An Improved Wi-Fi Indoor Positioning Method via Signal Strength Order Invariance

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***Abstract*—It is well known that Wi-Fi indoor positioning accuracy is vulnerable to environmental fluctuations. In this paper, we propose a novel Wi-Fi indoor positioning method which applies signal strength order invariance (SSOI) to overcome the problem of environment influence and hence improve the positioning accuracy. In the off-line phase we save not only the signal strength of reference points but also the corresponding signal strength order. Then in the online phase, the measured signal strength and the associated order are used jointly to estimate the unknown point's coordinate. Simulation and experimental results both demonstrate that our proposed algorithm can achieve better positioning accuracy than the methods using the traditional nearest neighbor (NN) or K-nearest-neighbors (KNN) fingerprinting algorithm only.**

***Keywords*—indoor positioning; fingerprinting algorithm; received signal strength statistical order invariance; weighted matching.**

I. Introduction

Recently almost all modern buildings are equipped with Wi-Fi access points (AP), and thus indoor positioning using IEEE 802.11 standard has become a realistic alternative. Meantime, it is common for a smart phone to be equipped with Wi-Fi sensors, which makes them capable to implement an indoor positioning system. So far, two approaches have been widely used for indoors Wi-Fi positioning. The first is based on a mathematical modeling of the wireless channel [1], [2], which makes the use of the measurements of the received signal parameters, such as the received signal strength (RSS) attenuation, the angle of arrival (AOA), the time of arrival (TOA) and the time difference of arrival (TDOA). The second is the well-known fingerprinting method [3], [4], which seems to be adopted more often in wireless local area network (WLAN) applications and be more likely to give an accurate location in indoor environments. Generally, the fingerprinting-based method consists of two phases: an offline phase and an online phase. The purpose of the offline phase is to collect information of the Wi-Fi AP signal strengths at different locations. During the online phase, the measured signal strengths are compared to the offline measurements to estimate the user position.

Most existing fingerprinting localization algorithms have not considered outliers, such as the accidental environment changes, AP attacks. One way to overcome the above drawbacks is to resist outliers, for example using robust and attack resistant probabilistic fingerprinting localization method [5]. Another way is to use only the rankings of the RSS values [6].

In this paper, we propose a novel fingerprinting positioning algorithm which uses the property of signal strength order invariance (SSOI) to improve positioning accuracy. In addition, our proposed method can achieve the improved performance without any increase in computational complexity.

II. Signal Strength Order Invariance (SSOI)

A. *Proof of SSOI*

Assume that in region A, as shown in Fig. 1, without obvious obstacles, there are K APs with same transmitter power. Let us consider the Wi-Fi signal propagation model as an exponential loss model given by [7]

$$PL = PL(d_0) + 10\gamma \lg \frac{d}{d_0} + X_\sigma \tag{1}$$

where γ is the path loss exponent indicating the rate at which the path loss increases with distances, d_0 is the close-in reference distance which is determined from measurements close to the AP, d is AP-$L(x,\ y)$ separation distance, and X_σ is a zero-mean Gaussian distributed random variable (in dB) with standard deviation σ. $L(x,\ y)$ denotes any point in region A. The received signal strength of $L(x,\ y)$ from K APs can be expressed as

$$\mathbf{p} = \begin{pmatrix} P_1 + 10\gamma \lg d_1 + X_\sigma \\ P_2 + 10\gamma \lg d_2 + X_\sigma \\ \vdots \\ P_K + 10\gamma \lg d_K + X_\sigma \end{pmatrix},\ K \geq 3 \tag{2}$$

where $P_k = PL(d_0) - 10\gamma \lg d_0,\ 0 \leq k \leq K$. Here we assume that all APs have the same transmitter power, which leads to $P_1 = P_2 = \ldots = P_K$. By defining $P_0 = P_k,\ 0 \leq k \leq K$, and sorting the vector $\mathbf{p}$ from the strongest to the weakest, we obtain

$$\widetilde{\mathbf{p}} = \begin{pmatrix} P_0 + 10\gamma \lg d_1^{'} + X_\sigma \\ P_0 + 10\gamma \lg d_2^{'} + X_\sigma \\ \vdots \\ P_0 + 10\gamma \lg d_K^{'} + X_\sigma \end{pmatrix},\quad d_i^{'} \in d,\ 1 \leq i \leq K \tag{3}$$

