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Combined AOA and TOA NLOS Localization With Nonlinear Programming in Severe Multipath Environments

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Abstract—**In this paper, a novel nonlinear programming (NLP) approach for non-line-of-sight (NLOS) localization in severe multipath environments is proposed. It leverages on the bidirectional estimation of the Angle of Arrival (AOA) and the Time of Arrival (TOA) of signals between the mobile station (MS) and the reference stations (RSs), and has the ability to work with just two paths. Basic Approach (BA) and Extended Approach (EA) are addressed, and the latter employs a simple method to identify one-bound path with high probability. Simulation results illustrate that the proposed algorithm can improve the localization accuracy greatly, especially when only few one-bound scattering paths exist.**

Keywords-localization; multipath; non-line-of-sight (NLOS); nonlinear programming (NLP)

I. INTRODUCTION

Accurate location finding techniques and location-based applications have received considerable attention over the past few years. Undoubtedly, the Global Positioning System (GPS) is the most well-known location service in use today, which can provide high precision and real-time location information; however, it is not applicable for dense urban area and indoor environment, since the signals from the satellites will very likely be greatly attenuated by various blockages. Therefore, extensive research has been done on GPS-less localization algorithms.

Various positioning algorithms have been proposed that utilize various measured information such as Time of Arrival (TOA) [1], Time Difference of Arrival (TDOA) [2], [3], Angle of Arrival (AOA) [4], Received Signal Strength (RSS), etc., in various combinations [5]. These algorithms assume the existence of the line-of-sight (LOS) paths. Unfortunately, in most terrestrial wireless signal propagation environments, particularly indoors or in urban scenario, LOS paths do not always exist between the reference nodes and the mobile node, which adversely degrades the accuracy of the conventional localization algorithms.

In the presence of the non-line-of-sight (NLOS) paths, the major positioning errors result from the measurement noise and the NLOS propagation error, which is the dominant factor [6]. Recent literature also explore the NLOS problem in positioning [7]-[13]. Broadly speaking, these algorithms fall into two categories: NLOS identification [7], [8], and NLOS mitigation [9]-[13]. NLOS identification refers to the distinguishing between LOS and NLOS range information. In [8], a residual weighting algorithm is proposed to identify the Base Station (BS) which suffers from NLOS propagation, based on the weighted residuals for all possible BS combinations. NLOS mitigation tries to alleviate the adverse impact of NLOS range errors on the accuracy of location estimates. In [9], the Kalman filtering technique is used in mobile location tracking and mobile velocity estimation for a moving mobile station. [10] attempts to reconstruct LOS TOA measurements from a series of LOS and NLOS measurements made over time and assumes knowledge of the NLOS standard deviation for identifying NLOS BSs; however, it requires occasional LOS paths and is not effective when signal propagation is only through the NLOS path. A low-complexity linear-programming method is used in [11], which requires the identification between LOS and NLOS paths. In [12], a method that takes advantage of one-bound (signals are only reflected once) scattering NLOS signals is proposed. This method utilizes the bidirectional TOA and AOA data from both the reference and mobile nodes, and exhibits good performance when only one-bound NLOS paths are present. The presence of multiple-bound paths (signals are reflected more than once) in severe multipath environments, however, will seriously impair the accuracy if the multiple-bound paths are mistakenly used. [13] suggests a multipath selection scheme to discard multiple-bound paths before a similar method as described in [12] is applied.

In this paper, we propose a new nonlinear programming (NLP) localization algorithm for the severe multipath environment with the presence of multiple-bound paths. The algorithm has the ability to work with just two paths. Simulation results reveal that the proposed algorithm outperforms what we referred to as the Original Least Square approach (OLS, described in section III.B) in positioning accuracy, particularly when only one or two one-bound paths are available. The rest of the paper is organized as follows. Section II introduces the system model. Section III describes the proposed NLOS localization schemes -- Basic Approach

(BA) and Extended Approach (EA), for the severe multipath environment. Numerical results are presented in section IV, and the conclusion is drawn in section V.

