Adaptive Whale Optimization Algorithm with simulated annealing strategy and Its Application in Magnetic Target Location

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Adaptive Whale Optimization Algorithm with Simulated Annealing Strategy and Its Application in Magnetic Target Location

Aiming at the problem that the detection of underground magnetic targets is greatly affected by the measurement accuracy and the recognition effect is not ideal, this paper proposes a magnetic target positioning method based on an adaptive whale optimization algorithm. As the whale optimization algorithm has problems such as easy to fall into local optima and slow convergence speed, this paper introduces two strategy improvements, simulated annealing (SA) and adaptive weighting (AW). Through 16 standard test functions, the improved whale optimization algorithm in this paper is compared with the standard whale optimization algorithm (WOA), particle swarm optimization algorithm (PSO), and cuckoo algorithm (CS). The results show that the improved whale optimization algorithm proposed in this paper has higher optimization precision and faster convergence speed. Finally, the optimization algorithm in this paper is applied to the research of magnetic target positioning, and the effectiveness of the algorithm is verified through simulation experiments, and the accuracy of positioning the target is optimized.

Keywords: whale optimization algorithm; magnetic target location; simulated annealing; adaptive weight

0 Introduction

The use of magnetic anomaly signals to detect and locate underground or underwater objects using a magnetometer has always been a research field that has attracted much attention. Compared with the vector magnetometer, the measurement accuracy of the total field magnetometer array is less affected by its own attitude, and is suitable for magnetic anomaly detection of mobile platforms. Whale optimization algorithm (WOA) is an emerging meta-heuristic optimization algorithm proposed by Professor Seyedali Mirjalili[1] in 2016 to simulate the predation behaviour of whale groups. The algorithm has the characteristics of simple structure, few adjustment parameters, fast convergence speed and strong global optimization ability. In this paper, based on the relationship
between the array dynamometer space and the magnetic anomaly of the magnetic target, the optimization problem of the magnetic target is constructed. Through the optimization problem, the improved WOA algorithm is used to realize the positioning of the magnetic target. Based on the total field magnetometer array, this paper uses an adaptive whale optimization algorithm to achieve the positioning of the magnetic target by solving the optimization problem.

In the research of target magnetic detection theory, a magnetic target is usually regarded as a magnetic dipole, which is described by six parameters: three position parameters and three magnetic moment parameters. According to the magnetic dipole model, Wynn\(^2\) proposed an algorithm to locate the magnetic dipole using magnetic anomaly tracking and inversion. This method uses the three components of the magnetic field and the rate of change to uniquely determine the parameters of the magnetic target when the speed of the magnetic detection system is known. Nara\(^3\) converted the Euler equation into an integral form to obtain the linear equation related to the position of the magnetic dipole and the surface integral of the magnetic flux density on the cube. Finally, the closed form of the position of the magnetic dipole was obtained by solving the equation solution.

At present, extensive research has been carried out on the positioning method of magnetic targets. Zhang\(^4\) proposed a magnetic gradient tensor positioning method, which uses 4 vector sensors to form a planar measurement array. Under the condition of translation of the carrier, through 2-point tensor data, a nonlinear equation containing positioning information is obtained. Group, through the genetic algorithm iterating continuously the unknown information in the equation, solving the position information. Yin Gang\(^5\) used 4 vector magnetometers and 1 scalar magnetometer to construct a planar array structure, and solved the eigenvalues and eigenvectors of the magnetic
gradient tensor matrix obtained by single point measurement, and then estimated the uniqueness of the target position and magnetic moment. He proposed to use tensor invariants and matrix eigenvalues to locate magnetic targets. In 2017, Kang et al. [6] proposed a target positioning method based on the total geomagnetic field array. The optical pump magnetometer constitutes the positioning array, and the continuous positioning of the moving magnetic target is achieved by measuring the magnetic anomalies generated by the moving target. Lu Junwei [7-8] proposed an improved positioning method based on the hexahedral magnetic gradient tensor measurement system. This method effectively eliminates the error in the STAR system of tensor reduction, thereby improving the positioning accuracy of the target. In view of the inherent spherical error of the total field gradient method and the tensor modulus gradient method, Jin et al. [9] proposed a joint method without spherical error. This method combines the total magnetic field gradient and the magnetic tensor modulus gradient, and the positioning accuracy is higher.

