# Mobile Localization based on Improved Non-Line-of-Sight Classification

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*Abstract*— **One of the main problems facing accurate localization using Time-of-Arrival (TOA) measurements in wireless communication systems is Non-Line-of-Sight (NLOS) propagation. Classification is among the important NLOS mitigation approaches whereby the system attempts to identify and localize with the LOS base stations (BSs) only. In this paper, the impact of the number of NLOS BSs and their geometrical distribution on the localization process is investigated. With the use of a residual test (RT) classification algorithm, it is shown that, under certain conditions, the system that localizes with all BSs (including both LOS and NLOS) can benefit from error cancellation, and may perform better than the system that implements "pure" classification. Based on this observation, it is concluded that BSs identified as NLOS should not always be dropped, and a modified classification algorithm is proposed. The new algorithm drops BSs identified as NLOS only when there are enough geometrically "well distributed" BSs to localize with. Simulation results show that the proposed algorithm can outperform other conventional classification schemes.**

***Index Terms*—Mobile positioning, non-line-of-sight (NLOS), time-of-arrival (ToA), localization, NLOS Classification.**

## I. Introduction

The need for localization of mobile stations is increasing rapidly in wireless cellular systems and sensor networks. In network-based localization, the mobile terminal or wireless sensor is located by the network using some measured parameters like Angle of Arrival (AOA), Time of Arrival (TOA), Time Difference of Arrival (TDOA), or signal strength (SS). Error can be introduced to the localization process in different ways. The equipment that is used to measure location parameters limits the accuracy that can be achieved by a given positioning algorithm. Even with perfect measurements, error could still result from the propagation channel over which signals must travel before being measured by the base station (BS) equipment. In this regard, the main sources of location error in wireless communication systems include multipath propagation, non-line-of-sight propagation (NLOS), and multiple access interference. Steps must be taken to mitigate these impairments to improve the location accuracy [1-2].

Out of the three main sources of error, NLOS propagation in TOA-based localization is found to be a critical issue [2]. NLOS propagation pertains to the scenario where the direct (or LOS) path between the mobile station (MS) and the BS is blocked by some structures like buildings or mountains. With NLOS propagation, the signal arriving at the BS from the MS is reflected or diffracted and takes a path that is longer than the direct path. As an indication of the severity of this problem, an experimental study has found that the typical ranging error introduced by NLOS propagation in GSM networks can average between 500-700 meters [3].

NLOS propagation introduces a bias in the TOA or TDOA measurements even in the absence of multipath interference, and when high-resolution timing estimation techniques are employed. Therefore, it is important to find methods to mitigate the NLOS bias, and different techniques have been recently proposed for this purpose. For example, classification-based, approaches attempt to identify LOS base stations to be solely used for localization. Other methods rely on weighting to provide relative scaling of the measured propagation parameters in order to minimize the effects of the NLOS bias.

The main idea behind NLOS classification is to find some distinct properties of NLOS range measurements and develop hypothesis tests to separate LOS measurements from NLOS measurements in order to use only LOS measurements in the localization process. In [4], the identification is done by a time-history based hypothesis test. By using the time history of the range measurements in a simple hypothesis test, and by knowing the standard deviation of the measurement noise, the algorithm in [4] could determine if the measurements are LOS or NLOS. The algorithm presented in [5] can detect the NLOS BSs using the redundant information present in the TOA measurements when more than the minimum numbers of BSs are present. In this case, several hypotheses of the set of BSs under NLOS scenarios are formulated and, on the basis of the Maximum Likelihood (ML) detection principle, the most suitable hypothesis can be selected. Different tests are also presented in [6-7] for identifying LOS measurements. In all these models, a zero-mean (about the true range) Gaussian distributed error is assumed with a certain variance for the LOS case. Thus, the different tests correspond to different available information about the distribution of the NLOS measurements. All the tests compare a likelihood ratio to some threshold and use the fact that the variance of NLOS measurements will be larger than LOS measurements.

The algorithms in [4-7] perform well provided that there is a large number of BSs available with the majority being LOS with the MS. For more realistic scenarios having zero or one LOS BS, the algorithms provide little improvement in location accuracy and in fact, can perform worse than traditional algorithms, as will be shown in this work.

