An RSS Based Localization Algorithm in Cellular Networks

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***Abstract*— Localization in cellular networks has attracted significant interest in responding to localization accuracy driven by the emergency services (U.S. Enhanced 911) and the security applications. This study focuses on the Mobile Station (MS) localization employing the measurements of the detected Base Stations (BSs) Received Signal Strength (RSS). A localization algorithm based only on measurements of BS RSS and BS basic information is proposed. Experimental results are presented illustrating the performance of the proposed localization algorithm in a dense multipath environment with uneven geographical area.**

***Index Terms*— Localization, positioning, Received Signal Strength, cellular networks, Global Positioning System (GPS)**

I. Introduction

The significance of localization, navigation and tracking has been exemplified in many systems such as guidance systems in military applications, disaster rescue, cellular systems, satellite systems, commodity tracking and of course cellular networks. Localization in cellular networks refers to the attaining of the current position of a mobile phone or Mobile Station (MS), stationary or moving, which may occur either via multilateration of radio signals between Base Stations (BS) and the MS, or via GPS. Cellular network operators in the United States have to support the Federal Communication Commission Location Services requirements [1]. This requires that for any E911 emergency call the location accuracy of the calling MS shall be for any operator using a network centric position method, e.g. Time of Arrival (TOA): 100 meters for 67% of E911 calls and 300 m for 95% of calls and for any network using a mobile centric position method, e.g. GPS: 50 meters for 67% of E911 calls and 150 m for 95% of calls. Currently, similar requirements are being developed in Europe. The following presents some localization solutions pertaining to cellular networks. Localization can be divided into two types of techniques: Unmodified Handset Techniques and Modified Handset Techniques. In the Unmodified Handset Techniques solutions can encompass the use of RSS, Time of Arrival (TOA), Angle of Arrival (AOA), Time Difference of Arrival (TDOA), Cell Identification (Cell-ID), or hybrid techniques using a combination of the said solutions. The Modified Handset Techniques include the use of GPS, mobile assisted TOA, and mobile assisted TDOA. TOA and TDOA can provide acceptable accuracy without necessitating excessive hardware or software changes to the existing cellular infrastructure. TOA performs well when the MS is located close to the serving BS. TDOA performs better when the MS is located at a significant distance from the serving BS. However, performance of TDOA significantly deteriorates in presence of obstacles. The literature includes studies based on TOA [2], TDOA [3], AOA [4], RSS [5] and [6], Cell-ID [7] and [8]. The proposed localization algorithm presented in this paper is based on the measurements RSS from neighboring base stations. That is, based on RSS measurements provided at any time instant, the MS location can be estimated. The inputs to the system are BS numbers along with their respective accurate positions and RSS measurement, and typical parameters pertaining to the log-distance path loss model. The proposed algorithm first estimates the location of the MS based on averaging the positions of the detected BS. Based on the latter, the estimated MS location is employed in order to estimate the azimuth angle between the MS and all detected BS. The log-distance model is employed in order to extract the BS-MS distance from the angle-loss compensated RSS measurements. The proposed algorithm constructs different MS location estimates based on all possible detected BS pair combination using the triangulation concept. Finally, the final MS location is estimated by taking the average, excluding outliers, of all obtained estimates. This implementation is backed by an experimental study. The remaining part of the paper is organized as follows: in Section II, the proposed localization algorithm is presented. The experimental results illustrating the performance of the proposed system are presented in Section III. Conclusions and future work are described in Section IV.

II. Proposed Localization Algorithm

This section first describes the localization problem considered in this manuscript. After that a range model and its respective error model associated with RSSI measurements are summarized. Finally, a pseudo-code describing the main steps involved in the proposed localization algorithm is presented.

Problem statement: Given the serving and non-serving Base Station (BS) ID, position, and Received Signal Strength (RSS) in the neighborhood of the Mobile Station (MS), estimate the position of the MS. The power level of the signal or RSS at the MS propagated from a nearby BS is largely random due to variation in the transmission path between the BS and MS. The path can vary from line-of-sight to one that is obstructed by foliage, hills, and buildings. The RSS also depends on distance, d, between BS and MS, BS transmitted power and antenna gain, MS antenna gain, and the BS-MS angle-dependent loss due to the fact that both antennas are directional. For the application under consideration it is assumed that the RSS has two “deterministic” independent variables: d, and the azimuth angle, ϕ, between the BS and th

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MS antennas, neglecting elevation angle, θ. All the other variables will be lumped together and modeled in a statistical fashion using log-normal shadowing.

