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Fast and Cost-Efficient Signal Strength Prediction based Wi-Fi Positioning

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***Abstract*—This paper proposes cost-efficient and easy-to build RSSI based indoor positioning algorithm designed for Wi-Fi networks. Proposed algorithm combines the calibration procedure with a fingerprint prediction, and it does not require the physical location of wireless access points in order to predict the signal strength for fingerprint database installation; thus, making the implementation of indoor location system more cost-effective. Our results show that proposed algorithm sufficiently reduces the installation price and calibration time while providing location accuracy comparable to that of calibration based RTLS.**

***Keywords*—Indoor positioning; Wi-Fi based RTLS; RSSI;**

I. INTRODUCTION

With the rapid development of wireless technologies and advent of greater mobility, a significant need for localization has emerged. This is true not only for automotive applications, but also for personal purposes, thus leading to the necessity of having a technical solution for accurate wireless geolocation. The positioning of mobile users is highly desirable for many location based services, entertainment, traffic management and so on [1]-[3].

There have many localization techniques been proposed, and positioning systems such as Global Positioning System (GPS) have already been successfully deployed in markets. However, GPS has a number of drawbacks, namely, GPS users have difficulties in urban areas, as well as in indoor environments, where buildings and other objects block the weak signals that are transmitted from GPS satellites. There are also hybrid methods that utilize both GPS and cellular infrastructure, which provide accurate location estimation in urban areas. Nonetheless, when the mobile user is located in deep indoor environment surrounded by obstacles, the positioning accuracy dramatically decreases. Therefore, there is a huge demand for stand-alone indoor positioning systems.

Different physical requirements of the indoor environments need alternative systems to provide accurate location information. Various technologies have been suggested as a base for indoor positioning systems, such as Bluetooth and Infrared, Ultra-Wideband and Ultrasonic technologies [4]-[7]. On the other hand, most of these systems were difficult to deploy because of high-complexity and necessity of building new network infrastructures. Thus, IEEE 802.11 based WLANs can be a good option for indoor positioning systems due to its wide-range deployment in urban areas and the growing number of mobile gadgets equipped with Wi-Fi chipsets.

Signal strength based indoor localization systems have grown importance and commercial interest among other indoor positioning systems, for the reason that the only available information at receiver side is the power of signal received from each access points. Moreover, techniques like weighted centroids, triangulation and probabilistic methods use this information [8], and the RSSI fingerprinting algorithm was one of the most widespread methods for WLAN positioning [9].

The RSSI fingerprinting algorithm is normally organized by two steps [10]. The first procedure, *calibration process* builds the RSSI fingerprint database of a target site. RSSI fingerprint consists of Media Access Control (MAC) address of an access point and the measured RSS value of a specific location. On the next stage of the algorithm, usually termed as *online tracking*, the location of the mobile user is determined by matching the received signal values to the closest fingerprint value at the database. Due to the extensive calibration phase for building fingerprint database, and the huge influence of minor changes in the target area to the RSSI fingerprint values, the implementation of this algorithm in large-scale areas becomes expensive.

Even though several methods have been proposed to reduce calibration time by predicting signal strength in given locations [10]-[12], these methods require the physical location information of wireless access points in order to predict the signal strength in given areas. However, this information is usually unknown and difficult to gather due to the large number of access points in urban areas and in indoor environments.

Therefore, in this study we propose RSSI prediction based indoor positioning algorithm, which does not require the physical location information of APs, thus increasing the cost-efficiency while providing the reliable location accuracy.

The rest of the paper is organized as follows. We introduce our proposed positioning algorithm in Section II. Section III describes the test environment and shows the experiment results. The final concluding remarks are given in Section IV.

II. PROPOSED ALGORITHM

In this section, we describe our proposed indoor positioning algorithm, which consists of four basic steps.

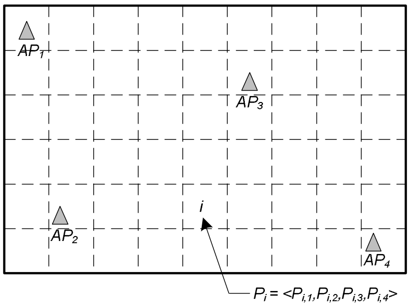

Figure 1. Basis elements of analysis based on RSSI

A. Reference Data Collection

The initial step is to collect reference data in the target building, which shall be used during the positioning phase. Firstly, we choose several reference points in a given area, where the RSSI values from each access points will be measured. Please refer to Fig. 1 for an explanation of how the RSSI values are measured. The access points are marked as AP_1, AP_2 and etc. The profiled signal strength vector at location i is P_i, whose components are the RSSI values from different access points. For example, $P_{i,n}$ is the RSSI at location i from the access point AP_n.

