Improved Particle Swarm Optimization Geomagnetic Matching Algorithm Based on Simulated Annealing

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ABSTRACT As a new assistant navigation technology using geophysical field for navigation, geomagnetic matching navigation can effectively alleviate the problems such as the unavailability of satellite and the easy divergence of position data of inertial navigation system in the process of navigation. It can also carry out real-time assistant navigation with high concealment, all-around area and all-weather. According to the principle of geomagnetic matching and the geomagnetic affine model, considering that the basic particle swarm optimization algorithm is easy to fall into local extremum, this paper introduces particle swarm optimization geomagnetic matching algorithm based on simulated annealing(SAPSO) for limitations of traditional matching algorithm. What's more, the SAPSO is improved from three parts: constraints, parameters and function of fitness. Finally, the simulation analysis is carried out from five aspects to verify the effectiveness and accuracy of the improved SAPSO.

INDEX TERMS Geomagnetic matching, particle swarm optimization, simulated annealing.

I. INTRODUCTION

As a multi-disciplinary engineering technology, navigation and positioning technology is essential in many fields, such as aviation, navigation and land. From the early exploration of the earth to the current exploration of the earth and space, the demand for improving the accuracy of navigation is growing day by day. Some disadvantages of the navigation and positioning technology which was put into use in the early stage are gradually revealed. In view of these disadvantages, geomagnetic matching navigation has been paid more attention.

The latest research shows that due to large-scale changes and local disturbances, measurement of magnetic field exhibits its uniqueness in location. These observable changes in the earth's magnetic field can provide unique information for navigation. As a ubiquitous physical field, the geomagnetic field has the following advantages: i) As a vector field, the geomagnetic field has very rich features related to geographic location, such as horizontal and vertical magnetic field strength, magnetic inclination, magnetic declination, total magnetic field strength and so on [1]. Various feature information increases the flexibility, diversity and reliability of the navigation scheme. ii) The geomagnetic field is the basic physical field inherent to the earth. It has strong penetrability and concealment. It is widely distributed in the ocean, land, and near-Earth space, and will not be subject to external interference and restrictions of the carrier's environment. iii) The error of geomagnetic matching navigation will not accumulate over time, which makes up for the accumulation of errors of inertial navigation system (INS) over time [2]. It is very suitable for assisting INS for navigation and positioning. The magnetic sensor for geomagnetic measurement can be widely used for the characteristics of low power consumption, small size and low cost. The geomagnetic matching navigation has the advantages of high concealment, all-area, all-weather, real-time navigation and so on. To a certain extent, using the geomagnetic matching navigation to assist INS to confirm the information of position and posture of the carrier can make up for the shortcomings of other auxiliary navigation methods, which realizes the long-time navigation and positioning in the modern complex battlefield.

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As a multi-disciplinary technology, geomagnetic matching and positioning technology mainly include four aspects: geomagnetic characteristics research, geomagnetic matching modeling, geomagnetic matching strategy and geomagnetic database retrieval [3]. The basic principle of geomagnetic matching navigation: Taking the position information provided by INS as a reference, the real-time measured geomagnetic sequence is registered with the existing geomagnetic database through various strategies and algorithms, and then the accumulated system error of INS over time is constantly corrected to achieve the autonomous navigation. It is called geomagnetic matching to search the geomagnetic sequence matching the measured geomagnetic data in the geomagnetic map formed by the geomagnetic database. The efficiency and accuracy of geomagnetic matching are largely affected by the search speed and matching accuracy of geomagnetic matching strategy, so geomagnetic matching strategy is the core of geomagnetic matching [4].

Like the terrain and gravity navigation algorithm based on the reference map, the geomagnetic matching algorithm also uses the geomagnetic map as a reference for auxiliary navigation [5]. Considering the differences in data processing, matching algorithms can be divided into batch processing algorithm and sequential algorithm. Although the update frequency of the batch algorithm is not as fast as the sequential algorithm, in actual navigation, the matching error of the batch processing algorithm is bounded, more robust, and less affected by the constant error component. Magnetic contour matching (MAGCOM), Iterative Closest Contour Point (ICCP) [6], etc. are all common geomagnetic matching algorithms in batch processing algorithms. However, MAGCOM can only perform geomagnetic matching for pure translation models, and is more sensitive to heading angle errors. ICCP does not have global optimality and can only converge to a local minimum. When the initial position error is large, its matching accuracy will be greatly reduced [7]. As an auxiliary positioning technology that needs to be put into practical application, geomagnetic matching positioning requires high efficiency and real-time performance. Traditional geomagnetic matching algorithms cannot meet the requirements of real-time navigation update, and the resulting time delay will produce an error larger than the matching error [8]. Based on the principle of batch processing and considering the high positioning accuracy of INS in a short time, this paper proposes an improved particle swarm optimization search strategy based on simulated annealing(SAPSO) combined with the research of geomagnetic characteristics. As a newly optimized algorithm in batch processing algorithm, it has simple implementation principle and fast convergence speed, which guarantees the accuracy and efficiency of geomagnetic matching real-time auxiliary navigation. The main contributions of this research are as follows:

1) Aiming at the limitation of the traditional geomagnetic matching algorithm to the initial position and heading angle error, based on the geomagnetic affine model, particle swarm optimization geomagnetic matching

algorithm improved by the simulated annealing algorithm is introduced.

2) For the randomness of the algorithm, the parameter initialization method is improved through the isoline domain constraints.

3) According to the actual geomagnetic matching navigation requirements, the fitness function of the algorithm is redefined, and the adaptive correction of the parameters is added.

4) The simulation analysis was carried out with the measured geomagnetic data in Nanjing, which verified the effectiveness of the proposed algorithm.

