Comparative Performance Analysis of Empirical and Radio Propagation Model for Bluetooth Indoor Localization

Idigo V.E., Azubogu A.C.O., Ohaneme C.O., Isizoh A.N.

Abstract: ***This work presents the possibility of using channel simulated results as alternative to site measurement for RSS based indoor localization. Three reference radio maps were generated for on-site measurement, Wall Attenuation factor (WAF) and Ray Tracer (RT) channel models. The Bayesian localization algorithm was applied to the three radio maps. An important performance metric called localization error was used which depends on the resolution of the reference radio map. Results obtained show that the performance of an RT model is comparable to a system based on on-site measurement for grid resolutions greater than 10 meters, on the other hand, the WAF model produced results that are very close to the on-site results for grid resolutions less than 8 meters.***

Keywords: Grid resolution, Localization error, propagation model, Radio Channel, reference point

I INTRODUCTION

Position information is essential in many indoor applications. A hospital or health-care facility may wish to be informed of the locations of all its patients at all times; a military unit may wish to extend its reconnaissance capabilities beyond the line of sight; a search and rescue team can locate and provide help quickly if the location of the individual in distress may be known accurately in advance [1]. Recent indoor applications include mobile e-commence (m-commerce), e-museums, locating objects in warehouses and big shops (mall), locating books in libraries, etc. In addition, software packages have become available in the market that can locate a predefined object almost precisely but still there is strong interest for even more accurate systems for indoor applications comparable to outdoor geo-locations systems such as Global Positioning System (GPS).

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The harsh site-specific multipath environment in indoor areas introduces difficulties in accurately tracking the position of objects and people. The behaviour of the channel changes from building to building and even within a single floor of a building. The channel may vary with added objects and people moving in the vicinity.

Basically, the indoor geo-location procedure begins with collecting metrics related to the position of the mobile terminal relative to the reference point. Almost any sort of metrics which are used in telecommunication systems can also be used in geo-location systems. Angle of Arrival (AOA) and Received Signal Strength (RSS) are the most popular ones but Time of Arrival (TOA) and Phase of Arrival (POA) can be used as well. These metrics are used widely in location estimation systems. Global Positioning System (GPS), which is the most well-known positioning systems, estimates the location of the desired object by using TOA of received signal [1,2].

The second step is to process the gathered metrics and estimate the location of the desired person or object. This step usually requires signal processing knowledge unless the finger printing method is used. In using the finger printing method, it is required that a grid-network be built prior to any location estimation. After building the database for a new location, the new metric is measured irrespective of the viewed location and compares it with the database to find the best node, which could be referred to the desired point. Processing the received data is the most tedious task in other methods of positioning.

The Bluetooth specification [3] provides no specific support for positioning service. In the absence of such support, various research efforts have been made in this area with alternating conclusions. The Bluetooth signal strength information has been used to create a system for locating and tracking users inside buildings [4]. Again, the concept of reference tags and readers that work with both the possibilities of Bluetooth supporting and not supporting the signal strength parameter has also being introduced [5].

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However, other works suggest an unreliable relationship between the positioning and the signal strength and hence avoids this parameter for positioning with Bluetooth [6,7].

II RECENT EMERGING INDOOR MODELS

In general, indoor channels may be classified either as line-of-sight (LOS) or obstructed (OBS), with varying degree of clutter. Some of the key models which have recently emerged are presented below:

(i) Partition Loses (same floor):- Buildings have a wide variety of partitions and obstructions which form the internal or external structure. Partitions that are formed as part of building structure are called "hard partitions", and partitions that may be moved and which do not span to the ceilings are called "soft partitions". Partitions vary widely in their physical and electrical characteristics making it difficult to apply general models to specific indoor installations. Nevertheless, researchers have formed extensive data bases of losses for a given number of partitions [8, 12].

