Indoor Localization Improvement via Adaptive RSS Fingerprinting Database

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***Abstract*— In location fingerprinting based indoor positioning system, received signal strength (RSS) indications from a set of Wi-Fi access points are used as a unique fingerprint to identify a specific location. However these RSS fingerprints may become outdated when there are unanticipated environmental changes. Re-measuring RSS fingerprints for all locations to maintain an up-to-date RSS database incurs high operational cost, which is impractical in dynamically changed environment. In this paper, we propose a method to estimate the RSS fingerprint of a specific location from a set of neighboring re-measured RSS fingerprints, called "feedbacks". The proposed method searches for new feedbacks and some necessary old RSS fingerprints in the cut-off area and then applies plane-interpolation to calculate the new RSS fingerprint for a specific location. Based on simulation results, about 5% of re-measured RSS feedbacks are required to satisfy 80% of positioning correctness in the simulated 30x30 m^2 area.**

Keywords: Location estimation, Wi-Fi fingerprint, adaptive RSS fingerprint, plane-interpolation, feedback

I. INTRODUCTION

Generally, received signal strength (RSS) location fingerprinting is based on the idea that each position has its unique set of signal values – called RSS fingerprint. A fingerprint can be referred to a location and vice versa. When an indoor localization system is set up, RSS fingerprinting database is initially created for mapping relationships between each physical location and its unique RSS fingerprint. When the system operates, it takes an RSS fingerprint at a location of device as a sample to lookup into the RSS fingerprinting database, and then it chooses the most similar entry to the sample and uses the location of the chosen entry as the estimated location.

The major problem of typical RSS fingerprinting system is that real RSS fingerprints at any locations are changeable over time by interference object and multipath fading effect [1], while RSS fingerprinting database is static. Therefore, RSS fingerprint measured at the current time can differ from the previous fingerprint stored in the database and this may cause incorrect location estimating. To solve this problem, the fingerprinting database should be adaptive to keep as small difference as possible to the current RSS fingerprint. One technique to equalize the fingerprint in the database and the real fingerprint is re-measuring signals during operating time at any locations which are called feedbacks. Unfortunately, the more feedbacks incur the higher operational cost and time [2]. Even though a localization system in [3] tries to utilize a small number of feedbacks, the limitation of this system is that only feedback locations are maintained. In this paper, we present a method to adapt some specific locations in RSS fingerprinting database. Not only feedback locations are adapted, but adjacent locations are also adapted. By using the spatial correlation of adjacent locations, it can calculate a fingerprint of a specific location from a set of nearby feedback locations with interpolation technique [4]. The aims of this method are to enhance accuracy, precision (correctness), and robustness of the location estimation system with respect to dynamically changed environment.

The remainder of the paper is organized as follows. Section II describes approaches and techniques used in this work. Section III proposes our system and shows how to estimate a specific location by using surrounding feedbacks in dynamically changed environment. Section IV presents simulation designs and results. Finally, Section V draws conclusion from this work and discusses about the future work.

II. APPROACHES AND TECHNIQUES

A. RSS fingerprint

RSS location fingerprinting has two phases: training and positioning [5]. In training phase, the system initially creates a RSS fingerprinting database which keeps entries of correlation between each physical location and its signal values from various access points (RSS fingerprint). All interested locations are kept inside this database. In positioning phase, a device measures RSS fingerprint from a location, then the measured RSS fingerprint is compared with all entry locations in the RSS fingerprinting database. With appropriate search algorithm, the system returns the outcome as an estimated location whose RSS fingerprint is the likeliest one to the currently measured one from the device.

There are many search algorithms for computing location of a device. The basic algorithm is the *K*-nearest neighbor algorithm (KNN) [6]. The *K*-nearest neighbor (KNN) method is a deterministic approach that uses fingerprint from a specific location and from the database to estimate the mobile device's location. Firstly, it finds the Euclidean distance (D_i) of the current measured fingerprint to the pre-stored fingerprint in the database.

$$D_i = ||\bar{y} - \bar{a_i}|| \ , \tag{1}$$

where $\bar{y}$ is the current measured fingerprint and $\bar{a_i}$ is the fingerprint from a location i stored in the database. The first K locations of i in the database who have smallest D_i are chosen to estimate the location p'(x,y):

$$p'(x,y) = \sum_{i=1}^{K} \frac{w_i}{\sum_{j=1}^{K} w_j} p_i(x,y), \tag{2}$$

where p_i is a chosen location and all weight w_i are nonnegative, which are obtained by inversion of D_i in (1).