The remainder of this paper is organized as follows. Section 2 provides details of the principle and model of geomagnetic matching. In Section 3, the working principle of PSO and SA is described in the beginning, and we present the combination of PSO with SA. Then three improvements were implemented on SAPSO. Section 4 demonstrates the simulation results of the proposed algorithm, and the initial PSO algorithm and traditional ICCP algorithm are contrastive experiments to validate the performance of the proposed algorithm. Section 5 concludes this paper.

II. PRINCIPLE AND MODEL OF GEOMAGNETIC MATCHING

The establishment of the model of geomagnetic matching is the basis of the algorithm of geomagnetic matching. Whether the matching model fully considers all kinds of error factors will greatly affect the whole matching process and the accuracy of matching results.

A. PRINCIPLE OF GEOMAGNETIC MATCHING

As a data association problem, geomagnetic matching is actually a more complex data search. Suppose X is a data sequence in the geomagnetic database, Y is the sequence about geomagnetic value obtained by the real-time measurement of the magnetic sensor. If there are n_c tracks to be matched in the matching area, there are sets

$$C = \{X_j \mid j = 1, 2, \ldots, n_c\}. \qquad (1)$$

The set of n_c positions corresponding to each track to be matched in C is expressed as

$$P = \{p_j \mid j = 1, 2, \ldots, n_c\}. \qquad (2)$$

In an ideal case, there must be a point closest to the real position in set P, that is, the best matching point p_b. If the association algorithm is $D_j(X, Y)$, then the matching position p_m can be detected, which meets the following requirement.

$$m = \arg_j \{\max (D(X_j, Y)), j = 1, 2, \ldots, n_c\}. \qquad (3)$$

where m represents the geomagnetic serial number corresponding to the matching position with the highest correlation with the real position. The main goal of the matching algorithm is that p_b and p_m are consistent, which means that the match is successful.

B. MODEL OF GEOMAGNETIC MATCHING

The process of geomagnetic matching can be described by the following two equations [9].

Track information

$$s_i = f(s_r + \Delta p_0) + w. \quad (4)$$

Measurement information

$$z_k = h^k(s_r) + \eta_k. \quad (5)$$

where s_i represents the output trajectory of INS, $f(\cdot)$ represents track transformation relationship, s_r represents the real track, Δp_0 indicates the initial position error, w represents the measurement noise in the matching process, z_k represents real-time information of geomagnetic characteristics measured by magnetic sensors, $h(\cdot)$ represents map reading function, η_k represents the noise and error of geomagnetic measurement. The so-called geomagnetic matching, that is, according to the information contained in the indicating track s_i of INS and the measured geomagnetic anomaly sequence z_k, calculate the track transformation relationship $f(\cdot)$ and the initial positioning error Δp_0. It is essentially a spatial transformation.

Under the influence of heading error and speed error, there is a large deformation between the real track and the measured track in the actual system, as shown in Fig.1. At this time, the track transformation function in (4) belongs to the category of elastic transformation, rather than simple rigid transformation. Therefore, the elastic transformation needs to be simplified, transformed into rigid transformation and compensated. The dashed lines in Fig.1 represent a series of to-be-matched tracks obtained by translation of the track indicated by INS. The so-called geomagnetic matching is to traverse all the tracks to be matched, search the geomagnetic database to get a series of geomagnetic reference sequences, and select the one with the smallest difference from the measured geomagnetic sequence. The matching track corresponding to the geomagnetic reference sequence is the best matching track obtained by geomagnetic matching.
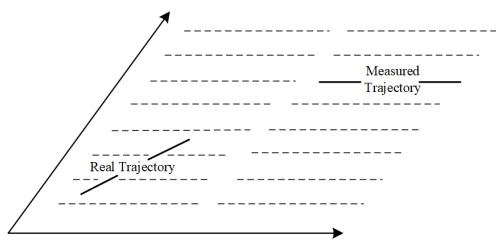

FIGURE 1. Geomagnetic matching (considering deformation).

The transformation relationship between the track of INS and the real track can be obtained by simple curve affine [10]. The initial position error, velocity error, and track yaw correspond to the three transformations of translation, zoom, and rotation, respectively [9]. The expression is

$$\begin{bmatrix} x_{\text{INS}} \\ y_{\text{INS}} \end{bmatrix} = \alpha \begin{bmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} x_r \\ y_r \end{bmatrix} + \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix}. \quad (6)$$

where α is the scaling factor, θ is the yaw caused by the velocity error, Δx and Δy are the translation factors. Through a variety of search strategies to find the four appropriate transformation factors, and then estimate the location of the carrier, that is, one-dimensional matching.

III. GEOMAGNETIC MATCHING ALGORITHM

A. PARTICLE SWARM OPTIMIZATION

Particle swarm optimization(PSO) is a kind of parallel stochastic optimization algorithm based on the idea of iteration, which simulates the aggregation of fish and the foraging of birds [11]. Its main idea is: a particle represents a possible solution of the optimization problem, and each potential solution of the optimization problem corresponds to a particle with the best state in the space [12]. Influenced by the memory of particles themselves, they have thinking and cognitive behaviors. Under the influence of particle swarm, there is information sharing and cooperation among particles. Therefore, the particle swarm algorithm has a unique memory ability, which can dynamically track the existing state of the particles, and then change the search method according to the current state.

