Data−Driven Joint Estimation for Blind Signal Based on GA−PSO Algorithm

Abstract: Without any prior information about related wireless transmitting nodes, joint estimation of the position and power of a blind signal combined with multiple co-frequency radio waves is a challenging task. Measuring the signal related data based on a group distributed sensor is an efficient way to infer the various characteristics of the signal sources. In this paper, we propose a particle swarm optimization to estimate multiple co-frequency "blind" source nodes, which is based on the received power data measured by the sensors. To distract the mix signals precisely, a genetic algorithm is applied, and it further improves the estimation performance of the system. The simulation results show the efficiency of the proposed algorithm.

Keywords: Particle Swarm Optimization (PSO); Genetic Algorithm (GA); spatially distributed sensor; blind signal detection

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1 Introduction

As mobile broadband traffic and end-user demands continue to grow, the radio frequency spectrum has become an expensive and limited resource for wireless communications. Therefore, how to reasonably allocate spectrum resources, avoid conflicts, and detect interference have become an extremely worthwhile research issue. Spatially distributed sensor networks can effectively detect a certain frequency band in a certain area [1]. The power information can be bused in a variety of applications, such as indoor positioning, interference detection, signal recognition, and cognitive radio systems. As a major threat to wireless communications, interference creates significant usage and financial impact on users and operators. Interference is generally processed by several related techniques, such as interference monitoring, interference detection and isolation, interference classification, interference localization, and interference mitigation. Interference localization is what we are concerned about.

General interference signals are blind source signals, with unknown transmission power, which also brings difficulties to interference location [2]. For some communication systems, interference sources can cause very serious consequences if they cannot be located and eliminated in real time [3]. For instance, the signals in the communication based train control system (CBTC) communicate with the base station in the 2.4 GHz public band and are easily interfered by other devices in the same band. Especially when there are non-protocol signals in the environment, the system signals may be interfered by them. Once the same frequency signals are mixed, the signal sources are difficult to locate. Therefore, it is necessary to use appropriate methods to detect blind signals. Currently, common spectrum sensing techniques include matched filter detection, cyclostationary detection, and energy detection, which are mainly based on physical layer signal processing. Several methods were proposed to solve the problem of blind signal detection, by the use of a path loss model. The most used is the theoretical analysis method of using received power measurements at spatially distributed monitors [4], [5], [6]. Some scholars have proposed a method to detect the co-frequency blind signal by using the topology of the receiver and the mathematical models [6]. Some methods use k-means clustering algorithm combined with Particle Swarm Optimization (PSO) to estimate the position of nodes [2]. Other methods use SDR equipment for inter-

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ference detection [7]. From the simulation results, the PSO has better adaptability and performance when dealing with such interference problems [8], [9]. The PSO has caught great attention and various improved algorithms are continuously proposed, such as the local PSO through changing the topology of the particle population. There are some methods combined with other algorithms such as Genetic Algorithm (GA) and clustering algorithms to improve performance [10], [11]. The PSO is then extended to use for the multi-objective estimation problem [10]. Genetic algorithms are also widely used in smart applications [12]−[14]. Similarly, improvements to genetic algorithms have never stopped, such as the elite genetic algorithm, adaptive genetic algorithm, multi-objective genetic algorithm, and hybrid genetic algorithm [15]−[18].

However, there are few works concerning the data-driven method using sensors or detecting equipment.

According to the received signal power measurement and free-space path loss model, the sensor network can be utilized to estimate the relative position of the target node based on the mutual measurements from other nodes in the network. A natural question that then arises is what if only the general path loss model is utilized, this makes it infeasible to locate one or multiple co-frequency nodes when the transmit power is unknown [19], [20].

In this paper, we utilize the sensor measurement data which contains the spatial diversity of the source signals to estimate the unknown node's coordinates and power based on a proposed particle swarm optimization algorithm. We formulate the sum of squared error of the mathematical model of the sensor system as the objective function of the PSO algorithm and find the minimum value. According to the path loss model and the limited range of the spatially distributed sensor receiving area, the unknown nodes' transmit power range is estimated. The major contributions are listed as follows:

1) We use spatially distributed sensor networks and PSO to study the joint estimation of the position and power of multiple unknown nodes. In the absence of transmitter power information, a unique estimation method is proposed based solely on the received power information on the sensor. For locating multiple co-frequency unknown nodes, the received power is the superposition of the co-frequency unknown nodes power. The mathematical model of this sensor system is non-convex, and the function has multiple minimum points. We reduce the range of the objective function solution by pre-estimating the power and coordinates of unknown nodes to reduce the number of local optimal solutions and improve the accuracy of joint estimation.