B. Simulation of RSS using wireless fading channel models

Instead of collecting real location fingerprints, RSS is simulated based on wireless fading channel models at every location in the environment. The channel models are described phenomena by path loss and multipath propagation that occur in wireless communication system as formulated in [1] as:

$$RSS(dBm) = P_t(dBm) - L_p(dBm) + X_\sigma \, , \tag{3}$$

where RSS represents received signal strength at a distance position from a transmitter. P_t is power at the transmitter in decibel milliwatts (dBm). The calculation consists of two models that affect signal variations which are large-scale fading L_p and small-scale fading X_σ [1].

Large-scale fading L_p represents average or mean path loss over large distance. The statistic of large-scale fading provides a mean to compute an estimate of the mean path loss as a function of distance which can be calculated by [1]:

$$L_p(d)(dBm) = L_s(d_0)(dBm) + 10\, n \log(\frac{d}{d_0})(dBm), \tag{4}$$

where $L_s(d_0)$ is the free-space path loss at the calibration distance of d_0 = 1 m. The variable n donates the path loss exponent, which varies for different surrounding environments ($2 \leq n \leq 6$ for indoor environment [1]).

The small-scale fading X_σ in (3) refers to the dramatic changes or fluctuations in signal amplitude and phase that cause small changes to signal. This fading is sometimes called random or scatters or diffuse component. The small-scale fading can be described by Rician probability distribution function (PDF) if there is no a dominant fading signal component present or Rayleigh PDF if there is dominant fading signal component present. In this work, we focus on the line-of-sight (LOS) propagation path which is explained by Rician fading [7] as:

$$PR(r) = \frac{r}{\sigma^2} e^{-\frac{V^2+r^2}{2\sigma^2}} I_0(\frac{Vr}{\sigma^2}), \ r \geq 0, \tag{5}$$

where r is random variable, V is an additional vector of specular signal path, and $I_0(\cdot)$ is the modified Bessel function of order 0. When $V=0$, the Rician PDF reverts to the Rayleigh PDF [1].

C. Estimate RSS fingerprint using plane-interpolation

Using the spatial correlation of adjacent locations, RSS of a specific location can be calculated from a set of nearby feedback locations by linear interpolation technique. The technique is adopted from [8]. This estimation uses exactly three surrounding feedbacks and coordinate of estimated location as inputs. The output returns as RSS of estimated location of one access point.

Given a set of RSS fingerprints $FP_1(X_1,Y_1,RSS_1)$, $FP_2(X_2,Y_2,RSS_2)$, and $FP_3(X_3,Y_3,RSS_3)$ as feedback information, we try to find $FP_n(X_n,Y_n,RSS_n)$ that is surrounded by FP_1, FP_2, and FP_3 where X_n and Y_n are known coordinate. We can represent FP_n by using a vector N that is normal to all FP_1, FP_2, and FP_3. We have

$$N = \overrightarrow{FP_1FP_2} \times \overrightarrow{FP_1FP_3} \, , \tag{6}$$

where

$$P = \overrightarrow{FP_1FP_2} = \begin{bmatrix} X_2 - X_1 \\ Y_2 - Y_1 \\ RSS_2 - RSS_1 \end{bmatrix}, \text{and} \tag{7}$$

$$Q = \overrightarrow{FP_1FP_3} = \begin{bmatrix} X_3 - X_1 \\ Y_3 - Y_1 \\ RSS_3 - RSS_1 \end{bmatrix}, \tag{8}$$

From (6), (7), (8), we have

$$N = \overrightarrow{FP_1FP_2} \times \overrightarrow{FP_1FP_3} = \begin{vmatrix} i & j & k \\ P_1 & P_2 & P_3 \\ Q_1 & Q_2 & Q_3 \end{vmatrix}. \tag{9}$$

Solving (9) by resulting determinant and rewriting the equation as:

$$FPn = N = Ai + Bj + Ck + D = 0, \tag{10}$$

where A, B, C, and D are arbitrary numbers. Given X_n and Y_n are known, therefore we have:

$$FP_n(X_n, Y_n, RSS_n) = AX_n + BY_n + CRSS_n + D = 0, \tag{11}$$

Here we can obtain RSS_n and use this value as an estimated RSS fingerprint. This process can only consider one access point in RSS fingerprint at a time. If there are more than one access points in the fingerprint, we then repeat this process to all of them.

