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A Weighting Localization Algorithm with LOS and One-Bound NLOS Identification in Multipath Environments

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Mobile station (MS) localization often suffers from hybrid line of sight (LOS), one-bound (OB) and multiple-bound (MB) non-line of sight (NLOS) propagation in multipath environments. Due to the unknown propagation path, accurate position estimate of MS is challenging through using the measured angle of departure (AOD), angle of arrival (AOA), and time of arrival (TOA) of signal between MS and base station (BS). To address this problem, a new weighting localization algorithm based on LOS and OB NLOS identification is proposed in this paper. For each propagation path, by utilizing the geometric relation between AOD and AOA, a theoretic threshold is derived to decide whether it is LOS or NLOS propagation. Moreover, in order to further discriminate OB or MB NLOS propagation, an effective cost function is formulated and an iterative OB NLOS identification method is proposed to discard MB NLOS propagation paths. Finally, a weighting localization algorithm is applied for fusing the measured data of LOS and OB NLOS propagation paths. Simulation results demonstrate that simulation of LOS identification method is consistent with theoretic one, and the proposed algorithm can greatly improve the localization accuracy of MS in different multipath environments, especially when LOS path is available.

Keywords: localization, LOS, OB, MB, weighting

1. INTRODUCTION

Location-based services and applications required an accurate position estimate of mobile station (MS) play a fundamental role in current and future wireless communications systems. Cell planning of wireless cellular networks, emergency road assistance, and location-based advertisement are some examples of location-based services and applications [1]. There are several fundamental approaches to implement the position estimate of MS in a cellular network, including those based on received signal strength [2], angle of arrival (AOA) [3], time of arrival (TOA) [4], and time difference of arrival (TDOA) [5]. Recently, with the advent of 5G cellular network, Multiple Input Multiple Output (MIMO) technology is indispensable. Thus, if both MS and base station (BS) are equipped with antenna array, three important measured parameters, such as angle of departure (AOD), angle of arrival (AOA), and time of arrival (TOA) of the propagation path, can be estimated with advanced array signal processing in multipath environments. Some researchers have done research on how to estimate the parameters of AOD, AOA and TOA, the interest reader can read the literature in [6-8]. To limit the scope of this

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work, we do not consider it.

Non-line of sight (NLOS) propagation of signal between MS and BS is a major problem to affect the localization accuracy of MS, where the absence of a direct line of sight (LOS) path between MS and BS results in biased measurements. Further, it can be divided into one bound (OB) or multiple bound (MB) NLOS propagation. By assuming prior knowledge about AOD, AOA and TOA measurements of each path, the work in [9] takes advantage of OB NLOS propagation path and proposes the least square (LS) localization algorithm in multipath environments. Based on a ring of scatterers NLOS propagation model, a single MIMO BS localization algorithm with the virtual BS is proposed in [10]. In [11], with the assumption of OB NLOS propagation paths, Doppler-shift (DS) measurement is introduced and an online Bayesian recursive localization algorithm with TOA/AOD/DS measurements is proposed. The work in [12] proposes an iterative TDOA/AOD/AOA-based OB NLOS localization algorithm with a first order Taylor series. In [13], it presents virtual reference device-based OB NLOS localization algorithm in multipath environments and only requires one signal path. By estimating the position of scatterer, the work in [14] proposes two-step elliptical Lagrange constrained optimization method with the OB NLOS scattering paths. Based on the circular scattering NLOS propagation model, a nonlinear constrained optimization localization approach with the position of scatterer is formulated in [15]. However, all these works assume only OB NLOS propagation paths are available, and do not consider the presence of LOS and MB NLOS propagation paths. The theoretical bound for MIMO localization using TOA/AOA/AOD measurements is derived in [16], and it is proved that multipath effect can be mitigated by the spatiotemporal separation. In order to jointly estimate position and rotation angle of MS in MIMO system, a novel two-stage algorithm consisted of coarse estimation stage and refinement stage is proposed in [17]. By utilizing TOA/AOD/AOA measurements from multiple BSs, a gradient-assisted particle filter method is proposed in [18] to accurately estimate the position of MS as well as the position of scatterers. However, LOS and OB NLOS paths are assumed and MB NLOS paths are not considered. Comparing with LOS and OB NLOS paths, MB NLOS paths experience excess distance and lead to incorrect linear equation derived from TOA/AOD/AOA measurements due to the increased number of scatterers. As a result, MB NLOS paths can cause erroneous position estimate if they are mistakenly treated as LOS or OB NLOS paths. In [19], a multipath selection scheme called statistical proximity test (SPT) is proposed to discard MB NLOS paths before the least square (LS) algorithm in [9] is applied. In dense multipath environment, the work in [20] proposes a nonlinear programming (NLP) localization algorithm with the presence of MB NLOS paths. However, it doesn't consider the LOS propagation path.