Calculating the statistics mean of the vector $\widetilde{\mathbf{p}}$, we have

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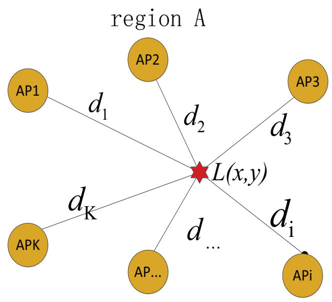

Fig. 1. Assumed Region A.

$$\mathcal{E}(\widetilde{\mathbf{p}}) = \mathcal{E}\left(\begin{array}{c} P_0 + 10\gamma \lg d_1^{'} + X_\sigma \\ P_0 + 10\gamma \lg d_2^{'} + X_\sigma \\ \vdots \\ P_0 + 10\gamma \lg d_K^{'} + X_\sigma \end{array}\right) = \left(\begin{array}{c} P_0 + 10\gamma \lg d_1^{'} \\ P_0 + 10\gamma \lg d_2^{'} \\ \vdots \\ P_0 + 10\gamma \lg d_K^{'} \end{array}\right) \quad (4)$$

where $\mathcal{E}(\cdot)$ represents the expectation operator. Now we may reach the conclusion that the order of the expectation of $\mathcal{E}(\widetilde{\mathbf{p}})$ keeps unchanged.

B. SSOI Algorithm

In the offline phase, the fingerprinting database is built up first. The positioning area is divided into many small cells with each cell referred to as reference point (RP). Devices detect APs at each RP, then the signal strength order (from the strongest to the weakest) and the corresponding averaged signal strength values are stored in the following two vectors

$$\mathbf{s} = [S_1,\ S_2, \cdots, S_m], \quad m \geq 3 \quad (5)$$

$$\mathbf{q} = [Q_1,\ Q_2, \cdots, Q_m], \quad m \geq 3. \quad (6)$$

In the online phase the user device measures the signal strengths from all APs. Then the signal strength order is stored in the vector $\widetilde{\mathbf{s}}$ and the corresponding signal strength values in $\widetilde{\mathbf{q}}$ as follows

$$\widetilde{\mathbf{s}} = [S_{ap1},\ S_{ap2}, \cdots, S_{apn}], \quad n \geq 3 \quad (7)$$

$$\widetilde{\mathbf{q}} = [Q_{ap1},\ Q_{ap2}, \cdots, Q_{apn}], \quad n \geq 3 \quad (8)$$

Then a correlation matrix of $\widetilde{\mathbf{s}}$ and $\mathbf{s}$ is defined as

$$\mathbf{R}(\mathbf{s},\widetilde{\mathbf{s}}) = \left(\begin{array}{cccc} C(S_{ap1},S_1) & C(S_{ap1},S_2) & \ldots & C(S_{ap1},S_m) \\ C(S_{ap2},S_1) & C(S_{ap2},S_2) & \ldots & C(S_{ap2},S_m) \\ \vdots & \vdots & \ddots & \vdots \\ C(S_{apn},S_1) & C(S_{apn},S_2) & \ldots & C(S_{apn},S_m) \end{array}\right) \quad (9)$$

with

$$C(S_{api},S_j) = \begin{cases} 0, & S_{api} \neq S_j,\ i \in (1,n),\ j \in (1,m) \\ a, & S_{api} = S_j,\ i \neq j,\ i \in (1,n),\ j \in (1,m) \\ 1, & S_{api} = S_j,\ i = j,\ i \in (1,n),\ j \in (1,m) \end{cases} \quad (10)$$

The matching weight coefficient is computed by

$$r(\mathbf{s},\widetilde{\mathbf{s}}) = \sum_{i=1}^{m}\sum_{j=1}^{n} C(S_{api},S_j). \quad (11)$$

Then $r(\mathbf{s},\widetilde{\mathbf{s}})$ is used to evaluate the distance to the RP. The larger $r(\mathbf{s},\widetilde{\mathbf{s}})$ the closer the unknown point to the reference point. In order to reduce the computation complexity, here the secondary matching weight calculation principle is used, which can be described as: $r(\mathbf{s},\widetilde{\mathbf{s}})$ is zero if $C(S_{ap1},S_1)$ and $C(S_{ap2},S_2)$ are both equal to zero. Using the secondary matching weight calculation principle, we can effectively reduce the computation burden when the scope of the positioning area is broadened or the fingerprinting RP distribution is scattered. Now the SSOI algorithm consists of the following steps.

