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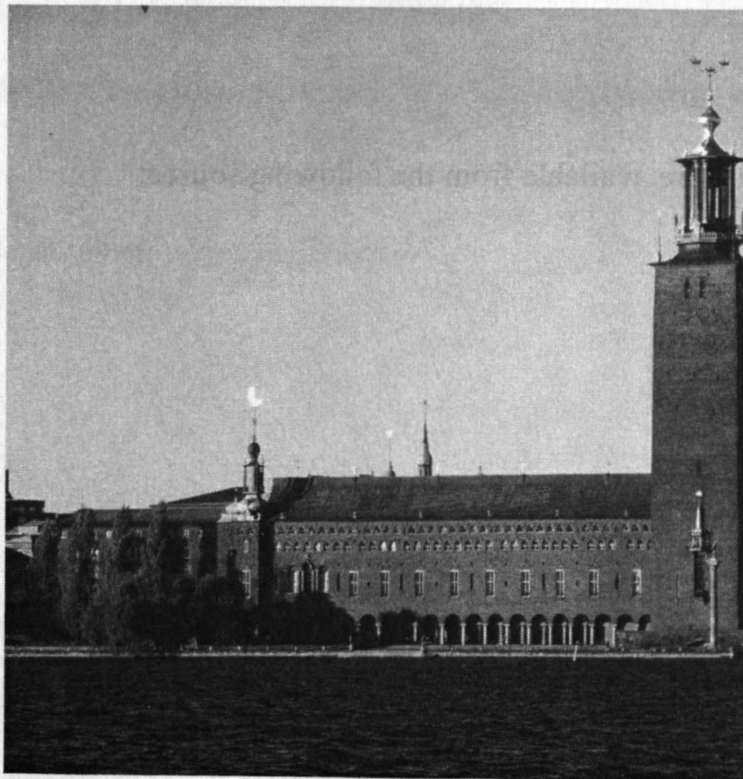
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Indoor/Outdoor Location of Cellular Handsets Based on Received Signal Strength

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Abstract—This paper demonstrates the feasibility of received signal strength (RSS) methods for locating wireless handset calls in a real cellular environment. An extensive measurement campaign conducted on the Georgia Tech campus indicates that RSS location techniques can locate handset calls within 100 m error distance to its ground truth up to 78% of the time and less than 300 m error distance up to 98% of the time for a network with a majority of indoor users. This is well above the safety requirements mandated by FCC in the US. We also propose a Received Signal Strength Aggregate (RSSA) method for identifying and locating indoor handsets.

Keywords—RSS; Radiolocation; Cellular; Propagation

I. INTRODUCTION

In recent years, radiolocation technology has received increasing international attention, particularly in the United States, where the Federal Communication Commission (FCC) now requires cellular service providers to locate cell phone users within 100 m error distance 67% of the time. TOA [1], AOA [2], GPS, and RSS signatures [3] technologies have been developed to provide wireless service providers with more accurate location estimates. Compared with most other cellular location solutions, a RSS location method does not require expensive base station equipment, has faster deployment speed, and covers current and legacy handsets making it a low-cost solution for emerging location-based services across the world.

The RSS technique estimates a cellular phone's location by matching signal strengths measured at the handset with signal strengths recorded in a database of radio frequency (RF) maps. These RF maps are generated through a combination of propagation modeling and field measurement. The technique has found its most common application in indoor wireless local area data networks [4]. Laitinen, et. al. in [5] report location performance statistics for outdoor users in a GSM network, but there has been no previous research that includes indoor users – which now constitute the bulk of today's cellular network traffic.

In this paper, we demonstrate the viability of Received Signal Strength (RSS) techniques in a semi-urban environment to meet the safety requirements set forth by the Federal Communications Commission (FCC). Furthermore, we conclusively show that RSS location techniques are also accurate for indoor users – a characteristic unique among all currently

proposed E911 technologies. Since most cellular phone calls are now placed from indoor environments, this result has enormous implications for public safety. We also show that the RSS technique can discriminate between indoor/outdoor users with up to 94% reliability. Results from an IS-136 network in Atlanta Georgia show that the proposed method can locate outdoor users within 100 m 74% of the time and 300 m 97% of the time when only 6-sector information is available. When the system is loaded with indoor users, the accuracy falls to 70% of the time within 100 m and 96% of the time within 300 m. Three different databases of RF maps were compared side by side so that the accuracy effects of different ratios of RF modeling and measurement can be seen.

