

Research Article

Probability Weighting Localization Algorithm Based on NLOS Identification in Wireless Network

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In this paper, a localization scenario that the home base station (BS) measures time of arrival (TOA) and angle of arrival (AOA) while the neighboring BSs only measure TOA is investigated. In order to reduce the effect of non-line of sight (NLOS) propagation, the probability weighting localization algorithm based on NLOS identification is proposed. The proposed algorithm divides these range and angle measurements into different combinations. For each combination, a statistic whose distribution is chi-square in LOS propagation is constructed, and the corresponding theoretic threshold is derived to identify each combination whether it is LOS or NLOS propagation. Further, if those combinations are decided as LOS propagation, the corresponding probabilities are derived to weigh the accepted combinations. Simulation results demonstrate that our proposed algorithm can provide better performance than conventional algorithms in different NLOS environments. In addition, computational complexity of our proposed algorithm is analyzed and compared.

1. Introduction

Wireless localization which can determine the position of mobile station (MS) in wireless network has received considerable attention over the past years, especially the application of the location based services (LBSs). The existing wireless localization techniques such as received signal strength (RSS) [1], time of arrival (TOA) [2, 3], time difference of arrival (TDOA) [4, 5], angle of arrival (AOA) [6–9], and the combination of the above one are often used in wireless network. The non-line of sight (NLOS) propagation is one of the dominant factors to affect the localization accuracy of MS, and it happens when the direct signal path between MS and base station (BS) is blocked. Comparing with the line of sight (LOS) propagation, the signal travels extra distance, inducing power loss and angle bias in NLOS propagations.

There are two ways to cope with the NLOS condition. The first way localizes with all NLOS and LOS measurements, but provides weighting, nonlinear optimization, or scaling to minimize the effects of the NLOS error. Residual weighting algorithm (Rwgh) [10] is very effective in reducing the NLOS error for TOA-based localization system. Its main idea is to

divide the range measurements into different combinations, each combination obtains the intermediate position estimate of MS with nonlinear least square (NLS) algorithm, and the final position estimate of MS is weighted by the intermediate position estimate and the corresponding normalized residual. However, it does not discard any combination which may be corrupted greatly by the NLOS propagation and also has high computational complexity when the number of involved BSs is big. As we know, if the home BS is equipped with antenna array, AOA measurement is obtainable, and it is helpful to improve the localization accuracy of TOA-based wireless network. In [11], Geometric Dilution of Precision (GDOP) is introduced into hybrid TOA/AOA measurements to propose GDOP-weighted localization algorithm. A nonlinear constrained optimization algorithm whose constraints on range and angle are inferred from geometry with hybrid TOA/AOA measurements is proposed in [12]. Based on a single bounce scattering environment, a joint TOA/AOA constrained minimization method which incorporates the unknown scatterers into the nonlinear optimization model is proposed in [13, 14]. By introducing scale factors to build the relation between the true distances and measured distances, the work in

[15] proposes a geometric method to locate MS with only two BSs. Taylor series least square (TS-LS) algorithm which is developed for TOA-based systems to incorporate AOA measurements is proposed in [16]. However, all the nonlinear optimization algorithms or scaling algorithms with hybrid TOA/AOA measurements have a good localization accuracy at the cost of computational complexity. The second way attempts to identify and localize with the LOS BSs. NLOS identification is done with a time-history based hypothesis test [17, 18], the feature of channel statistics [19–21], or a residual test which compares the residuals of a group against a predetermined threshold [22, 23]. However, the selection of a predetermined threshold is obtained by experience.