In terms of decibels the deterministic model of the RSS at MS, $P_{rec}(d, \phi)$, can be expressed as

$$P_{rec}(d, \phi) = P_r(d) + L_D(\phi) \quad (1)$$

where $P_r(d)$ is the received power in the direction of the strongest emission, $L_D(\phi)$ is the angle-dependent loss.

Notation: The "^" above a variable denotes an "estimate" of the variable.

The proposed localization algorithm is based on the following steps:

Step 1. *Initial MS location estimation*: Given all the detected BS locations (*x, y* and *z*-coordinates), $(x_i^{BS}, y_i^{BS}, z_i^{BS}), 1 \le i \le N_{BS}$, neighboring the MS, then the initial estimate of the MS location is determined as follows

$$(\hat{x}_o^{MS}, \hat{y}_o^{MS}, \hat{z}_o^{MS}) = \frac{1}{N_{BS}} \sum_{i=1}^{N_{BS}} (x_i^{BS}, y_i^{BS}, z_i^{BS}) \quad (2)$$

Step 2. *Estimation of the azimuth angle*: Using the MS location estimate, $(\hat{x}_{init}^{MS}, \hat{y}_{init}^{MS}, \hat{z}_{init}^{MS})$, and the BS locations $(x_i^{BS}, y_i^{BS}, z_i^{BS}), 1 \le i \le N_{BS}$, determine the azimuth angle, $\hat{\phi}$, between the MS and each BS. Consequently, $L_D(\phi)$ is estimated.

Step 3. *Extraction of the angle-dependent loss from RSS*: Based on the estimate of $L_D(\phi)$ and each received measurement (1), the angle-compensated RSS is given by: $\hat{P}_r(d) = P_{rec}(d, \phi) - L_D(\hat{\phi})$.

Step 4. *Estimation of the range between MS and BS,* $\hat{d}$: Given the angle-compensated RSS, $\hat{P}_r(d)$, estimate d using the model under consideration.

Step 5. *-Different estimations of MS location*: First, estimate the MS location by making use of all possible BS pairs. That is, consider a 2D positioning problem with available range estimates from three ($N_{BS} = 3$) different BS, $(\hat{d}_1, \hat{d}_2, \hat{d}_3)$ with an initial MS location estimate, $(\hat{x}_{init}^{MS}, \hat{y}_{init}^{MS}, \hat{z}_{init}^{MS})$.

Then there could be $\binom{N_{BS}=3}{2} = \frac{N_{BS}(N_{BS}-1)}{2} = 3$ different combinations from which MS location can be estimated using the concept of triangulation. In particular,

$(\hat{d}_1, \hat{d}_2) \rightarrow (\hat{x}_1, \hat{y}_1)$, $(\hat{d}_1, \hat{d}_3) \rightarrow (\hat{x}_2, \hat{y}_2)$, and

$(\hat{d}_2, \hat{d}_3) \rightarrow (\hat{x}_3, \hat{y}_3)$. Consequently, the number of different MS location estimates could increase quadratically as N_{BS} increases.

Step 6. *Estimation of MS location using various estimations*: The MS location estimate is based on averaging all values (excluding the outliers),

$$\underset{i}{\text{Average}}(\hat{x}_i, \hat{y}_i).$$

The model of $L_D(\phi)$ can be modeled based on specific antenna radiation pattern.

In what follows, a mathematical model for extracting d from RSS is presented.

Range Model

The measured signal level model adopted in this manuscript is entirely based on the average received signal decreasing logarithmically with distance and log-normal shadowing. That is, at a specific distance separation between BS and MS, d, the measured signal levels (or RSS) in dBm units, $P_r(d)[\text{dBm}]$, have a Gaussian or normal distribution about the path loss distance-dependent mean. Consequently, the signal level model is given by [10]

$$P_r(d)[\text{dBm}] = P_t[\text{dBm}] - PL(d), \text{ and}$$

$$PL(d) = E[PL(d_o)] + 10q\log\left(\frac{d}{d_o}\right) + X_\sigma$$

where $E[.]$ is the expectation operator, P_t is the BS transmitted power, $PL(.)$ is the average large-scale path loss, d_o is the close-in reference distance, q is the path loss exponent, and X_σ is a zero-mean Gaussian distributed random variable in dB with standard deviation σ also in dB.

Remark 1. The variation in altitude among different neighboring BS and MS are assumed to be insignificant. Without loss of generality, the 3D localization becomes a 2D localization problem. In addition, the *z*-coordinate of the MS can be estimated using the method presented in Equation (2).

