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Optimal station placement based on grey wolf optimizer for regional target localization

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Abstract

The accuracy of target passive localization is influenced by the placement of signal receiving stations; therefore, many studies have been performed to optimize station placement. However, most of the present placement methods focus on the localization error of one target, and if the exact position of the target cannot be determined, but only the range of the target activity is known, how to study the localization station placement in a region is a problem that needs to be solved. This paper proposes a grey wolf optimization algorithm based on the regional target error model to solve the optimal station placement problem. Firstly, a regional target localization error model is established using the measured TDOA, and the overall error matrix within a region is derived. Then, by taking the trace of the error matrix as a criterion, the objective function is established to find the optimal location of the receiving station by grey wolf optimizer. The optimization parameters are also improved to increase the global search ability of the algorithm. Finally, the feasibility and reliability of the overall error model and the grey wolf algorithm proposed are verified by experiments from multiple perspectives. The station placement method proposed in this paper can effectively solve the localization problem of targets that are only known to be in a general activity region in advance, which is more realistic.

Keywords: Grey wolf optimizer, Optimization parameter, Overall error matrix, Regional localization error, Station placement

1 Introduction

Passive localization technology uses signal receiving stations to obtain signals in space and determine the location of the signal source. This technology plays an important role in multiple fields such as radar, hydroacoustic, and wireless sensor networks. Common methods of passive localization are the use of angle of arrival (AOA), time difference of arrival (TDOA), frequency difference of arrival (FDOA), and hybrid measurements to achieve position of the target source. Among them, the method of localization based on TDOA of the target signal to different receiving stations has high accuracy. It also requires fewer processing parameters and is widely used in many localization devices [1].

The accuracy of passive localization depends not only on the localization algorithm but also heavily on the position of the receiving stations. Research has shown that the location of the station that receives and processes the signal determines the theoretical minimum localization error [2]. The selection of station positions is influenced by various aspects such as regional terrain, communication conditions and resource scheduling [3, 4]. Therefore, the problem of station placement has become an important direction in the study of passive localization.

For the station placement problem based on TDOA localization, scholars generally establish the Cramér–Rao lower bound (CRLB) matrix, the inverse of the Fisher information matrix (FIM) [1], that represents the localization error in different scenario. Then, they establish an objective function based on the A optimization criterion (or choose D, E criteria) to minimize the CRLB matrix to solve the optimization problem [5]. Research and articles that solve this optimization problem can be divided into two categories. One is to find the interrelationship of the independent variables by the conditions of the constraints, and this independent variable is the location of the receiving station. This category of research generally obtains quantitative conclusions containing some special geometric relationships among the positions of the receiving stations [6–13]. The most common of these is the law of station placement without any constraints, and research has shown that the position of the receiving stations should be uniformly distributed around the target in order to minimize the localization error [6]. The other major category is the optimization algorithms solely to solve this optimization problem when the station placement problem becomes complex. Since the objective function of this problem is a non-convex one, it is difficult to find the geometrically special solutions of station positions by constraint conditions. Therefore, an optimal placement needs to be found by an optimization algorithm [5, 14–18]. This class of research focuses on a specific localization scenario, such as the area where the deployed station is constrained. Zhao used Boolean vectors to solve the optimal station placement problem in localization by transforming a non-convex problem into a semi-definite programming problem to find an optimal solution [16]. Meng proposed a motion coordination approach to solve this nonlinear placement optimization problem [18]. They all strive in their optimization algorithms to find a station deployment method in a fast way that makes the localization error smaller.

However, for the placement problem, most of the research is aimed at minimizing the localization error for a specific target, which requires us to know the approximate location of the target in advance. In actual situations, we usually can only determine the region where the target may appear, so we cannot accurately estimate the target location and can only give a region range. Therefore, we believe that it is necessary to estimate the position of a target that may appear in a region, which is a real problem that needs to be solved urgently. The problem of station placement for multi-target localization has already appeared in the research of Xu [11], and we draw on this research idea to explore how to optimize station placement when all the targets in a region need to be localized. There are similarities between multiple targets and the fact that targets may appear at many locations within a region. We draw on this line of research to explore the station placement problem in the localization of target regions.

Studying such an optimization problem, the non-convexity of its objective function becomes higher and much more complex than the case of station placement in single objective localization. Therefore, we would like to use the improved grey wolf algorithm for station placement optimization [19]. Grey wolf algorithm is a swarm intelligence algorithm proposed in recent years and has been used in many optimization problems. Daniel has proposed the optimal wavelet-based homomorphic image fusion with grey wolf optimization in fusion technology, which uses the grey wolf algorithm to make a feature of the fusion optimal [20]. Ojha proposed an intelligent data routing mechanism for wireless sensor networks based on multi-objective grey wolf optimization for selecting the optimal intersection point in IoT intelligent systems [21]. Shi et al. used an improved grey wolf optimization algorithm for adaptive multi-UAV path planning [22]. All of their researches use the better optimization search and more accurate global optimal solution of the grey wolf optimization algorithm to fit the needs of practical problems, which are gradually being studied in the areas of resource scheduling and strategy selection [23, 24]. However, these studies are mainly focused on their scenario and do not apply to our proposed station placement problem. Currently, there are few studies on station placement optimization for target localization in a region, and there are no articles that use the grey wolf algorithm to solve this realistic problem. Therefore, we are interested in proposing a regional error model and consider the grey wolf optimization algorithm for station placement optimization.

The innovations and contributions of this paper are mainly in two aspects. Firstly, a more realistic localization scenario is considered, that is, the target may appear within a region. We derive the CRLB matrix of the target region error, and use the overall error as the objective function to derive the optimal location of the receiving stations. Secondly, for this objective function, we use the grey wolf algorithm for station placement optimization. We analyse the performance of the grey wolf algorithm to optimize the station positions and increase the global search capability of the algorithm by improving the optimization parameters. In this paper, we also verify the proposed model and algorithm in detail through relatively sufficient experiments.

The rest of the paper is organized as follows. Section 2 mainly introduces the error model of this paper and derives the CRLB matrix of the target overall regional error. Section 3 focuses on solving the optimal station placement problem using the grey wolf algorithm. Section 4 analyses the performance of solving the station placement problem with the grey wolf algorithm for the overall target localization, and improves the optimization parameter to enhance the global search capability. Section 5 is a simulation experiment from multiple perspectives to verify the reliability of the model and algorithm proposed in this paper. Section 6 is the conclusion.

2 Regional localization error model

We consider the placement of receiving stations to locate the targets of radiation signals. The possible locations of the target are within a known region in Fig. 1, which was acquired through the accumulation of our prior experience. The locations where receiving stations are not arbitrary, but limited to a specific range by geography, signal beam angle, etc. [8].

