

# Passive location estimation using scatterer information for non-line-of-sight environments

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**Abstract:** In order to improve the performance of the traditional hybrid time-of-arrival (TOA)/ angle-of-arrival (AOA) location algorithm in non-line-of-sight (NLOS) environments, a new hybrid TOA/AOA location estimation algorithm by utilizing scatterer information is proposed. The linearized region of the mobile station (MS) is obtained according to the base station (BS) coordinates and the TOA measurements. The candidate points (CPs) of the MS are generated from this region. Then, using the measured TOA and AOA measurements, the radius of each scatterer is computed. Compared with the prior scatterer information, true CPs are obtained among all the CPs. The adaptive fuzzy clustering (AFC) technology is adopted to estimate the position of the MS with true CPs. Finally, simulations are conducted to evaluate the performance of the algorithm. The results demonstrate that the proposed location algorithm can significantly mitigate the NLOS effect and efficiently estimate the MS position.

**Key words:** passive location; time-of-arrival/angle-of-arrival (TOA/AOA); non-line-of-sight (NLOS) mitigation; adaptive fuzzy clustering

Wireless location has received significant attention since many standards such as Enhanced 911 in USA and E-112 in Europe enforce more stringent boundaries for localization errors. It also has some of the available market forecasts. According to the estimated data, the location-based services (LBSs) will generate annual revenues of 15 billion dollars<sup>[1]</sup>. It implies that the location information also has many applications, such as location-sensitive billing, the intelligent transport system (ITS), and the resource management<sup>[2]</sup>.

Authors in Ref. [3] proved that combining two location techniques can lead to more accurate location estimations. The hybrid TOA/AOA location technique has attracted much attention from both academia and industry recently. In this paper, we use the hybrid technique to estimate the mobile station (MS) position in a passive location system.

There are still some open issues remaining unsolved in the hybrid TOA/AOA location system. One of the key challenges is the efficiency and preciseness of the estimation in the non-line-of-sight (NLOS) environments<sup>[4]</sup>. Due to the lack of a line-of-sight (LOS) path between the MS and the base station (BS), the TOA and AOA measurements may signif-

icantly deviate from their true values. So, traditional algorithms based on LOS assumptions perform very poorly when the TOAs and AOAs are corrupted by an NLOS error.

Today, antenna arrays are used for both the BS and the MS, so the spatial distribution of the scatterers is important in determining the location accuracy. So it is necessary to use the scatterer information to estimate the MS position. Several approaches for mitigating NLOS error using scatterer information were proposed in Refs. [5–8]. In Ref. [5], the authors added the Doppler shift parameter to common TOA and AOA measurements and required a moving MS. A ray-tracing algorithm was proposed in Ref. [6], which used a single BS to locate an MS. The system required the nearest scatterer position to identify LOS and NLOS. The technique proposed in Ref. [7] attempted to locate the MS using the probability density function (PDF) of the scatterers around the serving BS and the maximum likelihood (ML) estimator. In Ref. [8] a new grid-search based technique taking considerations of the geometrical relationships among the MS, scatterers and the BS was proposed to solve the constrained nonlinear equations under the assumption of a single bounce model.

In this paper, a new approach is proposed to tackle the NLOS problem using scatterer information. Our positioning system belongs to the passive location. Compared with the previously proposed techniques, it has some key differences. First, we do not require *a priori* knowledge of the scatterer information and only use one scatterer which is different from Refs. [6–7]. Secondly, unlike the systems discussed in Refs. [6, 8], all the BSs play an equal role in the location process. We do not distinguish the serving BS. Finally, we use the adaptive fuzzy clustering (AFC) technique to estimate the MS position, which renders our approach extremely robust.