The attributes of each particle include position, speed and fitness function. Suppose a group $X = (x_1, x_2, x_3, \ldots, x_N)$ composed of N particles moves at a certain speed in the D-dimensional search space, where the position of the i_{th} particle at time t is $x_i^t = (x_{i1}^t, x_{i2}^t, x_{i3}^t, \ldots, x_{iD}^t)^T$, the speed is expressed as $v_i^t = (v_{i1}^t, v_{i2}^t, v_{i3}^t, \ldots, v_{iD}^t)^T$, and the fitness function is $f_{x_i^t}$. The smallest value of fitness function corresponds to the searched optimal solution. The individual extreme value is denoted as $P_i = (p_{i1}, p_{i2}, p_{i3}, \ldots, p_{iD})^T$, and the global extreme value, that is, the global optimal position is denoted as $P_g = (p_{g1}, p_{g2}, p_{g3}, \ldots, p_{gD})^T$, where $i = 1, 2, \ldots, N$, and D is the dimension of the vector represented by the particle. In each iteration of the search process, the particle continuously adjusts its position and speed according to the individual optimal position and global optimal position at the previous moment [13].

$$v_{id}^{t+1} = \omega v_{id}^t + c_1 r_1(p_{id} - x_{id}^t) + c_2 r_2(p_{gd} - x_{id}^t). \quad (7)$$
$$x_{id}^{t+1} = x_{id}^t + v_{id}^t. \quad (8)$$

In the formula, $i = 1, 2, \ldots, N$ and $d = 1, 2, \ldots, D$. ω represents the weight of inertia. The learning factors c_1 and c_2 are non-negative constants. r_1 and r_2 are random numbers and obey the uniform distribution on $[0, 1]$. The speed $v_{id} \in [-v_{\max}, v_{\max}]$. The maximum speed $v_{\max}$ is a constant.

In formula (7), P_{id} and P_{gd} represent the individual and global optimal positions of the particle swarm, respectively. c_1 and c_2 represent the weight of the statistical acceleration term that pushes each particle to the individual best position and global best position. A lower value allows the particles to hover outside the target area before being pulled back, and a higher value will cause the particles to suddenly rush toward or over the target area. When $c_1 = 0$, the particle loses the cognition of its "self-experience" and the model becomes

a social-only model, which is called global PSO algorithm. In this case, the particles only can expand the search space and have a faster convergence rate. However, due to the lack of local search, it is easier to fall into the local optimum when dealing with complex problems. When $c_2 = 0$, there is no social information transmission between particles, and the model becomes a cognition-only model, which is called local PSO algorithm. In this case, there is no information exchange between individual particles. The entire group is equivalent to a blind random search of multiple particles. And the convergence speed is slow, so the possibility of obtaining the optimal solution is small. Suganthan's experiment [14] shows that a better solution can be obtained when c_1 and c_2 are constants, usually set $c_1 = c_2 = 2$, but not necessarily equal to 2. The parameters can be adjusted according to the experimental experience. Generally, $c_1 = c_2 \in [0, 4]$. We choose $c_1 = c_2 = 1.4996$ in the geomagnetic matching simulation.

B. SIMULATED ANNEALING

The idea of simulated annealing(SA) algorithm comes from the process of simulated solid annealing and cooling, which belongs to the global optimization algorithm [15]. In practice, the temperature T can be used to simulate the control parameters, and the value f of the objective function can be used to simulate the internal energy. Firstly, an initial solution is given, and a random solution is generated in the neighborhood of the initial solution. When the objective function is within a certain range, the acceptance criterion allows the objective function to abandon the existing better solution and accept the inferior solution that makes itself worse. The whole iterative process is carried out by "generating new solutions, calculating the difference of objective function, judging whether to accept new solutions, accepting or discarding new solutions" [16], which is similar to the solid cooling process, that is, the process of solid gradually becoming thermally stable when the temperature is constant. When the control parameters are given, the relative optimal solution can be obtained by trying various solutions. Then reduce the control parameters and repeat the above iterative steps. In the process of reducing the control parameters to zero, the controlled system also gradually transits to the steady state, and finally enters the optimal state of the optimization problem to obtain the global optimal solution [17].

Simulated annealing is actually a greedy algorithm, but its search process introduces random factors. When the algorithm iteratively updates the feasible solution, it accepts a solution that is worse than the current solution with a certain probability, so it may jump out of this local optimal solution and reach the global optimal solution. The optimization process is controlled by annealing temperature to approach to the optimal solution, and judges whether to receive the poor solution by the probability $\exp(-\Delta f / T_k)$. Therefore, the annealing process which is slow enough can effectively promote the convergence of the optimization process to the global optimal solution. And as long as the initial temperature

is high enough, the algorithm will not fall into the local extreme point [18], [19]. The simulated annealing algorithm consists of three parts: the generation of initial solution, the acquisition of equilibrium state and operation of annealing. The process of the whole algorithm is as follows,

1) Initialize the annealing temperature T_k and randomly generate the initial solution x_0 [20].
2) Repeat the following steps (i.e. Metropolis Sampling Criteria) at temperature T_k until the equilibrium state of temperature T_k is reached[11]: Randomly choose a new feasible solution x' (within the neighborhood of the solution x); calculate the difference $\Delta f = f(x') - f(x)$ between value $f(x')$ of the target function corresponding to x' and the value $f(x)$ of the target function corresponding to x; accept x' when the probability satisfies $\min\{1, P = \exp(-\Delta f / T_k)\} > random[0, 1]$, where $random[0, 1]$ represents the randomly generated number in the interval of $[0, 1]$ [20].
3) Operation of annealing: $T_{k+1} = CT_k, k \leftarrow k + 1$, where $C \in (0, 1)$. If the convergence is met, end the annealing; otherwise, go to step 2) [20].

The algorithm flexibly uses the characteristics of sudden jumps in probability. Through the principle of random judgment, the feasible solution can be updated randomly in the iterative process. Although the criterion may lead to suboptimal solution in an iterative process, it can make the whole process of optimization separate from local extremum and improve the ability of global search.