2.1 TDOA localization model

In a planar localization scenario, assume that the point P is the target, which may appear at any position in the region $\boldsymbol{T}$ at position $\mathbf{u} = [x, y]^T, \mathbf{u} \in \boldsymbol{T}$. It is assumed that there

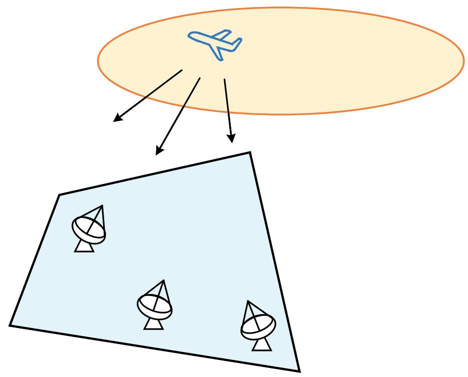


Fig. 1 Schematic diagram of the placement of receiving stations for localization scenarios

are N receiving stations, denoted as $\mathbf{S} = [\mathbf{s}_1, \mathbf{s}_2, \ldots, \mathbf{s}_N]^T$, where the location of the i-th receiving station is $\mathbf{s}_i = [x_i, y_i]^T, (i = 1, 2, \ldots, N)$. The distance between the i-th receiving station and the target P is

$$r_i = \sqrt{(u - s_i)^T (u - s_i)}. \tag{1}$$

We set the receiving station $\mathbf{s}_1$ with $i = 1$ to be the primary station (or the reference station), then the distance difference between the target to $\mathbf{s}_i$ and $\mathbf{s}_1$ is

$$r_{i1} = r_i - r_1, (i = 2, 3, \ldots, N). \tag{2}$$

It is to note that r_{i1} is the distance difference, which is obtained by multiplying the measured TDOA by the constant c (the speed of light). We consider them to be consistent and therefore use distance difference to denote the directly measured quantity in the subsequent expressions. If $\hat{r}_{i1}$ denotes the measured value of r_{i1}, containing the noise n_{i1}, then

$$\hat{r}_{i1} = r_{i1} + n_{i1}, (i = 2, 3, \ldots, N). \tag{3}$$

Denote $\mathbf{r} = [r_{21}, \ldots, r_{N1}]^T$, $\hat{\mathbf{r}} = \left[\hat{r}_{21}, \ldots, \hat{r}_{N1}\right]^T$, $\mathbf{n} = [n_{21}, \ldots, n_{N1}]^T$, and transform the localization measurement model into matrix form as

$$\hat{\mathbf{r}} = \mathbf{r} + \mathbf{n}. \tag{4}$$

2.2 Regional localization error model of target

Equations (1)–(4) describe the localization model only for one target. However, the scenario considered in this paper is that the target may appear at a location within $\boldsymbol{T}$, while $\mathbf{u}$ is unknown. Therefore, we should analyse the localization model for all positions in $\boldsymbol{T}$, and calculate the localization error for each position in $\boldsymbol{T}$.

First of all, we have to be clear that in the background of localization that we mentioned, it is one target that may appear at a certain location in the whole $\boldsymbol{T}$ region.

However, when we study the localization error, it is the error at each location that is studied, so we can think of it as localization of several targets all over the $\boldsymbol{T}$ region. That is, the several targets are multiple possibilities for that one target.

We assume that the number of possible targets at all locations in $\boldsymbol{T}$ is M, and they are $\{\mathbf{u}^{(1)}, \mathbf{u}^{(2)}, \ldots, \mathbf{u}^{(M)}\}$. From the point of view of calculus, the number of possible locations of the target is actually infinite. That means the set of targets is actually $\{\mathbf{u}^{(1)}, \mathbf{u}^{(2)}, \ldots, \mathbf{u}^{(M)}\}\|_{M\to\infty}$. Since the number of targets tends to positive infinity will cause inconvenience in handling error equations and matrix operations, we still use an infinite series of M targets as the basis of calculation. The M targets should be evenly filled in the entire $\boldsymbol{T}$ region. Then, the localization model in (4) is changed to the overall localization model in the region

$$\hat{\mathbf{r}}^{(j)} = \mathbf{r}^{(j)} + \mathbf{n}^{(j)}, \left(j = 1, 2, \ldots, M\right). \tag{5}$$

When computing the measurements in the whole $\boldsymbol{T}$ region, we write them in the form of an augmentation matrix $\mathbf{R} = \left[\hat{\mathbf{r}}^{(1)}, \hat{\mathbf{r}}^{(2)}, \ldots, \hat{\mathbf{r}}^{(M)}\right]$, which is an $M \times (N-1)$ matrix. In practical measurements, the signal-to-noise ratio (SNR) is affected by the distance. It will affect the variance of the noise, but the effect is small and can be negligible [9, 15]. Therefore, we consider that the measured noise variance is the same for all receiving stations, which is written as

$$\begin{aligned}\mathbf{Q_n} &= E\left[\mathbf{n}\mathbf{n}^T\right] = E\left[(\mathbf{n}_i - n_1)(\mathbf{n}_i - n_1)^T\right] \\ &= {\sigma_1}^2 \mathbf{1}_{M(N-1)} + diag\left({\sigma_2^{(1)}}^2, {\sigma_2^{(2)}}^2, \ldots, {\sigma_2^{(M)}}^2, {\sigma_3^{(1)}}^2, {\sigma_3^{(2)}}^2, \ldots, {\sigma_3^{(M)}}^2, \ldots, {\sigma_N^{(1)}}^2, {\sigma_N^{(2)}}^2, \ldots, {\sigma_N^{(M)}}^2\right) \\ &= \sigma^2 \mathbf{1}_{M(N-1)} + diag\left(\sigma^2, \ldots, \sigma^2\right)_{M(N-1)},\end{aligned} \tag{6}$$

where $\mathbf{1}$ denotes a matrix where all elements are 1.

We start with a Gaussian model of the distance difference measure and obtain a conditional probability density function for $\mathbf{R}$ over the overall region as

$$f(\mathbf{R}\|\mathbf{U}) = \frac{\exp\left\{-\frac{1}{2}\left[\hat{\mathbf{R}} - \mathbf{R}(\mathbf{U})\right]^T {\mathbf{Q_n}}^{-1}\left[\hat{\mathbf{R}} - \mathbf{R}(\mathbf{U})\right]\right\}}{\sqrt{(2\pi)^{M(N-1)} \det\left(\mathbf{Q_n}\right)}}, \tag{7}$$

where $\mathbf{U} = \left[{\mathbf{u}^{(1)}}^T, {\mathbf{u}^{(2)}}^T, \ldots, {\mathbf{u}^{(M)}}^T\right]^T$ denotes the augmentation matrix of all target locations with dimension $2M \times 1$. If the unbiased estimate of the target location is $\hat{\mathbf{U}}$, its CRLB matrix is denoted as $CRLB_{\mathbf{U}}$, the information matrix as $\mathbf{F_U}$, then

$$E\left[\left(\hat{\mathbf{U}} - \mathbf{U}\right)\left(\hat{\mathbf{U}} - \mathbf{U}\right)^T\right] \geq CRLB_{\mathbf{U}} = {\mathbf{F_U}}^{-1}. \tag{8}$$

