Wi-Fi Radio Map Interpolation with Sparse and Correlated Received Signal Strength Measurements for Indoor Positioning

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***Abstract*—Wi-Fi based positioning fingerprint offers an accurate solution for indoor positioning techniques. It estimates the coordinates of a user or object by consulting an offline Wi-Fi radio map and searching for the best match of the currently observed Wi-Fi received signal strength (RSS) measurements. The construction of an offline Wi-Fi radio map is a laborious task in a large indoor floor plan. The offline radio map needs frequent maintenance if the data get faulted or need update due to the changes in indoor surroundings. This paper studies the effect of spatial correlation in the densely collected Wi-Fi measurements to enhanced the positioning accuracy. The K-nearest neighbour (KNN) and inverse distance weight (IDW) algorithms were implemented to interpolate the incomplete Wi-Fi radio map. The interpolation error is analysed with and without the correlation in the RSS measurements over different sparsity parameters. It is shown that at some sparsity parameter, the interpolation error reduces by 54% when the correlation exists in the collected Wi-Fi measurements.**

***Index Terms*—Wi-Fi Radio Map, indoor Positioning, received Signal Strength, fingerprint, spatial interpolation, k-nearest neighbour, inverse distance weight.**

I. Introduction

Indoor positioning is a process of finding a user or device exact coordinates in an indoor setting or environment. The coordinates information is a technology enabler for many location-based services such as e-Health, cybersecurity, environment surveillance, smart home, logistics, tourism, transportation, precision plantation, etc. Without the coordinate information, data acquisitions are meaningless. For example, in e-health, knowing the coordinates (location) of the medical personnel or equipment in the hospital building can improve the response time during emergency events. In tourism, indoor positioning services can guide tourist in some large museums to see artefacts in different places in a timely and efficient manner. Other applications including to locate cargo in a large warehouse, to locate people in a large crowd, to identify demographic and business opportunities for mobile advertising companies, to find the nearest point of interests according to the current position, etc.

Global Positioning Services (GPS) can be a solution to all these services. But GPS is expensive, high power consumption, and operate poorly in indoor environments. In areas where the line of sight between the GPS devices and the satellites is clear, accurate positioning is seamlessly achieved. However, in areas where the transmission of signals from satellites to GPS is obstructed, e.g., in indoor environments, urban city, etc., the GPS may fail to function. Alternatively, positioning algorithms can make use of wireless signals from many wireless technologies such as Wi-Fi [1], ZigBee [2], Bluetooth [3], RFID [4], etc to estimate the coordinates of a user or device in indoor environments. Positioning algorithms can be divided into two types: triangulation, and fingerprint. Triangulation positioning algorithms use the geometric properties of triangles to estimate a user or object coordinates which can be based on lateration (distance metric) and angulation (angle metric). Some positioning algorithms based on triangulation are TOA [5], TDOA [6], RSS [7], RTOF [8], Signal Phase [9], AOA [10]. Next, the fingerprint positioning algorithms refer to techniques that match an online of some characteristics of a signal to an offline fingerprint map. Examples of algorithms are the probabilistic methods [11], K-nearest neighbours (KNN) [12], neural networks [13], support vector machine [14], etc.

The fingerprint technique estimates the user (target) coor-

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dinates in a network by matching the received radio signal of unknown coordinate with a pre-collected database of radio signals. Each entry in the unknown coordinate of a database consists of fingerprint of radio signal characteristics (e.g. received power) corresponding to its coordinate information. The coordinate of a user is estimated by the best matching received radio signal value with the database value. In [15], probabilistic approach to mapping radio frequency (RF) signals for user positioning is reviewed. The approach viewed the RF signal as the received signal strength (RSS) measurements at a specific coordinate to follow a probabilistic model. Then, the user positioning is estimated by maximizing the joint probability of likelihood with the RSS measurements. The probabilistic algorithm in [16] is fused with the user motion collected by sensors to build the RSS fingerprint map. This added diversity in the RSS fingerprint map, making coordinate estimation with similar fingerprints can be accurately distinguished. Several techniques based on the sparsity of the fingerprint map were also considered. Here, the missing values of the fingerprint map are reconstructed using interpolation methods.