In this paper, the impact of the number of NLOS BSs and their geometrical distribution on the localization process is investigated. The performance of the localization algorithm that implements a Residual Test (RT) for classification is investigated under different scenarios. It is shown that, under certain conditions, the system that localizes with all BSs can outperform the system that implements "pure" classification. BSs identified as NLOS should not be always dropped. Based on this observation a modified classification algorithm is proposed.

In the remaining part of the paper, we introduce the system model and review the utilized localization algorithm. Section IV is dedicated to illustrate the impact of relative NLOS BSs position on the final localization error. Some examples are given where NLOS error from different BSs could add up or cancel out. Next, we introduce classification and examine its performance under different conditions. In section VI, based on the previous results, a geometry-dependent NLOS mitigation technique is introduced and evaluated. The paper concludes with some remarks and suggestions.

## II. System Model

We consider a wireless network topology with a given mobile station (MS) of interest and several serving base stations (BSs). The mobile is located at $\Theta=(x, y)$, and its signal is received at different BSs located at $(x_i, y_i)$, where $i$=1, 2, …, $N$ ($N$ is the number of BSs). Signal propagation speed is given by $c = 3\times10^8$ m/s. Synchronization is assumed (i.e. all BSs have the same time reference). The true distance between the MS and the $i^{th}$ base station ($BS_i$) is $R_i$ and the measured distance is

$$l_i = c \times TOA_i \ , \tag{1}$$

where $TOA_i$ is the one way propagation time between the MS and the $BS_i$. The network layout model consists of seven BSs surrounding the MS from different directions as shown in Figure 1. The coordinates for the given distribution of BSs is summarized in Table 1.

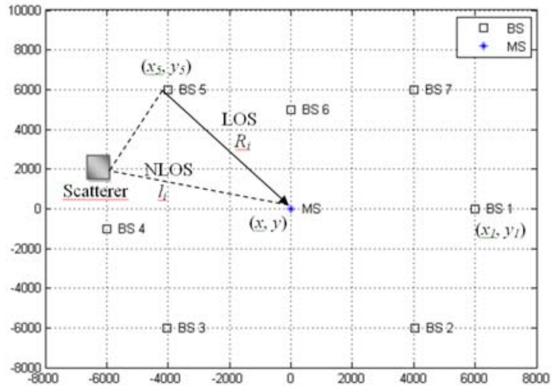


Figure 1. Mobile Station and Base Stations Layout

Table 1. Location of MS and BSs (all units are in km)

| | MS | $BS_1$ | $BS_2$ | $BS_3$ | $BS_4$ | $BS_5$ | $BS_6$ | $BS_7$ |
|---|---|---|---|---|---|---|---|---|
| ***x*** | 0 | 6 | 4 | -4 | -6 | -4 | 0 | 4 |
| ***y*** | 0 | 0 | -6 | -6 | -1 | 6 | 5 | 6 |

## III. NLOS Analysis and Localization Technique

There are different techniques to estimate the MS position. The maximum likelihood algorithm is optimal but it is complicated. A suboptimal solution proposed by [8] has a performance comparable to the optimal algorithm with a reduced complexity. This algorithm, which is adopted in this research, is known as Approximate Maximum Likelihood (AML) algorithm. Based on the system model, let

$$l_i = R_i + \varepsilon_i \ . \tag{2}$$

where $\varepsilon_i$ is assumed to be independently and identically distributed (i.i.d.) zero mean Gaussian random variables denoting TOA measurement noise in the $i^{th}$ BS. It is shown in [7] that the maximum likelihood (ML) estimate, $\mathbf{\Theta}$, minimizes $J$, where

$$J = \sum_{i=1}^{N} (l_i - R_i)^2 \ , \tag{3}$$

and

$$R_i^2 = (x - x_i)^2 + (y - y_i)^2 \ . \tag{4}$$

Setting the differentials of (3) with respect to $\mathbf{\Theta}$ to zero gives the likelihood equations

$$\sum_{i=1}^{N} \frac{(l_i - R_i)(x - x_i)}{R_i} = 0 \, ,$$

$$\sum_{i=1}^{N} \frac{(l_i - R_i)(y - y_i)}{R_i} = 0 \ . \tag{5}$$

Equations in (5) are nonlinear in $\mathbf{\Theta}$ and have no closed form solutions. However, [8] was able to manipulate (5) into a set of linear equations in $\mathbf{\Theta}$, in the form of