The information matrix can be written as

$$\mathbf{F_U} = E\left[\left(\frac{\partial \ln f(\mathbf{R}\|\mathbf{U})}{\partial \mathbf{U}}\right)\left(\frac{\partial \ln f(\mathbf{R}\|\mathbf{U})}{\partial \mathbf{U}}\right)^T\right] = \mathbf{J}^T {\mathbf{Q_n}}^{-1} \mathbf{J}. \tag{9}$$

Matrix $\mathbf{J}$ is the Jacobian matrix as

$$\mathbf{J}=\begin{bmatrix}\frac{\partial \hat{\mathbf{r}}^{(1)}}{\partial \mathbf{u}^{(1)^T}} & \mathbf{0} & \dots & \mathbf{0}\\ \mathbf{0} & \frac{\partial \hat{\mathbf{r}}^{(2)}}{\partial \mathbf{u}^{(2)^T}} & \dots & \mathbf{0}\\ \vdots & \vdots & \ddots & \vdots\\ \mathbf{0} & \mathbf{0} & \dots & \frac{\partial \hat{\mathbf{r}}^{(M)}}{\partial \mathbf{u}^{(M)^T}}\end{bmatrix}, \tag{10}$$

where $\mathbf{0}$ denotes the $N \times 2$ matrix of zeros. The individual partial derivatives in the matrix are expressed as

$$\begin{aligned}&\frac{\partial \hat{\mathbf{r}}^{(j)}}{\partial \mathbf{u}^{(j)^T}}=\begin{bmatrix}\cos\theta_2{}^{(j)}-\cos\theta_1{}^{(j)} & \sin\theta_2{}^{(j)}-\sin\theta_1{}^{(j)}\\ \cos\theta_3{}^{(j)}-\cos\theta_1{}^{(j)} & \sin\theta_3{}^{(j)}-\sin\theta_1{}^{(j)}\\ \vdots & \vdots\\ \cos\theta_N{}^{(j)}-\cos\theta_1{}^{(j)} & \sin\theta_N{}^{(j)}-\sin\theta_1{}^{(j)}\end{bmatrix},\\ &\left.\begin{aligned}\cos\theta_i{}^{(j)}&=\frac{x_i-x^{(j)}}{\sqrt{\left(x_i-x^{(j)}\right)^2+\left(y_i-y^{(j)}\right)^2}}\\ \sin\theta_i{}^{(j)}&=\frac{y_i-y^{(j)}}{\sqrt{\left(x_i-x^{(j)}\right)^2+\left(y_i-y^{(j)}\right)^2}}\end{aligned}\right.,\left(j=1,2,\dots,M\right).\end{aligned} \tag{11}$$

At this point, the error information matrix $\mathbf{F_U}$ and its CRLB matrix are computed for the target position in the entire region. In this way, the localization error of the whole region can be characterized by the matrix $CRLB_{\mathbf{U}}$, where the subscript $\mathbf{U}$ denotes the set of points consisting of all targets in $\boldsymbol{T}$.

It is necessary to clarify that the $CRLB_{\mathbf{U}}$ matrix is a theoretical error matrix of all target measurements in the region, and it is not a simple splicing and augmentation of the error matrix for a single target, due to the possible correlation of the measured TDOA of the targets in the region. If we do a chunking of the Jacobian matrix in (10), it is indeed an augmented form of the Jacobian matrix for each target, but this is only derived by considering the receiving station returning measurements for one target at a time. Once the measured TDOA of a target is correlated, the other matrix blocks are not necessarily 0-matrices. Therefore, when we adopt the A-criterion [5] (the principle of minimizing the trace of the error matrix) to constrain the error as the objective function, the regional measurement error consisting of the target locations is not equal to the sum of the measurement errors of individual targets, which can be expressed as

$$Tr(CRLB_{\mathbf{U}}) \neq \sum_j Tr\left(CRLB_{\mathbf{u}^{(j)}}\right). \tag{12}$$

3 Optimization method

In single-target localization problems, people often use the error matrix to establish the objective function for optimization. In the same way, we utilize the error matrix CRLBU, derived from the regional overall error model, to establish the objective function. Using the A-optimality criterion to minimize the trace of the overall error matrix, the station placement optimization problem described in this paper can be formulated as

$$\underset{\mathbf{s}_i, i=1,2,\ldots,N}{\arg\min} \; Tr(CRLB_{\mathbf{U}}), s.t. \mathbf{s}_i \in \boldsymbol{B}, \tag{13}$$

where $\boldsymbol{B}$ is a constrained region that limits the location of the receiving stations. This has been mentioned in Fig. 1. Due to the environment and the signal beam angle, etc., the receiving station can only be deployed in a specific region. Therefore, the station placement approach taken in this scenario is transformed into the optimization problem described in (13).

It is a highly non-convex problem for the reasons that (i) CRLB matrix contains information on the measured values of multiple targets, which are all nonlinear functions of the independent variables; (ii) in the constraints, the region of the station placement is mostly irregular, resulting in potentially complex boundary conditions. Therefore, this is a highly non-convex optimization problem, which we choose the grey wolf optimizer, the more balanced in global search and local search, as the placement method in this paper to deal with.

3.1 Grey wolf optimizer

Grey wolf optimizer is a novel swarm intelligence optimization algorithm, which mainly simulates the hierarchy and hunting methods of grey wolf packs in nature [19, 25]. In the wolf pack, it is divided into α wolf, β wolf, δ wolf and ω wolf according to its hierarchy from high to low, which represent different classes. In the hunting process, the α wolf pack occupies the best position, which is the closest to the prey capture, the β wolf pack is the second, the δ wolf pack is the third. And the ω wolf pack is defined as the ordinary wolves, so they will move towards the position of the first three wolf packs until they capture the prey.

In the following, we briefly describe the grey wolf optimizer. Suppose there are L wolves in the pack, denoted by $\mathbf{Z}^{(1)}, \mathbf{Z}^{(2)}, \ldots, \mathbf{Z}^{(L)}$, where the position of the l-th wolf is $\mathbf{Z}^{(l)} = [z_1, z_2, \ldots, z_D]^{T^{(l)}}$ and its dimension is D. The top three wolves with the best positions in the pack are $\mathbf{Z}^{(\alpha)}$, $\mathbf{Z}^{(\beta)}$ and $\mathbf{Z}^{(\delta)}$ in order. We use ${\mathbf{Z}_t}^{(i)}$ to denote the current position of the i-th wolf and ${\mathbf{Z}_t}^{(p)}$ to denote the current position of the target grey wolf, then the position of the i-th wolf at the next moment after it moves towards the target ${\mathbf{Z}_t}^{(p)}$ is

$${\mathbf{Z}_{t+1}}^{(i,p)} = {\mathbf{Z}_t}^{(p)} - A\left\| K{\mathbf{Z}_t}^{(p)} - {\mathbf{Z}_t}^{(i)} \right\|. \tag{14}$$

The subscript t denotes the current moment, $t+1$ denotes the next moment, and the superscript (i, p) denotes the result of the action of the p-th wolf on the i-th wolf. A and K denote the step size and prey weight, respectively. A is a uniform random number within $(-a, a)$, and a is the convergence factor, which is a constant that decreases linearly from 2 to 0 with the number of optimization iterations; K is another random number on $(0, 2)$. From a practical perspective, the direction of the i-th wolf moving towards the target wolf is determined by K, and its moving distance is determined by A. Since the range of A is decreasing, it can be obtained that eventually it will be got closer to the target wolf.