The Kriging interpolation method is proposed in [17] to built RSS fingerprint map by interpolating the missing values of the RSS readings. The Kriging method demonstrated lower interpolation error over the different level of sparsity when compared to the KNN and inverse distance weight (IDW) algorithms. In [18], the Kriging interpolation method is combined with the KNN and naive Bayes classifier to improves the interpolated fingerprint database. The results show that the accuracy of the coordinate estimate is enhanced by consulting an accurate interpolated fingerprint database. Furthermore, in [19] the crowdsourced fingerprint techniques are proposed to construct a fingerprint of city radio map. The experiment is practically performed in a city composed of buildings with various types and showed promising accurate results for each building type, thus demonstrating the feasibility of the proposed framework. A recent paper [20] proposed the use of weighted centroid (WC) along with signal strength and rank of the nearby beacons as a feature that defined reference points (RP) in indoor fingerprinting positioning. The proposed methods significantly improve the performance of the positioning system in both the positioning accuracy and radio-map database size.

Several indoor positioning techniques have been proposed to exploit the spatial and temporal signal patterns to achieved higher positioning accuracy. The spatial patterns are related to the geographical distribution of signals and the temporal patterns refer to the signal sequence patterns due to the time of the transmitted signal. This paper studies the effect of spatial correlation in the densely collected Wi-Fi measurements towards enhancing the indoor positioning accuracy. The KNN and IDW algorithms are chosen to interpolate the incomplete Wi-Fi radio map due to its ease of implementation. The key contributions of this paper are: (i) to model spatially correlated Wi-Fi signals for fingerprint database reconstruction; and (ii) to exploit the spatial correlation in the Wi-Fi signals.

II. Fingerprinting Positioning Method

In indoor positioning, fingerprint refers to the techniques that match the collected online radio signals with the offline radio signals map that is location dependent. The fingerprint process is executed in two stages: an offline stage followed by an online stage. In the offline stage, a site survey is performed where the coordinates of reference points (RP) are determined and its respective received signal strength (RSS) measurement from nearby base stations/Wi-Fi transmitters was measured and stored as an offline Wi-Fi radio map. In the online stage, the currently observed Wi-Fi RSS measurements by a user (or device) is compared with the offline Wi-Fi radio map. Then using positioning algorithms, an estimated coordinate of a user in the network is deduced. Positioning algorithms can be deterministic or probabilistic based methods. Deterministic methods use similarity signal metrics such as Euclidean distance and cosine similarity for signal comparison between offline and online stages. Contrarily, probabilistic methods use statistical inference between the observed Wi-Fi RSS and the offline Wi-Fi radio map. The statistical inference includes maximum likelihood, Bayesian, expectation-maximization, Gaussian process, etc. Probabilistic methods give accurate indoor positioning estimates however, the implementation is complex and computationally high. In contrast, the deterministic method can be easily implemented and often computationally low.

III. Wi-Fi Radio Map Interpolation Method

Constructing the fingerprint of offline Wi-Fi radio map for indoor positioning is a laborious task. As the size of the floor plan become larger, the number of RP needed also increases since Wi-Fi measurements have to be collected at every point of RP in the floor plan to construct a complete Wi-Fi radio map. Intuitively, densely collected Wi-Fi measurements will increase the resolution of the Wi-Fi radio map, which could yield high accuracy in coordinate estimates, however, it also significantly increases the offline workload. Moreover, the existing fingerprint of Wi-Fi radio map needs maintenance if the data get faulted or need to update due to the changes in the floor exterior and/or interior environment. Not all locations are accessible for adequate RSS data collection such as apartment, office rooms, etc. Thus for such places, the interpolation method can be applied to construct a complete fingerprint of Wi-Fi radio map based on sparsely collected RSS measurements.

A. KNN Interpolation

The KNN method interpolates the missing Wi-Fi measurements in the offline Wi-Fi radio map using Euclidean distance, given by

$$D_m = \sqrt{\sum_{m=1}^{M} \left(x_m - x_i\right)^2}, \tag{1}$$

where M represents the total number of missing Wi-Fi measurements, x_m is the coordinate of m^{th} missing Wi-Fi measurements, x_i is the coordinate of available Wi-Fi measurements at i^{th} RP for $i = \{1, 2, \dots, N\}$ where N is the total number of available Wi-Fi measurements. After that, K nearest Wi-Fi measurements with smaller D_m value are selected and the missing measurement is interpolated, given by

$$\hat{Z}(x_m) = \frac{1}{K}\sum_{i=1}^{K} Z(x_i), \tag{2}$$

where $\hat{Z}(x_m)$ is the interpolated Wi-Fi measurement at coordinate x_m and $Z(x_i)$ is the Wi-Fi measurements at coordinate x_i of the RP.