$$\mathbf{A\Theta} = \mathbf{b} \tag{6}$$

but with $\mathbf{A}$ and $\mathbf{b}$ being functions of $\mathbf{\Theta}$. A suboptimal but linear algorithm [9] first gives an initial estimate of $\mathbf{\Theta}$, which can then give values of $\mathbf{A}$ and $\mathbf{b}$. Solving (6) then produces a new value of $\mathbf{\Theta}$ to update $\mathbf{A}$ and $\mathbf{b}$, and then $\mathbf{\Theta}$. The procedure, called the approximate ML (AML) estimator [8], stops after five updates and takes the $\mathbf{\Theta}$ that gives the smallest $J$ in (3) as the solution. This ensures that the AML will not diverge, and will, at worst, have the errors of the linear estimator.

For the case of NLOS measurements, equation (2) becomes

$$l_i = R_i + \varepsilon_i + \eta_i \; . \qquad (7)$$

where $\eta_i$ is the NLOS error molded as i.i.d. random variable. For simulation purposes different scattering models that produce different NLOS error distributions can be used. Depending on the location environment used in the localization system, one of these models is used to generate the NLOS error in performance evaluation simulations. NLOS error is usually modeled by assuming a certain distribution for the scatterers. The most important and widely used ones are the Disk of Scatterers (DOS), Ring of Scatterers (ROS), Reversed Disk of Scatterers (RDOS), and the uniformly distributed models [10]. The algorithms to be discussed next have been validated with these different models. However, for the sake of brevity, we only consider the case of the uniform model in the rest of the paper.

## IV. Impact of Relative Base Station Positions on the Mobile Localization Accuracy

In most previous works, the NLOS measurements are dealt with as unwanted biased data, which diminishes the performance of the positioning algorithms [7]. As a result, classification techniques are used to identify and eliminate the NLOS BSs and use only the LOS ones. This implicitly assumes that the information provided by LOS measurements provide sufficient statistics for optimal localization.

In the following analysis, we show that the NLOS information can be useful in some special scenarios if it is properly weighted and utilized in the positioning algorithms. The relative importance of this information is geometry dependent. To clarify the geometry dependence, we consider different scenarios that illustrate how BSs positions affect the performance of the positioning algorithms.

### A. Geometries with Additive NLOS Error

To illustrate how NLOS errors add up depending on the BS relative positions, simulations are performed with 500 independent NLOS errors uniformly generated between zero and 400m, and assigned to BSs located on "the same side" vis-a-vis the MS. Because the NLOS bias is always positive, if two or more NLOS BSs are on the same side relative to the MS their effect will be added up and the region of their effect can be easily determined by the region enclosed by the straight lines passing through the NLOS BSs and the MS and away from the MS. For example, consider $BS_1$ and $BS_7$ to be the NLOS BSs. Figure 2 shows the estimated MS positions for this case. Note that the location error of the MS position estimation directionally add up because the two NLOS BSs are on the same side. The large values of error are in the range of 120m in the case of two NLOS BSs versus 60m in the case of single NLOS BS.

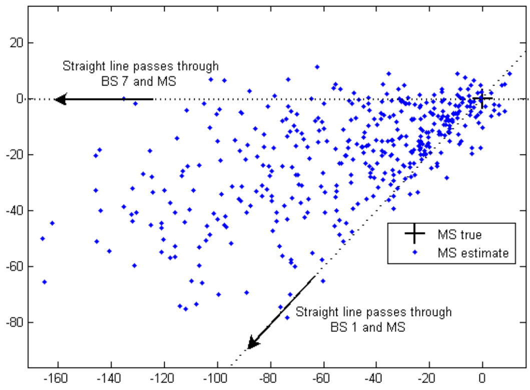


Figure 2. Additive errors with BS1 and BS2 set as NLOS

Similarly, for more than two NLOS BSs, each NLOS BS will affect the position estimation and the cumulative error will also directionally add up within the region determined by the straight lines passing through the NLOS BSs and the MS.