II. System Model

The system model considered in this paper is shown in Fig. 1. When the Mobile Station (MS) wants to localize itself, it transmits signals to the surrounding Reference Stations (RSs). As shown in Fig. 1, in a severe multipath environment, there are clusters of LOS and NLOS signal paths (both one-bound and multiple-bound) surrounding the RSs and the MSs. Sometimes even no LOS paths exist. Each propagation path is characterized by three parameters: angle of departure (AOD) from the MS, Angle-of-Arrival (AOA) to the RS, both referenced to the east, and the distance of the propagation path. We assume that the parameters are obtainable at either the RS or the MS, and sent to an Information Processing Center (IPC) which will execute the localization algorithm.

Development of new technologies such as Multiple-Input Multiple-Output (MIMO) system and directional antenna in recent years makes AOA and AOD measurements possible at the RS and the MS. For example, AOA can be estimated by applying the multiple signal classification (MUSIC) method [14] or via rotational invariance techniques [15] using an antenna array. AOD can be obtained by the space-alternating-generalized-expectation-maximization algorithm when both the RS and the MS are equipped with multiple antennas, or by design of the signal transmission manner when the MS is equipped with directional antenna [12]. The distance of the path can be estimated by measuring TOA, TDOA or RSS. In this paper, we choose TOA [16] for distance measurement; precise synchronization among all the MSs and RSs in the system is required.

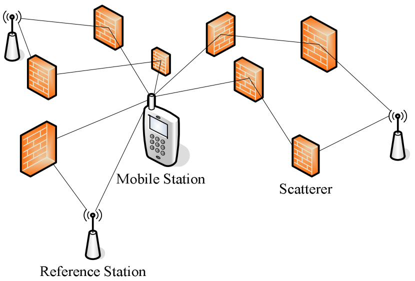

Fig. 1. System model in the severe multipath environment

III. Proposed Localization Algorithm

A. Notations

We assume there are altogether M RSs that can receive the transmitted signal from the MS to be localized. Notations used in this paper are defined below:

(x_i, y_i): the known position of the ith RS.

(x, y): the unknown position of the MS.

t_{ij} : TOA of the jth signal path of the ith RS.

α_{ij} : AOD of the jth signal path of the ith RS.

β_{ij} : AOA of the jth signal path of the ith RS.

N_i : total number of the signal paths for the ith RS.

c : speed of the light.

B. Basic Approach (BA)

Consider the case where there are only one-bound paths and LOS paths. The possible region of the MS can be determined as described in [12]. As shown in Fig. 2, the three measured parameters of the jth path between the ith RS and the MS are known, i.e., AOD α_{ij}, AOA β_{ij} and TOA t_{ij}, where i = 1,2,…,M, and j = 1,2,…N_i. The actual location of the jth path scatterer for the ith RS lies along the line that is initiated from RS_i with an angle β_{ij}. Together with the information of α_{ij} and t_{ij}, we can derive the possible regions for the scatterer and the MS respectively. One possible solution is depicted in Fig. 2, denoted as SC' and MS'. The distance between the RS_i and the *SC*' plus that between the *SC*' and the *MS*' equals the measured TOA times the speed of the light, i.e., ct_{ij}. As a result, it can be shown that the possible position of the MS lies on the piecewise line AB. The exact location can then be determined by intersecting two such lines that are not parallel to each other using two paths. For an over-determined case, e.g., M RSs with N paths each for a given MS, the location can be estimated by using the Least Square (LS) approach with MN piecewise lines, which we will refer to as the Original LS (OLS) approach in the rest of this paper.

It should be noted that there might be no LOS and one-

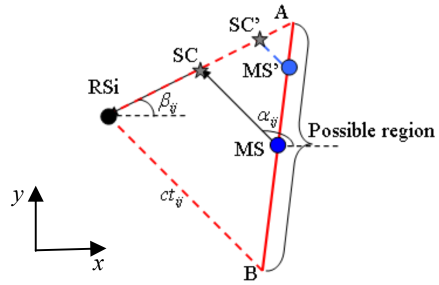

Fig. 2. Possible region of the MS using TOA and AOA

bound scattering paths for some RSs, especially in severe multipath environment. In this case, multiple-bound paths will be mistaken for LOS paths or one-bound paths, causing erroneous location estimation under the OLS approach. To alleviate this problem, we propose a two-step NLOS localization algorithm based on the OLS approach: 1) Use the measured information α, β and t of the detected paths to find the possible region of the MS. (2) Minimize the sum of the squares of the residual-error with TOA constraints. The details are elaborated below.