Notations: Let (upper case) P denote the power in dBm and let (lower case) p denote the corresponding power in mW and $l_D(\phi) = 10^{L_D(\phi)/10}$.

Another representation of the signal level model is

$$P_r(d) = P_r(d_o) - 10q\log\left(\frac{d}{d_o}\right) + X_\sigma \text{ where } P_r(d_o) = P_t - E[PL(d_o)]$$

Taking into consideration the angle-dependent loss $P_{rec}(d, \phi) = P_r(d) + L_D(\phi)$ can be thought of as the RSS nominal value. Therefore, the value of the nominal distance, d, can be extracted from $P_{rec}(d, \phi)$ as follows [Saab, 2011]

$$d = d_o 10^{\frac{P_r(d_o) + X_\sigma + L_D(\phi) - P_{rec}(d,\phi)}{10q}} = d_o[p_r(d_o)]^{1/q}\varepsilon[p_{rec}(d,\phi)]^{-1/q}\lambda \text{ where}$$

$\varepsilon \equiv 10^{\frac{X_\sigma}{10q}}$ and $\lambda \equiv [l_D(\phi)]^{-1/q}$. One reasonable model for the measurement of the received power, in the absence of knowledge of X_σ, ϕ, and $L_D(\phi)$, is given by

$$P_{rec}(d,\phi) = P_r(d_o) - 10q\log\left(\frac{\hat{d} = d - \delta d}{d_o}\right)$$

where $\hat{d}$ corresponds to the distance estimate of d, and δd is the corresponding distance error. Consequently,

$$\hat{d} = d_o 10^{\frac{P_r(d_o) - P_{rec}(d,\phi)}{10q}} = d_o[p_r(d_o)]^{1/q}[p_{rec}(d,\phi)]^{-1/q} \quad (3)$$

The corresponding error model is presented in [9].

III. Experimental Results

Experimental Setup: Trimble 5700 GPS system was employed to locate BS, and the MS reading sites. The setup consisted of a base GPS station and a radio transmitter setup on top of the engineering building, at the Lebanese American University, on a point with accurately known GPS coordinates (seismic data collection point). The second part of the GPS system, which consisted of a second portable GPS station with a radio receiver synchronized with fixed GPS station in order to receive accurate differential GPS readings. After each field trip, the Trimble Geomatics Office software was used to collect, convert from World Geodetic System 84 to local plane (x-y coordinates) and also to visualize the GPS plots. For the MS part the NOKIA 6600 phones (GSM) were used running a special firmware along with the Agilent E6474A Wireless Network Optimization Platform kit records the power and ID of each Tx BS cell antenna. The experiment was conducted in the city of Byblos. There are 13 different MS locations that are under study. Around the different location of the MS, 12 different BS were detected in total. However, since the BS use directional sectored antenna, groups of the detected BS shared 6 different locations as shown in the Figure 1. The vertical elevation between different BS ranges from 75-265 m, whereas for MS locations, it ranges from 37-105 m.

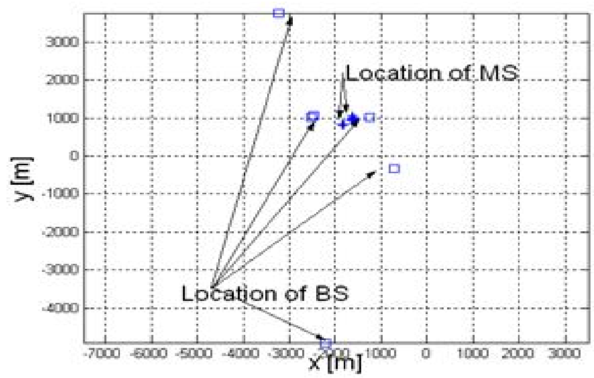

Figure 1. Location of BS and MS under study

Initial MS location estimation: Figure 2 shows the initial estimates of MS locations, $(\hat{x}_{init}^{MS}, \hat{y}_{init}^{MS}, \hat{z}_{init}^{MS})$, which are obtained using Equation (2). It is worth noting that the average (over the 13 different MS locations) of the absolute error in the z-coordinate, $\underset{1\le i\le 13}{\text{Avg}}\left|z-\hat{z}_{init}^{MS}\right| = 59.57m$.