## 1 Related Works

### 1.1 Conventional methods

The conventional method for hybrid TOA/AOA measurements is based on LOS assumptions<sup>[7]</sup>. Fig. 1 depicts a rough passive location system using hybrid TOA/AOA measurements. The MS coordinates are determined as follows:

$$x_{\text{MS}} = \frac{1}{N} \sum_{i=1}^N (x_{\text{BS}_i} - l_i \cos \theta_i) \quad (1)$$

$$y_{\text{MS}} = \frac{1}{N} \sum_{i=1}^N (y_{\text{BS}_i} - l_i \sin \theta_i) \quad (2)$$

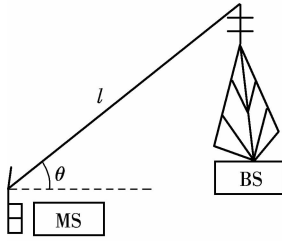
where  $(x_{\text{MS}}, y_{\text{MS}})$  is the coordinate of the MS;  $(x_{\text{BS}_i}, y_{\text{BS}_i})$  is the coordinate of the BS<sub>*i*</sub>;  $N$  is the number of the BSs;  $l_i$

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**Fig. 1** A rough passive location system using hybrid TOA/ AOA measurements

and  $\theta_i$  are the corresponding TOA and AOA measurements of the  $BS_i$ .

The method above is simple to use but not accurate in the NLOS environments because the TOA and AOA measurements face deviation errors from their true values. So the conventional methods are not adopted in the NLOS environments.

## 1.2 Scattering model

For the development of a smart antenna, the spatial and temporal properties of the channel have an enormous impact on the performance of the location system. Several basic models were studied in Refs. [9–10]. They include the ring of scatterers (ROS) model, the disk of scatterers (DOS) model and the elliptical model. All of these models are referred to as single bounce models which assume that the signal undergoes a single reflection during its propagation between the MS and the BS. Even in multiple bounce scenarios, the single bounce paths can be picked out from all the measured multipaths by resorting to a proper method<sup>[8, 11]</sup>.

In this paper, a single bounce disk scatterers model (SBDSM) is adopted in the location system and it is described as follows: 1) We only consider one scatterer between the MS and each BS; 2) The scatterers are located on a solid circular disk of a fixed radius  $R_d$  centered about the MS; 3) The distance from an MS to a scatterer is uniformly distributed in the range of  $[0, R_d]$ ; 4) The angle  $\theta$  is uniformly distributed in the range of  $[0, 2\pi]$ .

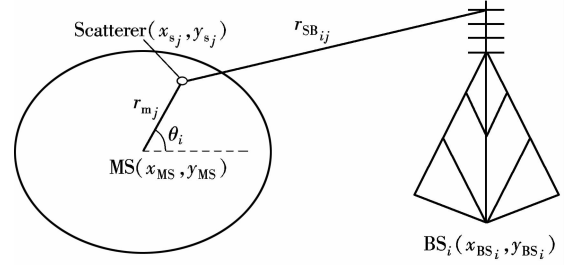
## 1.3 MS location model

In this section, we provide an MS location model using the SBDSM in the NLOS environments, which is the base of the proposed algorithm.

A single bounce disk scatterer model with the geometry is shown in Fig. 2. Based on this model, we obtain

$$L_i = r_{m_i} + r_{SB_{ij}} \quad (3)$$

where  $L_i$  is the measured range between the MS and  $BS_i$ ;  $r_{m_i}$  is the distance between the MS and the  $j$ -th scatterer;  $r_{SB_{ij}}$  is the distance between the  $j$ -th scatterer and  $BS_i$ ;  $\theta_j$  is the measured AOA between the MS and the  $j$ -th scatterer.



**Fig. 2** Geometry of single bounce disk scatterer model

From the above, we obtain

$$x_s = x_{MS} + r_{m_j} \cos \theta_j \quad (4)$$

$$y_s = y_{MS} + r_{m_j} \sin \theta_j \quad (5)$$

## 1.4 Adaptive fuzzy clustering technique

Compared with traditional data processing methods which take the average value of all the candidate points (CPs) as the estimated result<sup>[8]</sup>, the AFC technique estimates the MS position according to the degree of correlation and rejects outliers. A more detailed explanation is given in Refs. [12–13].

