TOA Based Localization Under NLOS in Cognitive Radio Network

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Abstract. In this paper, we consider cooperative localization of primary users (PU) in a cognitive radio network (CRN) using time-of-arrival (TOA). A two-step none-line-of-sight (NLOS) identification algorithm is proposed for the situation where both NLOS error distribution and channel model are not available. In the first step the TOA measurements are clustered into groups. The groups with a dispersion higher than a predefined threshold are identified as NLOS and discarded. In order to make the threshold more reasonable, Ostu's method, a threshold selection method for image processing is utilized. The second step is introduced to correct the error of possible surviving NLOS. To increase the accuracy of estimated position when line-of-sight (LOS) paths are limited, we proposed a result reconstruction method. Simulation results show that our algorithm can effectively identify NLOS paths and improve positioning accuracy compared to existing works.

Keywords: Cognitive radio network · LOS identify · Time of arrival · Location estimation · Least square method

1 Introduction

The available spectrums are very limited due to the character of electromagnetic wave itself. Cognitive radio has emerged as a promising technology to improve the spectrum utilization dramatically. One of the most important tasks for CRNs is to detect the presence or absence of primary users (PUs), which is called the spectrum sensing technique. In cognitive radio technology, there are two types of users-the primary (licensed) user and the secondary (unlicensed) user (SU). The PUs have the right of priority in using a certain frequency spectrum. The SUs on the other hand have restricted access to the available unused frequency spectrum. The SUs are allowed to use the frequency spectrum only if they do not interfere with the PUs. Information about the locations of PUs can allow cognitive networks to identify spectrum holes in space more reliably and accurately and perform location-aware intelligent routing and power control mechanisms in

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a CRN [1,2]. Hence, locating the PUs position in a CRN is an important but challenging task.

Networks similar with the wireless sensor networks (WSN) are composed when SUs proceed cooperative spectrum sensing, which SUs are similar with the wireless sensor nodes, PUs are similar with the unknown source node (USN). Therefore, wireless sensor networks localization algorithms can be used in acquiring position of PUs of CRNs.

TOA, signal strength, and angle-of-arrival (AOA) legacy location estimation techniques can be considered as candidates for localization of PUs. AOA techniques are mostly implemented by means of antenna arrays which not suitable for rich multipath environments. On the other hand, signal strength based methods provide high accuracy only for the short ranges. Moreover, the performance of the estimator for signal strength techniques depends on the channel parameters that CRNs cannot control. Since the accuracy of TOA techniques mainly depends on the parameter that transceiver can control, it is the most suitable location estimation technique [3]. Time-of-arrival (TOA) based positioning system is also widely used for positioning in WSNs. Accurate synchronization and none-line-of-sight (NLOS) are two significant problems of TOA. Accuracy of synchronization mostly depends on bandwidth.

NLOS is another notorious factor in positioning system for degrading the accuracy of estimated results, benefiting from a large number of anchor nodes (ANs) in WSNs distributing around the detection region, much measurement information can be obtained. Four LOS paths are enough to achieve accurate TOA localization. As a result, it is generally assumed that four LOS paths exist. Therefore, we can simply identify and discard the NLOS paths and utilize the LOS for TOA positioning to improve accuracy.

A lot of study has been undertaken to deal with the problem of NLOS identification. In [4] an NLOS identification method for mobile location estimation is proposed. NLOS identification is achieved by comparing the standard deviation of TOA measurement with a threshold calculated from historical measurement noise. However, in order to obtain reliable result, the threshold needs to be determined by field experiment. In [5–8], a class of channel estimation based NLOS identification algorithms is proposed. In these methods, NLOS identification can be accomplished by examining the statistics of the multipath channel coefficients. The problem of these methods is that both signal model and the channel model are needed. Some localization algorithms require a-priori knowledge of the probability density function (PDF) of NLOS noise. In [9], a distribution test model for NLOS identification is formulated, where the positioning error is modeled as Gaussian zero mean. [10] proposed a residual weighting(RW) algorithm, in which the weight of every sensor is calculated by summing up the weighted residuals of all possible combinations and the one with the heaviest weight is identified as NLOS.