2) We find that the ratios of power between unknown nodes will affect the final estimate of the algorithm. To avoid the wrong estimation of the PSO, we designed a unique GA and combined it with the PSO, which greatly reduced the probability of the error estimation of the PSO and improved the estimation performance of the system. When a signal has higher pow-

er, it is easy to obtain a smaller estimation error. However, the signal with lower power cannot be estimated accurately. The greater the ratio of the power of the signals, the more pronounced this phenomenon is. Moreover, when multiple signal power values are similar, the PSO may be confused. In this case, the PSO algorithm cannot distinguish the phenomenon of each signal because the PSO falls into the local optimal solution. Therefore, we combine the GA with the PSO algorithm to avoid the pre-matureness of the algorithm and enable it to jump out of the trap of the local optimal solution.

Through simulation, we found that the combined performance of PSO has been significantly improved after combining GA. The estimated error is reduced by a maximum of 0.6 m, and the estimation accuracy is improved by nearly 30%. Compared with the PSO with the exhaustive method, the performance gap is about 30%.

The rest of this paper proceeds as follows. Section 2 introduces the system model. The PSO algorithm improved according to system characteristics is proposed in Section 3. Section 4 mainly deals with unique GA and the method combined with PSO. In Section 5, the algorithm combined with the proposed PSO and GA is simulated and verified. Section 6 concludes this paper.

2 System Model

We assume a scenario where there are M transmitters and N sensor nodes within a certain square area. There is no reflective medium in the area, and there will be no multipath effect. In general, spatially distributed sensor networks are placed according to a certain spatial topology. This usually enables the system to have better estimation performance and to preliminarily position the target node. However, in order to make the study without loss of generality, we randomly placed the sensor in the hypothetical area and recorded its coordinates. The locations of the transmitters and sensors are represented in Cartesian coordinates. The uppercase notation denotes the coordination and power of transmitters such as (X_1, Y_1) and $(P_{T1}$, while the lowercase denotes the coordinates and power of sensors such as (x_1, y_1) and (p_{r1}). For example, a diagram of the square region containing M transmitters and N receivers is shown in **Fig. 1**. Here, we only consider the line-of-sight channels from each transmitter to each sensor.

$$p_r = \frac{P_T}{\beta d^a}, \tag{1}$$

where d denotes the Euclidean distance between the transmitter and the sensor, p_r denotes the measured power of sensor, P_T denotes the transmitted power of the blind signal, and β is a known constant selected based on the carrier frequency and the antenna structure. In practice, $\alpha \in [2,6]$ depending on the environment. Here, we make the value of $\alpha = 2$. Since the estimation system only utilizes the received power level of the sen-
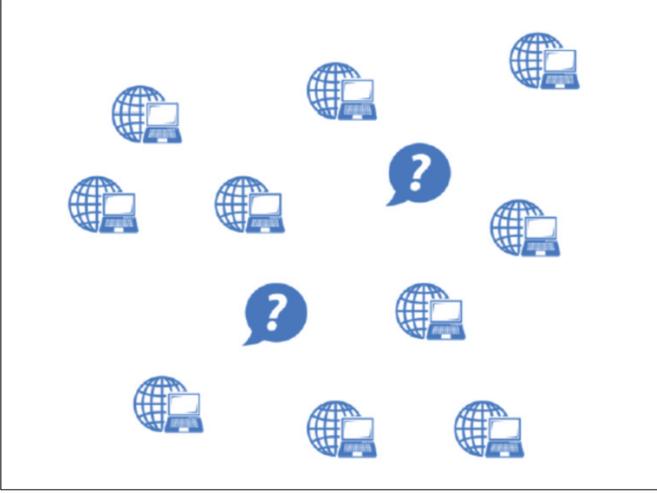
▲Figure 1. M transmitters (question marks) and N sensors placed within a certain square area.

sor, we do not consider short- term fading.

