Poster Abstract: Link Line Crossing Speed Estimation with Narrowband Signal Strength

Alemayehu Solomon Abrar, Anh Luong, Peter Hillyard
University of Utah
Salt Lake City, UT 84112
{aleksol.abrar,anh.n.luong,peter.hillyard}@utah.edu

Neal Patwari
University of Utah and Xandem Technology
Salt Lake City, UT 84112
npatwari@ece.utah.edu

ABSTRACT

We present results from a system which uses received signal strength (RSS) measurements to estimate the speed at which a person is walking when they cross the link line. While many RSS-based device-free localization systems can detect a line crossing, this system estimates additionally the speed of crossing, which can provide significant additional information to a tracking system. Further, unlike device-free RF sensors which occupy tens of MHz of bandwidth, this system uses a channel of about 10 kHz. Experiments with a person walking from 0.3 to 1.8 m/s show the system can measure walking speed within 0.05 m/s RMS error.

1 INTRODUCTION

Radio frequency (RF) signals have been widely explored in device-free localization, including detection of line crossings and use of line crossing measurements to track people [3, 4]. In these applications, the speed of a person is a fundamental parameter to track a subject. Typical methods first perform RF-based device-free localization [3, 10] and then derive the speed from the coordinate estimates over time; however, such systems require many transceivers deployed around the area of interest. A few other techniques directly measure speed or range using a radar measurement system [2, 8]; however, such systems use multiple GHz of bandwidth to generate range-Doppler responses, and they become less effective in the presence of interfering communication systems. Similarily, Wang *et al.* [9] use channel state information (CSI) measurements from WiFi devices to determine human speed for activity recognition. Even though such CSI-based sensing might be convenient in terms of infrastructure by using the same channel for both communication and sensing, it still puts more strain on an increasingly crowded spectrum. In this poster abstract, we propose speed estimation using the spectrogram of single-channel RSS measurements. Our transceivers are narrowband, reducing the bandwidth requirement to 11 kHz.

When a person moves near a wireless link, the RSS changes due to their presence, but in ways that are challenging to model. The model of Rampa *et al.* [7] predicts the RSS as a function of a person's location with respect to the transceivers, modeling a human as a perfect cylinder and applying diffraction theory. Based on this model, as the person moves towards the link line, the peak frequency in the spectrogram of the RSS decreases, as shown in Fig. 2a, directly proportional to the speed and the distance from the crossing. However, an actual human is not like a cylinder as assumed in the model of [7]. Different body parts such as the legs, torso and hands move at different instantaneous velocities. In Fig. 2b, we show the spectrogram of the measured RSS during a time when an actual walking person crosses the link line, which differs visually from the spectrogram in Fig. 2a.

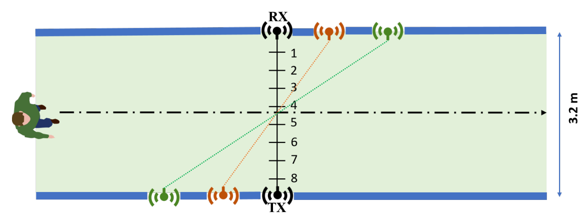
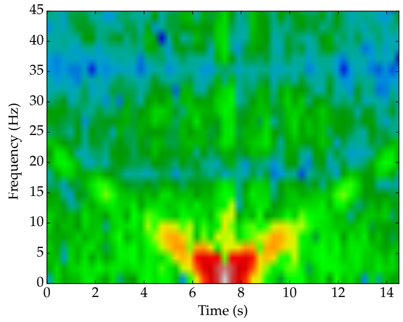


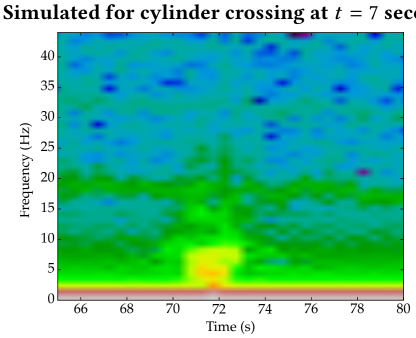
Figure 1: Experimental setup for line crossing.