### B. Geometries with NLOS Error Cancellation

We now consider another case where the NLOS BSs are not on the same side relative to the MS (e.g., co-linear BSs with MS is between). For example, setting BS 3 and BS 7 as the NLOS BSs, Figure 3 shows the MS estimated positions (scattering plot) for this case. Each NLOS bias is in the opposite direction of the other and most of the position estimations are about 18m far from the MS and located on the straight line passing through the co-linear BSs 3, 7 and MS. The NLOS effect does not add up as it did in the previous example when the two BSs on the same side relative to MS. As expected, similar observations hold when we have more than two NLOS BSs opposite each with respect to the MS. To sum up, these examples clearly show that the "geometry" of the NLOS BSs and MS is very important and has a direct impact on the performance of localization algorithms.

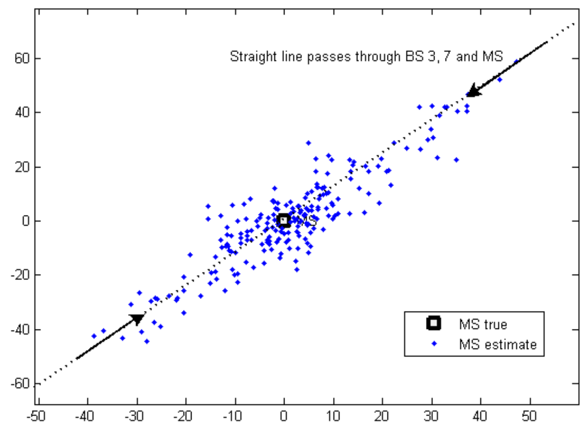


Figure 3. Additive errors with Two NLOS BSs (BS 3 and 7)

To further illustrate the impact of NLOS bias and relative positions BS and MS positions, we consider varying the upper bound, *UB,* of the uniformly selected NLOS error, the performance of the localization algorithm can be examined under different degrees of NLOS bias. Figure 4 shows the average localization error for different scenarios considered for the cases of two and four NLOS BSs. The NLOS bias added to these BSs is uniformly selected between zero and a maximum upper bound, *UB*. It is clear that as the upper bound of the NLOS error model increases, the average location error increases. The performance of the co-linear NLOS BSs scenario is better than the one-sided NLOS BSs scenario with both two and four NLOS BSs as shown in the figure. It is evident from Figure 4 that the performance of the co-linear cases is almost identical, which reflects the importance of the NLOS BSs positions in the accuracy of the localization.

Therefore, based on the above observations, if a BS is identified as a source of NLOS error, it should not always be dropped from the localization algorithm. The added NLOS bias is directional and can cancel out in some scenarios. This fact is further exploited in the coming sections and used to develop an improved localization process.

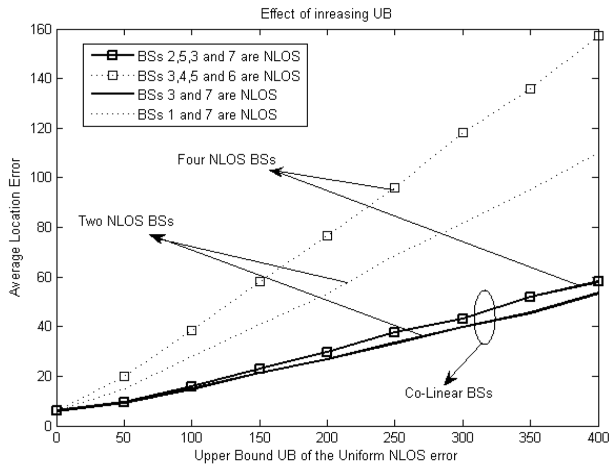


Figure 4. Average location error vs. upper bound of the Uniform NLOS error model *UB*

## V. Classification Technique in TOA-Based Localization

The Classification-based approach for NLOS mitigation attempts to identify and localize with only LOS measurements. If the identification is correct, the localization accuracy is what the localization algorithm can provide, but there is always the possibility of wrong identification.

One of the tests that demonstrate good results is the residual test (RT) proposed in [7]. The residual test determines the LOS dimension (*D*), *i.e.*, the number of LOS-BS and identifies those BS in order to localize only with them. The word residual reflects the error or residue because of using a subset of the base stations as opposed to using all of them. The residual test compares the residuals of a group of *k* BSs, against a predetermined threshold TH. If only a small percentage, say 20%, of the residuals are above TH, then $D = k$. Otherwise, the test moves to groups of $(k - 1)$ BS. This process stops when it has determined *D*, or when $D = 3$, the minimum value necessary for a unique localization. In this case ($D$=3) another test known as the delta test is initiated.