II. EXPERIMENT ENVIRONMENT

Tests were performed on an 850 MHz IS-136 cellular network in mid-town Atlanta on the campus of the Georgia Institute of Technology. The campus approximates a typical semi-urban or dense suburban area with streets, moderate green space, and many 4-5 story academic and office buildings. There are no skyscrapers or "urban canyons" that would be associated with dense urban environments. The measurement area has length of 700m and width of 500m, as shown in Fig. 1. Three base stations were inside the measurement area, where eight medium-tier sectors are in use. Another five base stations in the neighborhood also provided coverage at the edge of the test area. The distance between base stations was approximately 400-500 meters. A database of RF coverage maps for all nearby serving sectors was created from a combination of propagation modeling and varying levels of indoor and outdoor measurement calibration using a Comarco IS-136 scanner with baseband decoding. Real pedestrian-style handset measurements were taken with an Ericsson handset connected to an Ericsson TEMs data collection unit.

This measurement campaign lasted for 4 months (January through April) in the beginning of 2004. Due to the limitations of GPS, many outdoor coordinates and all indoor coordinates had to be painstakingly estimated from geo-referenced maps of campus and manually entered into the database. This is one source of error in our measurements. There are other unique sources of error in our measurements that may make our results somewhat pessimistic. For example, there was a



Fig. 1. Satellite photograph of the indoor/outdoor “radiolocation laboratory” at Georgia Tech campus in semi-urban Atlanta, GA.

seasonal change in the middle of our data collections where leaves grew back on the campus trees, changing the propagation characteristics by several dB. Also, one of the large buildings within our test area was demolished in the middle of our campaign. We also used a fairly simple location algorithm since we were concentrating on the more complicated question of indoor feasibility. There are many other algorithms that have been proposed which could improve the performance [5], [6], [7].

III. RSS LOCATION SYSTEM

A. How RSSI-based Radiolocation Works

The operation of RSSI-based position location is straightforward. A cellular network area is represented in a computer by a large, two-dimensional raster array with uniform grid spacings of 10m squares. Each raster point in the grid corresponds to a location within the network and contains a vector of received signal strength indicator (RSSI) values in dBm for all audible base stations. A complete raster array of RSSI is called an RF Map Database (RFMD). Once an RFMD has been constructed for a network area, the RSSI-based location engine must compare received signal strength measurements made by the handset to the RFMD vectors. The best match determines the xy-coordinates of the most likely handset location.

B. Calibration Level of RF Map Database:

The database used in the location experiments is a collection of raster-based RF maps (10m by 10m resolution). The basic propagation prediction technique used to make the initial RF maps. All pure signal strength predictions are based on a modified version of the Hata model [8]. The radio link budget used for this type of link is given below:

$$P_R = P_T + G_R + G_T \cos(\theta - \theta_b) - 10n \log_{10} \left(\frac{d}{1 \text{ m}} \right) - 20 \log_{10} \left(\frac{4\pi}{\lambda} \right) + C_{\text{db}} \quad (1)$$

where the terms in Equation 1 are summarized as follows:

- P_R - power received by a handset (dBm)
- P_T - power transmitted by a sector (dBm)
- G_R - estimated handset antenna gain (0 dBi)
- G_T - estimated peak sector antenna gain (7 dBi)
- θ - bearing angle of predicted location (degrees)
- θ_b - sector antenna bearing angle (degrees)
- d - separation distance (m)
- n - path loss exponent (3.3)
- λ - wavelength of radiation (m)
- C_{db} - constant offset (dB)

In this manner, we construct every raster RF map at 10m $\times$ 10m resolution for each sector in and around the campus of Georgia Tech. A modeled estimate of signal strength, P_R , is placed at every raster point in an RF map.