In this paper, we proposed a two-step NLOS identification algorithm which none priori information is needed. In the first step, based on the fact that NLOS errors often result in high dispersion of estimated results, we cluster all the measurements into groups. And the groups with dispersion higher than a threshold are abandoned. Considering the similarity of application scene, A threshold selection method for image processing is utilized to determine the value of threshold. We find some NLOS may survive if they are grouped with certain measurements. So in the second step, a reliability factor is defined for each remaining measurement. Then the top four measurements with the largest reliability factors are utilized for position estimating. Considering that the assumption of 4 LOS measurements may be rejected, we proposed an estimated result reconstruction method to increase the robustness under NLOS environment. Finally, simulation combined with actual measurement data is conducted to verify the performance of our algorithm and compare it with existing works.

The rest of the paper is organized as follows. In Sect. 2, we analysis the impact of NLOS errors on the estimated results. In Sect. 3, our proposed two-step algorithm for NLOS identification is detailed. In Sect. 4, the estimated result reconstruction method is introduced. Simulation results are presented to demonstrate the reliability of the method in Sect. 5 and conclusion is presented in Sect. 6.

2 System Model

2.1 LS Method for Location Estimation in TOA System

The system model under consideration is for TOA-based location estimation. There are N sensors and one USN to be localized. We define $X = (x, y)$ as the real position of the USN, $\hat{X} = (\hat{x}, \hat{y})$ the estimation of the USN location, $X_i = (x_i, y_i)$ the position of the ith sensor, $\hat{d}_i$ is the measured distance between the USN and the ith sensor. The simplified assumption of $\hat{d}_i$, which can be expressed as

$$\hat{d}_i = ct_i = d_i + v_i, \tag{1}$$

where t_i is the measured transmission time, c is the speed of light, and $d_i = \sqrt{(x_i - x)^2 + (y_i - y)^2}$ is the actual distance between the USN and the ith sensor.

$$v_i = \begin{cases} e_i, & if\ ith\ path\ is\ LOS \\ e_i + n_i, & if\ ith\ path\ is\ NLOS \end{cases} \tag{2}$$

is the total error, e_i and n_i are the TOA measurement noise and the NLOS error respectively. We assume that e_i is a Gaussian random variable with zero mean and variance σ_i. The PDF of n_i is assumed to be unknown in this paper.

Based on the above signal model, LS method in [12] can be utilized to estimate the location of USN.

Let $R = \sqrt{x^2 + y^2}, R_i = \sqrt{x_i^2 + y_i^2}$. A simplified equation incorporating all the information for localization is

$$h = G\theta + v, \tag{3}$$

where

$$h = \begin{bmatrix} \hat{d}_1^2 - R_1^2 \\ \hat{d}_2^2 - R_2^2 \\ \vdots \\ \hat{d}_N^2 - R_N^2 \end{bmatrix}, G = \begin{bmatrix} -2x_1 & -2y_1 & 1 \\ -2x_2 & -2y_2 & 1 \\ \vdots & \vdots & 1 \\ -2x_N & -2y_N & 1 \end{bmatrix} \tag{4}$$

are the constant vector and coefficient matrix respectively.

$\theta = \begin{bmatrix} x & y & R^2 \end{bmatrix}^T$ is the vector we are to estimate eventually with $v = \begin{bmatrix} v_1^2 - 2\hat{d}_1 v_1 & v_2^2 - 2\hat{d}_2 v_2 & \cdots & v_N^2 - 2\hat{d}_N v_N \end{bmatrix}^T$ being the estimation error. The least square solution can be expressed as

$$\hat{\theta} = \left(G^T G\right)^{-1} G^T h. \tag{5}$$

2.2 Deviation Caused by NLOS Noise

A minimum TOA system is illustrated in Fig. 1. Three sensors are involved to estimate the location of USN in 2-dimentional location system. If all the sensors are LOS paths, the three circles can almost intersect at the same point, which will be the estimated position of the USN. However, if one sensor (AN_3) suffers from NLOS noise, it will lead to a large fuzzy localization area. Therefore, the final estimated result will be inaccurate. So the size of fuzzy area can be used to determine the existence of the NLOS paths in a certain group. As a result, the relationship between the fuzzy area and NLOS errors should be analyzed.

