Research on improvement of hybrid particle swarm algorithm in underwater active electric field positioning technology

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Abstract. Since the underwater active electric field positioning algorithm based on the MP-MUSIC algorithm has a slower positioning search speed, the hybrid particle swarm algorithm is introduced to speed up the positioning search speed and positioning accuracy. This paper improves the particle swarm algorithm, adopts dynamic learning factors, and uses natural selection-hybrid particle swarm algorithm to improve the search speed and positioning accuracy of the positioning algorithm.

1. Introduction
Underwater active electric field detection technology is based on the principle of weak electric fish perceiving the surrounding environment, by imitating the weak electric fish to form an electric field in the water, and then using the receiving device to obtain the disturbance signal of the electric field to realize underwater detection and positioning[1].

The underwater active electric field positioning algorithm in this article is the MP-MUSIC algorithm, which is a high-resolution positioning algorithm based on subspace. However, using MP-MUSIC algorithm for positioning requires a large amount of calculation and slower calculation speed. Therefore, we combine particle swarm algorithm to improve the speed and positioning accuracy of the positioning algorithm.

This paper mainly studies the particle swarm algorithm used in underwater active electric field positioning technology. By introducing natural selection-hybrid particle swarm algorithm and improving the dynamic learning factor to improve the search speed and positioning accuracy of the positioning algorithm.

2. Underwater active electric field positioning algorithm
The underwater active electric field positioning system discussed in this article uses a pair of transmitting electrodes to emit sinusoidal signals with an amplitude of 5V and a phase difference of 180 underwater to form an active electric field in the water, and then arrange a receiving electrode array in the water[2]. When the metal sphere appears, the electric field will be disturbed, and the metal sphere can be positioned by receiving the disturbance information of the electric field collected by the electrode.

MP-MUSIC algorithm is a high-resolution positioning algorithm based on subspace. The polarization of the incident signal does not need to be known and is suitable for underwater target positioning[3]. Underwater active electric field positioning uses receiving electrodes arranged underwater to receive the disturbance of the electric field, generate a voltage matrix from the
disturbance signals collected by the receiving electrodes, and then use the MP-MUSIC algorithm to estimate the position of the metal sphere\[4,5\].

3. Particle swarm algorithm
For the three-dimensional space, the MP-MUSIC algorithm is used to scan the search space point by point, and the positioning operation speed is slow, which is not conducive to real-time search. The MP-MUSIC algorithm finds the position of the target by finding the smallest generalized eigenvalue corresponding to the coordinates of the point in the search space, while the particle swarm algorithm is an optimization algorithm that actively locates the underwater electric field based on the MP-MUSIC algorithm. The problem is to find the target position by searching for the maximum value of the spatial spectrum of the target point in space, so as to achieve rapid positioning\[6\].

During the optimization process, the particle adjusts its speed and position according to the following formula:

\[
\begin{align*}
v_{id}^{t+1} &= v_{id}^t + c_1 r_1 (p_{id}^t - x_{id}^t) + c_2 r_2 (p_{gd}^t - x_{id}^t) \\
x_{id}^{t+1} &= x_{id}^t + v_{id}^{t+1}
\end{align*}
\]  

(1)

In formula (1), \(c_1\) and \(c_2\) are called learning factors, \(r_1\) and \(r_2\) are uniform random numbers in the range \([0,1]\). By comparing the objective function values of neighboring particles, find the local optimal value of the particle, and then compare all the local optimal values to find the global optimal value. In the underwater active electric field positioning algorithm, the smallest eigenvalue in the search space is found after a finite number of iterations, and the point corresponding to the smallest eigenvalue is the target position\[7\].

3.1. Improvement of particle swarm algorithm
The main problem of the particle swarm algorithm is that as the number of iterations increases, it is easy to fall into a local extremum and the convergence speed will decrease. Therefore, we make some improvements to the particle swarm algorithm to make the search speed and positioning accuracy of the positioning algorithm meet the requirements.

3.2. Inertia weight
The inertia weight represents the tendency of particles to maintain their original flight speed\[8\]. Here we use linearly decreasing inertia weight:

\[
\omega = \omega_{\text{max}} - (\omega_{\text{max}} - \omega_{\text{min}}) / k_{\text{max}}
\]

(3)

Where \(\omega_{\text{max}}\) is the initial inertia weight, \(\omega_{\text{min}}\) is the inertia weight at the maximum number of iterations, \(k_{\text{max}}\) is the maximum number of iterations. We set \(\omega_{\text{max}} = 1.0\), \(\omega_{\text{min}} = 0.5\).

3.3. Learning factor
Here the learning factor changes according to the following formula:

\[
\begin{align*}
c_1 &= 1 + \cos \left( \frac{k\pi}{M} \right) \\
c_2 &= 2 - \cos \left( \frac{k\pi}{M} \right)
\end{align*}
\]  

(4)

(5)

Here \(k\) represents the current number of iterations, and \(M\) represents the maximum number of iterations. Since the cosine function is a monotonically decreasing function in \([0,\pi]\), it is larger in the...
early stage and strengthens the global search, and larger in the later stage, strengthens the approach to the optimal solution.

