Performance of CSI and RSS in Indoor Localization

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***Abstract*—Localization in WiFi networks has become an important research area due to its wide range of applications in various domains. In this paper, we focus on the evaluation of the localization performance achieved for fingerprinting localization using Channel State Information (CSI) and Received Signal Strength (RSS) in WiFi networks. CSI and RSS are two types of measurements that can be extracted from WiFi signals and utilized to estimate the location of a mobile device. However, the accuracy and reliability of localization can vary depending on these measurements. In this paper experimental evaluation of the performance of the WiFi based positioning based on RSS and CSI measurements is presented. Both CSI and RSS data from two access points were collected under identical conditions and used to estimate the position of a mobile device. The performance was compared based on achieved localization errors for both approaches.**

***Keywords*—CSI, KNN, localization, RSS, WiFi, WKNN**

I. INTRODUCTION

Localization in WiFi networks has emerged as a crucial research area with a wide range of applications in various domains. This is mainly due to the rapidly growing number of access points in recent years and the lack of global navigation systems in indoor environments [1]-[2]. The ability to accurately estimate the location of users or devices in WiFi networks is essential for enabling these applications. Received Signal Strength (RSS) and Channel State Information (CSI) are two key parameters that can be extracted from WiFi signals and used for localization purposes. However, the accuracy and reliability of localization can vary between these parameters.

While RSS has been extensively studied and utilized for WiFi network localization [3], CSI has recently gained attention as a promising alternative due to its more fine-grained signal characteristic information in the wireless channel. It provides detailed insights into the multipath propagation and other channel characteristics, which can potentially lead to improved localization accuracy [4].

In the paper, the localization error of fingerprinting algorithms utilizing CSI and RSS in WiFi networks is examined. Our objective is to analyze the performance of both parameters. To achieve our goal, we conduct extensive experiments in a real-world WiFi network environment. Deterministic fingerprinting algorithms will be used to estimate the position of the mobile device. The operation of fingerprinting algorithm is based on the creation of radio maps of the area divided into several reference points. On each reference point, data required for positioning are measured. In this work, We collect CSI and RSS data from multiple access points and utilize K-Nearest Neighbor (KNN) and Weighted K-Nearest Neighbors (WKNN) algorithms to estimate the location of the device. By comparing the estimated location with the ground truth, we evaluate the localization error for both CSI and RSS.

The rest of this paper is organized as follows. In Section II, we provide elementary information about data, methods, and algorithms used in our experiment. Section III describes the experimental setup and methodology used for estimating location. The results and analysis of our experiments are discussed in Section IV. Finally, Section V concludes the paper with a summary of our findings and suggestions for future research directions.

II. RELATED WORK

A. Channel State Information

IEEE 802.11b/g/n/ac standards use the Orthogonal Frequency Division Multiplexing (OFDM) modulation technique. OFDM divides the channel into multiple subcarriers. Each of the subcarriers is used for data transmission. The individual subcarriers overlap but do not interfere with each other. The CSI describes the channel parameters of wireless communication networks and takes into account the various elements that influence signal propagation, such as distance attenuation, signal scatter, and environmental attenuation. Therefore, it is very sensitive to environmental changes. The aim of CSI implementation was to provide effective and dependable data transfer by assessing channel fading and modifying the signal transmission rate [5]. The signal at the receiver may be defined as:

$$y_i = H_i x_i + n_i, \tag{1}$$

where i is the subcarrier index, y_i is received, x_i is transmitted signal. The noise vector is defined by n and H denotes the CSI matrix of the subcarrier i

$$H_i = \begin{pmatrix} h_i^{11} & h_i^{12} & \cdots & h_i^{1N_T} \\ h_i^{21} & h_i^{22} & \cdots & h_i^{2N_T} \\ \vdots & \vdots & \ddots & \vdots \\ h_i^{N_R1} & h_i^{N_R2} & \cdots & h_i^{N_RN_T} \end{pmatrix}, \tag{2}$$

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where h is a complex number that defines the CSI of the ith subcarrier, N_r is the number of receiver antennas and N_t is the number of transmitted antennas. Complex number h can be represented as follows:

$$h_i^{mn} = |h_i^{mn}| e^{j\angle h_i^{mn}}, \tag{3}$$

which includes the amplitude $|h_i^{mn}|$ and phase $\angle h_i^{mn}$ of the CSI [6].

