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Research Article

A TDOA/AOA Hybrid Positioning Based on Improved Sparrow Search Algorithm for Mobile Position Estimation

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To address the difficulty in calculating the nonlinear equation of time difference of arrival (TDOA) positioning, as well as the problem of measurement error in the hybrid time difference of arrival/angle of arrival (TDOA/AOA) positioning algorithm, an improved sparrow search algorithm is proposed to optimize positioning, and the optimization mechanism is retained on the basis of improving the performance of the original algorithm. The maximum likelihood estimation method is used to calculate the objective function, and then, the estimated function of the mobile station is used as the fitness function to generate the initial population of sparrows. Then, using particle swarm optimization, optimize the sparrow search algorithm and obtain the population's optimal solution in order to obtain the optimal position. The simulation results show that, when compared to the existing algorithm, increasing the number of base stations increases the average accuracy of the sparrow search algorithm (SSA) positioning method by 18.54% and 4.5%, respectively, and, when compared to the proposed particle swarm optimization (PSO) positioning method, by 13.79% and 11.6% as the radius increases. The SSA hybrid positioning algorithm performs better in terms of positioning accuracy, convergence speed, and robustness.

1. Introduction

Positioning refers to determining the position of an object in a coordinate system on the Earth's surface. Through receiving radio waves between base stations and mobile stations, detect the amplitude, signal incidence angle, transmission time difference, etc. of radio wave signal. The predicted geometric position of the mobile station is derived using the positioning algorithm's parameters [1]. A mobile station's location information is its coordinates on the plane, including two-dimensional coordinates, three-dimensional coordinates, longitude, latitude, longitude, and longitude, and altitude information [2]. In the current research, positioning technology can be divided into direction-based positioning technology and distance-based positioning technology. The existing technologies include TOA [3], TDOA [4], RSS [5], OA [6], and their combined positioning methods [7].

Positioning is the key to many location-based wireless sensor network (WSN) applications. [8, 9]. However, almost every method of wireless location has its advantages and limitations. Several researchers have offered superb positioning technologies to boost positioning accuracy [10, 11]. The TOA-based positioning method requires the positioning system to have precise time synchronization and is only suitable for the positioning of cooperative targets. TDOA's method requires at least 4 correctly positioned nodes for three-dimensional target positioning [12, 13]. RSS-based methods are easily affected by multipath signals, which limits the application scenarios in the field of open terrain sensors [14]. The AOA-based method highly relies on the distance range. When the target distance node is relatively close, the positioning result is more accurate [15]. The hybrid TDOA/AOA method has the advantage of reducing the number of nodes and preventing the occurrence of the so-called virtual targets [16]. This research proposes a hybrid TDOA/AOA positioning strategy that is more accurate than TDOA alone. This paper studies the application of the hybrid system based on TDOA/AOA in 3D positioning and further improves it.

Since there is a nonlinear connection between the target position and the observed value, and maximum likelihood estimation is asymptotically effective, it is used to estimate the position. However, closed-form solutions are difficult to find or closed-form solutions simply do not exist, which enables the application of iterative numerical search techniques [17].

In 2002, a hybrid TDOA/AOA placement method was presented. For reducing the deviations easily generated by traditional positioning methods, many scholars have improved the TDOA/AOA hybrid algorithm [18]. A hybrid positioning strategy based on TDOA/AOA was suggested by Jiang et al. to enhance the position performance utilizing just two sites [19]. The sensor networks containing the positioning optimization models based on AOA and TDOA are established, respectively. Aiming at multiobjective optimization problem, a majorization-minimization (MM) method is proposed. The hybrid localization problem is solved by the projected gradient descent (PGD) method [20]. Although domestic and foreign researchers have made certain progress and achievements in the research of wireless positioning algorithms, there are still shortcomings in their positioning performance and application scenarios.

In terms of solving optimization problems of different specialties, the combination of intelligent optimization algorithm and this method has become very popular, for example, the naked mole-rat (NMR) algorithm [21]. Therefore, in addition to traditional analytical algorithms, swarm intelligence optimization algorithms like PSO [22], genetic algorithm [23], and salp swarm algorithm [24] have also been applied to TDOA/AOA hybrid positioning. This type of algorithm evaluates their pros and cons by establishing a fitness function, then iteratively updates the position of random points through optimized mechanism, and finally converges to the best position. The swarm intelligence optimization algorithm omits the complex solution process, and there is no problem that the analytical algorithm is unsolvable [25]. According to the no free lunch theory, there are few intelligent optimization algorithms suitable for all optimization problems. For example, in the application process, there may be problems of slow convergence in the later stages and falling into local optimum [26].

In this study, the algorithms PSO, CPSO, SSA, and CSSA were compared. Among them, PSO, which was put out in 1995, discovers the ideal answer through communication and cooperation inside the group. The PSO method also has drawbacks, including a tendency to fall into local extreme points, a sluggish rate of convergence in the last phases of evolution, and subpar accuracy [22]. As a result, the concept of chaotic optimization is added to PSO, which enhances convergence speed and accuracy and clearly increases convergence over classical PSO [27]. SSA is one of Xue and Shen's most recent suggestions for swarm intelligence optimization algorithms [28]. In view of the defects of traditional SSA, CSSA uses chaos mapping methods to initialize sparrow population. At the same time, Gaussian variation and chaotic disturbance are introduced. When the population appears to "aggregation" or "divergence," the individuals are adjusted to make them jump out of the local optimal [29]. The SSA has the preponderances of strong robustness, high precision, stability, and short convergence time. However, the SSA algorithm tends to converge toward the origin in the search. Therefore, when the search result is near the origin, although the SSA algorithm has excellent performance, for most scenarios, the location of the optimal solution is not around the origin [30]. Therefore, this paper proposes an improved SSA combined with PSO, which enhances the search ability and performs well in the global range. If it is used in the calculation stage of node position, it will get a better positioning effect and meet the needs of positioning.

This research suggests a hybrid sparrow-based TDOA/AOA positioning method to improve outcomes in order to meet the strict standards for positioning accuracy in industrial applications. SSA has good performance in high-dimensional function optimization [31], feature selection [32], and fault diagnosis [33]. This paper improves SSA algorithm and applies it to the TDOA/AOA localization problem for the first time and proposes a strategy for improving the location of sparrow finder by particle swarm. The estimate function of the mobile station was first obtained using the maximum likelihood approach, and it was afterwards employed as the fitness function to create the initial population of sparrows. In order to get the best sparrow population solution and the best location outcomes, the SSA is optimized using the PSO mechanism. This increases the optimization accuracy and convergence speed of the method. The simulation results demonstrate that the PSO-SSA method outperforms previous algorithms in terms of positioning accuracy, convergence speed, and resilience.

The remainder of this paper is structured as follows: the associated work and the TDOA/AOA hybrid position algorithm model are briefly covered in Section 2. SSA is introduced in Section 3, followed by the suggested PSO-SSA in Section 4 and the use of the PSO-SSA for TDOA/AOA in Section 5, and Section 6 presents the computer simulation and result analysis. Finally, Section 7 discusses the conclusion and introduces the perspectives for future work.

2. TDOA/AOA Hybrid Position Algorithm

Combining the two algorithm models can significantly improve positioning accuracy and lessen the effects of measurement errors when compared to using either the TDOA position algorithm or the AOA position algorithm separately. Figure 1 depicts the three-dimensional Cartesian coordinate system used to create TDOA/AOA hybrid positioning. MS stands for mobile station, and BS stands for base station. The BS's locations are (x_i, y_i, z_i), and The MS's

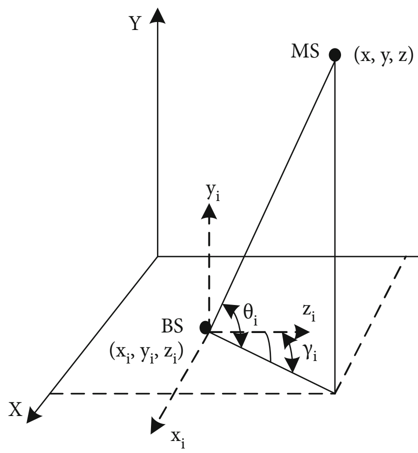


FIGURE 1: Model diagram of TDOA/AOA hybrid positioning system.

locations are (x, y, z). If z is set to be 0, the BS and the MS are in a two-dimensional plane.

In the case of two-dimensional planar placement, assuming that M base receivers are randomly distributed on a two-dimensional plane, the position of the i-th base station receiver BS is (x_i, y_i, z_i), and the position of the mobile station MS is (x, y), the distance from the mobile station MS to the base station i is r_i, the actual distance difference between MS and BS i $(i \neq 1)$ and BS 1 is denoted as $r_{i,1}^0$, and the measured value is denoted as $r_{i,1}$; then, the distance equation is

$$r_{i,1} = cd_{i,1} = r_{i,1}^0 + cn_{i,1} = r_i - r_1 + cn_{i,1}. \tag{1}$$

In (1), $d_{i,1}, i = 2, \cdots, M$ is the measured arrival time difference, the speed of light is denoted by c, and $n_{i,1}, i = 2, \cdots, M$ is the noise introduced when measuring the TDOA. When the SNR is high, the TDOA measurements are usually Gaussian data and follow an approximately normal distribution, so the noise $n_{i,1}$ also follows an approximately normal distribution. It can be regarded as Gaussian white noise with a variance σ^2 of IID.

