

Research Article

A Hybrid AOA and TDOA-Based Localization Method Using Only Two Stations

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Target localization plays an important role in the application of radar, sonar, and wireless sensor networks. In order to improve the localization performance using only two stations, a hybrid localization method based on angle of arrival (AOA) and time difference of arrival (TDOA) measurements is proposed in this paper. Firstly, the optimization model for localization based on AOA and TDOA are built, respectively, in the sensor network. Secondly, the majorization-minimization (MM) method is employed to create surrogate functions for solving the multiple objective optimization problem. Next, the hybrid localization problem is solved by the projected gradient decent (PGD) method. Finally, the Cramer-Rao lower bound (CRLB) for the joint AOA and TDOA method is derived for the comparison. Simulations proved that the proposed method has improved localization performance using AOA and TDOA measurements from only two base stations.

1. Introduction

Source localization in the sensor network is a fundamental problem which has received an upsurge of attention in recent years. A number of separated sensors in the network will be employed to measure the emitted or reflected signal from the target [1]. Many algorithms have been presented in literature to determine the source position, based on the time of arrival (TOA), time difference of arrival (TDOA), angle of arrival (AOA), and received signal strength (RSS) method.

Localization problem based on the TOA method in the quasi-synchronous network is addressed in [2], in which a two-step linear algorithm is presented for estimating the passive object position. TOA-based localization problem in an adverse environment is solved in [3], which employs two convex relaxation methods for mitigating non-line-of-sight (NLOS) effect. Using a single transmitter and multiple receivers, the optimal geometries for TOA localization configuration in the two-dimensional environment are analyzed in [4]. With the help of floor plan information, Liu et al. [5] propose an effective geometrical localization method based on TOA in the non-line-of-sight (NLOS) environment without considering multiple-bound scattering signal paths.

A coarse position estimation algorithm-based TDOA is presented in [6], which is robust with regard to the initial position without redundant receivers. As a further step, a low-complexity nonlinear expectation maximization localization algorithm is presented in [7]. Target location is estimated by the TDOA data in [8], where empirical mode decomposition is used to decompose seismic signals, and multiple features of intrinsic mode functions are extracted. The work of [9] transforms a TDOA model into a TOA model, by presenting a semidefinite programming method. The TDOA method is also employed in passive radar source localization [10], taking advantage of the characteristics of the same sensor in different positions.

For obtaining the best localization performance, the angular separation requirements for AOA sensors are established in [11]. A closed-form solution for 3D localization using AOAs is presented in [12] to handle the effect of sensor position errors in a wireless sensor network. In the AOA localization system, an evaluation function by frame theory is derived and proved in [13], in order to solve the sensor augmentation problem.

Localization algorithm based on the RSS method in NLOS environment is presented in [14], by correcting the

NLOS measurements. A novel fingerprinting paradigm is introduced for RSS localization in [15], which obtains a significant gain for multiple sources and multipath environments. In [16], RSS localization methods based on convex optimization are presented to solve the noncooperative and cooperative problems in sensor networks.

However, localization based on the TOA method needs an accurate time synchronization. TDOA-based approach requires at least four located sensors. RSS algorithms are based on known exact received signal without multipath effect, and the AOA method can perform well only when the target is not far away from the sensors [17]. There are many advantages with the hybrid localization method [17, 18], which has already attracted many attentions. Using the hybrid-bearing AOA and TDOA sensors [19], the constrained optimization method is employed to estimate the maximum likelihood values. The RSS-assisted TOA-based localization method is presented in [20], which improves the efficiency and localization accuracy of the indoor geolocation system. In adverse NLOS environment, a new mitigation method is proposed using the combined RSS and TOA measurements in [21]. Combining TDOA and RSS measurements, a two-step position estimator is presented in [22] for the visible light positioning system. The hybrid AOA- and RSS-based localization method is presented in [23] for 3D wireless sensor network without central processor. Using the same hybrid method, a simple closed-form solution method is proposed by using the spherical coordinate conversion in [24]. Using the hybrid measurements of TDOA and AOA methods, the mean square error matrix is derived under small error condition in [25], and a closed-form solution based on two base stations (CFS-2BSs) is proposed. In order to reduce the sensors for target localization, we propose a hybrid TDOA/AOA localization approach only with two sensors, taking advantage of the complementary property between the TDOA- and AOA-based localization methods.

This paper investigates the localization problem based on AOA and TDOA measurements from two stations. The main contributions of this paper are summarized as follows:

- (1) A localization model using only two stations is developed, which is converted to be a multiple optimization problem.
- (2) The MM method is used to solve this optimization problem, which maximizes the similarity between unknown and known information for AOA and TDOA measurements.
- (3) A single objective optimization model is constructed after the derivation based on the MM. The PGD method is employed to solve this problem effectively.
- (4) Simulations prove the superior localization performance using only two stations in the sensor network.