2.1 Multiple Transmitter System

Since we chose PSO as the primary tool to solve joint estimation problems, we transform the system model into an objective function that serves as the basis for particle search. We define that the objective function is the sum of the squared difference between the actual measured power of each sensor and the predicted received power based on the estimated transmitter power and coordinates and causes the population of particles to search for its minimum value.

$$F = \sum_{i=1}^{N} \left(p_{r,i} - \sum_{j=1}^{M} \frac{P_{T,j}}{\beta d_{i,j}^{\alpha}} \right)^2, \tag{2}$$

where $p_{r,i}$ denotes the measured power of sensor i. $P_{T,j}$ denotes the transmitted power of the transmitter j. $d_{i,j}^{\alpha}$ denotes the Euclidean distance between the transmitter j and the sensor i. Our objective function is not convex concerning the estimated transmitter locations. Note that there may be many local optimal solutions when the number of sensor nodes is small, and the estimation error does not approach zero endlessly as the number of sensor nodes increases.

3 Particle Swarm Optimization

PSO is a population-based evolutionary algorithm. The classical PSO is used for balancing the weights of a neural network. The basic unit of the PSO population is the particle. The algorithm forms the search behavior through the interaction between each particle. Each particle represents a solution to the objective function and corresponds to a fitness function value. The merits of the fitness function value directly determine the quality of the solution. The target position is considered a global optimal solution.

PSO has two important concepts:

1) Exploration means that particles leave the original search trajectory to a certain extent and search in a new direction, which reflects the ability to develop into unknown regions.

2) Exploitation refers to the fact that particles continue to perform more detailed searches on the original search trajectory to some extent.

Population searches for optimal solutions in exploration and development. To control these two kinds of search better, the inertia weight is introduced. Its value can adjust the global and local search ability of PSO. When α is large, global optimization ability tends to be strong. On the contrary, the local search ability is enhanced. In this paper, we utilize the equation with inertia weights. The topology of the population directly determines the way in which particles interact. The classical PSO is a global topology and the learning samples for each particle are all other particles in the population. Subsequently, scholars proposed a variety of local PSO algorithms with excellent performance, and found that local PSO algorithm has better performance in local search. But what our system needs most is the global search ability of the algorithm. Therefore, it is more appropriate for us to choose a global topology.

We generate a certain number of particle populations, and then initialize the particles and randomly generate their speeds and positions. All particles are initialized, giving them random values in each dimension, as shown in Equ. (3), where k is the number of the particle and j is the number of the transmitter. Then we calculate the fitness function value of each particle according to Equ. (4), where F^k denotes the fitness function of particle k. i is the number of the sensor, and update the particles' speeds and positions according to Equs. (5) and (6) in each iteration until the end of the algorithm. The equations and pseudo code of the standard PSO (Algorithm 1) are as follows.

$$\begin{cases} x^k = \left[X_1^k, Y_1^k, P_{T,1}^k, ..., X_M^k, Y_M^k, P_{T,M}^k \right] \\ v^k = \left[\dot{X}_1^k, \dot{Y}_1^k, \dot{P}_{T,1}^k, ..., \dot{X}_M^k, \dot{Y}_M^k, \dot{P}_{T,M}^k \right] \end{cases}, \tag{3}$$

$$F^k = \sum_{i=1}^{N} \left(p_{r,i} - \sum_{j=1}^{M} \frac{P_{T,j}^k}{\beta \left[(X_j^k - x_i)^2 + (Y_j^k - y_i)^2 \right]} \right)^2, \tag{4}$$

$$v^k(t+1) = \omega \times v^k(t) + c_1 \times r_1 \times (pbest^k(t) - x^k(t)) + c_2 \times r_2 \times (gbest(t) - x^k(t)), \tag{5}$$

$$x^k(t+1) = x^k(t) + v^k(t+1), \tag{6}$$

where $v^k(t)$ denotes the speed of particle k at iteration time t. x^k denotes the position of the particle k. The $pbest^k$ is the optimal position experienced by the particle k. The $pbest$ denotes the position of the particle that operates optimally in the population. c_1 and c_2 denote the acceleration constants of the particles. In order to make the particles have stronger self-search-

ing ability in the initial stage, they can converge to the global optimum at the later stage. We linearize c_1 and c_2 so that c_1 has a larger initial weight and gradually decreases. And c_2 is the opposite.