Also because

$$r_i = cd_i = \sqrt{(x_i - x)^2 + (y_i - y)^2}, \tag{2}$$

so have

$$r_{i,1} = \sqrt{(x_i - x)^2 + (y_i - y)^2} - \sqrt{(x_1 - x)^2 + (y_1 - y)^2} + cn_{i,1}, \quad i = 2, \cdots, M. \tag{3}$$

From the AOA measurement α, an equation can be established:

$$\alpha = \arctan\left(\frac{y - y_1}{x - x_1}\right) + n_\alpha. \tag{4}$$

In (4), n_α is the AOA measurement error, which has a normal distribution with a mean of 0 and a variation of $\mathrm{std}^2\alpha$.

Record as follows: $\Delta\vec{r} = [r_{2,1}, r_{2,1}, \cdots, r_{M,1}]^T{}_{(M-1)\times 1}$, $\vec{r} = [r_2, r_3, \cdots, r_M]^T{}_{(M-1)\times 1}$, $\vec{r}_1 = [r_1, r_1, \cdots, r_1]^T{}_{(M-1)\times 1}$, and $\vec{n} = [n_{2,1}, n_{3,1}, \cdots, n_{M,1}]^T{}_{(M-1)\times 1}$.

Then, there are

$$\Delta\vec{r} = \vec{r} - \vec{r}_1 + c\vec{n}. \tag{5}$$

In circumstances when there are redundant measurement parameters, that is, where, and the number of effective measurement base stations exceeds 4, the maximum likelihood technique (ML) is employed to calculate the position (x, y) of the mobile station MS. $\Delta\vec{r}_i$ follows a normal distribution with a mean of $r_i - r_1$ and a variation of σ^2; α follows a normal distribution with a mean of $\arctan((y - y_1)/(x - x_1))$ and a variance of $\mathrm{std}^2\alpha$. If the measured values are unaffected by one another, the maximum likelihood estimate is

$$\begin{aligned}(x, y) = \arg\min \Bigg[&\left(\Delta\vec{r} - \vec{r} + \vec{r}_1\right)^T\left(\Delta\vec{r} - \vec{r} + \vec{r}_1\right) \\ &+ \frac{\sigma^2}{\alpha^2}\left(\alpha - \arctan\left(\frac{y - y_1}{x - x_1}\right)\right)^2\Bigg].\end{aligned} \tag{6}$$

Equation (6) shows that in order to solve the coordinate value, we must discover the nonlinear function's minimal value. In practice, however, it is extremely difficult to complete the minimum of the nonlinear function of Equation (6) using the usual technique; hence, the PSO-SSA is employed to find the ideal coordinate value.

3. SSA Algorithm

The SSA is inspired by the foraging and anti-predation behavior of sparrows. The process of sparrow foraging is an algorithm optimization process. The SSA is made up of three different sorts of sparrows: finder, follower and scout. Followers always follow and monitor the finder's foraging area or direction When the scouts found the predators, they immediately sent out an alarm signal, and the entire sparrow population evolved antipredation strategies [34].

If there are N sparrows in a D-dimensional search space, the location of the i-th sparrow in the D-dimensional search space is $X_i = [x_{i1}, \cdots x_{id}, \cdots x_{iD}]$, $i = 1, 2, \cdots, N$, and x_{id} indicates the position of the i-th sparrow in the d-th dimension.

The finders make up 10% to 20% of the population on average, and the position update formula is

$$x_{id}^{t+1} = \begin{cases} x_{id}^t \cdot \exp\left(\dfrac{-i}{\alpha T}\right) & R_2 < S_T, \\ x_{id}^t + QL & R_2 \geq S_T. \end{cases} \tag{7}$$

In (7) [25], the current iteration number is t. The maximum number of iterations is T. The α parameter is a uniform random integer between 0 and 1. Q is a chance number with a conventional normal distribution. The parameter L is a $1 \times d$ matrix with all members being 1. The warning and safety values are denoted by $R_2 \in [0, 1]$ and $S_T \in [0.5, 1]$, respectively.

With the exception of the finder, other sparrows are the followers whose positions are updated according to formula (8):

$$x_{ib}^{t+1} = \begin{cases} Q \cdot \exp\left(\dfrac{xw_d^t - x_{id}^t}{i^2}\right) & i > \dfrac{n}{2}, \\ xb_d^{t+1} + \left|x_{id}^t - xb_d^{t+1}\right| A^+ \cdot L & \text{others}. \end{cases} \quad (8)$$

There is a slight deviation in (8) in the original text, and it is modified as follows [35]:

$$x_{ib}^{t+1} = \begin{cases} Q \cdot \exp\left(\dfrac{xw_d^t - x_{id}^t}{i^2}\right) & i > \dfrac{n}{2}, \\ xb_d^{t+1} + \dfrac{1}{D}\sum_{d=1}^{D}\left(\text{rand}\{-1, 1\} \cdot \left|x_{id}^t - xb_d^{t+1}\right|\right) & i \le \dfrac{n}{2}. \end{cases} \quad (9)$$

The parameter A is a matrix of dimension $1 \times D$ among them. xw_d^t is the worst position. xb_d^{t+1} is the best position.

The scout's position has been modified as follows:

$$x_{ib}^{t+1} = \begin{cases} xb_d^t + \beta\left(\mathrm{x}_{id}^t\text{-}\mathrm{xb}_d^t\right) & f_i \ne f_g, \\ x_{id}^t + K\left(\dfrac{x_{id}^t - xw_d^t}{|f_i - f_w| + e}\right) & f_i = f_g. \end{cases} \quad (10)$$

In (10), β is a random integer that follows the usual normal distribution. K is a random number between -1 and 1, representing the control parameters of the sparrow's traveling direction and step size; f_i is the adaptive value of the particular bird at this time. f_g is the current worldwide ideal fitness value; f_w is the global worst fitness value. Epsilon is a constant with an infinitesimal denominator [36].

4. Improved Sparrow Search Algorithm

4.1. PSO. PSO algorithm is proposed by Afzal and Ramis and inspired by the graphical simulation of the beautiful and unpredictable movement of birds [37]. In the PSO algorithm, the maximum food source is defined as the final solution, and a single bird is regarded as an inanimate particle. The search process is as follows: first, random particles are in the space of the final solution, and a single particle is searching for the final solution in the space every moment. A particle swarm's individual optimal value is also its overall optimal value. Secondly, the direction and velocity of the particle are adjusted by the individual and global optimal values of the particle itself. Finally, after several iterations, most of the particles will converge around the final solution [35].

Define the inertia factor as ω; the value is

$$\omega = \omega_{\max} - \frac{z(\omega_{\max} - \omega_{\min})}{T}. \quad (11)$$

In (11), with the iterative evolution of particles, $\omega \in (\omega_{\min}, \omega_{\max})$ gradually becomes smaller. c_1 and c_2 are learning factors, also known as acceleration constants, the position update formula is illustrated where x_i^{t+1} is the position of the i-th particle in the t-dimensional solution space, gb^t is referred to as the global extreme value, and pb_i^t is the optimal value (12), and the velocity update formula is shown in (10):

$$\begin{aligned} v_i^{t+1} &= \omega v_i^t + c_1 r_1\left(pb_i^t - x_i^t\right) \\ &\quad + c_2 r_2\left(gb^t - x_i^t\right), \quad i = 1, 2, \cdots, n\, \mathrm{v}_{\min} \le v_i^{t+1} \le v_{\max}, \end{aligned} \quad (12)$$

$$\begin{aligned} x_i^{t+1} &= x_i^t + v_i^{t+1}, \\ x_{\min} &\le x_i^{t+1} \le x_{\max}. \end{aligned} \quad (13)$$

4.2. SSA Optimized by PSO. This paper offers a hybrid SSA optimized by particle swarm since the population variety of SSA decreases in successive iterations, making it easier to slip into the local extreme value, and the optimization accuracy is low. On the one hand, the upgraded technique can fully utilize the benefits of the PSO algorithm in development as well as the benefits of the SSA in exploration. On the other hand, in consideration of the problems in the SSA, the PSO algorithm has strong universality, simple principle, and few adjustable parameters. The complementary advantages of PSO and SSA algorithms make the proposed algorithm have better performance. As a result, the primary goal of the fitness function is to discover the optimum answer for the individual in a short period of time while still retaining relevant information. In SSA, discoverers have the greatest adaptability in food finding. Followers observe and obey finders by increasing their predation value by providing the best food source.

In line with the finder position update, in the early stages of the process, the value will tend to converge to 0 and approach the global optimal solution. This may easily lead to premature convergence. As a result, this study innovates the position update strategy of the PSO algorithm's global search phase in order to enhance the finder's position update formula in SSA. The following is the position update formula:

$$x_{id}^{t+1} = \begin{cases} x_{id}^t \cdot \left[\omega v_i^t + c_1 r_1\left(pb_i^t - x_i^t\right) + c_2 r_2\left(gb^t - x_i^t\right)\right] & R_2 < S_T, \\ x_{id}^t + QL & R_2 \ge S_T. \end{cases} \quad (14)$$

By introducing the PSO into the SSA, the improved PSO-SSA algorithm utilizes the large-scale fast search ability of particle swarms, which improves the convergence speed of sparrows. The corresponding relationship between improved sparrow search algorithm and moving position estimation is shown in Table 1.

Table 1: Correspondence between improved sparrow search algorithm and mobile position estimation.

PSO-SSA	Mobile position estimation
Population N	Number of mobile base stations
Improve sparrow individuals	A candidate solution for unknown node location
Fitness function	Objective function for solving unknown node position coordinates
Global optimal solution	Minimum node of positioning accuracy error
Location of global optimal solution	Estimated position coordinates of unknown nodes
Time required to improve sparrow activities	Algorithm simulation time

4.3. Time Complexity Analysis. The computing effort required to run an algorithm is referred to as its time complexity. Suppose N is the overall scale, D is the dimension, T is the maximum number of iterations, and $f(D)$ is the time necessary to solve the objective function.