In this paper, a new weighting localization algorithm based on LOS and OB NLOS identification is proposed when LOS, OB and MB NLOS paths are present. The main contribution of this paper are threefold: (1) by analyzing the geometric relation of AOD and AOA in LOS propagation, the close form of the probability of detection and the corresponding threshold about LOS identification is derived; (2) In order to reduce the effect of MB NLOS propagation paths, an iterative OB NLOS identification method is presented through building the linear relation between the position of MS and position of scatterer; (3) By formulating two cost functions, a new weighting localization algorithm based on residual weighting is proposed. Comparing it with the existing localization algorithms, simulation results demonstrate that the proposed algorithm outperforms the existing algorithms, particularly when LOS path is available.

2. SYSTEM MODEL

As shown in Fig. 1, only one BS is deployed in multipath environments, the signal propagation between BS and MS is LOS or NLOS, and NLOS propagation can be further divided into OB or MB scattering paths. Due to the development of MIMO system in 5G cellular network, we can obtain three parameters, such as AOD from the MS, AOA to the BS and the range of the propagation path from each propagation path, when both BS and MS are equipped with antenna array [17-20]. Thus, the mathematical expression of measured parameters with LOS path is

$$\left.\begin{aligned} r_i &= \sqrt{(x-x_1)^2+(y-y_1)^2}+n_i \\ &= d_i + n_i = c\cdot t_i \\ \alpha_i &= \alpha_i^0 + m_i = atan(\frac{y_1-y}{x_1-x})+m_i \\ \beta_i &= \beta_i^0 + v_i = atan(\frac{y-y_1}{x-x_1})+v_i \end{aligned}\right\} LOS, i=1,\cdots,L_{los} \tag{1}$$

where (x_1, y_1) is the position of home BS, (x, y) is the position of MS, c is the speed of light, t_i is the TOA of the ith propagation path, atan is the function of inverse tangent, α_i and α_i^0 are the measured and actual AOD of the ith propagation path, respectively. β_i and β_i^0 are the measured and actual AOA of the ith propagation path, respectively. L_{los} is the number of LOS propagation path, n_i, m_i and v_i are white Gaussian random variable with mean zero and the same standard deviation σ_n, σ_α, and σ_β, respectively.

If signal experiences OB scattering, the mathematical expression of it is described as

$$\left.\begin{aligned} r_i &= \sqrt{(x-x_i')^2+(y-y_i')^2}+\sqrt{(x_1-x_i')^2+(y_1-y_i')^2}+n_i \\ &= r_i^0 + n_i = c\cdot t_i \\ \alpha_i &= \alpha_i^0 + m_i = atan(\frac{y_i'-y}{x_i'-x})+m_i \\ \beta_i &= \beta_i^0 + v_i = atan(\frac{y_i'-y_1}{x_i'-x_1})+v_i \end{aligned}\right\} OB, i=1,\cdots,L_{ob} \tag{2}$$

where (x_i', y_i') is the position of scatterer from MS to home BS in ith OB scattering path, L_{ob} is the number of OB scattering paths. When signal experiences MB scattering path, as shown in Fig. 1, the number of scatterers is bigger than one, the measured parameters, such as AOD, AOA and TOA, will result in extra range and angle deviation.

As shown in Eqs. (1) and (2), the simple and direct method is to construct the nonlinear objective function about residual error, and then uses the numerical search methods, such as the steepest descent or the Gauss-Newton techniques to obtain the position estimate of MS. However, the numerical search methods cost computationally and require good initialization in order to avoid converging to local minimization of the residual error function. Moreover, the correct identification of LOS and OB NLOS paths is necessary, and it is difficult to identify LOS and OB NLOS paths when MB NLOS paths are present. Further, the positions of scatterer are unknown in Eq. (2), this will lead to higher computational complexity of numerical search methods. In order to deal with or avoid the above three problems, we can transform the nonlinear TOA/AOD/AOA measurements into linear form through using the geometric relation among them when signal experiences OB scattering path. For one OB NLOS propagation path, if we ignore the measured noise in Eq. (2), the position of A and B shown in Fig. 2 can be calculated as [20]

$$\begin{aligned} x_A &= x_1 + r_i^0 \cdot \cos(\beta_i^0) \quad x_B = x_1 + r_i^0 \cdot \cos(\alpha_i^0), \\ y_A &= y_1 + r_i^0 \cdot \sin(\beta_i^0) \quad y_B = y_1 + r_i^0 \cdot \sin(\alpha_i^0). \end{aligned} \tag{3}$$

