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I. INTRODUCTION

The demand for accurate localization under indoor environments has increased dramatically in recent years with a large variety of the applications such as guidance, rescue operation, virtual reality game, etc [1]–[3]. For example, indoor positioning can help to guide customers in a shopping mall towards store, food court, etc., or passengers in an airport to the right terminal. In a museum, accurate indoor localization can transform a customer’s phone into a virtual guide to give them contextual information based on his/her location. In this paper, the main application is to locate a walking human using the WiFi signals of the carried smartphone with an acceptable accuracy around a few feet. In general, WiFi indoor localization methods can be grouped in two categories: one is signal propagation model based ranging, which utilizes received signal strength (RSS), the time of flight (TOF) and/or angle of arrival (AOA) [4] to estimate the location of the target; the other is fingerprinting based [4], [5], which discriminates between locations by associating physically measurable properties as fingerprints or signatures for each discrete point. Due to the strong multipath effects, exact propagation model is difficult to obtain. Therefore, fingerprinting approach is more favourable for the WiFi based localization.

Fingerprinting based WiFi localization can be realized by deterministic and probabilistic approaches [5]. The former uses a similarity metric to differentiate the measured signal and the fingerprint data in the database before estimating the user’s position as the closest fingerprint location in the signal space. Some typical examples of this approach are artificial neural network (ANN) [6], [7], support vector machine (SVM) [6], [8] and K nearest neighbors (KNN) [9], [10], all of which require the collection of the fingerprints in the training phase to be compared with the measured signal in the testing phase for localization. Among these algorithms, ANN estimates location non-linearly from the input by a chosen activation function and adjustable weightings [7]. Despite its highest accuracy [11], [3], this method is sophisticated in nature and requires extremely high computational complexity in the training phase [6]. In contrast, SVM is simpler than ANN [8] but still relatively high in complexity. Compared to SVM and ANN, KNN has the lowest complexity while its accuracy is comparable to SVM [6]. On the other hand, the probabilistic algorithms are all based on statistical inference between the target signal measurement and stored fingerprints using Bayes rule [12]. Therefore, some probabilistic approaches assume the probability density function (PDF) of the RSSIs as empirical parametric distributions (e.g., Gaussian, double-peak Gaussian, lognormal [13], [2]). This may not emulate the actual situation well [14], leading to substantial localization errors. In order to achieve better performance, non-parametric methods [15], [16] make no assumption on the PDF of RSSI but require a large amount of data at each reference point, large storage and high computational resources to form the smooth and accurate PDF. Moreover, improvement of localization accuracy has been achieved by exploiting the measurements in previous time steps. For example, Kalman filter [17]–[20] is used to estimate the most likely current location based on prior measurements, assuming a Gaussian noise and linear motion dynamics. In real scene, however, the assumption of Gaussian noise is not necessarily true [21], neither is the user’s linear motion assumption a good approximation. A better motion model was proposed in [19] with two Kalman filters, one for constant velocity case and the other one for a greater acceleration. The application of these two filters and switching in-between them increases the computational complexity significantly. In order to tackle the non-Gaussian and non-linear cases, extended Kalman filter [22] or particle filter [23]–[26] can be applied. However, the major drawback of those filters is associated with high computational workloads and failure due to sample impoverishment [21], [25].

This paper focuses on the study of KNN because of its low complexity suitable for practical use. In general, KNN computes the distance between the current WiFi RSSI fingerprint and the learned fingerprint in database to determine K nearest neighbours. Different distance metrics such as Euclidean distance, Manhattan distance, and Mahalanobis distance can be used in KNN [2]. Although being extensively investigated in
literature, KNN still has the following open challenges:

1. Spatial ambiguity \cite{27}: Some physically distant locations may have similar fingerprints or similar fingerprint distances compared with the current location. This could mislead the KNN algorithms, leading to high localization errors.

2. RSSI instability: Moving objects, constantly varying electromagnetic wave landscape in ambient environments, directionality of antenna and RF interference, etc., contribute to the wide fluctuation of WiFi signal \cite{21}. Therefore, the observed fingerprint of a location in the testing phase may not match that collected in the training phase.

3. RSSI short collecting time per location: Usually RSSI instability can be mitigated by taking the average of a large number of RSSI readings at one location. However, due to the mobile nature of the locating target, the RSSI sampling at each specific location in the testing phase is typically shorter than 2 seconds. Within that duration, only a few number of RSSI readings can be collected. Consequently, the localization accuracy is severely impaired.