It can be seen from the literature [38, 39] that the SSA algorithm's time complexity is

$$T = O(D + f(D)). \tag{15}$$

Initialization takes the following time:

$$T_1 = O(N \cdot (D + f(D))). \tag{16}$$

The proportion of finders in the SSA is set as r_1, the proportion of scouts is set as r_2, and the calculated individual fitness is $O(N)$. The number of finders is $N \times r_1$. The particle swarm optimization strategy only changes the update method of the finder and does not increase the process. Therefore, the time complexity required for the finder position update is

$$T_2 = O(D \times N \times r_1). \tag{17}$$

The number of followers in the SSA is $N \times (1 - r_1)$. Therefore, the temporal complexity of the location update of the follower is

$$T_3 = O(D \times N \times (1 - r_1)). \tag{18}$$

The number of scouts in the sparrow search algorithm is $N \times r_2$. Therefore, the scout's position update has the following temporal complexity:

$$T_4 = O(D \times N \times r_2). \tag{19}$$

Thus, the PSO-overall SSA's time complexity is

$$T' = T_1 + \text{iter}_{\max}(T_2 + T_3 + T_4) = O(D + f(D)). \tag{20}$$

And $T' = T$. To sum up, compared with the SSA, the PSO-SSA will not increase its time complexity.

5. Application of Improved SSA for TDOA/AOA

5.1. Fitness Function. The fitness function used has a direct impact on the modified sparrow algorithm's convergence speed and ability to locate the best solution. The fitness function and parameters of this paper are referred to [22]. Take the fitness function as

$$\text{Fitness}(Y) = \left[(\Delta r - r + r_1)^T(\Delta r - r + r_1) + \frac{\sigma^2}{\alpha^2}\left(\alpha - \arctan\left(\frac{y - y_1}{x - x_1}\right)\right)^2\right]. \tag{21}$$

Among them, the coordinates (x, y) corresponding to the best fitness value are the coordinates of the optimal position estimation.

5.2. Improve the Implementation Process of SSA. The PSO-SSA implementation phases are as follows:

(1) Initialization: initialization parameters include the population number N, T which is the maximum number of iterations, ratio of finders and scouts, alert thresholds and safety thresholds, acceleration factors $c1$ and $c2$, maximum inertia factor $\omega_{\max}$, and minimal inertia factor $\omega_{\min}$; calculate the moment of inertia ω according to formula (10)

(2) Place the population in its initial state

(3) Calculate the fitness value of sparrows and rank them

(4) Select a part of the sparrow species with a better position as the finder and update the position of the finder in accordance with formula (14)

(5) The remaining sparrows serve as followers. Scouts are chosen at random from the entire population. And according to the update formula of the followers and the scouts, update its position

(6) Determine the global optimal sparrow by computing the fitness values following an update

(7) Judge whether the end condition of the iteration loop is reached, go to the next step, or jump to step 3

(8) The algorithm execution ends

Figure 2 depicts the flow chart for the PSO-SSA position approach.

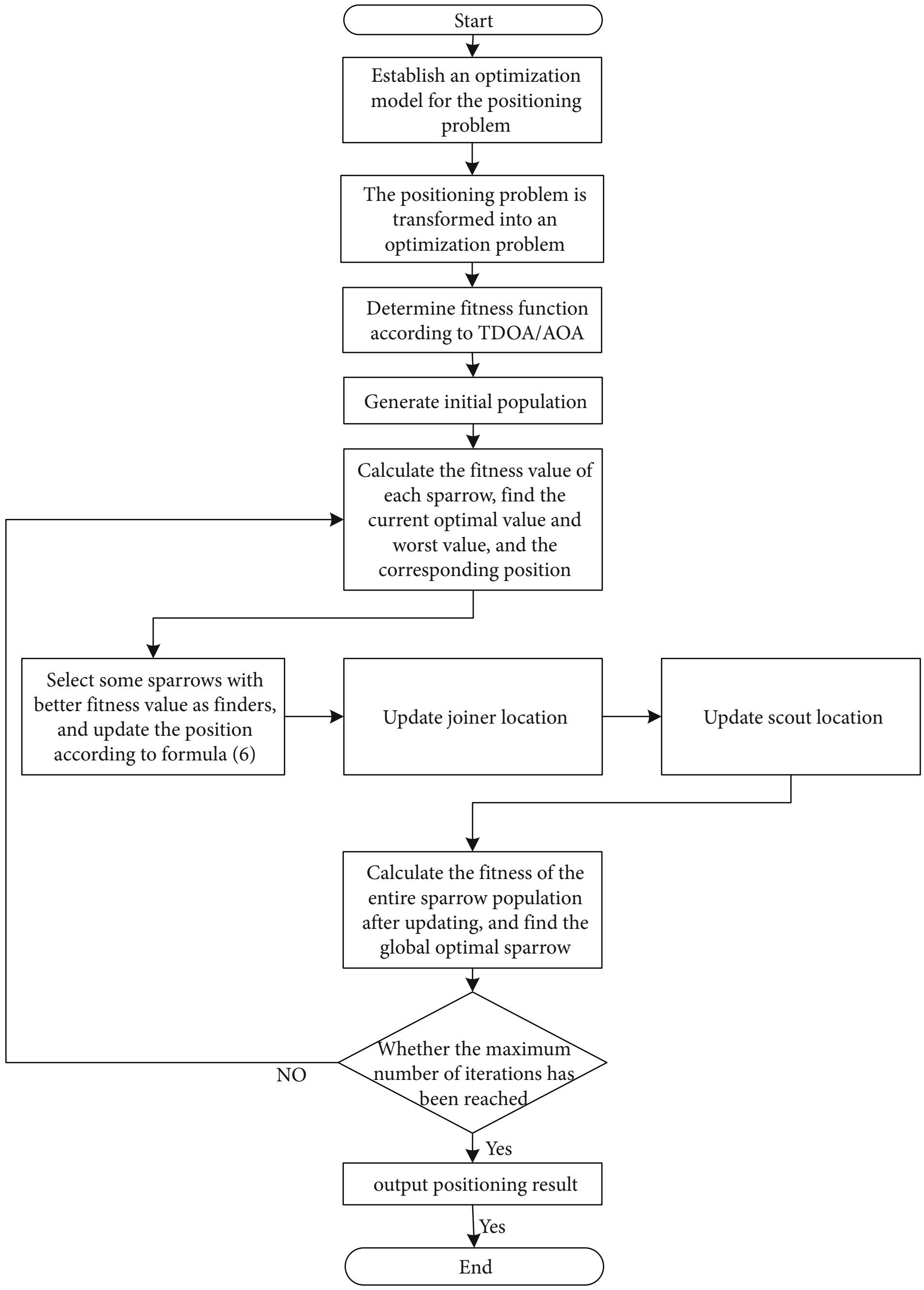


Figure 2: The PSO-SSA positioning flow chart.

6. Computer Simulation and Result Analysis

6.1. Function Optimization. For the sake of verifying the superiority of the PSO-SSA in solving the optimization function, seven standard benchmark functions are used for simulation. Table 2 is the test function for dimension 30. To be more convincing, run the improved sparrow search algorithm independently 200 times. The test function results are compared to the SSA, CSSA, PSO, and CPSO. Each algorithm's common parameters were set to 50 as the maximum number of iterations and 50 as the population size. Table 3 shows the particular parameters for algorithm selection.

For the sake of testing the stability and convergence of the five algorithms, the function optimization analysis of each algorithm is shown in Figure 3. From the overall convergence curve, as can be seen that the SSA and the improved SSA have the best convergence accuracy, the CPSO algorithm is the second, while the PSO algorithm is the least expensive, indicating that the SSA and its enhanced algorithm have increased convergence speed and accuracy. Moreover, the SSA and its improved SSA converge first, and the optimization accuracy reaches the optimal value.

The SSA, CPSO, and PSO-SSA iterate around 5 times to obtain the global optimal solution while solving F1, F2, F3,

Table 2: Test functions.

Function	Equation	Dimension	Bounds	Optimum
F1	$\max\{\lvert x_i\rvert, 1 \leq i \leq d\}$	30	[-100, 100]	0
F2	$\sum_{i=1}^{d}\lvert x_i \sin(x_i) + 0.1x_i\rvert$	30	[-10, 100]	0
F3	$10d + \sum_{i=1}^{d}\left[x_i^2 - 10\cos(2\pi x_i)\right]$	30	[-100, 100]	0
F4	$-20\exp\left(-0.2\sqrt{1/d\sum_{i=1}^{d}x^2}\right) - \exp\left(1/d\sum_{i=1}^{d}\cos(2\pi x_i)\right) + 20 + \exp(1)$	30	[-5.12, 5.12]	0
F5	$\left(1/500 + \sum_{j=1}^{25}\left(1/j + \sum_{i=1}^{2}\left(x_i - a_{ij}\right)^6\right)\right)^{-1}$	30	[-65, 65]	0
F6	$-\sum_{i=1}^{7}\left[(X-a_i)(X-a_i)^T + c_i\right]^{-1}$	30	[0, 10]	-10.4028
F7	$-\sum_{i=1}^{10}\left[(X-a_i)(X-a_i)^T + c_i\right]^{-1}$	30	[0, 10]	-10.5363

Table 3: Initial settings of algorithm control parameters.