B. Fingerprinting

Recently, the fingerprinting method has become very popular, especially due to the increased use of machine learning. Fingerprints represent some set of signal features, such as RSS or CSI. These are then mapped to specific coordinates so that each fingerprint corresponds to a specific location. Better localization accuracy is achieved with more distinct information that is obtained at a single location, or with the denser the fingerprints. The fingerprinting method can be divided into two phases: offline and online. In the offline phase, measurements are collected, they are processed and stored in the database, associating each fingerprint with its known location. This database serves as a reference for subsequent localization requests. In the online phase, when a device needs to be localized using the fingerprinting method, it measures the signal in its vicinity and extracts its own unique fingerprint. This fingerprint is then processed and compared to the fingerprints stored in the database. By finding the closest match or applying statistical algorithms, the device's location can be estimated based on the known locations associated with the matching fingerprints. [7], [8].

C. KNN: K-Nearest Neighbor

The K-Nearest Neighbors (KNN) is an algorithm that aims to classify or predict the location of an object based on its proximity to other known locations in a given dataset, i.e. radio map. Traditionally, the KNN algorithm selects neighbors based on the Euclidean distance between the features of the unknown location and the known locations in the dataset. It selects the K nearest neighbors, where K is a user-defined parameter [9]. The estimated location x, y is then calculated using:

$$(x, y) = \frac{1}{k} \sum_{n=1}^{k} (x_i, y_i), \tag{4}$$

where k is the number of neighbors, x_i, y_i is location of the i-th selected neighbor [10].

D. WKNN: Weighted K-Nearest Neighbors

Weighted K-Nearest Neighbors (WKNN) is the variant of KNN algorithm. What sets WKNN apart from traditional KNN is the introduction of weights. Each neighbor's influence on the final prediction is determined by a weight factor, which is calculated based on the neighbor's similarity with the fingerprint in the localization request. Neighbors with higher similarity are assigned higher weights, indicating that they have a more significant impact on the prediction [11]. The estimated location x, y is then calculated as:

$$(x, y) = \frac{1}{k} \sum_{n=1}^{k} w_i (x_i, y_i), \tag{5}$$

where k is the number of neighbors, x_i, y_i is location of the i-th selected neighbor [10] and w_i is the weight. The weight of the i-th neighbor can be chosen as a constant value or calculated by different methods based on distance from the target.

III. Experimental setup

A. Data Collection

The experiments were performed in a room shown in Fig. 1 with computers where multipath signal propagation can be expected. CSI was extracted in IEEE 802.11ac with the tool Nexmon CSI [12]. To estimate location fingerprinting method with KNN and WKNN algorithms was used.

As can be seen from the experimental setup shown in Fig. 2, two Raspberry Pi (RPi 1 and RPI 3) have been set as access points and placed in the room. Both APs transmit beacons every 100 ms on channel 36 (5180 MHz) with a frequency bandwidth of 80 MHz. The transmission power was set to 5 dBm. Fingerprints were collected using another Raspberry Pi (RPi 2) every 1 m in raster with size 10 m $\times$ 4 m. In total 44 points were used as fingerprints. At each point was collected a total of 40 samples, 20 from each access point. A single sample consists of RSS and CSI. To evaluate localization error, 9 points were used in the online phase. Setup is shown in Fig. 3.

B. Data Processing

Raw data cannot be used directly as fingerprints because contains noise, especially in CSI. We need to preprocess them and create fingerprints suitable for localization algorithms.

Fig. 1: Room where experiments were performed.

