Nonline-of-Sight Error Mitigation in Mobile Location

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***Abstract*—The location of mobile terminals has received considerable attention in the recent years. The performance of mobile location systems is limited by errors primarily caused by nonline-of-sight (NLOS) propagation conditions. We investigate the NLOS error identification and correction techniques for mobile user location in wireless cellular systems. Based on how much *a priori* knowledge of the NLOS error is available, two NLOS mitigation algorithms are proposed. Simulation results demonstrate that with the prior information database, the location estimate can be obtained with good accuracy even in severe NLOS propagation conditions.**

***Index Terms*—Angle of arrival (AOA), mobile location, nonline-of-sight (NLOS) propagation, time difference of arrival (TDOA), wideband code-division multiple-access (CDMA) cellular systems.**

I. Introduction

MOBILE location has received considerable attention in the recent years. Generally, two different location schemes have been extensively investigated [1]–[3]: one is a time-based scheme, to measure the time of arrival (TOA) or time difference of arrival (TDOA) of incoming signals; the other is to measure the angle of arrival (AOA), which involves the use of an antenna array. Because TOA/TDOA and AOA approaches have their own advantages and limitations, a hybrid TDOA/AOA mobile location scheme is proposed in [4] and [5] for the future wideband code-division multiple access (CDMA) cellular systems. To achieve high location accuracy and minimize the increased cost on mobile station (MS) receivers, the location scheme combines the TDOA measurements from the forward link pilot signals with the AOA measurement at the home base station (BS) from the reverse link pilot signal.

The major error sources in the mobile location include Gaussian measurement noise and nonline-of-sight (NLOS) propagation error, the latter being the dominant factor [2]. A field test shows that the average NLOS range error can be as large as 0.589 km in an IS-95 CDMA system [6], which is much greater than the average Gaussian measurement noise. To protect location estimates from NLOS error corruption, NLOS error mitigation techniques have been investigated extensively in the literature [6]–[15]. Most of these techniques assume that NLOS corrupted measurements only consist of a small portion of the total measurements. Since NLOS corrupted measurements are inconsistent with line-of-sight (LOS) expectations, they can be treated as outliers. Similar to the global positioning system (GPS) failure detection algorithm in [16], measurement errors are first assumed to be Gaussian noise only, then the least square residuals are examined to determine if NLOS errors are present [8], [9], [12]. Unfortunately, this approach fails to work when multiple NLOS BSs are present, as the outliers tend to bias the final estimate precision to reduce the residuals. This behavior motivates the use of deletion diagnostics in which the effects of eliminating various BSs from the total set are computed and ranked, as in [9] and [12]. Other approaches include using the well-established robust estimation theory, such as the Huber Window [17], to form an estimator which is insensitive to small numbers of outliers.

All the above-mentioned algorithms in the literature only work well with a large size of samples and a small number of outliers. However, in a practical cellular system, two problems arise: 1) the number of available BSs is always limited and 2) multiple NLOS BSs are likely to occur. It has been shown that even by increasing the correlation time or enforcing an idle period to reduce interference, typically only 3–6 BSs can be heard by the MS at any time [18]. Among those BSs, one cannot assume that the majority are LOS BSs. This is because in macrocells, the propagation between an MS and its home BS is usually modeled as NLOS when the MS is far away from the BS. Home BS can only be viewed as LOS if we focus our attention on large NLOS bias and neglect small NLOS errors caused by local scatterers around the MS. All other neighboring BSs can be NLOS since they are farther away from the MS. In microcells, although the MS is typically modeled as being LOS with its home BS, one cannot expect the MS to be LOS with other surrounding BSs. Thus, we can only reasonably assume that the home BS is LOS BS and that all other BSs can be NLOS BS in the worst case. Several approaches are proposed in [2], [13], and [14] to reduce estimation errors for TOA when the majority of BSs are NLOS. Based on the fact that NLOS error always appears as a positive bias in TOA measurements, a constrained optimization is used to reduce the NLOS bias [2], [14].

Generally, the distributions of NLOS errors are location dependent. When the MS is stationary or slowly moving, the NLOS error can be assumed to be static. That gives rise to nonparametric approaches based on empirical data from various locations. For example, pattern recognition algorithms [19]–[21] have been proposed to improve the handoff performance. Based on the statistical pattern of the received signal strength, the system can determine if a user has arrived at or near a certain location and if a handoff is necessary. Due to the signal strength attenuation caused by multipath effect and shadowing, this can only be used for rough estimation of the MS

Manuscript received February 21, 2003; revised August 4, 2003 and December 21, 2003; accepted February 23, 2004. The editor coordinating the review of this paper and approving it for publication is H. Boelcskei. This work was supported in part by the Canadian Institute for Telecommunications Research (CITR) and by the National Science and Engineering Research Council (NSERC) of Canada.

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Digital Object Identifier 10.1109/TWC.2004.843040

location. To obtain a more accurate location estimate and to ensure one-to-one correspondence of the pattern and the location, other characteristics of the signal have to be exploited. In [22], a database of delay measurements at fixed locations is used. It requires survey samples of field measurements taken at known locations to generate approximate conditional density functions of user location given a delay measurement. A mapping method utilizing location database and a ray launch simulation tool is proposed in [11] to improve GPS positioning accuracy for the NLOS situation. These approaches give significantly better location accuracy at the cost of setting up and maintaining an empirical database. The data can come from field measurements conducted during the cellular system planning and/or computer-aided prediction based on digital terrain and land cover information [23], [24]. A field trial conducted in New York City [25] suggests that it takes 500 human hours of work to build up an accurate mapping database covering 50 km^2 of metropolitan area, and the estimated cost is $1000 per cell (of radius 1 km). Therefore, it is not impractical to set up the empirical database which includes the NLOS information at all possible MS locations.

In this paper, we continue to investigate the NLOS error mitigation problem in TDOA and TDOA/AOA location schemes. Our results can be extended to a TOA scheme as well. Depending on how much *a priori* information is available, two approaches are proposed: an NLOS state estimation (NSE) algorithm can be used if some prior information on NLOS errors is available from the empirical database; in the case where we do not have any knowledge about NLOS, an improved residual algorithm can be applied to detect a small number of NLOS BSs. Simulation results demonstrate that location accuracy improvement is possible even in severe NLOS propagation conditions.

The paper is organized as follows. The system model is given in Section II. Section III describes the proposed NLOS mitigation algorithms. The performance of the proposed NLOS mitigation techniques is studied via simulation and presented in Section IV. Final conclusions are drawn in Section V.

II. System Model

The system model under consideration is a wideband CDMA cellular system. We focus on the case of macrocells and two-dimensional (2-D) mobile location. The BS serving the target MS (to be located), denoted by BS_1, is called the home BS for the MS. All neighboring BSs can get involved in an MS location process, provided the signal-to-interference-plus-noise ratio (SINR) of the signal from each BS is above a certain threshold at the MS. At all times, the MS keeps monitoring the forward pilot channel signal levels received from the neighboring BSs and reports to the network those that cross a given set of thresholds. The cross correlators at the MS receiver are capable of measuring the TDOA between the signal from the home BS and that from any other BS.

Adaptive antenna arrays have been proposed for radio transmission in third-generation cellular communication systems to facilitate the initial acquisition, time tracking, Rake-receiver coherent reference recovery, and power-control measurements for the MS. If an adaptive antenna array is available at the BS site, the home BS can dedicate a spot beam to a single MS under its jurisdiction by dynamically changing the direction of the antenna pattern as the MS moves to provide the arriving azimuth angle of the signal from the MS. This AOA measurement can be used together with TDOA measurements for improved location accuracy.

It is assumed that at any time the MS to be located can receive forward-link pilot signals from its home BS and at least one neighboring BS. Upon receiving the location service request, two types of measurements are carried out for location purposes [4], [5].

1) TDOA measurements at the MS receiver:
   The MS receiver can measure the time arrival difference between the pilot signals of a nonhome BS and the home BS by a pseudo-random (PN) code tracking loop which cross correlates the pilot signal from the nonhome BS with the pilot signal from the home BS. The pilot signal from each of the neighboring BSs can be used in the MS location, provided that the SINR of the received signal at the MS is above a certain threshold. The TDOA measurements can be obtained with an accuracy better than a half-chip duration if wireless propagation channel impairments are not severe [26]. However, for nonhome BSs, fading, and delay spread due to multipath propagation can introduce large errors to TDOA measurements.
2) AOA measurements at the home BS:
   With an adaptive antenna array, the home BS steers its antenna spot beam to track the dedicated reverse-link pilot signal from the MS for improved reception. This provides the arriving azimuth angle (with respect to a specified reference direction) of the signal from the MS. In a macrocell environment, the AOA measurements can be obtained with an accuracy of a few degrees [3].

The forward-link TDOA measurements are forwarded to the home BS via the wireless channel, where both the forward-link TDOA and reverse-link AOA measurements are combined together. Based on the NLOS situation, some measurements will be chosen to give a location estimate of the MS.

A BS is said to be LOS BS if there exists a direct path from the BS to the MS. Since we are mainly interested in NLOS errors that cause a large deviation to the MS location estimate, it is reasonable to neglect NLOS errors resulting from local scatterers near the MS, as those errors are relatively small. Therefore, in the rest of this paper, an NLOS BS means that there does not exist a direct path from that particular BS to the MS, and the signal has to travel an extra distance of several hundred meters to reach the MS via reflection.