Step 1: In this step, we first assume that none of the perceived paths are multiple-bound so that we can derive the mathematical representation of the possible regions for all the paths. With reference to Fig. 2, the coordinates of the two endpoints A and B can be expressed as:

$$x_A = x_i + ct_{ij} \cos \beta_{ij} \tag{1}$$

$$y_A = x_i + ct_{ij} \sin \beta_{ij} \tag{2}$$

$$x_B = x_i - ct_{ij} \cos \alpha_{ij} \tag{3}$$

$$y_B = x_i - ct_{ij} \sin \alpha_{ij} \tag{4}$$

Using (1)-(4), the equation for the line AB can be written as

$$a_{ij} x + b_{ij} y = c_{ij} \tag{5}$$

where

$$a_{ij} = \sin \beta_{ij} + \sin \alpha_{ij},$$
$$b_{ij} = -(\cos \beta_{ij} + \cos \alpha_{ij}),$$
$$c_{ij} = x_i (\sin \beta_{ij} + \sin \alpha_{ij}) - y_i (\cos \beta_{ij} + \cos \alpha_{ij}) + ct_{ij} (\sin \alpha_{ij} \cos \beta_{ij} - \cos \alpha_{ij} \sin \beta_{ij}).$$

For M RSs, each with N_i multipaths (i=1,2,…M) (assuming N multipaths in total), we can rewrite (5) in the matrix form as

$$\mathbf{AZ} = \mathbf{C} \tag{6}$$

where

$$\mathbf{Z} = [x \quad y]^T \tag{7}$$

$$\mathbf{A} = \begin{bmatrix} \sin \beta_{11} + \sin \alpha_{11} & -(\cos \beta_{11} + \cos \alpha_{11}) \\ \vdots & \vdots \\ \sin \beta_{MN_N} + \sin \alpha_{MN_N} & -(\cos \beta_{MN_N} + \cos \alpha_{MN_N}) \end{bmatrix}_{N \times 2} \tag{8}$$

$$\mathbf{C} = \begin{bmatrix} x_1 (\sin \beta_{11} + \sin \alpha_{11}) - y_1 (\cos \beta_{11} + \cos \alpha_{11}) \\ + ct_{11} (\sin \alpha_{11} \cos \beta_{11} - \cos \alpha_{11} \sin \beta_{11}) \\ \vdots \\ x_M (\sin \beta_{MN_M} + \sin \alpha_{MN_M}) - y_M (\cos \beta_{MN_M} + \cos \alpha_{MN_M}) \\ + ct_{MN_M} (\sin \alpha_{MN_M} \cos \beta_{MN_M} - \cos \alpha_{MN_M} \sin \beta_{MN_M}) \end{bmatrix}_{N \times 1} \tag{9}$$

In the presence of measurement errors and multiple-bound paths, equation (5) will not hold in general, and solving these equations simultaneously may not yield a unique solution. Resorting to the error-minimization approach, we define the residual error for every potential solution $\mathbf{Z}$ as

$$\varepsilon_{ij} = c_{ij} - a_{ij} x - b_{ij} y, \quad i = 1,2,...,M, j = 1,2,...,N_i \tag{10}$$

Express these in a matrix form, we have

$$\mathbf{AZ} + \mathbf{E} = \mathbf{C} \tag{11}$$

where

$$\mathbf{E} = [\varepsilon_{11} \quad \cdots \quad \varepsilon_{MN_M}]^T_{1 \times N} \tag{12}$$

and the matrices **Z**, **A**, **C** are defined in (7)-(9), respectively.

Step 2: In this step, we apply the optimization problem formulation to estimate the position.

As mentioned in [11], the NLOS error is always positive and assumed to be much larger than the range-measurement noise. Therefore, the true range is always overestimated with high probability. This observation is also valid under LOS in UWB system using P/FS sequence [16], [17]. Note that we can perform NLOS identification first using various methods if the statement does not hold. Specifically, the MS will always lie within each circle with radius ct_{ij} centered at RS_i.

$$(x - x_i)^2 + (y - y_i)^2 \le (ct_{ij})^2 \quad i = 1,2,...,M, j = 1,2,...,N_i \tag{13}$$