In this paper, we investigate hybrid TOA/AOA NLOS identification with a residual test and the weighting localization approach to minimize the effect of NLOS error. Different from the residual test in [22, 23], the selection of a predetermined threshold is based on theoretical analysis. Moreover, different from the Rwhg algorithm in [10], AOA measurement from home BS is introduced, and the weight of each combination is the corresponding probability rather than the corresponding normalized residual. Specifically, we divide the range and angle measurements into different combinations. For each combination, the position estimate of MS and its corresponding covariance matrix are computed by linear least square algorithm. Then, the range errors from different BSs are easily obtained with the position estimate of MS, and a statistic is derived and constructed by utilizing the first-order Taylor series. If the combination is derived from LOS measurements, this statistic obeys the chi-square distribution; otherwise it is not. Thus, given a false alarm probability, a theoretical threshold whose value can be computed from chi-square probability density function is derived to identify the combination whether it is LOS or NLOS. If the statistic is larger than the threshold, it is rejected; otherwise it is retained. Next, for those retained combinations, the corresponding probabilities are used to weigh the intermediate position estimates. Simulation results show that the proposed probability weighting localization algorithm based on NLOS identification has better performance than the existing algorithms in different NLOS environments.

The rest of the paper is described as follows. In Section 2, the system model is presented. In Section 3, the probability weighting localization algorithm is proposed. Section 4 presents the simulation results and computational complexity. Finally, Section 5 provides some conclusions.

2. System Model

There are N BSs available to localize MS in wireless network, without loss of generality; we suppose that BS_1 is the home BS which can obtain range and angle measurements, while the neighboring $BS_i, i = 2, \dots, N$ only has range measurement [10, 12]. The system model is described as

$$r_i = \sqrt{(x - x_i)^2 + (y - y_i)^2} + e_i + n_i = ct_i, \\ i = 1, \dots, N$$

$$\beta = \text{atan} \left(\frac{y - y_1}{x - x_1} \right) + n_\beta \quad (1)$$

where t_i is the measured TOA between MS and BS_i , c is the speed of light, the position of MS is (x, y) , and (x_i, y_i) is the position of BS_i . e_i and n_i are the NLOS error and measurement noise, respectively. Measurement noise is a Gaussian distribution $n_i \sim N(0, \sigma_i^2)$. If BS_i has a LOS path to MS, then $e_i = 0$. r_i is the range measurement from i -th BS. β is the angle measurement in home BS. atan is the function of inverse tangent and the angle measurement error n_β is the sum of the angle measurement noise and NLOS angle deviation. If the home BS experiences LOS propagation, the angle measurement noise is a Gaussian distribution $n_\beta \sim N(0, \sigma_\beta^2)$. Due to the obtainable parameters about range and angle measurement noise in [24], we assume that the variances of range and angle measurement noise are known, whereas the NLOS errors are unknown in this paper.

3. Probability Weighting Localization Algorithm

In this section, we present the proposed NLOS identification and probability weighting localization algorithm in terms of system model shown in Section 2. The proposed algorithm contains two steps: NLOS identification and probability weighting.

3.1. NLOS Identification. As shown in Section 2, N range measurements and one angle measurement are available to localize MS. Generally speaking, two range measurements and one angle measurement can provide the position estimate of MS. Moreover, it was explained that the measurements in the serving BS are more reliable than ones in the neighboring BSs [12]. Thus, we can divide the range and angle measurements into different combinations; each combination must contain the measurements in serving BS. N BSs have $2^{N-1} - 1$ combinations. In LOS environment, the model shown in (1) can be described as

$$\begin{aligned} r_1 &= d_1 + n_1 = \sqrt{(x - x_1)^2 + (y - y_1)^2} + n_1 \\ &\vdots \\ r_N &= d_N + n_N = \sqrt{(x - x_N)^2 + (y - y_N)^2} + n_N \end{aligned} \quad (2)$$

$$\beta = \text{atan} \left(\frac{y - y_1}{x - x_1} \right) + n_\beta$$

For AOA equation in (2), using the fact that $\sin(n_\beta) \approx n_\beta$ when $|n_\beta| \ll 1$, we have the following geometrical relationship [16, 25]:

$$x \sin(\beta) - y \cos(\beta) \approx x_1 \sin(\beta) - y_1 \cos(\beta) + d_1 n_\beta \quad (3)$$

