Poster: Comparison of Channel State Information driven and RSSI-based WiFi Distance Estimation

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Abstract

The ubiquity of WiFi and its wide adoption in consumer electronic devices is a major advantage of this technology with regard to radio-frequency based localization. For the distance estimation between devices, WiFi-based solutions either make use of the Received Signal Strength Indicator (RSSI) or of the Channel State Information (CSI). This work outlines the implementation of distance estimation approaches based on both RSSI and CSI measurements using the *Nexmon CSI Extractor* on Raspberry Pi 4 devices. Distances are estimated with the free-space attenuation model for RSSI data and with the FILA method for CSI data. We conducted preliminary experiments in the 2.4 GHz band, which show that distances calculated from CSI values have a smaller absolute median error than those calculated from RSSI values and therefore corroborate further research in this context. The gained results will serve as a benchmark for future WiFi-based distance estimation studies.

1 Introduction

Indoor localization applications often make use of radio-frequency based technologies, such as Radio-Frequency Identification (RFID), Bluetooth, Ultra Wideband or IEEE 802.11 (WiFi). Especially WiFi's ubiquity and availability pose an important advantage and several WiFi-based indoor localization approaches achieving a decimeter-level localization accuracy have been proposed [11].

Early localization approaches used the Received Signal Strength Indicator (RSSI), which is not very robust against multipath propagation [7, 10] and limits the achievable accuracy. To counter these drawbacks, current approaches use time-of-flight [6], or angle-of-arrival measurements based on Channel State Information (CSI) [8]. CSI replaced RSSI in indoor localization research thanks to its finer-grained information and higher temporal stability, as it represents the channel's response in the frequency domain for each Orthogonal Frequency Division Multiplexing (OFDM) subcarrier, instead of aggregated values like RSSI [9].

Access to CSI is only provided by certain WiFi chipsets in combination with specific tools: at the time of this research, only three commonly-used CSI extraction tools are available (i.e., Nexmon CSI Extractor, Linux 802.11n CSI Tool and Atheros CSI Tool). The main goal of this work is to benchmark an RSSI-based distance estimation against a simple CSI-based distance estimation method [7] on state-of-the-art-hardware, that is supported by the newest CSI-extraction tool, i.e., the *Nexmon CSI Extractor* released in 2019 [3]. The results of this benchmarking effort will be used for the purpose of comparison with a re-implementation of Chronos [6] (i.e., an approach for a single WiFi access point localization) within the same hardware, which is currently work in progress.

2 Methods and Experiments

For RSSI-based distance estimation the free-space path loss attenuation model was used. The parameters of this model describing the relationship between the measured RSSI and the distance need to be trained beforehand for a specific environment with known data [10]. The CSI-based distance estimation used in this work resembles the FILA method proposed by Wu et al. [7], which achieved a median accuracy of 0.45 m in a research laboratory. Multipath mitigation in the time-domain and the compensation of frequency-selective fading is also applied according to [7]. The effective CSI (CSI_{eff}) denotes the weighted sum of CSI amplitudes for the OFDM-subcarriers and is used to establish a model based on a modified version of the free-space path loss model. As the CSI is extracted after the Automatic Gain Control (AGC), leading to the loss of distance information in the CSI amplitudes, the calibration of CSI values with the received signal strength suggested by Gao et. al. [2] was applied before calculating CSI_{eff}.

The experimental setup is illustrated in Fig. 1(a), whereas Fig. 1(b) shows the data processing steps. The Nexmon CSI tool is installed on the Raspberry Pi 4B working as receiver. A second Raspberry Pi acts as access point (AP) and sender, where the transmission of WiFi frames is controlled using `ping`. Measurements are all taken outdoors for distances be-

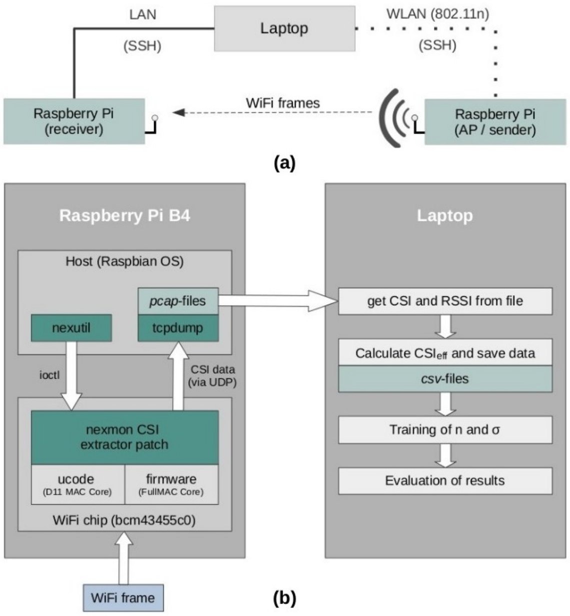

Figure 1: Experimental Setup: (a) Hardware setup with two Raspberry Pi 4B; (b) Schematic of the data processing, where n is the path loss exponent and σ the environment factor (which represents other factors such as radio-frequency gain, antenna gain or shadowing [7]) .

tween 1 and 10 m with a step size of 1 m, between 12 and 20 m with a step size of 2 m, as well as at 25, 30 and 40 m, respectively. An outdoor environment was chosen deliberately to reduce the influence of multipath propagation and thus create a best case scenario. Indoor tests will be carried out in future work. `tcpdump` was used to capture the UDP packets containing the CSI data and to save them into `pcap` files for further data processing. Per distance, all UDP packets received within a measurement time of 20 seconds were used to estimate the distance.

