate estimates from both metrics in Fig. 6, as a function of the downsampling rate P. Having $P \leq 12$ (for a raw RSS sampling rate of 21.75 Hz) results in relatively constant performance, with estimates within about 0.1 bpm of the RIP belt, on average. We note average error stays below 1 bpm until the sampling rate falls below 7 Hz. In [5], an MA error of 0.12 bpm was achieved, but using 16 Zigbee channels (across 80 MHz) each sampling

Figure 5: Post-processing of RSS data to allow evaluation w/ lower sampling rate & different quantization.

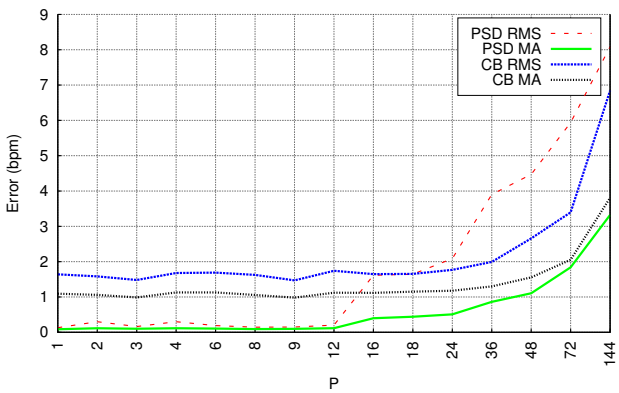

Figure 6: Breathing rate RMS and average (MA) error vs. downsampling rate P. The effective RSS sampling rate is $348/P$ Hz.

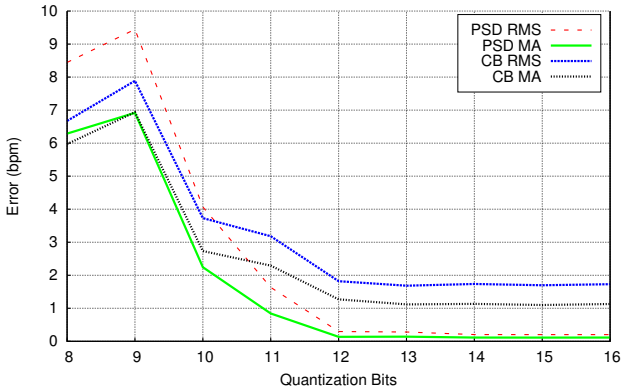

Figure 7: Breathing rate RMS and average (MA) error vs. RSS bits ($Q = 8$ means 1 dB step size).

RSS at 31.25 Hz. We achieve similar performance transmitting only on one channel (across 12.5 kHz) with 30% fewer RSS samples. Sub-dB quantization allows the transmitter to transmit less often and use 6000 times less bandwidth.

Sub-dB provides floating point RSS. However, breathing monitoring does not require this precision. We quantized the sub-dB RSS measurement to Q bits, for $8 \leq Q \leq 16$, when $P = 12$. The results, shown in Fig. 7, show that breathing rate estimation does not gain in accuracy as the number of quantization bits exceeds 12 bits. We note that 12 bits corresponds to 1/16 dB step size.

4. GESTURE RECOGNITION

Another application of sub-dB RSS is gesture recognition. When a person makes a gesture with their arms or legs in the presence of a wireless link, they cause a temporal pattern in RSS measurements that depends on the action [11]. If the gesture is very close to a receiver, the received power changes can directly be used for gesture recognition [6]. However, when the person is distant from either transceiver, the state-of-the-art is to use micro-Doppler from OFDM for gesture recognition [10]. In this section, we show that RSS changes are small but observable with sub-dB RSS, despite a person's distance from the transceivers.

In our setup, we place two antennas 6.7 m apart. The person stands 2.4 m from the midpoint of the line between the devices. We test four gestures:

- *Punch*: Move arm forward and return it swiftly
- *Kick*: Move foot forward and return it swiftly
- *Zoom in & zoom out*: Stretch both arms wide open and bring them back together
- *Bowling*: Move right arm back and forward in a smooth motion while keeping torso low and one leg back

Each gesture has its unique signature in the RSS measurements as shown in Figure 8. However, the peak-to-peak change is always below about 0.75 dB. Based on that, we can see that an RSS measurement quantized to the nearest integer dBm would not provide much information about the gesture.