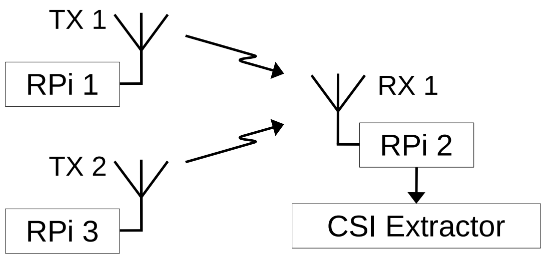

Fig. 2: Scheme of the architecture.

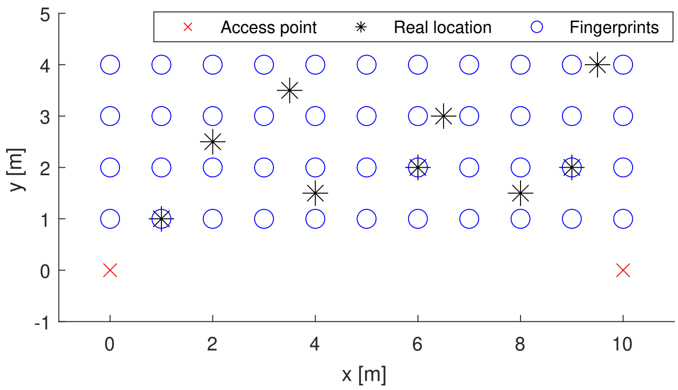

Fig. 3: Setup of the experiment.

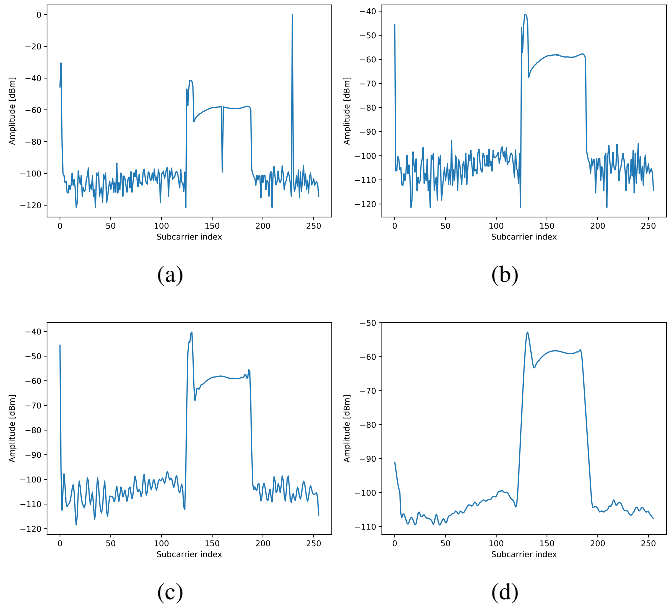

Fig. 4: CSI in different process phases; (a) Raw CSI, (b) CSI after Hampel filter, (c) CSI after low-pass filter, (b) CSI after running mean.

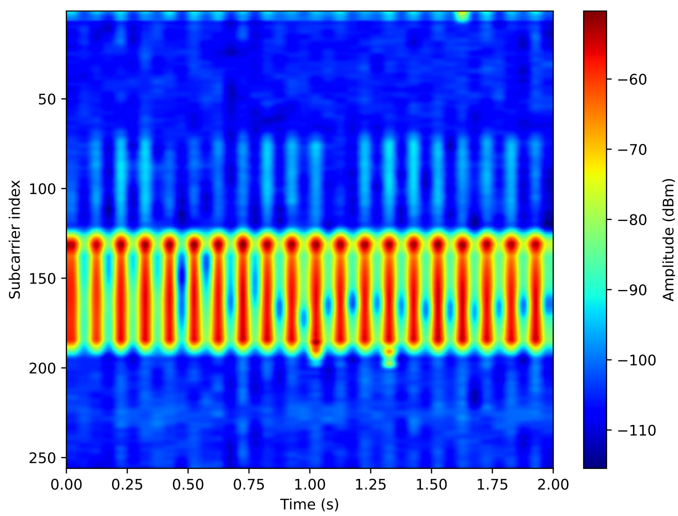

Fig. 5: Radio spectrum image in coordinate (1, 10).