Based on the system model with seven BSs, the residual test (RT) begins by checking if $D = 7$. An approximate maximum likelihood (AML) positioning algorithm [8] can then be used to obtain a total of 99 estimates of $\mathbf{\Theta}$ (corresponding to all combinations of three and more BSs). For example., in the case of $_7C_3 = 35$, there are 35 different estimates of $\mathbf{\Theta}$, obtained from seven measured distances, taken three at a time.

Letting these estimates be $\hat{\mathbf{\Theta}}(k)$, $k = 1 . . . 99$, the RT computes the square of the normalized residuals

$$\chi_x^2(k) = \frac{\left[\hat{x}(k) - \hat{x}(99)\right]^2}{B_x(k)},$$

$$\chi_y^2(k) = \frac{\left[\hat{y}(k) - \hat{y}(99)\right]^2}{B_y(k)}, \quad k = 1,2,\ldots,98 \tag{8}$$

When all measurements are LOS, the random variables in (8) should have a central $\chi^2$ (chi-square) distribution. This implies that estimates of MS location coordinates $\hat{x}_k$ and $\hat{y}_k$ should be Gaussian zero mean. The reference estimate is $\hat{\mathbf{\Theta}}(99)$, because it is generally the best estimate of the true $\mathbf{\Theta}$ among all $\hat{\mathbf{\Theta}}(k)$ since $\hat{\mathbf{\Theta}}(99)$ is the estimate from all BSs.

In (8), $B_x(k)$ and $B_y(k)$ are approximations obtained by the Cramer-Rao Lower Bound (CRLB) of $\mathbf{\Theta}$ from the $l_i$ combinations that produce $\hat{\mathbf{\Theta}}(k)$. This bound is a theoretical lower bound, valid when $\varepsilon_i$ in $l_i = R_i + \varepsilon_i$ are i.i.d. zero mean Gaussian random variables, and is a function of the radiolocation geometry. Its computation requires knowledge of the true $\mathbf{\Theta}$. Since this is not available, the $\hat{\mathbf{\Theta}}(k)$ location is used as a substitute to produce $B_x(k)$ and $B_y(k)$.

Now, if $D = 7$ (all BSs are LOS) and $\hat{\mathbf{\Theta}}$ is an ML estimate of $\mathbf{\Theta}$, then the two normalized quantities

$$\frac{\hat{x}(k) - x}{\sqrt{B_x(k)}}, \quad \frac{\hat{y}(k) - y}{\sqrt{B_y(k)}} \tag{9}$$

have a standard Gaussian normal distribution. It follows that all random variables in (8) have an approximate central $\chi 2$ (Chi square) PDF of one degree of freedom. If, however, one or more of the $l_i$ are NLOS, then some random variables in (8) will have a non-central $\chi 2$ PDF.

For the residual test to work, an appropriate threshold TH must be chosen to compare the residuals with. Choosing TH is done in a way to minimize both the probability of over-determination (POD) (e.g. when $D$ <7 but the RT decides that $D = 7$) and the probability of under-determination (PUD) (i.e. when $D = 7$ but the decision is $D < 7$). For example, for a threshold TH= 2.71, $D = 7$ if only 20% or less of the r.v. are larger than TH=2.71, the pdf is central $\chi^2$. Otherwise, the PDF is non-central $\chi 2$, and $D$<7.

It is noted that for the case $D$ =3, the next task is to identify three LOS-BSs from the seven. Since three BSs do not provide enough number of R.Vs. for a reliable RT, a different test called the delta test (DT), is used [7]. is called The DT takes two BS as the reference set and combines with another BS out of the remaining BSs, to see if these three are LOS. Even if there is no three LOS BSs, the DT will find a set of three BSs that contains the smallest error, or closest to be LOS BSs. Due to their excellent performance, the RT combined with the DT are used in this work. For the full details of these algorithms, the reader is referred to [7].