Squaring the range equations in (2), two noise terms are present. Since the measurement noise is relatively small,

the square term of noise is assumed to be negligible in comparison with the first-order term of noise. Thus, we have the following approximate equations:

$$r_i^2 \approx d_i^2 + 2d_i n_i, \quad i = 1, \dots, N \quad (4)$$

By fixing the first equation in (4) as the reference, subtracting it from the rest of equations and combining them with equation (3), we can obtain the following linear equations:

$$\mathbf{A}\mathbf{x} = \mathbf{b} + \mathbf{C}\mathbf{n} \quad (5)$$

where

$$\mathbf{A} = \begin{bmatrix} 2(x_1 - x_2) & 2(y_1 - y_2) \\ 2(x_1 - x_3) & 2(y_1 - y_3) \\ \vdots & \vdots \\ 2(x_1 - x_N) & 2(y_1 - y_N) \\ \sin(\beta) & -\cos(\beta) \end{bmatrix}_{N \times 2}, \quad (6)$$

$$\mathbf{b} = \begin{bmatrix} r_2^2 - r_1^2 - x_2^2 - y_2^2 + x_1^2 + y_1^2 \\ r_3^2 - r_1^2 - x_3^2 - y_3^2 + x_1^2 + y_1^2 \\ \vdots \\ r_N^2 - r_1^2 - x_N^2 - y_N^2 + x_1^2 + y_1^2 \\ x_1 \sin(\beta) - y_1 \cos(\beta) \end{bmatrix}_{N \times 1},$$

$$\mathbf{C} = \begin{bmatrix} 2d_1 & -2d_2 & 0 & \cdots & 0 \\ 2d_1 & 0 & -2d_3 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 2d_1 & 0 & \cdots & -2d_N & 0 \\ 0 & 0 & \cdots & 0 & d_1 \end{bmatrix}_{N \times (N+1)},$$

$$\mathbf{n} = \begin{bmatrix} n_1 \\ n_2 \\ \vdots \\ n_N \\ n_\beta \end{bmatrix},$$

$$\mathbf{x} = \begin{bmatrix} x \\ y \end{bmatrix}.$$

The position estimate of MS $\hat{\mathbf{x}} = (\hat{x}, \hat{y})^T$ can be determined by solving (5) using least square algorithm,

$$\mathbf{x} = \hat{\mathbf{x}} + \mathbf{D}\mathbf{n}, \quad (7)$$

where $\hat{\mathbf{x}} = (\mathbf{A}^T \mathbf{A})^{-1} \mathbf{A}^T \mathbf{b}$, $\mathbf{D} = (\mathbf{A}^T \mathbf{A})^{-1} \mathbf{A}^T \mathbf{C}$, \mathbf{A}^T is the transpose of matrix \mathbf{A} , and \mathbf{A}^{-1} is the inverse matrix of \mathbf{A} . Due to the unknown actual distance d_i , we can use the range measurement r_i to replace them for estimating \mathbf{C} .

We choose $\hat{\mathbf{x}}$ as the initial estimate and use the first-order Taylor Series expansion to approximate the nonlinear range equations in (2). Then we obtain

$$\mathbf{err} = \mathbf{H} \cdot (\mathbf{x} - \hat{\mathbf{x}}) + \mathbf{E} \cdot \mathbf{n} \quad (8)$$

where

$$\mathbf{err} = \begin{bmatrix} r_1 - f_1(\hat{\mathbf{x}}) \\ r_2 - f_2(\hat{\mathbf{x}}) \\ \vdots \\ r_N - f_N(\hat{\mathbf{x}}) \end{bmatrix},$$

$$f_i(\hat{\mathbf{x}}) = \sqrt{(\hat{x} - x_i)^2 + (\hat{y} - y_i)^2}, \quad i = 1, \dots, N,$$

$$\mathbf{H} = \begin{bmatrix} \frac{\partial f_1(\mathbf{x})}{\partial x} & \frac{\partial f_1(\mathbf{x})}{\partial y} \\ \frac{\partial f_2(\mathbf{x})}{\partial x} & \frac{\partial f_2(\mathbf{x})}{\partial y} \\ \vdots & \vdots \\ \frac{\partial f_N(\mathbf{x})}{\partial x} & \frac{\partial f_N(\mathbf{x})}{\partial y} \end{bmatrix}_{\mathbf{x}=\hat{\mathbf{x}}}, \quad (9)$$

$$\mathbf{E} = \begin{bmatrix} 1 & 0 & \cdots & 0 & 0 \\ 0 & 1 & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & 1 & 0 \end{bmatrix}_{N \times (N+1)}.$$