B. Inverse Distance Weight (IDW) Interpolation

The Inverse distance weight method interpolates the missing Wi-Fi measurements in the offline Wi-Fi radio map of coordinate x_m for $m = \{1, 2, \dots M\}$, where M represents the total number of missing Wi-Fi measurements, given by

$$\hat{Z}(x_m) = \sum_{i=1}^{k} W_i Z(x_i), \tag{3}$$

where $Z(x_i)$ is the Wi-Fi measurements at coordinate x_i of the RP for $i = \{1, 2, \dots, k\}$ where k is the total number of nearest available Wi-Fi measurements and W_i is the interpolation weight at i^{th} RP, given by [21]

$$W_i = \frac{1/d_i^p}{\sum_{i=1}^{k} 1/d_i^p}, \tag{4}$$

where d_i is the Euclidean distance between the coordinate x_m and the coordinate x_i of the RP, and parameter p denotes the power factor that effect on the neighbouring RP coordinates.

IV. Simulations and Results

A. Simulation Setup

Network deployment is depicted in Fig. 1 which is simulated over a floor area of $150m \times 150m$ and is divided into 30×30 grids which correspond to 900 grid centre points. Three Wi-Fi transmitters are deployed to broadcast Wi-Fi signal and the RSS of the Wi-Fi signal at all RP is modelled using the log-distance path-loss model, given by

$$Z_i^j = Z_0 + 10\beta \log_{10}(d_i^j) + V_i^j, \tag{5}$$

where Z_i^j is the RSS from the j^{th} Wi-Fi transmitter at the i^{th} RP, Z_0 is the path loss at a reference distance (usually measured at 1 meter distance), β is the path los exponent, d_i^j is the Euclidean distance between the i^{th} RP and the j^{th} Wi-Fi transmitter, and V_i^j is the shadowing noise from the i^{th} RP and the j^{th} Wi-Fi transmitter, which is modelled as a zero mean Gaussian distribution with the variance, $\sigma^2 \in [1, 9]$.

The RSS measurement in (5) is modelled to be spatially correlated due to the proximity distance between RPs where the correlation is exist in the shadowing noise parameter of the path-loss model. Let $\mathbf{U}_i^j = [U_1^1, U_2^1, \dots, U_N^1]^T$ be the uncorrelated shadowing noise where N is the total number of Wi-Fi

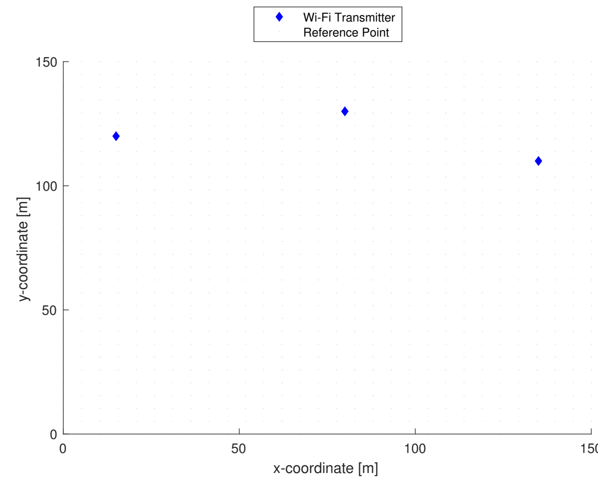

Fig. 1. Network deployment.