It is possible that the home BS does not have LOS propagation with the MS, therefore adding bias to all the TDOA measurements and to the AOA measurement. In Section III-C, we present a residual algorithm which can detect the NLOS home BS situation. The NLOS bias can then be reduced by referencing the TDOA with an LOS nonhome BS and discarding the home BS's AOA measurement.

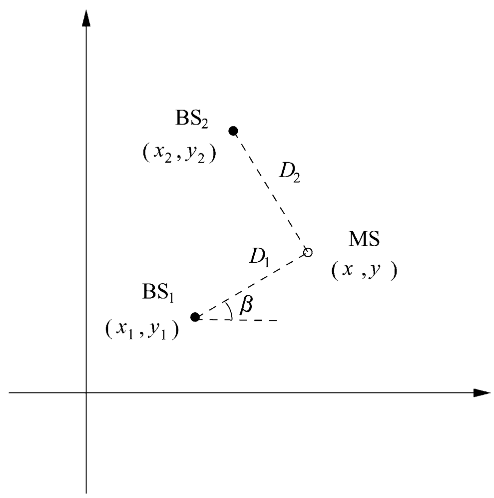


Fig. 1. Hybrid TDOA/AOA location.

The generalized location estimation problem in matrix form is given by

$$\boldsymbol{m} = \boldsymbol{f}(\boldsymbol{\theta}) + \boldsymbol{n} + \boldsymbol{e} \tag{1}$$

where $\boldsymbol{m} = [m_1, m_2, \ldots, m_N]^T$ denotes the measurement matrix, N is the number of equations, $\boldsymbol{\theta}$ is the true location of the MS, $\boldsymbol{f}(\boldsymbol{\theta})$ is a function of $\boldsymbol{\theta}$ and is usually nonlinear, $\boldsymbol{n}$ is the zero mean Gaussian noise vector, and $\boldsymbol{e}$ is the NLOS error vector. Let L denote the minimum number of BSs needed for location estimation. We have $L = 3$ for TDOA location and $L = 2$ for hybrid TDOA/AOA location. When there are $N(\geq L)$ BSs available for location, the redundant BSs will provide an $N - L$ degree of freedom in determining the NLOS BSs. As illustrated in Fig. 1, the hybrid TDOA/AOA location equations [5] that incorporate the measurement noise and NLOS error are given by

$$\begin{aligned} Ct_i &= D_i - D_1 + n_i + e_i \quad (i = 2, \ldots, N) \\ \beta &= \tan^{-1}\left(\frac{y - y_1}{x - x_1}\right) + n_\beta \end{aligned} \tag{2}$$

where C is the speed of light, t_i is the measured TDOA between the ith BS and BS_1, D_i is the distance from the MS to the ith BS, D_1 is the distance between the MS and BS_1, n_i, and e_i are the TDOA measurement noise and NLOS error, respectively, n_β is the AOA measurement noise, (x, y) and (x_1, y_1) are the coordinates of the MS and home BS, respectively. We assume that n_i and n_β are independent Gaussian random variables with zero mean and variances σ_i^2 and σ_β^2, respectively. If BS_i has an LOS path to the MS, then $e_i = 0$; otherwise, e_i is a positive random variable with mean μ_{nlos_i} and variance σ_{nlos_i}. We further assume that $\mu_{\mathrm{nlos}_i} \gg \sigma_i$, which is consistent with field test results [6]. Note that the number of BSs is N in TDOA location and $N - 1$ in TDOA/AOA location.

III. NLOS Error Mitigation Algorithms

Depending on how much *a priori* information we have about NLOS error prior probabilities and distributions, three cases can be distinguished.

1) The exact distribution of the random NLOS error for each BS at the MS location is known. This is an easy but unrealistic case. We use this, however, as a starting point for the design of NLOS error mitigation algorithm, which is then extended to more realistic situations, for example, by replacing unknown NLOS errors by estimated values or values measured *a priori*.
2) Limited prior information of the NLOS errors is available. For example, at the MS location the probability of each BS being NLOS and the mean of the NLOS error are known for the MS location. This type of information can come from a database of field measurements or a computer simulation utilizing ray tracing techniques and digital terrain plus land cover information.
3) No information of the NLOS error is available. This situation is obviously the most interesting case from a practical point of view, but also the most difficult one in the design of NLOS error mitigation algorithms.

A. Ideal Case: With Known NLOS Statistics

Let $P_{\mathrm{LOS}i}$ denote the prior probability of BS_i being LOS at the MS location, and $P_{\mathrm{NLOS}i} = 1 - P_{\mathrm{LOS}i}$. The location equation for BS_i becomes

$$\mathrm{LOS}: \; m_i = f(\boldsymbol{\theta}) + n_i \tag{3}$$

$$\mathrm{NLOS}: \; m_i = f(\boldsymbol{\theta}) + n_i' + e_i. \tag{4}$$

As mentioned earlier, usually the measurement noise n_i and n_i' are modeled as zero-mean Gaussian random variables with variance σ_i^2 and $\sigma_i'^2$, respectively. Theoretically, if we know the exact distribution of NLOS errors e_i, we can have the optimum maximum likelihood (ML) detection of the NLOS BSs. The ML estimator aims at maximizing the joint conditional probability density function (pdf) of the measurement matrix $\boldsymbol{m}$

$$f_{\boldsymbol{M}}(\boldsymbol{m} \,|\, \boldsymbol{\theta}) = f_{\boldsymbol{\varepsilon}}(\boldsymbol{m} - f(\boldsymbol{\theta}) \,|\, \boldsymbol{\theta}) \tag{5}$$

where $f_{\boldsymbol{\varepsilon}}(\,\cdot\,)$ is the joint pdf of measurement errors $\boldsymbol{\varepsilon} = \boldsymbol{n} + \boldsymbol{e}$. Under the assumption that NLOS errors and Gaussian measurement noise are independent random variables, we have

$$\begin{aligned} f_{\boldsymbol{\varepsilon}}(\boldsymbol{m} - f(\boldsymbol{\theta}) \,|\, \boldsymbol{\theta}) = \prod_{i=2}^{N} &(f_{\varepsilon_i}(m_i - f(\boldsymbol{\theta}) \,|\, \mathrm{NLOS}) P_{\mathrm{NLOS}i} \\ &+ f_{\varepsilon_i}(m_i - f(\boldsymbol{\theta}) \,|\, \mathrm{LOS})\,(1 - P_{\mathrm{NLOS}i})) \end{aligned} \tag{6}$$

where $f_{\varepsilon_i}(x \,|\, \mathrm{LOS})$ is the pdf of the Gaussian measurement noise, and $f_{\varepsilon_i}(x \,|\, \mathrm{NLOS})$ is the pdf of the NLOS error plus noise and is usually unknown. Numerical methods can be used to find the location which maximizes the conditional pdf given in (6). This ML estimator actually combines the NLOS BS identification and NLOS error correction into one single step and is able to achieve the optimum result when the empirical NLOS error distributions are accurate.

Given a set of TDOA measurements, a three–dimensional (3-D) plot of the conditional pdf in (6) over the home BS coverage area usually reveals multiple peaks (local maxima), as shown in Fig. 2, each corresponding to a possible NLOS/LOS BS scenario, and the magnitude of the peak corresponding to

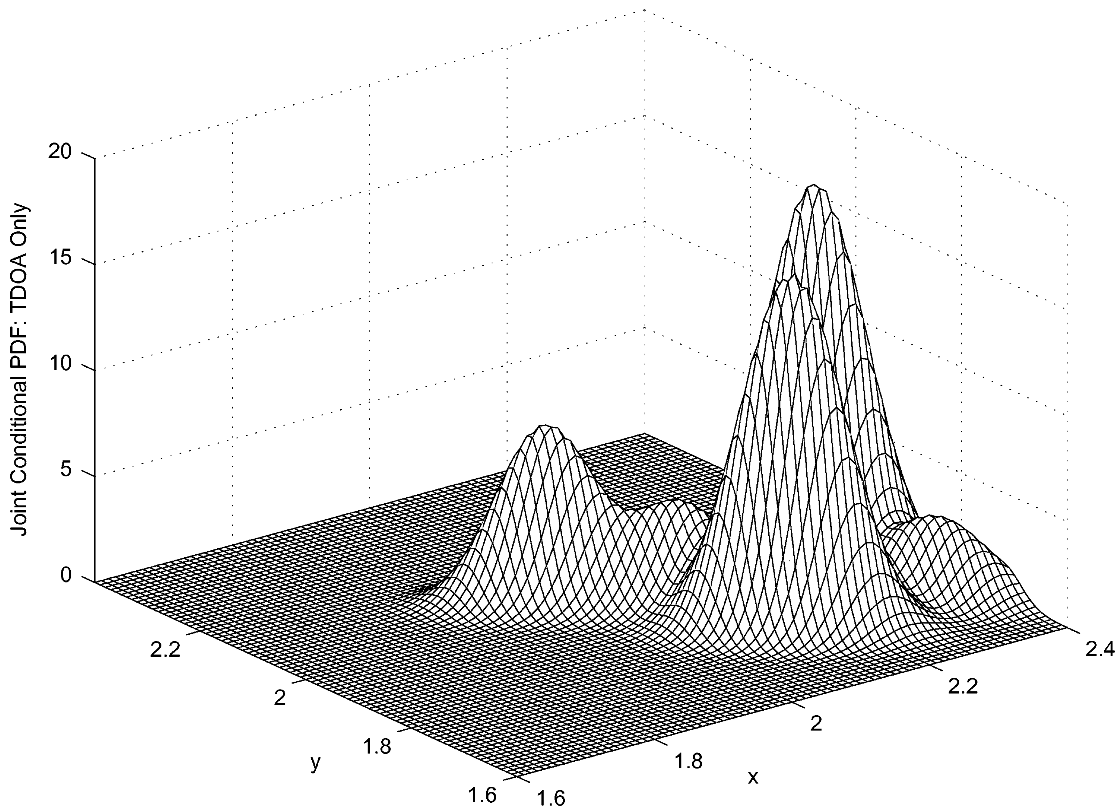


Fig. 2. Joint conditional pdf of the TDOA estimator (four BSs).