Then the modeled RF maps are compared to any available scanner measurements, which are also grouped into 10m by 10m rasters with linear power averaging to remove small-scale fading effects. The variable C_{db} in Equation 1 is the constant offset term that accounts for additional gains and losses due to antenna height and pattern, RF hardware, frequency offset, or any other consistent, unmodeled effects in the RF chain. The value for C_{db} is chosen to minimize the standard deviation error between the raw modeling and any drive test measurements corresponding to the sector. It can be expressed in the following Equations. Let vector $a = D_{\text{rss}}(x_i, y_i) \ i = 1 \dots M_n$ denotes driving test RSS measurement, where (x, y) are the coordinate of the i -th measurement point and M_n is the total measurement number. Let vector $b = \text{RFMD}(x_j, y_j)$ denotes the RSS of the same dedicate control channel (DCCH) in RFMD.

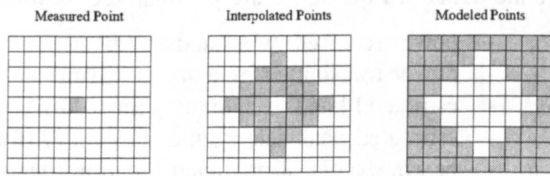
$$C_{\text{db}} = (i^T \cdot i)^{-1} \cdot i^T \cdot (b - a) = \frac{1}{M_n} \sum_{i=1}^{M_n} (D_{\text{rss}}(x_i, y_i) - \text{RFMD}(x_i, y_i)) \quad (2)$$

where $i = [1, 1, \dots, 1]^T$ of $1 \times M_n$

In map areas that are far from measured points, we are forced to rely on purely modeled signal strength. For areas in an RF map that are several raster points away from measured data points, we use a weighted combination of the modeled values and the value of nearby measurement point. This process of blending modeled signal strength with nearby measurements is called *local interpolation*. Thus, each RF map contains scanner measurements which gracefully blend into modeled, unmeasured regions.

There are many imaginable schemes for local interpolation. The scheme used in our RF maps is a 2D cubic interpolation scheme over a diamond-shaped area that surrounds every measured raster point. The difference between measured, interpolated, and modeled signal strength regions is illustrated in Figure 2. Enlarging the radius of the diamond around each measurement point leads to more aggressive interpolation. All RF maps in this study use interpolation with a radius of 3 raster points (30 meters) from measurement center.

(a) Single Measurement Point



(b) Measurements Taken Along a Path

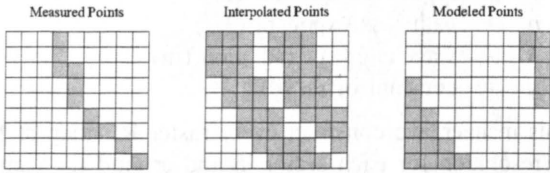


Fig. 2. Marked raster regions (in gray) for (a) a single measurement and (b) a path of measurements.

It should be noted that most measured points do not occur in isolated regions as illustrated in the upper part of Figure 2. Measured data points tend to cluster along paths due to the walking or driving methods of collection. For this reason, the lower part of Figure 2 represents a more realistic separation of interpolation regions. For clusters or paths of measured points, the diamond-shaped interpolation region are cumulatively masked together for every single collected point.

Also note that each measured point is actually the linear average of every instantaneous RF scanner measurement made at a frequency whose longitude and latitude happen to fall within the 10m $\times$ 10m raster point. This effectively removes any small-scale fading effects or other anomalies in the collection procedure. Drive-test measured points typically have 3 to 5 instantaneous power measurements averaged within a single raster point. Pedestrian collections typically have 5 to 15 (or more) averaged power measurements due to the slower collection speed.

Our study reports location performance using 3 different levels of RF map database. The Level 1 database of RF maps is calibrated with only outdoor drive-test scanner measurements. The Level 2 database of RF maps is identical to the Level 1 database of RF maps, except raster points corresponding to indoor locations are modified with additional penetration loss based on a simple, georeferenced map of building footprints. The Level 3 database of RF maps is constructed from extensive outdoor and indoor measurements. Figure 3 is one example measured at architecture building. Due to the difficulties, time, and expense of taking indoor measurements in every building, the Level 3 database of RF maps may not be practical for widespread deployment. But the Level 3 database does show the upper-limit of performance for an indoor/outdoor location algorithm.