(ii) Partition losses between floors:- The losses between floors of a building are determined by the external dimensions and materials of the building, as well as the type of construction used to create the floors and the external surroundings[3,9]. Even the number of windows in a building and the presence of tinting (which attenuates radio energy) can impact the loss between floors. Typical average floor attenuation factor in dB for one, two, three and four floors in two office buildings are given in [9].

(iii) Log distance Path loss Model:- Indoor path loss has been shown by many researchers to obey the distance power law as shown in equation 1. $\bar{P}L(d)[dB] = \bar{P}L(d_0) + 10\alpha \log\left({}^{d}/_{d_0}\right) + X\sigma$ (1)

where α = path loss exponent which indicates the rate at which the path loss increases with distance and depends on the surroundings and building type, and $X\sigma$ represents a normal random variable in dB having a standard deviation of σ dB, d_o is the close-in reference distance which is determined from measurements close to the transmitter, d is the transmitter-receiver distance.

Typical values of various buildings are provided in [9,10].

(iv) Attenuation Factor Model:- This model provides flexibility and was shown to reduce the standard deviation between measured and predicted path loss to around 4dB, as compared to 13dB when only a log-distance model is used in two different buildings[2]. The attenuation factor model is given by.

$$\bar{P}L(d)[dB] = \bar{P}L(d_0) + 10\alpha_{nF} \log\left({}^{d}/_{d_0}\right) + FAF[dB] + \sum PAF\,[dB] \quad (2)$$

where α_{nF} = the exponent value for the "same floor" measurement.

FAF = floor attenuation factor for a specified number of building floors.

PAF = the partition attenuation factor for a specified obstruction encountered by a ray drawn between the transmitted and receiver in three dimension (3-D).

Alternatively, in equation (2), FAF may be replaced by an exponent which already considered the effects of multiple floor separation.

$$\bar{P}L(d)[dB] = \bar{P}L(d_0) + 10\alpha_{MF} \log\left({}^{d}/_{d_0}\right) + \sum PAF\,[dB] \quad (3)$$

Where α_{MF} denotes a path loss exponent base on measurements through multiple floors.

In [11], it was shown that in building path loss obeys space plus an additional loss factor which increases exponentially with distance. Based on this work in multi-floor buildings, it would be possible to modify equation 2 such that;

$$\bar{P}L(d)[dB] = \bar{P}L(d_0)[dB] + 20 \log\left({}^{d}/_{d_0}\right) + \alpha d + FAF[dB] + \sum PAF[dB] \quad (4)$$

where α = attenuation constant for the channel with units of dB per meter (dB/m).

(v) Wall Attenuation Factor (WAF) model

A good compromise between simplicity and accuracy was found in the Floor Attenuation Factor propagation model FAF suggested by [12]. This model seems appropriate because it provides flexibility in accommodating different building lengths while taking into account large-scale path loss. This work adapted the original model proposed by Seidel and Rappaport, which included attenuation factor for building floors to disregard the effects of floors and instead consider the effects of obstacles (walls) between the transmitter and the receiver. The Wall Attenuation Factor (WAF) model is described by;

$$P(d)[dB] = P(d_0)[dB] + 10\alpha \log\left({}^{d}/_{d_0}\right) - \begin{matrix} nW.XWAF, & nW<C \\ C.WAF & nW\geq C \end{matrix} \quad (5)$$

where, α = Path loss exponent that indicates the rate at which the path loss increases with distance.

P(do) = the signal power at some reference distance do.

d = the transmitter-receiver (T-R) separation distance.

C= the maximum number of obstructions (walls) up to which the attenuation factor makes a difference.

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nW = the number of obstruction (walls) between the transmitter and the receiver.

WAF = the wall attenuation factor.