The above methods mainly study the magnetic target positioning method of the magnetic target, which often requires complicated theoretical derivation, formula calculation, algorithm design, and a large number of analytical calculations on the magnetic survey data, and it is inseparable from the scope of the forward and inversion of the magnetic survey data. Limited by the accuracy of the measurement data, the magnetic measurement target cannot be expressed in detail and clearly.

Generally, a magnetic target can be described by six parameters: three position parameters and three magnetic moment parameters. In order to estimate the parameters of the target, we need to construct at least six uncorrelated equations, which are high-order nonlinear equations about the target parameters [10-11]. Compared with the above magnetic target positioning method, when solving the high-order nonlinear equations,
the problem can be transformed into an optimization problem, and related algorithms can be used to solve the problem. Zheng\cite{12} performed real-time continuous positioning of the moving magnetic target based on the ion swarm optimization algorithm. These methods prove that artificial intelligence and machine learning are applicable to the field of geophysics, have a certain foundation of engineering application, and have great research potential.

1 Magnetic target array and positioning principle

When the distance between the magnetic target and the sensor exceeds 2 times or more of the target's own size, the magnetic field generated by the target can be regarded as a magnetic dipole far field. In order to obtain the target position and magnetic moment information, a magnetic field array as shown in the figure is designed. The array is composed of 7 optical pump magnetometers, and the distance between two adjacent magnetometers is $b$. The coordinates of represents the position of the $i$-th sensor in the array coordinate system, and the $x$-axis direction of the array coordinate system points to the direction of the geographic north pole. Due to the existence of the magnetic target, the magnetic field distribution in the surrounding space changes, resulting in a magnetic anomaly. Therefore, the magnetic anomaly can be used to track and locate the target. The total field magnetic anomaly is expressed as:

$$\Delta B \approx \mathbf{u} \cdot \mathbf{B}_a$$

where $\mathbf{B}_a$ is the function of the distance from the target to the sensor and the target magnetic moment, expressed as:

$$\mathbf{B}_a = \begin{bmatrix} B_{ax} \\ B_{ay} \\ B_{az} \end{bmatrix} = \frac{\mu_0}{4\pi} \left( \frac{3(\mathbf{M} \cdot \mathbf{R}) \mathbf{R}}{R^5} - \frac{\mathbf{M}}{R^3} \right)$$
where the vacuum permeability is \( \mu_0 = 4\pi \times 10^{-7} H/m \), \( \mathbf{R} \) is the position vector of the magnetic target to the magnetometer, and \( \mathbf{M} \) is the magnetic moment vector of the magnetic target. Substituting formula (2) into (1) to obtain:

\[
\Delta B \approx \mathbf{u} \cdot \mathbf{B}_a = \left[ \begin{array}{c}
\cos I \\
\cos I \sin D \\
\sin I
\end{array} \right] \left[ \begin{array}{c}
B_{ax} \\
B_{ay} \\
B_{az}
\end{array} \right] = \frac{\mu_0}{4\pi} \left[ \begin{array}{c}
\cos I \\
\cos I \sin D \\
\sin I
\end{array} \right] \left( \frac{3(xM_x+yM_y+zM_z)}{R^3} \right)
\]

\[
\begin{bmatrix}
M_x \\
M_y \\
M_z
\end{bmatrix}
\]

where \( I \) and \( D \) represent the magnetic inclination and declination of the earth's magnetic field. \( (M_x, M_y, M_z) \) represents the components of the magnetic moment of the magnetic target on the three coordinate axes. \( (x, y, z) = (x_t - x_o, y_t - y_o, z_t - z_o) \) indicates the relative position of the magnetic target and the magnetometer. \( (x_t, y_t, z_t) \) is the position of the magnetic target and \( (x_o, y_o, z_o) \) is the position of the magnetometer.

