RF based Indoor Positioning using RSSI fingerprints

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***Abstract*—Indoor positioning systems have recently become of interest following the need for location determination in indoor environments with rising applications such as shopping and asset tracking. This is mainly due to the limitations of the Global Positioning System (GPS) because its signals are heavily attenuated indoors and multipath occurs in signal propagation leading to poor accuracy. Indoor positioning using Radio Frequency (RF) technology is a viable option since wireless beacons and mobile phones are ubiquitous nowadays. In this work, an algorithm for RF Indoor positioning using RSSI fingerprints is implemented and tested. Under a practical test set, the RSSI fingerprinting algorithm delivered an average accuracy of 1.2meters when measured RSSI fingerprints is used and 1.7meters when theoretical RSSI fingerprints is used.**

***Index Terms*—Indoor positioning, RSSI fingerprints, RSSI fingerprints Algorithm**

I. Introduction

The Global Positioning System (GPS) often fails to deliver the required accuracy and reliability when it comes to indoor location determination due to the complex channel environment indoors. Multipath occurs frequently indoors which makes a line of sight signal quite difficult to obtain. The techniques used in GPS require mostly a line of sight signal for reasonable accuracy. They are several technologies used for indoor positioning – such as Radio Frequency (RF), Visible Light Communication (VLC), magnetic fields, etc. The main components of RF Indoor positioning systems are the beacons and a mobile phone. The proliferation of these devices in modern times makes RF- based indoor positioning very attractive. A key application scenario is shopping in a large retail store or shopping mall. The customers wanting to know their location inside the shop as they try to locate items already pointed out in the map of the store on an application on their mobile phones. Also the data of customer's locations and movement of people in the shop could be used for gaining insight into customer's needs or even assist targeted advertisement.

Methods of RF Indoor Positioning often use time of arrival, angle of arrival or the Received Signal Strength Indication (RSSI) of the beacons received by the mobile phone. The use of time of arrival faces synchronization issues as well as multipath. This worsens its accuracy and reliability [1]. Using the angle of arrival, determining the angle of arrival of an RF signal requires using multiple antennas. Although this technique yields a high accuracy up to 40 cm on average as reported in [2], they would require special devices - mobile phones that use multiple antennas. RF indoor positioning methods based on RSSI include: trilateration (which as a poor accuracy), Particle filtering (which is good), Kalman filtering (which is also good), and the RSSI Fingerprinting method [3]–[5].

The goal of this paper is to investigate the RSSI Fingerprinting method, implement and test an RSSI Fingerprinting Algorithm (RSSIFA) with a measured fingerprints database and then a theoretical fingerprints database. The entire implementation and tests of the RSSIFA is carried out in Matlab. The rest of the paper is as follows: In Section II the RSSIFA will be discussed and creating both measured and theoretical RSSIF Database will be presented. In section III and IV are the results and conclusion respectively. Please note that location determination and indoor positioning are synonymous and are used interchangeably through out this paper.

II. Method

A. The RSSI Fingerprinting Technique

1) The concept of RSSI Fingerprinting: The RSSI Fingerprinting is based on the idea that the RSSIs received from all the beacons will be different at each position, storing these data and using them for location determination. Indoor positioning using RSSI fingerprinting method works in two phases:

The offline (Training) phase: This is where RSSIs are collected, processed and stored. The collected RSSIs are called RSSI fingerprints. The locations where the RSSIs are collected are called collection locations. RSSI fingerprints can also be constructed using theoretical propagation models. These are called Theoretical RSSI fingerprints.

The online (Location-determination) phase: This is the phase where the RSSI fingerprints are used for location determination. This is done using an algorithm. The algorithm is called a RSSI Fingerprinting Algorithm.

2) Classes of RSSI Fingerprinting Algorithms: There are two main classes of positioning algorithms using RSSI fingerprints, the deterministic and the probability based one. In the deterministic type, the RSSIs are stored as a scalar value. One deterministic technique is the K-Nearest Neighbor (K-NN)[3]. In the offline (Training) phase of the K- Nearest Neighbor technique, the RSSI from each of the beacon at each collection location is stored as a tuple- $(x_{p1,}y_{p1}) = (s_1, s_2, s_3, \dots s_n)$. Where s_n is the RSSI from the nth beacon. During the online phase, the euclidean distance between RSSIs at the unknown location and that of each collection location in the database is computed. Then the location with the smallest euclidean distance is returned as the estimated location. A theoretical study of the K-NN technique was done in [6]. It was revealed that the technique can easily give the wrong position due to the multimodal distribution of the RSSIs tuples. A probability based algorithm is used in this paper instead of the K-NN.