Assume that one of the three sensors used for estimating the location of USN suffers from NLOS error, and the other two are LOS paths. Thus the estimation

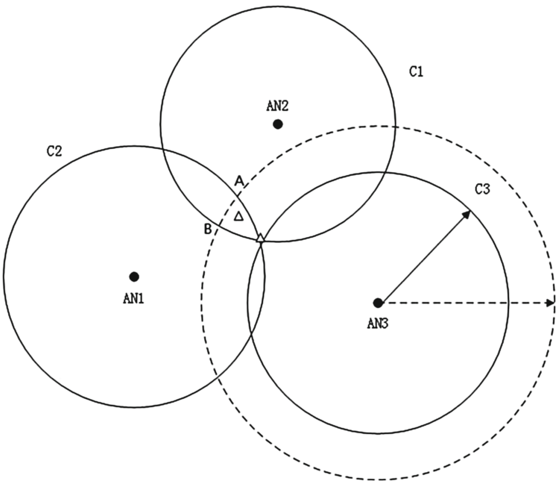

Fig. 1. NLOS effect on the TOA location estimation

error will be introduced into positioning result. According to (5), the equation which contains NLOS error can be

$$\begin{bmatrix} x + n_x \\ y + n_y \\ R^2 + n_{R^2} \end{bmatrix} = \left(G^T G\right)^{-1} G^T \begin{bmatrix} \left(d_1 + n_{NLOS}\right)^2 - R_1^2 \\ d_2^2 - R_2^2 \\ d_3^2 - R_3^2 \end{bmatrix}, \tag{6}$$

where n_{NLOS} is the measurement error caused by NLOS noise. n_x and n_y are the estimation errors of X-coordinate and Y-coordinate caused by NLOS noise respectively. n_{R^2} is the deviation of R^2. The deviation between the estimated location and the actual location is

$$\bar{d} = \sqrt{n_x^2 + n_y^2}. \tag{7}$$

The value of $\bar{d}$ only has concern with the value of n_x and n_y, which can be calculated by

$$\begin{bmatrix} n_x \\ n_y \\ n_{R^2} \end{bmatrix} = \left(G^T G\right)^{-1} \begin{bmatrix} -2x_1 \\ -2y_1 \\ 1 \end{bmatrix} \left(2d_1 n_{NLOS} + {n_{NLOS}}^2\right). \tag{8}$$

According to (8), we can see that the effect of NLOS noise on estimated results not only depends on the value of NLOS errors themselves, but also concerns with point coordinates of all the sensors. That is to say, when a certain NLOS point is introduced into different ANs combinations, the deviations of results are different. So it is difficult to make quantitative analysis, but we can summarize two qualitative conclusions to provide the theoretical support for our work.

- NLOS errors will surely cause fuzzy localization area, which can lead to inaccurate results.
- NLOS measurements may not cause large positioning errors when the certain NLOS measurements are introduced into specific groups. So the information obtained from some of the NLOS paths can be used to improve the positioning results when LOS paths are limited.

3 NLOS Identification

In view of the above-mentioned fact, a reasonable two-step method is proposed to determine and discard NLOS measurements in the situation without any previously known knowledge of NLOS error distribution or channel model. Then the coordinate of the USN can be calculated by LS method with the information of LOS measurements.

3.1 The First Step: Group Decision

We define a deviation factor Δd to reflects the deviation between the estimated position and the actual position.

$$\Delta d = \sqrt{\left(x - \hat{x}\right)^2 + \left(y - \hat{y}\right)^2}. \tag{9}$$

However, Δd is unavailable for (x, y) is unknown. So we need another approximate parameter to replace Δd.

We assume that there are N sensors available for location estimation. All the N sensors are divided into $M = C_N^K$ groups, where K is the number of sensors in each group. As was mentioned above, the minimum number of sensors required for 2-D TOA location estimation is 3. So C_K^3 estimated point coordinates of USN can be obtained in each group. After calculating the distances between all two different estimated points combinations, the distance with the maximum value $\Delta\hat{d}_k (1 \leq k \leq C_N^K)$ is defined as the dispersion degree of location results in the kth group G_k.

$$\Delta\hat{d}_k = \max_{1 \leq i,j \leq C_K^3, i \neq j} \sqrt{(\hat{x}_{ki} - \hat{x}_{kj})^2 + (\hat{y}_{ki} - \hat{y}_{kj})^2}, \tag{10}$$

where $(\hat{x}_{ki}, \hat{y}_{ki})$ and $(\hat{x}_{kj}, \hat{y}_{kj})$ are the two different estimated point coordinates in group G_k.

Then a threshold γ is set to make a distinction between the two extreme dispersion degrees cause by measurement errors and NLOS errors separately. If $\Delta\hat{d}$ is smaller than γ, that means all the paths in the group are LOS, or the deviation caused by NLOS errors is not large enough. On the contrary, at least one NLOS path must exist.