4. Heavy initial training phase: in order to construct the sufficient fingerprint map for accurate localization, a large number of reference points are required \cite{28}, which is time-consuming and labor-intensive \cite{5}.

To address the first three challenges, this paper incorporates the information of a user’s previous position to KNN. Since the moving speed of the user in an indoor environment is bounded, the proposed soft range limited KNN still has the following open challenges:

Therefore, in addition to WiFi AP-sequence, \cite{25} also adopts the inertial-measurement unit (IMU) sensors and FM signal to refine the estimated location. In our experiment, we address the training phase challenge with the support of an autonomous robot. Our 3-wheel robot (Fig. 2(a)) has multiple sensors including wheel odometer, an inertial measurement unit (IMU), a LIDAR, sonar sensors and a color and depth (RGB-D) camera. The robot can navigate to a target location to collect WiFi fingerprints automatically. The localization accuracy of the robot is 0.07 m ± 0.02 m. Therefore, the time consumption and degree of human involvement for fingerprinting map construction is significantly reduced.

The rest of the paper is organized as follows. Section II introduces related works on KNN, followed by details of SRL-KNN in Section III. Section IV reports the experimental set-up and results for the performance evaluation. Finally, Section V concludes this paper.

II. RELATED WORK

The original research on KNN indoor localization dates back to 2000 when a group from Microsoft demonstrated RADAR \cite{9}. In that work, the mean and standard deviation of RSSI from multiple base stations are collected in the training phase and the Euclidean distance is used in the testing phase to determine the user’s position. There are 70 reference points (RPs) with 2.8 m distance spacing (grid size). Testing points are picked randomly among these reference points. The average accuracy of this system is around 3 m with 75% of the localization errors are below 4.7 m.

A refinement of the above method is the weighted KNN (WKNN) proposed by Brunato et al. \cite{6}, which calculates the user’s position by the weighted average of the RSSI distance between estimated nearest neighbours and the current measurement. The experiment is implemented with 207 reference locations, 50 testing locations and a grid size of 1.7 m. The accuracy of WKNN is 3.1 ± 0.1 m and 75% of the localization errors are below 3.9 m.

To accommodate device heterogeneity, Zou et al. \cite{30} proposed signal tendency index - weighted KNN (STI-WKNN) by adopting the similarity index STI between RSSI curve shapes to improve the localization accuracy. The raw RSSI signal is first transformed to a normalized object based on procrustes analysis (PA) method \cite{31}. Then signal tendency index is computed according to Euclidean distances between real time PA object and those stored in the fingerprint database. The final location will be determined by weighting among K nearest neighbours that provide the smallest STI. Their experiment shows that STI-WKNN improves the localization accuracy by 23.95% over the original WKNN across heterogeneous mobile devices.

In a following research, Shin et al. \cite{32} proposed to dynamically change the number of nearest neighbours \(K\). Firstly, the RSSI Euclidean distance \(D_i\) of each reference point \(i\) is computed and \(N\) numbers of which smaller than a threshold \(T\) are picked. In a second step, the average of the selected \(D_i\) is calculated to obtain a value \(E\) and \(K\) neighbours that satisfy \(D_i < E\) are chosen. In general, this method only provides slightly lower average localization error.
than the classical KNN in RADAR [9], except in the corridor where the testing scene is de facto one-dimensional.

Taking into account the limited movement capabilities of a mobile user in an indoor environment, some researchers tried to utilize the information from the previous locations to improve the accuracy of KNN. In [33], Khodayeri et al. predicted the next probable location of the user by determining the speed and movement direction based on his/her last two recorded locations. Then, this prediction will be considered only when the localization result of WKNN [6] is substantially deviated from the prior location. The underline assumption is that users moving at both constant speed and direction, which is not the case in many practical scenes. In [34], Altintas et al. added a short term memory which stores the recent signal strength observations as the historical data. In the testing phase, the current RSSI readings and all historical RSSI readings in the memory are added and taken the average. This helps to eliminate the unexpected signal strength readings due to the reflection, diffraction and scattering of the radio waves. However, this method is valid only when the variation of RSSI between the current and previous positions is small, which is not always true.