3) The Selected Method- Probability based Approach: In the offline phase of the probability based approach, the probability distribution of the RSSIs from each beacon at each collection is used. Basically, the mean and standard deviation

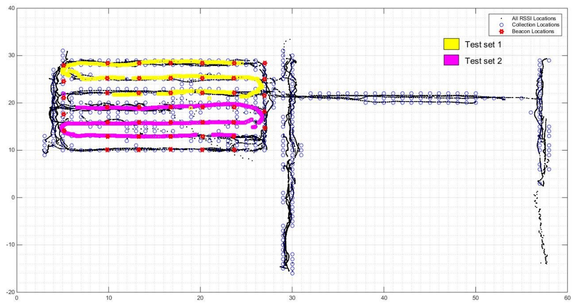

Figure 1: 2-D Plot of the RSSI Location, Resulting Collection Locations the Beacon Locations, and Test sets

of each RSSIs collected from each beacon in each collection is stored. The distribution is simply modeled to be a Gaussian distribution. More complex distribution modeling yields only a slight improvement [4]. In the online phase where the actual positioning takes place, the discrete space estimator, and other enhancement components are used, namely: time averaging, center of mass and correlation compensation [5].

4) Creating a measured RSSI fingerprints Database: Fig.2 shows the entire process of creating a fingerprint database from the raw RSSI data . RSSIs where collected by walking around the environment. This is different from the way it was done in [3]–[5], where certain locations are chosen and RSSIs are collected at those locations alone. Fig. 1shows a plot of the RSSI locations, the resulting collection locations and the beacon locations. RSSI at a collection location from a beacon make up a cell. The average standard deviation of a cell is 3.7dBm and the maximum standard deviation is 19dBm. The dimension of the shop was 88m by 100m. 44 beacons were used. The entire collected RSSI was about 350 000, collected at different times and days. The median number of samples in each cell is 7. A number of collection locations had only one RSSI from some beacons. Fig. 3, shows a histogram of the number of cells that have a certain number of samples. The standard deviation of a sample is equal to zero. Cells with only one sample degrades the quality of the database because the standard deviation of one sample is equal to zero.

5) Creating a Theoretical RSSI fingerprints Database: RSSI fingerprints can be constructed using a theoretical propagation model. A simple propagation model given by:

$$P_R(dBm) = P_T - (40.2dB + 20log(d)) \tag{1}$$

was derived from the well-known Friis equation: $P_R = P_T + 20log(\lambda/(4\pi)) - 20log(d)$. The frequency of operation is 2.45GHz. The optimal value of P_T was -25dBm . A fixed standard deviation of 5dBm was used throughout the Theoretical fingerprints Database.

6) Deviations and Optimal values: Due to the non-ideal RSSI Fingerprint database, measures were taken to ensure that the algorithm works properly. In the database some cells had no data and while there was data from that beacon at a test location. In this case, 1/10th of the maximum possible probability from P(s/x) assuming a variance of 4.5dBm was

Parameter	Value
Time Interval	0.1s
Map spacing	1m
Time averaging window	40
Center of mass	10
Correlation	0.5
Number of beacons available	44

Table I: Optimal values of System Parameters

assigned to it. This was calculated to be 0.088, and optimized to be 0.0051. In most previous work done on RSSI Fingerprinting, each cell (a set of RSSI from a particular beacon at a collection \location) had a uniform number of samples, and the test set had the same number of RSSI in each cell [5], [7]. One effect of this was that the standard correlation of 0.7-0.9 used for the correlation compensation module led to a performance degrade. 0.5 was found to be optimal.

7) Testing the algorithm: 2 test sets were used, test set 1 was a walk around the shop for about 57 seconds with a Samsung galaxy phone, while test set 2 was a walk around the shop for about 58 seconds with a Nexus phone. Fig. 2 shows a 2-D plot of the test set 1 and test set 2 locations. A test sample is obtained by processing all the RSSI received within a time interval of 0.1 seconds, sorting them according to their beacons and taking the average of the RSSIs. To obtain the accuracy of a sample, the distance between the actual location and the location estimated by the algorithm is calculated by:$\sqrt{((x_{actual} - x_{RSSIFA})^2 + (y_{actual} - y_{RSSIFA})^2)}$.