## VI. Examples and Discussion of Results

### *A. Effect of the Number of NLOS BSs*

Simulations were performed to study how the average location error is affected by varying the number of NLOS BSs with and without classification. The NLOS range errors in these simulations were modeled as uniform random variables having support over $0 \le \eta_i \le 400$m. Based on Figures 5, as the number of the NLOS BSs is increased the average location error increases. The average location error decreases slightly in localization without using the classification algorithm when most BSs are NLOS. This is because the average location error considering co-linear NLOS BSs is small compared to NLOS BSs located on the same side.

If the classification algorithm is employed in the localization process, the average location error will be very small compared to the unclassified algorithm when the number of NLOS BSs is small (i.e. $D$ = 6, 5 and 4), as shown in Figure 5. As the number of NLOS BSs exceeds 4, classification performance degrades and it will reach its worst case when all BSs are NLOS.

These results reflect the capability of the RT in improving the performance of the radiolocation algorithm when there are *enough* LOS BSs to locate with ($D$=6, 5 and 4). However, if there aren't enough LOS BSs ($D \le 3$), the classification algorithm leads to a very large error that can severely limit the accuracy of the localization algorithm. To clarify the causes of the large location errors associated with these cases, the behavior of the classification algorithm when $D \le 3$ is examined in the following section.

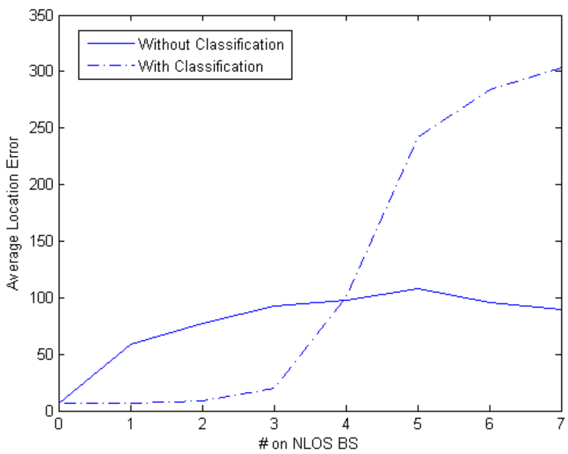


Figure 5. Effect of the number of NLOS BS

### *B. Classification Performance when D≤3*

Pervious results show that the performance of the localization algorithm using classification deteriorates when $D$=3 and it becomes worst when $D$<3. It is worth recalling that the delta test (DT) is used if $D$=3 because three BSs don't provide a sufficient number of r.v for a reliable residual test (RT). By selecting three BSs out of seven in the simulated cell layout, the performance will be poor unless the three selected BSs are LOS. In the case where the selected BSs are not LOS (i.e. $D$<3), the DT selects three BSs only, where at least one is NLOS (depending on the assumed $D$), and removes the remaining BSs.

In contrast, as our previous simulation results showed, when the number of BSs considered in the localization algorithm increases (even if they are NLOS BSs), there will be some cancellation of localization error, especially when the NLOS BSs are co-linear. In order to clarify this point, simulations of the classification algorithm performance when $D$=3 ($BS_1$, $BS_4$, and $BS_6$ are LOS) are done using 1000 independent trials. An estimate of the MS location is computed with and without the aid of classification. The NLOS error was randomly selected between 0 and 400m according to a uniform NLOS distribution model. The additive Gaussian measurement timing error has a variance of 81m. The maximum and the average location error in addition to the confusion matrix when $D$=3 is given in Table 2. From the table, 31% of the estimated dimensions are the true three LOS BSs and the location error is mostly less than 30m. The classification algorithm mistakenly estimates the dimension as $D$>3 for 331 out of the 1000 independent trials, 63% of those cases have a single NLOS BS and the remaining have two NLOS BSs.

Scattering plots when the classification algorithm estimate the dimension as $D$=3 and those three BSs are not all LOS is shown in Figure 6. Depending on the position of those NLOS BSs used in localization process, the MS will be located as shown in the figure. The resultant location error in this case is relatively large since there is no cancellation of errors.

The performance of the classification algorithm when $D$=3 becomes poor. The maximum location error is about 140m if all BSs are used to locate the MS. If the classification algorithm is considered for the same case (i.e. $D$=3), the location error could reach 600m. The performance becomes even worse by using classification with $D$=2 or less.

This poor performance of the classification algorithm, when $D$ is small, unveils the power and weakness of the classification technique. The sources of errors can be summarized into three: limited use of information, wrong dimensionality and wrong identification, and correct dimensionality but wrong identification.