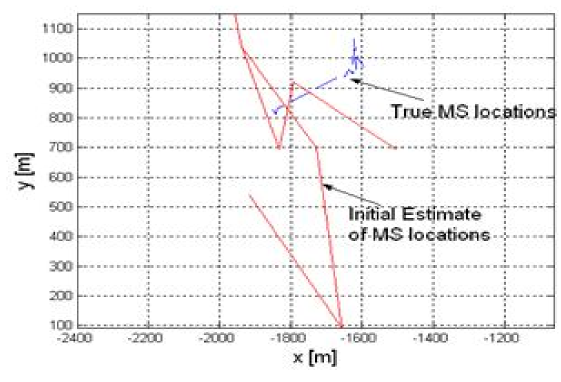

Figure 2. MS: True locations (dashed blue) and Initial Estimates (Red solid)

Relevant Modeling Parameters: Several side experiments were carried out in the region, considering different BS, to estimate path loss, q, and the corresponding standard deviation about the mean value, σ. The minimum mean square error was implemented. Although different values of q and σ, were obtained for different BS and different zones, the values used during this experiment were q = 2.7 and corresponding σ H” 8 associated with the close-in reference distance d_o = 100 m and P_o = “47dBm. Figure 3 illustrated the measured RSS, $P_{rec}(d,\phi)$, the angle-compensated RSS, $\hat{P}_r(d) = P_{rec}(d,\phi) - L_D(\hat{\phi})$, and the log-distance model versus distance. By examining Figure 3, it can be noted the level of non-deterministic part of the RSS.

The radiation pattern or the angle-dependent loss of the reader-tag, is obtained by a polynomial fit in least-squares sense applied on data obtained experimentally, $L_D(\phi) = -1.11\times10^{-3}\phi^2$ dB, where the latter model assumes ϕ to be in degrees. Consequently, the beamwidth H” 104°,

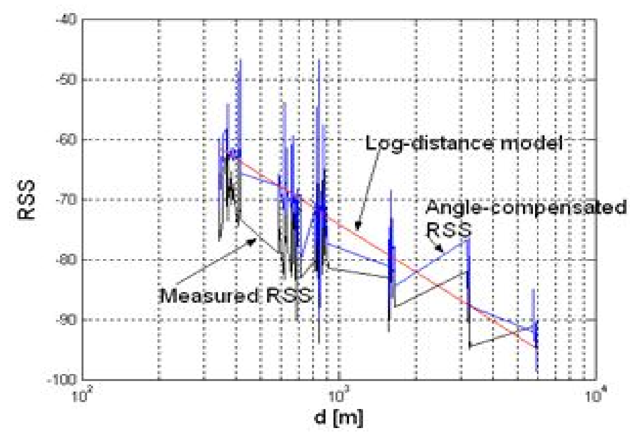

Figure 3. RSS [dBm]: $P_{rec}(d, \phi)$ (black), $P_r(d)$ (blue), and corresponding log-distance model (red).

Performance: The estimation of the distance between BS and MS as well as the estimates of the 13 different MS location coordinate are assessed using average (avg) and standard deviation (std) of absolute errors.

Assessment 1: The estimates of distances between BS and MS are first examined. It is first shown that the significance improvement when the losses, $L_D(\phi)$, due direction of the sectored BS are compensated for. The overall errors listed in Table 1 (with $L_D(\phi)$ being neglected) are significantly larger (about 43%) than the error listed in Table 2 (with $L_D(\phi)$ being compensated for). Tables 1 and 2 illustrate both the performance of distance estimation and the performance of each BS. Only 8 BS were significantly detected, that is, the RSS is above “80dBm. N_{MS} is the number of MS locations detecting a specific BS. For example, BS with ID 6 is detected from 6 out of the 13 MS locations, which happens to have overall largest distance estimation errors.

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TABLE 1. MS-BS DISTANCE ERRORS WITHOUT ANGLE COMPENSATION

BS-ID	N_{MS}	$\underset{1\le i\le N_{MS}}{\text{Avg}} \left\| d_i - \hat{d}_i \right\|$	$\underset{1\le i\le N_{MS}}{\text{std}} \left\| d_i - \hat{d}_i \right\|$
1	13	435.05	275.57
2	13	257.81	153.61
3	13	369.46	237.30
4	13	314.28	271.70
5	13	491.28	285.73
6	12	214.43	251.27
7	6	98.86	182.75
8	2	41.22	103.03

TABLE 2. MS-BS DISTANCE ERRORS WITH ANGLE COMPENSATION

BS-ID	N_{MS}	$\underset{1\le i\le N_{MS}}{\text{Avg}} \left\| d_i - \hat{d}_i \right\|$	$\underset{1\le i\le N_{MS}}{\text{std}} \left\| d_i - \hat{d}_i \right\|$
1	13	197.35	62.75
2	13	165.04	87
3	13	164.99	106.53
4	13	181.68	140.6
5	13	244.71	224.17
6	12	303.37	323.97
7	6	220.4	335.72
8	2	80.33	211.49

Assessment 2: Performance of the MS *x-y* coordinate estimates. Figure 4 shows the estimates of 13 different MS location *x-y* coordinates versus the nominal values. Figure 5 shows the resulting distance errors determined using the estimates of 13 different MS location *x-y* coordinates. Table 3 shows the significant improvement of the overall proposed algorithm versus the proposed initial MS estimates using Equation (2).

