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Differential evolution particle swarm algorithm for vector map declassification problem

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Abstract: In order to solve Optimization of coordinate transformation in vector map declassification, a novel scheduling solution based on differential evolution particle swarm optimization algorithm (DEPSO) was proposed. The mathematical model of Vector map declassification problem was expound, the framework of differential evolution particle swarm optimization algorithm was given, the information exchange mechanism between PSO population and DE population for the optimal particle location was introduced to make proposed algorithm easily jump out of local optimum with effective dynamic adaptability. Experimental result shows that compared with genetic algorithm (GA), artificial bee colony algorithm (ABC) and firefly algorithm (FA), proposed algorithm can solve the scheduling problem of Vector map declassification, and has the advantage of good application value.

Keywords: Differential evolution; particle swarm optimization algorithm; Vector map; Declassification.

1. Introduction

In recent years, the wave of informatization characterized by digitization and networking has swept the world, and various digital products have emerged as the times require. Geographic Information System (GIS) has been developed unprecedentedly and has penetrated into all walks of life in society. However, the confidentiality and security of vector map data has become the bottleneck of the development of GIS technology in China, which makes my country's GIS technology show the characteristics of low penetration rate and low resolution. Reference [1] researches and discusses the main problems existing in the encryption and declassification in my country's current geographic information security policy, and puts forward corresponding countermeasures. Reference [2] proposed a geometric de-densification method for vector geographic data with topology and geometry preservation based on the Compact Supported Radial Basis Function (CSRBF), and constructed corresponding topological conformal rules for different types of geographic elements. Using CSRBF to generate a decryption function model, according to the geometric decryption requirements of vector geographic data, the vector geographic elements of point, line and area structure are dedensified respectively. Reference [3] Aiming at the contradiction between the security protection and sharing application of geographic information, a vector data decryption model based on Chebyshev polynomial is established. The algorithm can effectively control the deciphering error, the deciphered data has both overall transformation and local random disturbance, has strong anti-attack ability, and better maintains the topological relationship of vector data. Reference [4] proposes a multi-swarm-parallel chaotic particle swarm (PSO) optimization algorithm for reducing the precision of vector data. Through chaotic serialization of initial particles, the global search ability and convergence efficiency of PSO can be effectively improved, and the topological relationship of elements in different layers of vector data can be maintained.

Differential Evolution (DE) is an algorithm based on population evolution, which was proposed by Storn in 1995 [5].The algorithm has the characteristics of memorizing the optimal solution of individuals and sharing information within the population, that is, the solution of the optimization problem is realized through the cooperation and competition among individuals in the population. [6].The algorithm has the advantages of simplicity and efficiency, fast convergence speed and good robustness. It has been widely used in filter design, PID control, image segmentation and other scientific or engineering applications.

Particle swarm optimization algorithm is a simple and efficient intelligent optimization algorithm, but the basic particle swarm optimization algorithm has the shortcomings of easy to fall into local optimum and low search accuracy. Based on this, this paper combines the advantages of the differential evolution algorithm and the particle swarm algorithm, and through the information exchange between the PSO population and the DE population, the probability of particles falling into a local optimum is greatly reduced. In this paper, a differential evolution particle swarm optimization algorithm is proposed to solve the problem of vector map decryption.

2. Mathematical model of vector map deciphering problem

Multivariate functions scatter the interpolation or fitting process of data, and the interpolation of multivariate functions is more difficult and complicated than the interpolation of unary functions. Multivariate function interpolation is actually the process of superposing multiple function spaces to solve the interpolation function, and the radial basis function is the simplest multivariate function that meets this condition.

Given a unary function θ: $\mathrm{R}_+ \to R$,in the domain of definition $x \in R^d$,All function controls such as $\Phi(x-c)=\phi(\|x-c\|)$ and its linear combination become the radial basis function space derived from function ϕ .The radial basis function interpolation model can be described as,Given θ: $\mathrm{R}_+ \to R$ function a in a multidimensional space,for data $\{x_i, f_i | i=1,2,...,n\} \in R^d \otimes R$,Need to find a function such as formula (1).

$$f(x)=\sum_{i-1}^{n} c_i \phi(\|x-x_i\|) \tag{1}$$

Make it satisfy the condition as formula (2).

$$f(x_k)=\sum_{i-1}^{n} c_i \phi(\|x_k-x_i\|) \tag{2}$$

Where x_k is any coordinate point in space, x_i is the radial basis function center, $f(x_k)$ is the function value corresponding to x_k , $\|x_k-x_i\|$ represents the Euclidean distance from any node to the center of the radial basis function, $\phi(\|x_k-x_i\|)$ is the value of x_k at the center of x_i , c_i is the linear combination coefficient.

The commonly used radial basis functions include Gaussian basis functions, high-order basis functions and inverse high-order basis functions. The Gaussian basis function and the inverse high-order basis function are positive definite in any dimension space, and the Gaussian basis function is used as the radial basis function in this paper.

Linear transformation is topologically invariant, and the relative positions of elements before and after transformation do not change, which does not affect the use of data. Non-linear transformation loses topological invariance, and maintenance of topological relationship is required during transformation.