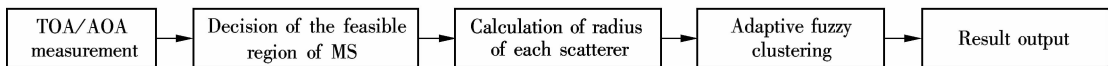
The idea of the AFC contains two phases. In the proposed algorithm we only use cluster analysis to find an area with the maximum density of possible locations. Then all the CPs of the MS in that area are averaged as the final MS position. More details are described in the following section.

The main reason for us to adopt this technique is that the possible locations with small errors always gather around the true location of the MS, while possible locations with large errors are inclined to spread out. So the AFC is capable of finding the location of the MS correctly with a minimal error.

## 2 Proposed Location Estimation Algorithm

### 2.1 General algorithm description

In this section we propose a framework for the proposed algorithm. The procedure of location is summarized in Fig. 3 and explained in the following subsections.



**Fig. 3** Block diagram of the proposed location estimation algorithm

Typically, the proposed algorithm consists of three steps. The first step is to decide the feasible region of the MS. The second step is the calculation of the scatterer radius for each CP of the MS. If the entire computed scatterer radius is smaller than the maximum scatterer radius, we think that this CP is the possible position of the MS. The final step is the data fusion of all the possible position points using the AFC.

### 2.2 Feasible region of the MS

Because there are no serving BS in the location system in this paper, we determine the feasible region of the MS with the TOA measurement. The linearized feasible region of the MS can be obtained according to Refs. [4, 14–15].

The feasible region of the MS can be relaxed as<sup>[15]</sup>

$$x_{BS_i} - L_i \leq x_{MS} \leq x_{BS_i} + L_i \quad (6)$$

$$y_{BS_i} - L_i \leq y_{MS} \leq y_{BS_i} + L_i \quad (7)$$

So the feasible region of the MS is as follows:

$$\max(x_{BS_i} - L_i) \leq x_{MS} \leq \min(x_{BS_i} + L_i) \quad (8)$$

$$\max(y_{BS_i} - L_i) \leq y_{MS} \leq \min(y_{BS_i} + L_i) \quad (9)$$

### 2.3 Calculation of the scatterer radius

From Fig. 2, we have

$$(L_i - r_{m_i})^2 = (x_{MS} + r_{m_i} \cos \theta_j - x_{BS_i})^2 + (y_{MS} + r_{m_i} \sin \theta_j - y_{BS_i})^2 \quad (10)$$

Rearranging the terms, Eq. (10) can be written as

$$r_{m_i} = \frac{1}{2} \frac{L_i^2 - (x_{MS} - x_{BS_i})^2 - (y_{MS} - y_{BS_i})^2}{L_i + \cos \theta_j (x_{MS} - x_{BS_i}) + \sin \theta_j (y_{MS} - y_{BS_i})} \quad (11)$$

If  $0 < r_{m_i} < R_d$  for all the scatterers between the MS and the BS, we think that the CP is the true candidate point of the MS. Otherwise, we think it is not the candidate point of the MS.

### 2.4 Adaptive fuzzy clustering

Since we have obtained all the CPs of the MS, we introduce the second phase of the AFC technique. The following briefly describes how the algorithm works in the second phase.

- 1) Compute the center of gravity of the set of the CPs.
- 2) Compute the distance from all the CPs to the center of gravity.
- 3) Compute the average distance  $l$  among all the distances.
- 4) Remove the CPs whose distances are greater than  $l\beta$  ( $\beta$  is to be determined).
- 5) Compute the center of gravity of the remaining CPs, which is used as the final position of the MS.

The proposed algorithm, in which the AFC is carried out once, is shown as follows:

Sub function for adaptive fuzzy clustering

Input: The set of candidate points CP, Num\_CP,  $\beta$ .

Output: The final position of the MS ( $x_{MS}$ ,  $y_{MS}$ ).