In order to improve the localization stability, Xie et al. [10] used Spearman distance based on the RSSI ranking between APs. According to [10], although the absolute RSSI readings of a set of APs in a fixed location might be quite different, their rankings are more likely to remain the same, making it feasible to form a stable fingerprint. The drawback is that this algorithm is limited by the number of APs available. In the simulation of [10], there are 400 reference locations but only 4 APs which can provide a maximum of 4! = 24 ranking fingerprints. Consequently, many different locations have the same fingerprints, leading to localization errors in the testing phase.

In general, all of the above methods provide acceptable accuracy within around twice the distance between two consecutive reference points (grid size), but the problems of KNN algorithm mentioned in Section I are not effectively solved. For example, previous KNN research have not sufficiently investigated the inadequate sampling of RSSI due to the user’s movement, i.e., only 1 or 2 RSSI readings are available in each testing location. Obviously this ignores a very important factor and affects the localization accuracy. In addition, in the methods that use historical data, the assumption that users moving in constant speed and direction is unrealistic in many scenes. Therefore, a new KNN algorithm, which addresses the aforementioned problems of KNN, is proposed.

III. SYSTEM MODEL

A. Localization Scene

The fingerprinting localization system is generally divided into two phases: a training phase (offline phase) and a testing phase (online phase). In the training phase, features of the WiFi signals at each predefined reference point (RP) location, are collected and stored to a database. Those features typically include the mean and standard deviation of RSSI, the RSSI ratio between a pair of APs, the ranks of the APs, etc [2]. They individually or collectively form fingerprints at each RP. Here, we assume the area of interest has $P$ APs and $M$ RPs. For each RP $i$ at its physical location $l_i(x_i, y_i)$, a corresponding fingerprint vector is denoted as $f_i = \{F_1, F_2, ..., F_N\}$, where $N$ is the number of available features and $F_j(1 \leq j \leq N)$ is the $j$-th feature at point $i$. In the testing phase, each unknown location of the user, denoted as a testing point, is determined by the localization algorithm. During the training phase, multiple RSSI scans ($S_1$ scans) can be obtained at each location, and hence a set of RSSI values correspond to one RP while in the testing phase, only a small number of RSSI readings ($S_2$ scans), e.g., $S_2 = 1$ or $S_2 = 2$, is available for the fingerprint matching. Fig. 1(a) illustrates our localization scheme with 6 APs, 365 RPs and 175 testing points. Fig. 1(b) shows the heat map of 6 APs, where we represent signal strength by color. Clearly, the signals from 6 APs already cover the whole targeting area including 1 room and 3 corridors.

B. The classical KNN algorithm

The fingerprint distance between the unknown current point $l$ and each reference point $i$ in database is first calculated as follows

$$D_i^l = \sqrt{\sum_{j=1}^{N} (F_j - F_j^i)^2}$$

where $F_j$ is the $j$-th fingerprint feature at the unknown location, $N$ is the number of available fingerprints. Then $K$ locations with the minimum distances are chosen as the $K$ nearest neighbours. Finally, the position $l$ of the user is determined by taking the average of all those $K$ neighbours’ locations.

C. Proposed Soft Range Limited KNN (SRL-KNN) method

1) SRL-KNN algorithm: This paper proposes to leverage the information of the user’s previous position, as the moving speed of a user is limited and one cannot instantaneously move to an unrealistic distant position from the prior one during the consecutive measurements. In a simple form, a circle can be drawn around the previous location to limit the nearest neighbour search space to within the circle, whose radius is determined by the user moving speed and time duration between two consecutive measurements. Instead of using that hard range limit, we here devise a novel soft range limiting factor to the fingerprint distance calculation where the locations near the user’s previous position are given higher likelihood to become one of $K$ nearest neighbour candidates. To achieve that, we modify the Euclidean distance in (1) as follows

$$D_i^l = \frac{W_i^l \times D_i^l}{\sum_{i=1}^{M} W_i^l}$$

$$W_i^l = \exp\left(\frac{(x_i - x_{pre})^2 + (y_i - y_{pre})^2}{4\sigma^2}\right)$$