a) CSI: The First step was to calibrate the measured CSI amplitudes that were affected by automatic gain control. We used solution [13] and multiplied CSI with coefficient s that was calculated by:

$$s = \sqrt{\frac{10^{RSS/10}}{\Sigma CSI_i^2}}, \tag{6}$$

where CSI_i is extracted CSI from i-th subcarrier and RSS is received signal strength in dBm. As we can see in Fig. 4a, some subcarriers are affected by a large decrease or increase of amplitude caused by fast fading as well as noise in the extraction phase of CSI. Therefore, a Hampel filter was used in the second step to remove outliers. Moreover, the Butterworth low-pass filter was used to filter out environmental fluctuations and other factors that contribute to high-frequency noise. The experiment was performed indoors with the static device but we assumed the localization of people so we took into account the maximum walking frequency of 2.5 Hz [14] which was set as the cutoff frequency. For a smooth progression, we used a moving average filter with a window size of 10 that gave us good results. After CSI processing, the image of the radio spectrum was created which formed the fingerprint of the point. It consists of 40 samples of CSI alternated between the first access point and the second, so 20 samples for each access point. The image of the radio spectrum on coordinates (1, 10) is shown in Fig. 5.

b) RSS: On the other hand, the processing of RSS was simpler. Each fingerprint of the point consists of the average value of collected RSS for every access point. In our case, the fingerprint is made up of 2 values: average RSS from 1st access point and average RSS from 2nd access point.

C. Location Estimation

We estimate location with measured data in real points shown in Fig. 3 and processed exactly as fingerprints. For both CSI and RSS, KNN and WKNN algorithms were used. The first step was to choose k nearest neighbors. At CSI nearest neighbors were selected by calculating the correlation coefficient between the measured CSI at the point and the fingerprints database of CSI. Then fingerprints were sorted from highest correlation to lowest. The k nearest neighbors were the first k fingerprints with the highest correlation. At RSS nearest neighbors were selected based on Euclidean distance between measured RSS and fingerprints for each access point. Then k nearest neighbors were the first k with the lowest Euclidean distance. For the WKNN algorithm weights need to be set. Based on simulation with different weights, the best ones was chosen that gained better localization error. For RSS, weight w was calculated by

$$w = \frac{1}{|RSS - RSS_i|}, \quad (7)$$

where RSS is measured RSS at point and RSS_i is RSS of i-th fingerprint.

IV. Results and analysis

All of the experiments were carried out to establish which localization data achieved the best accuracy and the lowest variance. The distance error was employed as a metric to evaluate the accuracy of localization approaches. The results of the experiment using CSI are shown on boxplot in the Fig. 6. It shows that WKNN gains better distance error using 3, 4, and 5 nearest neighbors. Also, the variance is smaller with 3, 4, and 5 nearest neighbors using WKNN. The median of distance error is shown in Table I. The best distance error in median using KNN is obtained with 4 nearest neighbors. WKNN compared to KNN obtained better median distance error with all values of k except k=2.

Fig. 7 showing results of localization error using RSS. The best variance of localization error is obtained using 4 and 5 nearest neighbors using KNN. Performance of WKNN compared to KNN showing that distance error is similar with using different numbers of nearest neighbors. The median distance error of WKNN and KNN with RSS is shown in Table II. WKNN compared to KNN achieves better median distance error of all nearest neighbors. The smallest median error was using 2 nearest neighbors with WKNN.