Algorithm	Parameter	Values
PSO	$C1$, $C2$	2
	$w1$, $w2$	0.9, 0.4
CPSO	$C1$, $C2$	2
	$w1$, $w2$	0.9, 0.4
SSA	PD	20%
	SD	10%
	ST	0.8
CSSA	PD	20%
	SD	10%
	ST	0.8
PSO-SSA	PD	20%
	SD	10%
	ST	0.8
	$C1$, $C2$	2
	$w1$, $w2$	0.9, 0.4
	$V_{\max}$	6

F4, and F5, and the solution accuracy on other functions is also greater than other methods. When attempting to solve F6, it is evident that the convergence speed of the PSO-SSA and the CSSA is faster, followed by the SSA, and finally the CPSO algorithm and PSO algorithm. The PSO-SSA outperforms the CSSA while iterating 5-10 times; when iterating 15-35 times, the CSSA outperforms the PSO-SSA; but after 35 iterations, the PSO-SSA outperforms the CSSA and the first close to the most optimal solution. It demonstrates that the search performance at the start of iteration, as well as the development performance at the conclusion of iteration, is superior to the other four algorithms. For solving F7, the PSO-SSA outperforms the CSSA, but the SSA outperforms the PSO-SSA by a little margin. To sum up, the PSO-SSA can fully guarantee the search ability while ensuring the development ability, without losing the population diversity and optimization stability.

6.2. Positioning Simulation Experiment

6.2.1. Experimental Scenarios and Evaluation Indicators. In this experiment, in the environment of MATLAB2018b, NVIDIA GeForce GTX 1660, and Windows 10, 64-bit, the suggested TDOA/AOA hybrid positioning method based on hybrid sparrow search is subjected to a positioning performance simulation test. And this experiment selects the classic positioning algorithms.

The simulation scenarios and main parameters in this paper are set as follows: considering that the cellular network uses 9 receivers, the structure shown in Figure 4, the serving base station is bs1. The service BS's AOA measurement error has a Gaussian normal distribution with a mean of zero. In the experiment, the population sizes of PSO, CPSO, SSA, CSSA, and PSO-SSA were all 60. The maximum number of iterations is set at 20 as the termination condition for the six algorithms. The comparison of the RMSE indicators of six algorithms is shown in the figure below. The positioning accuracy evaluation index chosen was the RMSE:

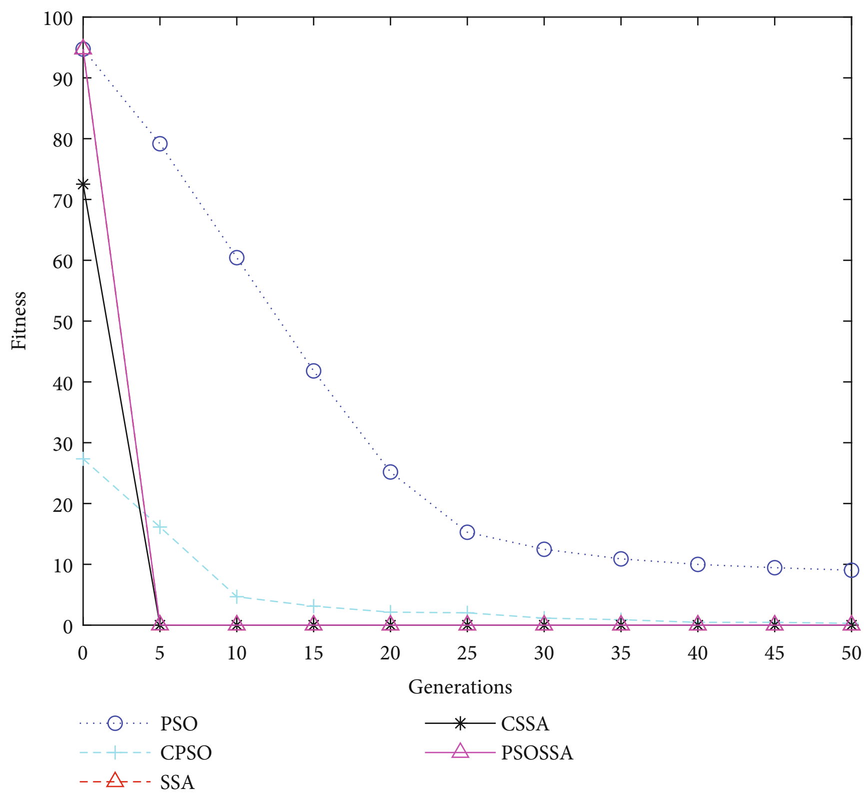
$$\mathrm{RMSE} = \sqrt{\frac{1}{P}\sum_{p=1}^{P}\left(x_p - \hat{x}_p\right)^2 + \left(y_p\hat{y}_p\right)^2} \tag{22}$$

P is the total number of test points, and among them, (x_p, y_p) and $(\hat{x}_p, \hat{y}_p)$ represent the p-th test point's actual position and estimated position, respectively.

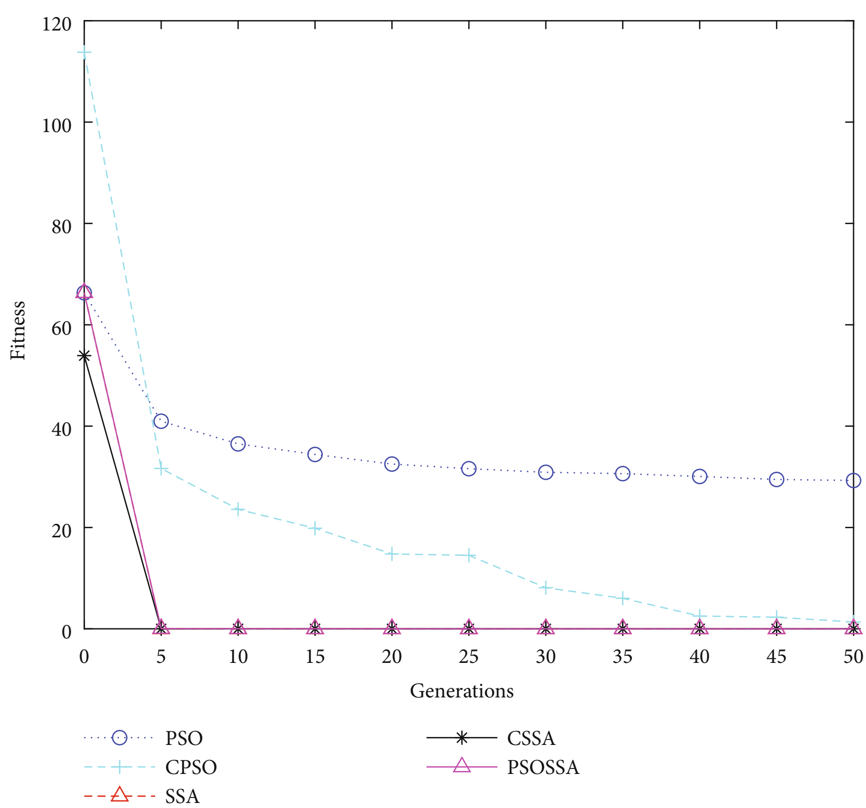
The environment-related parameters in wireless positioning are shown in Table 4.

6.2.2. The Number of Base Stations, Cell Radius, and Measurement Error Are Used as Variables to Compare the Positioning Performance of the Algorithm. The initial position of the mobile station is assumed to be (0.8, 0.2).

(1) The standard error of positioning is proportional to the number of base stations. In the simulation