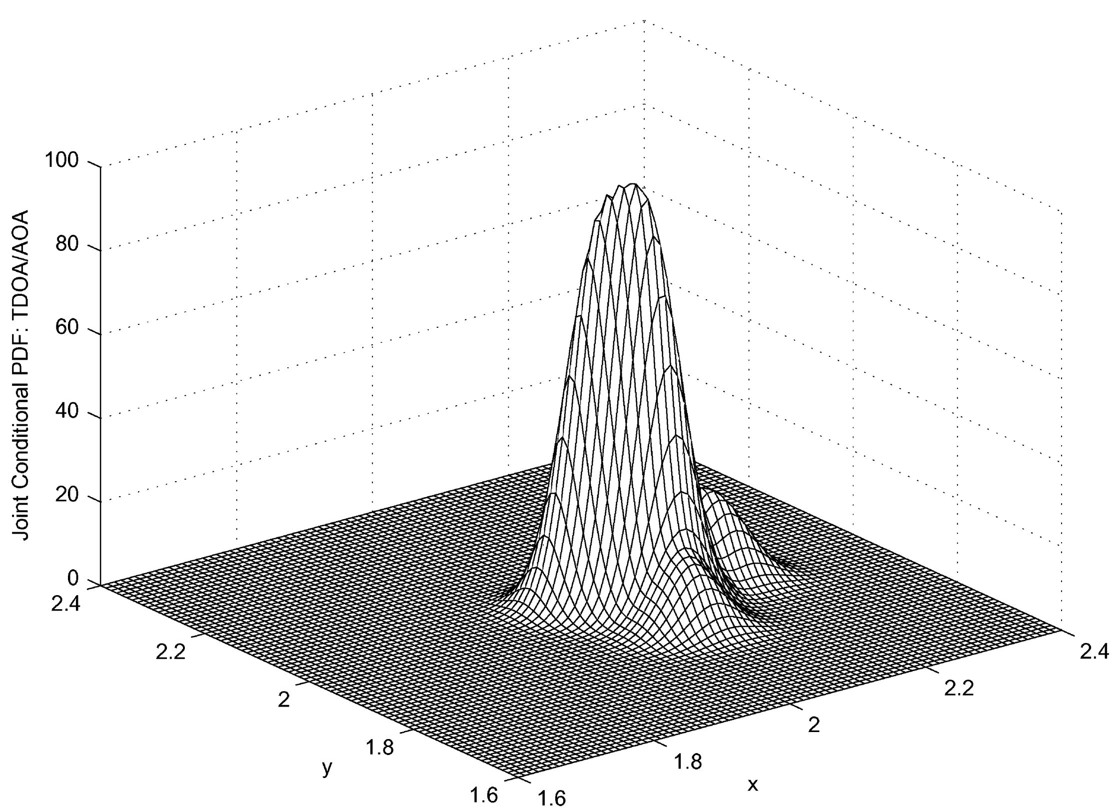


Fig. 3. Joint conditional pdf of the TDOA/AOA estimator (four BSs).

the relative likelihood of such scenario. The location corresponding to the highest peak (global maxima) is the output of the location estimator. Fig. 3 shows the same conditional pdf for TDOA/AOA location. The additional AOA information helps to suppress some peaks so there is less ambiguity as to where the true MS location is.

Because making a wrong NLOS/LOS BS scenario decision can introduce a significant root mean square (rms) location error (as large as several hundred meters), we propose a soft-decision location estimator to further reduce the location error. Instead of giving a hard location estimate, the soft-decision robust estimator outputs several possible MS location estimates and their relative likelihoods. As the MS continues to carry out new measurements, the time history data will help to reduce the ambiguity of the MS location, since the movement of the MS in a short period of time is limited to a small region.

To make a soft decision, we need to separate the NLOS BS(s) identification and correction into two steps. For each BS_i, a hypothesis test can be employed to determine its NLOS status. First, consider a simple case where only one NLOS BS is present. We use the maximum *a posteriori* probability (MAP) criterion to make a decision based on the actual measurement m_i in order to minimize the average false NLOS identification rate. The posterior probability $P(\mathrm{NLOS} \mid M_i = m_i)$ is given by

$$\frac{f_{\varepsilon_i}(m_i - f(\boldsymbol{\theta})|\mathrm{NLOS})P_{\mathrm{NLOS}i}}{f_{\varepsilon_i}(m_i - f(\boldsymbol{\theta})|\mathrm{NLOS})P_{\mathrm{NLOS}i} + f_{\varepsilon_i}(m_i - f(\boldsymbol{\theta})|\mathrm{LOS})P_{\mathrm{LOS}i}}$$

The decision rule is then

$$\frac{f_{\varepsilon_i}(m_i - f(\boldsymbol{\theta}) \mid \mathrm{NLOS})P_{\mathrm{NLOS}i}}{f_{\varepsilon_i}(m_i - f(\boldsymbol{\theta}) \mid \mathrm{LOS})\, P_{\mathrm{LOS}i}} \underset{\mathrm{NLOS}}{\overset{\mathrm{LOS}}{\lessgtr}} 1. \tag{7}$$

Therefore, making a decision about BS_i requires the knowledge of prior probability of $P_{\mathrm{NLOS}i}$ and the conditional probability $f_{\varepsilon_i}(m_i - f(\boldsymbol{\theta}) \mid \mathrm{NLOS})$, which in turn requires the knowledge of the true MS location. The intermediate MS location estimate using all BSs except BS_i can be used to approximate the true MS location.

Now let us consider the case of multiple NLOS BSs in TDOA and TDOA/AOA location. In the worst case, all of these N BSs are NLOS BSs. Let $\boldsymbol{S} = (s_1, s_2, \ldots, s_N)$ denote the system state, where $s_i = 1$ if BS_i is NLOS, and zero otherwise. There are altogether 2^N possible states and the task of NLOS BS detection is to correctly determine the right system state. Let $\boldsymbol{S}_0$ denote the special state that all BSs are LOS. To optimally determine the NLOS state, we propose the following NLOS state estimation (NSE) algorithm.

1) For each of the 2^N possible states $\boldsymbol{S}$, obtain a location estimate $\hat{\boldsymbol{\theta}}$ using the known NLOS information.
2) Using $\hat{\boldsymbol{\theta}}$ to approximate the true MS location and calculate the weighted *a posteriori* probability for each possible state

$$P_{\boldsymbol{S}} = w_{\boldsymbol{S}} \prod_{i=1}^{N} f_{\varepsilon_i}(m_i - f(\hat{\boldsymbol{\theta}}) \mid s_i) P(s_i) \tag{8}$$

where $w_{\boldsymbol{S}}$ is a weight assigned to state $\boldsymbol{S}$, $P(s_i = 1) = P_{\mathrm{NLOS}i}$, and $P(s_i = 0) = P_{\mathrm{LOS}i}$.

3) Calculate the ratio $P_{\boldsymbol{S}}/P_{\boldsymbol{S}_0}$ for each of the $2^N - 1$ NLOS states.
4) For a hard decision, the state which has the largest ratio is selected, and the corresponding ML estimate is the output location. For a soft decision, those states whose ratio is above a certain threshold λ are selected, and the magnitude of the ratio corresponds to the relative likelihood of that NLOS state.

If the prior probabilities $P(s_i)(i = 1, 2, \ldots, N)$ are unknown, the weight $w_{\boldsymbol{S}}$ in (8) can be used to control the false alarm rate and detection probability. For example, a heavier weight for LOS state $\boldsymbol{S}_0$ provides a cushion for false alarm, but also reduces the NLOS detection probability. The optimal values of the weights depend on the desired detection probability and false alarm rate, and of course how severe the NLOS situation is. Since minimum rms location error is the final goal, a cost/reward function can be formulated which includes the penalty of a false alarm and the reward of a correct detection in terms of rms errors. The optimal values of the weights are the values that minimize the cost function.

In summary, if we have an empirical database available from field measurements which provides the information of P_{NLOS_i} and the stochastic model of e_i, we can derive $f_{\varepsilon_i}(m_i - f(\boldsymbol{\theta}) \mid s_i)$ and then apply the NSE algorithm. The algorithm can work for both TDOA and TDOA/AOA location systems, under the assumptions that the NLOS errors, the TDOA, and AOA measurement errors are all independent.