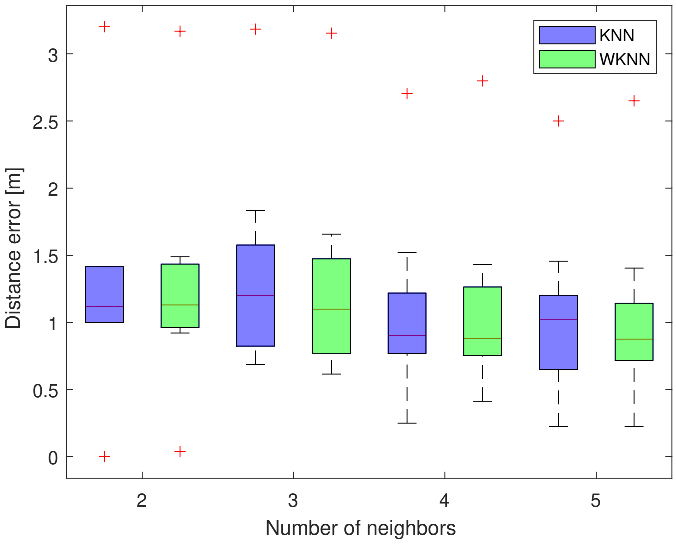

Fig. 6: Localization error using CSI.

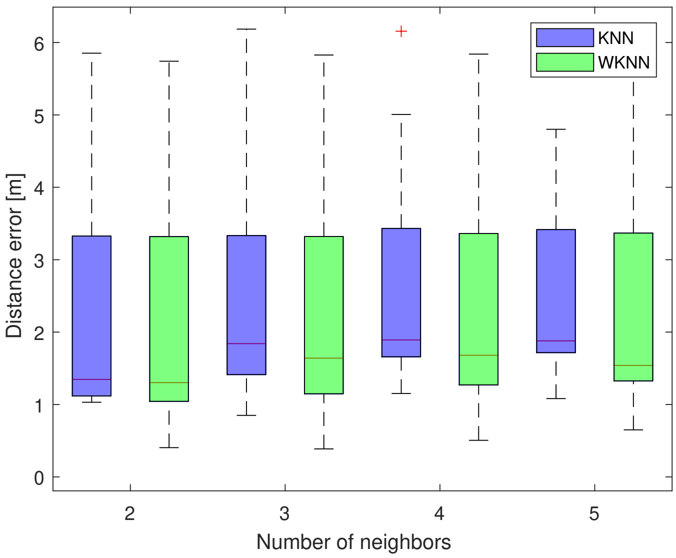

Fig. 7: Localization error using RSS.

TABLE I: Median of distance error CSI

Algorithm	Number of neighbors			
	2	3	4	5
KNN	1.12 m	1.20 m	0.90 m	1.02 m
WKNN	1.13 m	1.10 m	0.88 m	0.88 m

TABLE II: Median of distance error RSS

Algorithm	Number of neighbors			
	2	3	4	5
KNN	1.35 m	1.84 m	1.89 m	1.88 m
WKNN	1.30 m	1.64 m	1.68 m	1.54 m

V. Conclusion

Based on the analysis and comparison of different localization data, it can be concluded that utilizing CSI for localization is superior to using RSS in IEEE 802.11ac. CSI provides more detailed and comprehensive information about the wireless channel characteristics. The WKNN algorithm achieves better results based on a smaller localization error for both CSI and RSS measurements. While both CSI and RSS can be used for localization, the superiority of CSI in terms of accuracy and robustness makes it a preferred choice for achieving precise and reliable localization results with using WKNN compared to KNN. It is important to note that the effectiveness of CSI for localization may still depend on factors such as the quality of the CSI measurements, the deployment environment, and the specific algorithm used. Future work will be focused on the use of AI techniques to estimate position, which can be more accurate because of deeper analysis and more robust algorithms to find connections between fingerprints.

REFERENCES

[1] H.-M. Cheng and D. Song, *Localization in Inconsistent WiFi Environments*, ser. Springer Proceedings in Advanced Robotics. Cham: Springer International Publishing, 2020, vol. 10, p. 661–678. [Online]. Available: http://link.springer.com/10.1007/978-3-030-28619-4_47

[2] J. Machaj, P. Brida, and S. Matuska, "Proposal for a localization system for an iot ecosystem," *Electronics*, vol. 10, no. 23, p. 3016, Dec. 2021.