where $W_i^l$ is the penalty function for the location $l$, $M$ is the total number of RPs in the database, $(x_{pre}, y_{pre})$ is the most recent previous location of the user, $\sigma$ is the maximum distance which the user can move in a consecutive sampling time interval $\Delta t$. For example, people tend to walk in indoor environments at a speed from 0.4 m/s to 2 m/s [35]. [36] (maximum speed $v_{\text{max}} = 2$ m/s) and the user location will be updated every 1 second (consecutive sampling time interval
\( \Delta t = 1 \text{ s} \). Therefore, \( \sigma = v_{\text{max}} \Delta t = 2 \text{ m} \). As shown in Fig. 2(c), the penalty function has the form of a Gaussian distribution with the mean being the previous location and the standard deviation being \( \sigma \). Note that the prior position is only used here to form the soft range limit scaling factor as shown in (3), unlike in Kalman filter approaches which directly include the history position in the current location calculation. Moreover, our formulation only assumes a maximum moving speed, but does not require knowledge of the exact moving speed and direction of the user. The user’s location \( l \) is determined through a weighted average of \( K \) nearest neighbours \( l_j \) as follows
\[
l = \frac{\sum_{j=1}^{K} l_j \bar{D}_j}{\sum_{j=1}^{K} 1 / \bar{D}_j}, \tag{4}
\]
where \( \bar{D}_j \) is the modified Euclidean fingerprint distance which was presented in (2).

2) Fingerprint combination: In the WiFi fingerprinting method, the more stable the fingerprint is, the better the localization accuracy will be. However, the RSSI collected by a client device often experiences substantial fluctuations due to dynamically changing environments such as human blocking and movements, interference from other equipment and devices, receiver antenna orientation, etc., [37], [38]. Therefore, this paper proposes to use the combination of a set of different fingerprints to ensure sufficient stability and distinctive values in each location. The most common fingerprint used is the mean of RSSI [4], [9] which fluctuates significantly due to the previously mentioned effects. In contrast, one of the more reliable fingerprints is the mean difference of RSSI between a pair of APs. In [39], Dong et al. used two devices, i.e., a laptop and a smart phone to collect RSSI in a fixed location. They observed that although the individual RSSI readings of these devices fluctuate significantly, the mean differences of RSSI between pairs of APs are more stable. Therefore, the mean difference of RSSI can be used to address the received signal strength offset problem between different mobile devices. In addition, the rank fingerprints described in [10] can also be used as an additional fingerprint if there are enough number of APs available. Recently, Tian et al. [40] utilize a new fingerprint named temporal correlation of the RSSI to improve the location estimation accuracy. However, in order to get the stable RSSI temporal correlation, a sufficient number of RSSI readings in each testing location is required, which is not feasible in our test cases. In our experiment, we first utilize some fingerprint types such as the RSSI differences and/or the AP rank to get \( n \) nearest neighbours RPs according to the shortest distance computed from (2). Within the chosen nearest neighbours, we then refine our selection to \( K \) (\( K < n \)) nearest neighbours by using the mean of RSSI as the fingerprint. For example, Fig. 2(b) illustrates the scenario where we have a user trying to locate his location with the information of both the mean of RSSI and the rankings from 3 different APs. By using the rank fingerprints, two neighbours \( L_1 \) and \( L_2 \) are chosen based on the minimum fingerprint Euclidean distances. However, these points have the same rank fingerprints so we need to use the mean of RSSIs as the additional information to determine which point is the true neighbour of the user’s location. With regard to mean fingerprints, neighbour \( L_1 \) that provides the smaller Euclidean distances is more likely the exact neighbour which we want to find.

3) Histogram of RSSI: As mentioned above, the raw RSSI readings at a location are unstable, fluctuating widely up to 10 dB [21]. Therefore, they may not represent well the feature of the RSSI at each location. In order to solve this problem, one may include the histogram of RSSI in the fingerprint distance calculation, which defines the probability of the original RSSI reading of the \( j \)th AP falling into \([R_j - 0.5 \text{ dBm}, R_j + 0.5 \text{ dBm}]\).
dBm] at the reference location $i$ as follows [41]

$$p_{R}^{i,j} = \frac{n_{R}^{i,j}}{n_{R}^{i,\text{total}}}$$

(5)

where $n_{R}^{i,j}$ is the total number of RSSI scans of the $j$th AP at location $i$, $n_{R}^{i}$ is the number of RSSI readings of the $j$th AP falling into the range between $R_{j} - 0.5$ dBm and $R_{j} + 0.5$ dBm ($R_{L}^{j} \leq R_{j} \leq R_{U}^{j}$). $R_{L}^{j}$ and $R_{U}^{j}$ are the minimum and maximum values of RSSI of $j$th AP respectively. Consequently, (1) can be modified as a weighted distance according to

$$\bar{D}_{i,\text{hist}}^{j} = \sqrt{\frac{\sum_{j=1}^{N} \sum_{R_{j}=R_{L}^{j}}^{R_{U}^{j}} p_{R}^{i,j} (F_{j} - R_{j})^{2}}{\sum_{i=1}^{M} W_{i}^{j}}}$$