C. PARTICLE SWARM OPTIMIZATION ALGORITHM BASED ON SIMULATED Annealing (SAPSO)

Theoretically, many optimization problems can be solved by either PSO or SA. However, these two algorithms have some defects in searching the optimal solution independently: PSO has the problem of "premature" particles, that is, it may converge to the minimum value prematurely during the particle search and fall into the local extreme value, which greatly reduce the ability of global search; SA relies too much on the process of cooling. If global convergence is to be achieved, harsher temperature-limiting conditions are required, leading to reduced optimization efficiency [21]. Therefore, PSO and SA are combined and constrain the search of PSO at the same time, which not only solves the problem of local optimization, but also realizes the requirement of high efficiency of the algorithm. The flow chart of SAPSO is shown in Fig.2.

How to find the track that matches the measured geomagnetic data best in the search space is a key issue for SAPSO to successfully achieve geomagnetic matching navigation. According to the geomagnetic affine model of Section 2, the four parameters of scaling factor, yaw angle, and position translation factors are variables to be optimized. Then the individual state of the particle can be expressed as

$$X = (\alpha, \theta, \Delta x, \Delta y). \tag{9}$$

Considering points O and D as the origin and destination of the track respectively, they can represent
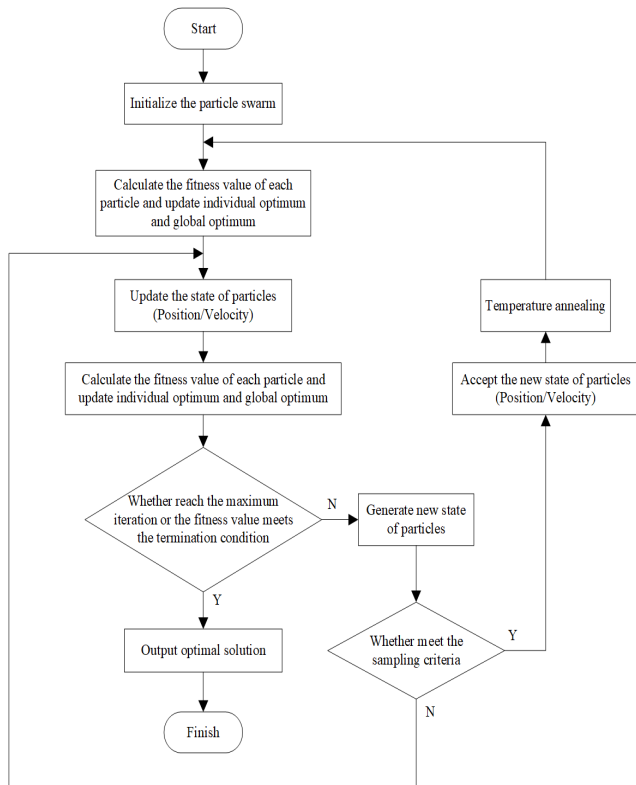
FIGURE 2. The flow chart of SAPSO.

a track combined with intermediate sampling points $\{S_1, \cdots, S_i, \cdots, S_{n-2}\}$. The $path_i = \{O, S_1, \cdots, S_i, \cdots, S_{n-2}, D\} \in R^{3n}$ is shown in Fig.3.

A solution is made up of n subcomponents, each of which corresponds to a sampling point of the track to be matched [22]. According to (6), each bit of the subcomponents represents the scaling factor, yaw angle and two translation factors respectively. Fig.4 is a randomly generated particle corresponding to its position.

D. IMPROVED SAPSO

The computational complexity and efficiency of SAPSO are affected by the size of uncertainty domain, number of particles and number of iterations. A large uncertainty domain will cause the search range to be too large, reducing the speed of the global search and making the search time significantly longer. The smaller uncertainty region may lead to the missing of the optimal solution and the inability to obtain the accurate matching trajectory [23]. If the number of particles and number of convergence iterations are too large, it will directly affect the calculation time of the whole algorithm. The smaller number of convergence iterations will cause the optimization algorithm to fail to obtain the optimal solution and terminate early, which will seriously affect the accuracy of the algorithm [24]. If we want to reduce the calculation to improve the real-time performance of the system, we need to reduce the number of particles, choose an appropriate range of uncertain domains, or speed up the convergence of the particle swarm. To solve these problems, some constraints are

added to the particle swarm optimization search, and the static parameters are optimized to dynamic variables to improve the SAPSO.

1) CONSTRAINTS OF CONTOUR DOMAIN

The performance of PSO is greatly affected by the initialization process of the particles. With the increase of the number of particles, the coverage of the solution space will expand accordingly, so that the optimal solution can be obtained with greater probability. However, this also increases the computation of the entire algorithm, which violates the original intention of the optimization search. In order to improve the matching probability and searching efficiency of the algorithm, isoline domain is used to constrain the position parameters obtained by the initialization of particles, that is, the horizontal position parameter (x, y) of the particles must be located in the contour field corresponding to the control point, which meets the constraint

$$readmap(x, y) \in [M - \xi, M + \xi]. \tag{10}$$

Among them, $readmap(\cdot)$ represents the function of reading map; ξ is the standard deviation of the measurement noise. With this constraint, particles can be distributed near the true trajectory with greater probability during initialization. This achieves the goal of obtaining an optimal solution with fewer particles, which greatly improves the efficiency of search process and performance of the algorithm.