[3] P. Roy and C. Chowdhury, "A survey on ubiquitous wifi-based indoor localization system for smartphone users from implementation perspectives," *CCF Transactions on Pervasive Computing and Interaction*, vol. 4, no. 3, p. 298–318, Sep. 2022.

[4] X. Dang, X. Tang, Z. Hao, and Y. Liu, "A device-free indoor localization method using csi with wi-fi signals," *Sensors*, vol. 19, no. 14, p. 3233, Jul. 2019.

[5] S. Tan, Y. Ren, J. Yang, and Y. Chen, "Commodity wifi sensing in ten years: Status, challenges, and opportunities," *IEEE Internet of Things Journal*, vol. 9, no. 18, p. 17832–17843, Sep. 2022.

[6] Y. He, Y. Chen, Y. Hu, and B. Zeng, "Wifi vision: Sensing, recognition, and detection with commodity mimo-ofdm wifi," *IEEE Internet of Things Journal*, vol. 7, no. 9, p. 8296–8317, Sep. 2020.

[7] D. Dogan, Y. Dalveren, and A. Kara, "A mini-review on radio frequency fingerprinting localization in outdoor environments: Recent advances and challenges," in *2022 14th International Conference on Communications (COMM)*. Bucharest, Romania: IEEE, Jun. 2022, p. 1–5. [Online]. Available: https://ieeexplore.ieee.org/document/9817189/

[8] H. Subakti, H.-S. Liang, and J.-R. Jiang, "Indoor localization with fingerprint feature extraction," in *2020 IEEE Eurasia Conference on IOT, Communication and Engineering (ECICE)*. Yunlin, Taiwan: IEEE, Oct. 2020, p. 239–242. [Online]. Available: https://ieeexplore.ieee.org/document/9301994/

[9] X. Zheng, R. Cheng, and Y. Wang, "Rssi-knn: A rssi indoor localization approach with knn," in *2023 IEEE 2nd International Conference on Electrical Engineering, Big Data and Algorithms (EEBDA)*. Changchun, China: IEEE, Feb. 2023, p. 600–604. [Online]. Available: https://ieeexplore.ieee.org/document/10090664/

[10] X. Ge and Z. Qu, "Optimization wifi indoor positioning knn algorithm location-based fingerprint," in *2016 7th IEEE International Conference on Software Engineering and Service Science (ICSESS)*. Beijing, China: IEEE, Aug. 2016, p. 135–137. [Online]. Available: http://ieeexplore.ieee.org/document/7883033/

[11] H. Pirzadeh, C. Wang, and H. Papadopoulos, "Machine-learning assisted outdoor localization via sector-based fog massive mimo," in *ICC 2019 - 2019 IEEE International Conference on Communications (ICC)*. Shanghai, China: IEEE, May 2019, p. 1–6. [Online]. Available: https://ieeexplore.ieee.org/document/8761452/

[12] F. Gringoli, M. Schulz, J. Link, and M. Hollick, "Free your csi: A channel state information extraction platform for modern wi-fi chipsets," in *Proceedings of the 13th International Workshop on Wireless Network Testbeds, Experimental Evaluation & Characterization*. Los Cabos Mexico: ACM, Oct. 2019, p. 21–28. [Online]. Available: https://dl.acm.org/doi/10.1145/3349623.3355477

[13] Z. Gao, Y. Gao, S. Wang, D. Li, and Y. Xu, "Crisloc: Reconstructable csi fingerprinting for indoor smartphone localization," *IEEE Internet of Things Journal*, vol. 8, no. 5, p. 3422–3437, Mar. 2021.

[14] A. Pachi and T. Ji, "Frequency and velocity of people walking," vol. 83, pp. 36–40, 02 2005.