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# A dynamic *K*-nearest neighbor method based on strong access point credibility for indoor positioning



**Key words:** RSS path loss; Fingerprint indoor positioning; Dynamic *K*-nearest neighbor

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# Motivation

1. A traditional indoor positioning technology, fingerprint indoor positioning, often employs the *K*-nearest neighbor (KNN) algorithm to identify the closest *K* reference points (RPs) via the received signal strength (RSS) for location prediction. However, RSS is susceptible to environmental interference, leading to the selection of RPs that are not physically the closest to the user.

2. Moreover, using a fixed *K* value is not the optimal strategy.

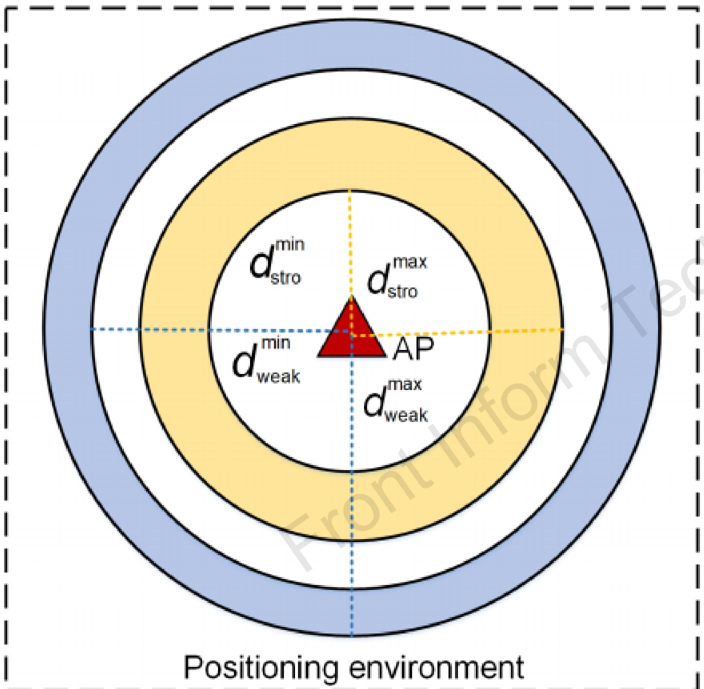
# Main idea

1. We propose a novel approach, the dynamic KNN method based on strong access point (AP) credibility (SAPC-DKNN), for indoor positioning. In SAPC-DKNN, we leverage prior knowledge of RSS path loss and employ the RSS fluctuation area to quantify the significance of different APs. We integrate the similarity of AP sets within the range of strong APs and formulate a weighted distance metric for RSS based on the credibility of strong APs.

2. We introduce a dynamic *K*-value algorithm based on neighbor density (ND-DKA) for the automatic optimization of the *K* value for each test point.

# Method

## 1. Strong AP weighted distance measurement method



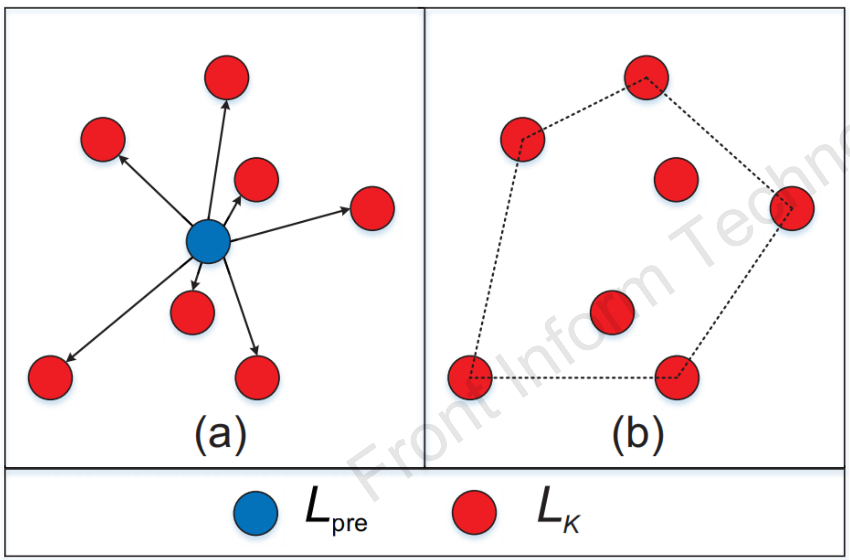

RSS fluctuation range under strong and weak APs

Relying solely on RSS measurements for distance assessment may not accurately depict the physical closeness of two points.

We introduce a method that employs the RSS fluctuation area as AP credibility to account for the significance of the RSS corresponding to a single AP.

# Method

2. Dynamic $K$-value algorithm based on neighbor density




Proximity of the neighbor to TP: quantify the proximity of $K$ RPs to their weighted geometric centers.