(6)

and the final fingerprint distance is obtained as

$$\bar{D}_{i} = \frac{W_{i}^{j} \times D_{i,\text{hist}}^{j}}{\sum_{j=1}^{M} W_{i}^{j}}$$

(7)

IV. EXPERIMENT AND ANALYSIS

A. Experimental Setup

All experiments have been carried out on the third floor of Engineering Office Wing (EOW), University of Victoria, BC, Canada. The dimension of the area is 21 m by 16 m. It also has 3 long corridors as shown in Fig. 1(a). The RSSI measurements were taken in 365 pre-determined RPs. A mobile device (Google Nexus 4 running Android 4.4) mounted on a 3-wheel robot (Fig. 2(a)) was sent to target locations to collect fingerprints. The localization accuracy of the robot is 0.07 m ± 0.02 m. At each location, 100 instantaneous RSSI measurements ($S_{1} = 100$) were collected to a database. There are 6 APs and 5 of them provide 2 distinct MAC addresses for 2.4 GHz and 5 GHz communication channels respectively. Equivalently, in every scan, 11 RSSI readings from those 6 APs can be collected.

In the testing phase, we conducted both one-location test and trajectory test. In the one-location test, RSSI values at a fixed position were collected and the user’s position was determined in every consecutive sampling time interval $\Delta t$. In the trajectory test, the robot carried a mobile device and moved along the direction as shown by the red solid line in Fig. 1(a). RSSI readings were collected continuously by the phone and were transmitted to a server in real time. The server analyzed the data to locate the user’s position. The mean fingerprint in each location was determined by the average of $S_{1}$ RSSI readings for training and $S_{2}$ RSSI readings for testing. On the other hand, the mean difference of RSSI fingerprint for a test location was calculated by taking the average of $S_{1}$ ($S_{2}$) RSSI differences between a pair of APs.

B. One-Location Test

In this test, the mobile device was put on the location $P(7, 4)$ as shown in Fig. 1(a). The experiment was conducted in busy hours when many students (up to 10) used WiFi and moved around the lab. A maximum RSSI standard deviation of 5.5 dB was recorded over 100 consecutive RSSI readings.

The large fluctuation of RSSI is due to the factors explained in Subsection [III-C2].

Fig. 3 shows the comparison of the localization accuracy among the classical KNN fingerprinting algorithms in RADAR [9], WKNN [6], STI-WKNN [30] and our proposed SRL-KNN algorithm. All algorithms use the mean of RSSI as the fingerprint, the consecutive sampling time interval $\Delta t = 1$ s and the number of nearest neighbours $K = 3$. The user location is estimated based on 1 RSSI scan ($S_{2} = 1$) collected every $\Delta t$. Over all 19 tests conducted at different time instants within one hour, the localization results of RADAR, WKNN and STI-WKNN fluctuate more than 1.7 m from 0.70 to over 2.40 m, while SRL-KNN reports a much lower fluctuation with 0.3 m from 0.40 to 0.70 m. The accuracy of SRL-KNN is 2 times better than the other methods with average distance error being 0.60 m compared with over 1.20 m of the others.

C. Trajectory Test

In this test, the robot moved along a pre-defined route as shown in Fig. 1(a) with an average speed around 0.6 m/s. All the testing locations (total 175 locations) along the trajectories are randomly picked. In this experiment, the maximum speed in our algorithm is set to $v_{\text{max}} = 2$ m/s, so the maximum distance which user can move is $\sigma = v_{\text{max}} \times \Delta t = 2$ m. The initial position of the user in these testing trajectories is assumed to be known. All the other parameters are the same as those in the one-location test.