This paper is organized as follows. Section 2 describes the basic TDOA localization model. Section 3 proposes the hybrid localization method based on AOA and TDOA data from two base stations. CRLB is derived for evaluating the localization performance in Section 4. Section 5 shows the

simulation results based on the proposed method. Section 6 gives the conclusion of this paper.

Notations. Bold uppercase (e.g., \mathbf{H}) and lowercase (e.g., \mathbf{b}) letters represent the matrices and vectors, respectively. The notations $(\cdot)^T$ and $(\cdot)^H$ stand for transpose and Hermitian of their argument, respectively. $\|\cdot\|_2$ denotes the l_2 norm of a vector. The gradient of f at x is denoted by $\nabla f(x)$.

2. Basic Localization Methods Based on TDOA

Let $\mathbf{A}_i = [x_i, y_i]^T$ denotes the position of i th base station and $\phi = [x, y]^T$ represents the unknown position of the master station. The distance d_i between the i th base station and the master station can be written as

$$d_i = \sqrt{(x - x_i)^2 + (y - y_i)^2} = \|\phi - \mathbf{A}_i\|_2, i = 1, 2, \dots, M, \quad (1)$$

where M is the number of base stations. Time difference $\Delta t_{i,1}$ from the i th and 1th base station can be defined as

$$\Delta t_{i,1} = \frac{d_i}{c} - \frac{d_1}{c}, \quad (2)$$

where c is the propagation speed. Distance difference can be derived as

$$\Delta d_{i,1} = c\Delta t_{i,1}. \quad (3)$$

Taylor iteration method and Chan's method are proposed, respectively, as the classical localization methods based on the time difference.

An iterative method is employed to solve the hyperbolic equations for estimating the MS position in the Taylor iteration method, where a local linear least square (LS) solution is selected based as the deviation $(\Delta x, \Delta y)$ of each iteration. The position of master station can be written as

$$\begin{aligned} x &= x_0 + \Delta x, \\ y &= y_0 + \Delta y, \end{aligned} \quad (4)$$

where (x_0, y_0) is initial coordinate values for the iteration and Δx and Δy can be derived as

$$[\Delta x, \Delta y]^T = (\mathbf{G}_t^T \mathbf{C}^{-1} \mathbf{G}_t)^{-1} \mathbf{G}_t^T \mathbf{C}^{-1} \mathbf{h}_t, \quad (5)$$

where \mathbf{C} is the covariance matrix for the time difference estimation and \mathbf{G}_t and \mathbf{h}_t are written as, respectively, as follows:

$$\mathbf{G}_t = \begin{bmatrix} \frac{x_1 - x}{d_1} & \frac{x_2 - x}{d_2} & \frac{y_1 - y}{d_1} & \frac{y_2 - y}{d_2} \\ \frac{x_1 - x}{d_1} & \frac{x_3 - x}{d_3} & \frac{y_1 - y}{d_1} & \frac{y_3 - y}{d_3} \\ \dots & \dots & \dots & \dots \\ \frac{x_1 - x}{d_1} & \frac{x_M - x}{d_M} & \frac{y_1 - y}{d_1} & \frac{y_M - y}{d_M} \end{bmatrix},$$

$$\mathbf{h}_t = \begin{bmatrix} \Delta d_{2,1} \\ \Delta d_{3,1} \\ \dots \\ \Delta d_{M,1} \end{bmatrix}. \quad (6)$$

Besides, Chan's method is proposed to obtain a non-iterative solution. Let $\phi_c = [\phi, d_1]$ be the solution, which can be derived as

$$\phi_c = (\mathbf{G}_c^T \mathbf{C}^{-1} \mathbf{G}_c)^{-1} \mathbf{G}_c^T \mathbf{C}^{-1} \mathbf{h}_c, \quad (7)$$

where

$$\mathbf{h}_c = \frac{1}{2} \begin{bmatrix} \Delta d_{2,1}^2 - (x_2^2 + y_2^2)(x_1^2 + y_1^2) \\ \Delta d_{3,1}^2 - (x_3^2 + y_3^2)(x_1^2 + y_1^2) \\ \dots \\ \Delta d_{M,1}^2 - (x_M^2 + y_M^2)(x_1^2 + y_1^2) \end{bmatrix}, \quad (8)$$

$$\mathbf{G}_c = \begin{bmatrix} x_2 - x_1 & y_2 - y_1 & d_{2,1} \\ x_3 - x_1 & y_3 - y_1 & d_{3,1} \\ \dots & \dots & \dots \\ x_M - x_1 & y_M - y_1 & d_{M,1} \end{bmatrix}.$$

3. Hybrid Localization Method Based on AOA and TDOA

3.1. Multiple Objectives' Design. The unknown location of the target from the noisy measurements of angle of arrival (AOA) can be estimated, as there is a nonlinear relationship between the AOA and target location. Only two base stations with two angles $[\theta_1, \theta_2]$ are considered, $\mathbf{C}_1 = [\cos \theta_1, \cos \theta_2]^T$, which is assumed to be known in Figure 1.