Ostu's method [11] was used in [13] to determine a threshold to divide two peaks in gray images. Considering the similarity of the application scenario, it is also utilized to obtain a reasonable threshold γ.

In the previous work, totally M dispersion degrees were obtained. With a interval (e.g. 10 m), we divide all these values of dispersion degrees into l intervals. Let $t = \lceil \gamma/10 \rceil$, the value level ranges within $G = \{1, 2, \cdots, l\}$ can be divided into two classes, as $C_0 = \{1, 2, \cdots, t\}$ and $C_1 = \{t+1, t+2, \cdots, l\}$. We define the between-class variance σ_B^2 and total-variance σ_T^2 as

$$\sigma_T^2 = \sum_{i=0}^{l-1} (i - \mu_T)^2 P_i, \;\; \sigma_B^2 = \omega_0 \omega_1 (\mu_1 - \mu_0)^2, \tag{11}$$

where

$$\begin{aligned} & P_i = n_i/n, \;\; \omega_0 = \sum_{i=1}^{t} P_i, \;\; \omega_1 = 1 - \omega_0 \\ & \mu_T = \sum_{i=1}^{l} i P_i, \;\; \mu_t = \sum_{i=1}^{TH} i P_i, \;\; \mu_0 = \tfrac{\mu_t}{\omega_0} \\ & \mu_1 = \tfrac{\mu_T - \mu_t}{1 - \omega_0}. \end{aligned} \tag{12}$$

Here, n_i indicates the number of dispersion degrees in ith interval. $n = \sum_{i=1}^{l} n_i$ is the total number of dispersion degrees. For a selected threshold t, the class probabilities ω_0 and ω_1 represent the portions of areas occupied by object and NLOS classes respectively.

The optimal threshold can be determined by maximizing the following criterion function against the threshold.

$$\eta = \frac{\sigma_B^2}{\sigma_T^2}. \tag{13}$$

After calculating both dispersion degrees $\Delta\hat{d}_k$ and the threshold γ, we can determine whether there exist NLOS measurements in a certain group. But unfortunately, according to the conclusion we draw from (8), a small part of NLOS measurements may survive even when the groups meet the threshold condition. As a result, we propose a method to further find 4 LOS sensors from the result of the first step.

3.2 The Second Step: Weighted Ranking

Assume that there are L groups and S sensors remained in the result of group decision. Use $G_k, k = 1, 2, \cdots L$ to denote the kth group and $A_i, i = 1, 2, \cdots S$ to denote the ith sensors. For each group G_k, every AN in it will be assigned a weight of W_i, which is calculated by

$$W_k = 1/\Delta\hat{d}_k. \tag{14}$$

After evaluating all the L groups, A_i will have a total weight w_i by summing the weights of all the groups it belongs to.

$$w_i = \sum_{k=1}^{L} \lambda W_k \begin{cases} \lambda = 0, & if \quad A_{i'} \notin G_k \\ \lambda = 1, & if \quad A_{i'} \in G_k \end{cases}. \tag{15}$$

Rank these sensors according to their total weights. The 4 sensors with the heaviest weights are determined to be LOS sensors. And the final estimated position of USN can be obtained by solving the equation established only by the measurement information of these 4 sensors.

3.3 Geometric Dilution of Precision

Position results will deviate right positions a lot even if all the WSNs are LOS when all WSNs are in the similar direction of the USN. So, we define Geometric Dilution of Precision(GDOP) to determine if the group is effective.

$$\mathrm{GDOP} = \sqrt{\mathrm{trace}(\mathrm{G}^T\mathrm{G})^{-1}} \tag{16}$$

G can be obtained from (4). The value of GDOP reflects the reversibility of coefficient matrix. The smaller of the value of GDOP, more accurate of the position results. Threshold of GDOP can be set up to determine if the WSNs group can be used to judge NLOS. From this step, some effective groups could be eliminated, complexity values can be reduced the reasonable.

Algorithm 1. Two-step Algorithm for NLOS Identification

Input: The TOA measurements $\hat{d}_i$ of the signals received by all the available sensors and the position coordinates (x_i, y_i) of all sensors;

Output: The estimated coordinate of USN;

1: Group all the N available sensors into all possible groups with different K sensors; Assume that a network with 10 sensors, there will be C_{10}^{K} groups.