(vi) Channel Modeling Using Ray Tracing

Existing channel models do not use the geometrical characteristics of an environment directly. This is a major shortcoming for these models especially in a multipath rich indoor environment. *Ray-tracing* (RT) is a simulation tool encompassing the geometrical information of a floor plan in addition to the reflection and transmission coefficients of building materials that models the radio channel behavior in different areas [13,14]. For a pair of transmitter-receiver at some known locations, RT determines the necessary information of a channel such as arrival angle, departure angle, phase, number of reflections, and number of transmissions by sending a set of rays from the transmitter and tracing them until they either reach the receiver or largely attenuated that they cannot be detected by the receiver. The TOA, magnitude, and phase of each path are recorded for each ray. In small indoor areas with soft surfaced walls reflection and transmission are the dominant mechanisms for radio propagation at frequencies around 1 GHz; whereas for high-rise and urban canyons with roof top antennas diffraction is the main mechanism for signal propagation.

The predictions from ray tracing software are particularly accurate for propagation of radio signals at frequencies greater than 900 MHz where electromagnetic waves can be described as traveling along localized ray paths. This method is shown to be accurate for indoor environments. RT can be used to produce large databases of channel impulse responses for statistical analysis of the channel. Therefore RT is a viable alternative to physical measurement [10].

III EXPERIMENTAL SETUP AND CHANNEL CHARACTERIZATION

A set of measurements of RSSI were taken in the experimental test bed located at the permanent site of Nnamdi Azikiwe University Awka.

The first testbed is located at the first floor of the 3-storey Administrative building of the university. The layout of the testbed is shown in figure 1. The floor has a dimension of 20m by 18m, an area of 360sqm. This floor has 10 rooms.

The testbed is segmented by a square of 1x1 meters as shown in figures 1 and 2. A Pentium based laptop equipped with Bluetooth device was placed at positions shown in the testbeds. The mobile host carried by the user being tracked, was another Pentium based laptop equipped with a Bluetooth device.

The protocol stack used in this experiment was provided by the Bluetooth simulator (BlueHoc). BlueHoc is IBM's new Bluetooth released under IBM public license. It allows one to evaluate how Bluetooth performs under various ad-hoc networking scenarios. The key issues addressed by the simulator are [3,5]:

- Device discovery performance of Bluetooth.
- Connection establishment and quality of service (QoS).
- Medium access control scheduling schemes.
- Radio characteristics of Bluetooth systems.
- Statistical modeling of the indoor wireless system-
- Performance of TCP/IP based applications over Bluetooth.

General measurements were taken to see how distance co-relates to signal strength. During this test four Bluetooth access points were place in the testbeds.

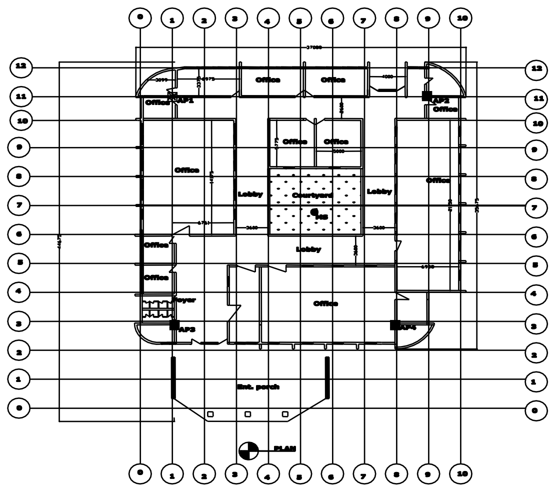

Fig 1: First Test Bed: Administrative Block

A. R.F Channel Characterization

Ten measurements each were taken at distance of 5, 10 and 15 meters from access points AP1, AP2, AP3 and AP4.

During experiments, it was discovered that signal strength at a given location varies quite significantly (by up to 5dBm) depending on the user's orientation i.e. the direction he/she is facing. In one orientation, the mobile host's antenna may have Line-of-sight (LOS) connectivity to a base stations antenna while in the opposite orientation; the user's body may form an obstruction. These variations suggest that depending on a single statistical value, e.g. the average signal strength, to capture the signature of the access point at a fixed position leads to the loss of a lot of information and affects the accuracy of the location determination system significantly.

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In all, during the off-line phase, RSSI values were collected in each of the 4 directions at 40 distinct physical locations in the testbed. For each combination of location and orientation (i.e (x,y,d)), at least 20 RSSI samples were collected.