Similarly, for another OB NLOS path, the position of C and D can be also obtained. As shown in Fig. 2, only two paths can decide the possible position of MS whose position is the intersection point of line AB and line CD. Thus, the true nonlinear measured parameters in Eq. (2) can be transformed into linear form [9, 19, 20]

$$\begin{aligned} &\left(\cos(\alpha_i^0) + \cos(\beta_i^0)\right) y - \left(\sin(\alpha_i^0) + \sin(\beta_i^0)\right) x = y_1 \left(\cos(\alpha_i^0) + \cos(\beta_i^0)\right) \\ &-x_1 \left(\sin(\alpha_i^0) + \sin(\beta_i^0)\right) - r_i^0 \sin(\alpha_i^0 - \beta_i^0), i = 1, \cdots, L_{ob}. \end{aligned} \tag{4}$$

Putting the measured parameters in Eqs. (2) into (4) and ignoring the measured noise, we can obtain the following approximate matrix form

$$Z = H \cdot X \tag{5}$$

where $X = [x, y]^T$

$$Z = \begin{bmatrix} y_1 \left(\cos(\alpha_1) + \cos(\beta_1)\right) - x_1 \left(\sin(\alpha_1) + \sin(\beta_1)\right) - r_1 \sin(\alpha_1 - \beta_1) \\ y_1 \left(\cos(\alpha_2) + \cos(\beta_2)\right) - x_1 \left(\sin(\alpha_2) + \sin(\beta_2)\right) - r_2 \sin(\alpha_2 - \beta_2) \\ \vdots \\ y_1 \left(\cos(\alpha_{L_{ob}}) + \cos(\beta_{L_{ob}})\right) - x_1 \left(\sin(\alpha_{L_{ob}}) + \sin(\beta_{L_{ob}})\right) - r_{L_{ob}} \sin(\alpha_{L_{ob}} - \beta_{L_{ob}}) \end{bmatrix}_{L_{ob} \times 1},$$

$$H = \begin{bmatrix} -\sin(\alpha_1) - \sin(\beta_1) & \cos(\alpha_1) + \cos(\beta_1) \\ -\sin(\alpha_2) - \sin(\beta_2) & \cos(\alpha_2) + \cos(\beta_2) \\ \vdots & \vdots \\ -\sin(\alpha_{L_{ob}}) - \sin(\beta_{L_{ob}}) & \cos(\alpha_{L_{ob}}) + \cos(\beta_{L_{ob}}) \end{bmatrix}_{L_{ob} \times 2}.$$

Then, we can obtain the position estimate of MS with LS algorithm

$$\hat{X} = (H^T H)^{-1} H^T Z. \tag{6}$$

Min-Max algorithm [21] is a simple and straightforward estimate, its main idea is to build a square region around BS and guarantee the position of MS is inside the square region. This square region can be drawn with the position of BS and the range measurements. Thus, we can introduce the idea of this method into our localization model. If we put the TOA/AOD/AOA measurements into Eq. (3), the position of A and B or C and D can be easily obtained. Then the square region AA′BB′ or CC′DD′ can be drawn as

$$[x_{low}^i, x_{upp}^i] \times [y_{low}^i, y_{upp}^i],\ i = 1, \ldots, L \tag{7}$$

where

$$x_{low}^i = \min\{x_1 + r_i \cdot \cos(\beta_i), x_1 - r_i \cdot \cos(\alpha_i)\},\ x_{upp}^i = \max\{x_1 + r_i \cdot \cos(\beta_i), x_1 - r_i \cdot \cos(\alpha_i)\},$$
$$y_{low}^i = \min\{y_1 + r_i \cdot \sin(\beta_i), y_1 - r_i \cdot \sin(\alpha_i)\},\ y_{upp}^i = \max\{y_1 + r_i \cdot \sin(\beta_i), y_1 - r_i \cdot \cos(\alpha_i)\}.$$

The intersections of L square regions as like as two square regions AA′BB′ and CC′DD′ shown in Fig. 2 are determined

$$[\max(x_{low}^i), \min(x_{upp}^i)] \times [\max(y_{low}^i), \min(y_{upp}^i)]. \tag{8}$$