$$\begin{cases} c_1 = \dfrac{-t}{T} + 2 \\ c_2 = \dfrac{t}{T} + 1 \end{cases}. \tag{7}$$

r_1 and r_2 are two random numbers distributed uniformly in [0, 1]. ω is generally a constant, and the linearly decreasing weight is currently used more frequently as the value of the inertia weight.

$$\omega = \omega_{max} - \frac{(\omega_{max} - \omega_{min}) \times t}{T}, \tag{8}$$

where T denotes the total number of iterations and t denotes the number of iterations that have taken place.

The population size of particles affects the performance of the algorithm. Different estimation problems apply to different population sizes, and it is generally proportional to the dimension of the objective function. Some results suggest that using $(2m + 1)^2$ particles work better, where m is the number of dimensions the objective function has. For our simulation, each unknown transmitter needs to estimate three dimensions (x, y, P_T). Therefore, for each additional transmitter, there are three dimensions added. We need to change the population of particles according to the different dimensions of the objective function. Otherwise, too few particles may miss the global optimal solution, while too many particles may produce many repeated results, reducing the efficiency of the algorithm. So we use $(2m + 1)^2$ particles, which is enough for most of the estimation problems. Using excess particles within the algorithm can indeed make the estimation more accurate. However, it will cause the algorithm calculation volume to increase, affecting the overall performance of the system. In Section 4, with the help of the exhaustive method, we use a large number of particle population to approximate the estimation error limit of the objective function in this paper.

Algorithm 1. Particle Swarm Optimization

1: Establish the objective: minimize $\{F^k\}$.

2: Initialize, randomly generated particle position and velocity.

3: **While** $t \leqslant T$ // T is the maximum number of iterations

4:   **If** $F^k < pbest^k$ **then**

5:     $pbest^k = x^k$

6:     **If** $pbest^k < gbest$ **then**

7:       $gbest = pbest^k$

8:     **End if**

9: **End if**

10: Update particle. Update particle velocity and position according to Equs. (5) and (6).

11: **End While**

To evaluate the effectiveness of the proposed joint estimation technique, we attempted to simulate the performance of three to twenty sensors and one to four transmitters based on different systems. As mentioned earlier, each additional transmitter will add 3-dimensions that need to be estimation to the system. For the estimation problem, the number of equations should be more than or equal to the estimated dimensions. In other words, every time an unknown transmitter is added, at least three receivers need to be added. Increasing the number of transmitters and receivers does increase the computational burden of the simulation, but the proposed method has no inherent limits to the dimensionality it can handle. However, as the dimension increases, the performance of the PSO deteriorates. In the standard PSO, the learning object of each particle is a particle in the population that has the best fitness function value. When the dimensions are large, it is difficult to ensure that the global-best particle can search for the optimal solution in every dimension.

After a large number of simulation experiments using only the particle swarm algorithm, we found that the ratio between the powers of multiple transmitters had different effects on the results. The impact can be divided into two situations. In each case, the algorithm falls into a special local minimum. In the first case, when there are two or more transmitters with similar actual power, the particle swarm algorithm may easily match the estimated power of one transmitter with the estimated position of another transmitter with similar power. Because the objective function is a multi-dimensional estimate, when the estimated value of some of the dimensions is close to the actual value, the overall fitness function value is too small. The algorithm tends to converge and falls into a local minimum.

In the second case, the high power transmitter estimates better than the low power transmitter. This situation is caused by the objective function. High-power transmitters have a greater impact on fitness function values than low- power transmitters. Although the dimensions are synchronous estimates, the convergence of various dimensions of the high power transmitter is significantly faster than the dimensions of the low power transmitter. When the various dimensions of the high-power transmitter obtain relatively accurate estimates, the fitness function value is already small and the algorithm tends to converge.