After all the reference points have been selected on the map, the RSSI value of each reference point will be measured using Wi-Fi equipped device with special software installed, and stored in a fingerprint database. In order to get more stable RSSI values, several measurements per each point are made, and the final RSSI value is obtained by averaging the measurement data

B. AP Location Estimation

One of the biggest drawbacks of conventional prediction algorithms is that, in order to predict the RSSI values at given locations, the physical location information of APs must be known. This might be an expensive or sometimes even non-trivial step to build the Wi-Fi positioning system in urban areas due to the large number of "hidden" access points.

Therefore, in this paper we tried to increase the cost-efficiency of the system by calculating the location of APs, using reverse trilateration method before predicting the RSSI values in target area.

After building the RSSI fingerprint database, we select the MAC ID of to-be located access point and choose the highest three RSSI values received from this access point. We choose the highest signal strength values assuming that those fingerprints are in the closest distance from the access point. Having selected three fingerprint values, we measure the distance between these fingerprints and the access point using One-Slope prediction model (OSM). OSM assumes a linear dependence between path loss and the logarithm of the distance d between a receiver and transmitter:

$$P[dB] = P_0 + 10\gamma \log(d / d_0) \tag{1}$$

where, P_0 is the reference path loss at distance d_0, and γ is the power decay index. In general, d_0 assumed to be equal to 1. P_0 and γ are empirical parameters for a given environment, which fully control the prediction [13].

From the OSM equation, the distance d_n between access point and n^{th} fingerprint location can be written as:

$$d_n = 10^{\frac{P_n - P_0}{10\gamma}} \tag{2}$$

Having calculated all three distances from nearest calibration points to the access point, we apply Chan's three sensor-based hyperbolic equation to find the location of access point. Chan's system requires at least three distances in order to do the positioning, which is why we have chosen three calibration points in the target area. The equation has the form of:

$$\begin{bmatrix} x \\ y \end{bmatrix} = H^{-1}\left(d_1 h + \frac{1}{2} r\right) \tag{3}$$

where,

$$H = -\begin{bmatrix} x_2 - x_1 & y_2 - y_1 \\ x_3 - x_1 & y_3 - y_1 \end{bmatrix}, \qquad h = -\begin{bmatrix} d_2 - d_1 \\ d_3 - d_1 \end{bmatrix},$$

$$r = -\begin{bmatrix} x_2^2 + y_2^2 - (d_2 - d_1)^2 \\ x_3^2 + y_3^2 - (d_3 - d_1)^2 \end{bmatrix},$$

and, (x_n, y_n) are the coordinates of n^{th} calibration point, while d_n denotes the distance from that calibration point to the access point.

Knowing the location information of access points, we can perform the prediction stage of our system.

C. RSSI Prediction

Once the reference samples are collected and distances are measured, we can predict the signal strength value in other parts of the target area. As we have M reference samples, using OSM for each prediction point we can obtain M different path loss values from one AP. In ideal case, without any channel distortions these values should be equal. However, in real environment we will get slightly different results, and by averaging these values we will get final, more accurate RSSI.

Concluding from aforesaid we modify the conventional one-slope model as follows:

$$P_{OSM} = \frac{1}{M}\sum_{m=1}^{M}\left[P_{0_m} + 10\gamma \log\left(\frac{d}{d_{0_m}}\right)\right] \tag{4}$$

where, M is the number of reference samples.

One of the advantages of this method is that prediction points can be selected as much as possible close to each other. Furthermore, compared to conventional calibration procedure, this prediction algorithm greatly reduces the sample collection time, thus increasing the cost-efficiency of the system.

III. EXPERIMENTAL RESULTS

Our test field at the Information and Communication Department of Yeungnam University in South Korea represents a high-density office environment, with number of obstacles, electronic devices and etc. For RSSI calibration of the test area, we used HP iPaq 112 with special calibration software. The test space was partitioned into an equally-spaced grid with side length of 2 meters. On every grid crossing point we collected around 100 RSSI data from each access point. As a result, the final

Figure 2. Calibration difference between existing and proposed algorithms

fingerprint database contained 50 calibration points with 100 observations at each point. The final RSSI fingerprint value for each calibration point is then averaged by the one hundred observation data, and this value is then stored in database.