Putting (7) into (8) can obtain the error vector \mathbf{err} as follows:

$$\mathbf{err} = \mathbf{G} \cdot \mathbf{n} \quad (10)$$

where $\mathbf{G} = \mathbf{H} \cdot \mathbf{D} + \mathbf{E}$.

Due to the Gaussian distribution of $n_i, i = 1, \dots, N$ and n_β in \mathbf{n} , the error vector \mathbf{err} is a Gaussian distribution with mean $\mathbf{0}$, covariance matrix \mathbf{S} .

$$\mathbf{err} \sim \mathbf{N}(\mathbf{0}, \mathbf{S}) \quad (11)$$

where

$$\mathbf{0} = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}_{N \times 1},$$

$$\mathbf{S} = \mathbf{G} \cdot \mathbf{Q} \cdot \mathbf{G}^T, \quad (12)$$

$$\mathbf{Q} = \begin{bmatrix} \sigma_1^2 & 0 & 0 & 0 \\ \vdots & \ddots & \vdots & \vdots \\ 0 & \cdots & \sigma_N^2 & 0 \\ 0 & \cdots & 0 & \sigma_\beta^2 \end{bmatrix}.$$

In order to validate (11), we define the following hypotheses and alternatives:

$$\begin{aligned} H_0 : \mathbf{err} &\sim N(\mathbf{0}, \mathbf{S}) \\ H_1 : \text{not } H_0 \end{aligned} \quad (13)$$

The hypothesis H_0 holds true, if the BSs from the combination are LOS. The alternative H_1 holds if at least one BS from the combination is corrupted by NLOS errors. If the error vector \mathbf{err} is computed from LOS BSs, we can construct the test statistic $\nu = \mathbf{err}^T \mathbf{S}^{-1} \mathbf{err}$ and compare it with the threshold γ , based on preset false alarm probability $P_{FA} = p(H_1 | H_0)$ under assumption (13). The distribution of ν under H_0 is the chi-square distribution with N degree of freedom [26]. If ν is larger than the threshold γ , the hypothesis H_0 is rejected; otherwise it is retained. Then, the false alarm probability P_{FA} expressed as the probability to decide NLOS combination if this combination is derived from LOS measurements is defined as follows:

$$\int_0^\gamma f_{\chi^2(N)}(x) dx = 1 - P_{FA} \quad (14)$$

where $f_{\chi^2(N)}(x) = ((1/2)^{N/2} / \Gamma(N/2)) x^{N/2-1} e^{-x/2}$ is the chi-square probability density function with N degrees of freedom and $\Gamma(N/2) = \int_0^\infty x^{N/2-1} e^{-x} dx$ is the gamma function.

In the above discussion, we only consider the combination that all the BSs are involved. It is easily extended to other combinations. For example, if the combination contains two range measurements and one angle measurement, there are $N - 1$ combinations with N BSs. These combinations have the same threshold γ whose value can be computed from (14) based on the chi-square probability density function with 2 degrees of freedom. By constructing the corresponding matrix or vectors \mathbf{A} , \mathbf{b} , \mathbf{C} , \mathbf{D} , \mathbf{H} , \mathbf{E} , and \mathbf{G} shown above with two range measurements and one angle measurement, each combination can obtain the position estimate of MS, the error vector \mathbf{err} , and covariance matrix \mathbf{S} from (7), (8), and (11), respectively. Then a test statistic $\nu = \mathbf{err}^T \mathbf{S}^{-1} \mathbf{err}$ is computed and compared with the threshold γ to decide whether this combination is LOS or NLOS.