These inequalities can serve as constraints for the optimization problem, or as the feasible region for the variables **Z**. According to [18], relaxing the nonlinear constraints on **Z** will yield linear constraints as shown below:

$$\begin{aligned} x \le ct_{ij} + x_i, &\quad -x \le ct_{ij} - x_i \\ y \le ct_{ij} + y_i, &\quad -y \le ct_{ij} - y_i \end{aligned} \tag{14}$$

Equation (14) defines a rectangular constraint region which encloses and replaces the original circular constraint region of (13). Rewrite (14) in matrix form, we have

$$\mathbf{u}_{ij} \mathbf{Z} \le \mathbf{B}_{ij} \quad i = 1,2,...,M, j = 1,2,...,N_i \tag{15}$$

where

$$\mathbf{u}_{ij} = \begin{bmatrix} 1 & 0 \\ -1 & 0 \\ 0 & 1 \\ 0 & -1 \end{bmatrix}, \quad \mathbf{B}_{ij} = \begin{bmatrix} ct_{ij} + x_i \\ ct_{ij} - x_i \\ ct_{ij} + y_i \\ ct_{ij} - y_i \end{bmatrix} \tag{16}$$

Based on the above equations and inequalities, we can derive the optimization problem. Define the vector of variables as $\boldsymbol{\theta} = [\mathbf{Z}^T \quad \mathbf{E}^T]^T_{2+N}$, where **Z** and **E** are defined in (7) and (12) respectively. The complete NLP problem can be formulated as

$$\min_{\boldsymbol{\theta}} \quad \|\mathbf{E}\|^2$$

Subject to

$$[\mathbf{A} \quad \mathbf{I}]\boldsymbol{\theta} = \mathbf{C}$$

$$[\mathbf{D} \quad \mathbf{0}]\boldsymbol{\theta} \le \mathbf{S}$$

where

I is an identity matrix with dimension $N \times N$,
A and **C** are defined in (8), (9), respectively,
0 is an all zero matrix with dimension $4N \times N$,

$$\mathbf{D} = [\mathbf{u}_{11}^T \quad \cdots \quad \mathbf{u}_{MN_M}^T]^T, \tag{17}$$

$$\mathbf{S} = [\mathbf{B}_{11}^T \quad \cdots \quad \mathbf{B}_{MN_M}^T]^T. \tag{18}$$

The above approach works as long as no fewer than two paths with measured parameters are available. It should be noted that the performance of the BA is much better than that of OLS in the severe multipath environment, i.e., there are only a couple of or none one-bound paths. Furthermore, BA can be implemented efficiently using the interior-point method at the IPC.

C. *Extended Approach (EA)*

The performance of BA can be further improved if we are able to identify the multiple-bound paths correctly at the beginning. In this section, we introduce the proposed EA in detail.

Based on the observation that the MS will always lie within each circle with radius ct_{ij} centered at RS_i, it is possible to discard the paths that are likely to be multiple-bound, and then perform BA with the remaining paths. The approach consists of three steps as follows

1) From N equations in (6), pick any two of them to get a solution. Altogether, we can obtain $\binom{N}{2}$ solutions.

2) Check if the solution $[x' \quad y']$ is within the possible region. If $(x'-x_i)^2+(y'-y_i)^2 \le (ct_{ij})^2$, for i = 1,2,…,M, j = 1,2,…N_i, then record the two paths involved in yielding this solution. Repeat this step until all the solutions have been checked.

3) (i) If the recorded set of possible one-bound paths is nonempty , then use this set to estimate the position using the NLP formulation as specified in BA. It is important to note that the recorded set will be nonempty only when more than one one-bound path is attainable.

(ii) If the recorded set of possible one-bound paths is empty, then use BA to infer the possible solution, and also mark the result as less reliable.

IV. NUMERICAL RESULTS

Simulations are conducted to evaluate the performance of the proposed localization algorithms. This section presents simulation results which demonstrate that our schemes are quite effective in improving the positioning accuracy compared with the OLS approach.

A. *Simulation Configurations*

One MS and four RSs are employed in the simulation. Their distribution and the NLOS propagation paths involved are shown in Fig. 3. The model is similar to the one used in [12]. The positions of the MS, RSs and Scatterers are given in Table I. Note that there is only one one-bound path and one multiple-bound path between the MS and each RS. Furthermore, no LOS paths exist.