In Figure 1, β_1 and β_2 are the azimuth angles of the base stations. θ_1 can be written as follows:

$$\theta_1 = \beta_1 - \beta_2. \quad (9)$$

Based on the AOA measurements of every BS, the first fitness function is designed as follows:

$$\min_{\phi} \|\mathbf{F}_1 - \mathbf{C}_1\|_2^2, \quad (10)$$

where the vector \mathbf{F}_1 is designed as follows:

$$\begin{aligned} \mathbf{F}_1(i) &= (\cos \beta_1, \sin \beta_1)(\cos \beta_2, \sin \beta_2)^T \\ &= \frac{\mathbf{A}_i^T}{\|\mathbf{A}_i\|_2} \frac{(\phi - \mathbf{A}_i)}{\|\phi - \mathbf{A}_i\|_2} \\ &= \frac{\mathbf{A}_i^T (\phi - \mathbf{A}_i)}{\|\mathbf{A}_i\|_2 \|\phi - \mathbf{A}_i\|_2}. \end{aligned} \quad (11)$$

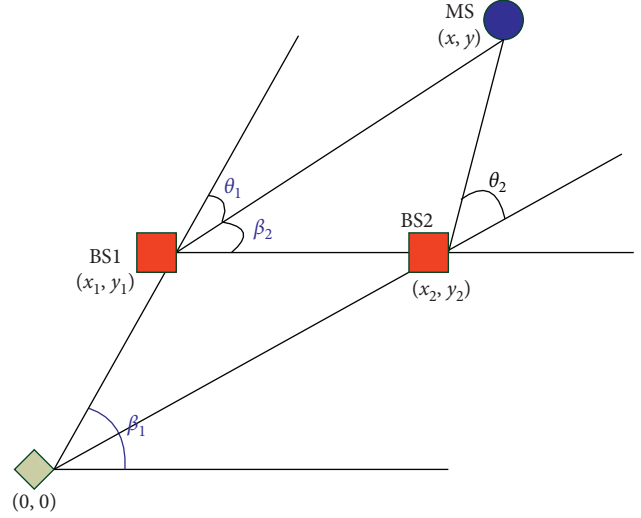


FIGURE 1: Angles of MS and BSs.

Using the TDOA data from the two base stations, the sum of squared range difference errors is used to design the second fitness function, which is defined as

$$\min_{\phi} \|\mathbf{F}_2 - \mathbf{C}_2\|_2^2, \quad (12)$$

where

$$\begin{aligned} \mathbf{F}_2(i) &= \|\phi - \mathbf{A}_i\|_2 - \|\phi - \mathbf{A}_1\|_2, \\ \mathbf{C}_2(i) &= \Delta d_{i,1}. \end{aligned} \quad (13)$$

3.2. Hybrid Optimization Model. In order to solve the hybrid optimization problems based on (10) and (12), the minorization-maximization method is employed to create the surrogate functions here. Let $\Gamma_1 = \|\mathbf{F}_1 - \mathbf{C}_1\|_2^2$, where Γ_1 can be majorized by $g_1(\phi|\phi^{(t)})$, which is derived as follows:

$$g_1(\phi|\phi^{(t)}) = \Gamma_1(\phi^{(t)}) + \frac{\partial \Gamma_1}{\partial \phi} \Big|_{\phi^{(t)}} (\phi - \phi^{(t)}), \quad (14)$$

where $\phi^{(t)}$ is the solution at the t th iteration, and

$$\frac{\partial \Gamma_1}{\partial \phi} = 2 \frac{\partial \mathbf{F}_1}{\partial \phi} (\mathbf{F}_1 - \mathbf{C}_1). \quad (15)$$

Let $\mathbf{B}_i = \mathbf{A}_i^T / \|\mathbf{A}_i\|_2$; then,

$$\mathbf{F}_1(i) = \frac{\mathbf{B}_i (\phi - \mathbf{A}_i)}{\|\phi - \mathbf{A}_i\|_2}. \quad (16)$$

The gradient of $\mathbf{F}_1(i)$ can be written as

$$\frac{\partial \mathbf{F}_1(i)}{\partial \phi} = \frac{\mathbf{B}_i^T \|\phi - \mathbf{A}_i\|_2^2 - \mathbf{B}_i (\phi - \mathbf{A}_i) (\phi - \mathbf{A}_i)}{\|\phi - \mathbf{A}_i\|_2^3}, \quad (17)$$

$$\frac{\partial \mathbf{F}_1}{\partial \phi} = \left[\frac{\partial \mathbf{F}_1(1)}{\partial \phi}, \frac{\partial \mathbf{F}_1(2)}{\partial \phi} \right].$$