C. Handset RSS Properties:

The additional penetration losses experienced by indoor cellular users were large enough to reliably distinguish them from the outdoor users. Accurate distributions of RSS from indoor

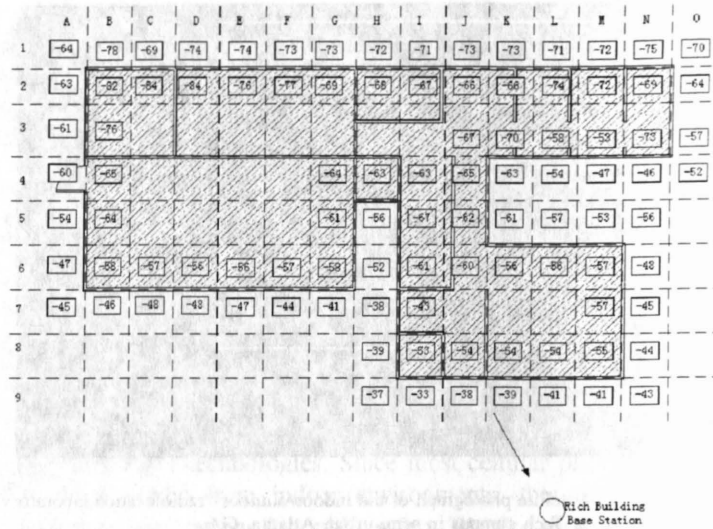


Fig. 3. Measured received signal strength of the architecture building at Georgia Tech. (in dBm)

and outdoor callers can be used to calculate from where a call originates. Based on these handset measurements, the average RSS over the N strongest channels was calculated, which we call the *received signal strength aggregate* ($RSSA_N$). We can assume that the distributions of the six strongest channels are independent and that their dB-sum is log-normal distributed. Based on our experiment, the mean of indoor $RSSA_6$ is -97.8 dBm and the standard deviation is 14.1 dB. For outdoor $RSSA_6$, the mean is -85.5 dBm and the standard deviation is 9.7 dB. Thus, average penetration loss is 12.3 dB. The probability density function of indoor and outdoor $RSSA_6$ is shown in Equation 3 and 4, respectively. Figure 4 shows the distribution of RSSA between indoor calls and outdoor calls in side-by-side plots.

$$p_{i6}(x) = \frac{1}{14.1\sqrt{2\pi}} e^{-\frac{(x-(-97.8))^2}{(2*198.81)}} \quad (3)$$

$$p_{o6}(x) = \frac{1}{9.7\sqrt{2\pi}} e^{-\frac{(x-(-85.5))^2}{(2*94.09)}} \quad (4)$$

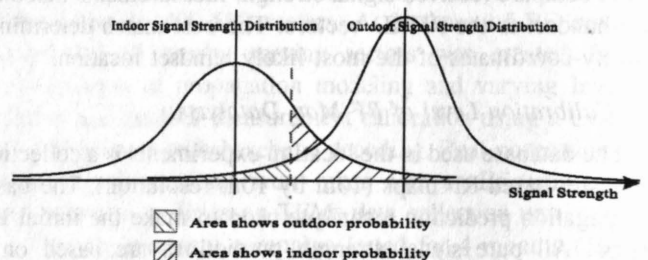


Fig. 4. Lognormal distributions for Indoor and outdoor RSSA.

D. Location Algorithm

The inputs to the location algorithm are a calibrated RFMD and a sequence of NMRs. After normalizing the RSS vector

from NMR and RSS vector at each raster point of RFMD, Euclidean distances between the vectors are calculated. Indoor/Outdoor decision is used to weight the Euclidean distance. The location estimation is the coordinates pair (x, y) with the lowest weighted Euclidean distance.

A handset NMR that contains N received signal strength measurements is like a point in N -dimensional space. The RSS of each control channels is one dimension in the N -dimensional space. This is also true for the collection of signal strengths in a RFMD. Each physical xy location modeled in the Georgia Tech campus RFMDs contains up to 26 received signal strength values, each corresponding to different IS-136 800 MHz control channels. From these values, a location algorithm selects a subset of N values that corresponds to the same control channels present in the NMR. Thus, we need a general formula for calculating the matching distance between two N -length vectors of received signal strength.