Fig. 2 depicts the Cumulative Distribution Function (CDF) of the ranging errors. The absolute median error for all samples was 2.02 m with calibrated CSI data and 2.87 m with RSSI data. The overall accuracy depends on the propagation model trained for a certain scenario. As the measured data did not fit the model perfectly, it results in relatively high ranging errors. Measurement results for RF-based technologies are highly depending on different factors such as the environment and the used frequency band, and also the 20 MHz bandwidth in 2.4 GHz channels leads to a too low time resolution to distinguish individual multipath components [5, 4]. A higher bandwidth and more advanced data processing and distance estimation techniques should help to decrease the ranging errors for the given hardware. Nevertheless, the availability of CSI from just one embedded antenna might limit the overall accuracy for the given setup and would have to be investigated further, as the CSI extraction on Raspberry Pis has recently become possible [1, 10].

3 Conclusion

This poster compared distance estimation methods based on CSI and RSSI measurements in the IEEE 802.11n standard, using a new CSI extraction tool and cheap off-the-shelf hardware. The comparison suggests that the median ranging error of the CSI-based approach is smaller than the one of the RSSI-based method, which corresponds to results of previous research. In the future the results will serve as baseline benchmarks for other WiFi-based distance estimation approaches which are currently under development.

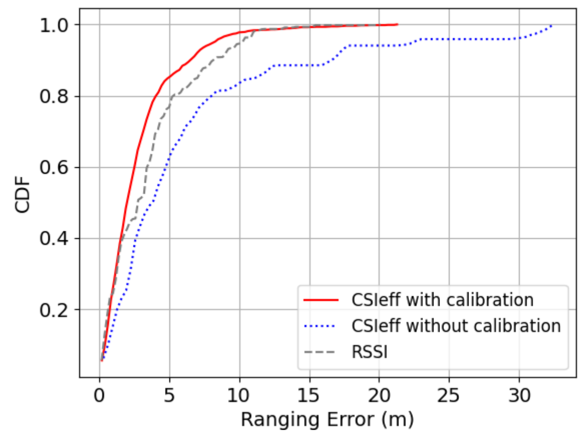

Figure 2: CDF of ranging errors for calibrated CSI using [2], non-calibrated CSI, and RSSI-based distance estimation.

Acknowledgements

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4 References

[1] G. Forbes, S. Massie, and S. Craw. WiFi-based Human Activity Recognition using Raspberry Pi. In *Proc. of the 32nd International Conference on Tools with Artificial Intelligence (ICTAI)*, Nov. 2020.

[2] Z. Gao, Y. Gao, S. Wang, D. Li, Y. Xu, and H. Jiang. CRISLoc: Reconstructable CSI Fingerprintingfor Indoor Smartphone Localization. *CORR – arXiv preprint 1910.06895*, Oct. 2019.

[3] F. Gringoli et al. Free Your CSI: A Channel State Information Extraction Platform For Modern Wi-Fi Chipsets. In *Proc. of the 13th International Workshop on Wireless Network Testbeds, Experimental Evaluation and Characterization (WiNTECH)*, pages 21—-28, 2019.

[4] Z. Li, T. Braun, and D. C. Dimitrova. A Passive WiFi Source Localization System based on Fine-grained Power-based Trilateration. In *Proc. of the 16th International Symposium on A World of Wireless, Mobile and Multimedia Networks (WoWMoM)*, pages 1–9, 2015.

[5] D. Munoz, F. Bouchereau, C. Vargas, and R. Enriquez. *Position Location Techniques and Applications*, chapter Signal Parameter Estimation for the Localization Problem, pages 23–65. Elsevier, 2009.

[6] D. Vasisht, S. Kumar, and D. Katabi. Decimeter-Level Localization with a Single WiFi Access Point. In *Proc. of the 13th USENIX Symposium on Networked Systems Design and Implementation (NSDI)*, pages 165–178, Mar. 2016.

[7] K. Wu, Jiang Xiao, Youwen Yi, Min Gao, and L. M. Ni. FILA: Fine-grained Indoor Localization. In *Proc. of the IEEE International Conference on Computer Communications (INFOCOM)*, 2012.

[8] J. Xiong and K. Jamieson. ArrayTrack: A Fine-Grained Indoor Location System. In *Proc. of the 10th USENIX Symposium on Networked Systems Design and Implementation (NSDI)*, pages 71–84, 2013.

[9] Y. Xu and K. David. When Indoor Localization Meets New Communication Technologies. In *Proc. of the IEEE 90th Vehicular Technology Conference (VTC)*, 2019.

[10] Z. Yang, Z. Zhou, and Y. Liu. From RSSI to CSI: Indoor Localization via Channel Response. *ACM Computing Surveys*, 46(2), Dec. 2013.

[11] F. Zafari, A. Gkelias, and K. K. Leung. A Survey of Indoor Localization Systems and Technologies. *IEEE Communications Surveys and Tutorials*, 21(3):2568–2599, 2019.