The position estimate of MS is the center of the intersections of these squares

$$x = \frac{1}{2}(\max(x_{low}^i) + \min(x_{upp}^i), y = \frac{1}{2}[\max(y_{low}^i) + \min(y_{upp}^i)). \tag{9}$$

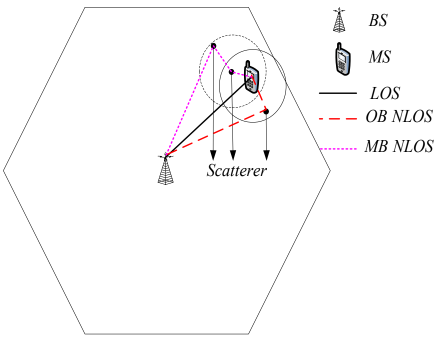

Fig. 1. System model in multipath environments.

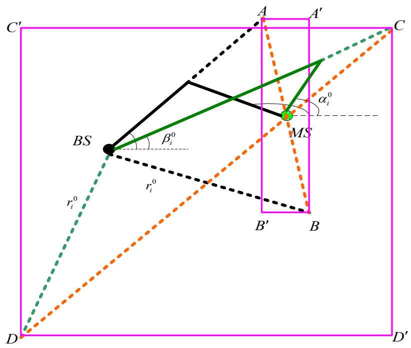

Fig. 2. Possible position of MS with two OB scattering paths.

3. PROPOSED LOCALIZATION ALGORITHMS

In multipath environments, signal may experience LOS, OB or MB NLOS propagation path. However, most of the previous analysis is based on OB scattering paths and it has two drawbacks. One is nonexistence of the inverse matrix of H in Eq. (5) when two paths are detected and one of them experiences LOS propagation, the other is that large localization error happens when MB scattering paths are available. Therefore, it’s a meaningful work to distinguish the detected path whether it is LOS, OB, or MB NLOS propagation. The flowchart of our idea is illustrated in Fig. 3. When L paths are detected with three measured TOA/AOD/AOA parameters, we firstly identify LOS and OB NLOS paths, then use residual weighed algorithm (Rwgh) to fuse the measured data of LOS and OB NLOS paths.

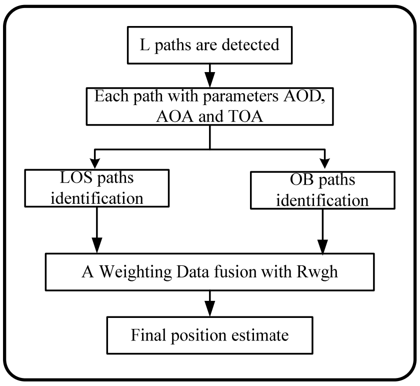

Fig. 3. The flow chart of the proposed algorithm.

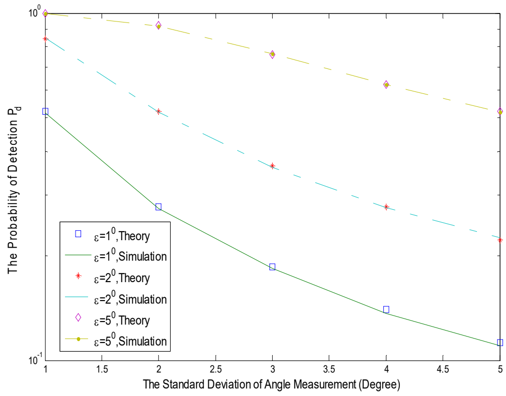

Fig. 4. Standard deviation of angle measurement VS the probability of detection.

3.1 LOS and OB NLOS Identification

(1) LOS Identification

If one path experiences LOS propagation, the actual AOD and AOA have an equal relation as $|\alpha_i^0 - \beta_i^0| = \pi$. Due to the measured noise of angle, we introduce a small positive number ε as a threshold to evaluate the performance of LOS identification. Then, each path with measured AOD and AOA is decided as LOS propagation when it satisfies the following condition

$$\pi - \varepsilon \le |\alpha_i - \beta_i| \le \pi + \varepsilon,\ i = 1, \ldots, L. \tag{10}$$

Putting Eq. (1) into Eq. (10), it is easy to know that Eq. (10) is always true when $-\varepsilon \le m_i - v_i \le \varepsilon$. Because the random variable $m_i - v_i$ is the Gaussian distribution with mean zero and variance $\sigma_\alpha^2 + \sigma_\beta^2$ written as $m_i - v_i \sim N(0, \sigma_\alpha^2 + \sigma_\beta^2)$, we can obtain the probability of detection p_d as

$$1 - 2 \cdot Q\left(\frac{\varepsilon}{\sqrt{\sigma_\alpha^2 + \sigma_\beta^2}}\right) = p_d \tag{11}$$

where $Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^\infty e^{-t^2/2} dt.$