3.2. Probability Weighting. For our system model in Section 2, there are $2^{N-1} - 1$ combinations. The NLOS identification is performed for each combination and the accepted ones are weighted with different probabilities. Note that the accepted combinations are labeled as z_j , $j = 1, \dots, N_v$ ($N_v \leq 2^{N-1} - 1$), where N_v is the number of the accepted combinations. We assume that the corresponding error vector, covariance matrix, and test statistic of each accepted combination are denoted as \mathbf{err}_j , \mathbf{S}_j , and $\nu_j = \mathbf{err}_j^T \mathbf{S}_j^{-1} \mathbf{err}_j$, respectively. As we know, the smaller the value of ν_j is, the bigger probability the combination is LOS. Therefore, the probabilities of each accepted combination can be obtained approximately as $\alpha'_j =$

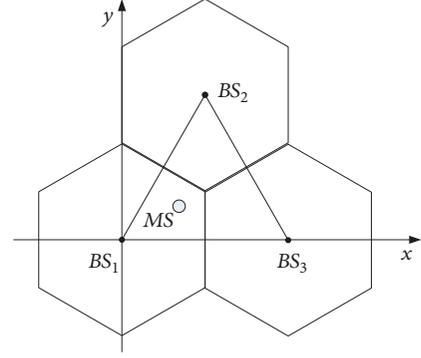


FIGURE 1: Simulation scenario in wireless network.

$1 - \int_0^{\nu_j} f_{\chi^2(N)}(x) dx$. To ensure that the sum of probabilities is one, we normalize α'_j as

$$\alpha_j = \frac{\alpha'_j}{\sum_{i=1}^{N_v} \alpha'_i}, \quad \forall j = 1, \dots, N_v \quad (15)$$

The final position estimate of MS is weighted as

$$\mathbf{X} = \sum_{j=1}^{N_v} \alpha_j \widehat{\mathbf{X}}_j \quad (16)$$

where $\widehat{\mathbf{X}}_j$ is the intermediate position estimate of the j -th accepted combination.

In extreme circumstances, none of these combinations is accepted in the tests; the proposed algorithm will not output a valid position estimate of MS. If this situation happened, it means that the range measurements in neighboring BSs deteriorate significantly. The localization accuracy will be degraded if they are combined with the range and angle measurements in home BS. Thus, only home BS is reliable to provide the position estimate of MS. With the assumption of LOS propagation, the position estimate of MS is easily obtained as $x = r_1 \cos(\beta) + x_1$, $y = r_1 \sin(\beta) + y_1$.

4. Simulation Results

In this section, we carry out some simulations to prove the performance of the proposed NLOS identification and probability weighting localization algorithm. Three BSs with a hexagonal layout shown in Figure 1 are deployed. Without loss of generality, we assume that the position of BS_1 is $(0, 0)$, being the home BS. Because the radius of hexagon is 1000m, the position of BS_2 and BS_3 can be easily obtained as $(500\sqrt{3}, 1500)$ and $(1000\sqrt{3}, 0)$, respectively. The position of MS is $(250\sqrt{3}, 400)$.

The range measurement consists of three parts, the true distance, the NLOS error, and the measurement error. The standard deviations of three range measurement errors are assumed to have the same value $\sigma_1 = \sigma_2 = \sigma_3 = 45m$. The NLOS error $e_i = c \times \tau_i$ shown in (1) refers to [10, 27–29], where

TABLE 1: Typical parameters in different environments. Table 1 is reproduced from Wu et al. (2015) [under the Creative Commons Attribution License/public domain].

Environments	T_1 (μs)	ε	σ_ρ (dB)
Bad Urban	1.0	0.5	4
Urban	0.4	0.5	4
Suburban	0.3	0.5	4
Rural	0.1	0.5	4

τ_i is a random variable with an exponential distribution, and the probability density function of τ_i is

$$P(\tau_i) = \begin{cases} \frac{1}{\tau_{rms}} e^{-\tau_i/\tau_{rms}}, & \tau_i > 0 \\ 0, & otherwise \end{cases} \quad (17)$$

where $\tau_{rms} = T_1 d_i^\varepsilon \rho$ is the root mean square (rms) delay spread, T_1 is the median value of the rms delay spread at one kilometer, d_i is the distance between BS_i and MS, ε is the path loss exponent, and ρ is a lognormal variable that $10 \log \rho$ is a zero mean Gaussian variable with standard deviation σ_ρ . For different environments, typical parameters are given in Table 1.