Let $\Gamma_2 = \|\mathbf{F}_2 - \mathbf{C}_2\|_2^2$, where Γ_2 can be majorized by $g_2(\phi|\phi^{(t)})$, which can be written as follows:

$$g_2(\phi|\phi^{(t)}) = \Gamma_2(\phi^{(t)}) + \frac{\partial \Gamma_2}{\partial \phi} \Big|_{\phi^{(t)}}^T (\phi - \phi^{(t)}), \quad (18)$$

where

$$\begin{aligned} \frac{\partial \Gamma_2}{\partial \phi} &= 2 \frac{\partial \mathbf{F}_2}{\partial \phi} (\mathbf{F}_2 - \mathbf{C}_2), \\ \frac{\partial \mathbf{F}_2}{\partial \phi} &= \frac{\phi - \mathbf{A}_i}{\|\phi - \mathbf{A}_i\|_2} - \frac{\phi - \mathbf{A}_1}{\|\phi - \mathbf{A}_1\|_2}. \end{aligned} \quad (19)$$

Based on (14) and (18), the final objective function for the localization using two stations is designed as

$$\Phi(\phi) = g_1(\phi|\phi^{(t)}) + \lambda g_2(\phi|\phi^{(t)}), \quad (20)$$

$$= \eta + \mathbf{f}_1^T (\phi - \phi^{(t)}) + \xi + \mathbf{f}_2^T (\phi - \phi^{(t)}), \quad (21)$$

where λ is the scalarization coefficient, and

$$\eta = \Gamma_1(\phi^{(t)}), \quad (22)$$

$$\mathbf{f}_1 = \frac{\partial \Gamma_1}{\partial \phi} \Big|_{\phi^{(t)}}, \quad (23)$$

$$\xi = \lambda \Gamma_2(\phi^{(t)}), \quad (24)$$

$$\mathbf{f}_2 = \lambda \frac{\partial \Gamma_2}{\partial \phi} \Big|_{\phi^{(t)}}. \quad (25)$$

Then, we use the PGD method to solve the optimization problem. ϕ_k can be calculated iteratively by

$$\phi_k = \text{pro}_\phi(\phi_{k-1} - t_k \nabla \Phi(\phi_{k-1})), \quad (26)$$

$$= \arg \min_{\phi} \|\phi_{k-1} - t_k \nabla \Phi(\phi_{k-1})\|_2^2, \quad (27)$$

where pro_ϕ is the Euclidean projection. The gradient of Φ can be written as

$$\nabla \Phi(\phi) = \mathbf{f}_1 + \mathbf{f}_2. \quad (28)$$

In conclusion, the hybrid localization procedure based on the TDOA and AOA data is described in Algorithm 1.

4. Derivation of Cramer–Rao Lower Bound

Only Gaussian range sampling error is assumed in the localization here, so Fisher's information matrix [26] is then given by

$$\mathbf{J}(\phi) = \begin{bmatrix} J_{11} & J_{12} \\ J_{21} & J_{22} \end{bmatrix} = \begin{bmatrix} -E_\phi \left[\frac{\partial^2 \Gamma_1}{\partial x^2} \right] & -E_\phi \left[\frac{\partial^2 \Gamma_1}{\partial x \partial y} \right] \\ -E_\phi \left[\frac{\partial^2 \Gamma_1}{\partial x \partial y} \right] & -E_\phi \left[\frac{\partial^2 \Gamma_1}{\partial y^2} \right] \end{bmatrix}, \quad (29)$$

where $\mathbf{I}(\phi)$ is defined as the inverse matrix of $\mathbf{J}(\phi)$:

$$\mathbf{I}(\phi) = \begin{bmatrix} I_{11} & I_{12} \\ I_{21} & I_{22} \end{bmatrix} = \mathbf{J}^{-1}(\phi) = \frac{1}{J_{11}J_{22} - J_{12}J_{21}} \begin{bmatrix} J_{22} & -J_{12} \\ -J_{21} & J_{11} \end{bmatrix}, \quad (30)$$

where $J_{i,j}$ and $I_{i,j}$ are, respectively, the element of \mathbf{J} and \mathbf{I} , $i, j = 1, 2$. The localization CRLB based on the AOA method can be computed as follows:

$$\sigma_{\text{CRLB-AOA}}^2 = E_\phi[(\hat{\phi} - \phi)^2] = I_{11} + I_{22}. \quad (31)$$

Based on the AOA measurements, (31) can be derived as

$$\sigma_{\text{CRLB-AOA}}^2 = \frac{b_1}{b_2 - b_3}, \quad (32)$$

where

$$\begin{aligned} b_1 &= \sigma_R^2 \sum_{i=2}^N [(\cos \theta_i - \cos \theta_1)^2 + (\sin \theta_i - \sin \theta_1)^2], \\ b_2 &= \sum_{i=2}^N (\cos \theta_i - \cos \theta_1)^2 \sum_{i=1}^N (\sin \theta_i - \sin \theta_1)^2, \\ b_3 &= \left[\sum_{i=2}^N ((\cos \theta_i - \cos \theta_1)(\sin \theta_i - \sin \theta_1)) \right]^2, \end{aligned} \quad (33)$$

where σ_R^2 is the Gaussian error variance of \mathbf{C}_2 and θ_i denotes the angle between the MS and i th BS with respect to a reference direction.