In the next section, a proposed algorithm that gets rid of the poor characteristics of the classification algorithm (when $D \le 3$) and maintains its advantage (when $D \ge 4$) is introduced.

Table 2. Confusion Matrix when $D$ =3

| Estimates | Average Error | Max Error | Number of NLOS BS included | | |
|---|---|---|---|---|---|
| | | | **1** | **2** | **3** |
| **331** | **67.5** | **438.0** | 208 / 331 | 123 / 331 | 0 / 331 |
| **359** | **218.4** | **653.2** | 178 / 359 | 181 / 359 | 0 / 359 |
| **310** | **9.5** | **30.1** | 0 / 310 | 0 / 310 | 0 / 310 |

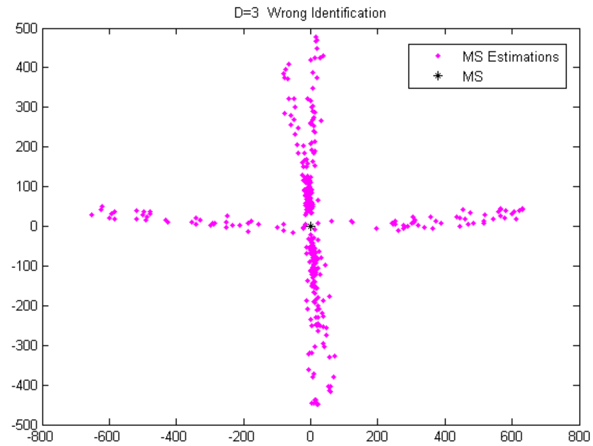


Figure 6. Classification Performance when $D$=3 (*estimated as D=3 and* wrong identification)

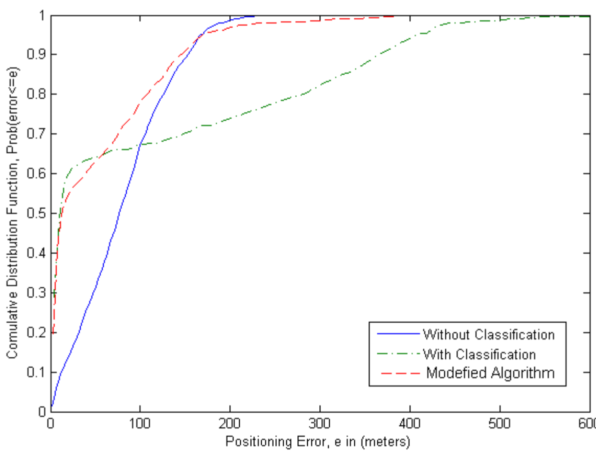


Figure 7. CDF plots of the average radiolocation error

## VII. The Proposed Positioning Algorithm for Better NLOS Mitigation

The previous simulation results confirm that "strict" classification is not always the best choice for MS localization. It performs poorly in the cases of $D \leq 3$, and its degradation becomes worse as the magnitude of the NLOS error increases in high NLOS environments. In contrast, for cases where $D \geq 4$, using classification always gives almost the optimum performance in all considered NLOS environments. In other words, one can depend on the classification only when it estimates the LOS dimension as $D \geq 4$. Note that depending on the specific network layout, classification performs well if there is a minimum required number of LOS BSs properly distributed for reliable MS position estimation.

For the examined network layout, the modified algorithm utilizes classification when the LOS dimension is $D \geq 4$, but when $D \leq 3$ it includes all the BSs in the localization process in order to benefit from the inherent error cancellation when there are co-linear NLOS BSs.

Simulations are performed to assess the improvement of location accuracy achieved using the modified algorithm. The modified algorithm is examined and compared with the classification-based and non-classification approaches. The number of NLOS BSs and their position are randomly chosen between 0 and 7. The CDF plots are shown in Figure 7.

Similar to the classification algorithm, when there are enough LOS BSs, the modified algorithm has a high likelihood of getting small location error. Moreover, when the performance of the classification algorithm starts to degrade by getting very large location error values, the modified algorithm takes advantage of error cancellation by including all BSs in the localization process, which limits the location error as shown in the CDF plots.