Normally, since the magnetic anomaly generated by the long-distance magnetic target is small, it is necessary to eliminate the influence of the time-varying magnetic field. The method of setting reference points can be used, but this method is mainly suitable for terrestrial magnetic fields. When conducting ocean geomagnetic surveys, it is difficult to determine a suitable reference point. Generally, the generalized characteristics of the time-varying geomagnetic field are consistent in local areas. Therefore, when the magnetometer array is used for magnetic anomaly detection, the influence of the time-varying geomagnetic field can be effectively eliminated through the measurement difference between the magnetometers or the gradient measurement. According to formula (3), the difference between the magnetometers is used to eliminate the time-varying geomagnetic field to obtain accurate magnetic anomalies, namely:

\[
\Delta B_{ij} = u \cdot B_{ai} - u \cdot B_{aj} = \left( U^T \alpha_i (\beta_i \mathbf{R}_i - \mathbf{M}) - U^T \alpha_j (\beta_j \mathbf{R}_j - \mathbf{M}) \right)
\]

(4)
where \( i, j \) represent the label of the magnetometer,

\[
\alpha = \frac{\mu_0}{4\pi ||R||^2}, \quad \beta = \frac{3}{||R||} \left( x + y + z \right), \quad R = \begin{bmatrix} x \\ y \\ z \end{bmatrix}, \quad U = \begin{bmatrix} \cos I \cos D \\ \cos I \sin D \\ \sin I \end{bmatrix}, \quad M = \begin{bmatrix} M_x \\ M_y \\ M_z \end{bmatrix}
\]

It can be seen from the above formula that a magnetic target can be represented by six parameters \( \mathbf{p} = (x, y, z, M_x, M_y, M_z) \), \( (x, y, z) \) describes the position of the magnetic target, and \( (M_x, M_y, M_z) \) describes the magnetic moment information of the magnetic target. To track and locate a magnetic target, six parameters of the target need to be calculated. This equation is a high-order nonlinear equation about the target parameter, which can often be transformed into an optimization problem when solving it, using the following error function:

\[
F = \sum_{i,j} \left( \Delta B_{ij} - \Delta \bar{B}_{ij}(\mathbf{p}) \right)^2
\]

where \( \Delta B_{ij} \) is the measured difference between the two magnetometers, \( \Delta \bar{B}_{ij}(\mathbf{p}) \) is the theoretical magnetic anomaly value, and \( F \) represents the square error between the measured value and the theoretical magnetic anomaly.

This paper introduces the simulated annealing strategy and weighting factors on the basis of the whale optimization algorithm, and further proposes an adaptive whale optimization algorithm and applies it to the research of magnetic target positioning.

2 Whale optimization algorithm

Whale optimization algorithm (WOA) is a heuristic optimization algorithm that simulates the predation behavior of whale groups. The algorithm is mainly divided into three processes: encircling prey, Bubble-net attacking method (exploitation phase) and search for prey (exploration phase).
2.1 Encircling prey

The WOA algorithm assumes that the current optimal individual position of the whale group is the position closest to the prey, and the mathematical expression is

\[
\bar{X}(t+1) = \bar{X}^*(t) - \bar{A} \cdot \bar{D}
\]

where \( t \) indicates the current iteration, \( \bar{X}^* \) is the position vector of the best solution obtained so far, \( \bar{X} \) is the position vector, \( \bar{D} \) represents the distance vector, \( | | \) is the absolute value, and \( \cdot \) is an element-by-element multiplication. \( \bar{A} \) and \( \bar{C} \) are coefficient vectors, are calculated as follows:

\[
\bar{A} = 2a \cdot \bar{r}_1 - \bar{a}
\]

\[
\bar{C} = 2\bar{r}_2
\]

where \( \bar{a} \) is linearly decreased from 2 to 0 over the course of it-erations (in both exploration and exploitation phases) and \( \bar{r}_1 \) and \( \bar{r}_2 \) are random vectors in \([0,1]\).