Using the same method, CRLB based on the TDOA method can be calculated as

$$\sigma_{\text{CRLB-TDOA}}^2 = \frac{a_1}{a_2 - a_3}, \quad (34)$$

where

$$\begin{aligned} a_1 &= \sigma_t^2 \sum_{i=1}^N \left[\left(\frac{t_i}{x_i - x} \right)^2 + \left(\frac{1}{x_i - x} \right)^2 \right], \\ a_2 &= \sum_{i=1}^N \left(\frac{t_i}{x_i - x} \right)^2 \sum_{i=1}^N \left(\frac{1}{x_i - x} \right)^2, \\ a_3 &= \left(\sum_{i=1}^N \frac{t_i}{(x_i - x)^2} \right)^2, \end{aligned} \quad (35)$$

where $t_i = y_i - y/x_i - x$, where t_i is supposed to contain a Gaussian error with average and variance of 0 and σ_t^2 , respectively.

The answer to the multiobjective optimization problem is a set of solutions that defines the best trade-off between competing objectives. Here, the log-likelihood function for the multiobjective optimization problem can be written as

$$\Gamma_3 = \frac{\Gamma_1}{\max(\Gamma_1)\sigma_t^2} + \frac{\Gamma_2}{\max(\Gamma_1)\sigma_R^2} = \frac{\Gamma_1}{c_1} + \frac{\Gamma_2}{c_2}, \quad (36)$$

where $c_1 = \max(\Gamma_1)\sigma_t^2$ and $c_2 = \max(\Gamma_1)\sigma_R^2$.

- (i) **Input:** Information of AOA and TDOA, Number of iterations (K_1, K_2)
(ii) **Result:** MS position
(1) Set $t = 0$; start from one random position $\phi^{(0)}$
(2) **repeat**
(3) Construct surrogate functions by using formulas from (22) to (25).
(4) Design objective function (20)
(5) Set $k = 0$ and ϕ_0 to some initial vector, e.g., $\phi_0 = [\phi^{(t)T}]^T$
(6) **repeat**
(7) Compute ϕ_k using (27)
(8) $k = k + 1$
until $k \leq K_2$;
(9) Obtain ϕ_{K_2}
(10) $t = t + 1$
until $t < K_1$;

ALGORITHM 1: The joint localization method based on TDOA and AOA information.

The CRLB for the localization based AOA and TDOA using two base stations can be derived as

$$\sigma_{\text{CRLB-TDOA-AOA}}^2 = \frac{2d_1}{d_2 - d_3}, \quad (37)$$

$$d_1 = \frac{1}{c_1} \sum_{i=1}^2 \frac{t_i^2 + 1}{(x_i - x)^2} + \frac{2}{c_2} (1 - \cos \theta_2 \cos \theta_1 - \sin \theta_2 \sin \theta_1), \quad (38)$$

$$d_2 = \left[\frac{1}{c_1} \sum_{i=1}^2 \frac{t_i^2 + 1}{(x_i - x)^2} \right] \left[\frac{2}{c_2} (1 - \cos \theta_2 \cos \theta_1 - \sin \theta_2 \sin \theta_1) \right], \quad (39)$$

$$d_3 = \left[\frac{1}{c_2} (\cos \theta_2 - \cos \theta_1) (\sin \theta_2 - \sin \theta_1) - \sum_{i=1}^2 \frac{1}{c_1} \frac{t_i}{x_i - x} \right]^2. \quad (40)$$

5. Simulations

To verify the effectiveness of the proposed approach, computer simulations are conducted for comparisons with other methods. As it is shown in Figure 2, the coordinates of the BSs are, respectively, set to BS₁: $[0, 0]^T$ cm, BS₂: $[60, 0]^T$ cm, BS₃: $[0, 60]^T$ cm, and BS₄: $[60, 60]^T$ cm; the MS location is chosen randomly according to a uniform distribution defined over the region formed by the BSs.

In our proposed localization algorithm, BS₁ and BS₂ are selected as the two stations. Then, 15 TDOA and AOA measurements from the selected BSs are obtained. The root of mean squared error (RMSE) of MS estimation $[\hat{x}_k, \hat{y}_k]^T$ from the k th BS is given by

$$\text{RMSE}(k) = \sqrt{(\hat{x}_k - x_0)^2 + (\hat{y}_k - y_0)^2}, \quad (41)$$

where $[x_0, y_0]^T$ denotes the true position of MS.