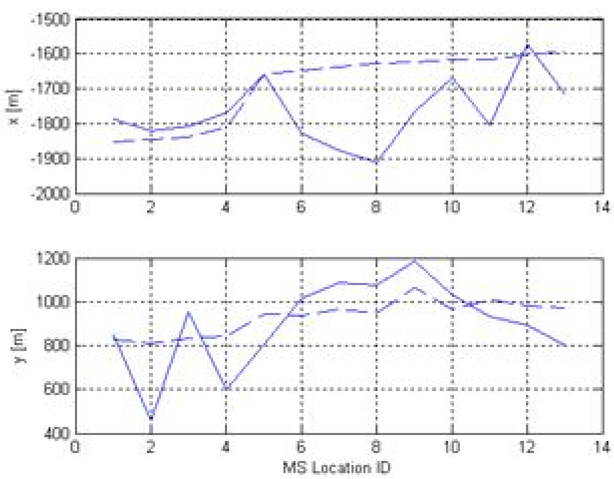

Figure 4. Estimates of MS *x-y* coordinates (solid) and their corresponding nominal values (dashed) versus various MS location IDs

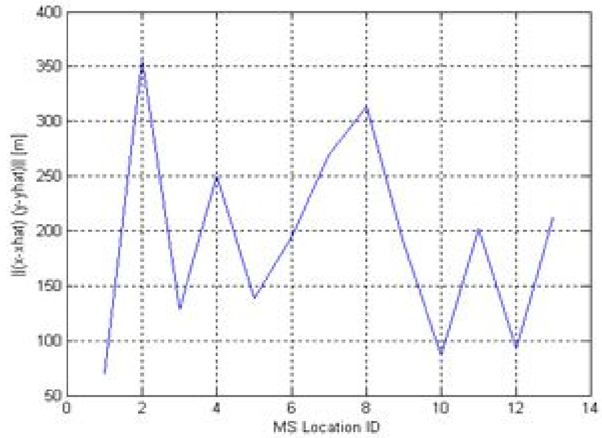

Figure 5. Euclidean norm of MS *x-y* coordinates, $\left\| \begin{matrix} x_i - \hat{x}_i \\ y_i - \hat{y}_i \end{matrix} \right\|_2$ versus various MS location IDs

TABLE 3. ERROR RESULTING FROM *X-Y* MS COORDINATES ESTIMATION

	$\underset{1\le i\le 13}{\text{Avg}} \left\| \begin{matrix} x_i - \hat{x}_i \\ y_i - \hat{y}_i \end{matrix} \right\|_2$	$\underset{1\le i\le 13}{\text{std}} \left\| \begin{matrix} x_i - \hat{x}_i \\ y_i - \hat{y}_i \end{matrix} \right\|_2$
Initial Estimate using Equation (2), $(\hat{x}^{MS}_{init}, \hat{y}^{MS}_{init})$	330.27	144.45
Estimates using RSS	192.51	88.76

CONCLUSIONS

This paper presented a localization algorithm based on BS RSS measurements and positions. The algorithm first estimated the MS location based on the detected BS positions, and then compensated angle-dependent loss factor from the BS RSS measurements. The BS-MS distances were extracted from the compensated RSS measurements and MS location estimate was found based on triangulation concept by exploiting all possible combinations detected BS pairs. An experiment was conducted and presented illustrating the performance of the proposed approach where most of the distances between any two BSs ranges from 1.5km to more than 9km. The average and standard deviation of the absolute positioning errors obtained is about 192.5m and 88.8m, respectively. We conclude that a localization algorithm based solely on BS RSS measurements can provide acceptable performance in a dense multipath environment with uneven geographical area. Future work: Since the estimation error of the MS-BS range increases proportionally to the increase in distance [9], then instead of taking the average (as indicated in Step 6), a weighted stochastic mean (e.g., a Kalman filter) may be incorporated in order to further improve localization accuracy. As future work, this issue will be investigated.

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