We propose to estimate human walking speed based on the spectral components of RSS measured when a person approaches and crosses a link line. We envision a setup as shown in Figure 1 where two sensors on opposite sides of a hallway are deployed. A person walking through the hallway has his speed estimated as she crosses through the link line. One fundamental challenge in extracting speed from RSS measurement is that RSS measurements are typically quantized to 1 dB, which is not sufficient in tracking small changes in RSS due to a distant human in motion. To overcome this challenge, we use a high resolution RSS estimate [5] from a TI CC1200 transceiver. Other challenges stem from the fact that different people walk with different gaits, and each person's different body parts have different instantaneous speeds during their walk. As a result the RSS spectrogram for a given walking speed varies by person. We address this challenge by tracking a time-averaged frequency from the spectrogram of RSS measurements, which is then used to estimate the average body speed. We first predict a link line crossing when the RSS average frequency drops below a certain threshold. We then estimate the speed of crossing from the minimum of the time-averaged RSS frequency during the crossing. In this poster abstract, we show experimentally that the use of spectral information of RSS data provides a bandwidth-efficient and inexpensive means for human speed estimation.

MobiCom'17, October 16–20, 2017, Snowbird, UT, USA.
 978-1-4503-4916-1/17/10…$15.00
DOI: http://dx.doi.org/10.1145/3117811.3131253



(a) Simulated for cylinder crossing at $t = 7$ seconds



(b) Measured from human crossing at $t = 72$ seconds

Figure 2: Spectrogram of of (a) simulated and (b)measured RSS data.

2 HARDWARE AND RSS ESTIMATION

Our RF sensing hardware is composed of a pair of inexpensive wireless nodes. Each node includes a Beaglebone Green (BBG) platform connected to a TI CC1200 narrowband radio transceiver, its matching network for the 434 MHz band, and an SMA-connected antenna. The parts for each node cost less than 50 USD, compared to more than 1000 USD for a USRP N200 used in other RF sensing systems [1, 2, 6].

We reproduce a high resolution RSS measurement system described in [5] using the CC1200 transceiver. One device transmits a CW signal at 434 MHz, while the other captures its receiver's complex baseband samples and sends them to the BBG via SPI, at a sampling rate of 54 kHz. The BBG caluculates each RSS estimate, $r(t)$, 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 high enough for most RF sensing applications, including human speed estimation.

3 WALKING SPEED ESTIMATION

As described in Section 1, the spectrogram of RSS measured during a line crossing differs significantly from that predicted by model, and varies by person. The peak frequency in the spectrogram is not, as would be predicted by the model, strongly related to the speed of the walking person.

We propose instead to utilize the average frequency of the spectrogram of the mean-removed RSS waveform, which we denote $f_{av}(t)$ at time t. The value $f_{av}(t)$ is calculated as

$$f_{av}(t) = \frac{\sum_i f_i S_r(f_i, t)}{\sum_i S_r(f_i, t)}, \tag{1}$$

where $S_r(f_i, t)$ is the power of the spectrogram S_r of the mean-removed RSS at frequency f_i at time t. The spectrogram is computed from a 2 s sliding window.

The estimated average frequency is then smoothed using a moving-average filter. We call the output of the filter as $f_s(t)$. Fig. 3 shows $f_{av}(t)$ and $f_s(t)$. Note that the average frequency decreases as the person approaches the link line, is minimum at the instant the person crosses the link line, and then rises again.