Figures 2 show the RSSI/Distance profile for the first testbed respectively at distances of 1 to 10 meters from AP1, AP2, AP3 and AP4 measured every 1 meter.

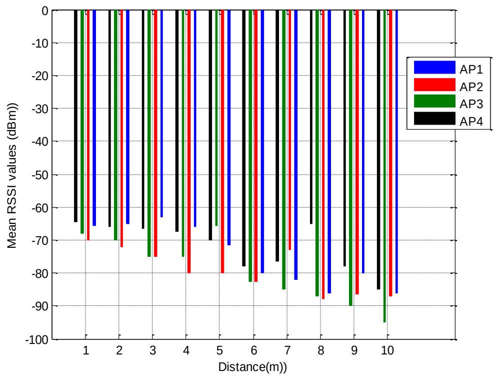

Figure 2: RSSI/Distance profile for the first testbed

B Samples from different access points.

An experiment to test the behaviour of access points with different average signal strength at the same location was performed. During this experiment, the signal strength from each access points were sampled at the rate of one sample per second.

Figure 3 shows the relationship between the average signal strength received from an access point and the percentage of samples received from it during a period of 5 minutes.

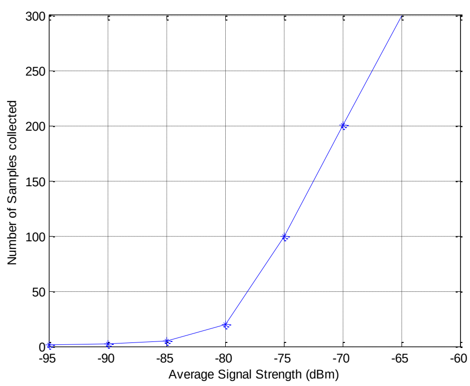

Figure 3: Relation between the average signal strength of access point and the percentage samples received from it during 5minutes intervals.

The figure 5 shows that the number of samples collected from access point is a monotonically increasing function of the average signal strength of this access point. Assuming a constant noise level, the higher the signal strength the higher the signal to noise ratio and the more probable it becomes that the Bluetooth device will identify the existence of a packet. Accuracy of the positioning system is closely related to the number of nodes in the database and distribution of them. For example, for a typical indoor area, at least we should gather location information for nodes as close as 2-3 meters to each other if we want to have an accurate positioning [7].

IV PROBLEM FORMULATION AND IMPLEMENTATION OF BAYESIAN LOCALIZATION MODEL

A. Problem Formulation

Two vectors are normally used in estimating the location of the mobile station (MS). The first vector consists of samples of the RSS measured at the mobile station from N access points in the area. We call it the sample RSS vector throughout this work. This vector is denoted as: S = [S_1, S_2, S_3, …, S_N]. The indoor positioning system estimates the mobile's location using this sample RSS vector. Each component in this vector is assumed to be a random variable with the following assumptions:

1. The random variable S_i (in dBm) for all i are mutually independent.
2. The random variables S_i (in dBm) are normally (or Gaussian) distributed.
3. The (sample) standard deviation of all the random variable S_i is assumed to be identical and denoted by σ (in dBm).
4. The true mean of the random variable S_i or E{S_i} is denoted as ri (in dBm).

The second vector that forms the fingerprinting of the location, consists of the true means of all the received signal strength random variable at a particular location from the N access points and its recorded in the location database. We call it the location fingerprint or the average RSS vector for the rest of this work and denote it by R= [r_1, r_2 r_3,…, r_N].

Let X be a 2 (or 3) dimensional physical space. At each location xεX we can get the signal strength from K access points. Let us denote the K-dimensional signal strength space as S. Each element in this space is a K-dimensional vector whose entries represent the signal strength readings from different access points. Sampling from the signal strength space S at locations x at time t, The problem becomes, given a signal strength vector S= (s_1, …, s_k), we want to find the location xεX that maximizes the probability P($^x/_s$).To solve this problem, the probabilistic method of finger printing, such as the Bayesian approach to WLAN Localization was used.