4 Genetic Algorithm

The genetic algorithm is a computational model that simulates the natural evolution of Darwin's biological evolution theory and the biological evolution process of the genetic mechanism. It is a method to search for optimal solutions by simulat-

ing natural evolutionary processes. The GA begins with a population that represents a potential solution set of problems, while a population consists of a certain number of individuals genetically encoded. Each is an entity with a characteristic chromosome. Chromosomes are the main carrier of genetic material, that is, a collection of multiple genes whose internal manifestation is a combination of genes that determine the external representation of the shape of the individual. Therefore, mapping from phenotype to genotype, that is, coding work, needs to be implemented at the beginning. Since the work of gene encoding is complex, we tend to simplify it. Here, we combine GA and PSO, which share a population. Next, we genetically encode each particle according to the category of information estimated on each dimension of the particle. The specific gene coding method is shown in **Fig. 2**.

The figure shows the situation where there are two unknown transmitters in the detection area. The coordinate (X_1, Y_1) of the transmitter 1 is used as a gene, and the coordinate (X_2, Y_2) of the transmitter 2 is used as another gene, and the transmission power of each transmitter is independently used as a gene.

In this paper, the PSO and the GA share an objective function. After one iteration of the PSO, the particle population is sent to the GA for a round of selection. We calculate the survival probability based on the fitness function value of each particle. Since the algorithm solves the problem of finding the minimum value of the objective function, it can be considered that the smaller the fitness function value is, the better the estimation result of the particle is. We give a larger probability of survival for particles with smaller fitness function values, while particles with larger fitness function values are given a lower probability of survival.

Then, the roulette strategy and the elitism are joined to select the paternal particle population. The previously calculated survival probability, at this time serving the roulette strategy, is used to select the paternal particle population.

The genes in the GA do not necessarily reflect the nature of the problem to be solved. Therefore, the genes are not necessar-

ily independent of each other. Simply hybridizing is likely to destroy a better combination. In this way, the purpose of accumulating better genes is not achieved, but the original good genes are destroyed. Rudolph used the finite Markov chain theory to prove that the Canonical Genetic Algorithm (CGA), which uses only three genetic operators of crossover, mutation, and selection (proportional selection), cannot converge to the global optimal value.

Therefore, we added elitism to the algorithm, so that the particles with the best value of fitness function in the particle population output from the PSO are directly crossed into the progeny particles without crossover, mutation, and selection.

It is assumed that the number of particle output from the PSO to the GA is L, with $L = (2m + 1)^2$. We select $2(L - 1)$ paternal particles by roulette strategy. The two pairs are combined to perform gene cross-interchange, and each pair of paternal particles produces only one progeny particle. The number of progeny particle population reaches $L - 1$, and finally, the optimal particles retained by the elitism. The number of particles guaranteed to be re-entered into the PSO is still L. The specific roulette and elitism is shown in Algorithm 2.

Algorithm 2. Roulette and Elitism

1: Calculate F^k of each particle.
2: Select the particle k with the $\min(F^k)$ and output it to the progeny population.
3: Calculate the survival probability:
$P_{\text{survival}} = ((\max(F^k) + \min(F^k)) - F^k (1 : L, 1)) /$
$\text{sum}((\max(F^k) + \min(F^k)) - F^k (1 : L, 1))$
4: Create a roulette based on P_{survival}.
5: **While** $ii \leqslant 2(L - 1)$ // $2(L - 1)$ is the number of paternal particles. And $ii = 1$.
6:     Select a paternal particle by roulette
7:     $ii = ii + 1$
8: **End While**
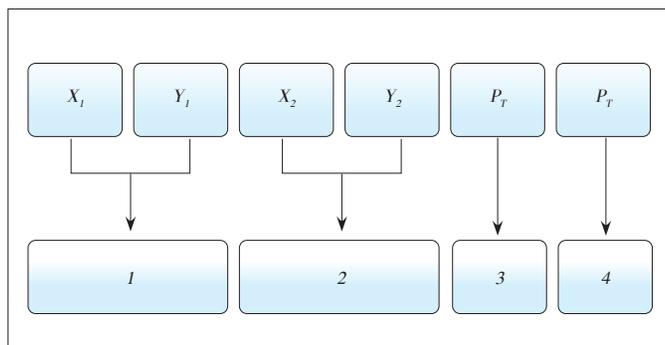
▲ Figure 2. The coordinate estimates of unknown node 1 are combined into one gene. The coordinate estimates of unknown node 2 are combined into one gene. Their respective power estimates are separated into a single gene.