B. With Limited a Priori Information

In reality, modeling the NLOS error is a difficult task, as the NLOS error is location dependent, influenced mainly by terrains and buildings. A much more realistic assumption is that for each BS we know μ_{NLOS_i} (the mean of the NLOS error) and $P_{\mathrm{NLOS}i}$ (the prior probability that BS_i is an NLOS BS) for different locations.

To approximate $f_{\varepsilon_i}(m_i - f(\boldsymbol{\theta}) \mid \mathrm{NLOS})$, we treat the NLOS error as a constant bias $\bar{e}_i = \mu_{\mathrm{NLOS}_i}$ superimposed on the zero mean Gaussian noise n_i'. Then

$$f_{\varepsilon_i}(m_i - f(\boldsymbol{\theta}) \mid \mathrm{NLOS}) = \frac{1}{\sqrt{2\pi}\sigma_i'} \exp\left[-\frac{(m_i - f(\boldsymbol{\theta}) - \bar{e}_i)^2}{2\sigma_i'^2}\right]. \tag{9}$$

The NSE algorithm can then be used again to provide a hard or soft decision. One difference is that in Step 1) before we make an estimate $\hat{\boldsymbol{\theta}}$ for each state, NLOS errors are compensated by subtracting the NLOS bias $\bar{e}_i$ from the measurements of BS_i if $s_i = 1$.

An even more interesting case is that we know nothing about the NLOS error except its bound of magnitude. For example, the NLOS error for BS_i, if present, is greater than 300 m. To obtain a suboptimal solution in this case, algorithms designed under the generalized likelihood ratio (GLR) [27] can be used. For each state, the ML estimator estimates not only the MS location $\hat{\boldsymbol{\theta}}$, but also the values of NLOS errors $\hat{e}_i$. Then, $f_{\varepsilon_i}(m_i - f(\boldsymbol{\theta}) \mid \mathrm{NLOS})$ can be approximated by using $\hat{e}_i$ to replace e_i in (9). However, that imposes a limit on the total number of NLOS BSs, as the equations will be underdetermined when more than $N - L$ NLOS BSs are present. For example, in TDOA location, four available BSs can only determine one NLOS BS when we apply the NLOS identification algorithm. With the additional AOA information, two NLOS BSs can be identified.

In the case when the empirical value of $P_{\mathrm{NLOS}i}$ is not available, a blind estimator can be used which arbitrarily sets the value of $P_{\mathrm{NLOS}i}$. When $P_{\mathrm{NLOS}i} = 0$, this blind ML estimator becomes the conventional LOS ML estimator. $P_{\mathrm{NLOS}i} = 1$ corresponds to a very aggressive estimator which treats every BS as NLOS BS. The value of $P_{\mathrm{NLOS}i}$ can be selected based on the SINR and/or desired robustness to the NLOS error.

C. Worst Case: No Knowledge of the NLOS Error

In the worst case, we do not have any knowledge about the NLOS error. If a limited number of BSs is available, and the majority are NLOS, little can be done to reduce NLOS errors. Therefore, to derive NLOS mitigation algorithms in the worst case, we have to assume that only a small subset of the total available BSs are NLOS BSs. It is worth mentioning that more NLOS BSs does not necessarily mean a larger bias in the final MS location estimate. NLOS BSs tend to bias the final estimate in such a way that the estimated location moves away from those BSs, so more NLOS BSs increase the chance of those NLOS errors cancelling each other. Taking the case of $N = 4$ for example, a large estimation error usually happens when one or two NLOS BSs are present.

We further assume that the home BS is LOS BS. Later, we will discuss the case of the home BS being NLOS. Based on the assumptions, we can make use of analytical redundancy relationships for NLOS error mitigation. The first step is to identify NLOS BSs among all the available BSs. Since nothing is known about NLOS errors, we have to treat NLOS corrupted measurements as outliers and rely solely on our knowledge of Gaussian measurement noise to detect NLOS BSs. Let K denote the number of NLOS BSs. Once the value of K is known, two scenarios can follow: 1) if there are sufficient BSs (i.e., $N - K \geq L$) to make a location estimate after the K NLOS BSs being identified and removed, we can obtain an improved MS location estimate using only the $N - K$ LOS BSs and 2) otherwise, we can only issue a warning that the output MS location estimate is not reliable due to NLOS errors or resort to some robust estimators (if they exist) that are insensitive to NLOS errors.

Two popular approaches are used in the outlier detection theory: one is to use the residual ranking and the other is based on the "3σ edit rule." The latter is based on the fact that for the Gaussian noise, the probability of observing a measurement further than three standard deviations from the mean is approximately 0.3%. The approach requires the knowledge of the Gaussian measurement noise variance, which is usually satisfied in practice.

Residual ranking can work very well when we have a large number of BSs and one of them is NLOS BS. A residual weighting algorithm was first proposed in [9] for the TOA location scheme. It divides all available BSs into subsets and weights the location estimate from each subset according to their residuals to obtain the final estimate. Similar approaches for AOA and TDOA have been proposed in [8] and [12], respectively. For a given measurement $\boldsymbol{m} = [m_1, m_2, \ldots, m_N]^T$ and a reference location $\hat{\boldsymbol{\theta}}$, the residual in [8], [9], and [12] can be generalized as $\sum_i (m_i - f(\hat{\boldsymbol{\theta}}))^2$. If $\hat{\boldsymbol{\theta}} \approx \boldsymbol{\theta}$, the residual reflects the magnitude of the NLOS error, since $\boldsymbol{e} \gg \boldsymbol{n}$. By trying different combinations of candidate BSs and ranking the residuals, the NLOS BSs can be identified with a certain probability.

The residual algorithms have several limitations. First, it does not make use of the variance of Gaussian noise $\boldsymbol{n}$. Signals from different BSs usually have different SINRs, thus different noise variance σ_i^2. The residual should be weighted according to σ_i^2 so that the BS with a larger noise component will have less contribution in the overall residual. Second, the NLOS error $\boldsymbol{e}$ is always positive. If $m_i - f(\hat{\boldsymbol{\theta}}) < 0$ for BS_i, it is less likely that BS_i is NLOS BS, as compared with $\mathrm{BS}_j (i \neq j)$ where $m_j - f(\hat{\boldsymbol{\theta}}) > 0$. However, the square operation in the residual removes the sign of $m_i - f(\hat{\boldsymbol{\theta}})$. Finally, as the residual is in a summation form, it can only indicate how likely a group of $N (\geq 3)$ candidate BSs contains NLOS BSs, but not which one(s). We have to rely on the residual ranking of all possible combinations to determine the NLOS BSs. Therefore, the previously proposed residual algorithms do not perform well when the number of candidate BSs is small.

In the following, we propose a new residual algorithm, which combines the two approaches in the outlier detection. Since we have no knowledge of the NLOS error, we have to rely on the conditional probability

$$f_{\varepsilon_i}(m_i - f(\boldsymbol{\theta}) \,|\, \mathrm{LOS}) = \frac{1}{\sqrt{2\pi}\sigma_i} \exp\left[-\frac{(m_i - f(\boldsymbol{\theta}))^2}{2\sigma_i^2}\right]. \tag{10}$$

For a measured value m_i and a reference location $\hat{\boldsymbol{\theta}}$, the corresponding conditional cumulative density function (cdf) provides a measure of how likely the random Gaussian noise will make the TDOA measurement smaller than m_i and is given by

$$P(M_i \leq m_i \,|\, \mathrm{LOS}) = \frac{1}{2} + \frac{1}{2}\mathrm{erf}\left(\frac{m_i - f(\hat{\boldsymbol{\theta}})}{\sqrt{2}\sigma_i}\right). \tag{11}$$

We define the new residual to be this cdf. Hence, the higher the new residual, the more likely the BS is biased by NLOS error(s). This new residual is asymmetric, giving more weight on the positive (i.e., $m_i - f(\hat{\boldsymbol{\theta}}) > 0$) side; it also takes the Gaussian noise variance into account. Therefore, by directly ranking the residuals for each candidate BS, or comparing them with a given threshold, we can overcome the limitations of the previous residual algorithms.

On the contrary, a very small residual of BS_i indicates a high probability of BS_i being LOS BS, provided that the reference location is close to the true value. This can be used in the special case when the home BS (i.e., BS_1) is NLOS BS. We can then use BS_i as the new home BS, making all the TDOA measurements using BS_i as the reference BS instead. In this way, the NLOS errors remain positive in TDOA.

