M-006

An Experimental Study of Fingerprint-based Localization in 5G Ultra Dense Network

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1. Introduction

Location-based services (LBS) are increasingly critical in settings like hospitals, factories and shopping malls, fueling demand for accurate indoor localization. The rise of 5G technology, particularly Ultra-Dense Networking (UDN), meets this need by supporting dense indoor base station deployments. Among localization methods, Received Signal Strength Indicator (RSSI)-based on fingerprinting stands out for its low cost and simplicity [1]. It comprises an offline phase, collecting RSSI data at known reference points (RPs), and an online phase, matching measurements from unknown points to the points in fingerprint database using algorithms like K-Nearest Neighbor (KNN) or Weighted-KNN (WKNN). These estimate positions by averaging the coordinates of the K nearest RPs based on RSSI Euclidean distance.

The traditional KNN algorithm often struggles to achieve accurate localization in complex indoor environments. It fails to reflect the true correlation between RSSI distances and spatial distance in complex environments. Such inaccurate reflection can lead to situations where a nearby RP is excluded due to a large RSSI difference caused by environmental interference from a single Wi-Fi Access Point (AP) or 5G Pico eNodeB (PeNB), even if others show only small differences. As a result, the overall Euclidean distance becomes large, and the algorithm may overlook this close RP. In contrast, the Feature-Scaling-based KNN (FS-KNN) algorithm proposed in [2] assigns different weights to RSSI differences. This scaling better captures the characteristics of RSSI variations in complex environments, leading to an improvement in localization accuracy over the traditional KNN algorithm. However, [2] only briefly discussed the impact of RSSI intervals. FS-KNN links RSSI values to geometric distances using weights based on RSSI interval counts, which are influenced by the RSSI range (i.e., a wider range allows finer granularity). Given that 5G UDN offers a significantly wider RSSI range than Wi-Fi [3], we investigated its potential to further improve FS-KNN's localization performance.

This study applies the FS-KNN algorithm to a 5G UDN scenario and evaluates its performance in both Wi-Fi and 5G UDN environments. We also analyze the effect of RSSI intervals on performance. Simulation results show that FS-KNN achieve higher accuracy in 5G UDN than Wi-Fi.

2. Simulation-based Evaluation of FS-KNN in 5G UDN

2.1 Simulation Environment

We simulated an indoor environment using MATLAB, as shown in Fig.1. The dimensions of this indoor environment are 20 m × 15 m, in which 10 PeNBs and 100 RPs are uniformly distributed. The horizontal spacing of each PeNB is 3.3 m, and the vertical one is 5 m. The horizontal spacing of each RP is 1.8 m, and the vertical one is 1.3 m. To simulate RSSI value, we adopted a general path loss model as shown in Eq.(1):

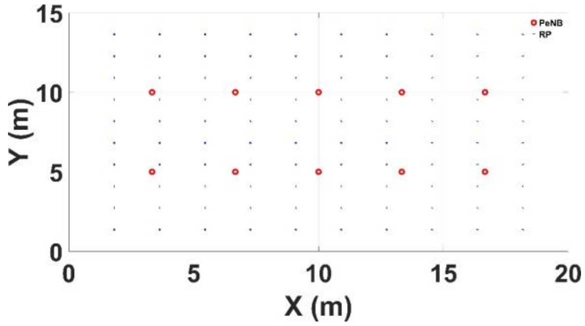

Figure 1: Simulated Indoor Environment with 5G UDN

$$P_L(d,f) = 10\alpha \log_{10}(d) + \beta + 10\gamma \log_{10}(f) + X_\sigma, \qquad (1)$$

where d is the distance between RPs and PeNBs. α is the coefficient related to distance d. β is a constant value. γ is the coefficient related to frequency f. X_σ is the noise, which is a normally distributed random variable that conforms to a mean of 0 and a standard deviation of σ. We set the specific parameters in the path loss model in the indoor office scenario of following 3GPP standard [4].

2.2 FS-KNN Algorithm Implementation

In the traditional KNN algorithm, the Euclidean distance between the observed RSSI vector and each RP is computed as:

$$d_i = \sqrt{\sum_{j=1}^{L} (RSSI_{i,j} - RSSI_j)^2}, \qquad (2)$$

where d_i is the Euclidean distance between unknown point and i^{th} RP. $RSSI_{i,j}$ is the RSSI value in the i^{th} RP from the j^{th} PeNB. $RSSI_j$ is the RSSI value in the unknown point from the j^{th} PeNB. L is the number of PeNBs.