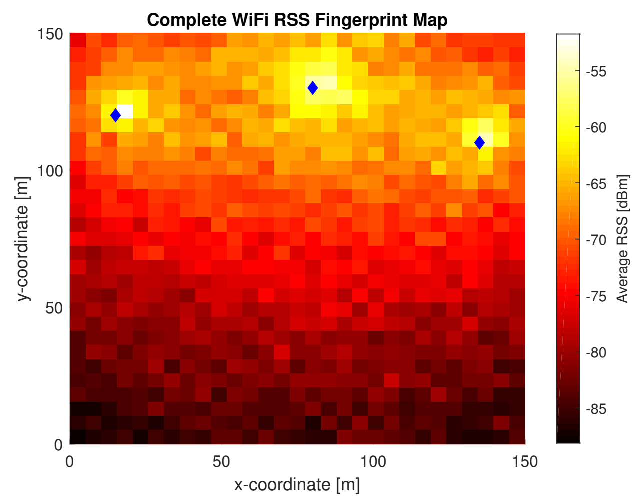

Fig. 2. The complete Wi-Fi RSS fingerprint map.

measurements at all RP. The variable $\mathbf{V}_i^j = [V_1^1, V_2^1, \dots, V_N^1]^T$ exhibits spatial correlation

$$\mathbf{V} = \mathbf{C}\mathbf{U}, \tag{6}$$

when where the covariance matrix $\mathbf{C}$ satisfied the correlation matrix $\mathbf{\Gamma}$, such that

$$\mathbf{\Gamma} = \mathbf{C}\mathbf{C}^T, \tag{7}$$

where

$$\mathbf{\Gamma} = \begin{bmatrix} 1 & \rho^{1,2} & \dots & \rho^{1,N} \\ \rho^{2,1} & 1 & \dots & \rho^{2,N} \\ \vdots & \vdots & \ddots & \vdots \\ \rho^{N,1} & \rho^{N,2} & \dots & 1 \end{bmatrix}. \tag{8}$$

Here, the spatial correlation coefficient between the k^{th} and l^{th} RP points is given by [22]

$$\rho^{k,l} = \exp\left(-\frac{d^{k,l}}{D_c}\right), \tag{9}$$

where D_c is the decorrelation distance. Thus, the covariance matrix that satisfied the correlation matrix $\mathbf{\Gamma}$, is given by [23]

$$\mathbf{C} = \begin{bmatrix} (\sigma_k^1)^2 & \rho^{1,2}\sigma^1\sigma^2 & \cdots & \rho^{1,N}\sigma^1\sigma^N \\ \rho^{2,1}\sigma^2\sigma^1 & (\sigma^2)^2 & \cdots & \rho^{2,N}\sigma^2\sigma^N \\ \vdots & \vdots & \ddots & \vdots \\ \rho^{N,1}\sigma^N\sigma^1 & \rho^{N,2}\sigma^N\sigma^2 & \cdots & (\sigma^N)^2 \end{bmatrix}, \quad (10)$$

where the variance of the correlated random variables $\mathbf{V}$ is the same as the variance of the uncorrelated random variables $\mathbf{U}$, that is $\sigma_{\mathbf{v}}^2 = \sigma_{\mathbf{u}}^2$.

The complete fingerprint of (offline) Wi-Fi Radio Map with the transmitter locations is shown in Fig. 2. The fingerprint map consists of 900 grid centre with each grid corresponding to different values of collected RSS measurements of the three transmitters. The collected RSS measurements are computed as the averages of 100 measurements with random shadowing noise for each RP. The shadowing noise can be caused by an obstruction during signal propagation such as walls, chairs, tables, etc.

Next, part of the RSS measurements in the complete Wi-Fi Radio map is removed using a Bernoulli process according to a sparsity parameter ρ. The probability of RSS value in the Wi-Fi Radio map would be retained is equal to ρ. Thus, $1-\rho$ indicated the probability of RSS value would be removed in the Wi-Fi radio map. Fig. 3 shows an incomplete Wi-Fi fingerprint map with $\rho = 0.30$.

B. Results and Analysis

To interpolate the missing Wi-Fi measurements in the fingerprint map, the KNN and IDW methods are utilized. Fig. 4 shows the constructed fingerprint map using the IDW interpolation method based on the measurement with the probability of retaining $\rho = 0.30$ as shown in Fig. 3. Fig. 5 shows the interpolation error of KNN and IDW based on 5 nearest neighbours concerning a different sparsity parameter. The interpolation error of KNN and IDW is compared with and without the correlated RSS measurements. The interpolation error for each missing Wi-Fi fingerprint at RP is computed as the root-mean-square error (RMSE), given by

$$RMSE = \frac{\sum_{m=1}^{M} \parallel \hat{Z}(x_m) - Z(x_m) \parallel}{M} \quad (11)$$

where $\hat{Z}(x_m)$ is the interpolated Wi-Fi measurements, $Z(x_m)$ is the original Wi-Fi measurements, and $\parallel . \parallel$ is the Euclidean distance operator.