B. Implementation of the Bayesian Model

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For localization, Bayes' rule can be written as [14]:

$$P\left({}^{I_t}/_{O_t}\right) = P\left({}^{O_t}/_{I_t}\right) P(I_t).N \qquad (6)$$

where, l_t = is a location at time t.

o_t = is an observation made at t (the instantaneous signal Strength values).

N = is a normalization factor that ensures that all probabilities sum to 1.

Equation 6 implies that the probability of being at location l given observation o is equal to the probability of observing o at location l, and being at location l in the first place. During localization, this conditional probability of being at location l is calculated for all fingerprints. The most likely location is then the localizers output.

In order to calculate $P(l_t/o_t)$ in equation 1, it is necessary to calculate the two probabilities on the right hand side of the equation $P(o_t/l_t)$ is known in Bayesian terms as the likelihood function. This can be calculated using the signal strength map. For each fingerprint, the frequency of each signal strength value is used to generate a probability distribution as a likelihood function. Other representations are also possible; the Bayesian approach allows us to use the algorithm capable of generating a probability distribution across all locations.

In its simplest incarnation, the Bayesian localizer calculates the prior probability $P(l_t)$ in equation 1 as the uniform distribution over all locations. This encodes the idea that before each attempt at localization, the target is equally likely to be at any of the locations in fingerprint map.

In order to achieve higher accuracy, we can calculate $P(l_t)$ using our knowledge of the target's likely motion, historical information from previous user habits, collision detection and anything else that affects the prior probability that can be modeled probabilistically.

Markov localization [9,14] suggests using the transitional probability between locations. This probability is described as;

$$P(I_t) = \sum P\left({}^{I_t}/_{I_t - 1}\right) P(I_{t-1}) \qquad (7)$$

In other words, $P(l_t)$ is the sum of the transitional probability from all locations at t-1 to l at current time t, multiplied by the probability of being at these locations at t-1. $P(l_{t-1})$ is known from previous localization attempts.

We calculate $P(l_t/l_{t-1})$ using a motion model, the details of which are specific to how we expect the target to move. For a walking person, the simplest and most effective approach is to calculate the probability based on how far the user can move between t and t-1. This is not very far if our localizer runs once every second. In practice, this extra calculation serves to remove noise affected outliers from the output.

Figure 4 shows the analysis of the average positioning distance error for the two cases considered (DEI – with two access points, DE2- with four access points)

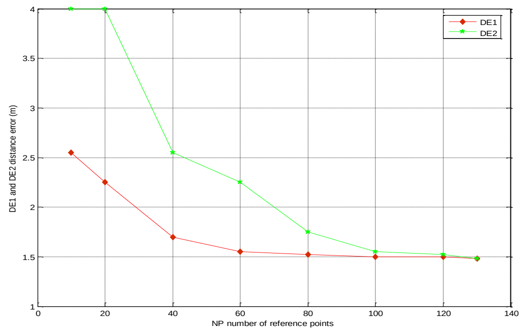

Figure 4 : Avarege Positioning Distance Error

In practice, the Bayesian localizer proves more accurate than the nearest neighbor technique because it takes into account more information from the training data and filters the output using motion model [13].

Figures 5 and 6 (generated using MATLAB) show the performance of Bayesian technique for static and mobile localization, respectively. Static localization is performed for targets not expected to move and takes the prior probability as the uniform distribution.For mobile localization, the prior probability was calculated using a simple motion model.The median error for static and mobile localization are 1.2 meters and 1.5 meters respectively compared with 2.5meters for the RADAR system using the Nearest Neighbour (NN) algorithm [16]. The basic model assumed discrete- space estimation and provided accuracy of 50% and 75% for the two cases respectively