Because the PSO is difficult to distinguish several blind source signals with similar power, it is extremely easy to fall into the local minimum. Therefore, when the genes are crossed, we allow the coordinate loci to be interchanged and the power loci can be interchanged, although this may make the progeny particle gene obtained after the crossover completely different from the paternal particle gene. Because of the existence of elite strategies, we do not need to worry that the PSO will lose the original possible correct estimation results.

We hope that when the PSO particles tend to converge, some particles can still jump out of the existing estimation results. The particles may quickly and accurately estimate the position and power of the high-power transmitter, especially when the power difference between the two transmitters is very large.

Therefore, the entire PSO algorithm tends to converge when the low power transmitter does not obtain an accurate estimate. And the estimated result falls into a local minimum. So the design of genetic mutation becomes extremely critical. The mutation may occur on any one or more genes of the particle, and the mutation is completely random in the range of values of the gene. We do not make any human intervention in the values and direction of mutation. The mutation probability is set to increase linearly with the number of iterations, as shown in Equ. (9), where *Pmuta* denotes the mutation probability.

$$P_{muta} = \frac{t}{T} \times 0.1 + 0.05. \tag{9}$$

The specific operation of the particle group gene crossover and mutation is shown in **Fig. 3**.

Referring to Fig. 3, the first two genes are the coordinate estimate genes, and the last two are the power estimate genes. Each of the two paternal particles that exchange genes takes out a coordinate estimate gene and a power estimate gene. These four random genes are randomly combined to form progeny particles with new gene sequences. Taking two unknown nodes as an example, the genetic composition of the progeny particles is 64 cases. And the genes of the progeny particles

are still arranged in the order of the genes of the paternal particles. Genetic mutation may also occur in progeny particles obtained after crossing.

The computational complexity of the GA-PSO algorithm is indeed higher than the PSO algorithm. For the traditional PSO algorithm, the time complexity is $O(N \times m \times (2m + 1)^2 \times T)$. That is the product of the number of receivers, the number of objective function dimensions, the total number of particles, and the number of iterations. In the GA-PSO algorithm, the main computational complexity still comes from the PSO part. And iterations do not run the GA algorithm every time. Instead, every other iteration of h runs the GA algorithm. Through simulation experiments, we found that when the value of h is less than 5, the algorithm works better. In the experimental part that follows, our default h has a value of 5. Therefore, the time complexity of the GA-PSO algorithm in this paper is $O(N \times m \times (2m + 1)^2 \times T + (1 + 4((2m + 1)^2 - 1)) \times T/5)$.

5 Simulation Results and Discussion

In this work, we set up a Monte-Carlo based simulation. We jointly estimate the power and position of 2 unknown transmitters. We fix the number of spatially distributed receivers to 20 and ensured that each receiver has the same weight and assume that the size of the test area is 10 m×10 m.

Before performing the simulation, we must first make a basic estimate of the power and location of the blind source nodes within the system. Some scholars have proposed to use the received power of spatially distributed receivers for clustering, and use the k-means algorithm to quickly narrow the search range of PSO. However, this proposed method is for known nodes with the same power. The problems we face are obviously much more complicated. When the power difference between two unknown transmitters is too large, we may no longer be able to use clustering to determine the approximate location of the blind source node. Because the blind source node with low power is likely to disappear in the signal strength of the high power blind source node. In this paper, we do not pre-estimate the position of the particle in order to more directly show the improvement of the performance of the PSO in dealing with this kind of problem. But we still make a preliminary estimate of the power of the unknown node. First, we set the lower limit of the estimated power to zero. Then we select the transmitter with the lowest received power, assuming that it is at the maximum distance from the transmitter (according to the estimated area, $d_{max} = 10\sqrt{2}$). Substituting the minimum received power and the maximum distance into Equ. (1), what is obtained is the upper limit of the transmission power. Note that this upper limit is the upper limit of the sum of the powers of multiple transmitters.