The new residual algorithm works for both TDOA and TDOA/AOA in the same manner. Similar to every residual algorithm, the approximation of the true MS location, $\hat{\boldsymbol{\theta}}$, plays an important role. Ideally, we should use the true location of the MS, but it is not achievable and can only be used as a performance benchmark. We can use measurement data from all the N BSs to determine an overall location estimate and use it as the approximated MS location. Under the assumption that the AOA measurement at the home BS is independent of TDOA

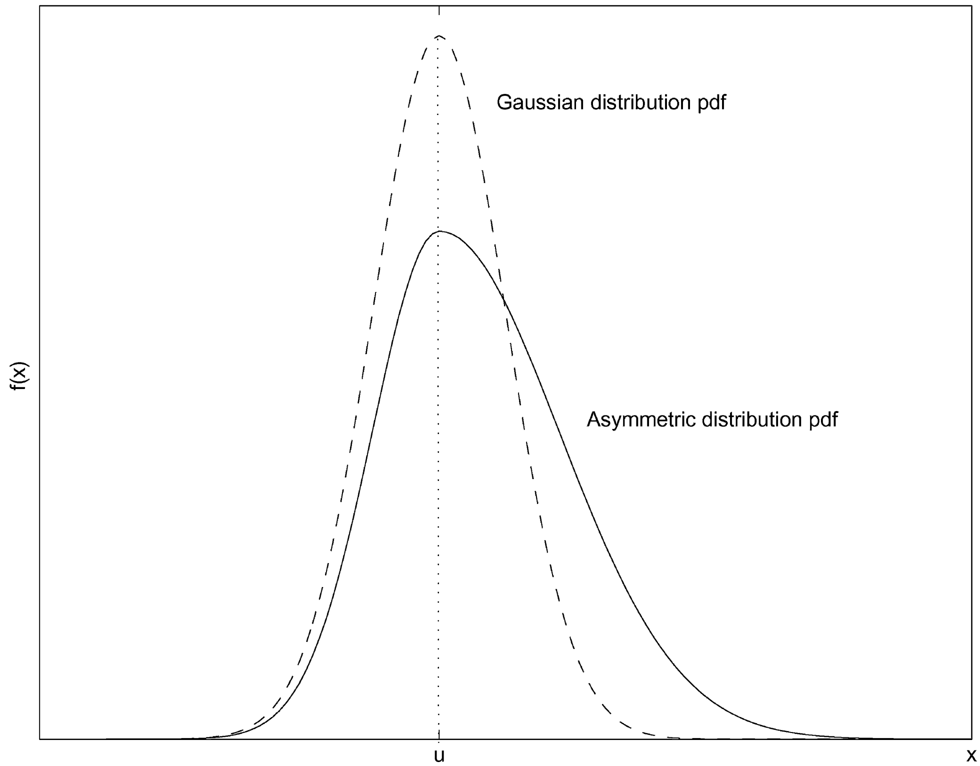


Fig. 4. Asymmetric pdf for robust estimation.

measurements [12], the AOA measurement can help to improve the accuracy of the reference location $\hat{\boldsymbol{\theta}}$ and therefore improve the performance of the proposed identification algorithm. In Section IV, we shall see that the additional AOA measurement in the hybrid TDOA/AOA location helps to obtain a more accurate MS location approximation and thus better NLOS identification accuracy.

The newly proposed algorithm of identifying NLOS BSs using TDOA or TDOA/AOA measurements has the following steps.

1) Use the TDOA measurements from all the $N-1$ nonhome BSs and, if the hybrid scheme, the AOA from the home BS as well, to obtain an initial MS location estimate $\hat{\boldsymbol{\theta}}$.
2) Calculate the new residual in (11) for each of the $N-1$ nonhome BS.
3) If any of the residuals is above a threshold λ, issue a warning that NLOS BSs are present and rank the $N-1$ residuals. If we know the number of NLOS BSs, K, pick up the K BSs with the largest residuals; otherwise, compare the residual with the threshold λ, and those BSs with residuals larger than the threshold will be deemed as NLOS BSs.

When we have a fairly large number of BSs (for example, $N > 6$), a deletion diagnostics scheme can be used to improve the accuracy of $\hat{\boldsymbol{\theta}}$. For each subset of the BSs (size 3 and up), calculate the reference location using measurements from all BSs in the subset and obtain the residual for each BS in the subset. Find the largest subset which satisfies the threshold for each of the residuals. If that subset can be found, use that subset's output as a reference location $\hat{\boldsymbol{\theta}}$ and calculate the $N-1$ residuals; if that subset does not exist, the location estimate using all measurements will be used to calculate the residual, as described in Step 1).

The choice of the threshold λ affects both the detection probability and false alarm probability. Both probabilities decrease when λ increases. For a given false alarm probability P_f, λ should be a function of P_f.

After successfully identifying the NLOS BSs, the next step is to remove the location bias caused by the NLOS errors. Without any knowledge of the NLOS errors, ideally we should remove those NLOS BSs from the set and use only LOS BSs for the location estimate. However, if the number of remaining LOS BSs is not enough for location estimation, we will have to use measurements from NLOS BSs as well. A simple approach can be used: use an asymmetric pdf $f(x)$ to model the effect of NLOS and noise, as shown in Fig. 4, to make the estimator less sensitive to the positive NLOS errors. The variance increase at the right side (i.e., $x > \mu$) is called a tuning constant; larger values of it produce more resistance to the NLOS errors, but at the expense of lower efficiency when NLOS errors are not present. Therefore, the tuning constant should be chosen to give a reasonably high efficiency in the LOS case and still offer protection against NLOS errors.

The residual approach works well when we have a large number of available BSs, among which only a small number of BSs are NLOS BSs. When multiple NLOS BSs are present, at least some knowledge of NLOS statistics will be required for NLOS error mitigation.

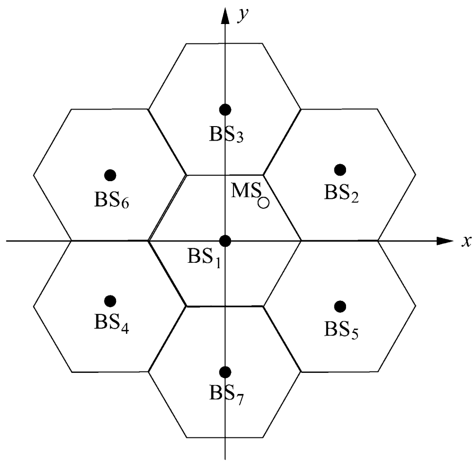


Fig. 5. Seven-cell system layout.

IV. Simulation Results

This section presents simulation results to demonstrate the performance of the proposed residual algorithm and the NSE algorithm. We assume that the standard deviation of the TDOA measurement noises $\sigma_i = 0.07$ km and the mean NLOS bias $\mu_{\mathrm{NLOS}_i} = 0.3$ km for $i = 2, 3, \ldots, N$, typical values confirmed by field tests [6]. For the 2-D array BS layout, we consider a center hexagonal cell (where the home BS resides) with six adjacent hexagonal cells of the same size, as shown in Fig. 5. The cell radius is 5 km and the MS location is uniformly distributed in the center cell. Each simulation is performed by 5000 independent runs.

For macrocells, there are usually multiple NLOS BSs. In the *worst* case, the majority or all of the BSs are NLOS. Our simulation results show that five or six out of seven BSs being NLOS is usually not as devastating as when three or four out of seven BSs are NLOS. The reason is that more NLOS BSs increases the chance of NLOS bias cancelling each other. As a result, we present the simulation results mainly for a medium size of the NLOS BS set.

A. NLOS BS Identification Using Residual

To study the performance of the proposed residual algorithm, we randomly select a certain number of BSs as NLOS BSs and introduce a positive bias to their measurements. Assuming no knowledge of the NLOS errors, the newly proposed residual is calculated for each nonhome BS using a reference MS location and then compared to the threshold λ. If the largest residual is found to be above the threshold, a warning is issued indicating that NLOS BSs are present. We can further rank the residuals to identify those NLOS BSs. A false alarm occurs when the warning is issued but no NLOS BS is present. A miss detection occurs when the algorithm fails to issue the warning in the case of an NLOS situation. The rates of successfully identifying all or part of the NLOS BSs are also obtained via simulation.

We first consider the case of TDOA-only location. It is clear that using the true location as the reference location consistently achieves the best performance, regardless of the MS/BSs geometric layout. In a practical situation, we can use all the available TDOA measurements from all the BSs to obtain an approximation of the true MS location. Table I compares the

TABLE I
NLOS BS Identification Rate for TDOA Only Location Using Estimated MS Location

Number of NLOS BSs (K)	Number of NLOS BS Correctly Detected	Total Number of BSs (N)			
		4	5	6	7
1 BS	1 BS	0.400	0.576	0.685	0.813
2 BSs	2 BSs	0.346	0.486	0.600	0.678
	1 BS	0.058	0.252	0.252	0.190
3 BSs	3 BSs		0.479	0.505	0.578
	2 BSs		0.390	0.401	0.312
	1 BS		0.000	0.040	0.054

TABLE II
NLOS BS Identification Rate for TDOA/AOA Location Using Estimated MS Location

Number of NLOS BSs (K)	Number of NLOS BSs Correctly Detected	Total Number of BSs ($N-1$)			
		4	5	6	7
1 BS	1 BS	0.663	0.755	0.790	0.877
2 BSs	2 BSs	0.601	0.659	0.733	0.797
	1 BS	0.044	0.161	0.162	0.121
3 BSs	3 BSs		0.642	0.624	0.668
	2 BSs		0.283	0.333	0.275
	1 BS		0.000	0.016	0.018

NLOS BS's identification rates in different scenarios, using the approximated location and the proposed residual ranking algorithm with the number of NLOS BSs being known. It is observed that the proposed algorithm works well when we have a large number of BSs and only a small portion of these BSs are NLOS. For example, in the case of seven BSs and one NLOS BS, the algorithm can successfully identify the NLOS BS with a probability of 0.813. When the number of NLOS BSs increases, however, the probability of detecting all of them decreases. It is also clear that when the number of total available BSs is small, the detection rate suffers. In the case of two NLOS BSs out of four BSs, the algorithm can only identify those two BSs with a probability of 0.346.