It should be noted that the proposed algorithm does not require gathering the fingerprint values in each 2 meters, and we have built the full database only to compare our results to the conventional fingerprinting algorithms.

Fig. 2 demonstrates the difference between existing and proposed algorithms. Black dots in Fig. 1 are the points where RSSI samples will be collected. In conventional calibration (Fig. 1a) procedure is that user measures RSSI values in every 2 meters, whereas in our algorithm, only 8 (as an example) samples are collected, and the rest of the samples (white dots in Fig. 1b) are estimated.

After building the fingerprint database and measuring the AP location information, we performed RSSI fingerprint prediction using obtained data. Parameters for prediction were selected as follows: reference path-loss P_0*=-24 dB* at reference distance d_0*=1 m;* power decay indexes $\gamma=3$.

Table 1 compares the accuracy of RSSI database predicted with real information of APs and RSSI database with predicted information of APs to the real fingerprint database. The gauges of fingerprint accuracy are the mean and standard deviation of difference between the measured and predicted RSSI values.

Results show that the difference between the database with predicted AP information and real information differs slightly while the aforementioned technique can be much cost-efficient.

Next, in the location test phase, different databases are used to estimate the location of mobile terminal. The location produced using different databases was compared to the correct coordinates. The error was measured by using Euclidean distance. The observation history was taken into account so that at each point, after having observed *n* test observations, the point estimate was smoothed to be the average of the corresponding *n*

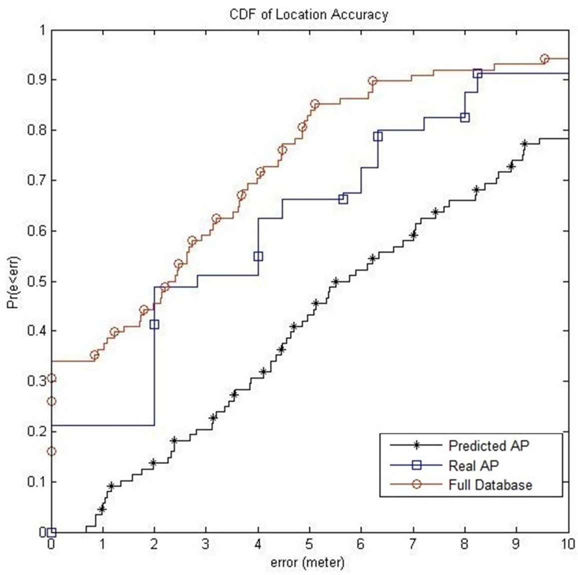

Figure 3. Location accuracy

For open space (lecture room)		
Predicted AP	$\mu = 5.37$	$\sigma = 2.96$
Real AP	$\mu = 4.18$	$\sigma = 2.66$
For office environment		
Predicted AP	$\mu = 3.92$	$\sigma = 3.13$
Real AP	$\mu = 3.59$	$\sigma = 3.11$

Table 1. Fingerprint accuracy

location estimates. The cumulative distribution function of location accuracy is shown in Fig. 3.

Experiment results show that, using proposed algorithm, cheap, fast, efficient and reliable indoor positioning can be implemented. Even though the accuracy of the conventional algorithms is higher, the proposed algorithm also provides reliable location information. We also believe that accuracy can be increased by decreasing the grid size (i.e. allocating more prediction points per given area), however, further studies are needed to answer this issue and investigate the optimum reference point selection methods.

IV. CONCLUSION

Optimal and cost-efficient RSSI based indoor positioning algorithm is proposed. In contrast to conventional RTLS, proposed algorithm requires only few samples to be collected and the rest of the samples will be predicted using modified OSM algorithm, moreover, the proposed algorithm does not require the physical location information of wireless access points in the target area. Results showed that proposed algorithm can sufficiently reduce the calibration time and increase the cost-efficiency while providing location accuracy comparable to the conventional based real-time location systems.

Authors believe that proposed algorithm can provide even higher location accuracy by increasing the number of prediction points and optimum reference points allocation, however these issues will be covered in further researches.

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