2) SELECTION OF ADAPTIVE PARAMETERS

As an important parameter in PSO, inertia weight ω has a great influence on the convergence of the algorithm [25]. It can balance the ability of local search and global search, and fully reflect the influence of historical velocity on the current velocity of particles. When the inertia weight is large, particles can explore new areas and have strong ability of global search. When the inertia weight is small, the particles tend to search locally, that is, developmental search. And learning factors c_1 and c_2 control the ability of particles to search for the best in the group and the best in themselves. Proper selection of inertia weights and learning factors can make the optimized search more efficient and accurate. Therefore, it is necessary to adjust these three parameters according to the fitness value of each particle, which obtains

$$\begin{cases} c_{1i} = c_1 \cdot (1.5 - k(i)/N) \\ c_{2i} = c_2 \cdot (1.5 - k(i)/N) \\ \omega = \omega_{\max} - (\omega_{\max} - \omega_{\min}) \cdot (t/t_{\max}) \\ \omega_i = \omega \cdot (0.5 + k(i)/N). \end{cases} \tag{11}$$

Among them, ω_i is the dynamic inertia weight of the i_{th} particle. c_{i1} and c_{i2} are the dynamic learning factors of the i_{th} particle. N is the number of particles. $k(i)$ represents the ordinal number corresponding to the i_{th} particle after the fitness value of the particles in the current search state is arranged. $\omega_{\max}$ and $\omega_{\min}$ denote the maximum and minimum values of ω. $t_{\max}$ denotes the maximum number of iterations, and t denotes the current number of iterations.
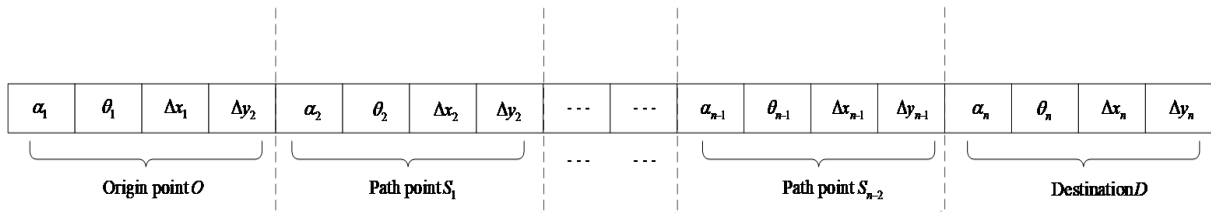
| α_1 | θ_1 | Δx_1 | Δy_2 | α_2 | θ_2 | Δx_2 | Δy_2 | - - - | - - - | α_{n-1} | θ_{n-1} | Δx_{n-1} | Δy_{n-1} | α_n | θ_n | Δx_n | Δy_n |

Origin point O Path point S_1 - - -   Path point S_{n-2} Destination D

FIGURE 3. Encoding of path.

| 0.9970 | -0.0035 | 0.0087 | 0.0587 | 1.0052 | -0.0014 | 0.1600 | 0.0460 | 0.9968 | -0.0045 | 0.1665 | 0.1697 | 1.0090 | -0.0038 | 0.0100 | 0.0230 | - - - |

Origin point O Path point S_1 Path point S_2 Path point S_3

| 1.0042 | 0.0007 | 0.0810 | 0.0717 | 0.9952 | 0.0044 | 0.1189 | 0.1157 | 0.9922 | 0.0003 | 0.0718 | 0.1943 | 0.9953 | 0.0025 | 0.1565 | 0.0213 | - - - |

Path point S_4 Path point S_5 Path point S_6 Path point S_7

| 0.9957 | -0.0030 | 0.0487 | 0.1613 | 0.9914 | -0.0043 | 0.1793 | 0.1343 | 1.0028 | 0.0051 | 0.1378 | 0.1900 | 0.9988 | 0.0030 | 0.1437 | 0.1786 | - - - |

Path point S_8 Path point S_9 Path point S_{10} Path point S_{11}

| 0.9935 | 0.0030 | 0.1099 | 0.0428 | 0.9993 | 0.0033 | 0.0044 | 0.0078 |

Path point S_{12} Destination D

FIGURE 4. A randomly generated particle.

3) SELECTION OF FITNESS FUNCTION

As a one-dimensional matching, geomagnetic matching is essentially a problem on data correlation, so the fitness function can be selected according to the correlation criterion [26]. From the perspective of accuracy, the mean square deviation algorithm(MSD) and the mean absolute difference algorithm(MAD) have similar performance. But compared with MSD, MAD is simpler to realize. Therefore, MAD is selected as the evaluation criterion of fitness function. The real-time measured geomagnetism is particularly susceptible to external interference, resulting in constant and random errors in the calculation. Therefore, the traditional MAD algorithm is improved as a function about fitness, obtaining

$$f = \frac{1}{N} \sum_{k=1}^{N} \left\| |H_m^k - \bar{H}_m| - |H_c^k - \bar{H}_c| \right\| \qquad (12)$$

Among them, $\bar{H}_m$ represents the average of the geomagnetic measurement sequence, and $\bar{H}_c$ represents the average of the geomagnetic sequence corresponding to the track to be matched obtained by querying the geomagnetic database. The fitness function is calculated by relative change, which greatly reduces the influence of noise on matching.

Based on the above analysis, an improved SAPSO geomagnetic matching algorithm is obtained. The specific implementation steps are shown in Tab.1.

IV. SIMULATION OF GEOMAGNETIC MATCHING ALGORITHM

In order to verify the effectiveness of the improved SAPSO, a simulation analysis of geomagnetic matching was performed according to steps of the proposed algorithm shown in Tab.1. In order to obtain more accurate matching results, the data used in all simulations are real geomagnetic anomaly data in Nanjing.

A. SETTINGS OF SIMULATION PARAMETERS

The initial settings of the parameters of the improved SAPSO are shown in Tab.2.