To quantitatively evaluate gesture recognition as a function of quantization, we use the following algorithm. We apply a support vector machine (SVM) classifier (purely for proof-of-concept). We select twenty features, including variance, skewness, eight percentiles evenly spaced from the 5th to 95th percentiles, and power spectrum in three different bands. We train the SVM classifier using a set of 43 trials of each gesture, and test using a set of 110 unlabelled gestures. In Figure 9, if we train and test on the two gestures "punch" and "zoom in & zoom out", the accuracy of classification improves from just above 50% with eight bits to 100% at 12 bits. With all four gestures, the performance similarly increases from 31% to around 85% at twelve bits, but the performance does not improve higher than 86%. In summary, as a proof-of-concept, we believe that gestures performed far from either transceiver can be recognized from link RSS measurements if the resolution of the measurements is twelve bits (equivalently, 1/16 dB step size) or higher.

5. CONCLUSION

In this paper, we describe sub-dB, a prototype using a TI CC1200 which exposes floating point RSS measurements to the application. Sub-dB estimates RSS with 0.013 dB median error, compared to 0.25 dB median error from a typical 1 dB step size RSS measurement. We evaluate the performance of RSS-based breathing monitoring and gesture recognition.

For RSS-based breathing monitoring, we achieve similar rate estimation performance to [5] but using 6000 times less bandwidth. Sub-dB enables gestures to be recognized from

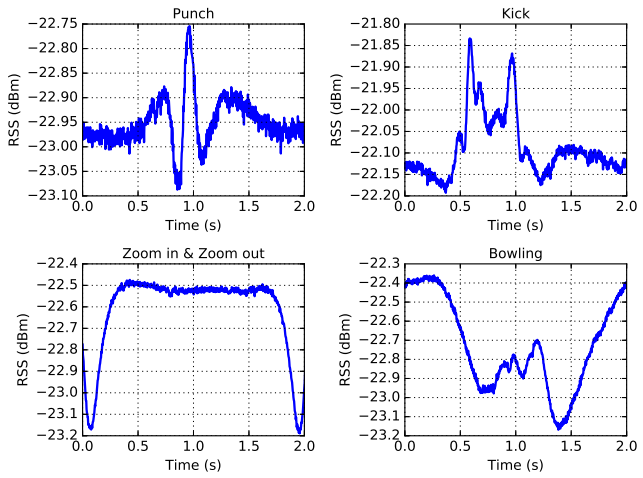

Figure 8: RSS signals for four different gestures.

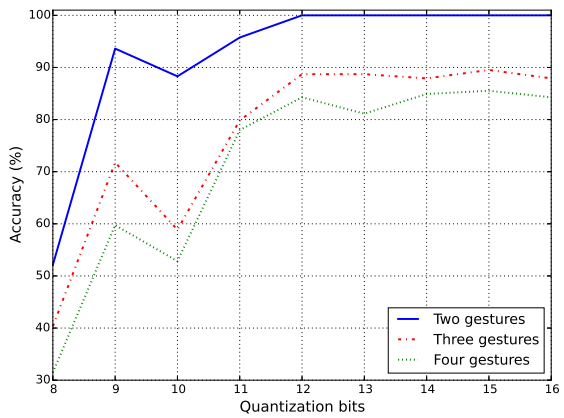

Figure 9: Classification accuracy vs. # of bits of RSS and gestures considered.

RSS even when the person is far from either transceiver. We demonstrate that twelve bits of RSS, rather than the typical eight bits, provides enough resolution for both gesture and breathing monitoring. This work provides motivation for RFIC designers to provide a few more bits of RSS resolution, as it requires only a few extra logic gates. Additional registers may be required for these bits, but applications that do not require high resolution RSS can ignore them.

Future work should directly compare the application performance when using sub-dB vs. other wider bandwidth channel measurements. CSI and UWB may be advantageous for the application but pose scalability challenges. This paper has demonstrated that performance of narrowband RF sensing can be improved simply with higher resolution power measurements.

Acknowledgments

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