2.2 Bubble-net attacking method (exploitation phase)

The spiral bubble net predation algorithm simplifies the predation behaviour into contraction and spiral ascent. These two behaviours are carried out at the same time, and the probability \( p \) is used as the selection threshold to decide which way to proceed. The mathematical model is:

\[
\bar{X}(t+1) = \begin{cases} 
\bar{X}^*(t) - \bar{A} \cdot \bar{D} & p < 0.5 \\
\bar{D} \cdot \bar{e}^{bi} \cdot \cos 2\pi l + \bar{X}^*(t) & p > 0.5 
\end{cases}
\]

where \( p \) is a random number in \([0,1]\). \( \bar{D} \) indicates the distance of the ith whale to the prey (best solution obtained so far), \( b \) is a constant for defining the shape of the
logarithmic spiral, $l$ is a random number in $[-1,1]$, and $\cdot$ is an element-by-element multiplication.

2.3 Search for prey (exploration phase)

When the value of the coefficient variable $\tilde{A}$ is not between $[-1,1]$, it jumps out of the optimal individual that has been found and searches for a new random individual. The mathematical model is as follows:

$$\tilde{X}(t + 1) = \overline{X_{\text{rand}}} - \tilde{A} \cdot \overline{D}$$  \hspace{1cm} (11)

where $\overline{X_{\text{rand}}}$ is a random position (a random whale) chosen from the current population.

3 Adaptive whale optimization algorithm with Simulated Annealing (AWOASA)

In view of the shortcomings of the standard whale optimization algorithm, such as slow convergence speed, insufficient global optimization ability, and easy to fall into local optimization, this paper improves the convergence factor and weight of the standard whale optimization algorithm. In the standard WOA algorithm, $A \in [-a, a]$ is used to adjust the global exploration and local search capabilities of the algorithm. When the parameter $|A| \geq 1$, the algorithm performs a random global search with a probability of 0.5, and when the parameter is used, the algorithm performs a local search. Where the adaptive weight coefficient $w$ is:

$$w = \frac{t^2}{t_{\text{max}}^2}$$  \hspace{1cm} (12)

where $t$ is the number of iterations, $t_{\text{max}}$ is the maximum number of iterations.

Then the convergence factor is:

$$a = \left(2 - 2 \frac{t}{t_{\text{max}}} \right) \times (1 - w)$$  \hspace{1cm} (13)
Then the standard whale optimization algorithm introduces an adaptive weight factor $w$ in the local optimization, and the formula (4) is improved as follows:

$$
\dot{X}(t + 1) = \begin{cases} 
  w \cdot X^*(t) - \vec{A} \cdot \vec{D} & p < 0.5 \\
  \vec{D} \cdot e^{bt} \cdot \cos 2\pi t + w \cdot \bar{X}(t) & p \geq 0.5 
\end{cases}
$$

(14)

In terms of global optimization, the global optimization is performed by introducing the simulated annealing algorithm (Simulated Annealing, SA). SA algorithm was first proposed by Metropolis in 1953 and later introduced into the field of combinatorial optimization. The algorithm is derived from the simulation of the solid annealing cooling process, and is characterized by accepting inferior solutions with a certain probability, and thus accepting inferior solutions with a certain probability. According to the Metropolis criterion, SA algorithm has the probability that the particle tends to balance at temperature $T$, where $E$ is the internal energy at temperature $T$.

Annealing is performed after the whale optimization algorithm solved\textsuperscript{[13]}. During annealing, a whale population is regenerated, which is used to adjust the position of the original population. The probability is adjusted to:

$$
P = \exp\left(-\frac{f_{new}(X_j) - f(X_j)}{t}\right)
$$

(15)

where $f_{new}(X_j)$ is the fitness of the $j$-th whale in the new population generated in the simulated annealing stage, and the acceptance probability $P$ of the poor solution is adjusted by the difference in the fitness of the new and old positions. The initial temperature of the SA algorithm is defined as the difference between the maximum and minimum initial fitness of the population.