B. RESULTS OF SIMULATION

1) SIMULATION OF ICCP AND IMPROVED SAPSO

In two different cases, ICCP and improved SAPSO are simulated and compared.

Case 1: The inertial navigation trajectory has no heading error. Suppose the initial position error of the carrier is (1000, 7000)m, and the white noise of the magnetic field measurement with a standard deviation of 20nT is added. The matching results of ICCP and improved SAPSO are shown in Fig.5(a).

Case 2: The heading error of the INS trajectory is 20°. Suppose the initial position error of the carrier is (3000, 8000)m, and the magnetic field measurement noise with a

TABLE 1. The improved SAPSO geomagnetic matching algorithm.

| Step	Description
1	Collect the track $(x_{\text{INS}k}, y_{\text{INS}k})$ of INS, and record the real-time geomagnetic measurement data sequence H_m^k through the magnetic sensor.
2	Parameter initialization: Population size N, maximum number of iterations $t_{\max}$, maximum and minimum inertia weight $\omega_{\max}$ and $\omega_{\min}$, initial annealing temperature T_0, learning factors c_1 and c_2, annealing rate λ.
3	Initialize a group of four-dimensional particles $X = (\alpha, \theta, \Delta x, \Delta y)$, in which position parameters satisfy the contour constraint condition of formula (9), and an initial velocity v_i is randomly assigned to each particle.
4	According to the trajectory sequence of INS and formula (6), a series of trajectories to be matched are obtained, and the fitness value of each particle is calculated and evaluated by formula (11).
5	Compare the fitness of each particle's current state with the best fitness of the individual. If the current fitness is small, set the current state to the best state of the individual and update the individual extreme. Compare the fitness of each particle's current state with the global best fitness. If the individual particle's fitness is small, set the current state of the particle to the global best state and update the global extremum.
6	According to formula (10) and the current state of the particle, adaptively modify the parameters, and update the state of the particle according to formula (7) and (8), including its velocity and position.
7	Calculate the change in fitness before and after the state update of the particle, and update the global and individual extreme values of the particle swarm. Combined with the Metropolis sampling criterion of SA, when $\Delta f \leq 0$ or $\Delta f > 0$ and $\exp\left(-\Delta f/kT\right) > random\,[0, 1]$, accept the new solution and cool down; otherwise, keep the current solution and return to Step 5.
8	Determine whether the conditions for the termination of the iteration are met. If the condition is met, the best matching track is output according to formula (6), and if the condition is not met, return to Step 4.

TABLE 2. Parameter settings of improved SAPSO.

Parameter	Value
initial velocity of particles	$v = \begin{bmatrix} 0 & 0 & 0 & 0 \end{bmatrix}$
maximum velocity	$v_{\max} = 1$
minimum velocity	$v_{\min} = -1$
learning factors	$c_1 = c_2 = 1.4996$
maximum inertia weight	$\omega_{\max} = 1.2$
minimum inertia weight	$\omega_{\min} = 0.4$
number of particles	20
range of scaling factor	$\alpha \in [0.5, 1.5]$
range of yaw	$\theta \in [-5°, 5°]$
range of translation factors	$\Delta x, \Delta y \in [-0.2°, 0.2°]$
cooling factor	$\lambda = 0.5$
initial temperature	$T_0 = 5000$

standard deviation of 20nT is added. The matching results of ICCP and improved SAPSO are shown in Fig.5(b).

It can be seen from Fig.5 that when the initial position error of the carrier is small and the trajectory of INS has no heading error, the matching accuracy of ICCP and improved SAPSO is high. However, when the initial position error of the carrier is large and the trajectory indicated by INS has heading error, the matching result of improved SAPSO is significantly better than ICCP.

2) SIMULATION OF PSO AND SAPSO

According to the parameter settings in Tab.2, in the case of using the same number of particles, results of geomagnetic matching based on PSO are shown in Fig.6(a), and results of geomagnetic matching based on SAPSO are shown in Fig.6(b).
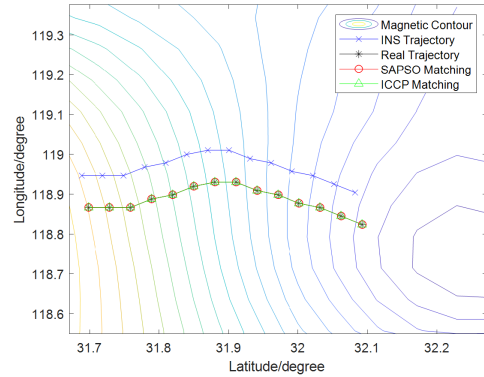
(a) Small Initial Error and No Heading Error
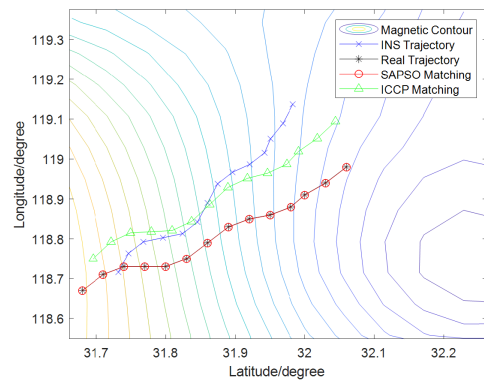
(b) Large Initial Error and Heading Error

FIGURE 5. Comparison of matching results between ICCP and improved SAPSO.

As mentioned above, theoretically, although PSO can get the optimal solution through optimization search, it is easy to fall into the local minimum value, converge to the minimum value prematurely, and result in the problem of "premature" of particles. It will stop iteration, and the final optimization result of the search is not the true optimal solution, but the local optimal solution. Therefore, a larger matching error occurs. At each iteration, the matching error is represented by the average of mean square root of errors in the longitude and latitude directions of the entire track sequence.