5.1. Comparison with the Classical TDOA Localization Methods Using More BSs. As we know, it is necessary for the classical TDOA-based methods to employ more than 3

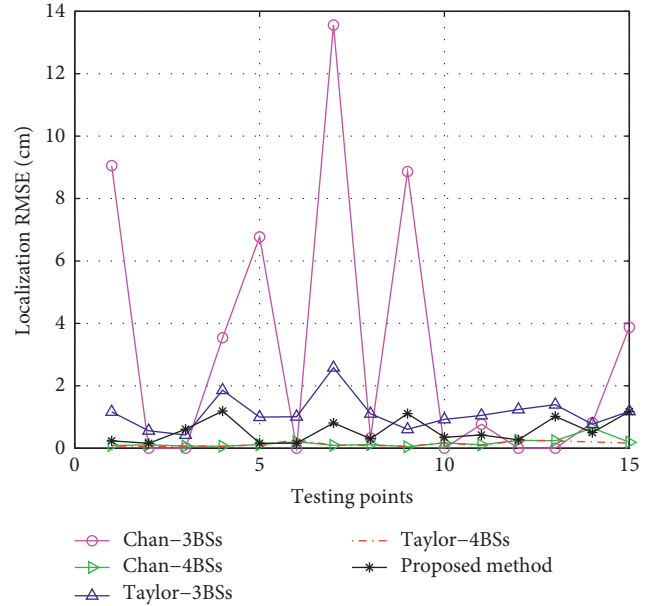


FIGURE 2: Positions of MSs and BSs.

stations realize the localization. To start with the comparison of the localization methods, the results of the classical source localization method are presented in Figure 3. Based on Taylor iteration method and Chan's method, it can be observed that the estimated value is much closer to the sensor position whenever more BSs are employed. This is because Taylor iteration and Chan's methods apply the iterative and noniterative solutions to achieve their optimum performance, respectively. Thus, they are considerably affected by the accuracy of TDOA measurements. Under the same TDOA measurement condition, it can be observed that the proposed algorithm has much better localization accuracy than the classical methods using three BSs, while it uses only two BSs. In some cases, e.g., Chan's method, using three BSs, a superiority of more than one order of magnitude is observable. Since increasing the number of BSs is expected to improve accuracy, reformulating the proposed method to a higher number of BSs is expected to result in even higher

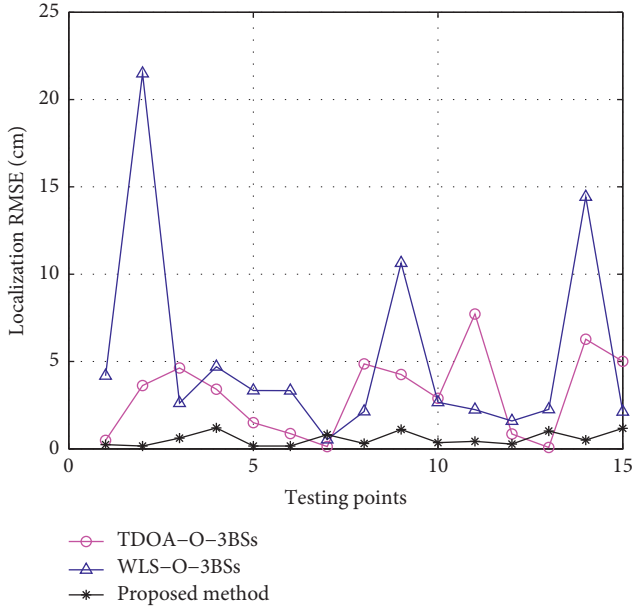


FIGURE 3: Performance of the classical source localization methods.

accuracy. However, the reformulation is beyond the topic of this article and can be addressed in future investigations.

5.2. Comparison with Single Objective Optimization-Based Methods. In order to prove the effectiveness of the proposed method using only two stations, source localization results using 3 BSs are presented here based on optimization methods, including weighted least squares (WLS-O-3BSs) [7], and optimization using time difference of arrival (TDOA-O-3BSs) [21]. They are then compared with the proposed methods. Figure 4 depicts localization error for a various number of testing points. It can be observed that the results obtained in this work outperform others, being able to achieve a lower localization error. Specifically, an improvement of the order of one degree of magnitude is observable in terms of peak localization error, i.e., the highest deviation in estimation.

Using two stations, the TDOA (TDOA-O-2BSs), AOA (AOA-O-2BSs) based on equations (10) and (12), and CFS-2BSs in [25] are realized, respectively. The results are demonstrated in Figure 5. Due to the lack of measurement information, there are large errors in the TDOA and AOA measurements, and the single objective function for optimization cannot perform very well in such an environment. CFS-2BSs, in [25], proves its good localization performance through the simulations, but its performance depends on the covariance matrix of the measurement noise. Interestingly, the proposed method shows very low localization error in a broad range for testing point numbers. When all methods use 2 base stations, the achieved accuracy improvement is about two orders of magnitude compared to TDOA and less than one order of magnitude compared to the AOA method in terms of peak localization error.