3.4. Natural selection-hybrid PSO
Natural selection-hybridization PSO draws on the natural selection and hybridization operations in genetic algorithms. The hybridization operation is to select particles in the hybridization pool according to the hybridization rate after obtaining the global maximum or global minimum in each iteration. Take the selected particles in the hybridization pool as the parent, randomly cross in pairs to obtain the offspring particles, and then replace the parent particles with the offspring particles. The position of the child particle is updated according to the following formula:

$$\text{child}(x_i) = r_i \cdot \text{parent}_1(x_i) + (1-r_i) \cdot \text{parent}_2(x_i)$$

(6)

Where $r_i$ is a random number between 0 and 1, $\text{parent}_1(x_i)$ is the position of the parent particle, and $\text{child}(x_i)$ is the position of the child particle. The child particle velocity is calculated according to the following formula:

$$\text{child}(v_i) = \frac{\text{parent}_1(v_i) + \text{parent}_2(v_i)}{[\text{parent}_1(v_i) + \text{parent}_2(v_i)]} \cdot \text{parent}_1(v_i)$$

(7)

Where $\text{parent}(v_i)$ is the velocity of the parent particle, and $\text{child}(v_i)$ is the velocity of the child particle[9].

Natural selection is to sort all particles according to the fitness value during each iteration, and divide the population into two. Half of the particles have a better fitness value, and half of the particles have a poor fitness value. Replace with the better half of the particles. The poorer half of the particles. Natural selection method can improve the fitness value of the population, which is conducive to the rapid convergence of the algorithm to the global optimal solution. We adopt the roulette selection method, assuming that the number of particles in the population is $n$ and the fitness value of the $i$-th particle is $f_i$, the probability of the particle being selected is:

$$p_i = 1 - \frac{f_i}{\sum_{i=1}^{n} f_i}$$

(8)

After calculating the probability of each particle being selected, multiple rounds of selection are required, each time a random number distributed between [0,1] is generated, and the selected individual is determined according to this random number[10].

4. Simulation test and analysis
We simulate the improved natural selection-hybrid PSO algorithm and analyze its operation speed and positioning accuracy. We also simulate the improved natural selection-hybrid PSO, natural selection PSO, hybrid PSO and simulated annealing PSO to compare the four algorithms Convergence speed and positioning accuracy. The position coordinates of the positioning target remain unchanged as (45, 43, 44), and the search range is set to $100cm \times 100cm \times 100cm$. 
Figure 1. The comparison of convergence.

Figure 1 and Figure 2 are the simulation results of a successful positioning. The red curve in the figure is the curve of the natural selection-hybrid PSO algorithm. It can be seen from the figure that the natural selection-hybrid PSO algorithm has the fastest convergence speed and the smallest positioning error.

Figure 2. Positioning error comparison.

Figure 3. Convergence of positioning coordinates.

Figure 3 is the convergence diagram of natural selection-selective hybrid PSO positioning coordinates. From the figure, we can get that the target position of the positioning algorithm is (45.32, 42.72, 43.89) and the positioning error is 0.4392cm.

We conducted 100 tests on the four PSO algorithms, positioning the positioning accuracy to 1cm, and stopping the iteration when the positioning accuracy was reached, and recording the number of iterations. Both the test target and search range remain unchanged.

The following table shows the comparison of the iterative calculations obtained by 100 tests of the four PSO algorithms.

Table 1. The comparison of the iterative calculations.

| algorithm                | the slowest iterations | the fastest iterations | the average number of iterations | the average calculation |
|--------------------------|------------------------|------------------------|----------------------------------|------------------------|
| Natural Selection-Hybrid PSO | 44                     | 3                      | 10.12                            | 303.6                  |
| Natural selection PSO    | 4                      | 88                     | 20.93                            | 627.9                  |
| Hybrid PSO               | 5                      | 82                     | 22.28                            | 668.4                  |
| Simulated annealing PSO  | 7                      | 200                    | 26.8                             | 804                    |
The calculation method of the average calculation amount here is that the product of the number of particles in the particle swarm algorithm and the average number of iterations is the average calculation amount. It can be seen from the table that the improved natural selection-hybrid PSO has the least amount of iterative calculation and the fastest positioning speed.

5. Summary
This paper combines the improved natural selection-hybrid PSO algorithm with the MP-MUSIC algorithm to improve the search speed and positioning accuracy of underwater active electric field positioning. We use dynamic learning factors to improve the convergence speed of the algorithm, and apply natural selection and hybridization methods to solve the problem of particle swarm optimization that may fall into local extremes. Simulation tests show that the speed of the positioning algorithm is improved, and the positioning accuracy is improved. Requirements for underwater active electric field positioning.

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