Wolves will move in the direction towards the three wolves in the best position following the law, that is, the i-th wolf will move in a way of ${\mathbf{Z}_{t+1}}^{(i,\alpha)}$, ${\mathbf{Z}_{t+1}}^{(i,\beta)}$ and ${\mathbf{Z}_{t+1}}^{(i,\delta)}$ under the effect of α, β and δ. Therefore, we define its final position as

$$ {\mathbf{Z}_{t+1}}^{(i)} = \frac{{\mathbf{Z}_{t+1}}^{(i,\alpha)} + {\mathbf{Z}_{t+1}}^{(i,\beta)} + {\mathbf{Z}_{t+1}}^{(i,\delta)}}{3}. \tag{15} $$

In this algorithm, the parameter $\|A\|$ is decreasing from 2 to 0. Therefore, when $\|A\| > 1$, the wolf individuals move away from the current optimal position and perform global search. When $\|A\| < 1$, the wolf individuals move close to the current optimal position. This makes the algorithm capable of both global search and local search with only two optimization parameters, taking into account both aspects of optimal solution seeking and algorithmic complexity.

3.2 Optimal station placement method

The grey wolf optimizer is used to implement the optimal station placement problem in the scenario of this paper, mainly considering the high non-convexity of the objective function and the high computation volume due to the target regional error. Therefore, taking into account the global solution and the search complexity, we use the grey wolf optimizer, which steps are as follows.

Step 1 Determine the region $\boldsymbol{T}$ in which the target may appear. Select the number N_S of wolf individuals and the maximum number of iterations N_i. Determine the range $\boldsymbol{B}$ for the distribution of stations.

Step 2 Perform initialization of the grey wolf population. Each station placement way is a position of each individual grey wolf, that is, one position $\mathbf{S} = [\mathbf{s}_1, \mathbf{s}_2, \ldots, \mathbf{s}_N]^T$ of N receiving stations represents one individual grey wolf. We initialize N_S values of $\mathbf{S}$ in $\boldsymbol{B}$, randomly initialize N_S position values within the station region $\boldsymbol{B}$.

Step 3 According to (9)–(11), the overall regional localization error $Tr(CRLB_{\mathrm{U}})$ is calculated, which is the adaptation degree of grey wolves, called *Fit* [19]. Select the positions of the three wolves with the best fitness, namely, the smallest error, as wolf α, β and δ. Calculate their fitness Fit_α, Fit_β and Fit_δ, and optimal positions $\mathbf{S}_\alpha$, $\mathbf{S}_\beta$ and $\mathbf{S}_\delta$ are $\mathbf{Z}^{(\alpha)}$, $\mathbf{Z}^{(\beta)}$ and $\mathbf{Z}^{(\delta)}$, respectively. The rest of the wolves are considered as wolf ω.

Step 4 According to (14)–(15), the hunting principle of grey wolves is used to calculate the moving position of wolves at the next moment, ${\mathbf{Z}_{t+1}}^{(i)}$, which is the position of all the remaining ω wolves, $\mathbf{S}_\omega$. At this point, the positions of all wolves are updated. Then, return to step 3 to recalculate the adaptation of wolves until the end of the iteration.

Therefore, we obtain the location that makes the best fitness by iterating through the grey wolf optimization algorithm, $\mathbf{S}_\alpha$, which is the optimal solution for the station placement we need.

4 Analysis of station placement methods based on grey wolf optimization

We propose to solve the station placement problem for regional target localization using the grey wolf optimization algorithm. With the steps in Sect. 3, we can implement this process. In the following, we will analyse the performance advantages that this algorithm brings in this problem.

4.1 Local and global solutions

For an optimization algorithm designed for a global optimal problem, one of the most important points is to avoid the solution of the problem from falling into local optimality. The localization error model of the target region developed in this paper is a function of a non-convex problem. When we set three receiving stations to localize multiple targets in a region, there are multiple minima in this error function, that is, there are multiple local optimal solutions. Moreover, this convex function becomes more complicated when the region where the receiving stations are deployed is strictly limited. Therefore, when seeking the optimal location for this problem, it becomes easy to fall into local optimality.

The grey wolf optimization algorithm utilized in this paper does a good job of avoiding falling into a local optimum when dealing with this problem. The grey wolf algorithm is to record the positions of the three best wolves in each computation, which increases the consumption in memory but can be exchanged for more reliable results in the global problem. We assume that the station locations are in the entire solution space L. The local optimal locations are L_1, L_2, and L_3, and there is one global optimal location among them, as shown in Fig. 2. At this point, we use the swarm optimization algorithm and the grey wolf optimization algorithm for comparison. After initializing the population position, if we record only one optimal position loc_1, then in the next iteration, it will move towards the closest local solution L_1 with a large probability. However, if we record three optimal positions, loc_1, loc_2, loc_3. First, in the process of initializing them, there will be a certain probability to fall near the three local solutions, and at this time, in the next iteration, they will move towards the three local optimal positions loc_1, loc_2, loc_3 with a larger probability. From this point of view, the idea of seeking the optimal three wolves in the grey wolf algorithm fits the case of multiple solutions at the location of our station deployment.

In addition, due to the variation of the optimization parameter A, there is a half probability that the wolves are located close to the current optimal solution (this may be the global optimum or the local optimum) and the other half of the probability that they are far away from the optimal solution for the global search. This is another measure of the algorithm in avoiding falling into local optimality. We know that for heuristic algorithms, the best way to avoid falling into a local optimum is to use randomization. It is because within the system, the randomized selection is able to traverse the global in a better way in the absence of regular samples. In the context of the station deployment in this paper, the error modelling of the targets in the region may involve the number of targets on the order of 10^3 or more, and thus the error function will produce many extreme points. Global search in this scenario is essential. Compared with the direct

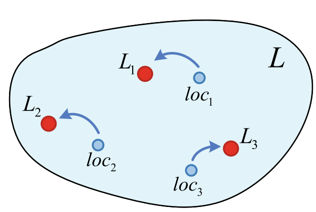


Fig. 2 Schematic diagram of the solution space

gradient descent in some optimization algorithms, the change of the value of A in (14) of the grey wolf algorithm fully reflects the stochastic global search process. The movement of the whole population balances the global search and the approach towards the local optimum under the control of A.