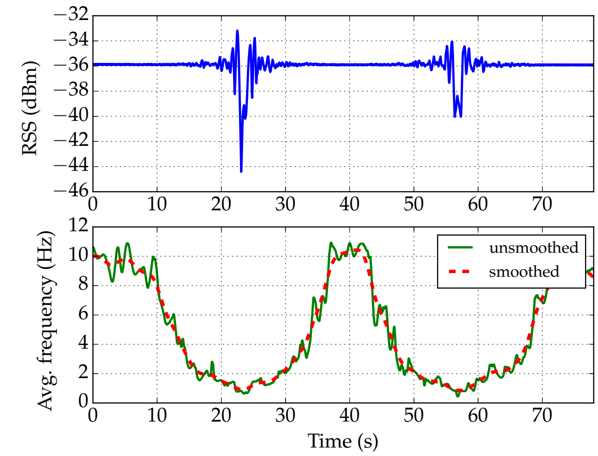


Figure 3: Average RSS frequency for measured line crossing with 2 second windows: The average frequency is smoothed using moving average filter before speed estimation.

We detect a line crossing by thresholding $f_s(t)$, i.e., when a person approaches a link line the smoothed average frequency drops below a certain threshold.

After detecting a crossing, we estimate the time of crossing as the minimum $f_s(t)$ within a wide window. Next, we estimate the speed by scaling the smoothed average frequency by a constant α,

$$\hat{v} = \alpha \min_t f_{av}(t),$$

where the minimum is taken over a set time interval.

4 RESULTS

We perform experiments in two different indoor hallways of width 3.2 m, with the nodes kept on either side of the hall way at 1 m high from the ground, as shown in Fig. 1. The person walks across the link line at a known speed. The person uses a metronome and distance markers to keep a constant speed over 14 m. We conduct the experiment while the subject walks in solitude through the hallway.

First, we evaluate human walking in the range of speeds from 0.30 m/s to 1.81 m/s. We determine the best linear fit between actual velocity and f_{av} and find that $\alpha = 0.88$ for hallway 1 and $\alpha = 0.72$ for hallway 2 during a training period. Clearly, the best linear fit α may vary per link.

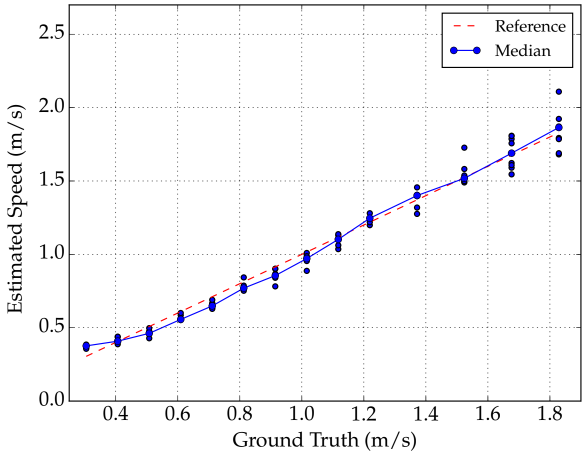


Figure 4: Estimated walking speed vs ground truth when a person crosses a link.

Fig. 4 shows the estimated speed $\hat{v}$ as a function of the ground truth walking speed, which has RMS error of 5.13 cm/s. For a person walking through a hallway at a constant rate, this means that we can accurately estimate a person's distance from the line over time and be off by less than 1 m for a period of 20 seconds, using measurements from only one link line.

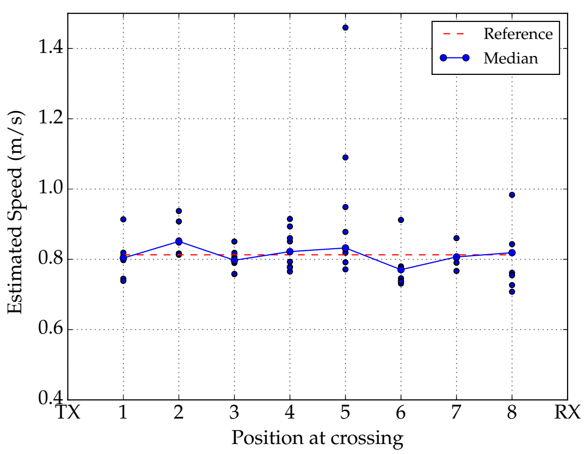


Figure 5: Estimated walking speed vs. ground truth when a person crosses a link at different position along the link line.