The specific steps of the WOASA algorithm are as follows:

(1) Algorithm parameter initialization. The independent variable $X = [X_1, \ldots, X_n]$ of the test function is used as the position information of the individual
whale, in the solution space, the population position is randomly initialized, and 
initialize the parameters at the same time, including population data $N$, adaptive 
weighting factor $w$, logarithmic spiral shape constant $b$, random number $l$, The initial 
number of iterations $j$, the maximum number of iterations $T_{\text{max}}$.

(2) Calculate the population fitness. Calculate the initial temperature $t_0$ of the 
SA algorithm and record the optimal individual position $X^*$ in the population. Calculate 
the adaptive weight $w$, update $a, A, C, l$, and $p$.

(3) When $p < 0.5$, if $A < 1$, re-determine the position of the individual whale by 
formula (8); if $A \geq 1$, determine the position of the individual whale randomly within 
the current population, and update the position of the whale by formula (5).

(4) If $a > 1$, update the position of the individual whale by formula (8).

(5) Entering the simulated annealing stage, first define a new group of whales, 
then randomize the individual positions of the whales, and calculate the fitness of the 
new group.

(6) Calculate the updated fitness of the original population. If the fitness of 
individual whales in the new population is better than that of the original population, the 
whale position in the new population is used to replace the whale position in the original 
population.

(7) If the fitness of the individual whale in the new population is worse than that 
of the whale in the original population, the position of the whale in the new population 
is used to accept the position of the whale in the new population with probability $P$.

(8) Temperature reduction operation: $t = 0.99 \times t$.

(9) Record the best individual position and its fitness. If $j > T_{\text{max}}$, continue to 
step (10); otherwise, $j = j + 1$, repeat steps (3) ~ (8) until the conditions are met.

(10) Output the optimal individual position and its fitness.
3 Function test and result analysis

This section is based on the Matlab2017b platform simulation to verify the performance of the algorithm to the test function. The population of all comparison algorithms is set to 30, the number of iterations is 500, and a total of 50 experiments are performed. In the particle swarm algorithm, both learning factors are taken as 1.

3.1 Test functions

In order to verify the performance of the algorithm, this paper selects a total of 16 standard test functions such as unimodal, multimodal and fixed latitude for calculation.

The test functions are shown in Table 1,2,3.

Table 1. Unimodal functions

<table>
<thead>
<tr>
<th>Function</th>
<th>Dimension</th>
<th>Range</th>
<th>Minimum</th>
</tr>
</thead>
<tbody>
<tr>
<td>( f_1(x) = \sum_{i=1}^{n} x_i^2 )</td>
<td>30</td>
<td>[-100,100]</td>
<td>0</td>
</tr>
<tr>
<td>( f_2(x) = \sum_{i=1}^{n}</td>
<td>x_i</td>
<td>+ \prod_{i=1}^{n}</td>
<td>x_i</td>
</tr>
<tr>
<td>( f_3(x) = \sum_{i=1}^{n} \left( \sum_{j=1}^{i} x_j \right)^2 )</td>
<td>30</td>
<td>[-100,100]</td>
<td>0</td>
</tr>
<tr>
<td>( f_4(x) = \max{</td>
<td>x_i</td>
<td>, 1 \leq i \leq n} )</td>
<td>30</td>
</tr>
<tr>
<td>( f_5(x) = \sum_{i=1}^{n-1} [100(x_{i+1} - x_i^2) + (x_i - 1)^2] )</td>
<td>30</td>
<td>[-30,30]</td>
<td>0</td>
</tr>
<tr>
<td>( f_6(x) = \sum_{i=1}^{n} (x_i + 0.5)^2 )</td>
<td>30</td>
<td>[-100,100]</td>
<td>0</td>
</tr>
<tr>
<td>( f_7(x) = \sum_{i=1}^{n} ix_i^4 + \text{random}(0,1) )</td>
<td>30</td>
<td>[-1.28,1.28]</td>
<td>0</td>
</tr>
</tbody>
</table>
Table 2. Multimodal functions