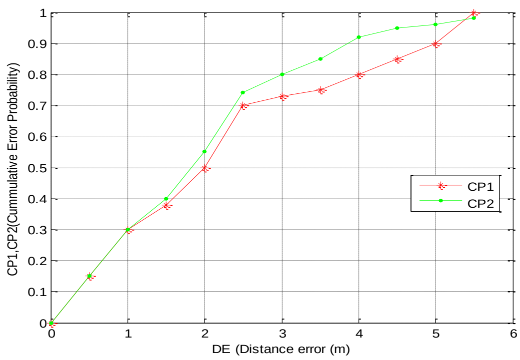

Figure 5: Cumulative error probability for static localization for the two cases(cp1 – for first case,cp2- for second case)

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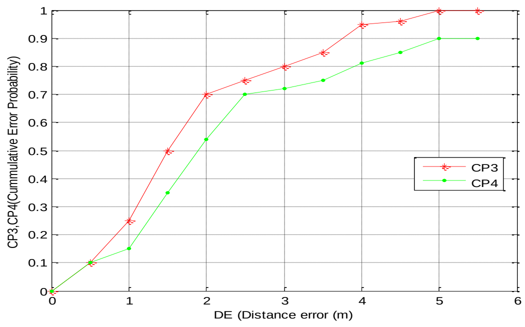

Figure 6: Cumulative error probability for mobile localization.(cp3 for first case, Cp4 for second case)

V. Comparative analysis of the Empirical and Radio propagation models.

Finally, the performance of the empirical model was compared with the proposed radio propagation models. That is, we compared the results from the measurement-based model with:

- ➢ The result from WAF model.
- ➢ The result from RT aided model.

This section has the following objectives:

- ➢ To study the possibility of using channel simulated results as alternative to site measurements for RSS based indoor localization.
- ➢ To find the average localization error as a function of a radio map resolution in typical RSS based localization system.

Major components of this testbed are shown in figure 7. Three reference radio maps were generated for on site measurement, WAF and RT channel models. The Bayesian Localization algorithm was used as localization algorithm.

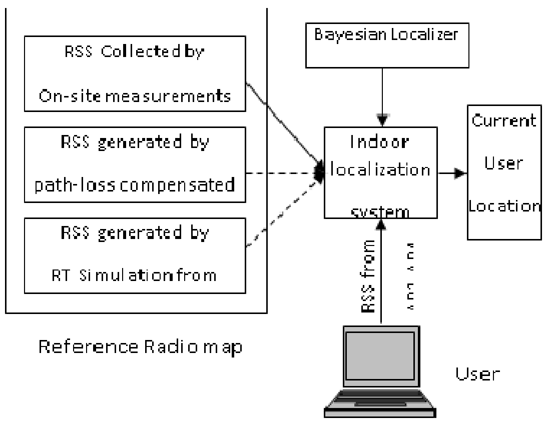

Figure 7: Major components of the comparison testbed.

A. Results and Discussions

An important performance metric in a positioning system called localization error was used which depends on resolution of the reference radio map. As shown in [6, 7, 16], the performance of a typical localization algorithm can be improved by using a finer grid of reference points.

Figure 8 shows the impact of the number reference points in the distribution of localization accuracy in a system using the Bayesian algorithm. Although we can increase the number of reference points to achieve any desired accuracy for scientific empirical performance comparisons, in real-world situation this approach is impractical. Creating and maintaining high resolution reference radio map using on site measurements is a challenging process in a dynamic WLAN environment. In order words, for practical application, the optimal obtainable accuracy is often not important goal but the issue is how easy it is to obtain a practically applicable accuracy. Here we explore the feasibility of radio channel modeling techniques to answer the question by demonstrating the average error as a function of the reference grid resolution. The Bayesian RSS based localization algorithms was used. This algorithm was applied to these different radio maps generated by means of on site measurement, WAF, and RT channel nodes with different number of reference points.