III. MEDTHODOLOGY

A. Adaptive RSS fingerprinting database

Typical RSS location fingerprint still uses static RSS fingerprinting database, which works ineffectively in environment with dynamical change. The problem occurs when the RSS fingerprint at a location is changed, while RSS fingerprinting database is still the same. When we measured a sample of RSS fingerprint, the positioning algorithm might choose wrong estimated locations from the static database. The chosen entry of RSS fingerprint may seem to be the likeliest one to the sample but such RSS fingerprint may refer to a physical location that is actually far away from the real location. This causes positioning error. Consequently, RSS fingerprinting database must be adaptive in order to keep track of change on real location.

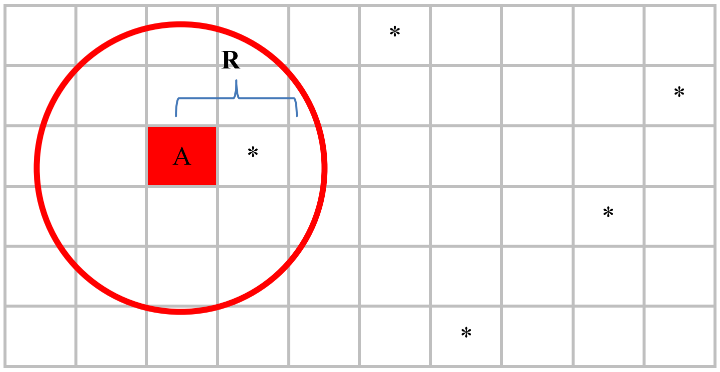

Figure 1: Cut-off area

To adapt RSS fingerprinting database, the system obtains new information from some measured locations called feedbacks and then estimates unmeasured location called non-feedback. The estimation is calculated by using the spatial correlation of adjacent locations and interpolation technique with feedback information. Assuming that we obtain feedback information in real time and feedback can be from any locations.

Adaptive RSS fingerprinting database is built based on the following assumptions:

1) Positions that are close to each other should get similar RSS fingerprint [2].

2) The smaller distance between the estimated location and the feedback, the more credible on such fingerprint from that feedback.

3) The more number of feedbacks in the system, the more estimated locations with high confidence.

According to assumption 1, we apply linear interpolation technique to estimate a specific location surrounded by feedbacks. Even though there is an article stating that some locations that are close together in physical location may not be close together in RSS value [9], the assumption 1 is still true in some situations [2]. According to assumption 2, when the specific location is estimated, only some feedbacks inside area of interest which we called *cut-off area* are used.

B. *Cut-off area*

Cut-off area is a circular area containing feedbacks which highly influence on an estimated location. The reason that the area is a circular shape is to make no bias on any directions from the estimated location. The estimated location aligns at the center of the area. Number of feedbacks inside cut-off area can be any numbers. As shown in Figure 1, the location *A* is a non-feedback location and needs estimation. Even though there are several feedbacks (denoted by *) on the entire area, the location *A* still chooses only feedback inside the cut-off area to take into account. The rest is ignored by the location *A* because they are out-of-range. Radius of the circular area called *R* can be defined by any arbitrary number in the unit of meter.