We also show the estimated speed for a person crossing the link line at different places, marked as 1 through 8 in Fig. 1, at a constant speed of 0.813 m/s. As shown in Fig. 5, the median of the estimated speed is within 0.05 m/s from the correct value. The physical model of [7] provides analytical justification for this result. In that model, assuming a transmitter and a receiver are located at $(0, 0)$ and $(0, d)$, for a person walking at a constant speed, the average RSS frequency at the link line crossing at y meters away from the transmitter is directly proportional to $\frac{1}{y(d-y)}$. This implies that the average RSS frequency is nearly constant with crossing position y unless the person is very close to either transceiver.

We have also experimentally found that the value of $\hat{v}$ is not a strong function of the angle between the person's walking path and the line between the transmitter and receiver, as shown in the green and red lines in Fig. 1. As the results are similar, they are omitted due to space limitations.

5 CONCLUSION

In this poster abstract, we present a human walking speed estimation method which is based on the frequency content of RSS measured from two low-cost single-carrier narrowband radio transceivers. We analyze the RSS spectral content and estimate speed from average frequency of the spectrogram of RSS measured when a person crosses a link line. Unlike other RF-based methods which require a few GHz of bandwidth to track human subjects, our RSS-based speed estimation approach utilizes only 11 kHz of RF bandwidth while maintaining accurate speed estimation with an error of 5 cm/s. The results indicate that RSS can be a rich source of information when it is provided without quantization to 1 dB step size.

We plan to explore the application of these speed estimates to improve device-free localization and tracking. Further, the work may have application in activity recognition and other context aware computing systems.

ACKNOWLEDGEMENTS

This material is based upon work supported by the U.S. National Science Foundation under Grants #1329755, 1407949, and 1622741.

REFERENCES

[1] 2017. USRP N210 . https://www.ettus.com/product/. (2017). [Online; accessed 30-Mar-2017].

[2] Fadel Adib, Zachary Kabelac, Dina Katabi, and Robert C Miller. 2014. 3D Tracking via Body Radio Reflections.. In *NSDI*, Vol. 14. 317–329.

[3] Maurizio Bocca, Ossi Kaltiokallio, Neal Patwari, and Suresh Venkatasubramanian. 2014. Multiple Target Tracking with RF Sensor Networks. *IEEE Transactions on Mobile Computing* 13, 8 (Aug 2014), 1787–1800.

[4] Peter Hillyard, Neal Patwari, Samira Daruki, and Suresh Venkatasubramanian. 2015. You're crossing the line: localizing border crossings using wireless RF links. In *Signal Processing and Signal Processing Education Workshop (SP/SPE), 2015 IEEE*. 249–254.

[5] Anh Luong, Alemayehu Solomon Abrar, Thomas Schmid, and Neal Patwari. 2016. RSS step size: 1 dB is not enough!. In *Proceedings of the 3rd Workshop on Hot Topics in Wireless*. ACM, 17–21.

[6] Qifan Pu, Sidhant Gupta, Shyamnath Gollakota, and Shwetak Patel. 2013. Whole-home gesture recognition using wireless signals. In *Proceedings of the 19th annual international conference on Mobile computing & networking*. ACM, 27–38.

[7] Rampa, Vittorio and Savazzi, Stefano and Nicoli, Monica and D'Amico, Michele. 2015. Physical modeling and performance bounds for device-free localization systems. *IEEE Signal Processing Letters* 22, 11 (2015), 1864–1868.

[8] Ph Van Dorp and FCA Groen. 2008. Feature-based human motion parameter estimation with radar. *IET Radar, Sonar & Navigation* 2, 2 (2008), 135–145.

[9] Wei Wang, Alex X Liu, Muhammad Shahzad, Kang Ling, and Sanglu Lu. 2015. Understanding and modeling of WiFi signal based human activity recognition. In *Proceedings of the 21st annual international conference on mobile computing and networking*. ACM, 65–76.

[10] Zheng Yang, Zimu Zhou, and Yunhao Liu. 2013. From RSSI to CSI: Indoor localization via channel response. *ACM Computing Surveys (CSUR)* 46, 2 (2013), 25.