If an NMR reports signal strengths from N control channels, then we may represent this measurement as a vector of length N :

$$[Nrssi_{i,1} \ Nrssi_{i,2} \ \dots \ Nrssi_{i,N}] \quad (5)$$

where $Nrssi_{i,j}$ is the i th reported signal strength of the j th control channel. Likewise, we may construct a similar vector for each discrete (x, y) location in the RFMD:

$$[Prss_{x,y,1} \ Prss_{x,y,2} \ \dots \ Prss_{x,y,N}] \quad (6)$$

where $Prss_{x,y,i}$ is the predicted signal strength of the i th control channel at the xy coordinate.

The steps of the location algorithm are listed below:

- 1) Linearly average a sequence of 10 NMRs

$$Nrss_j = \sum_{i=1}^{10} Nrssi_{i,j} \text{ for } j = 1 \dots N \quad (7)$$

- 2) Normalize the averaged-NMR vector by subtracting out the average dBm-power of all received channels to generate the relative received signal strength of the handset measurement Phr_j :

$$Phr_j = Nrss_j - \frac{1}{N} \sum_{i=1}^N Nrssi_i \quad (8)$$

- 3) For each raster point in the RFMD, the vector is subtracted out the average dBm-power of the same set of received channels to generate $[Pnr_{x,y,1} \ Pnr_{x,y,2} \ \dots \ Pnr_{x,y,N}]$:

$$Pnr_{x,y,i} = Pd_{x,y,i} - \frac{1}{N} \sum_{j=1}^N Pd_{x,y,j} \quad (9)$$

- 4) Calculate the Euclidean distance, $M(x, y)$, between these normalized NMR vector and database signal strengths

$$M(x, y) = \sqrt{\sum_{i=1}^N (Pnr_{x,y,i} - Phr_i)^2} \quad (10)$$

The xy -coordinate that corresponds to the minimum in M is the pre-estimate for the handset's location.

- 5) To further improve our location estimation, incorporate our pre-estimate above with indoor/outdoor discrimination information. Calculate the $RSSA_N$.

$$x = \frac{1}{N} \sum_{i=1}^N Phr_i \quad (11)$$

Calculate the indoor weight factor, which is the area marked with “/” in Figure 4 based on $RSSA$. The indoor weight factor is the probability that indoor $RSSA_N$ is greater than a value x in the indoor distribution.

Let μ_i denote the mean of $RSSA_N$ for an indoor handset and let σ_i denote the indoor standard deviation of $RSSA_N$. Then the probability that the handset is indoor is given by Equation 12.

$$\begin{aligned} P_{Ni}(x) &= \frac{1}{\sigma_i \sqrt{2\pi}} \int_x^{\infty} e^{-\frac{(x-\mu_i)^2}{(2\sigma_i^2)}} dx' \\ &= \frac{1}{2} \left(1 - \operatorname{erf}\left(\frac{x-\mu_i}{\sigma_i \sqrt{2}}\right) \right) \end{aligned} \quad (12)$$

Calculate the outdoor weight factor, which is the area marked with “\” in Figure4 based on $RSSA$. The outdoor weight factor is the probability that the outdoor $RSSA_N$ is less than a value x in the outdoor distribution. Let μ_o denote the mean of $RSSA_N$ for outdoor handsets and let σ_o denote the outdoor standard deviation of $RSSA_N$. Then the probability that the handset is Outdoor is given by Equation 13.

$$\begin{aligned} P_{No}(x) &= \frac{1}{\sigma_o \sqrt{2\pi}} \int_{-\infty}^x e^{-\frac{(x-\mu_o)^2}{(2\sigma_o^2)}} dx' \\ &= \frac{1}{2} \left(1 + \operatorname{erf}\left(\frac{x-\mu_o}{\sigma_o \sqrt{2}}\right) \right) \end{aligned} \quad (13)$$