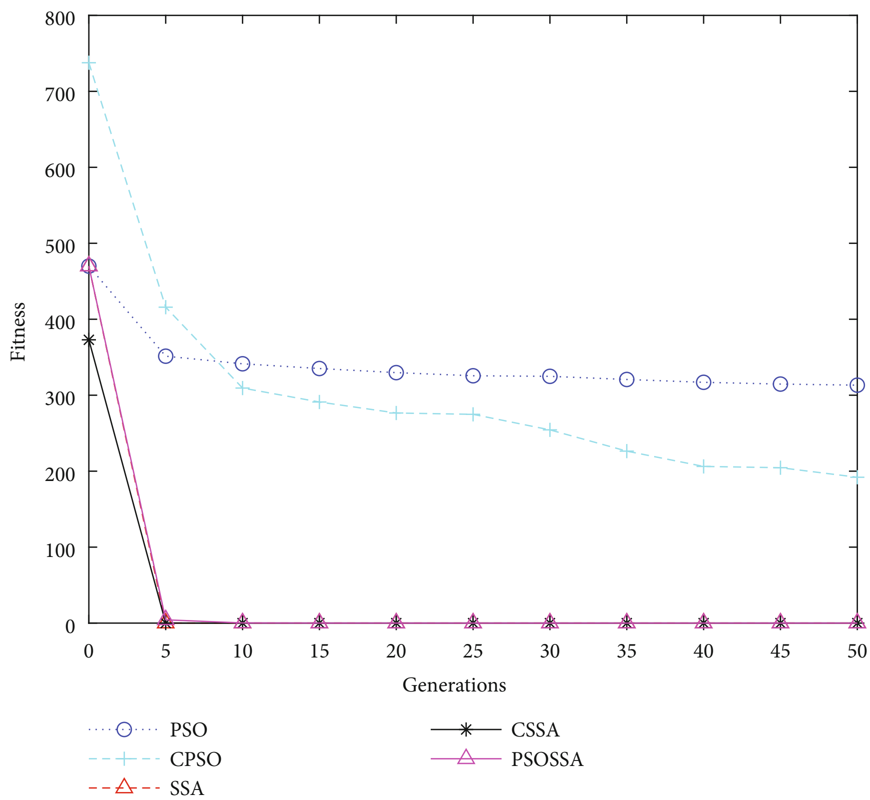


(a) F1

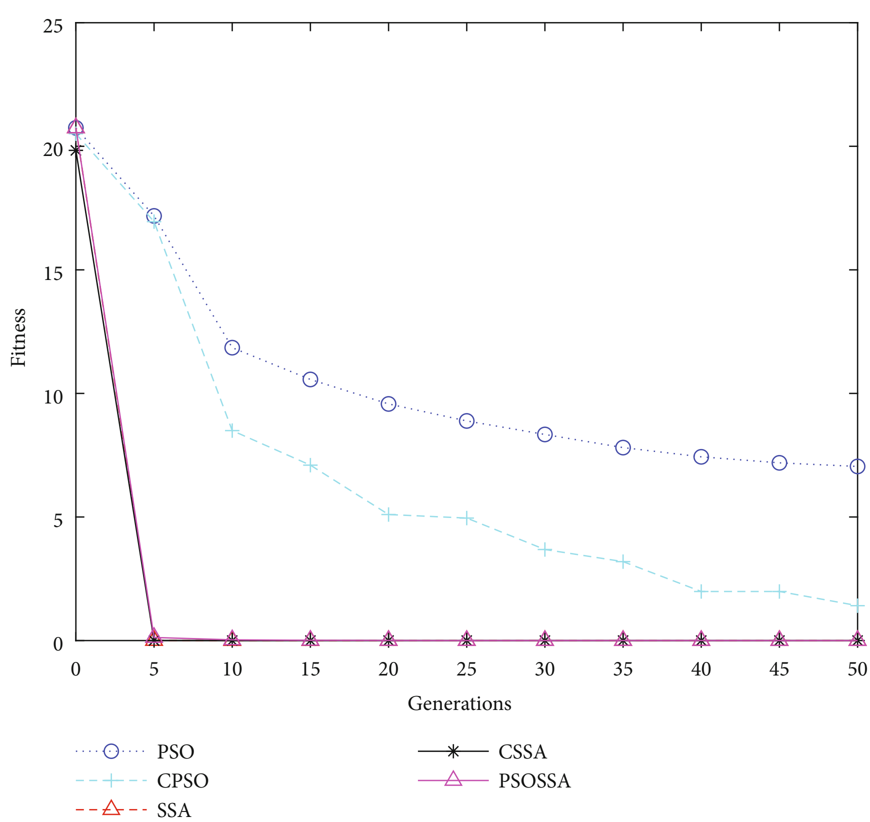


(b) F2

Figure 3: Continued.

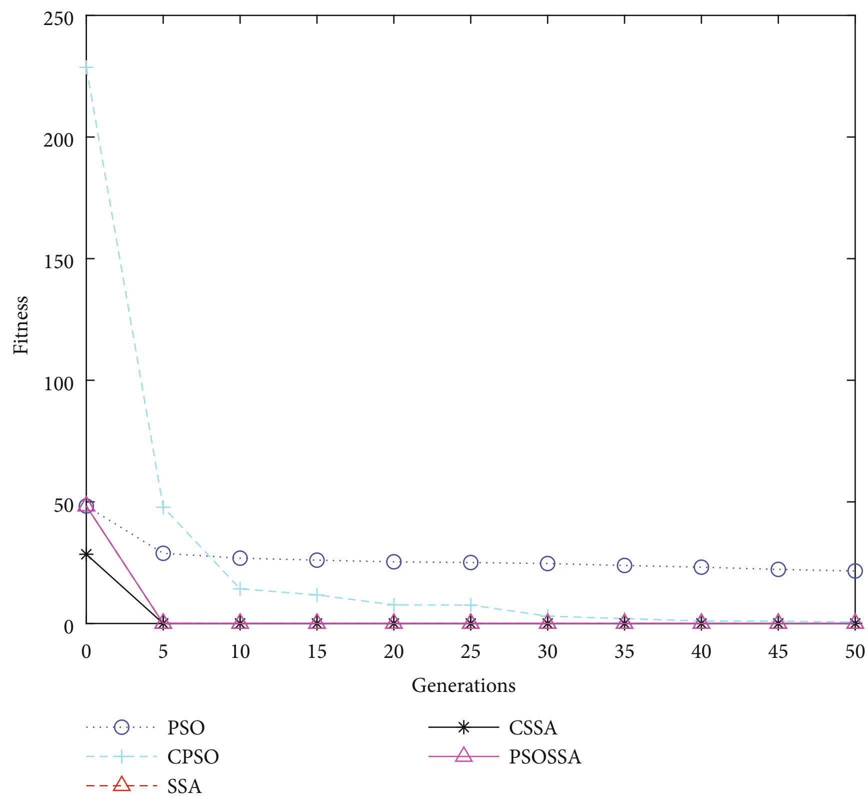


(c) F3

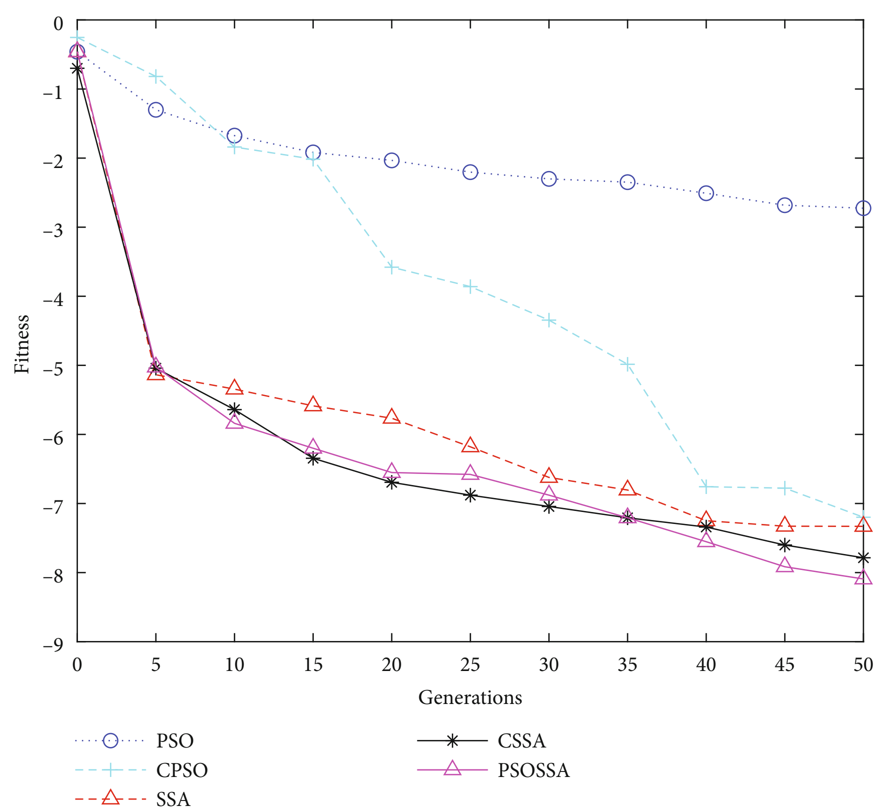


(d) F4

Figure 3: Continued.

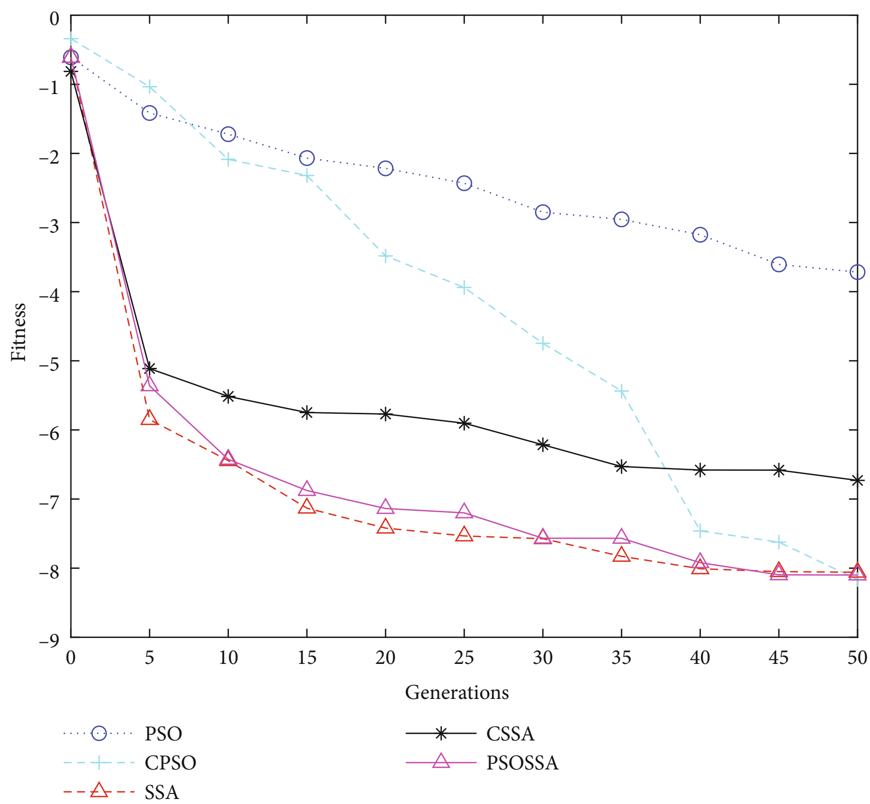


(e) F5



(f) F6

Figure 3: Continued.



(g) F7

Figure 3: Comparison of function iteration calculation results of the five algorithms.