The angle error n_β is the sum of the LOS angle noise and NLOS angle deviation. The LOS angle noise is a zero mean Gaussian random variable with standard deviation of approximately 3 degrees, whereas the NLOS angle deviation is a zero mean Gaussian random variable with standard deviation $\sigma_i = (c \times \tau_i)/d_i$, where d_i is the distance between BS_i and MS.

4.1. Simulation of NLOS Identification. In this subsection, we carry out simulation results to validate the performance of NLOS identification about our proposed algorithm. In Figure 2, we set $P_{FA} = 0.05$ and $N = 3$. Figure 2 shows the probability of LOS combination with different number of NLOS BSs in different NLOS environments. It is observed that the NLOS identification method can identify the LOS combination accurately if this combination is derived from LOS measurements. When the combination contains NLOS measurement, the probability of LOS combination which mistakenly determines NLOS combination as LOS combination becomes smaller as the increase of the number of NLOS BSs. It means that our NLOS identification method can correctly identify NLOS propagation, especially in serious NLOS environments. However, when the NLOS error is not serious, such as in rural condition, the performance of NLOS identification algorithm performs poor and most of the NLOS combinations are mistakenly decided as LOS combination. In Figure 3, we set $P_{FA} = 0.05$ and $N = 2$; the same conclusions can also be obtained. Comparing Figure 2 with Figure 3, we see that the probability of LOS combination increases as N gets larger when the number of NLOS measurement is fixed. It means that our NLOS

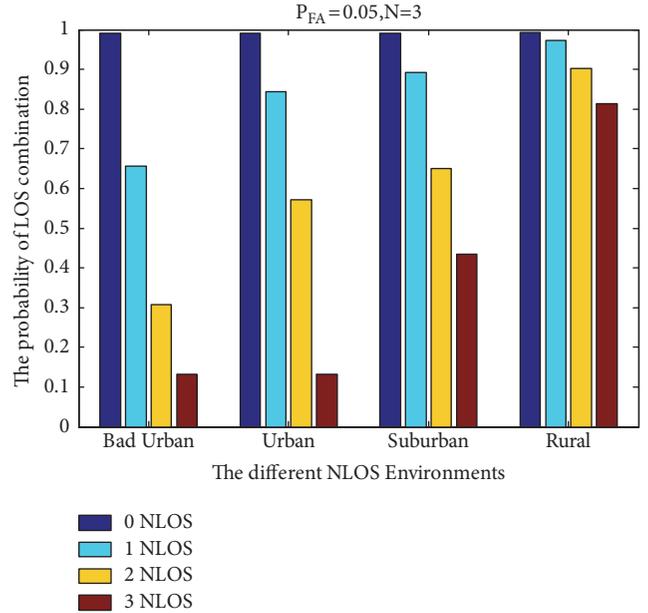


FIGURE 2: The probability of LOS combination with three BSs in different NLOS environment.

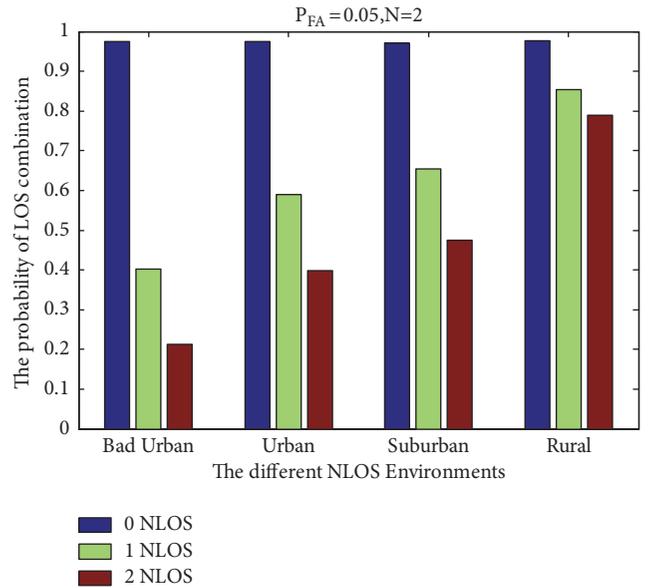


FIGURE 3: The probability of LOS combination with two BSs in different NLOS environment.

identification method is more possible to decide the combination as LOS combination when the LOS measurement is increased.