5.3. Comparison with Other Multiobjective Optimization-Based Methods. There are many optimization methods for the multiple objectives, such as the conventional

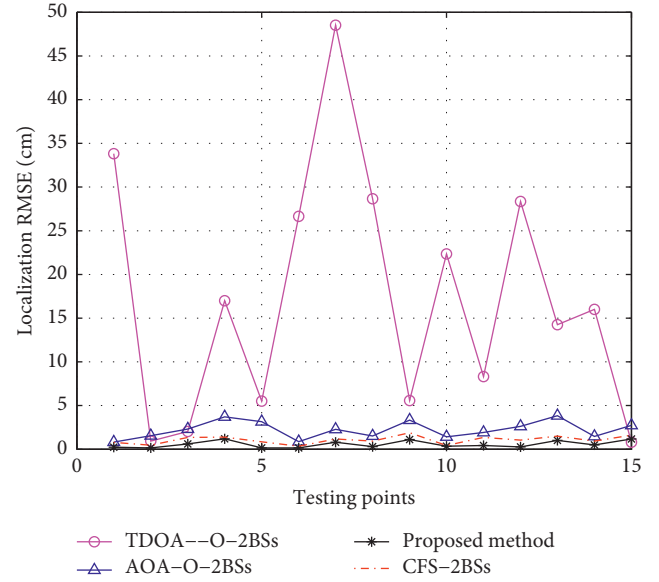


FIGURE 4: Performance of single objective optimization-based methods.

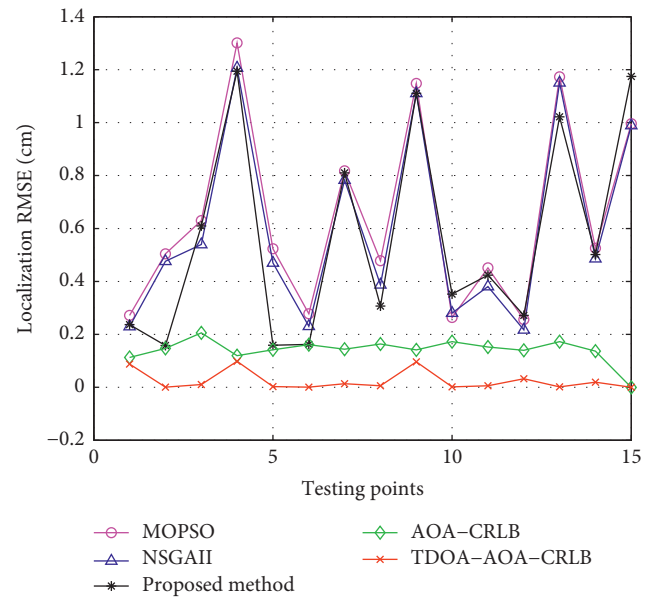


FIGURE 5: Performance of localization methods using 2 BSs.

multiobjective particle swarm optimization (MOPSO) [27] and nondominated sorting genetic algorithm (NSGAI) [28, 29], which can be used to solve the localization problems using two stations. Here, the proposed algorithm is compared with the MOPSO and NSGAI algorithms to demonstrate its superiority over a range of state-of-the-art investigations. In this regard, the population is set to 100 for all three optimizers, and the maximum number of iterations is set to 200. Four simulations are conducted using different optimization methods for the same multiple objectives in equations (10) and (12), where their results are demonstrated in Figure 6. Besides, the percentages of crossover and mutation populations and the mutation rate of NSGAI are

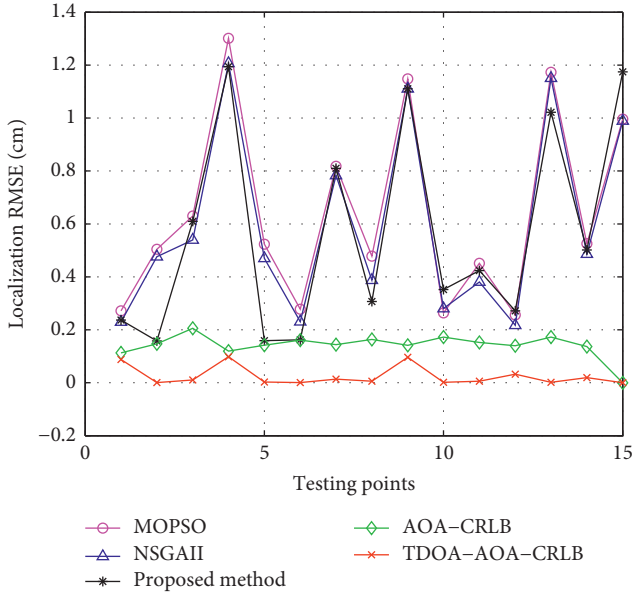


FIGURE 6: Localization performance comparison of optimization methods.