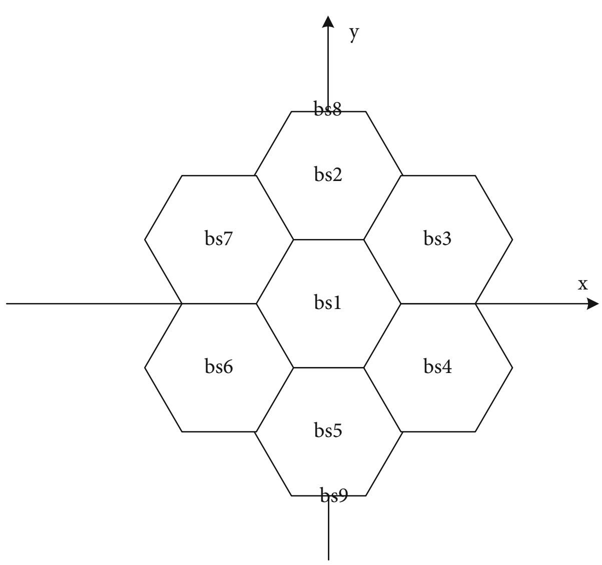


Figure 4: Schematic diagram of the position of the base station and the mobile station.

Table 4: Simulation environment parameters.

Name	Values
Number of base stations	4~9
Cell radius	3000 m
Number of initial particles	60
Number of iterations	20
PSO: $c1$, $c2$	2.4, 2.4
PSO: ω_{max}, ω_{min}	0.9, 0.2
SSA: ST	0.6
SSA: PD	0.7
SSA: SD	0.2

experiment, the count of base stations is raised from four to nine, the increment interval is set to one, the error is set to thirty meters, the radius is set to three thousand meters, and the root mean square error of each method is compared. The abscissa in Figure 5 represents the number of base stations, while the ordinate represents the root mean square error (m). There are now more base stations than ever before, the positioning accuracy of each algorithm is continuously improved, and thus, the standard error is decreased. Compared with the proposed PSO positioning method, the average accuracy of SSA positioning method has increased by 18.54% and 4.5%, respectively. Overall, the PSO-SSA has a lower curve than all other algorithms, and it performs the best in terms of positioning, followed by the CSSA and the SSA. When there are four to five base stations, the difference between the positioning performance of the SSA and the CSSA is not large. When the base

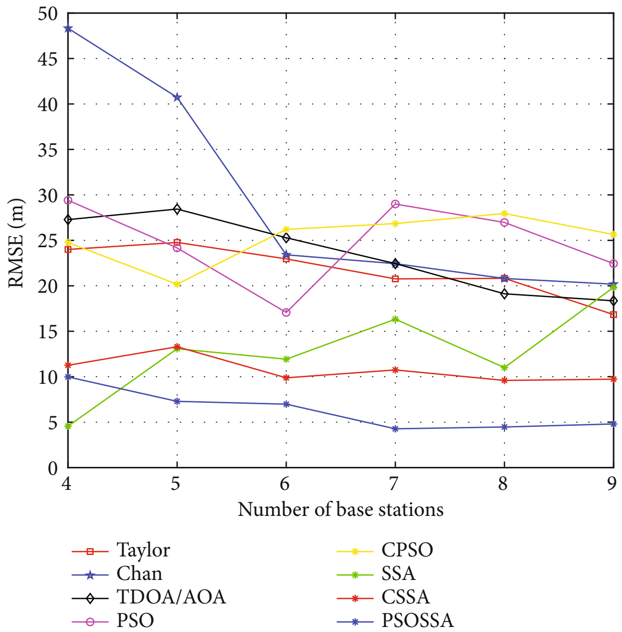


Figure 5: Relationship between standard error and base station.

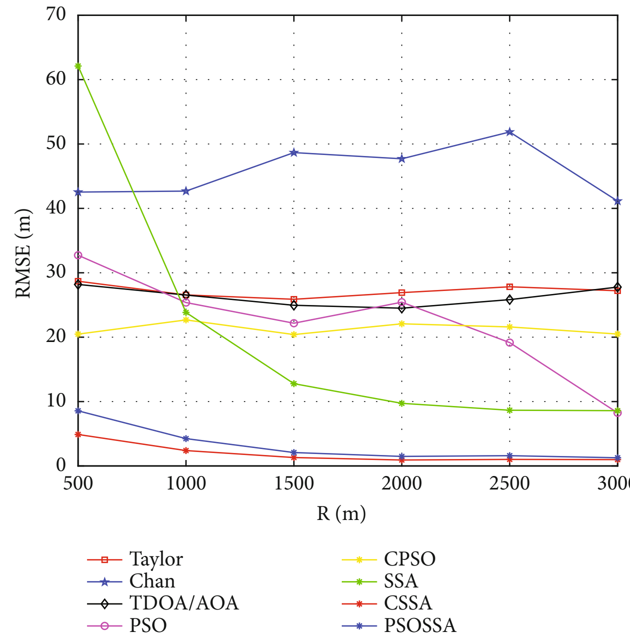


Figure 6: The standard error and cell radius relationship.

stations is between 5 and 9, from the overall average point of view, compared with the existing traditional positioning algorithms, unlike the CSSA and the SSA, the PSO-SSA performs positioning better, and the SSA is not much different from the chaotic sparrow algorithm. This fully shows that the PSO-SSA has obvious superiorities in the accuracy of position. However, from the aspect of algorithm stability, the fluctuation of the SSA curve in the figure is relatively large, indicating that the stability is slightly poor

(2) The positioning standard error is related to the cell radius. In the simulation experiment, the cell radius is increased from 500 m to 3000 m, the increment interval is 500 m, 4 base stations are selected, and the measurement error is 30 m, and the RMSE of each algorithm is compared. The abscissa represents the radius (m), and the ordinate is the RMSE (m), as illustrated in Figure 6. The overall graph shows a lower trend when the cell radius is increased continuously, as does the standard error, and the placement accuracy of each method improves. As the radius increases, compared with the proposed PSO positioning method, it has increased by 13.79% and 11.6%, respectively. The PSO-SSA algorithm provides more precise placement. As shown in Figure 6, the PSO-SSA and CSSA clearly outperform the classic positioning algorithms and the SSA in terms of positioning performance. When the radius is between 500 and 1000 m, the sparrow algorithm decreases greatly, while other algorithms change less, indicating that they have good stability. When the radius is 1000~3000 m, the localization performance and reliability of the hybrid SSA and the CSSA are obviously superior to other positioning algorithms. This is because the hybrid SSA and the chaotic SSA optimize the functional formula of TDOA/AOA, which eliminates a certain error; to some extent, the error caused by radius change is reduced and the positioning accuracy is improved

(3) Positioning performance is affected by measurement errors. The cell radius is set to 3000 m in the simulation experiment and the base station to 7, the measurement error variance is 30 m to 240 m, and the measurement error is $x = \sigma_{\mathrm{AOA}\times}c$, where c is the speed of light. Figure 7 displays a comparison of each algorithm's root mean square error. The ordinate denotes root mean square error (RMSE), whereas the abscissa denotes measurement error (m). The standard error of the other algorithms also rises as the measurement error does. However, the SSA and the PSO-SSA are more stable than other algorithms and are basically not affected by errors. This is because the chaotic process can, to some extent, mitigate the influence of mistakes on positioning precision. And the existing traditional positioning algorithms are greatly affected by errors. Therefore, the bigger the measurement error, the greater the risk of measurement result variation, and the algorithm becomes more unstable

Figure 8 depicts the link between the standard error and measurement error when all other variables are the same for four base stations: the standard errors of the Taylor method, Chan algorithm, and TDOA/AOA algorithm have all grown

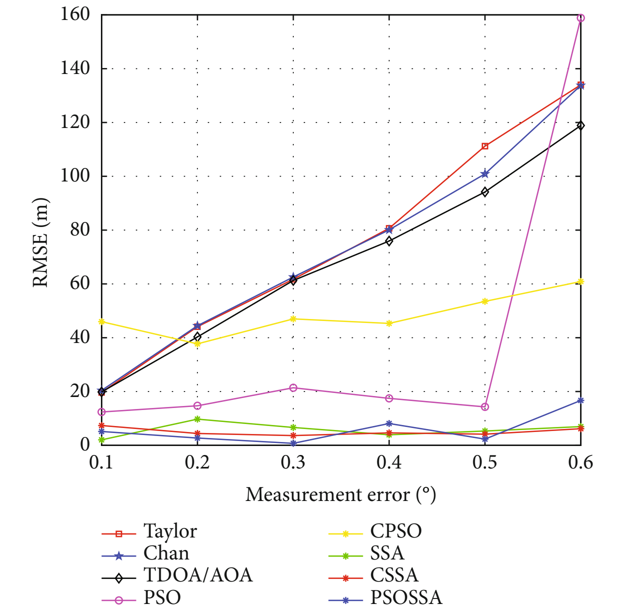


Figure 7: The connection between standard error and measurement error.

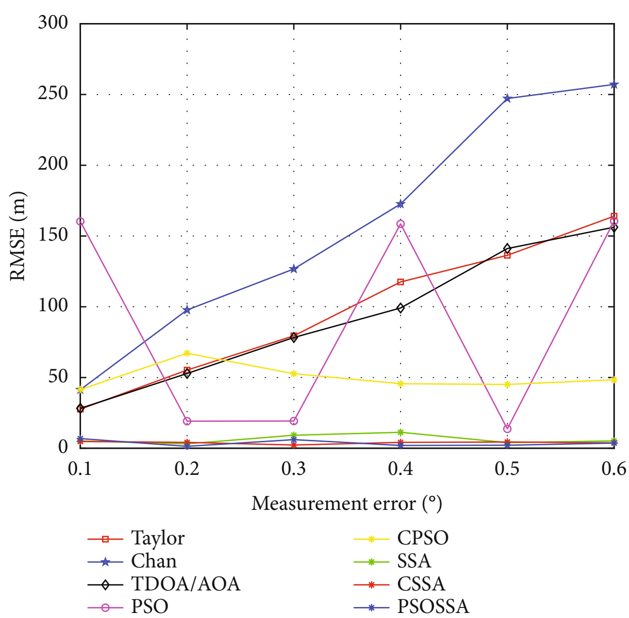


Figure 8: The connection between the measurement error and the four standard errors recorded by the base station.

since Figure 7. It demonstrates that base stations have a significant impact on RMSE, and the fall of base stations will make the measurement of TDOA/AOA erroneous, resulting in an increase in mistakes.