4.2 Cost consumption of algorithms

A corollary of global search is that it consumes a lot of time and computational cost. In case of our optimization problems, the time required to obtain the optimal solution is an important factor to consider. In this class of heuristic algorithms utilized in this paper, the optimal results are obtained by means of continuous iterative updating, so the computational cost is often linked to the number of iterations and iteration time.

The time consumption of the algorithm can be roughly considered as the number of iterations multiplied by the time consumption of each iteration. In the following, we briefly describe the iteration consumption comparison between the grey wolf algorithm and the classical particle swarm optimization algorithm in solving the station placement.

(A) *Iteration time* We know that the general principle of particle swarm optimization is that each flying particle provides the basis for the next move based on the combination of its best position and the best position of the population. Then, this process needs the optimal position of the whole population as a reference basis. The grey wolf algorithm used in this paper only uses the best three positions of the wolf pack, which greatly reduces the comparison calculation time in each iteration. Therefore, the grey wolf algorithm is advantageous in terms of the time of each iteration.

(B) *Number of iterations* In the iterations, the grey wolf algorithm records the optimal three positions at a time, whereas in the particle swarm optimization, only one best position is recorded at a time. Although it may be utilizing the best position of the population, this may increase the speed of convergence only for locally optimal solutions. When the problem has many locally optimal solutions, one best position is clearly not conducive to global search. That is, the particle swarm optimization needs to add greater random variation when we are assured that the overall optimization result is correct. At this point, recording only one optimal position at a time takes more time to seek the global optimum. In this way, the advantage of the grey wolf algorithm, which selects the three best populations, is highlighted.

4.3 Parameter improvement of grey wolf search

The station placement method in the paper is for the overall error of the target region and the error function contains a considerable number of target locations, which is highly non-convex, making it easy to fall into local solutions. In view of this, we consider improving the parameters of the grey wolf optimizer to achieve better global search capability.

From (14), we know that the convergence factor a, affecting the range of A, is linearly decreasing from 2 to 0, which causes the entire wolf pack to move as follows. Within

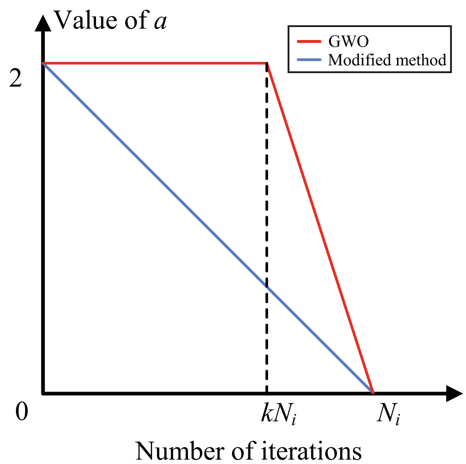


Fig. 3 Parameter improvement of convergence factor

the first half of the number of iterations, there is a 50% probability of moving away from the optimal wolf and a 50% probability of moving closer to the optimal wolf; within the second half of the number of iterations, all of them move closer to the optimal wolf. In this process, although 50% of the wolves within half of the number of iterations are in global search, this does not certainly meet our requirement for the overall global search volume. When we need to increase the global search process of the algorithm, we can increase the duration of A value greater than 1. So we modify the convergence factor a to the following form:

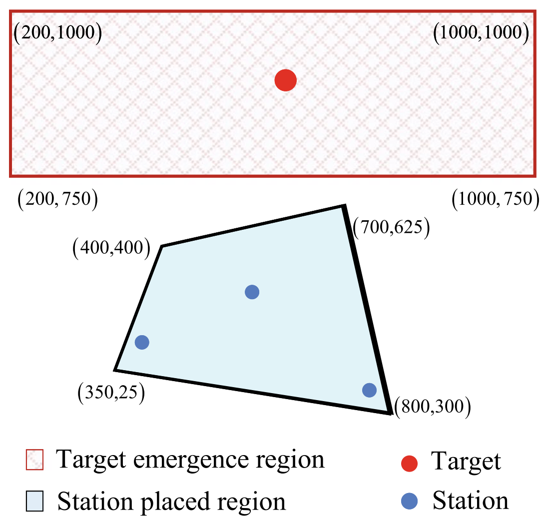
$$a = \begin{cases} 2, & 0 < i < kN_i \\ -\frac{2}{N_i(1-k)} i + \frac{2}{1-k}, & kN_i < i < N_i \end{cases}. \tag{16}$$

In (16), N_i is the maximum number of iterations and k is the adjustment factor, satisfying $k \in [0.5, 1)$. The variation of a is shown in Fig. 3. When the number of iterations i is less than kN_i, the value of the convergence factor a is always 2, and when the number of iterations i is greater than kN_i, the value of a decreases linearly. In this way, the upper bound of the range of A remains unchanged in the earlier iterations, indicating that the movement range of the wolves is always the whole region, thus increasing the ability of global search.

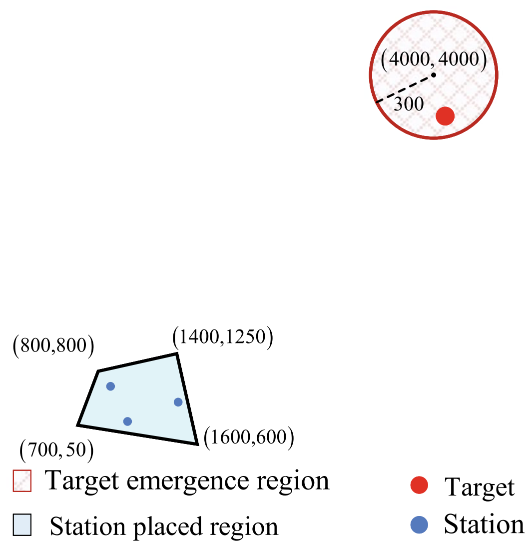
In terms of performance and cost consumption, the improvement of A can increase global search to a certain extent and avoid the risk of falling into local solutions. At the same time, changing the range of A only increases the possibility that some samples are far from the local optimal solution, but does not significantly increase the cost of time consumption.

5 Numerical results

In order to verify the effectiveness of the optimal station placement based on grey wolf optimizer for regional target localization proposed in this paper, some simulation experiments are set up in this section. We localize a target that may appear within a certain



(a) Near-field placement scenario



(b) Far-field placement scenario

Fig. 4 Different station placement scenarios for localization

region under the two-dimensional TDOA mechanism of target localization. We use a mechanism of target localization in two-dimensional TDOA to localize a target that may appear within a certain region. We use the A-criterion optimization model of the overall CRLB localization error to find the optimal station placement method within a specified range.