(2) Iterative OB NLOS Identification

If the position estimate of MS $\hat{X} = [\hat{x}, \hat{y}]^T$ can be obtained, we can compute residual error of range measurement $\bar{f}(\hat{X})$ when signal experiences OB scattering paths

$$\bar{f}(\hat{X}) = \sum_{i=1}^{L_{ob}} \left(r_i - \sqrt{(x_i' - \hat{x})^2 + (y_i' - \hat{y})^2} - \sqrt{(x_i' - x_1)^2 + (y_i' - y_1)^2}\right)^2. \tag{12}$$

However, the position of scatterer in each path is unknown from Eq. (12). As shown in Fig. 2, the position of scatterer is the intersection position of two lines. Line equations of these two lines can be expressed as the actual AOD and the position of MS, actual

AOA and the position of BS, respectively. We can easily derive the linear relation between the position of scatterer and position of MS as follow

$$\begin{pmatrix} x_i' \\ y_i' \end{pmatrix} = A + C \cdot X, i = 1, \cdots, L_{ob} \tag{13}$$

where

$$A = \frac{1}{\tan(\alpha_i^0) - \tan(\beta_i^0)} \begin{pmatrix} y_1 - x_1 \tan(\beta_i^0) \\ y_1 \tan(\alpha_i^0) - x_1 \tan(\alpha_i^0) \tan(\beta_i^0) \end{pmatrix}, B = \frac{1}{\tan(\alpha_i^0) - \tan(\beta_i^0)} \begin{pmatrix} \tan(\alpha_i^0) & -1 \\ \tan(\alpha_i^0) \tan(\beta_i^0) & -\tan(\beta_i^0) \end{pmatrix}$$

tan is the function of tangent.

Comparing with OB scattering path, the residual error of range measurement in Eq. (12) will have large residual error if signal experiences MB scattering path. This motivates us to iteratively reject the MB scattering path one by one and search the OB scattering paths. We assume that the number of MB is L_{mb}, the total number of NLOS propagation paths is $L_{nlos} = L_{ob} + L_{mb}$. The iterative OB NLOS identification method is described as the following steps:

1. Initialization

We denote $D_{\min} = \{1, \ldots, L_{nlos}\}$ as the set of NLOS propagation paths and $G(D_{\min})$ is the measured data of each path in set $D_{\min}$.

$$G(D_{\min}) = \begin{bmatrix} \alpha_1 & \beta_1 & r_1 \\ \alpha_2 & \beta_2 & r_2 \\ \vdots & \vdots & \vdots \\ \alpha_{L_{nlos}} & \beta_{L_{nlos}} & r_{L_{nlos}} \end{bmatrix}_{L_{nlos} \times 3}$$

2. Computing Residual Error

We can obtain the initial position estimate of MS $\hat{X}$ with the measured data $G(D_{\min})$ from Eqs. (5) and (6). For each path, the position of scatterer $[x_i', y_i']$ can be determined with $\hat{X}$ and the corresponding AOD, AOA measurements $[\alpha_i, \beta_i]$ from Eq. (13). Then, we can compute the residual error $\bar{f}(\hat{X})$ with the corresponding range measurement r_i from Eq. (12). Defining the normalized residual error as $\bar{f}_{\min} = \bar{f}(\hat{X})/L_{nlos}$.

3. Iteration

For set $D_{\min}$, we choose $L_{nlos} - 1$ elements from it to form $\begin{pmatrix} L_{nlos} \\ L_{nlos} - 1 \end{pmatrix} = L_{nlos}$ subset denoted as D_m, $m = 1, \ldots, L_{nlos}$. For each subset D_m, we can compute temporary position estimate of MS $\hat{X}^{(m)}$ and the residual error $\bar{f}(\hat{X}^{(m)})$ with measured data $G(D_m)$ as the same method in step 2. The minimum normalized residual error $\bar{f}$ and the set $D'_{\min}$ are decided as

$[f, k] = \min(\bar{f}(\hat{X}^{(m)}), m = 1, \ldots, L_{nlos})$,
$\bar{f} = f/(L_{nlos}\ 1)$,
$D'_{\min} = D_k$.