2: Separate K sensors in a certain group into all possible combinations with different 3 sensors. And there will be C_K^3 combinations. Using all the 3 sensors combinations to estimate the position of USN;

3: Calculating $\Delta\hat{d}_k$ for group G_k;

4: Comparing $\Delta\hat{d}_k$ with the threshold TH. If $\Delta\hat{d}_k$ is smaller than TH, every AN in group G_k should be assigned a weight of W_k. Calculating the total weight of each AN by summing the weights of all the groups it belongs to.;

5: Ranking all the sensors according to their weights. Using the measurements of 4 sensors with heaviest weights to estimate the position of USN.

4 Estimated Result Reconstruction

We have assumed that there are at least four LOS paths exist. So that the best accuracy can be achieved by identifying and discarding NLOS measurements, and only use the LOS measurements. However, under practical situation, this assumption may be rejected. Hence, we should use as much information as possible to obtain a relatively accurate estimated result, such as the NLOS measurements with small NLOS errors. So the estimated result reconstruction(ERR) method is proposed.

In the phase of group decision, we have acquired L groups meet the threshold condition. As mentioned above, $M = C_K^3$ estimated coordinates can be obtained in each group. We assume that $\hat{X}_{k,i} = (x_{k,i}, y_{k,i}), 1 \le k \le L$ and $1 \le i \le M$ is the ith estimated coordinate in kth group G_k. We define the variance of estimated results in G_k as

$$V_k = \frac{1}{M}\sum_{i=1}^{M}\sqrt{\left(\hat{x}_{k,i} - \bar{x}_k\right)^2 + \left(\hat{y}_{k,i} - \bar{y}_k\right)^2}, \tag{17}$$

where

$$(\bar{x}_k, \bar{y}_k) = \left(\frac{1}{M}\sum_{i=1}^{M}\hat{x}_{k,i}, \frac{1}{M}\sum_{i=1}^{M}\hat{y}_{k,i}\right). \tag{18}$$

Moreover, an estimated coordinate $(\hat{x}_k, \hat{y}_k)$ that include the information of all the measurements in G_k can be retrieved with the least square method.

For the kth group G_k, we define a weight as

$$\lambda_k = \frac{\zeta_k}{\sum\limits_{j=1}^{L}\zeta_j}, \tag{19}$$

where $\zeta_k = 1/V_k$ is the reciprocal of G_k's variance. And the final estimated position can be calculated by

$$(\hat{x}, \hat{y}) = \left(\sum_{k=1}^{L} \lambda_k \hat{x}_k, \sum_{k=1}^{L} \lambda_k \hat{y}_k \right). \tag{20}$$

Although the accuracy of estimated result obtained by the proposed ERR method will be lower than that obtained by using only the LOS measurements, the ERR method is practical when the number of LOS measurements is small.

5 Performance Analysis

In this section, simulation experiments are carried out to show the performance of the proposed NLOS identification method and ERR method. The measurement data was obtained by a filed measurement conducted around one of the television signal transmission towers in Beijing, China. Our purpose is to estimated the position of the transmission tower. We collected the digital television signal to estimate the TOA between the transmitter and the receiver. The instruments used include Agilent N6841A RF sensor and a laptop computer.

Totally 40 measurements are obtained, consisting of 20 obvious LOS paths and 20 NLOS paths. Each time we randomly select $M(0 \leq M \leq 10)$ NLOS measurements and $10 - M$ LOS measurements for simulation test. Every result is obtained from the average of 10,000 independent simulation experiences.

5.1 Success Rate of NLOS Identification

Figure 2 compares the success rate of finding 4 LOS measurements by using only the group decision algorithm and the two-step algorithm. In the former case, the 4 sensors being selected are the measurements appearing the most in the result of group decision. And the size of each group is set to be 4.

As shown in Fig. 2, compared with group decision method, the two-step method can obtain more accurate estimated results. At the same time, it also has better performance than the RW algorithm proposed in [7].

Further simulation is made to study the effects of groups' size K on the accuracy of the results.

As can be seen in Fig. 3, if there are enough LOS measurements available for NLOS identification, it can be sure to find 4 measurements with LOS paths successfully. The result of this simulation proves that the size of groups in the first step of this algorithm will affect the accuracy of estimated results. When the number of LOS measurements is fixed, the group with larger size will obtain a more accurate result. Figure 3 also shows that when the size of groups K is larger than the number of existent LOS measurements, it will fail to identify LOS measurements for the reason that at least one NLOS AN exists in the result.