Density of neighbors: quantify the proximity of $K$ RPs to each other.

# Major results

**Table 3 Performance of SAPC-DKNN on Tampere for 3D positioning**

| Method | Reference | Loss (m) |
|---|---|---|
| CNN | Arslantas and Okdem (2024) | 8.13 |
| SALLoc | Ayinla et al. (2024) | 9.52 |
| eAaT+ | Nguyen et al. (2024) | 8.14 |
| GrowNetLoc | Zhao et al. (2024) | 7.82 |
| EA-CNN | Alitaleshi et al. (2023) | 9.52 |
| bAaT | Nguyen et al. (2023) | 8.53 |
| GMM+WKNN | Lin et al. (2023) | 11.17 |
| Vanilla LSTM | Dong YH et al. (2022) | 8.66 |
| HADNN | Cha and Lim (2022) | 9.05 |
| RWKNN | Chen et al. (2022) | 6.53 |
| CNNLoc | Song et al. (2019) | 10.88 |
| SAPC-DKNN | This paper | **4.14** |

The best result is in bold

# Major results

**Table 4 Average positioning error for different methods**

| Trajectory | Average positioning error (m) | | | | | | |
|---|---|---|---|---|---|---|---|
| | SAPC-DKNN ($K \in [3, 30]$) | KNN ($K = 5$) | WKNN ($K = 5$) | STI-WKNN ($K = 5$) | Spearman-KNN ($K = 5$) | SIM-KNN ($K = 5$) | SRL-KNN ($K = 3$) |
| B0–P0 | **5.66±3.61** | 9.46±6.23 | 9.52±6.26 | 8.70±5.88 | 16.05±10.95 | 9.52±6.26 | 8.26±5.11 |
| B0–P4 | **4.18±3.92** | 6.87±5.11 | 6.84±5.08 | 6.73±4.59 | 10.97±9.10 | 6.84±5.08 | 5.76±4.45 |
| B0–P21 | **6.20±5.89** | 13.02±11.12 | 13.00±11.11 | 13.62±11.10 | 13.46±9.22 | 13.00±11.11 | 15.29±11.55 |
| B1–P4 | **6.90±4.27** | 10.67±7.22 | 11.33±7.95 | 10.72±8.82 | 16.65±10.75 | 11.33±7.95 | 10.15±6.84 |
| B1–P12 | **8.01±6.58** | 12.38±9.15 | 12.37±9.12 | 12.16±9.60 | 12.83±9.48 | 12.37±9.12 | 16.49±20.20 |
| B1–P13 | **7.70±7.22** | 11.11±8.82 | 11.04±8.88 | 10.51±9.37 | 12.55±10.36 | 11.04±8.88 | 11.34±10.27 |
| Val-1 | **4.56±2.20** | 5.87±2.69 | 5.87±2.72 | 5.87±2.87 | 5.39±2.32 | 5.87±2.73 | 5.57±2.64 |
| Val-2 | **4.68±1.97** | 5.73±2.70 | 5.73±2.70 | 5.76±2.80 | 5.87±3.07 | 5.72±2.75 | 5.74±2.77 |
| Val-3 | **4.52±1.90** | 6.43±3.02 | 6.45±3.02 | 6.27±2.96 | 7.31±3.44 | 6.44±3.03 | 6.14±2.89 |
| Val-All | **4.59±2.08** | 6.02±2.94 | 6.03±2.93 | 6.04±2.91 | 6.47±3.22 | 6.04±2.94 | 5.92±2.79 |
| Testing-CETC331 | **2.96±2.63** | 4.75±4.31 | 4.75±4.31 | 4.66±4.03 | 4.87±4.05 | 4.79±4.33 | 4.72±4.07 |
| Testing-HCXY-All | **2.20±1.93** | 3.15±2.99 | 3.01±2.79 | 2.84±2.58 | 4.35±4.17 | 3.00±2.80 | 2.98±2.82 |
| Testing-SYL-All | **3.68±5.01** | 5.19±5.27 | 5.18±5.27 | 4.78±5.25 | 5.18±5.30 | 5.08±5.30 | 5.02±5.30 |

The best results are in bold

# Conclusions

1. We have introduced a DKNN method based on strong AP credibility for indoor positioning (SAPC-DKNN). Leveraging the progression of the RSS path loss model, this method quantifies AP credibility and devises an RSS distance measurement technique incorporating strong AP weighting. In comparison with alternative weighting methods, SAPC-DKNN uses both the order and strength information at the AP level to mitigate similarity errors arising from RSS fluctuations, thereby significantly enhancing positioning accuracy.

2. Through integration with a dynamic *K*-value algorithm based on NN density, SAPC-DKNN achieves heightened precision and stability in real-time positioning.