In this paper, we address the problem of regional target localization and verify that the receiving station obtained by the proposed algorithm can obtain better localization results. We set up two localization scenarios. Scenario 1 is near-field localization, where the distance between the target region and the stations is in the magnitude of 10^2m. As shown in Fig. 4a, the target has a large range of activity (here it is assumed that the region in which it is likely to be found is a rectangular area, rectangular area of

800×250 m^2), and the entire region of activity is relatively close to the receiving station. Scenario 2 is far-field localization, the distance in the magnitude of 10^3 m or more. As shown in Fig. 4b, the target's range of activity is relatively small (it is assumed here that the area where it is likely to appear is a circular area, circle centred at (4000, 4000) m with a radius of 300 m), and the whole region of activity is far away from the receiving station. We are adding diversity by changing the shape of the target region. In Fig. 4, the red region is the range of the target, whose boundary values are indicated (with units of m), and the same for the blue region.

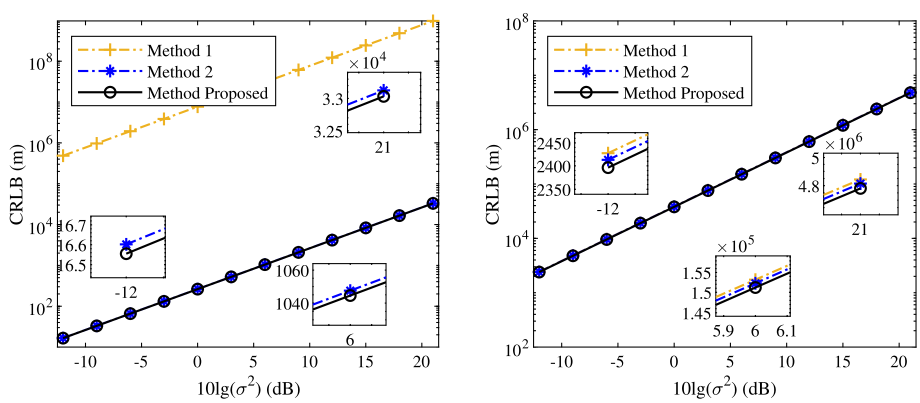
In this section, Sect. 5.1 focuses on verifying that the overall error model proposed in this paper is feasible and effective for the regional target localization problem, including experiments on the advantages of the model, the computational efficiency of the model in dealing with the problem, and experiments on the number of points of the model. Sections 5.2 and 5.3 mainly introduce the advantages of the algorithm for solving this problem, including the comparison between using the Grey Wolf optimization algorithm and other algorithms, and the results after improving the grey wolf optimizer. Section 5.4 mainly verifies that the model and method of this paper are still applicable in a multi-station (more than 3 stations) scenario.

5.1 Experiments on station placement methods based on target region model

In this paper, we address the station placement problem for target localization, and fully consider the situation that the target may appear in a region. On this basis, we set up an error model for regional targets, which is different from the positioning station of single-target points, and is not the accumulation of single-target errors. Therefore, we set up three methods to find out the optimal station placement, compare the localization errors after station selection, and verify the reasonableness and better performance of our proposed regional target error model.

Three methods to find out the optimal station placement are as follows:

1. *Method 1* Use the position of the centre point in the whole region of the target activity as the localization point to establish the error matrix, and find out the optimal receiving station position.



(a) Near-field placement scenario (b) Far-field placement scenario

Fig. 5 Localization error curves of different station placement methods

2. *Method 2* Use the objective function that minimizes the cumulative value of the errors of all the points in the target region, and find out the optimal receiving station position.
3. *Method proposed* The method proposed in this paper. Use the objective function that minimizes the A-criterion value of the overall error matrix in the target region, and find out the optimal receiving station position.

The three methods above led to the optimal three station locations under the experiment of localization scenario 1 and scenario 2, and we used them respectively to localize the targets in the whole target region to obtain the theoretical error curves. In the simulations, 500 points are uniformly picked as multiple targets for the entire target region $\boldsymbol{T}$. We set the error values of the measured TDOA in the range of − 12 to 21 dB. The position sampling within the target region is randomized and 1000 Monte Carlo simulations are performed. The error curves obtained are shown in Fig. 5, where Fig. 5a is the error curve in localization scenario 1 and Fig. 5b is the error curve in localization scenario 2. It can be seen from the experimental results that in the near-field condition, the final localization accuracy of the error model method established in this paper is significantly better than that of the other two methods. In the far-field condition, the proposed method is slightly improved.

From the error curves, we can see that the overall error matrix method proposed in this paper has a small improvement on the final localization results compared to the error accumulation of the single target as the objective function. At this point, we compare their algorithmic time-consuming. We take 50, 100, 300, and 600 points in the region $\boldsymbol{T}$ as the potential locations of targets in the region, and then compute the optimal receiving station locations using method 2 and the method in this paper and calculate their time-consuming (we ensure that the optimization algorithm and other settings remain exactly the same). We first calculate the computing time of the two methods at 20 iterations, which is the number of iterations for our simulation experiments. Then, we record the number of iterations until they converge to the optimum according to the error convergence curves of the two methods respectively, and observe the time consumed at this number of iterations for the two methods.

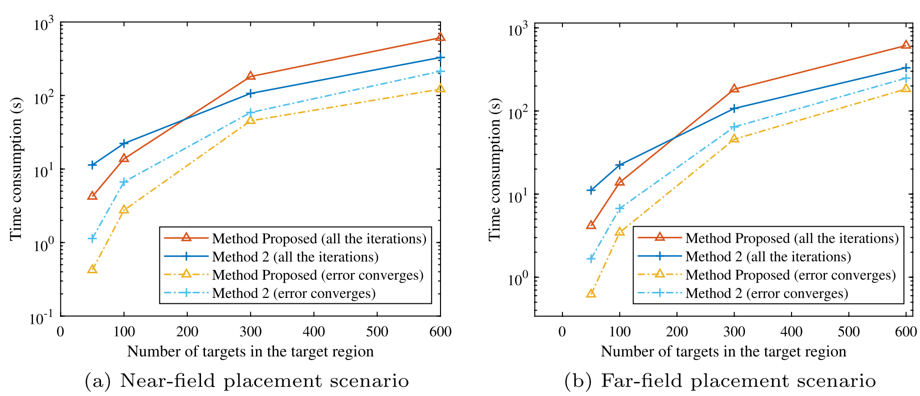


Fig. 6 Comparison of time consumption of algorithms

The experimental results of the algorithm time consumption are shown in Fig. 6, with (a) and (b) denoting the two scenarios of near-field and far-field, respectively. In the figure, we first compare the time consumption of the two methods for the same conditions under the full number of iterations, which are represented by two different coloured solid lines. In this case, the method proposed in this paper for region error modelling consumes less time than method 2 for the conditions of 50 and 100 points, but consumes more time than method 2 for the conditions of 300 and 600 points. It is analysed that this is due to the fact that the method in this paper establishes a regional error matrix, which will contain the errors of all the sampling points in the region. Therefore, when the sampling points are large, it will increase the operation time. However, this does not mean that the method in this paper is at a disadvantage in terms of time consumption. We study the error convergence of the two methods and find that the method in this paper will be faster than method 2 in convergence, that is, the optimal station location is obtained with fewer iterations. Therefore, we calculate the time consumed by the two methods at the converged location, which is represented by the dotted line in Fig. 6. It is clearly seen that the method of this paper for establishing regional targets consumes less time than method 2. To summarize, the method in this paper is advantageous in terms of the time consumed by the algorithm for obtaining the optimal station locations.