The NLOS range estimates are assumed to be positively biased Gaussian estimates [11], [19] of the true distances

$$ct_{ij} = \|\mathbf{Z}-\mathbf{Z}_i\| + b_{ij} + n_{ij}, \qquad i = 1,2,\ldots,M,\; j = 1,2,\ldots,N_i$$

where b_{ij} is the NLOS bias error and n_{ij} is the absolute value of the independently Gaussian distributed random variable $N(0,\sigma^2_{d_{i,j}})$ (n_{ij} is always positive [16], [17]). AOD and AOA estimates are also assumed to be independently Gaussian distributed random variables [12], i.e., $\alpha_{ij} \sim N(\alpha^{o}_{ij},\sigma^2_{\alpha_{i,j}})$ and $\beta_{ij} \sim N(\beta^{o}_{ij},\sigma^2_{\beta_{i,j}})$, where α^{o}_{ij} and β^{o}_{ij} denote the actual AODs and AOAs of the paths of interest. We assume that the parameters associated with different propagation paths have the same estimation error variance, i.e., $\sigma^2_{d_{i,j}} = \sigma^2_d$, $\sigma^2_{\alpha_{i,j}} = \sigma^2_\alpha$ and $\sigma^2_{\beta_{i,j}} = \sigma^2_\beta$, for i = 1,2,…,M, j = 1,2,…N_i. Unless otherwise stated, we assume $\sigma_d = 5m$ and $\sigma_\alpha = \sigma_\beta = 2^{o}$ [12].

TABLE I. COORDINATES OF THE MS, RS AND SCATTERERS (IN METERS)

MS	RS	Scatter for one-bound path	Scatter for multiple-bound path
(20,10)	(50,0)	(27,-10)	(30,30) (38,-10)
	(0,50)	(20,45)	(-10,32) (10,41)
	(-50,0)	(-30,-15)	(-10,18) (-31,-5)
	(0,-50)	(-28,-34)	(15,-24) (-20,-29)

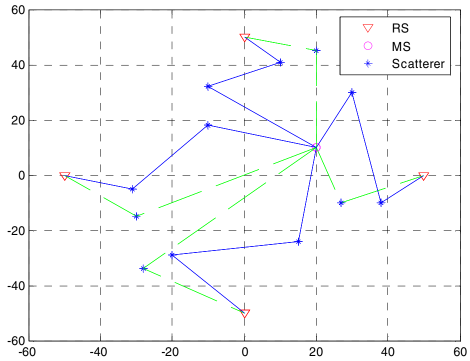

Fig. 3. Simulation Scenario

We assume that we have knowledge of at least two paths for the simulations. A scenario specifies a given number of one-bound paths and a given number of multiple-bound paths. Different choices of paths in a scenario will lead to different performances. Therefore, for each scenario, 1000 independent runs are executed where in each run, the given numbers of paths are randomly chosen from the four one-bound and four multiple-bound paths specified. Results are averaged over the 1,000 runs.

B. *Simulation Results*

For the performance criteria of the proposed schemes, we use the Mean Localization Error (MLE), defined as:

$$\text{MLE} = \frac{1}{M}\sum_{i=1}^{M}\sqrt{(x_i'-x^{o})^2+(y_i'-y^{o})^2}$$

where (x^{o}, y^{o}) is the true position of the MS, (x_i', y_i') is the estimated location, and M is the number of running times for one scenario.

We first compare the performance of the three algorithms, i.e., OLS, BA, and EA, for different combinations of paths. Fig. 4 – Fig. 8 depict the MLE of the three algorithms given different combinations of the number of one-bound and multiple-bound paths. The results illustrate the effectiveness of the proposed schemes in improving the positioning accuracy, especially when only few one-bound paths are available. BA increases the accuracy by about 33.7% to 48.6% compared to OLS while there is none or only one one-bound path available; e.g., in the case when only four multiple-bound paths are detected, MLE of BA is 50.9m, while that of OLS is 99.1m. This is because BA constrains the solution in the feasible region. When more one-bound NLOS paths are employed, the improvement of BA in localization accuracy is not that significant. The performances of the two approaches are