Similarly, when other conditions are the same, when 7 base stations are selected and the reference coordinates are selected (0.8, 0.6), the relationship between the RMSE and the measurement error can be seen from Figure 9: the reference coordinates are closely related to the positioning accuracy of the SSA. When it is close to the base station's center,

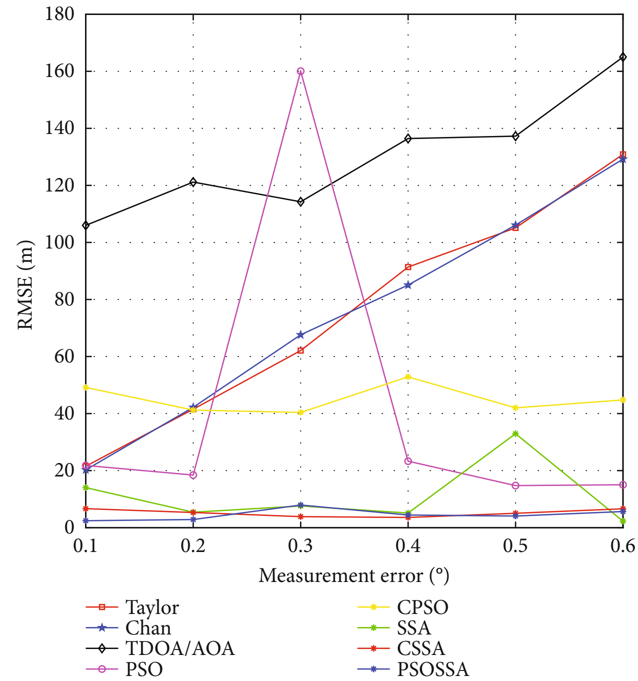


Figure 9: The influence of reference coordinates on positioning algorithm.

the algorithm performs better and achieves improved positioning accuracy. As a result, the choice of reference coordinates throughout the measurement procedure can help the positioning algorithm perform better.

(4) Following that, examine the link between measurement error, cell radius, number of base stations, and MSE. Let the abscissa represent the measurement error, the number of base stations, and the cell radius, and the ordinate represent $y = 10\,\lg$ (MSE). The MSE is determined using formula (23), where 200 is the number of experiments:

$$\mathrm{MSE} = \frac{\sum_{L=1}^{200} \left\| \tilde{x}(l) - x \right\|_2^2}{200} \tag{23}$$

As shown in Equation (21), $\tilde{x}(l)$ is the l-th estimated position value of x. The comparison of verification result is shown in Figures 10–12.

As shown in Figure 10, when measurement error increases, the MSE also increases, and the PSO-SSA shows better positioning performance in the MSE. This is because the PSO-SSA reduces the effect of measurement errors on the positioning, making the positioning more accurate.

As shown in Figure 11, when base station number is between 4 and 5, the SSA is comparable to the CSSA, and then, the CSSA has higher positioning accuracy. Once the number of base stations approaches 5, the change tends to remain steady. That is, the PSO-SSA outperforms the CSSA, SSA, and other algorithms in terms of placement accuracy.

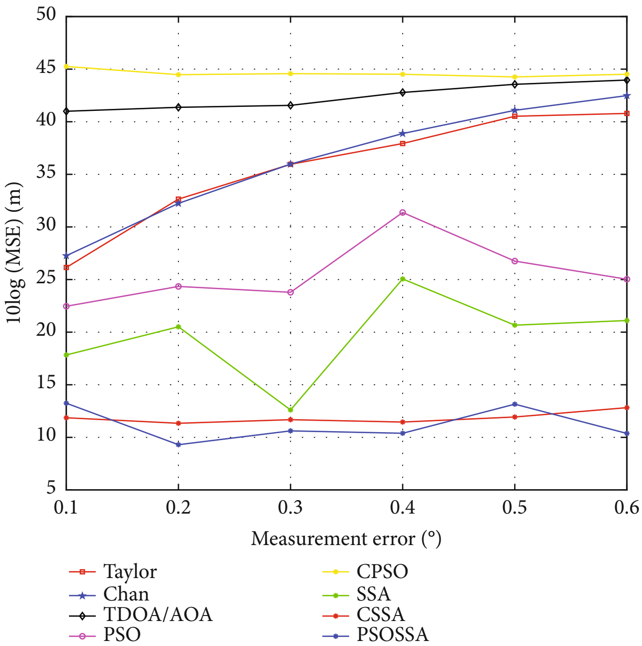


Figure 10: The connection between measurement error and MSE.

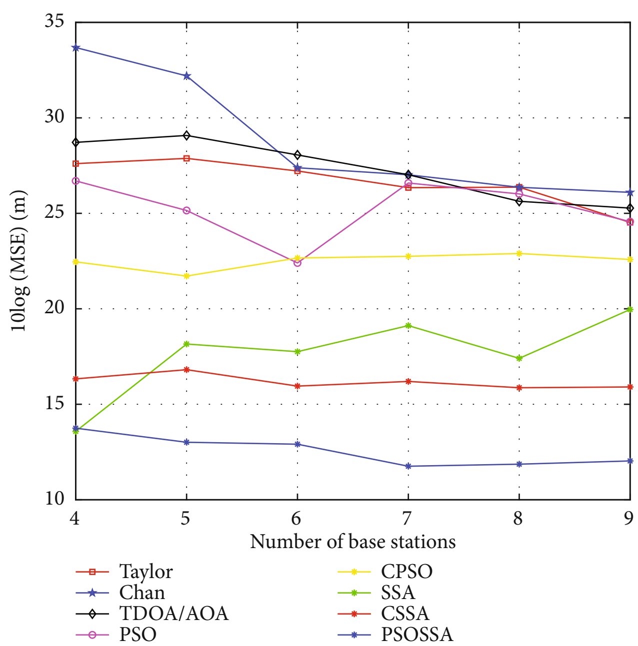


Figure 11: The connection between MSE and the quantity of base stations.

The localization performance of the hybrid sparrow algorithm proposed in this paper is better than the other three algorithms, as shown in Figure 12, but it makes full use of particle swarm position update to avoid linearization of nonlinearity, which causes the algorithm to fall into the problem of local optimal solution. Because the TDOA/AOA hybrid positioning performance has improved, the PSO-SSA is now employed for TDOA/AOA hybrid positioning, which may effectively increase positioning accuracy.

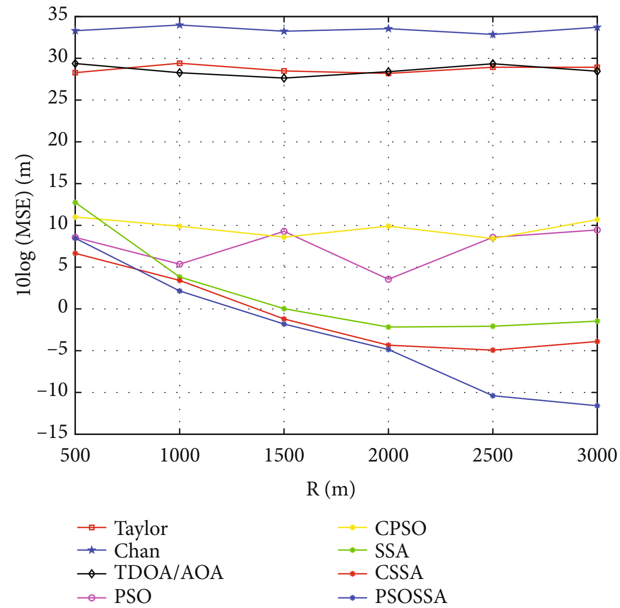


Figure 12: The radius and MSE relationship.

6.2.3. 3D Positioning Error Results of the Eight Algorithms. From the standpoint of three-dimensional positioning, this study compares the positioning performances of the conventional positioning algorithms, PSO algorithm, CPSO algorithm, SSA, and our PSO-SSA. Figures 13(a)–13(h) illustrate the results of the 3D position algorithm, accordingly.

By comparing the 3D positioning errors of the 8 algorithms, the RMSE of the traditional positioning algorithms, PSO algorithm, CPSO algorithm, and SSA will increase when measurement error and radius increase. The maximum positioning error of the Taylor method is 120 meters, the Chan algorithm is 126 meters, and the TDOA/AOA hybrid algorithm is 113.5 meters, among others. The swarm intelligence optimization algorithm PSO algorithm has a positioning error of 100 m, whereas the CPSO method has a positioning error of 85.43 m. The positioning error of the SSA reaches 24.8 m, and the positioning error of the CSSA reaches 19.3 m. It can demonstrate that the swarm intelligence optimization algorithm has a lower error than the traditional three positioning algorithms and that the SSA and CSSA have a better positioning impact than the PSO algorithm and CSSA. The positioning error of the PSO-SSA presented in this study is 11.7 m, which is substantially lower than the positioning errors of previous techniques. As can be shown, the PSO-SSA suggested in this study provides the best positioning impact and the minimum positioning error.