Another way of looking at this performance improvement using the modified algorithm is shown in Figure 8. In this figure, the effect of varying the number of the NLOS BSs on the average location error using the modified algorithm is shown and compared to the cases with and without full classification.

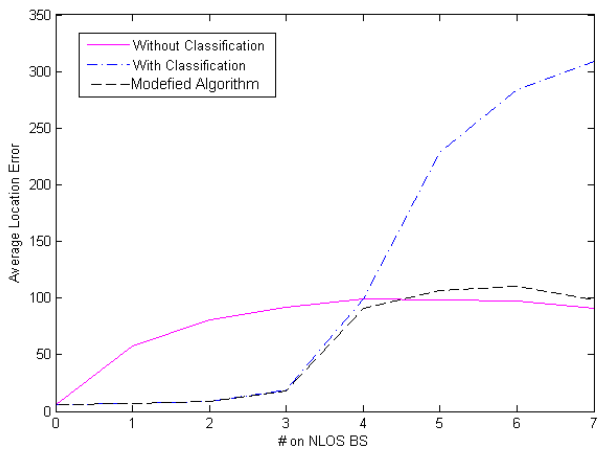


Figure 8. Illustration of the improved performance of the modified algorithm which tracks the best of both approaches, with and without NLOS BS classification.

## VIII. Conclusion

The localization of an MS can have significant errors when NLOS measurements are present. The impact of the relative position of the BSs on the localization geometry was carefully studied. Classification algorithm based on residual testing was used to mitigate the effect of the NLOS error. The RT determines the LOS dimension and simultaneously identifies the LOS BS. The performance of the classification algorithm has been examined when $D\leq3$ and proved that in this situation, using classification will destroy the accuracy of localization.

A modified classification algorithm was proposed and implemented. The main characteristic of the proposed algorithm is the selection between the classification algorithm and the un-classified one. If the estimated LOS dimension is $D\geq4$, classification is used and if the estimated dimension is $D=3$, all BSs will be used in the localization process. This modification limits any potential error due to the use of a small number of BSs, and at the same time gains the advantage of canceling the error of co-linear BSs. Simulations showed that this modification improves the localization performance dramatically.

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## References

[1] J. J. Caffery and G. L. Stuber. "Overview of radiolocation in CDMA cellular systems" *IEEE Communications Magazine*, vol. 36, no. 4, pp. 38–45, April 1998.

[2] Caffrey, James J.*'Wireless Location in CDMA Cellular Radio Systems'* Springer, 1999

[3] M. Silventoinen and T. Rantalainen, “Mobile Station Emergency Locating in GSM,” *Proc. IEEE Int’l. Conf. Pers. Wireless Commun*., 1996, pp. 232–38.

[4] M. P. Wylie and J. Holtzman, “The non-line-of-sight problem in mobile location estimation,” in *Proc. IEEE Int. Conf. Universal Personal Communications*, vol. 2, 1996.

[5] J. Riba and A. Urruela, “A non-line-of-sight mitigation technique based on ML-detection,” in *Proc. IEEE Int. Conf. Acoustics, Speech, and Signal Processing* ICASSP-04, vol. 2,Montreal, QC,Canada, May 2004, pp.153– 156.

[6] J. Borras, P. Hatrack, and N. B. Mandayam, “Decision theoretic framework for NLOS identification*,” in Proc. IEEE Vehicular Technology Conf.*, 1998.

[7] Y. T. Chan, C. H. Yau, and P. C. Ching "Time-of-Arrival Based Localization under NLOS Conditions" *IEEE Trans. Veh*, vol.55, no.1, 2006, pp.17- 24

[8] Y. T. Chan, C. H. Yau, and P. C. Ching, “Exact and approximate maximum likelihood localization algorithms,” *IEEE Trans. Veh. Technol,* vol. 55, no1, JAN 2006.

[9] Y. T. Chan and K. C. Ho, “A simple and efficient estimator for hyperbolic location*,” IEEE Trans. Signal. Process.*, vol. 42, no. 8, pp. 1905–1915, Aug. 1994.

[10] S. Al-Jazzar, J. Caffery Jr., and H.-R. You, “Scattering-model-based methods for TOA location in NLOS environments,” *IEEE Transactions on Vehicular Technology*, vol. 56, no. 2, pp. 583–593, 2007