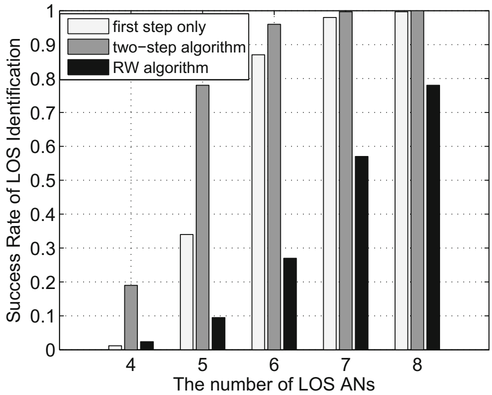

Fig. 2. Success rate of identification with different algorithm

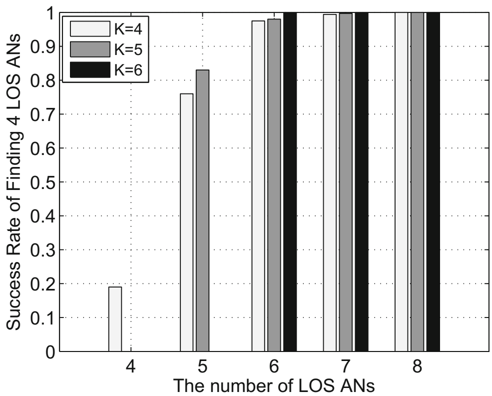

Fig. 3. Success rate of identification with different size of groups

5.2 The Accuracy of Position Estimation

Figure 4 shows the root-mean-square error (RMSE) of estimated results obtained by utilizing three different methods. The accuracy is low when all the TOA measurements are used to estimate the position of USN directly. By using the two-step algorithm, 4 optimal measurements are selected to estimate the final result. The simulation shows that it really helps improve the accuracy of estimated result. But it performs poorly when the number of LOS paths is fewer than four for the measurements with large NLOS errors are introduced into LS equations. ERR method is not particularly accurate in LOS environments, but it is robust to NLOS measurements. So it can be used when the number of LOS connections is limited.

Finally, it needs to be explained that why we didn't analyze the false alarm rate and the effects of a false detection in the positioning precision. As mentioned

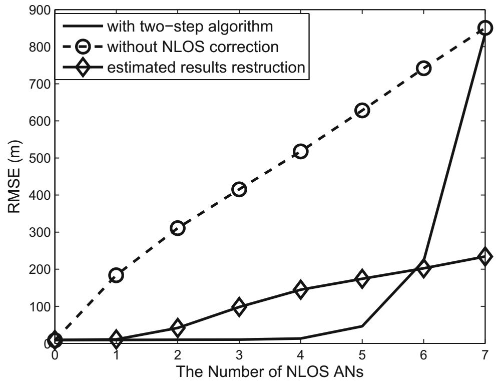

Fig. 4. Comparison of location error before and after using proposed algorithm

above, in the situation where the LOS paths are limited, both LOS measurements and the NLOS measurements with small NLOS errors are utilized to estimated the position of UNS in our proposed ERR method and the estimated results with certain precision can be obtained. For this reason, the accuracy of estimated results is more significant than alarm rate.

6 Conclusion

In this paper, we have proposed a two-step algorithm for NLOS identification in CRNs similar with WSNs through studying the effect of NLOS noise on estimated results. Compared with other methods, the proposed method can achieve NLOS error identification without any priori knowledge of NLOS environment. We divide the available measurements into all possible groups with the same size. Then the estimated results are used to determine the existence of NLOS paths in a certain group. At the same time, the weight calculated by the maximum distance between the estimated results is added to each node in the group. The ranking of the total weight for each AN determines the LOS ANs. The groups with larger size can obtain more accurate estimated results. But this will increase the requirements of both computational complexity and the number of LOS paths. So the second step of the proposed method is proposed to balance the computation complexity and the recognition accuracy. Simulation results demonstrate that the two-step algorithm performs well in determining LOS measurements, especially when the number of LOS paths is larger than 4. Accurate estimated position of USN(PU) can be obtained through solving the LS equation established by the LOS measurements information. Considering that the two-step algorithm performances poorly when the number of LOS paths is limited, we propose the ERR method to make full use of the information extracted from available measurements. Simulation shows that the ERR method is robust to NLOS environment.

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