Fig. 4(a) compares the cumulative distribution function (CDF) of localization errors between SRL-KNN and other KNN methods, i.e., RADAR [9], Spearman rank distance [10], STI-WKNN [30]. Here, for comparison, we used both mean of RSSI, rank of APs as our fingerprints. Clearly, the SRL-KNN (blue line) outperforms the other methods in terms of positioning accuracy. Further analysis shows that due to larger RSSI fluctuations, the other methods may choose a wrong location with similar fingerprints as its nearest neighbours. Note that such location could be far from the actual location, leading to an extreme large error in the scale of the testing site dimension. As shown in Fig. 4(a), a 4.80 m maximum localization error is recorded for RADAR, 3.50 m for STI-WKNN and the largest maximum localization error of over 5 m for Spearman rank method. In contrast, SRL-KNN eliminates such error pattern, resulting in a much smaller maximum errors of 2.20 m with the mean fingerprint. In particular, SRL-KNN using only mean fingerprint has 80% of the location error within 1.20 m while RADAR, STI-WKNN and Spearman
error of around two methods have the similar performance with the maximum $n$ to get cases, the rank or RSSI difference fingerprint is firstly utilized the mean RSSI with the rank fingerprint and use the mean we implemented two different fingerprint combinations: use fingerprint described in Subsection III-C2 is used. In this article, To achieve higher accuracy, the combination of different fin-
cer. The erroneous prior location $h(x', y')$ is obtained as: $x' = x + \delta x; y' = y + \delta y$, where $\delta x$ and $\delta y$ are random variables that follow Gaussian distribution
\[
x_e \sim \mathcal{N}(0, \sigma^2_{xe}) ; \ y_e \sim \mathcal{N}(0, \sigma^2_{ye}) ; \ \sqrt{\sigma^2_{xe} + \sigma^2_{ye}} = E
\]
previous position. If the value of error indicates that SRL-KNN is robust to localization error of the previous position. Furthermore, according to the survey in [42], the percentage of stationary time can exceed 80% for most mobile users. During the no movement period, the number of RSSI readings collected in one-location (S2) is sufficient to improve the conventional KNN accuracy. Therefore, in order to enhance the accuracy when locating a user’s position in a long trajectory, we can employ these stationary locations as aligning points where the prior locations can be ignored. In that case, some classical KNN approaches including RADAR [9], WKNN [6] or STI-WKNN [30] can be exploited to estimate the user’s location.

In order to prove the consistent effectiveness of SRL-KNN, our algorithm is implemented with another published dataset, namely UJIIndoorLoc [43]. The reported average localization error in [43] is 7.9 m. The training and validation data in all 3 buildings of the database from 2 random phone users (Phone Id: 13, 14) are used to implement SRL-KNN algorithm. The maximum distance between 2 consecutive locations in the testing trajectory can be up to 20 m so that the error is chosen. Note that the grid size of UJIIndoorLoc is different from our collected database so the average localization error for UJIIndoorLoc is different from that reported previously. However, the relative accuracy comparison between SRL-KNN and conventional KNN, e.g., RADAR [9] or STI-WKNN [30] can still reflect well the effectiveness of our algorithm. Table II shows the average errors in meter of SRL-KNN, RADAR, STI-WKNN for each separate building and for all 3 buildings in general. These results consistently illustrate that SRL-KNN is more robust than other conventional KNN algorithms including RADAR [9] and STI-WKNN [30]. For all 3 buildings, the average error of SRL-KNN using mean fingerprint is 5.0 m while the result of RADAR is 7.7 m and STI-WKNN is 7.0 m. Furthermore, Fig. 6 compares the CDF of localization errors between 3 methods. In total, a 16 m maximum localization error is recorded for SRL-KNN, 22 m for STI-WKNN and the largest maximum localization error of 25 m for RADAR. Besides, 80% of the error is below 7 m in the case of SRL-KNN, which is much lower than 13 m and 12 m in the case of RADAR and STI-WKNN, respectively.

V. CONCLUSIONS

In conclusion, we have proposed a low complexity soft range limited KNN (SRL-KNN) for WiFi indoor localization. This algorithm exploits the information of previous positions and simultaneously applies the soft range limiting factor for fingerprint distance calculation to achieve more accurate and stable positioning performance. We demonstrated that SRL-KNN can address effectively some main challenges of KNN including the spatial ambiguity, RSSI instability and the RSSI short collecting time, especially when RSSI histogram is taken into account in calculating fingerprint distance. Experimental results have shown that SRL-KNN achieves the best accuracy of 0.66 m with 80% of the error within 0.89 m, which outperforms existing KNN methods. In future research, we will apply the idea of the soft range limiting factor to other methods such as probabilistic methods or SVM to improve their performance.
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