FS-KNN enhances this by applying feature scaling (i.e., assigning different weights to RSSI differences based on their reliability). The modified 'weighted' distance is computed as:

$$d_i' = \sqrt{\sum_{j=1}^{L} (RSSI_{i,j} - RSSI_j)^2 \times \omega(RSSI_j)}, \qquad (3)$$

where d_i' is the weight distance. $\omega(RSSI_j)$ is the weight function. The weight depends on the specific RSSI value. The entire RSSI range is divided into equal intervals, and each interval is given a different weight. When we measure an RSSI value, we check which interval it belongs to and use the corresponding weight in distance calculations. To optimize the weight $\omega(\cdot)$, FS-KNN employed a Simulated Annealing (SA) algorithm. SA begins with a high exploration rate and gradually cools down, reducing randomness and converging toward an optimal solution.

3. Evaluation

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3.1 Settings

In the mentioned environment, we deploy FS-KNN in both Wi-Fi and 5G UDN scenarios. Specifically, we randomly divided the 100 RPs into a training set (80%) and a test set (20%). The carrier frequencies f in the Wi-Fi and 5G UDN scenarios were set to 2.4 GHz and 3.5 GHz, respectively. The RSSI range is [-100 dBm, -45 dBm] for Wi-Fi scenario and [-156 dBm, -31 dBm] for 5G UDN scenario. In addition, we set the number of RSSI intervals to 40, the number of selected RPs K to 2, and the maximum number of iterations in the SA algorithm to 5000.

3.2 KNN vs. FS-KNN in 5G UDN

To demonstrate the advantages of FS-KNN over traditional KNN, we applied both algorithms in the same 5G UDN setting. AS a case study, we selected a single test point (TP) located at (5.45,9.55) and examined the RPs chosen for localization by each method.

As shown in Fig.2, the KNN algorithm selected RP 13 (5.45, 10.91) and RP 35 (5.45, 13.64), resulting in an estimated position of (5.45,12.27). The corresponding localization error was 2.73 m. In contrast, FS-KNN selected RP 13 and RP 61 (5.45, 8.18), predicting a location of (5.45, 9.55) with a significantly lower error of 0 m. Although RP 61 is geometrically closer to the TP than RP 35, it was not selected by KNN due to its higher unweighted Euclidean distance in RSSI space (12.87 vs. 11.67), which reflects environmental interference. FS-KNN overcomes this limitation by applying interval-based weights to RSSI difference, resulting in weighted distances of 17.45 (for RP 61) and 18.75 (for RP 35). This adjustment enabled FS-KNN to identify a more appropriate RP, leading to superior localization accuracy. We further compared both algorithms across all TPs by repeating the experiment 10 times. Fig.3 shows that FS-KNN consistently outperformed KNN in 5G UDN scenario, achieving a lower average localization error of 1.759 m compared to 2.468 m. This improvement stems from FS-KNN's ability to assign weights that better reflect the true relationship between RSSI differences and geometric distances.

3.3 Performance of FS-KNN in Wi-Fi and 5G UDN

In this section, we evaluated FS-KNN in both Wi-Fi and 5G UDN scenarios under two RSSI intervals settings (40 and 80). The results in Fig.3 show that FS-KNN consistently achieved higher localization accuracy in the 5G UDN scenario (1.759 m vs. 2.457 m for 40 intervals; 1.558 m vs. 2.059 m for 80 intervals). The wider RSSI range in 5G UDN allows for finer interval division, enabling FS-KNN to capture signal variations more effectively. This improvement stems from the ability of FS-KNN to use interval-based weights to more accurately reflect the relationship between RSSI differences and spatial distances.

4. Conclusion

This paper applied the FS-KNN algorithm to both Wi-Fi and 5G UDN scenarios to enhance fingerprint-based indoor localization. By assigning interval-based weights to RSSI differences. FS-KNN better captures the relationship between signal variation and spatial distance in complex environments.

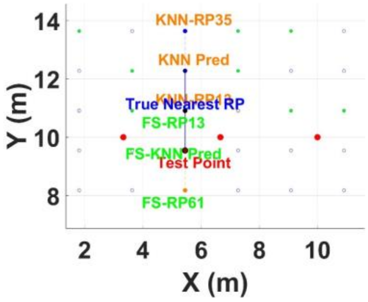

Figure 2: KNN vs. FS-KNN in Single TP

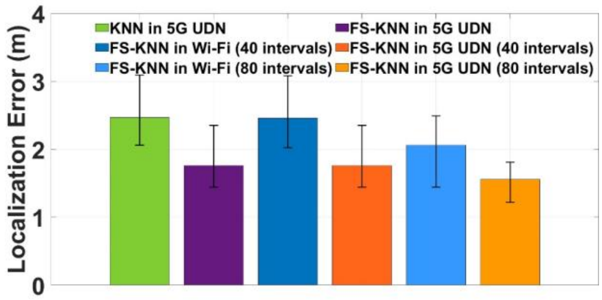

Figure 3: Localization under Different Settings

Experimental results show that FS-KNN achieves higher accuracy in 5G UDN than Wi-Fi, primarily due to the wider RSSI range, which allows for more effective interval division. These findings highlight the importance of adapting FS-KNN parameters to the characteristics of the deployment environment to maximize localization accuracy.

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