<table>
<thead>
<tr>
<th>Function</th>
<th>Dimension</th>
<th>Range</th>
<th>Minimum</th>
</tr>
</thead>
<tbody>
<tr>
<td>$f_8(x) = \sum_{i=1}^{n} -x_i \sin(\sqrt{</td>
<td>x_i</td>
<td>})$</td>
<td>30</td>
</tr>
<tr>
<td>$f_9(x) = \sum_{i=1}^{n} [x_i^2 - 10 \cos 2\pi x_i]$</td>
<td>30</td>
<td>[-5.12,5.12]</td>
<td>0</td>
</tr>
<tr>
<td>$f_{10}(x) = -20 \exp\left(-0.2 \sqrt{\frac{1}{n} \sum_{i=1}^{n} x_i^2}\right) \pi - \exp\left(\frac{1}{n} \sum_{i=1}^{n} \cos(2\pi x_i)\right)$ + 20 + e</td>
<td>30</td>
<td>[-32,32]</td>
<td>0</td>
</tr>
<tr>
<td>$f_{11}(x) = \frac{1}{4000} \sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n} \cos\left(\frac{x_i}{\sqrt{i}}\right)$ + 1</td>
<td>30</td>
<td>[-600,600]</td>
<td>0</td>
</tr>
<tr>
<td>$f_{12}(x) = 0.1 \left{ \sin^2(3\pi x_1) + \sum_{i=1}^{n} (x_i - 1)^2 [1 + \sin^2(3\pi x_i + 1)] + (x_n - 1)^2 [1 + \sin^2(2\pi x_n)] \right}$ + $\sum_{i=1}^{n} u(x_i, 5, 100, 4)$</td>
<td>30</td>
<td>[-50,50]</td>
<td>0</td>
</tr>
</tbody>
</table>
Table 3. Fixed latitude functions

<table>
<thead>
<tr>
<th>Function</th>
<th>Dimension</th>
<th>Range</th>
<th>Minimum</th>
</tr>
</thead>
<tbody>
<tr>
<td>( f_{13}(x) = \left( \frac{1}{500} \right) ) + ( \sum_{j=1}^{25} \frac{1}{\sum_{i=1}^{2} (x_i - a_{ij})^6} ) - 1</td>
<td>2</td>
<td>[-65,65]</td>
<td>1</td>
</tr>
<tr>
<td>( f_{14}(x) = \sum_{i=1}^{11} \left[ a_i - \frac{x_i (b_i^2 + b_i x_2)}{b_i^2 + b_i x_3 + x_4} \right]^2 )</td>
<td>4</td>
<td>[-5,5]</td>
<td>0.00030</td>
</tr>
<tr>
<td>( f_{15}(x) = 4x_1^2 - 2.1x_4^4 + \frac{1}{3} x_1^6 + x_1 x_2 - 4x_2^2 + 4x_2^4 )</td>
<td>2</td>
<td>[-5,5]</td>
<td>-1.0316</td>
</tr>
<tr>
<td>( f_{16}(x) = \left( x_2 - \frac{5.1}{4 \pi^2} x_1^2 + \frac{5}{\pi} x_1 - 6 \right)^2 + 10 \left( 1 - \frac{1}{8 \pi} \right) \cos x_1 + 10 )</td>
<td>2</td>
<td>[-5,5]</td>
<td>0.398</td>
</tr>
</tbody>
</table>

Figure 1 shows the typical 2D plots of the cost function for some test cases considered in this study, such as unimodal, multimodal and fixed-dimension multimodal functions.
3.2 Result analysis