( $x_{center}$ ,  $y_{center}$ )  $\leftarrow$  the center of gravity of all CPs

$l \leftarrow$  the distances between each CP and ( $x_{center}$ ,  $y_{center}$ )

$l_{average} \leftarrow$  the average value of  $l$

For  $i = 1$  to Num\_CP

IF  $l_i > l_{average}\beta$

THEN remove the  $i$ -th candidate point from the set

End

End

( $x_{MS}$ ,  $y_{MS}$ )  $\leftarrow$  the center of gravity of the remaining CPs

Main function of the proposed algorithm is shown as follows:

Receive radio signals (BS(1, 2, Num\_BS))

For  $i = 1$  to Num\_BS

$L_i \leftarrow$  TOA( $i$ )

$\theta_i \leftarrow$  AOA( $i$ )

End

//generate the set of candidate points

$j = 1$

While  $j < \text{Num\_CP}$

( $x_{cp}$ ,  $y_{cp}$ )  $\leftarrow$  Eqs. (8) and (9)

$r_{m_i} \leftarrow$  Eq. (10)

IF  $0 < r_{m_i} < R_d$  for Num\_BS BSs

THEN ( $x_{cp}$ ,  $y_{cp}$ ) is the true candidate point

$j = j + 1$

End

End

//Adaptive fuzzy clustering for the set

( $x_{MS}$ ,  $y_{MS}$ )  $\leftarrow$  sub function AFC

## 3 Simulation and Results

The proposed location algorithm uses more than three BSs to achieve the simulation. BS<sub>1</sub> is located at (0, 0) in meters, whereas the positions of the other four BSs (BS<sub>2</sub>, BS<sub>3</sub>, BS<sub>4</sub>, BS<sub>5</sub>) are located at (850, 1 500), (1 700, 0), (0, 1 000), and (1 000, 1 000) in meters. The true position of the MS is assumed to be at (500, 500) in meters. The measured TOA and AOA errors are assumed to be a zero means white Gaussian with known standard deviation 30 m<sup>[16]</sup> and 2°<sup>[18]</sup>, respectively.

The simulation parameters associated with two different cases are considered to study how the location accuracy is affected by the scatterer radius and the number of BSs.

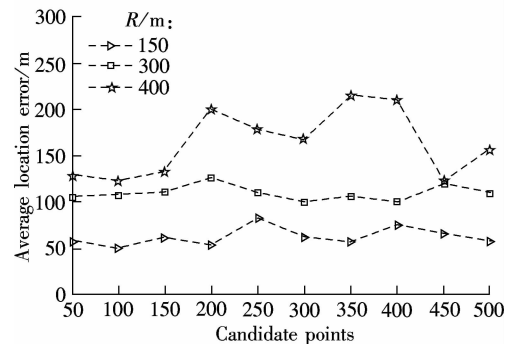
**Case 1** We evaluate the proposed algorithm with different scatterer radii.

Three BSs (BS<sub>1</sub>, BS<sub>2</sub>, BS<sub>3</sub>) are used for the location process with different CPs when  $R = 150$  m (small radius), 300 m (middle radius), and 400 m (large radius), respectively.

**Case 2** We evaluate the proposed algorithm with different BSs.

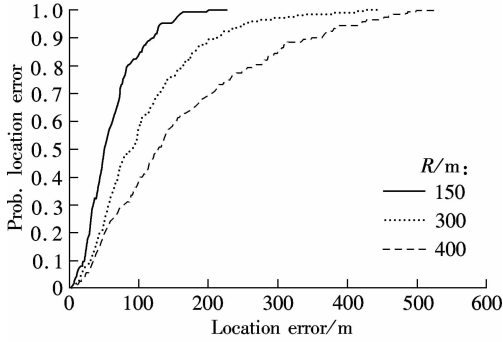
Four BSs (BS<sub>1</sub>, BS<sub>2</sub>, BS<sub>3</sub>, BS<sub>4</sub>) and five BSs (BS<sub>1</sub>, BS<sub>2</sub>, BS<sub>3</sub>, BS<sub>4</sub>, BS<sub>5</sub>) are used for the location process respectively with different CPs when  $R = 400$  m (large radius).

