Analysis of passive location communication system based on intelligent optimization algorithm

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Abstract. In a certain background of sea and air battlefield, the positioning accuracy of the multi-machine passive positioning communication system can be effectively improved by adjusting the position layout of each machine. In this paper, the GDOP formula of multi-machine time difference positioning algorithm error is deduced, the model of passive positioning communication system optimal station layout based on intelligent optimization algorithm is established, and the method of using improved particle swarm optimization algorithm and genetic algorithm to find the optimal station layout of multi-machine passive positioning communication system is put forward. Compared with the genetic algorithm, the improved particle swarm optimization (pso) reduces the positioning errors of regional targets and improves the instantaneous and rapid station distribution ability of multi-machine passive positioning communication system.

1. Introduction
Due to the advantages of passive positioning technology, such as good concealment, long positioning distance and many positioning methods and means [1], various military powers have invested a lot of scientific research efforts in this direction. In particular, multi-machine passive positioning technology has been developed by leaps and leaps in recent years.

Literature [2] and literature [3] systematically introduce the basic principle of multi-machine passive positioning technology and the available positioning system. In literature [4], factors affecting the positioning accuracy of multiple machines were analyzed in detail, and CRLB with site and velocity errors was deduced. More passive location system positioning accuracy were the major influencing factors of the system position error synfuels fiasco, target position error source, time of arrival (doas), and other measurement errors, in a certain air and naval battlefield environment, however, when certain circumstances, other error in the system synfuels fiasco location layout and the error is relatively great impact on the accuracy of positioning system. In literature [5], the positioning accuracy of several typical multi-machine cloth stations was simulated and analyzed, and the GDOP contour map of four-station star-shaped cloth stations was obtained. Furthermore, the quadratic autonomous planning of cloth station positioning based on typical cloth stations was further studied, but the strategy of automatic optimization of cloth stations was not given. Literature [6] introduced the method of optimal station layout for passive positioning system based on genetic algorithm, and solved the problem of optimal station layout for a certain target or region positioning system in space. However, the algorithm has slow convergence and is not suitable for instantaneous rapid positioning environment. Therefore, it is of great significance to study the optimal station layout strategy of multi-machine passive positioning communication system based on intelligent optimization algorithm for effectively improving the efficiency and accuracy of passive positioning.
2. GDOP for positioning accuracy of multi-machine passive positioning system

Geometric accuracy Dilution GDOP (Geometric Dilution of Precision, GDOP) is the characterization of passive location system positioning. Precision is a measure, by comparing the GDOP value to measure the positioning accuracy, GDOP value, the greater the location accuracy is lower, conversely, the higher \cite{7}. Literature [8-10] provides a detailed derivation process of GDOP, analyzes the influencing factor parameters, and applies its conclusions to give a multi-machine GDOP derivation formula.

There are \( N \) aircraft in the multi-aircraft passive positioning system, among which \( S_0 \) is the host, \( S_1, S_2, S_3 \ldots S_n \) is the auxiliary engine, and the target radiation source is \( T \), where \( S_i=(X_i,Y_i,Z_i), i \in \{0,1,2,3 \ldots N \} \), target \( T=(X,Y,Z) \). The positioning equation is:

\[
\begin{align*}
\Delta r_i &= r_i - r_0 = c \Delta t_i, \\
\Delta r_0 &= c \Delta t_0 = r_0, \\
\Delta r_1 &= c \Delta t_1 = r_1, \\
&\cdots \\
\Delta r_n &= c \Delta t_n = r_n.
\end{align*}
\]

In the formula, \( r_0 \) represents the distance from the target to the main platform, \( r_i (i =1,2,3 \ldots N) \) refers to the distance between the target and the secondary platform; \( \Delta r_i \) refers to the distance difference between the target and the main platform and each secondary platform; \( c \) refers to the propagation speed of electromagnetic waves; \( \Delta t_i \) refers to the time difference between the signal and the main platform and each secondary platform.

Differentiate both sides of equation (1) and get the following equation:

\[
d (\Delta r_i) = (c_i - c_0) dx + (c_y - c_0) dy + (c_z - c_0) dz + (k_i - k_0) \tag{2}
\]

In the formula:

\[
\begin{align*}
\frac{\partial c_i}{\partial x} &= \frac{x - x_i}{r_i}, \\
\frac{\partial c_i}{\partial y} &= \frac{y - y_i}{r_i}, \quad (i = 0,1,2,3, \ldots n), \\
\frac{\partial c_i}{\partial z} &= \frac{z - z_i}{r_i}.
\end{align*}
\]

Convert equation (2) into matrix expression:

\[
dY = CDX + dX_s \tag{3}
\]

After sorting out the above equation, the estimated value of positioning error is as follows:

\[
d\hat{X} = \left( C^T C \right)^{-1} C^T (dY - dX_s) \tag{4}
\]

Solve to get the covariance:

\[
P_{dX} = E \left[ d\hat{X} d\hat{X}^T \right] = B \left[ E \left[ dY dY^T \right] + E \left[ dX dX_s^T \right] \right] B^T \tag{5}
\]