4.2. Simulation of the Proposed Algorithm. In this subsection, we present simulation results to evaluate the localization accuracy of our proposed algorithm. Three other algorithms denoted as hybrid line of position (HLOP) [12], the combination of Rwhg and HLOP (Rwhg-HLOP) [10, 29], and TSLS [16] are selected as performance comparisons. For the

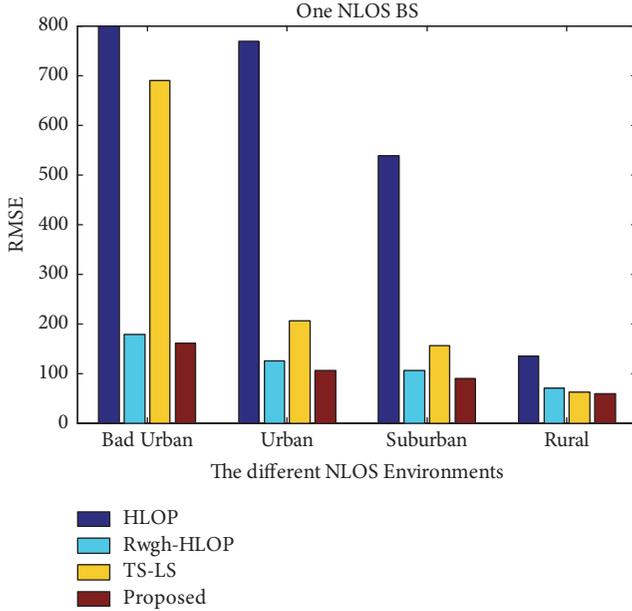


FIGURE 4: The performance comparison with one NLOS BS in different NLOS environments.

performance criterion of different algorithms, we use the root mean square error (RMSE), defined as

$$RMSE = \sqrt{\frac{1}{T} \sum_{i=1}^T (x - \hat{x}_i)^2 + (y - \hat{y}_i)^2} \quad (18)$$

where (\hat{x}_i, \hat{y}_i) is the position estimate of MS and $T = 10000$ is the number of the independent localization trials. In Figure 4, one BS is corrupted by NLOS propagation, and it is randomly generated from BS₂ or BS₃. It is observed that the localization performance of the proposed algorithm is better than HLOP, Rwgh-HLOP, and TS-LS in bad urban, urban, and suburban environment, whereas it is slightly better than Rwgh-HLOP and TS-LS in rural environment. Moreover, when the NLOS propagation becomes serious, the localization performance of all the algorithms is decreased. As shown in Figures 5 and 6, the localization performance of all the algorithms also decreases when the number of NLOS BSs is increased. However, the proposed algorithm is still better than three other algorithms, especially in bad urban environment. From Figures 4–6, we see that the performance improvement of the proposed algorithm is slight in rural condition; the reason is that the NLOS identification method cannot correctly identify LOS combination.

4.3. Complexity Comparison. In this subsection, computational complexity of our proposed algorithm is analyzed and compared. The proposed algorithm is consisted of different combinations; each combination contains two main steps: HLOP algorithm and construction of a statistic. HLOP algorithm is done by least square algorithm; its computational complexity is $O(i)$, where i is the number of measurements in each combination. Construction of a statistic is done by