Then, we investigate the choice of the number of points in the target region. In the experiments comparing the time consumption, we have made changes to the target sampling points in the target region, which is due to the fact that the number of points will inevitably affect the algorithm time. But whether the number of points has an impact on the localization performance brought by the station placement method in this paper is needed to be verified experimentally. We select the number of uniform sampling points of the region for the overall error modelling of the region as 1, 5, 10, 50, 100, 300, and 600 to get the station placement results. These station location results are used to localize the target in the region, at which 1000 more points are randomly taken from the

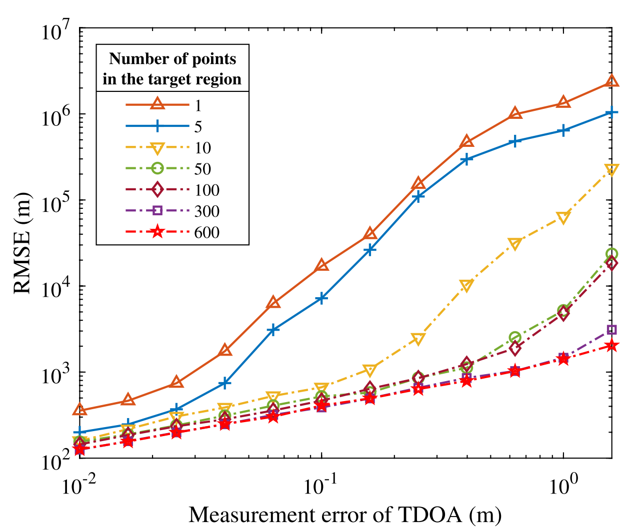


Fig. 7 Localization error curves for modelling different number of points in the target region

target region for simulation to calculate the localization error. The error of the TDOA measurements of this experiment is set to − 20 to 2 dB.

The experimental results are shown in Fig. 7, and it can be seen that the more points selected in the region model, the higher the localization accuracy of the station placement results obtained. Under the premise of this experimental setup, the accuracy is basically consistent when the number of regional target points is above 300. In particular, when the number of regional target points is only one, which is the case of single-target localization, the localization error is larger at this time. This simulation experiment verifies that our model is reasonable, that is, when the target is active in a region, it is necessary to establish a regional target error model for station placement in order to achieve better localization results.

5.2 Comparison of grey wolf algorithm with other optimization algorithms

After verifying that the regional error model developed in this paper can bring more accurate localization performance and lower computational cost, we will use simulation experiments to verify the advantages of the optimization algorithm used in this paper. In this paper, the station placement in the localization scenario of the regional target, using the grey wolf optimization algorithm can be a good balance between the global optimal solution and the optimization search time. We compare the optimization algorithm proposed in this paper with the genetic algorithm and particle swarm optimization algorithm to observe their effects on the problem in this paper.

In this experiment, we take the overall error model of the regional target established in the paper as a unified standard (the regional target samples 300 points), and carry out the receiving station optimization search with the genetic algorithm, particle swarm optimization algorithm, and the grey wolf algorithm mentioned in this paper, which are adopted for the established objective function. After obtaining the optimal station placement results, they are utilized to localize the target in the overall

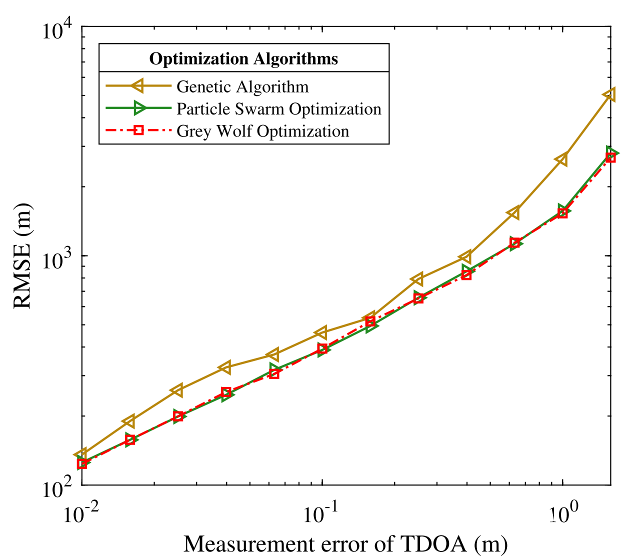


Fig. 8 Localization error curves of different optimization algorithms for station placement

Table 1 Time-consuming with different methods

Method	Consuming time (s)
Genetic algorithm	60.62
Particle swarm optimizer	41.72
Grey wolf optimizer	33.87

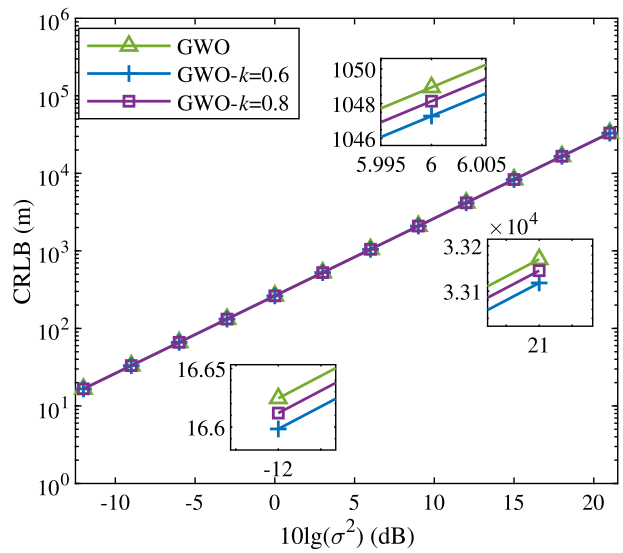


Fig. 9 Theoretical CRLB values with improved optimization parameters

target region. At this time, the target still appears in the form of probability in the whole target region. We used 1000 Monte Carlo simulations to randomly select target points and then calculated their localization error curves under the condition that the error of TDOA measurements is − 20 to 2 dB.

The error curves of different optimization algorithms are shown in Fig. 8. It can be seen that the localization error of the station placement results obtained by the grey wolf algorithm and the particle swarm algorithm are basically similar, which is better than the traditional genetic algorithm. Then, we compare their algorithms time-consuming. We record the number of iterations of the different algorithms in obtaining the location of the station (it is the number of iterations when the error begins to converge) as the time they take to obtain the best location. The calculated time consumption is shown in Table 1. It can be seen that the grey wolf algorithm in this paper is able to converge to the optimal solution of the position faster when it is able to obtain almost the same localization error.