6.2.4. Algorithm Time-Consuming Comparison. We compared the simulation times of the five algorithms, as shown in Figure 14. It is easy to see that the conventional positioning algorithms consume the least amount of time. From the simulation comparison of the 5 algorithms in Figure 14, it is shown that, first of all, the simulation time-consuming of the PSO positioning algorithm, the SSA, and the CSSA is less. The CPSO algorithm, the CSSA, and the proposed PSO-SSA are time-consuming. Secondly, CPSO algorithm

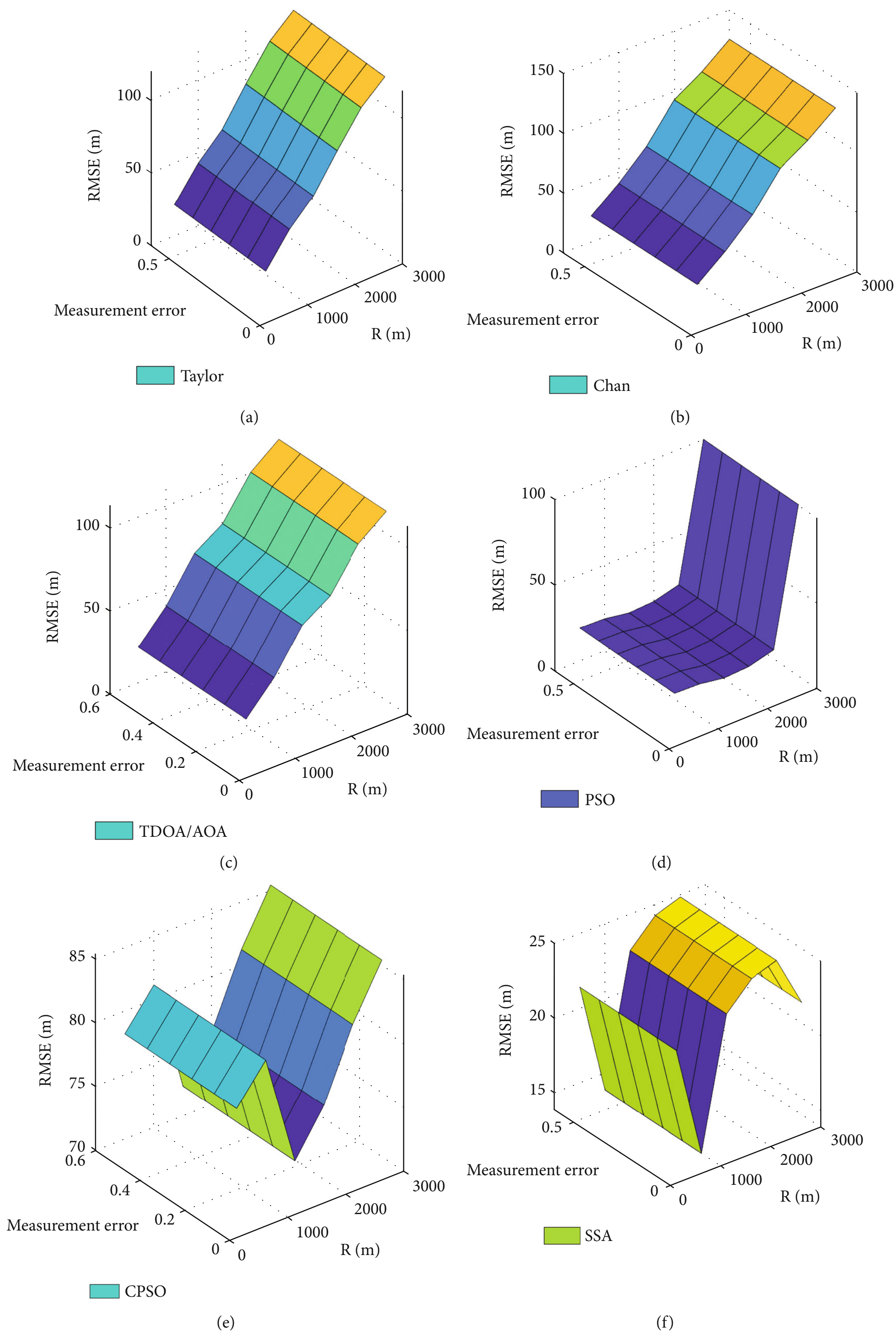
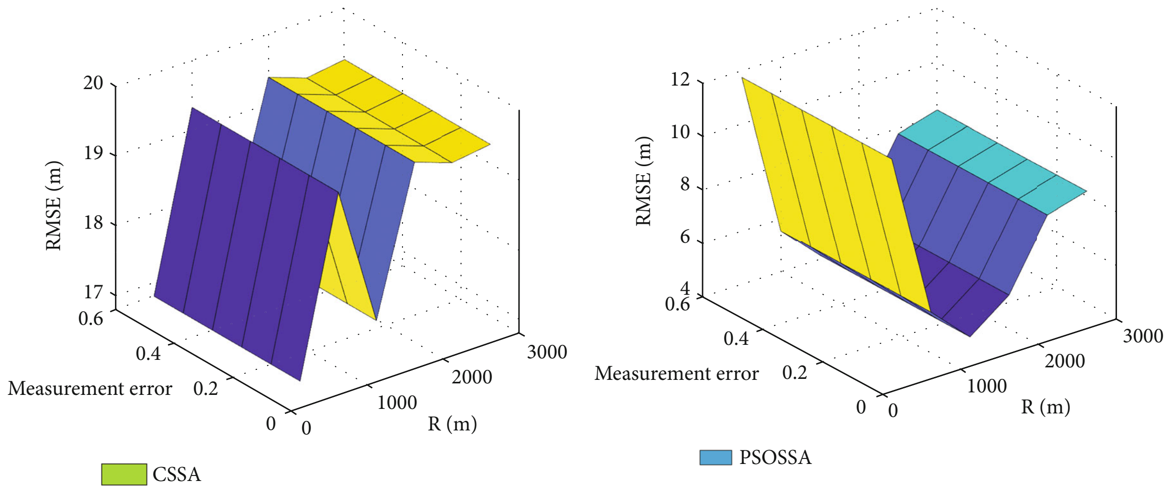


Figure 13: Continued.



(g) (h)

Figure 13: Comparison of three-dimensional errors of the eight algorithms.

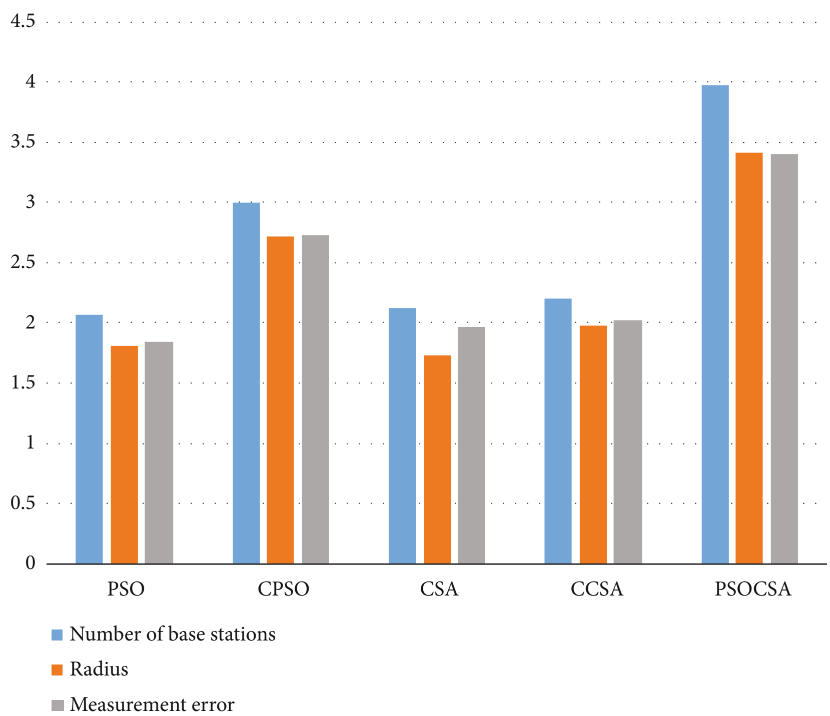


Figure 14: Time-consuming comparison of the five algorithms (s).

consumes more time than the PSO algorithm, because adding chaos mechanism in initialization phase requires optimization first. The PSO-SSA proposed in this paper takes the longest time.

7. Conclusion

In this study, the PSO-SSA is presented to solve the nonlinear issue of TDOA/AOA hybrid placement, which is strongly impacted by inaccuracy. Moreover, the starting population and fitness function are optimized to locate the coordinate point with the best fitness. The simulation results reveal that, when compared to the classic positioning method, the PSO-SSA has greater positioning accuracy, convergence speed, resilience, and so on under diverse cell radius and measurement error circumstances, which has research relevance in practical application.

In the research of this paper, some improved schemes and algorithm are proposed for the target positioning algorithm, and corresponding conclusions are drawn. However, these conclusions are only preliminary and theoretical, and the simulation experiments are only simulations under relatively ideal conditions. From the perspective of practical application, further research is needed, such as how to better solve the interference of multipath transmission and how to establish a more accurate wireless channel transmission model and find more accurate and anti-interference ability of TDOA and AOA parameter estimation methods. In future research, the following aspects can be considered and studied: further study the principle of SSA, improve the algorithm and apply it to TDOA/AOA hybrid positioning, and further enhance the positioning performance and accuracy. Secondly, this paper only studies the wireless location algorithm relatively independently, ignoring the influence of other factors, for example, the implementation of the positioning function in the network and the possible impact of various functions of various networks on the positioning. The next step must be to establish a system simulation platform, embed the real positioning function module, and test it in the real network environment. Lastly, we may use the technique provided in this work to address various position issues.

Data Availability

The data used to support the findings of this study are included in the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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