So the variance of positioning error in x, y and z components is:

\[
\begin{align*}
\delta^2_{x} &= m_{11} = \sum_{i=1}^{n} \sum_{j=1}^{n} b_i b_j \sigma^2 \delta^2 \\
\delta^2_{y} &= m_{22} = \sum_{i=1}^{n} \sum_{j=1}^{n} b_i b_j \sigma^2 \delta^2 \\
\delta^2_{z} &= m_{33} = \sum_{i=1}^{n} \sum_{j=1}^{n} b_i b_j \sigma^2 \delta^2
\end{align*} \tag{6}
\]

Then the GDOP expression of multi-machine time-difference passive positioning accuracy is:

\[
GDOP = \sqrt{\delta^2_{x} + \delta^2_{y} + \delta^2_{z}} = \sqrt{\sum_{i=1}^{n} \sum_{j=1}^{n} (b_i b_j + b_2 b_2 + b_3 b_3) \delta^2 \delta^2} \tag{7}
\]
3. Optimal station distribution method based on intelligent optimization algorithm

The generation of intelligent optimization algorithm is based on the development of optimization technology, which is an application technology based on mathematics to solve various engineering problems. With the development of recent years, intelligent optimization algorithm has been widely used in system control, artificial intelligence, communication system design and other fields. The typical intelligent optimization algorithms developed in recent years include genetic algorithm, simulated annealing algorithm, particle swarm optimization and tabu algorithm.

3.1. Particle swarm optimization and its basic procedures

Particle Swarm Optimization (PSO) is an effective global optimization algorithm, which was first proposed by American scholars Kennedy and Eberhart in 1995. It is an optimization algorithm based on swarm intelligence theory. Swarm intelligence is generated by cooperation and competition among particles in a swarm to guide optimal search.

Particle swarm optimization (PSO) has the characteristics of self-starting. Given the dimensions of particles and the size of the initial population, it can achieve random automatic initial assignment. The pso mentioned in this paper refers to the pso with activation factor. According to equation (8), when particle i reaches the current optimal position of the population, then \( z_{id} (t) = p_{id} (t) = p_{ng} (t) \), \( v_{id} (t+1) = \omega \times v_{id} (t) \), the particle will go in a straight line in the direction of \( V_{id} (t) \). Since \( \omega < 1 \), the forward velocity of the particle will decrease with the increase of iteration times until it reaches 0. Therefore, the search of the particle in the \( V_{id} (t) \) direction is limited, and the optimal solution cannot be guaranteed to be found. The algorithm may be trapped in the local optimal. In order to ensure that particles can reach the global optimal solution, \( P_{id} (t) \) and \( P_{ng} (t) \) must be weighted modified. The modified algorithm can be expressed as follows:

\[
\begin{align*}
    v_{id} (t+1) &= \omega \times v_{id} (t) + \eta_1 \times rand \times (p_{id} - z_{id} (t)) + \eta_2 \times rand \times (p_{ng} - z_{id} (t)) \\
    z_{id} (t+1) &= z_{id} (t) + v_{id} (t+1) \\
    \omega &= \omega_{max} - \frac{Iter(\omega_{max} - \omega_{min})}{MIter} \\
    a &= \begin{cases} 
    1.2, D \leq 2 \\
    2.0, D > 2 
    \end{cases}
\end{align*}
\]

(8)  (9)  (10)  (11)

In the above equation: \( \omega_{max} \) and \( \omega_{min} \) are the maximum and minimum weight coefficients respectively; \( Iter \) is the current iteration number; The total number of iterations that MIter predetermined for the algorithm. \( a \) is the vitality factor, whose function is to get rid of the local optimal point and continue to search for the better point after the particle reaches the local optimal position.

Particle swarm optimization (PSO) usually consists of particle swarm initialization, fitness value calculation, local optimal selection, global optimal selection, particle velocity and position evolution (generation of new particles) and iterative step output optimal results.

1. Population initialization (set particle swarm size, maximum iteration number and assign values to it);
2. The fitness value of each initial particle in the current state is calculated;
3. The fitness function value calculated is compared with the optimal value (the current optimal value and its own optimal value). If the optimal value appears, the previous optimal value will be replaced, and new particles will be used to replace the previous one.
4. The optimal fitness value of each particle is compared with the optimal fitness value of all particles. If the optimal value occurs, the global optimal value is replaced by the optimal value, and the optimal fitness value corresponding to the particle is recorded at the same time.
5. After the above calculation, judge whether the iteration number or accuracy requirements are met. If not, update the particle state in accordance with equations (8) and (9) and continue the calculation from step (2) until the conditions are met;
(6) when the conditions are satisfied, the optimal particle and the optimal fitness value are output.