In Fig.6(a), it is obvious that the optimal matching track obtained by the basic PSO converges in advance and falls into a local optimal state. Therefore, the matching error of the matched track is large. Compared with Fig.6(b), it can be seen that PSO is improved by SA with the obtained optimal track matching the real track better.

The speed of the iterative convergence becomes higher as well. Therefore, using SA to improve PSO can effectively solve the problem on local optimization of PSO, and achieve the matching track with higher matching accuracy.

3) CONVERGENCE OF PARTICLES IN CONTOUR-CONSTRAINED SAPSO

Constrain the initialization of particles through the contour domain, and randomly generate 20 particles. Suppose that
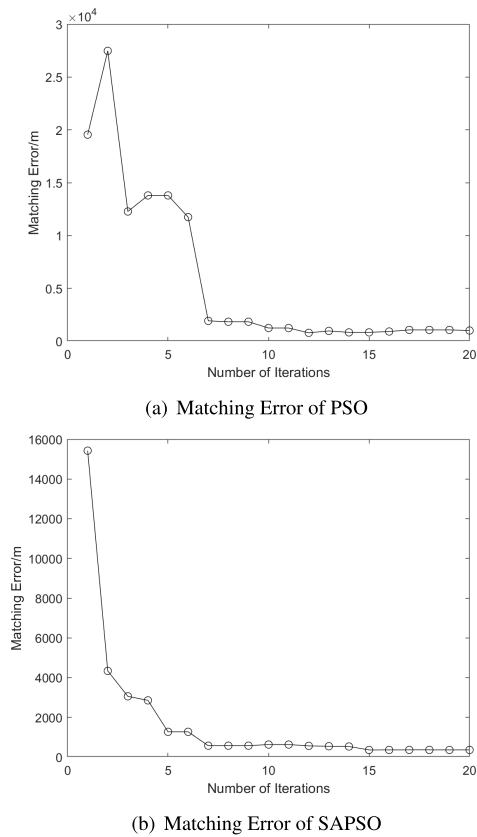
(a) Matching Error of PSO

(b) Matching Error of SAPSO

FIGURE 6. Matching error of PSO and SAPSO.

(a) the First Iteration

(b) the Third Iteration

(c) the Fifth Iteration

(d) the Seventh Iteration

FIGURE 7. The convergence state of particles.

there are M points in the region to be matched that meet the constraint requirements of isoline domain.If M is greater than 20, randomly select 20 points from M points to initialize the position of particles. If M is less than 20, then randomly generate $(20 - M)$ points in the region to be matched. The initial error of the position of the system is assumed to be (500, 100)m.Fig.7 shows the convergence state of particles relative to the starting point of the real track after the first, third, fifth and seventh iterations.

To meet the real-time requirements of the actual geomagnetic matching navigation, the matching algorithm should reduce the calculation and improve the efficiency of matching. Therefore, it can be considered to improve the algorithm by reducing the number of particles or increasing the convergence speed of the particles. And a certain number of particles can improve the ability of global search, so in contrast, improving the convergence speed of particles is chosen. It can be clearly seen that the constraints of the initial contour domain limit the range of particles during initialization, so that particles can be distributed near the true track with greater probability, effectively reducing the number of iterations of the matching algorithm. It only takes a small number of iterations to quickly converge to the true initial position. Therefore, the results of the simulation show that the constraints of the initial contour domain can effectively improve the efficiency of the entire matching algorithm, that is, improve the global convergence of the matching algorithm.
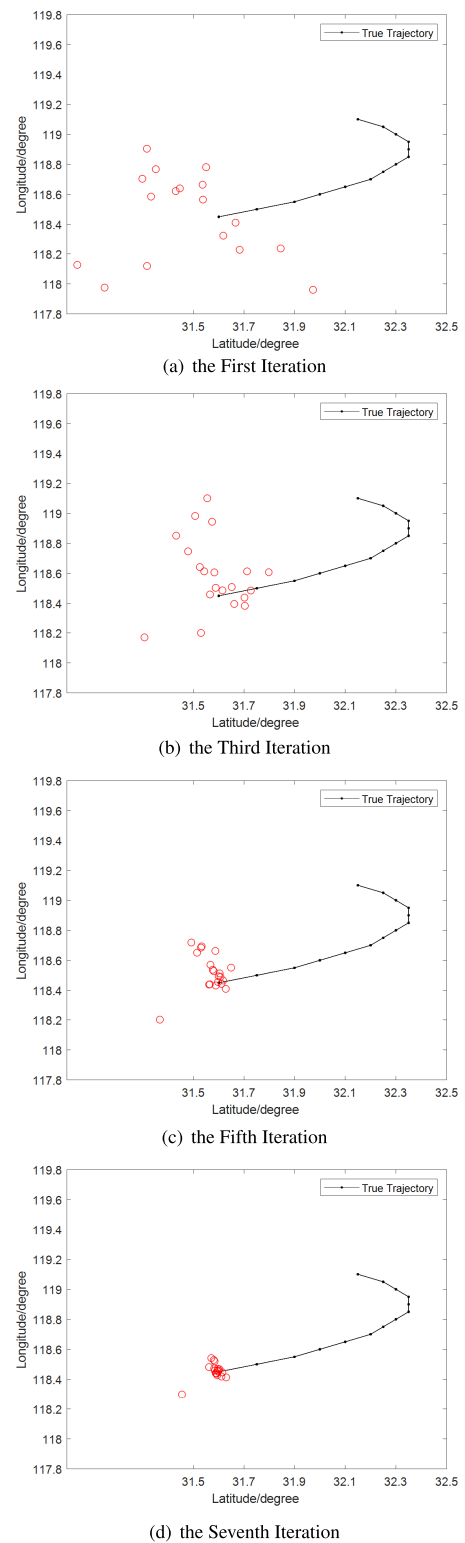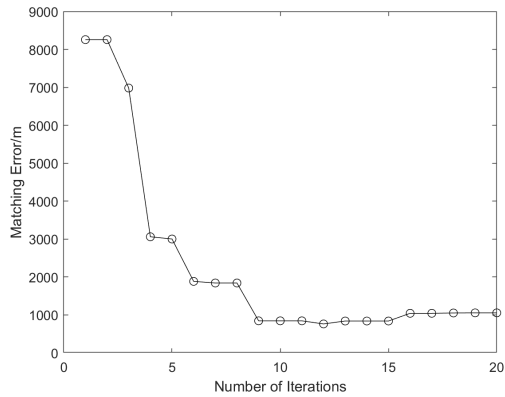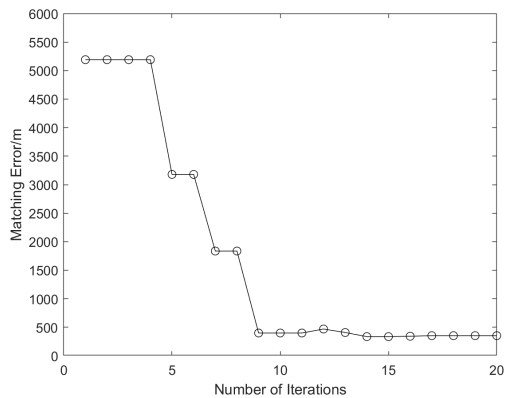
4) IMPACT OF ADAPTIVE MODIFICATION OF PARAMETERS ON ALGORITHM PERFORMANCE