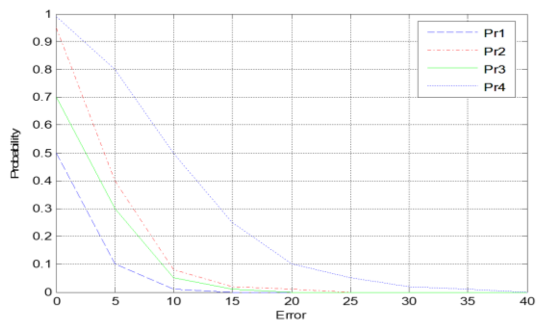

Figure 8: Impact of number of reference points on localization error using Bayesian algorithms Figure 9 to 11 shows the average distance error estimation as a function of grid resolution for the three radio maps. Using these curves, a system designer can determine the optimum number of reference points to achieve a desired localization accuracy which is dictated by the application requirements. From these plots we can see that the performance of an RT trained RSS based localization system is comparable to a system which is trained by on site measurements. For example a system which uses an RT generated reference radio map with 10m grid resolution is 7.2 meters which is a good approximation for the corresponding average error (7.0 meters) for any practical deployments.

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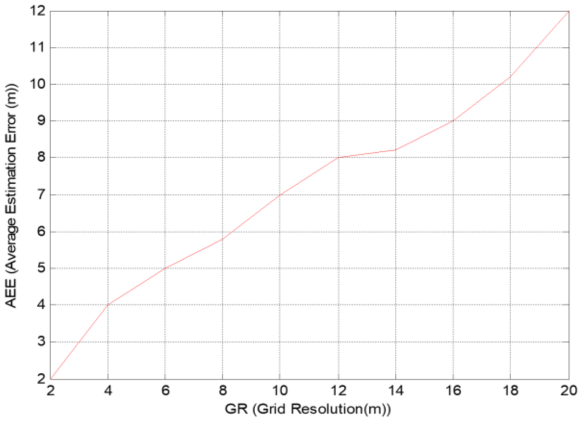

Figure 9 Average Localization error for a system trained with on site measurement.

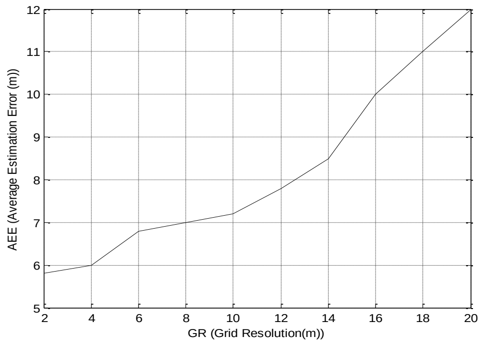

Figure 10: Average localization error for a system trained with RT Channel Simulation.

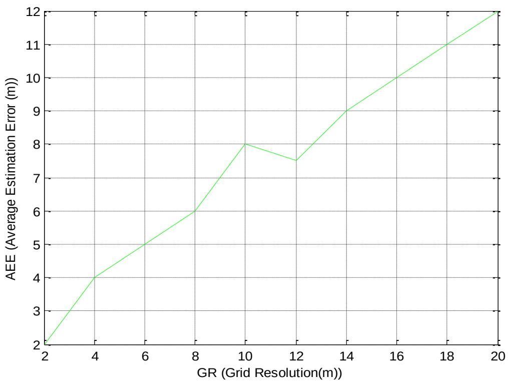

Figure 11: Average localization Error for system trained with WAF model

Between the two channel modeling methods, RT proved to be more robust technique (especially for grid resolution> 10 meters). The simulation results using RT software in these situations is very close to the onsite results. On the other hand, the WAF model produced results that are very close to the on-site results for grid resolution < 8 meters.Using channel modeling techniques, we can easily increase the grid resolution to achieve higher localization while increasing the number of reference points using on-site measurements is a real challenge. In both channel modeling techniques the system needs to know the exact locations of the APs in order to create the reference radio map. However, a positioning system trained with on-site measurements does not require knowing the location of the APs.

In Summary, the results demonstrated that WAF and RT, channels models can be used to generate a reference radio map for RSS based localization in the experimental testbed.

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