In the simulation, we assume that the transmit power of the unknown transmitter 1 is always 100 mw, while the transmit power of the unknown transmitter 2 is from 10 mw to 90 mw.
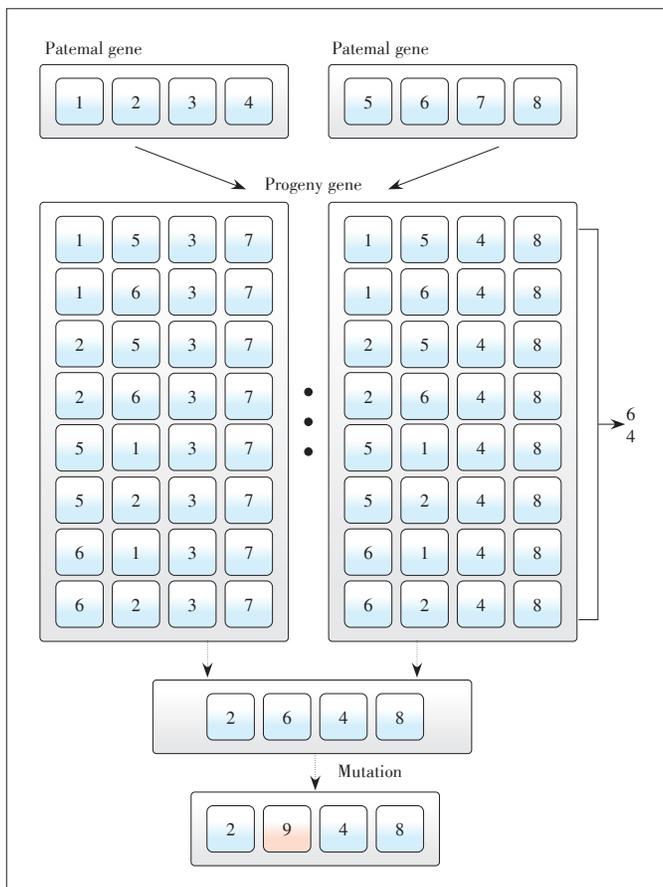
▲Figure 3. Particle gene exchange and genetic mutation process of two unknown nodes.

The power of each transmitter is still unknown to the system. We use P_{T2}/P_{T1} as the independent variable and the average estimation error as the dependent variable. In order to form a comparison, we also add the position estimation error of the GA-PSO algorithm under known power. At the same time, we use the idea of the exhaustive method to maximize the particle population of the PSO (excellent performance), and test the lower error limit of the objective function.

From **Fig. 4**, the estimation performance of the PSO algorithm is greatly improved after adding the GA. Especially when the value of P_{T2}/P_{T1} is in the range of [0.3, 0.7]. The average error is reduced by up to about 0.6 m, and the overall performance is increased by about 30%. However, when the power of the unknown nodes is similar or the difference is large, the system estimates that the performance improvement is slightly reduced. Compared with the results obtained by the exhaustive method, the algorithm proposed in this paper still has a certain gap and there is still room for improvement in the future. However, the difference between the joint estimate and the estimate with known power is not very large.

As shown in **Fig. 5**, as P_{T2}/P_{T1} gradually decreases, the difference between the estimation errors of the unknown node 2 and the unknown node 1 gradually increases. Although the genetic PSO algorithm has reduced both, it cannot suppress this trend. **Fig. 6** shows the case where the power estimation error varies with the ratio of P_{T2} and P_{T1}. When the power of two unknown nodes is similar, the power estimation error is only about 10%. And when the power difference between the two is large, the power estimation error is also steady.

The main reason for this trend is the design of the objective function. High power transmitters have a greater impact on the objective function than small power transmitters. Both PSO and GA are algorithms for finding suboptimal solutions. They only care if the fitness function value is small enough. As long as the power and position estimates of a high power transmitter are accurate, the fitness function value can be reduced to a small enough. Therefore, even if the power and position of the small power transmitter are not accurate enough, the algorithm will tend to converge.