This paper compares the improved whale optimization algorithm with the standard whale algorithm to obtain the experimental results. A total of 50 experiments are carried out, and 50 experimental results are averaged and the standard deviation is calculated. The experimental results are shown in Table 4.
Table 4. The experimental results

<table>
<thead>
<tr>
<th>Function</th>
<th>PSO</th>
<th>WOA</th>
<th>AWOASA</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Average value</td>
<td>Standard deviation</td>
<td>Average value</td>
</tr>
<tr>
<td>$f_1$</td>
<td>3.05E-1</td>
<td>8.73E+02</td>
<td>7.2012e-85</td>
</tr>
<tr>
<td>$f_2$</td>
<td>3.18136</td>
<td>3.78</td>
<td>2.027e-52</td>
</tr>
<tr>
<td>$f_3$</td>
<td>4.66E+02</td>
<td>8.23E+03</td>
<td>22700.6032</td>
</tr>
<tr>
<td>$f_4$</td>
<td>4.5597</td>
<td>8.09</td>
<td>19.8119</td>
</tr>
<tr>
<td>$f_5$</td>
<td>98.3521</td>
<td>61.3415</td>
<td>27.9262</td>
</tr>
<tr>
<td>$f_6$</td>
<td>0.000121</td>
<td>7.54e-05</td>
<td>0.55613</td>
</tr>
<tr>
<td>$f_7$</td>
<td>0.123527</td>
<td>0.05218</td>
<td>2.3244e-4</td>
</tr>
<tr>
<td>$f_8$</td>
<td>-7862.371</td>
<td>1231.612</td>
<td>-8639.346</td>
</tr>
<tr>
<td>$f_9$</td>
<td>46.82182</td>
<td>10.39811</td>
<td>0</td>
</tr>
<tr>
<td>$f_{10}$</td>
<td>0.284328</td>
<td>0.692381</td>
<td>4.4409e-15</td>
</tr>
<tr>
<td>$f_{11}$</td>
<td>0.008746</td>
<td>0.008632</td>
<td>0</td>
</tr>
<tr>
<td>$f_{12}$</td>
<td>0.007821</td>
<td>0.037212</td>
<td>0.20288</td>
</tr>
<tr>
<td>$f_{13}$</td>
<td>3.627351</td>
<td>2.539565</td>
<td>1.9411</td>
</tr>
<tr>
<td>$f_{14}$</td>
<td>0.000589</td>
<td>0.000371</td>
<td>0.00032668</td>
</tr>
<tr>
<td>$f_{15}$</td>
<td>-1.03163</td>
<td>6.23e-16</td>
<td>-1.0316</td>
</tr>
<tr>
<td>$f_{16}$</td>
<td>0.397887</td>
<td>0</td>
<td>0.39789</td>
</tr>
</tbody>
</table>
4 Inversion positioning results

In order to verify the effect of the proposed algorithm on magnetic target positioning, this section applies WOA and AWOASA algorithms to positioning simulation experiments respectively. The parameters set in the experiment are as follows: the magnetic target (-3m, 17m, -1m), the magnetic components of which are $M_x = 435A \cdot m^2$, $M_y = 115A \cdot m^2$, $M_z = 780A \cdot m^2$ respectively. The sensor array is composed of 7 scalar magnetometers, and the centre of the array is at the origin of the coordinate system. The sampling frequency of the magnetometer is 1 Hz, and the baseline of the array is selected as 1 m. In order to simulate the real measurement environment, Gaussian white noise with a mean value of 0 and a variance of 0.016nT is added to each sensor.

The maximum number of iterations set in the experiment for the two algorithms is 1000, and the optimization results of 10 times are counted. The algorithm parameters are set as follows: $x, y \in [-30m, 30m]$, $z \in [-3m, 3m]$, $M_x, M_y, M_z \in [-1500A \cdot m^2, 1500A \cdot m^2]$, the number of populations is 50.

The AWOASA algorithm parameters are set as follows: $w = 0.9$.