The IDW algorithm demonstrated lower interpolation error over all different level of sparsity when compared to the KNN algorithm. When both algorithms interpolated with spatially correlated Wi-Fi RSS measurements, the interpolation error of both algorithms reduced compared to the interpolation with uncorrelated Wi-Fi RSS measurements. At some sparsity parameter, the interpolation error reduces by 54% when the correlation exists in the collected Wi-Fi measurements. A spatial correlation exists due to the proximity distance between the RP points. This indicated that data correlation in Wi-Fi

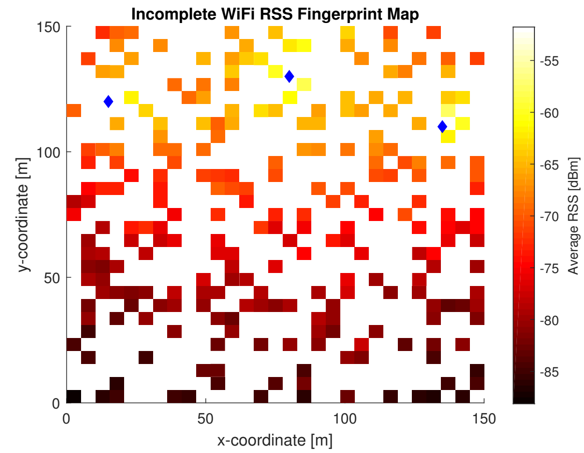

Fig. 3. The incomplete Wi-Fi RSS fingerprint map.

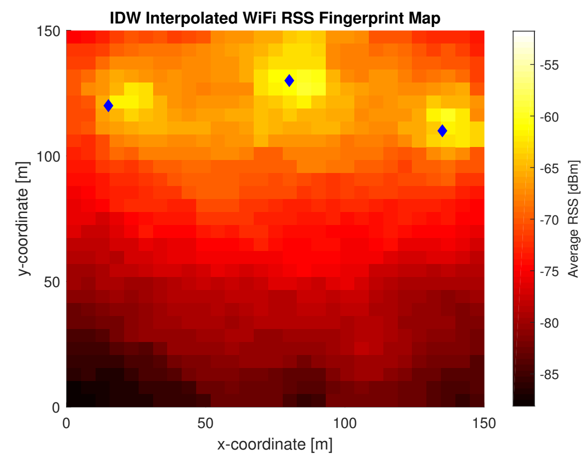

Fig. 4. IDW interpolation Wi-Fi RSS fingerprint map with measurement sparsity $\rho = 0.3$.

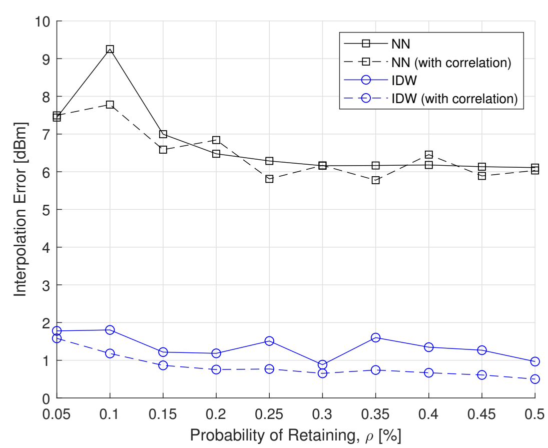

Fig. 5. Comparison of interpolation error of the KNN and IDW algorithms with respect to sparsity.

measurements can be exploited to achieve an accurate estimate of user or device in indoor positioning environments.

V. Conclusions

In this paper, the KNN and IDW are implemented to constructed incomplete Wi-Fi Radio map database with sparsely collected RSS measurements. The interpolation performance of both algorithms is analysed with and without the spatial correlation in the RSS measurements. The simulation results demonstrated that the IDW interpolation error is lower than the KNN interpolation error. When a spatial correlation exists in the collected Wi-Fi measurements of RP, both IDW and KNN yield lower interpolation error compared with uncorrelated Wi-Fi measurements. At some sparsity parameter, the interpolation error reduces by 54% when the correlation exists in the collected Wi-Fi measurements. Employing a lower interpolation error of the Wi-Fi Radio map database enhanced the indoor positioning accuracy.

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