By using the additional AOA information, we can further improve the NLOS BS identification performance. This is achieved by using the AOA information together with the TDOA measurements to get an improved true MS location approximation. When the AOA measurement is accurate, the improved reference location improves the detection rates significantly. In Table II, the detection rates for different numbers of BSs and NLOS BSs are compared, with $\sigma_\beta = 1$ degree. Taking the case of three NLOS BSs, for example, it is clear that the additional AOA information greatly improves the detection accuracy. With the AOA measurement, the algorithm also performs more consistently when the total number of BSs is small and depends less on the MS/BSs geometric layout. The same case of four BSs and two NLOS BSs in Table II yields a correct detection rate of 0.601.

If the number of NLOS BSs is unknown, we should use the threshold λ for the residual values to determine NLOS BSs. There is a tradeoff between the missed detection rate and the false alarm rate when choosing the value of λ, as shown in Figs. 6 and 7. A smaller λ reduces the missed detection rate but increases the false alarm rate at the same time. The value of

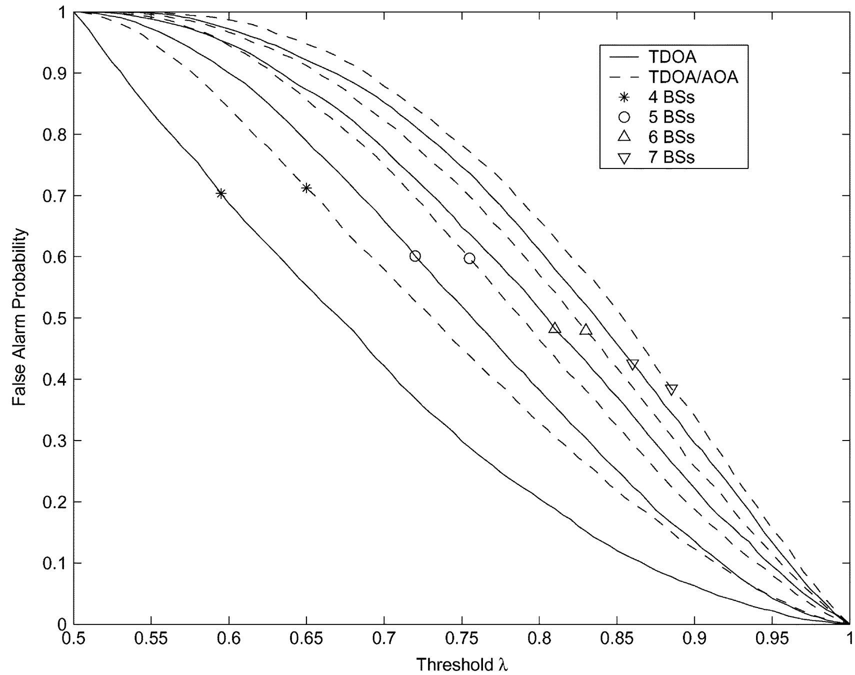


Fig. 6. Comparison of false alarm rates.

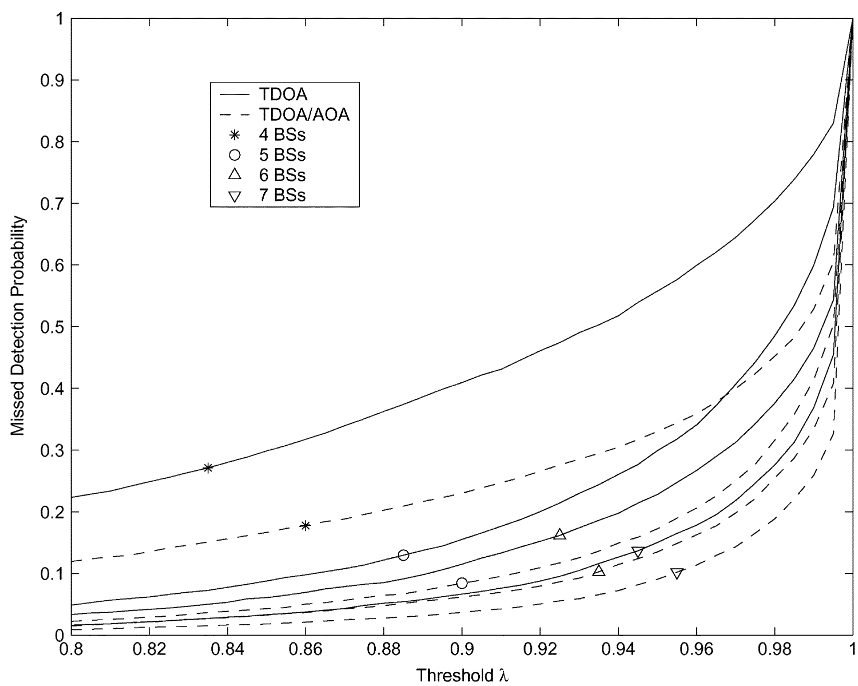


Fig. 7. Comparison of missed detection rates.

λ can be chosen according to the desired false alarm and detection probabilities as well as the total number of BSs. It is also observed that for a certain λ, the additional AOA measurement slightly increases the false alarm rate but reduces the missed detection rate significantly, especially for a small number of BSs.

B. NSE Algorithm Performance

We now study the TDOA location accuracy using empirical data of the NLOS error prior probability and mean value. A total of four BSs ($\mathrm{BS}_1, \mathrm{BS}_2, \mathrm{BS}_3$, and BS_4) are included and the mean NLOS error $\mu_{\mathrm{NLOS}} = 0.3$ km for all the NLOS BSs. The standard deviation of the TDOA measurement is 0.07 km. We compare the hard-decision rms location errors in three scenarios: 1) using the NLOS mean and prior probability to correct the NLOS error; 2) using only the NLOS error mean to correct the NLOS error; and 3) using TDOA measurements from all available BSs with no NLOS correction. Note that in the second scenario, the weight w_0 assigned to the state of all BSs being LOS can be used to control the false alarm rate. We let $w_{\boldsymbol{S}} = 1$ for all other system state $\boldsymbol{S}$. Assigning a larger weight of w_0 will reduce the false alarm rate,

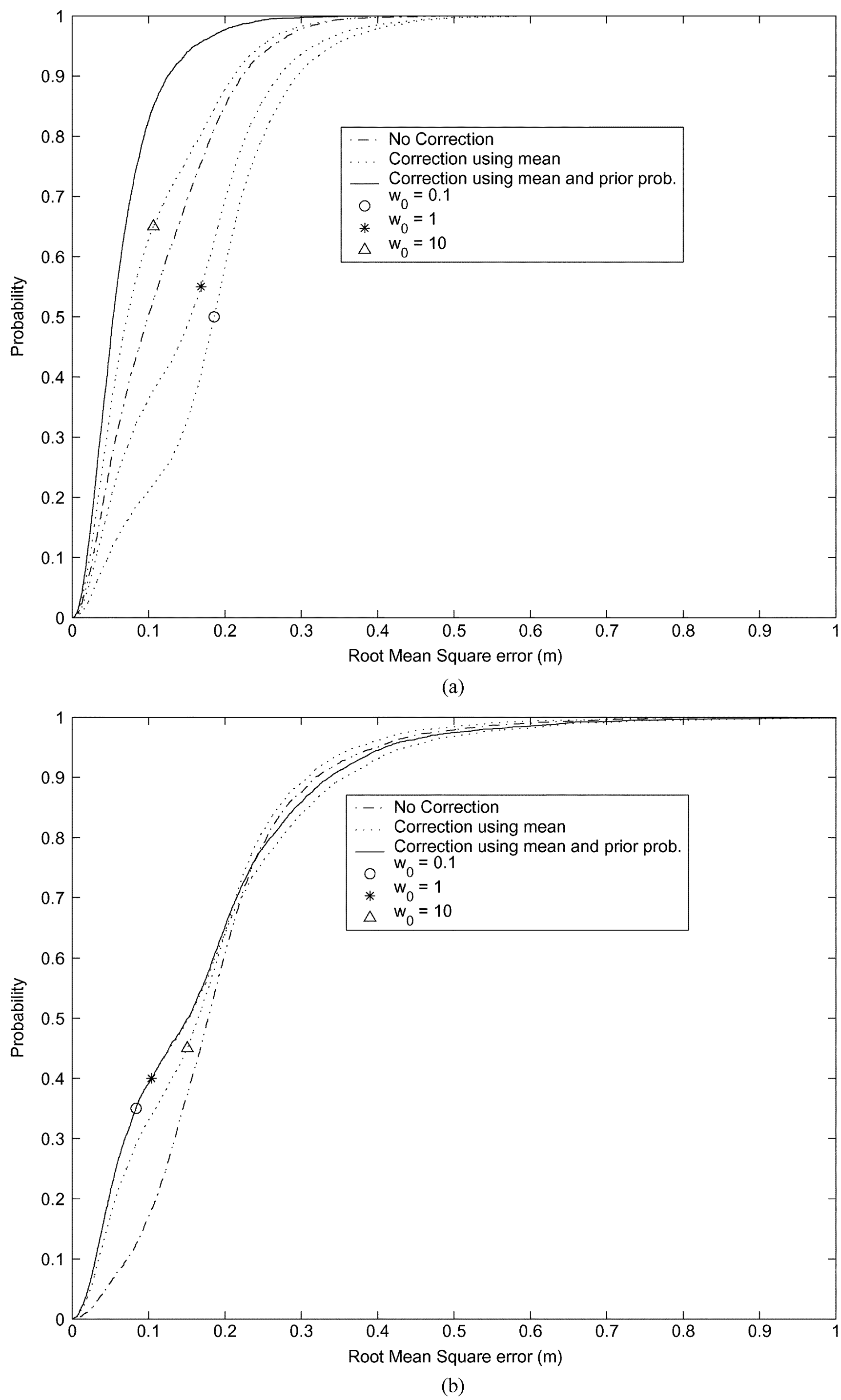


Fig. 8. Comparison of location accuracy for different NLOS situations. (a) One NLOS BS (BS_3) with probability 0.5. (b) Maximum of three NLOS BSs $(\mathrm{BS}_2, \mathrm{BS}_3$, and $\mathrm{BS}_4)$, each with probability 0.5.

at the cost of an increased miss detection rate. On the other hand, a smaller weight of w_0 will improve the location accuracy in the case of a heavy NLOS situation.