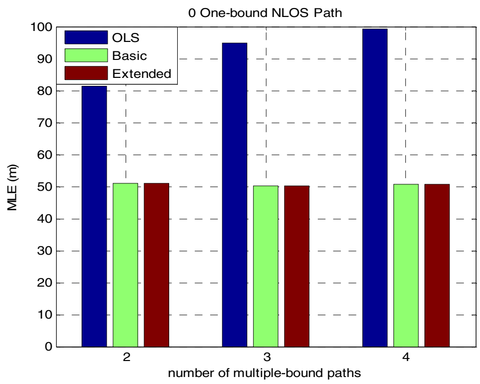

Fig. 4. MLE versus number of multiple-bound paths when no one-bound NLOS paths are available. ($\sigma_d = 5m$ and $\sigma_\alpha = \sigma_\beta = 2^\circ$)

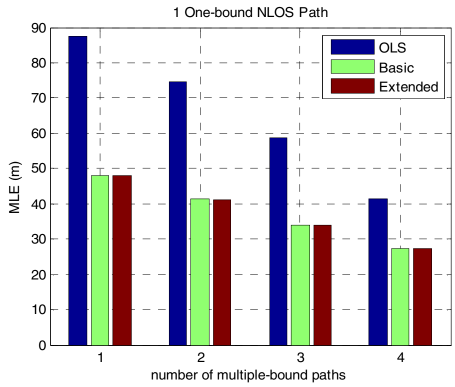

Fig. 5. MLE versus number of multiple-bound paths when only one one-bound NLOS path is available. ($\sigma_d = 5m$ and $\sigma_\alpha = \sigma_\beta = 2^\circ$)

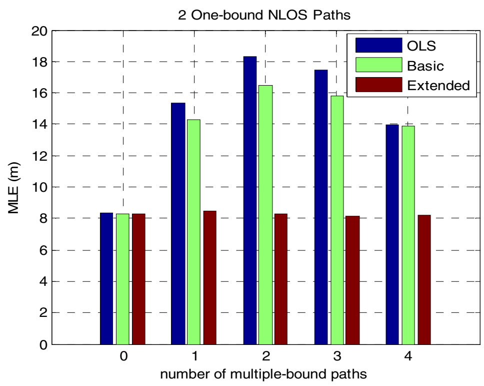

Fig. 6. MLE versus number of multiple-bound paths when two one-bound NLOS paths are available. ($\sigma_d = 5m$ and $\sigma_\alpha = \sigma_\beta = 2^\circ$)

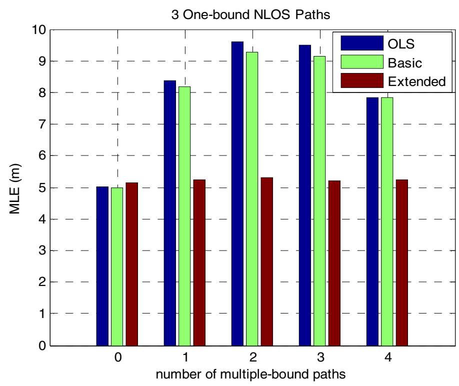

Fig. 7. MLE versus number of multiple-bound paths when three one-bound NLOS paths are available. ($\sigma_d = 5m$ and $\sigma_\alpha = \sigma_\beta = 2^\circ$)

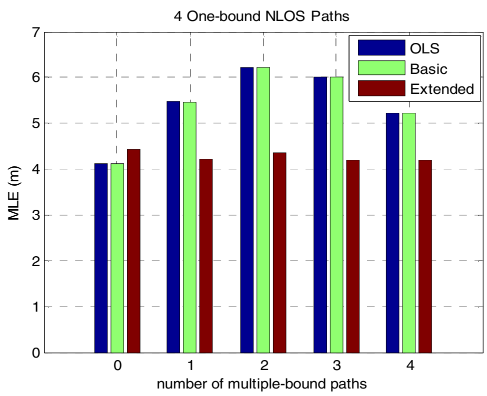

Fig. 8. MLE versus number of multiple-bound paths when four one-bound NLOS paths are available. ($\sigma_d = 5m$ and $\sigma_\alpha = \sigma_\beta = 2^\circ$)