If $\bar{f} < \bar{f}_{\min}$ and $L_{nlos} > 3$, then $L_{nlos} = L_{nlos} - 1$, $D_{\min} = D'_{\min}$, $\bar{f}_{\min} = \bar{f}$, repeat 3; else return $D_{\min}$ and $G(D_{\min})$.

3.2 A Weighting Data Fusion with Rwgh

Rwgh [22-23] is an effective method to fuse the different types of data and achieve high localization accuracy of MS. However, we cannot directly apply it because the residual error is almost zero if the combination with two paths are selected. In order to overcome this problem, we define another cost function, which is the sum of all residual error with OB scattering paths. Then, a weighting method of data fusion with Rwgh is described as following

1. Without loss of generality, we assume L_{los} LOS paths are identified. For the ith LOS path, we can compute the temporary position estimate of MS $\hat{X}^i = [\hat{x}^i, \hat{y}^i]$ and the corresponding residual error $f(\hat{X}^i)$ as follow

$$\hat{X}^i = \frac{1}{2}\begin{pmatrix} x_1 - \cos(\alpha_i) \\ y_1 - \sin(\alpha_i) \end{pmatrix} + \frac{1}{2}\begin{pmatrix} x_1 - \cos(\beta_i) \\ y_1 - \sin(\beta_i) \end{pmatrix},$$
$$f(\hat{X}^i) = (r_i - \sqrt{(\hat{x}^i - x_1)^2 + (\hat{y}^i - y_1)^2})^2,\ i = 1, \ldots, L_{los}.$$

2. After we do the iterative OB path identification method, we can get the set of OB paths. We assume that the size of set $D_{\min}$ is L_{ob}, then it can form $M = \sum_{i=2}^{L_{ob}} \binom{L_{ob}}{i}$ measurement combinations. For each combination, we can compute the temporary position estimate of MS $\hat{X}^k = [\hat{x}^k, \hat{y}^k]$ from Eq. (6) and the corresponding residual error $f(\hat{X}^k) = f_{ob}(\hat{X}^k)/L_{ob}$ from Eqs. (12) and (13).
3. The final position estimate of MS is the weighted linear combination of the intermediate position estimates, and it can be expressed as

$$\hat{X} = \frac{\sum_{i=1}^{L_{los}} \hat{X}^i / f(\hat{X}^i) + \sum_{k=1}^{M} \hat{X}^k / f(\hat{X}^k)}{\sum_{i=1}^{L_{los}} 1/f(\hat{X}^i) + \sum_{k=1}^{M} 1/f(\hat{X}^k)}.$$

4. SIMULATION RESULTS

This section presents simulation results to illustrate the performance of the proposed localization approach. In the simulation, the position of BS and MS are (0, 0) and (400, 300), respectively. The OB and MB scattering paths shown in Fig. 1 are the circular scattering model [15, 24-25] which assumes that the scatterer is uniformly distributed within a radius circle R around the MS or scatterer. Moreover, we assume that the angle measurements about AOD and AOA associated with different propagation paths have the same standard deviation.

4.1 Performance of LOS Identification

For our proposed LOS identification method, simulation results about the probability of detection or miss detection are obtained by doing 10,000 independent trials. For different thresholds ε, Fig. 4 shows the probability of detection with different standard deviation of angle measurement. From it, we see that simulation results about the probability of detection p_d are consistent with theoretic ones. Moreover, the probability of detection increases as the increase of ε and a big angle measurement deviation can greatly degrade the performance of LOS identification. When signal experiences OB scattering path, Fig. 5 demonstrates that the probability of miss detection increases as the increase of p_d. In addition, as the scattering radius R gets larger, the probability of miss detection slightly decreases.

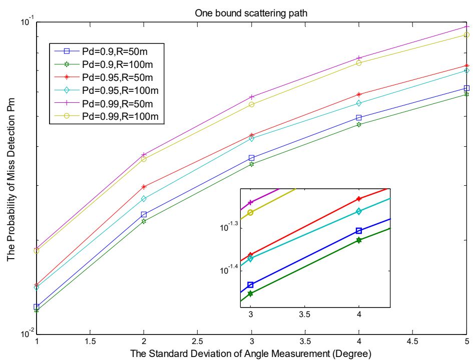

Fig. 5. Standard deviation of angle measurement vs. the probability of miss detection.