Let us first consider a light NLOS situation. Among the four BSs, BS_3 is the only BS which can be NLOS with probability 0.5. The NSE algorithm performance is shown in Fig. 8(a), where the y-axis coordinate represents the probability of the rms location error smaller than the x-axis coordinate. It is observed that applying the NLOS correction with prior probability information gives the best performance. However, the NLOS correction algorithm using only the NLOS error mean performs worse than no NLOS correction at all, due to a large number of false alarms in this light NLOS propagation environment. A large W_0 reduces the location error significantly.

When the NLOS situation gets worse, for example, multiple NLOS BSs are present, the NLOS correction scheme using NLOS error means and prior probabilities still gives the best performance; however, the performance gain over no NLOS correction becomes smaller, as shown in Fig. 8(b), where three of the four BSs are NLOS with probability 0.5. In this situation,

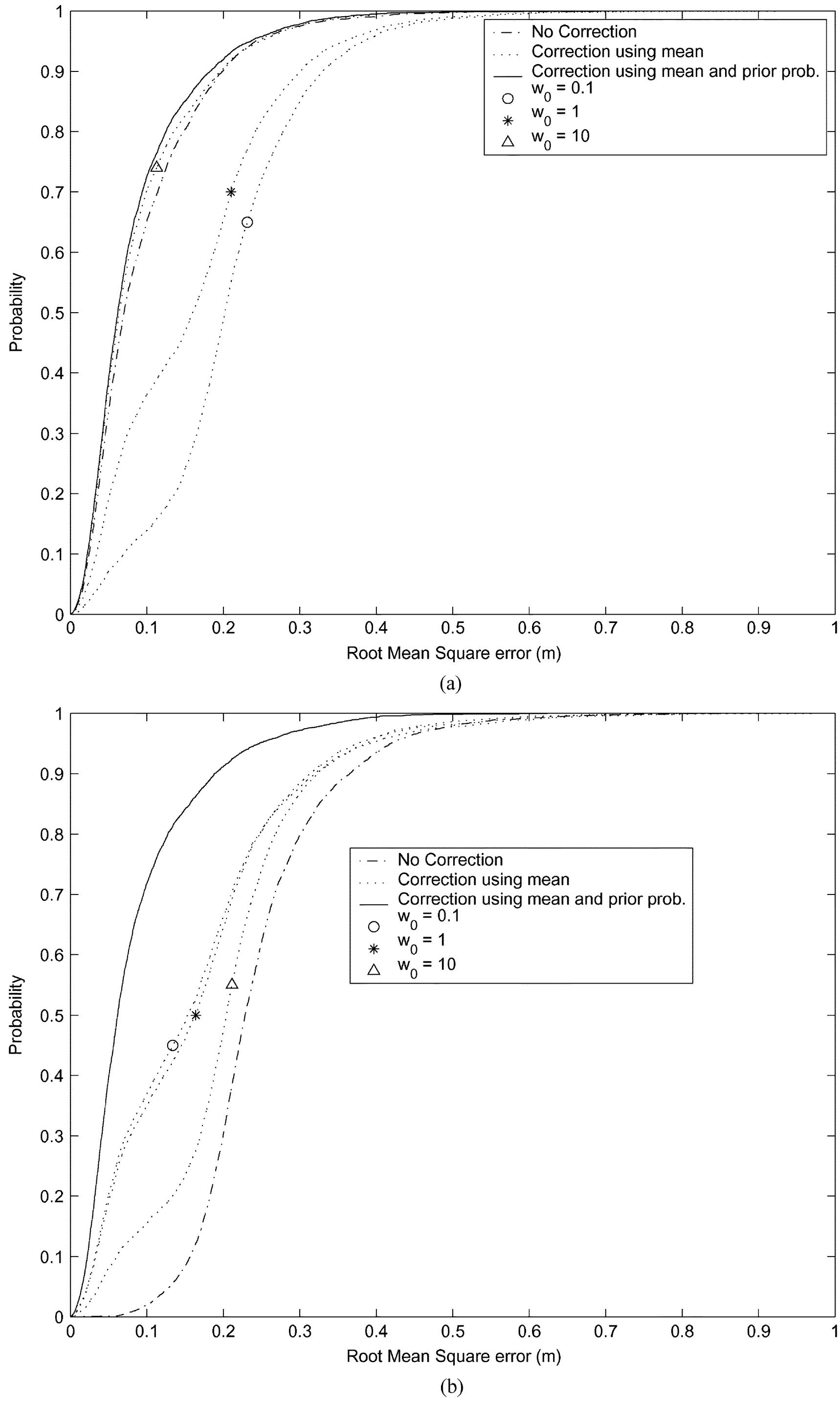


Fig. 9. Comparison of location accuracy for different NLOS situations. (a) Maximum of three NLOS BSs (BS_2, BS_3, and BS_4), each with probability 0.1. (b) Maximum of three NLOS BSs (BS_2, BS_3, and BS_4), each with probability 0.9.

even without NLOS prior probabilities information, NLOS correction using mean only starts to outperform the no NLOS correction case.

The NLOS error prior probability plays an important role in the NLOS mitigation. In Fig. 9(a), three of the four BSs are NLOS with probability 0.1. Since the prior probability is small, the NLOS correction using mean values actually performs worse than that using all measurements without NLOS correction. That is because the NLOS correction based on the mean NLOS error without the prior probability tends to assume that NLOS and LOS situations happen equally likely. We can assign a proper value to the weight w_S to alleviate this problem. Fig. 9(b) illustrates the opposite situation, when three of the four BSs are NLOS with probability 0.9. In this case, the NLOS correction without the prior probability gives much better location estimate as compared with the no NLOS correction scheme. In all cases, NLOS correction using the mean and the prior probability information always performs the best.

Fig. 10 shows the decrease of rms location error as the number of BSs increases. It can be observed that as the number of avail-

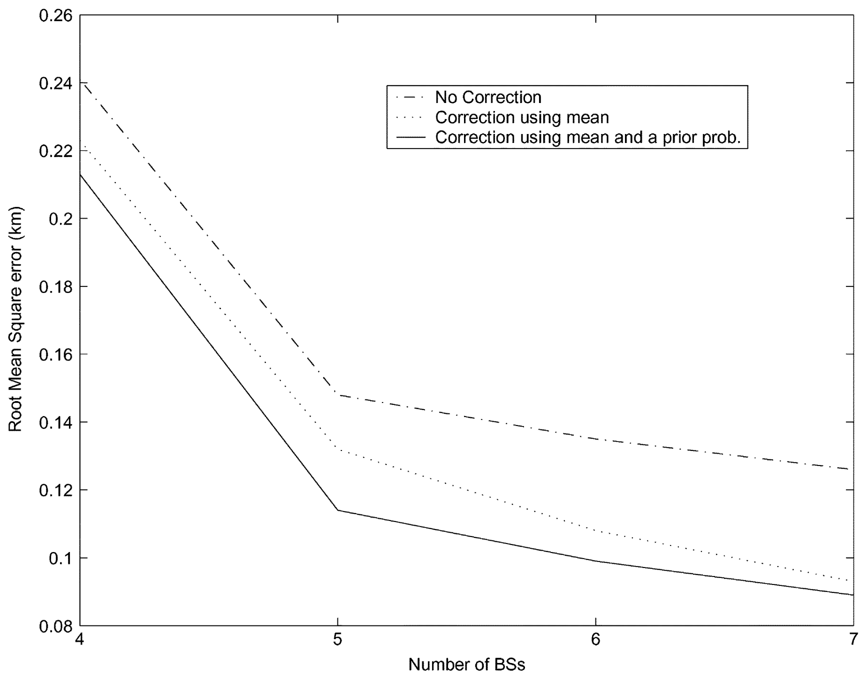


Fig. 10. Comparison of location accuracy, where each BS (except home BS) is NLOS with probability 0.5.