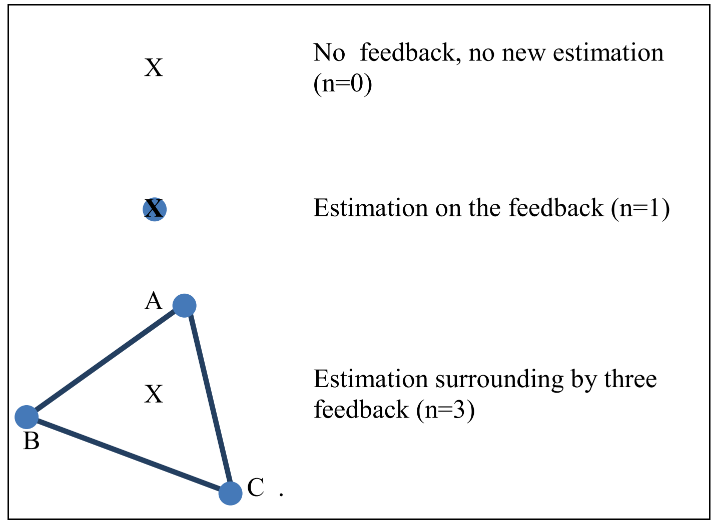

Figure 2: Ordinary cases of estimation

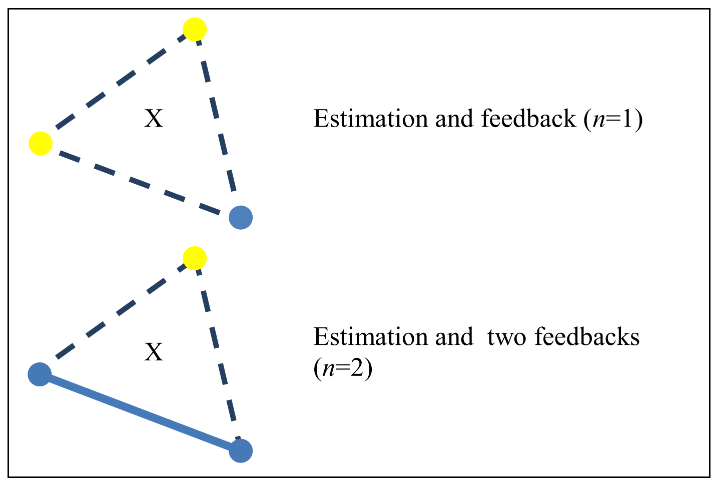

Figure 3: Other cases of estimation

C. *Estimation procedure*

The estimation is based on creation of adaptive RSS fingerprinting database. According to assumption 1, estimation is done by the interpolation technique which is described in Section II.C. The technique needs some reference locations and we donate feedbacks as reference locations because they are the most credible locations that we have. The feedbacks used for estimation is inside the cut-off area in which the number may be varied. It can be described by a number of ordinary cases with respect to the number of feedback as shown in Figure 2 where *X* is defined as an estimated location and a dark dot is defined as a feedback location.

The estimation procedure can be summarized as following cases.

1) If there is no feedback, there is no estimation.

2) If the single feedback and the estimated location are the same, then the estimated one is equal to the feedback.

3) If the estimated location is surrounded by a tri-angle of three feedbacks, then we determine the value of estimated location X on the linear plane ABC.

4) If the estimated location is surrounded by more than three feedbacks, then we choose three feedbacks that can construct the smallest area of a tri-angle and repeats case 3).

If an estimated location X is not surrounded by three feedbacks (denoted by dark dots) as shown in Figure 3, then we use an old information of a few non-feedback locations (denoted by light dots) within the cut-off area instead to construct a tri-angle and then we follow the ordinary cases of estimation listed in Figure 2. However, we must ensure that the chosen non-feedback locations are rarely changed. This condition occurs when the available feedbacks are not sufficient for the estimation. Therefore, the system uses additional previous information instead. If the chosen old information is considered as rarely changed information, it also has a credit which is similar to the actual feedback. With this assumption, the system should keep information in several time series in order to observe behavior of each location.

IV. SIMULATION SETUP AND RESULTS

A. Simulation setup

We conducted a simulation on the proposed algorithm for adaptive fingerprint database to encounter dynamic change in environment. In order to evaluate the performance of our proposed method, typical feedback system with no estimation of adjacent feedback locations was used as baseline. This baseline is used to show the effect of dynamic environments on the localization accuracy.

The simulation was conducted using Monte Carlo simulation tool – "MATLAB" [10] which simulated an empty space with no obstruction of square area of 30x30 m^2 (900 locations) with four access points attached to the corner of the square area. Minimum spacing between two adjacent locations was one meter apart. This number is recommended by [11] to obtain optimal performance. As described in Section II.A, the search algorithm used in the simulation is the K-nearest neighbor (KNN) where K=4.