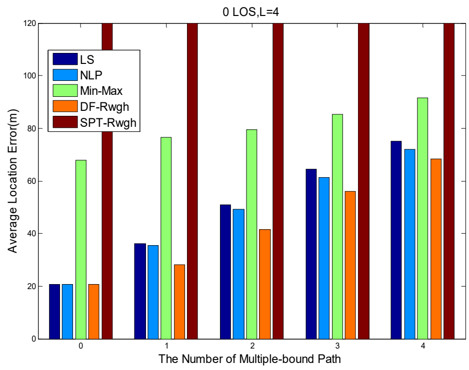

Fig. 6. ALE vs number of MB path when no LOS path is available, $p_d = 0.95$, $L = 4$, $\sigma_d = 5$m, $\sigma_\alpha = \alpha_\beta = 2^0$.

4.2 Comparison of Different Algorithms

In order to illustrate the effectiveness of our proposed algorithm, four other algorithms denoted as LS [9], NLP [20], Min-Max [21], and SPT-Rwgh [19] are chosen as performance comparison. Our proposed algorithm is denoted as DF-Rwgh. The performance criterion of the different algorithms is chosen as the average location error (ALE), which is defined as

$$ALE = \frac{1}{5000}\sum_{i=1}^{5000}\sqrt{(x-\hat{x}^i)^2 + (y-\hat{y}^i)^2} \tag{14}$$

where $(\hat{x}^i, \hat{y}^i)$ is the ith position estimate of MS.

We first compare the performance of five algorithms with different combination of paths. Figs. 6-9 depict the ALEs of five algorithms given different combinations of the number of LOS, OB and MB NLOS paths. The results illustrate the effectiveness of our proposed DF-Rwgh algorithm on improving the localization accuracy of MS, especially when LOS path is available. From Figs. 6 and 7, we see that DF-Rwgh algorithm has the similar localization accuracy with LS and NLP algorithms when only OB NLOS paths are available. As the number of MB NLOS paths increases, the localization accuracy of all the algorithms decreases, but DF-Rwgh algorithm is still better than four other algorithms. The performance improvement of DF-Rwgh algorithm is not obvious when all the paths are MB NLOS propagation. It is unexpected that SPT-Rwgh algorithm has the worst localization accuracy. This demonstrates that SPT is not an appropriate method to perform MB NLOS path identification about our localization model. Moreover, comparing Fig. 6 with Fig. 7, we clearly know that the increase of OB NLOS path can improve the performance of all the algorithms in different multipath environments. From Fig. 8 and Fig. 9, we know that the localization accuracy of DF-Rwgh algorithm is slightly worse than Min-Max algorithm when only LOS and OB NLOS paths are available, and greatly better than three other algorithms when LOS path is detected. When more MB NLOS paths are available, the localization accuracy of four other algorithms degrades significantly, while DF-Rwgh algorithm slightly decreases. In addition, comparing Fig. 8 with Fig. 9, we know that the increase of OB NLOS path can also improve the localization accuracy of LS, NLP and SPT-Rwgh algorithms when LOS path is available. However, it doesn't have obvious performance improvement about Min-Max and DF-Rwgh algorithms.

We then examine the effects of different parameters on the localization accuracy. Due to the bad localization accuracy about SPT-Rwgh algorithm, it is not compared in the following simulation. Fig. 10 depicts the effect of σ_d on the localization accuracy

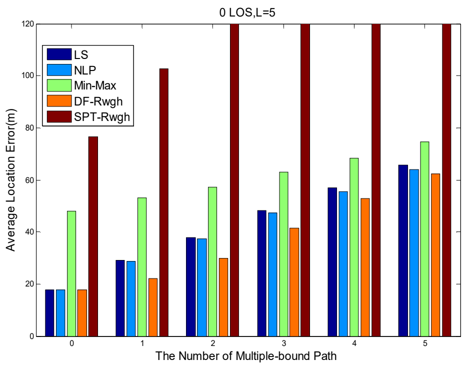

Fig. 7. ALE vs number of MB path when no LOS path is available, $p_d = 0.95$, $L = 5$, $\sigma_d = 5$m, $\sigma_\alpha = \alpha_\beta = 2^0$.

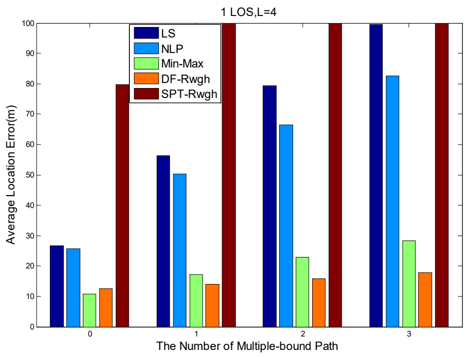

Fig. 8. ALE vs number of MB path when one LOS path is available, $p_d = 0.95$, $L = 4$, $\sigma_d = 5$m, $\sigma_\alpha = \alpha_\beta = 2^0$.