Fig. 4 and Fig. 5 illustrate the performance comparison between different CPs with  $R = 150$  m (small radius),  $R = 300$  m (middle radius), and  $R = 400$  m (large radius) respectively. It can be seen that the maximum average location error in a small radius is 82.79 m. The location accuracy



**Fig. 4** The location error for different scatterer radii vs. the number of CPs

of 100 m is 84.5%, and the location error of 225 m can reach 100%. So, in this case, it is obvious that the simulation results comply with the FCC regulations.

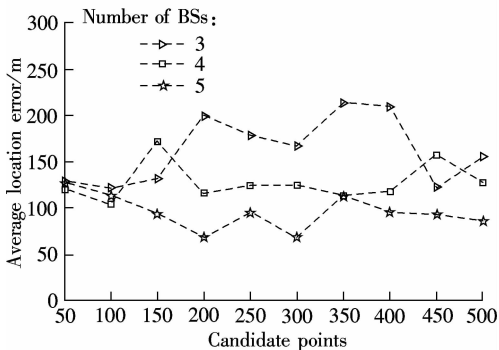


**Fig. 5** The CDF of location error for different scatterer radii vs. the number of CPs

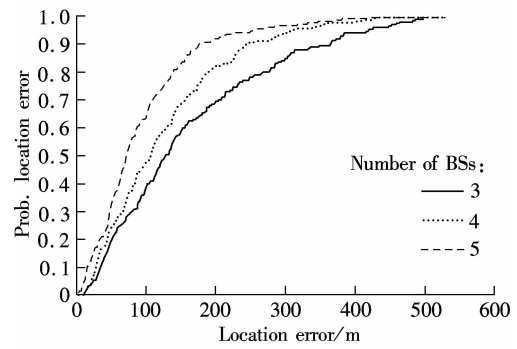
In the middle radius situation, the location error is greater than that in the small radius situation. From Fig. 4, the location error is between 99.37 m and 126 m. The location accuracy of 100 m is 61.5% while the location accuracy of 116 m can reach 67%, and the location accuracy of 300 m is 96.5%. It is noted that the location results basically comply with the FCC regulations more or less.

In the large radius situation, the location error is the largest one among the three cases. As can be seen from Fig. 4, even the smallest location error can reach 122 m. The location accuracies of 100 m and 300 m are 40% and 85.5%, respectively. We can conclude that they do not comply with the FCC regulations when only three BSs are used to locate the MS position.

In the following, we evaluate the proposed algorithm with different BSs in large radius and obtain some useful conclusions. Fig. 6 and Fig. 7 are the simulation results with the number of BSs being 3, 4, and 5, respectively. As shown in Fig. 6, the location error is the smallest one among the three cases when the number of BSs is 5. When the number of BSs is 4, the location accuracies of 100 m and 300 m are 51.5% and 95%, respectively, which do not comply with the FCC regulations. However, in the case of five BSs, the location accuracy of 100 m is 63.5%, and the location accuracy of 103 m reaches 67%; the location accuracy of 300 m is 96.5%. So we can conclude that when more than five BSs are used to locate the MS position, the location accuracy complies with the FCC regulations when  $R = 400$  m (large radius).



**Fig. 6** The location error for different BSs vs. the number of BSs ( $R = 400$  m)



**Fig. 7** The CDF of location error for different BSs vs. the number of BSs ( $R = 400$  m)

## 4 Conclusion

In this paper, a hybrid TOA/AOA algorithm using scatterer information in current passive location systems is presented. The feasible region for the MS can be relaxed to the linear constraints, while usually they are in the interior of each of the circular constraints. The CPs can be generated from this region. Compared with the prior scatterer information, the true CPs with the MS are obtained. The AFC technique is used to estimate the MS position. Our experiments indicate that the proposed method is a promising solution for NLOS environments in passive location systems.