For the same group of particles, the same random parameters are selected. Compare and analyze the effect of adaptive modification of parameters on the search performance of

(a) Matching Error Before Adaptive Correction

(b) Matching Error After Adaptive Correction

FIGURE 8. Matching errors of SAPSO before and after adaptive correction of parameters.

the SAPSO. The search results of geomagnetic matching algorithm before and after the adaptive correction of parameters are shown in Fig.8.

It can be found that before the adaptive modification of the parameters, the matching algorithm converges more slowly and requires more iterations to obtain smaller matching errors. Therefore, results simulation show that adaptive real-time correction of parameters can not only improve the accuracy of geomagnetic matching, but also accelerate the convergence of the geomagnetic matching algorithm.

5) ANTI-NOISE PERFORMANCE OF THE ALGORITHM

Simulate the same track under different noise levels, and analyze the effect of noise on the number of convergence iterations and matching errors. The standard deviation of the geomagnetic survey sequence is 121.4nT, and the simulation results are shown in Fig.9. The abscissa is taken as the standard deviation of noise, and 50 experiments are performed at each noise level, and the result is the statistical average. It can be seen from the variation curve that the number of convergence iterations is not greatly affected by noise, indicating that the algorithm has great performance of global positioning and convergence. From the curve of positioning error with noise, we can see that when the standard deviation of the noise is less than 100nT, the positioning accuracy can be basically
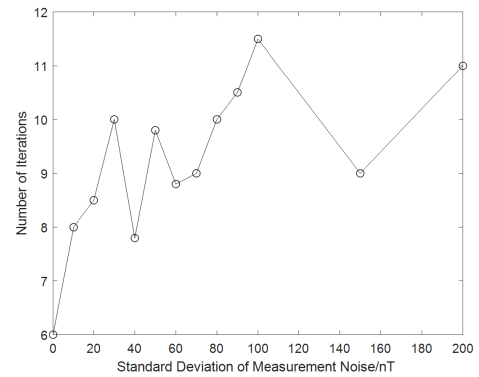
(a) Number of Iterations
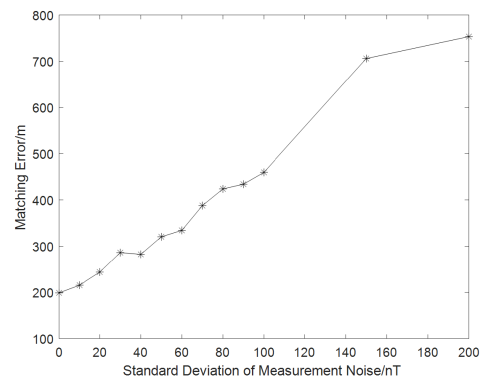
(b) Matching Errors

FIGURE 9. Anti-noise performance of the improved SAPSO.

kept within 500m. It can be seen that the algorithm has a certain robustness to noise.

V. CONCLUSION

As a new type of assisted navigation technology that uses the physical field of the earth for navigation, geomagnetic matching navigation can perform highly concealed, all-area and all-weather real-time assisted navigation [27]. Therefore, an improved PSO geomagnetic matching algorithm based on SA is proposed to assist the navigation and positioning of INS. The PSO based on SA can be well applied in one-dimensional matching, and effectively solve the problem on the local optimal solution of the basic PSO. The algorithm combined with the constraints of the initial contour domain greatly reduces the number of iterations of the entire algorithm and accelerates the convergence rate of the particle swarm. The matching error between the geomagnetic matching track and the real track is small, which effectively improves the accuracy and efficiency of the geomagnetic matching algorithm. What's more, the results of the simulation show that the improved SAPSO can modify the parameters adaptively in real time according to the current searching state of particles, so that the searching results of the whole particle swarm can converge to the optimal solution faster. This improves the matching speed, and better meets the real-time requirements of the geomagnetic matching.

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