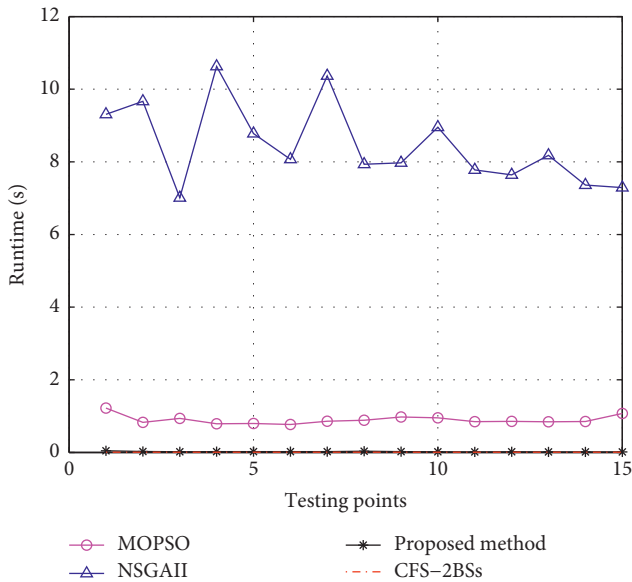


FIGURE 7: Runtime comparison of optimization methods.

set to 0.7, 0.4, and 0.02, respectively. The root CRLB in equations (34) and (38) is also computed and depicted in the same figure, labeled as AOA-CRLB and TOA-AOA-CRLB, respectively. Under the same conditions, the localization RMSE of the proposed method is smaller than other methods, being significantly close to CRLB.

Based on the theory of projected gradient descent, our proposed converges at rate $\mathcal{O}(1/k)$, where k is the iteration number. The runtime comparison results using the same computer are depicted in Figures 7 and 8. The experiments confirm the effectiveness of the proposed MM-based method in solving optimization and localization problems under the uncertainties of MS positions. This is because the

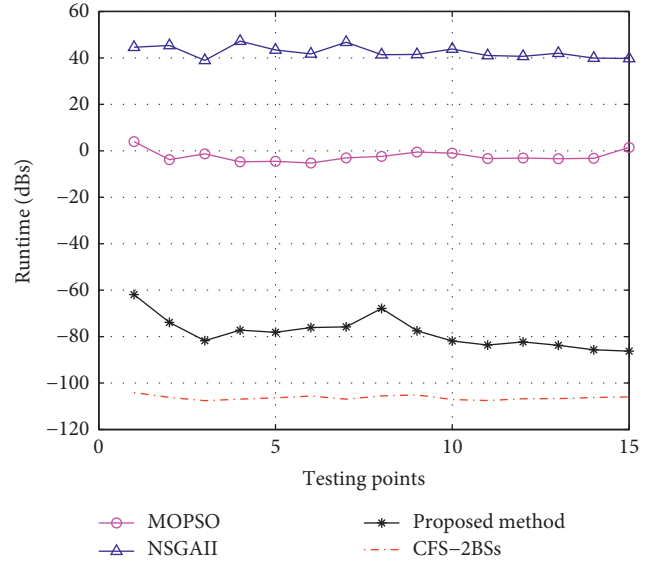


FIGURE 8: Runtime comparison of optimization methods.

nondominated sorting GA (NSGAI) must sort out all the individuals according to the Pareto-domination relationship and selects the individuals with better ranks to form the next-generation population, but with a lower convergence speed [30]. For conventional MOPSO, the neighborhood of one particle is formed by some nearest particles according to the objective space of one objective, but the best particle in the neighborhood cannot be determined very well by the fitness of the other objective. The CFS-2BSs method proposed by constructing relationships between the hybrid measurements and the unknown source position is not the iterative implementation method, which takes less computations.

6. Conclusion

In this paper, a significant increase in the positioning accuracy is achieved by using the MM and PGD methods, and the TDOA and AOA information together, while decreasing the number of required base stations. Accordingly, the localization problem is formulated for a two station scenario and is then derived by the MM method and then solved by the PGD method. Then, theoretical CRLB analysis is realized to establish a basis for the accuracy comparison. The extensive performance comparison with several state-of-the-art localization methods and some other optimization methods reveal the superiority of the proposed method. Specifically, they show that the proposed algorithm can achieve a superior localization accuracy using only two base stations compared to other recent methods required three or more base stations.

Data Availability

We note that there are no data-sharing issues since all of the numerical information is produced by solving the equations of the proposed algorithm, which are realized by MATLAB software in the paper.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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