We also conduct an artificial observation analysis of the error results and find that there are still cases where the two unknown nodes estimate the coordinate interchange because they fall into the local minimum. Comparing the values of the fitness function of the local minimum and the global optimal solution, it is found that their fitness function values are indeed very close. The introduction of the GA algorithm can make the algorithm jump out of the local minimum and can effectively guide the estimated value to the global optimal solution. However, there is still no guarantee that it will not fall into other local optimal solutions after jumping out. This shows that the objective function as a non-convex function has many non-inferior solutions. In future research, we can extend this problem from single-objective PSO to multi-objective PSO, and new de-
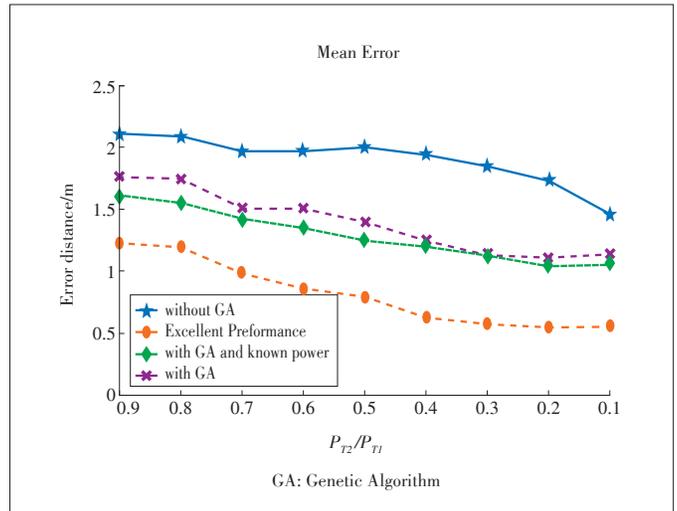
▲Figure 4. Mean estimation error distance of all transmitters.
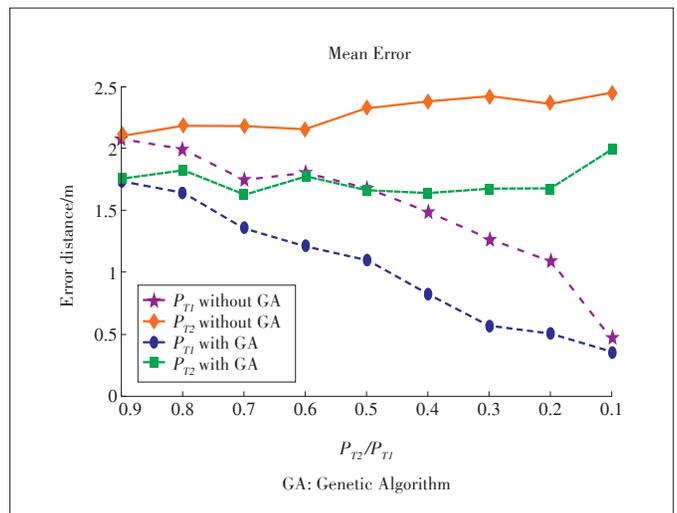
▲Figure 5. Mean estimation error distance of each transmitter.
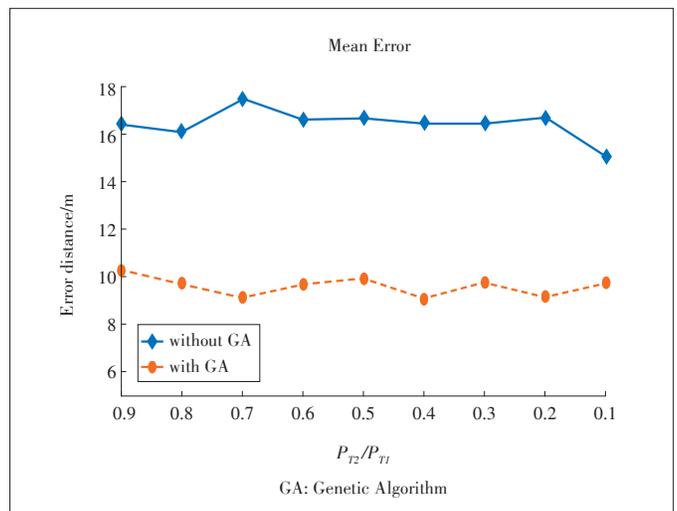
▲Figure 6. Mean estimation error power of each transmitter.

velopment may be made.

6 Conclusions

Joint estimation of power and positions for blind signals is essential to detect the co-frequency interference signal. We propose a data-driven based PSO algorithm combined with a special GA to estimate multiple co-frequency wireless blind source nodes with different powers. To avoid the local minimum problem, we use GA to help particle population jump out of local minima. The simulation results show that the proposed GA-PSO algorithm has better estimation performance than the classical PSO algorithm and can reduce the error distance by up to 30%.

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