- 6) Weighting the distances, $M(x, y)$, by dividing $M(x, y)$ by the indoor/outdoor weight factor as in Equ. 12 or Equ. 13 accordingly which is depended on whether the raster falls within the indoor footprint. If the raster point (x, y) is indoors:

$$M_H(x, y) = M(x, y) / P_{Ni} \left(\frac{1}{N} \sum_{i=1}^N Phr_i \right) \quad (14)$$

If (x, y) is an outdoor point:

$$M_H(x, y) = M(x, y) / P_{No} \left(\frac{1}{N} \sum_{i=1}^N Phr_i \right) \quad (15)$$

- 7) Finally, Choose the coordinates x, y with the lowest weighted matching distance to be the location estimation

$$x_m, y_m = \operatorname{Arg}(\operatorname{Min}(M_H(x_i, y_j))) \quad (16)$$

TABLE I
LOCATION PERFORMANCE OF RSS LOCATION METHOD.

	Indoor/Outdoor Discrimination Rate					
	M8	M8A	M6	M6A	O6	O6A
LVL1	90%	92%	86%	87%	90%	93%
LVL2	90%	92%	86%	87%	91%	93%
LVL3	90%	91%	87%	87%	89%	94%
Location Error Statistics— % error < 100 m						
LVL1	56%	61%	52%	62%	54%	68%
LVL2	56%	64%	53%	63%	54%	68%
LVL3	65%	78%	57%	70%	56%	74%
Location Error Statistics— % error < 300 m						
LVL1	96%	97%	93%	96%	93%	97%
LVL2	96%	98%	93%	96%	93%	97%
LVL3	96%	98%	93%	96%	94%	97%

Lvl1: RF database calibrated with outdoor measurement

Lvl2: Calibration with outdoor measurement and Indoor modeling

Lvl3: Calibration with exhaustive outdoor and indoor measurements

M: Mixed indoor/outdoor sample point (2/3 indoor points)

O: Trial includes only outdoor handsets

8/6: 8- or 6-sector information available

A: Linear averaging of 10 consecutive NMRs

IV. Results and Discussion:

A. Results

Table I shows results of various location algorithms operating with different types of RF map databases. The linear averaging of 10 consecutive NMRs is very effective in improving the location error statistics, raising the 100 m accuracy numbers between 5% and 18%. With averaging, the performance of the 8-sector cases is almost identical to the performance of the 6-sector cases. This suggests that the strongest 6 received signals contribute the bulk of accuracy to the overall system performance.

An experiments with maps calibrated from only outdoor data is compared with mixed sample point experiment. For 100m-location error statistics, the outdoor test case (O6) is only 6% better than the indoor/outdoor case (M6). This result shows very little degradation and suggests RSS location performance is consistent for indoor and outdoor cases.

B. Conclusion

The results in this study demonstrate the feasibility of RSS location techniques for satisfying FCC's requirement. The techniques remain accurate even when the majority of test data is from *indoor* handsets. Since most of today's cell phone calls are placed indoors, inclusion of the indoor data in the evaluation are absolute necessary. Although indoor radio wave propagation losses degrade the performance slightly, the accuracy of the RSS location method can be further improved by using advanced indoor modeling, calibrating RF maps with indoor measurement, and more a complex location algorithm.

Another unique ability of an RSS location technique is the particularly powerful feature for locating and discriminating indoor users, which is unlikely for other triangulation techniques. This could prove to be a very important additional

piece of information when dispatching help to the scene of an emergency.

Although the results were developed on a live IS-136 cellular network at 850MHz, the performance is likely similar to other cellular telephony air interface (such as GSM, CDMA, WCDMA, etc.)

C. Future work

This paper mainly discusses the feasibility of received signal strength (RSS) methods for locating wireless handset calls in a complicated cellular *indoor* environment. There are more commercial applications (location-based services) that need more accurate location information. To further improve the location accuracy, filtering techniques can be used to give a much better location estimation than the direct averaging method used in this paper.

Another direction for future work is accurate propagation modeling and measurement, which enhance location performance regardless of air interface. Propagation modeling will be increasingly important as RSS location system are deployed. Accurate propagation models reduces the time and cost of extensive drive-tests and also catch modifications to coverage when the cellular network undergoes optimization or build out. Good propagation practice undergirds this entire technology.

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