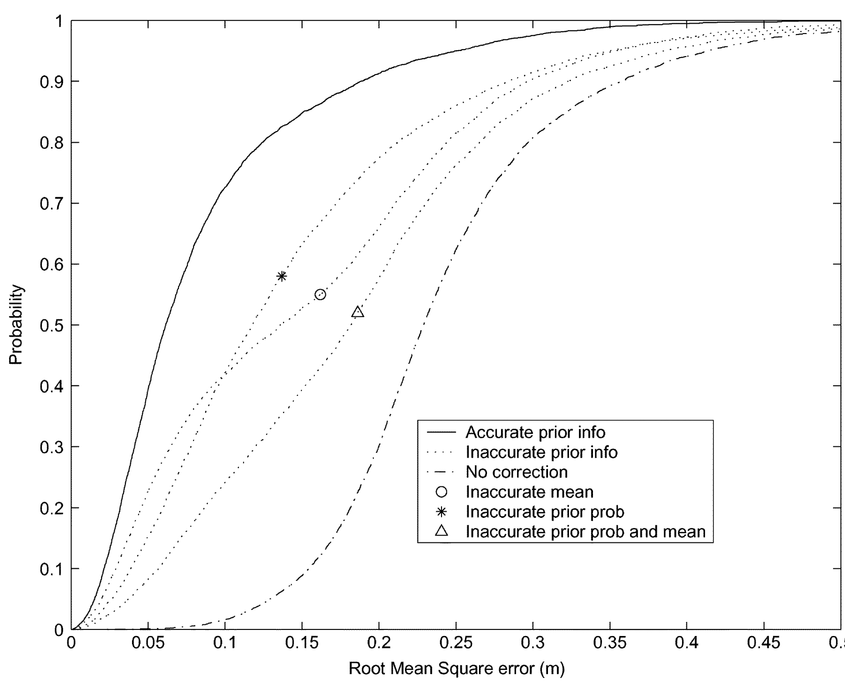


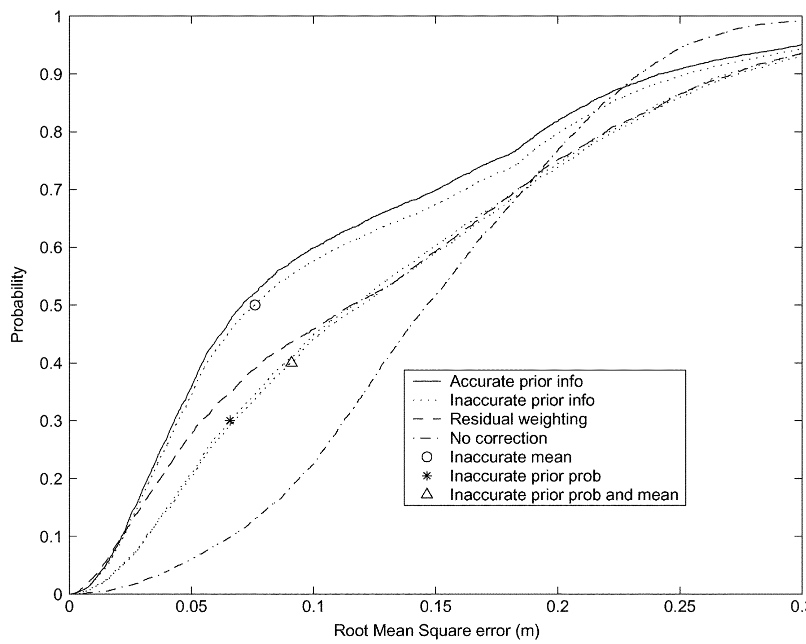
Fig. 11. Location accuracy using four BSs ($\mathrm{BS}_1, \mathrm{BS}_2, \mathrm{BS}_3$, and BS_4), each nonhome BS being NLOS with probability 0.9.

able BSs increases, the performance gain of the proposed NLOS mitigation scheme increases significantly.

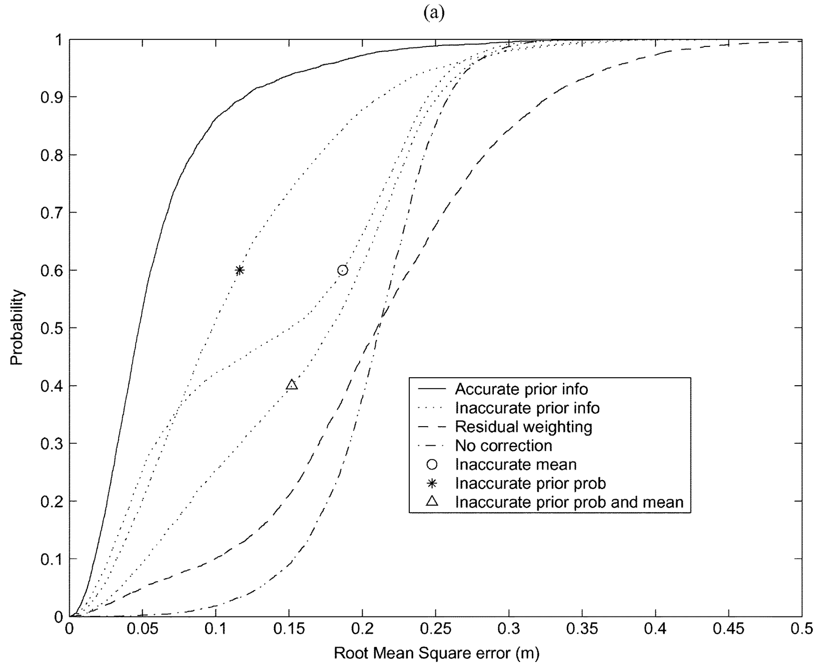
It is also observed during the simulation that if the prior information about the NLOS errors is not accurate (for example, the known NLOS mean deviates from the true value slightly), the NLOS mitigation algorithm can still provide performance improvement. We consider a four-BS case and deliberately add Gaussian noise to the NLOS prior probability and NLOS mean. The standard deviation of the noise on the NLOS mean is 0.1 km, and standard deviation of the noise on the NLOS prior probability is 0.1. Fig. 11 shows the impact of using inaccurate prior information on the location accuracy for the case of four BSs with a maximum of three NLOS BSs ($\mathrm{BS}_2, \mathrm{BS}_3$, and BS_4), each with probability 0.9 (the NLOS prior probability is denoted by vector [0, 0.9, 0.9, 0.9]). Table III summaries the NSE algorithm performance when NLOS prior information is not accurate. From the results we can see that even using inaccurate prior probability and/or inaccurate mean, the NSE algorithm still provides better accuracy as compared to the case of no NLOS correction at all. The only exception is when all three neighboring BSs are NLOS with probability 0.5 and inaccurate NLOS prior probabilities are used.

TABLE III
RMS LOCATION ERROR IN km USING INACCURATE PRIOR INFORMATION, FOUR BSs

NLOS Prior Probability of the 4 BSs	[0, 0.1, 0.1, 0.1]	[0, 0.5, 0.5, 0.5]	[0, 0, 0.5, 0]	[0, 0.9, 0.9, 0.9]
With true prior information	0.084	0.166	0.068	0.086
With wrong mean	0.089	0.173	0.068	0.153
With wrong prior prob	0.087	0.193	0.076	0.144
With wrong prior prob and mean	0.092	0.195	0.079	0.188
With no correction	0.092	0.190	0.115	0.245



(a)



(b)

Fig. 12. Comparison of the performances of different NLOS mitigation algorithms for a five-BS case. (a) Maximum of four NLOS BSs ($\mathrm{BS}_2, \mathrm{BS}_3, \mathrm{BS}_4$, and BS_5), each with probability 0.5. (b) Maximum of four NLOS BSs ($\mathrm{BS}_2, \mathrm{BS}_3, \mathrm{BS}_4$, and BS_5), each with probability 0.9.

Fig. 12 compares the performance of the proposed NSE algorithm with the residual weighting scheme in [9]. When applied to TDOA and TDOA/AOA location, the residual weighting algorithm requires at least five BSs. That is because the algorithm divides all available BSs into subsets and weights the location estimate from each subset according to their residuals. By the definition of the residual in [9], a subset of size 4 and up is required. So in Fig. 12(a), we consider the case of $N = 5$ and we assume that four of the nonhome BSs can be NLOS with probability 0.5. It is observed that both the NSE algorithm and the residual weighting algorithm can mitigate the NLOS error, and the NSE algorithm outperforms the residual weighting algorithm. Fig. 12(b) corresponds to a severe NLOS situation where the four nonhome BSs can be NLOS with probability 0.9. In this case, the residual weighting algorithm does not provide much performance gain. The NSE algorithm, on the other hand, greatly improves location accuracy, even when imperfect prior information is in use.

V. Conclusion

This paper studies the NLOS error mitigation techniques for time-based location systems. Based on the knowledge of NLOS error statistics, two different NLOS mitigation algorithms are proposed. A new residual algorithm is used for NLOS BS identification. The algorithm requires only the knowledge of Gaussian noise statistics. It can effectively identify a small number of NLOS BSs. Utilizing an accurate empirical database, the proposed ML location estimator can achieve the best location accuracy, even in the case where most BSs are NLOS BSs. Simulation results demonstrate that an accurate location estimate is possible even in severe NLOS conditions.

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