## References

- [1] Sayed A H, Tarighat A, Khajehnouri N. Network-based wireless location [J]. *IEEE Signal Processing Magazine*, 2005, **22**(4): 24–40.
- [2] Li C, Zhuang W. Non-line-of-sight error mitigation in TDOA mobile location[C]//*IEEE Global Telecommunications Conference*. San Antonio, TX, USA, 2001, **1**: 25–29.
- [3] Li C, Zhuang W. Hybrid TDOA/AOA mobile user location for wideband CDMA cellular systems [J]. *IEEE Transactions on Wireless Communications*, 2003, **1**(3): 439–447.
- [4] Guvenç I, Chong C C. A survey on TOA based wireless localization and NLOS mitigation techniques [J]. *IEEE Communications Surveys & Tutorials*, 2009, **11**(3): 107–124.
- [5] Thomas N J, Cruickshank D G M, Laurenson D I. Calculation of mobile location using scatterer information [J]. *Electron Letters*, 2001, **37**(19): 1193–1194.
- [6] Porretta M, Nepa P, Manara G, et al. A novel single base station location technique for microcellular wireless networks: description and validation by a deterministic propagation model [J]. *IEEE Transactions on Vehicular Technology*, 2004, **53**(5): 1502–1514.
- [7] Zhaounia M, Landolsi M A, Bouallegue R. Approximate maximum likelihood mobile localization using scatterer information [C]//*IEEE 69th Vehicular Technology Conference*. Barcelona, Spain, 2009, **2**: 1–3.
- [8] Xie Y Q, Wang Y, Zhu P C, et al. Grid-search-based hybrid TOA/AOA location techniques for NLOS environments [J]. *IEEE Communications Letters*, 2009, **13**(4): 254–256.
- [9] Al-Jazzar S, Caffery J Jr, You H R. Scattering-model-based methods for TOA location in NLOS environments [J]. *IEEE Transactions on Vehicular Technology*, 2007, **56**(2): 583–593.
- [10] Lei J, Tan S Y. Geometrically based statistical channel models for outdoor and indoor propagation environments [J]. *IEEE Transactions on Vehicular Technology*, 2007, **56**(6):

- 3578 – 3592.
- [11] Seow C K, Tan S Y. Non-line-of-sight localization in multipath environments [J]. *IEEE Transactions on Mobile Computing*, 2008, 7(3): 1 – 14.
- [12] Zhang J B, Yan T, Stankovic J A, et al. Thunder: towards practical, zero cost acoustic localization for outdoor wireless sensor networks [J]. *ACM Mobile Computing and Communications Review*, 2007, 11(1): 15 – 28.
- [13] Merhi Z, Elgamel M, Bayoumi M. A lightweight collaborative fault tolerant target localization system for wireless sensor network [J]. *IEEE Transactions on Mobile Computing*, to appear.
- [14] Venkatesh S, Buehrer R M. A linear programming approach to NLOS error mitigation in sensor networks [C]//*The Fifth International Conference on Information Processing in Sensor Networks*. Nashville, TN, USA, 2006: 301 – 308.
- [15] Larsson E G. Cramer-Rao bound analysis of distributed positioning in sensor networks [J]. *IEEE Signal Processing Letters*, 2004, 11(3): 334 – 337.
- [16] Lei J, Xing J P, Zhang X, et al. LCC-Rwgh: a NLOS error mitigation algorithm for localization in wireless sensor network [C]//*IEEE International Conference on Control and Automation*. Guangzhou, China, 2007: 1354 – 1359.

## 非视距环境下基于散射体信息的被动定位

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**摘要:**为了提高传统的 TOA/AOA 定位技术在非视距环境下的定位精度,提出了一种基于散射体信息的混合定位方法. 首先,利用基站坐标信息和 TOA 测量值确定线性化的可行区域,产生移动台的候选位置点. 对每一个移动台候选点,结合 TOA 和 AOA 测量值,计算各自散射体半径,通过与先验的散射体信息的比较,筛选候选移动台位置点. 然后,运用自适应模糊聚类算法估计移动台位置,完成定位. 最后,对所提出的定位算法进行了仿真验证. 仿真结果表明:所提出的基于散射体信息的混合 TOA/AOA 定位算法能够减轻非视距效应,有效估计移动台位置.

**关键词:**被动定位; TOA/AOA; 非视距消除; 自适应模糊聚类

**中图分类号:** TN911.7