Each fingerprint is consisted of four signals (RSSs) received from four access points. Each RSS is calculated from an average of 50 signal samples, which is generated by the simulation described in Section II.B. Each signal sample is simulated based on wireless fading channel models which consist of two models: the large-scale fading and the small-scale fading as explained in Section II.B. For small-scale fading, we assumed that mobile device received signal in LOS mode (Rician fading). For large-scale fading, P_t, *the* transmit power of the access point, in (3) is fixed at 20 dBm. The variable n denotes the path loss exponent in (4) is set to n=2 for LOS propagation. $L_s(d_0)$, the free-space loss at the reference point of d_0 = 1 m., is -41.5 dBm for LOS [12].

To evaluate the system, RSS fingerprints of all 900 locations were simulated by wireless fading channel models and kept as RSS fingerprinting database for training phase. In positioning phase, each location generated a new RSS fingerprint which was used to calculate an estimated location with search algorithm and to determine how many percentage of location was correctly estimated.

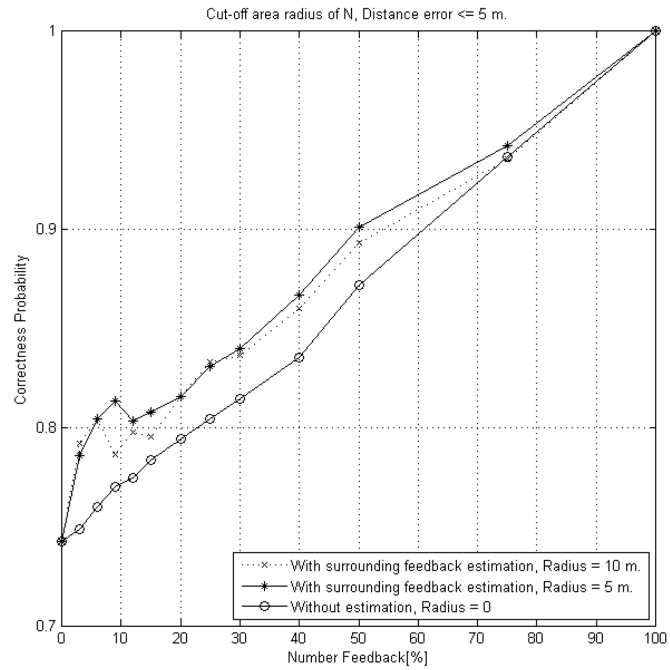

Figure 4: Comparison of system's precision at 5 meter accuracy

B. Impact of adaptive RSS fingerprinting database

Using simulation, we compared our proposed system which had estimations on non-feedback locations with a typical system which had no estimation around feedback. A number of feedbacks were varied to consider on how a number of feedbacks could affect the localization system. The feedback locations were chosen randomly. We assume that the correctness probability or precision of the localization system that meet a satisfied criterion is 80%.

Figure 4 shows the location correctness or precision within 5 meters of accuracy when varying the number of feedbacks. Although correctness of both systems increases when number of feedback increases, the proposed system outperforms the typical one with no estimation. At 80% correctness probability, the proposed method needs 5% of feedbacks (solid line with asterisk) to meet the criterion while the typical one needs 22% of feedbacks (solid line with circle). Therefore, our purposed system can reduce the number of required feedbacks by four times with respect to the typical system.

C. Impact of cut-off radius

The cut-off radius is used to limit the area that feedbacks influence on an estimated location. The size of cut-off radius limits the chance to find feedbacks. The smaller radius of cut-off area is used, the fewer feedbacks are found. In our experiment we varied the number of cut-off radius from 0 to 10 meters. The results are shown in Figure 4. When the radius of cut-off area is greater than 5 meters, the system has no significant improvement in localization performance.

V. Conclusion And Future Work

In this paper, we proposed a new algorithm to adapt RSS fingerprinting database by using surrounding feedback information. Within the accuracy of 5 meters and location resolution of 1 meter, the purposed method required about 5% of number of feedbacks to satisfy a criterion of 80% of correctness probability in the simulated area of 30x30 m^2. In addition, the proposed system can reduce the number of feedbacks by four times with respect to the typical system which has no estimation on location surrounding feedback locations. The simulation is based on situation of dynamically changed environment by using large-scale fading and Rician small-scale fading. We also observed from this experiment that the suggested value of cut-off radius is 5 meters. With the greater radius of cut-off area, the system has no significant improvement in localization performance. In the future work, we will compare our proposed system to existing adaptive RSS fingerprinting database schemes and perform experiments on a real environment and compare with our simulations.

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