It is important to note here that for the grey wolf optimization algorithm, the internal parameter of total population size affects the time consumption of the algorithm, and the setting also has an impact on the accuracy of the final station location. Similarly, the particle swarm algorithm has such internal parameters. These parameters cannot be kept consistent, so we are only comparing the shortest time it takes to be able to obtain the best location. For example, in this problem, the grey wolf population can be set to 100 or 1000, but when it is set to 100, the optimal station location can already be obtained, so we calculate the time taken when the population is 100.

5.3 Parameter improvement of grey wolf algorithm

We have already mentioned the internal parameter of the grey wolf algorithm—the number of populations. When the population number is large, it is easy to complete the global search after random initialization. However, when the computer memory is limited, the population setting can only be relatively small. At this time, it is necessary to optimize the algorithm by tuning the external parameters of the grey wolf algorithm. According to the theoretical derivation in Sect. 4.3, we improve the algorithm by adjusting the convergence factor a of the parameter A.

Firstly, we set the population number to 1000, and set the adjustment factor k of a to 0.6 and 0.8 while other conditions remain unchanged. We observe the effect of the station placement results obtained from their changes on the theoretical CRLB of localization error. As shown by the theoretical localization error curve in Fig. 9, the adjustment of the optimization parameters of the grey wolf algorithm brings about a very weak improvement in the localization performance. Therefore, we conduct the experiment with the population number of 50 instead, and observe the localization error curves in the actual measurements when k is set to 0.6 and 0.8. As can be seen from the experimental results in Fig. 10, the station placement results obtained by the improved algorithm obviously have better localization performance. This is because the global search of the grey wolf algorithm may face the emergence of insufficient process when the number of populations is small, so we adjusted the value of k to improve the parameter a, which can better complete the global search and get better station placement results.

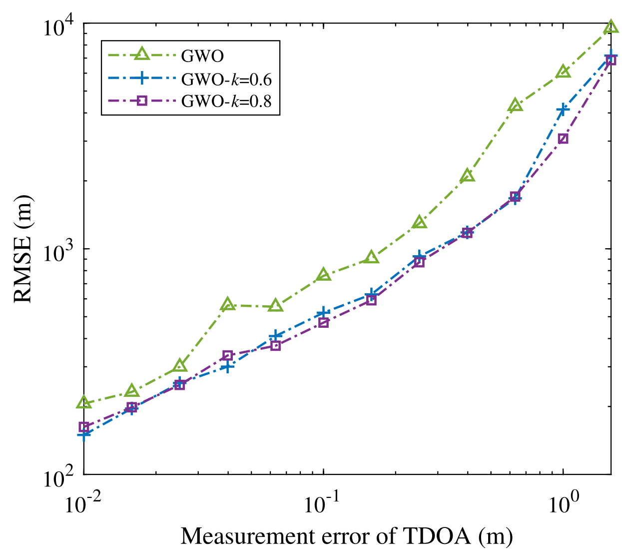


Fig. 10 Localization error curves with improved optimization parameters

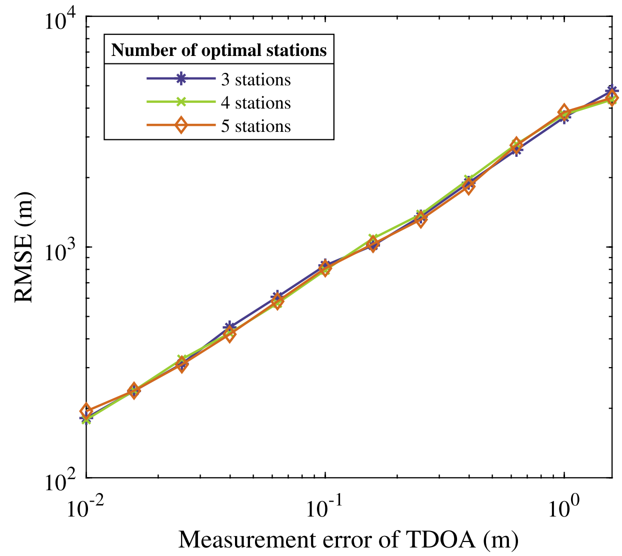


Fig. 11 Localization error curves for different number of stations

5.4 Experiments on expansion of station numbers

In the experiments above, the optimal receiving station selection for localization of regional targets is generally three stations, which also satisfies the minimum station requirement for 2D localization. However, for our proposed regional target localization model and grey wolf optimization algorithm to find the optimal stations, more stations can also be selected for localization in the station area. For the background of the problem, we use a set of experiments to verify that under the method proposed in this paper, more than three stations can be obtained to localize the target region and the localization performance is reliable. We take the sampling points of the target region as 300 points, and the number of grey wolf populations is set to 1000 for optimal station placement, and obtain the optimal station method of three, four and five stations, respectively, while other conditions remain unchanged. Then, their localization error curves are calculated under the condition that the error of TDOA measurement value is − 20 to 2 dB.

The experimental results are shown in Fig. 11, and the localization accuracy of the target region is roughly similar when different numbers of stations are deployed. That is to say, when we use the optimization algorithm in this paper to obtain the optimal station locations, no matter how many stations, we can achieve better localization results. Therefore, the optimization algorithm to solve the problem in this paper is not only limited to obtaining the optimal location of three stations, but also can be four stations or more.

The actual significance of this experiment lies in the fact that there may be more receiving station scenarios in our actual localization. For example, in some scenarios, it is necessary to catalog the receiving stations according to the division of the target emergence area, and strategically carry out the switch-on/switch-off behaviour of the receiving stations. It is like some communication wireless sensor network nodes that will need to be selected and repaired for environmental reasons [26].

In summary, through the above experiments, we have verified the effectiveness and advantages of the overall error model established in this paper, as well as the performance merits of the proposed improved grey wolf optimization algorithm.

6 Conclusion

The paper is mainly to propose an optimal station placement method based on the grey wolf optimizer for regional target localization. It established an objective function in terms of the overall error model of the target region and used the grey wolf algorithm to deal with the optimization problem of station placement. This paper analysed in detail the performance of solving this problem using the grey wolf algorithm and improved the optimization parameters to increase the ability of global search. Several sets of different experiments verify the feasibility and reliability of the model and proposed method. In actual localization scenarios, the station placement method in this paper provides effective support when coping with the problem that the target may appear in a certain region for localization. It can quickly find the location of the station and obtain better localization accuracy.

Abbreviations

TDOA	Time difference of arrival
AOA	Angle of arrival
FDOA	Frequency difference of arrival
CRLB	Cramér–Rao lower bound
FIM	Fisher information matrix
SNR	Signal-to-noise ratio

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Author Contributions
Z.W. mainly completed the deduction of relevant theories and the writing of the first draft, and D.H. provided financial support and constructive suggestions for thesis ideas. J.H., M.X. and C.Z. completed related experiments. All authors discussed and polished the final manuscript together.

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Availability of data and materials
The datasets generated during and analysed during the current study are available from the first author on reasonable request.

Declarations

Ethics approval and consent to participate
This paper does not contain any studies with human participants or animals performed by any of the authors.

Informed consent
Informed consent was obtained from all authors included in the study.

Competing interests
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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