The result value of the WOA algorithm optimization objective function is 0.0029576, as shown in Figure 4. The best solution obtained by WOA is $(x, y, z) = (-5.3, 30, 3)$, $(M_x, M_y, M_z) = (-212.9, -179.6, 282.5)$.

The WOA algorithm estimates the position parameters of the magnetic target, and the results are in Figure 2 and Figure 3.

According to Figure 2, the number of estimated parameters $x_0$ in the interval [-10m, -6m] is 8, accounting for 80%; the number of the estimated parameters $y_0$ are in
the interval [-20m-15m] is 6, accounting for 60%; the number of estimated parameters $z_0$ are in the interval [-1m, 0m] is 100, accounting for 100%. The results Parameters $x_0$ and $y_0$ are far away from the magnetic target value (-3m, 17m, -1m).

According to Figure 3, it is estimated that the number of estimated parameters $M_x$ in the interval [-800 A · m², -500 A · m²] is 8, accounting for 80%; the estimated number of parameters $M_y$ in the interval [-1000 A · m², -500 A · m²] is 10; the estimated parameters $M_z$ in the interval [300 A · m², 400 A · m²] is 96, accounting for 96%. According to the estimated magnetic moment parameters, $M_x$ are mainly concentrated in the interval [-700 A · m², -400 A · m²], the interval value is less than the true value $M_x = 435 A · m^2$. The estimated magnetic moment parameters, $M_y$ are mainly concentrated in the interval [-900 A · m², -500 A · m²] too, the interval value is less than the true value $M_y = 115 A · m^2$. The estimated magnetic moment parameters, $M_z$ are mainly concentrated in the interval [0 A · m², 500 A · m²] too, the interval value is less than the true value $M_z = 780 A · m^2$. Therefore, the accuracy of the magnetic target parameter solution calculated by the WOA algorithm is not high.
The AWOASA algorithm estimates the position parameters of the magnetic target, and the results are in Figure 4 and Figure 5.

According to Figure 4, the number of estimated parameters \( x_0 \) in the interval \([-10m, 0m]\) is 6, accounting for 60%; the number of the estimated parameters \( y_0 \) are in the interval \([15m, 18m]\) is 6, accounting for 60%; the number of estimated parameters
\( z_0 \) are in the interval \([-2m, 0m]\) is 10, accounting for 100\%. The target positions (-3m, 17m, -1m) set by simulation are relatively close.

It can be seen from the estimated position that the parameters calculated by the AWOASA algorithm are mainly concentrated in the interval \([-6m, -2m]\), the parameters are mainly concentrated in the interval \([14m, 20m]\), and the parameters are mainly concentrated in the interval \([-2.5m, 0.5m]\).

Figure 4. Magnetic target position \((x, y, z)\) calculated by AWOASA

Figure 5. Magnetic target position \((M_x, M_y, M_z)\) calculated by AWOASA
The comparison of the error results of WOA and AWOASA are shown in the figure 6. The result shows that the position prediction error of AWOASA is smaller than that of WOA.

Figure 6. Convergence curve of WOA and AWOASA

By changing the position of the test point, the detection algorithm dynamically tracks the effect, where the position of the X direction changes from -3 to 3, and the other two directions remain unchanged. The result of comparing the estimated position of the x-direction algorithm with the real value is shown in Figure 7. It can be seen from the results that the dynamic position detection error of the magnetic target is large in the initial stage of learning, and the tracking error gradually decreases after about 200 iterations of learning, and the error is small to between [0,1].
Figure 7. The real value and estimated value results of x-direction position

5 Conclusion
Aiming at the problem that the current underground magnetic target detection is greatly affected by the measurement accuracy and the recognition effect is not ideal, this paper proposes an underground magnetic target positioning method based on an adaptive whale optimization algorithm. Compared with the performance of the basic whale optimization algorithm on 16 functions, the method converges faster. The test results on underground magnetic target positioning found that the positioning error of the adaptive whale optimization algorithm is smaller than that of the basic whale algorithm, and the positioning accuracy is higher.

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References