III. RESULTS

A. Measured RSSI fingerprints Database

With optimal parameters stated in Table I, Table II shows the system performance on two different test sets: With the Discrete space estimator alone, then with center of mass, then with time averaging added, then with correlation compensation. An average accuracy of 1.17m was achieved in test set 1 and 1.78m in test set 2. The center of mass, time averaging and correlation compensation gave drastic improvement to the system. Time averaging proved to be the most important enhancement followed by center of mass and then correlation compensation.

B. Theoretical RSSI fingerprints Database

Table III Compares the results of using theoretical fingerprints with using the measured RSSIs. In the first test set using theoretical RSSI fingerprints was 50 cm less accurate on average than using the measured fingerprints. For the second test set it was 17cm less accurate on average.

IV. CONCLUSION

A probabilistic based RSSI Fingerprinting algorithm was implemented and tested. When measured RSSI fingerprints was used the system delivered an average accuracy of 1.17m. Using theoretical RSSI fingerprints the system was about 20-50cm less accurate on average. The measured RSSI fingerprints database was not optimal due to insufficient data and non-uniformity. Nevertheless, it still out-performed the

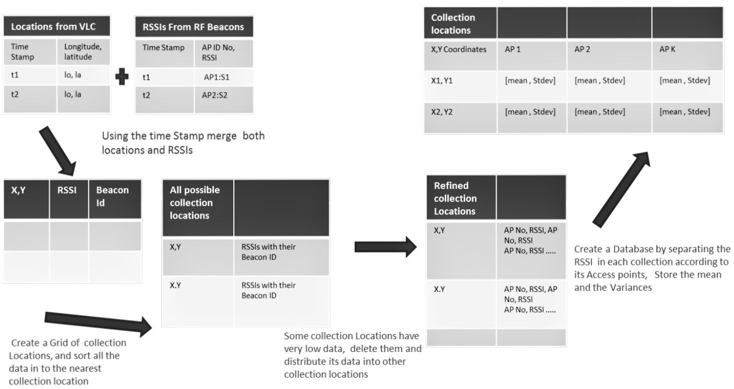

Figure 2: The process of creating the RSSI fingerprints database

	Mean (m)	Median (m)	Std. dev (m)	Max(m)
Test Set 1				
Discrete Space Estimator (DSE)	3.80	3.26	3.42	37.11
DSE + Center of Mass (CM)	3.24	2.91	2.50	24.14
DSE + CM + Time Averaging (TA)	1.30	1.18	0.70	2.91
DSE+CM+TA+Correlation Compensation	1.17	1.13	0.59	2.42
Test Set 2				
Discrete Space Estimator (DSE)	3.63	3.15	2.92	22.22
DSE + Center of Mass (CM)	3.08	2.59	2.38	19.07
DSE + CM + Time Averaging (TA)	1.79	1.62	0.97	3.95
DSE+CM+TA+Correlation Compensation	1.78	1.57	1.11	6.61

Table II: Performance of RSSIFA on measured fingerprints

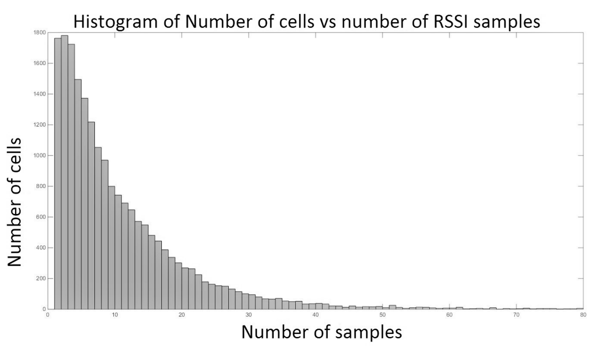

Figure 3: Histogram of the number of cells against the number of samples in each cell

	Mean	Median	Std. dev	Max
(all in meters)	Test set 1			
Theoretical RSSI FP	1.65	1.63	0.99	4.81
Measured RSSI FP	1.15	1.14	0.60	2.66
	Test set 2			
Theoretical RSSI FP	1.63	1.63	0.63	2.81
Measured RSSI FP	1.46	1.47	0.68	3.46

Table III: Comparing results of measured and theoretical fingerprints

theoretical RSSI fingerprints. This implies that the measured RSSI fingerprints have a potential to perform better if the RSSIs are very large and smartly sorted to reject outliers. The accuracy of the algorithm is well suited for location determination in large retail stores but may not be sufficient for high precision positioning applications such as tracking objects in a small room.

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