exactly the same in some cases, but BA will never perform worse than OLS. Considering results for EA, one sees that its performance is identical to BA when no more than one one-bound path is available, because the record set is empty and EA is just the same as BA in this case. When more one-bound paths are involved, EA further decreases the MLE greatly except the case when no multiple-bound paths exist. For example, in the case of two one-bound and two multiple-bound paths, EA decreases the MLE from 18.3m (OLS) and 16.5m (BA) to 8.3m. It also shows that the performance of EA is more stable than the other two with the same number of one-bound paths. We have investigated the problem why the MLE of EA is slightly higher than the others when no multiple-bound paths exist. Results show that in this scenario, EA performs similarly or slightly better than the other two most of the time. However, the simple identifying method in EA sometimes mistakenly discards one-bound paths with a probability of about 3.7% for three one-bound paths and 5.2% for four one-bound paths, respectively, resulting in lost information and higher MLE compared with the other two. In addition, it is observed that the accuracy of EA increases consistently when more one-bound paths are involved in the position calculation.

We then examine the effects of the standard deviations of estimated parameters, i.e., σ_d, σ_α and σ_β, on the accuracy of the positioning algorithms. We only present some cases here because of the space limitation; however, it should be noted that other cases show similar results. Fig. 9 depicts the effects of σ_α and σ_β on the positioning accuracy when altogether six NLOS paths are employed. Different combinations yield similar curves. That is, MLE of all the three methods increase as σ_α and σ_β get larger. It is also easy to see that, most of the time, EA has the highest accuracy, followed by BA and then OLS. Fig. 10 shows the effect of σ_d on the accuracy when four NLOS paths are employed. As σ_d gets larger, MLE gets higher. And the proposed schemes outperform OLS as expected. Note that the schemes perform likely in some cases.

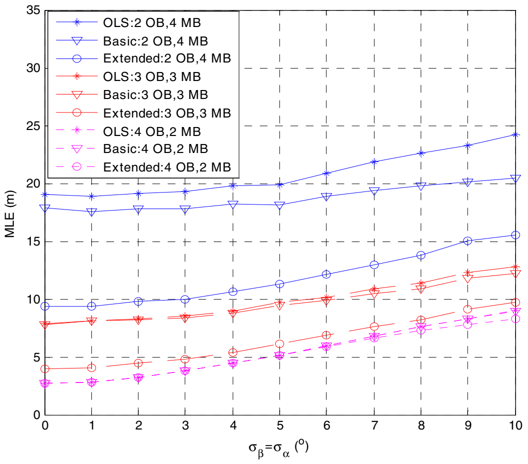

Fig. 9. MLE versus standard deviation of AOD and AOA when six paths are detected. (OB: one-bound path; MB: multiple-bound path. $\sigma_d = 5m$.)

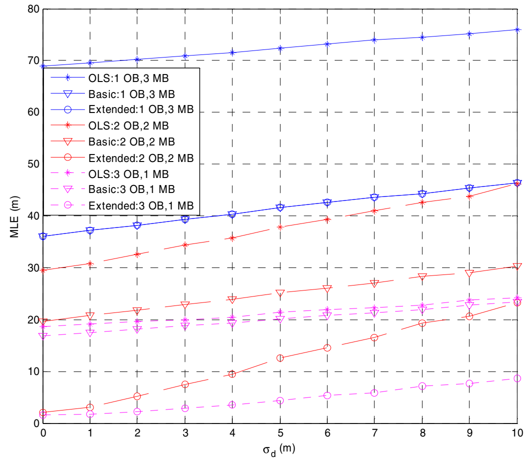

Fig. 10. MLE versus standard deviation of TOA when four paths are detected. (OB: one-bound path; MB: multiple-bound path. $\sigma_\alpha = \sigma_\beta = 2°$.)

V. CONCLUSION

In this paper, a novel NLP scheme for NLOS localization in severe multipath environment is proposed. The scheme has the ability to work with just two paths. BA utilizes the bidirectional TOA and AOA data, and takes the TOA measurements as the optimization constraints. EA first employs a simple method to identify one-bound paths with high probability, and then solves the NLP problem as in BA. Numerical results show that BA performs comparably with OLS when sufficient one-bound paths (i.e., no less than two) are available, but outperforms OLS significantly when only one or two one-bound paths exist. EA further improves the localization accuracy, and performs consistently with the existence of the same number of one-bound paths. Occasionally, however, MLE of EA is slightly higher than OLS and BA as described in Section IV.B. This problem can be addressed in future work.

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