1) In the offline phase the device measures signal strength from all APs at different RPs. The signal strength order is stored in the vector $\mathbf{s}$ and corresponding signal strength values in the vector $\mathbf{q}$.
2) In the online phase the user device measures signal strength from all APs. Then the signal strength order is stored in the vector $\widetilde{\mathbf{s}}$ and the corresponding signal strength values in the vector $\widetilde{\mathbf{q}}$. The matching weight coefficient $r(\mathbf{s},\widetilde{\mathbf{s}})$ is computed by (11) and the secondary matching weight calculation principle.
3) The unknown point is estimated as the RP which has the largest $r(\mathbf{s},\widetilde{\mathbf{s}})$. If there are more than one RP with the largest $r(\mathbf{s},\widetilde{\mathbf{s}})$, the unknown point can be estimated by the RP which has the least Euclidean distance of the signal strength value to the unknown point.

III. Simulation Results

A. Theoretical data

The simulation scenario is a 100m×100m area covered with 6 APs. The area is divided by 4m×4m block into 625 cells and a RP is located in the cell center. In the offline phase, we use a set of representative parameter setting: $PL(d_0) = 40.05$, $\gamma = 1.26$, and X_σ is a zero-mean Gaussian distributed random variable (in dB) with stand deviation $\sigma = 5$ (also in dB).

In the online phase, we estimate the position of one point using 100 samples with $\gamma = 1.3$, $\gamma = 1.4$, $\gamma = 1.5$ and $\gamma = 1.6$. Fig. 2 and 3 display the improvement in estimation error distribution to the nearest neighbor (NN) algorithm and K-nearest-neighbors (KNN) algorithm [8] when our SSOI algorithm is applied. As shown in Fig. 2 and 3, the error improvements are significant and positive.

B. Experimental measurements in UESTC

In the first experiment, the data is measured at Classroom A107 of Teaching Building A in University of Electronic Science and Technology of China (UESTC). The floor plan of the experimental Classroom A107 is depicted in Fig. 4 where black points stand for APs and red points for RPs. We deploy six APs and 36 RPs in our experiment with each grid 2m×2m. Each RP samples 60 times with sampling interval of one second. At point 1 and 2 160 samples are collected, in which the first 60 samples are used as fingerprinting data and the latter 100 samples are used as positioning test data.

The positioning accuracy probabilities using the NN algorithm and KNN algorithm without and with the SSOI method are illustrated in Table I and II respectively. It is clear that

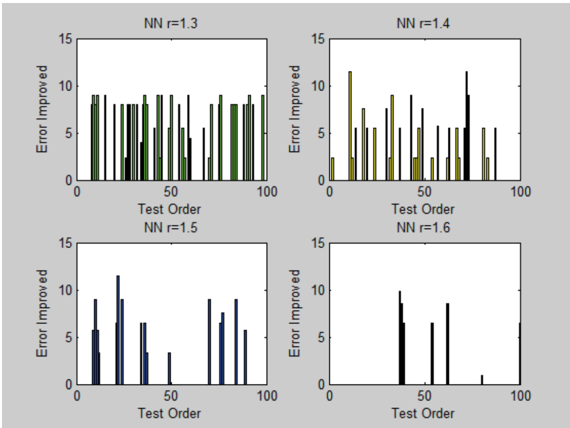

Fig. 2. Improved error distribution of NN algorithm using the SSOI method.

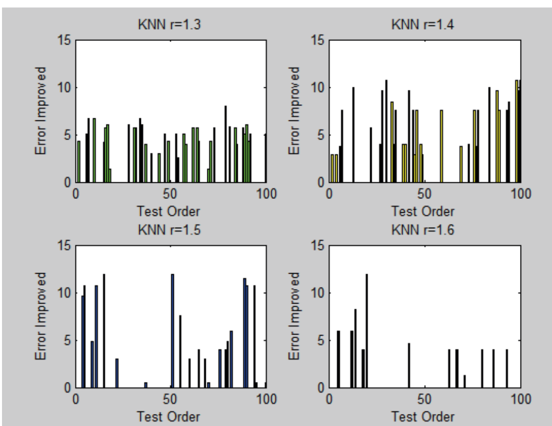

Fig. 3. Improved error distribution of KNN algorithm using the SSOI method.