3.2. Parameter setting and fitness function selection

3.2.1. Pso parameter setting
In the simulation, the number of passive positioning system stations is selected as N (N=4,5). Since each station is represented by three-dimensional coordinates of space, the single particle dimension is $3\times N$, and the size of particle swarm is selected as 20, so the initial population size is $3\times N\times 20$. Selection for convergence, $\omega=0.7298$, $\eta_1=2$, $\eta_2=2$.

3.2.2. Parameter setting of genetic algorithm
The population size of the genetic algorithm was set at 20, and the variation factor $P_m=0.08$ and crossover factor $P_x=0.1$ were selected as main parameters.

3.2.3. Selection of fitness function
The fitness function value is an important index to evaluate the advantages and disadvantages of individuals in the population, as well as a judgment criterion to retain and eliminate individuals. For multi-machine passive positioning system, selecting the GDOP value that represents the positioning accuracy index is more conducive to the optimization of distribution station. The smaller the GDOP value is, the higher the positioning accuracy is. In this paper, the average GDOP value of target location in a certain region by the positioning system is selected as the fitness function. The expression is:

$$Fitness = \frac{\sum_{n=1}^{N} GDOP_n}{N}$$

$N$ represents the number of selected points in the positioning region, and GDOP$_n$ represents the corresponding GDOP value of each point.

4. Simulation and result analysis
According to the theoretical derivation and modeling analysis in the first two sections, the average GDOP value of the target region is taken as the fitness function, and two intelligent optimization algorithms, genetic algorithm and particle swarm optimization algorithm, are respectively used for simulation optimization. The specific simulation conditions and conditions are set as follows:

4.1. Simulation analysis of passive positioning optimization layout of 4 stations in space
Assume that the positioning target area is $X=[-200,200]$, $Y=[100,200]$, $Z=0$, the host is fixed $S_0=[0,0,4]$, the upper limit of the position of each auxiliary machine is $[20,20,5]$, and the lower limit is $[-20,-20,3]$. Particle swarm optimization algorithm sets each parameter according to section 2.4, the results of passive positioning optimization layout of space 4 stations are shown in figure 1:
4.2. **Simulation analysis of passive positioning optimization layout of 5 stations in space**

The simulation conditions are the same as in section 3.1. The results of passive positioning optimization layout of 5 stations in space are shown in figure 2:

- **(a)** particle swarm optimization algorithm number diagram
- **(b)** schematic diagram of particle swarm iteration optimization station layout and target area
- **(c)** the graph of iteration times algorithm
- **(d)** schematic diagram of genetic of genetic algorithm station layout and target area

FIG. 2 results of passive location optimization layout of 5 spatial stations
4.3. Result analysis

Table 1 comparison of station distribution results between genetic algorithm and improved particle swarm optimization

| Intelligent algorithm | Number of stations | GDOP | Coordinates of each observation station |
|-----------------------|--------------------|------|----------------------------------------|
| ga                    | 4                  | 1119 | S₀= (0,0,4) km  S₁= (20,20,5) km S₂= (1.6706,-20,3.7095) km S₃= (-20,20,3) km |
| PSO                   | 4                  | 1117 | S₀= (0,0,4) km  S₁= (20,20,5) km S₂= (1.0574,-20,3) km S₃= (-20,20,3) km |
|                       | 5                  | 651  | S₀= (0,0,4) km  S₁= (20,20,5) km S₂= (20,-20,5) km S₃= (-20,20,3) km S₄= (-20,-20,3) km |
|                       | 5                  | 650  | S₀= (0,0,4) km  S₁= (20,20,5) km S₂= (20,-20,5) km S₃= (-20,20,3) km S₄= (-20,-20,3) km |

By comparing the station layout results of the two intelligent algorithms, we can see that:

1. Both intelligent algorithms can find the optimal distribution station results through iteration under the condition of satisfying the accuracy, and the fitness function value gradually decreases with the increase of iteration times, and finally can converge and stabilize at a fixed value, indicating that both intelligent algorithms can achieve the optimal distribution station.

2. By comparing the iteration diagram, it can be seen that the particle swarm optimization algorithm has higher efficiency and faster convergence speed than the genetic algorithm in the optimization of the layout station, and can reach the average GDOP value required for positioning accuracy in less iteration times and less time. Therefore, it is suitable to deal with the problem of rapid positioning of the layout station under dynamic conditions.

3. By comparing the coordinates of each station, it can be seen that there is no unique optimal distribution mode for target positioning within a certain range of space, but the positions of each station of the optimal distribution station are relatively concentrated in fixed positions.

4. Compared with genetic algorithm, pso has smaller positioning errors and higher accuracy.

5. As the number of observation stations increases, the positioning accuracy of the passive positioning system to the target in a certain area will improve. When other conditions are determined, the positioning accuracy can be improved by increasing the number of positioning stations.

5. Summarizes

In this paper, a method based on particle swarm optimization (pso) and genetic algorithm (ga) is proposed to optimize the location of multi-machine passive positioning stations. By means of experimental simulation, the coordinates of each station of 4 stations and 5 stations are obtained. Compared with genetic algorithm, particle swarm optimization (pso) is simple, efficient, accurate, and fast in convergence.

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