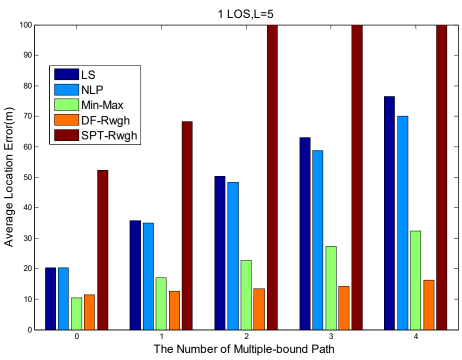

Fig. 9. ALE vs number of MB path when one LOS path is available, $p_d = 0.95$, $L = 4$, $\sigma_d = 5$m, $\sigma_\alpha = \alpha_\beta = 2^0$.

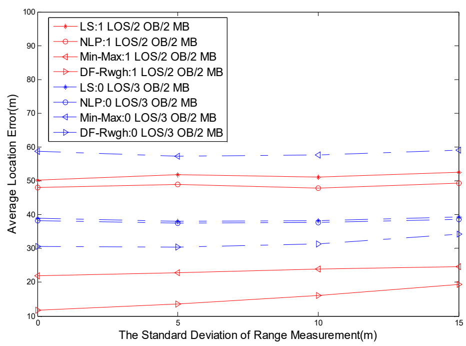

Fig. 10. ALE vs standard deviation of range measurement when five paths are detected.

when five paths are employed. ALEs of four algorithms increase as σ_d gets larger. Moreover, the DF-Rwgh algorithm has the highest localization accuracy, followed by NLP and then LS. When LOS path is available, Min-Max is better than NLP and LS. But, if LOS path doesn't exist, the performance of Min-Max algorithm is the worst. Thus, the localization accuracy of Min-Max algorithm is greatly dependent on LOS propagation path. Fig. 11 shows the effect of σ_α and σ_β when five paths are detected. As σ_α and σ_β get larger, ALE gets higher. For different multipath environments, DF-Rwgh algorithm outperforms NLP, LS and Min-Max as expected. From Fig. 12, the localization accuracy of all algorithms gets worse as scattering radius R increases. But, DF-Rwgh algorithm performs the similar performance when LOS path is available. The reason is that the scattering radius can rarely affect the performance of LOS identification shown in Fig. 5.

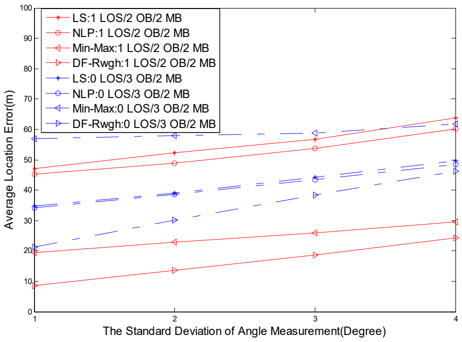

Fig. 11. ALE vs standard deviation of angle measurement when five paths are detected.

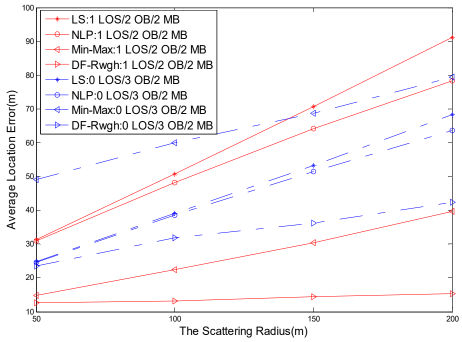

Fig. 12. ALE vs scattering radius when five paths are detected.

5. CONCLUSIONS

In this paper, by performing LOS and OB NLOS propagation paths identification, a new weighting localization algorithm with two different cost functions is proposed in multipath environments. Simulation results demonstrate: (1) the proposed DF-Rwgh algorithm has higher localization accuracy than LS, NLP, Min-Max and SPT-Rwgh with different LOS, OB and MB combinations; (2) Our proposed method can correctly identify the LOS path, and simulation results are consistent with theoretic ones. Moreover, LOS path can significantly improve the localization accuracy in multipath environments; (3) As the number of OB NLOS path increases, the localization accuracy of all the algorithms is improved. Thus, the OB NLOS propagation is beneficial to our localization model.

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