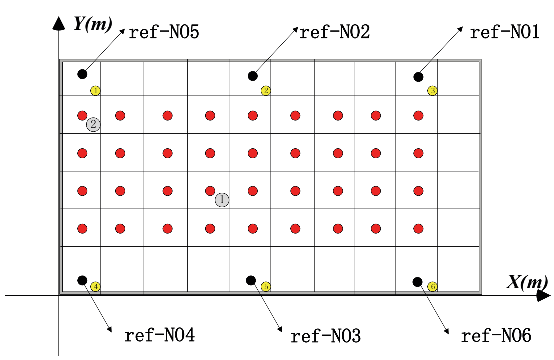

Fig. 4. Floor plan of the experimental Classroom A107.

TABLE I. POSITIONING ACCURACY PROBABILITY OF NN AND KNN WITHOUT SSOI

error range (m)	NN	KNN
0	0.649	0
< 2	0.649	0
< 3	0.649	0.415
< 4	0.745	0.851
< 5	0.788	0.979
< 6	0.788	1
< 7	0.894	1

TABLE II. POSITIONING ACCURACY PROBABILITY OF NN AND KNN WITH SSOI

error range (m)	NN	KNN
0	0.798	0
< 2	0.798	0.798
< 3	0.798	0.798
< 4	0.851	0.798
< 5	0.851	0.862
< 6	0.904	0.968
< 7	0.915	0.979

the NN algorithm and KNN algorithms with the SSOI method outperform that without SSOI.

We also carry out another experiment in the 5th floor in the dormitory of the School of Communication and Information Engineering at UESTC. AS shown in Fig. 5, there are 32 rooms in this floor and 13 APs are employed. Experimental measurements are operated in Room506 at 11:30am, 15:00pm and 17:00pm. We collect 100 positioning data at each room to evaluate the accuracy and stability of our SSOI algorithm. The normalized average signal strength values at three time slots are shown in Fig. 6. We can see that though the AP signal strength values are fluctuant, the signal strength order is invariant.

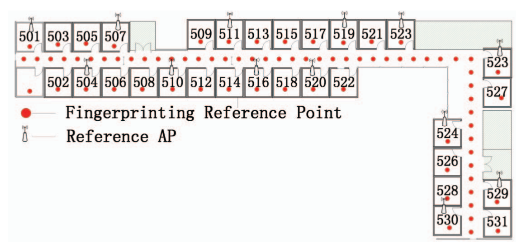

Fig. 5. The layout of positioning area.

IV. CONCLUSION

Compared with the traditional fingerprinting positioning method, our proposed SSOI algorithm uses both the signal strength order and the signal strength value. In the offline phase the signal strength order and signal strength value are all stored in the fingerprinting database. Then in the online phase, after preprocessing fingerprinting points using a weight-based matching algorithm, we select some RPs to estimate the unknown point position. Simulation and experimental results show that in comparison to the method using the traditional NN or KNN algorithm only, the SSOI algorithm can improve the positioning accuracy and stability.

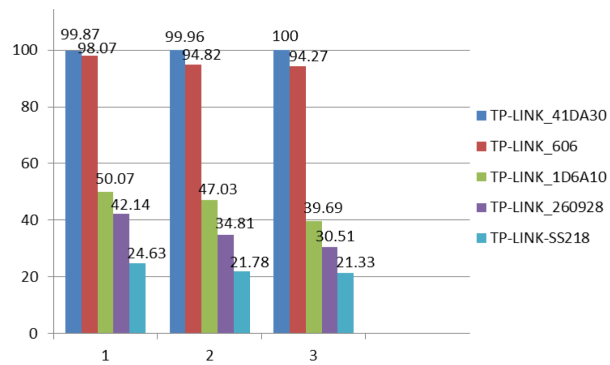

Fig. 6. The AP signal strength time slot 1 (11:30am), slot 2 (15:00pm) and slot 3 (17:00pm).

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