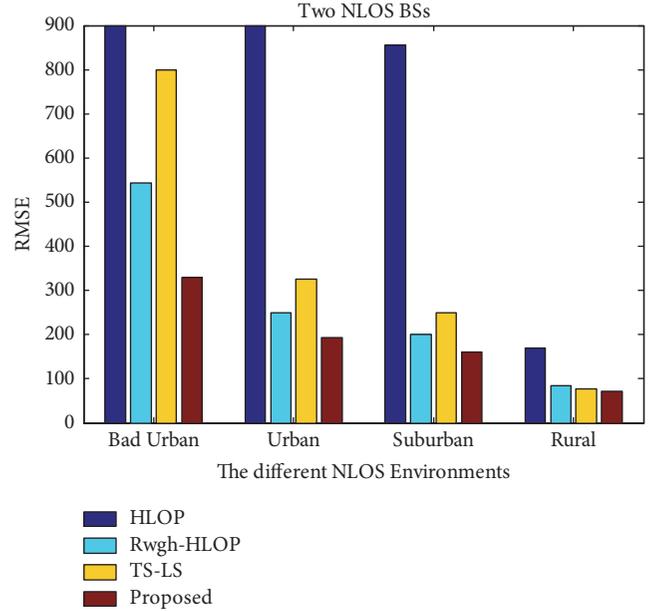


FIGURE 5: The performance comparison with two NLOS BSs in different NLOS environments.

TABLE 2: Computer running time of the four algorithms.

Algorithm	HLOP	TS-LS	Rwgh-HLOP	Proposed
Time (ms)	0.033±0.001	0.095±0.01	0.13±0.01	0.18±0.01

matrix multiplication, addition, and inverse operation from (8), (10), and (11); its computational complexity is $O(i^3)$. Therefore, the computational complexity of our proposed algorithm is $\sum_{i=1}^{N-1} \binom{N-1}{i} \cdot (O(i+2) + O((i+2)^3))$. Table 2 shows the complexity comparison results of four algorithms in terms of the actual computation time with one run. The experiments are processed on the computer with Intel® Core™ i5-6200U CPU 64 bit processor and 4GB memory. From Table 2, it shows that the computer running time of our proposed algorithm is the highest, followed by Rwgh-HLOP, then TS-LS, and at last HLOP. Therefore, the improved performance of our proposed algorithm is at the cost of an increased computational complexity.

5. Conclusions

In this paper, we investigate the hybrid TOA/AOA localization approaches and propose a new probability weighting algorithm based on NLOS identification. Simulation results show the following: (1) the NLOS identification method can correctly identify the LOS combination when this combination is derived from LOS measurement. Moreover, as the increase of the number of NLOS BSs, the probability of LOS combination decreases, especially in severe NLOS environments. (2) The proposed probability weighting algorithm has better performance than three other algorithms with different number of NLOS BSs in different environments. In addition, the analysis of computational complexity demonstrates that

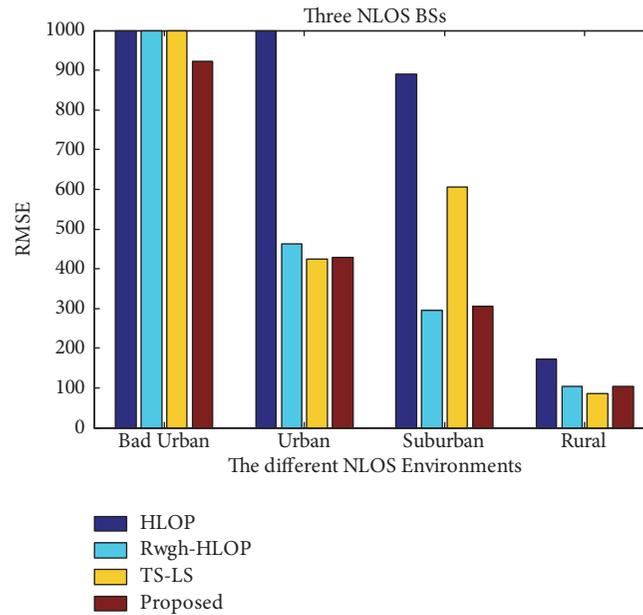


FIGURE 6: The performance comparison with three NLOS BSs in different NLOS environments.

the improved performance of our proposed algorithm is at the cost of the increased computational complexity.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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