Assume input data to be line or polygon features,The coordinate string is x_i, y_i .The threshold for setpoint insertion is α ,The separation distance is d .The deciphering nonlinear function F obtains the corresponding deciphering transformation from the coordinate value $(\Delta x, \Delta y)$,function as(3).

$$\lfloor \Delta x, \Delta y \rfloor = \mathrm{F}(x, y) \tag{3}$$

Take the minimum circumscribed rectangle T as the global sample, set the interval value inter, and select s=(xLen/inter)*yLen/inter) points in the minimum circumscribed rectangle as the sample points for calculating the error of the whole image.

The transformed sample points are obtained by calculating the sample points and weights using formula (4).

$$\begin{cases} sX_i = \omega_{x1}\phi(\|x - x_1\|)_2 + \omega_{x2}\phi(\|x - x_2\|)_2 + \ldots + \omega_{xN}\phi(\|x - x_N\|)_2 \\ sY_i = \omega_{y1}\phi(\|y - y_1\|)_2 + \omega_{y2}\phi(\|y - y_2\|)_2 + \ldots + \omega_{yN}\phi(\|y - y_N\|)_2 \end{cases} \tag{4}$$

Use formula (5) to calculate the median error of the medium error M_{smp}.

$$M_{smp} = \sqrt{\frac{1}{N}\sum_{i=1}^{s} \left[(sX_i - stX_i)^2 + (sY_i - stY_i)^2\right]} \tag{5}$$

Compare$M_{smp}$with the global decryption accuracy m. IfM_{smp}-mis greater than the limit, it means that the target accuracy has not been reached, and the iteration continues.IfM_{smp}<m,Then use formula (6) to increase σ .Otherwise reduce σ .

$$\sigma = \sigma \times \frac{m}{M_{smp}} \tag{6}$$

After getting new σ ,Go to the second step to recalculate the weight w, and iterate repeatedly, untilM_{smp}-m is less than the limit. If the number of iterations exceeds the maximum value, you can adjust the limit of the number of iterations and recalculate. otherwise, it will be regarded as a failure of the decryption calculation.

3. Vector Map Decryption Algorithm Based on Differential Evolution Particle Swarm Optimization

3.1 Basic Particle Swarm Optimization

In the basic particle swarm optimization algorithm, it is assumed that a D-dimensional problem space contains m particles, each particle is a feasible solution to the problem to be optimized in the search space, and the problem is found through cooperation and competition between particles the optimal solution.In the t th iteration, the current position of the i th particle is denoted as $x_i(t) = (x_{i1}(t), x_{i2}(t), \cdots x_{id}(t))$,The current speed is expressed as $v_i(t) = (v_{i1}(t), v_{i2}(t), \cdots v_{id}(t))$ .In each iteration, the best position searched by individual particles is denoted by $pb_i(t) = (pb_{i1}(t), pb_{i2}(t), \cdots pb_{id}(t))$, Referred to as $pbest$,called individual optimality;The best position searched is represented by $gb(t) = (gb_1(t), gb_2(t), \cdots gb_d(t))$,denoted as $gbest$,which is called the global optimum.The process of the optimization problem can be regarded as a process of continuous updating of particles. Each particle adjusts its own flight speed and direction according to formulas (7) and (8) with the current speed, individual optimality and global optimality. Through iteration n generation, Finally, the global optimal value of the n th generation is used as the solution of the problem.

$$v_{id}(t+1) = w * v_{id}(t) + c_1 * r_1 * (pb_{id}(t) - x_{id}(t)) + c_2 * r_2 * (gb(t) - x_{id}(t)) \tag{7}$$

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \tag{8}$$

Where $i = 1,2,\cdots m; d = 1,2,\cdots D; r_1, r_2$ is a random number on (0, 1); The constant c_1, c_2 is the learning factor, indicating the degree to which the particle is affected by individual cognition and social cognition,Adjusts the maximum movement step size for flying in the $pbest$ and $gbest$ directions.The first part in Equation (7) is called the momentum part, which represents the confidence level of the particle in the current state of its own motion, w is called inertia weight,make it inertial according to its own speed; The second part is called individual cognition , which represents the best position for particles to fly to themselves; the third part is called social part, which represents information sharing and mutual cooperation between particles, which guides particles to fly to the group. best location in . The mutual balance and constraints among these three parts determine the main search performance of the algorithm.

3.2 Differential Evolution Algorithm

Differential evolution starts from a randomly generated initial group, and iteratively calculates according to certain operating rules, namely selection, crossover, mutation, etc., and according to the fitness value of each individual, retains good individuals, eliminates inferior individuals, and guides The search process approaches the optimal solution.

For a minimization problem $\min F(x)$,The differential evolution algorithm starts with M initial populations $A(t)=\{A_j(t)\mid j=1,2,...,M\}$ containing N candidate solutions,where $\left|A(t)\right|=N$.

(1) Mutation operation: any random vector v_i^t is generated according to formula (9).

$$v_i(t)=x_{r1}(t)+\sigma\left(x_{r2}(t)-x_{r3}(t)\right) \tag{9}$$

Where $r1,r2,r3\in\{1,2,...,N\}$ is a random number, $\sigma\in\{0,1,2\}$ is the weighting factor.

(2) Crossover operation:The new population $A_j(t)'=\{x_{j1}(\mathrm{t})',x_{j2}(\mathrm{t})',...x_{jd}(\mathrm{t})'\}$ is generated by the random vector $v_j(t)=\left[v_{j1},v_{j2},...,v_{jd}\right]$ and the original population $A_j(t)=\{x_{j1}(\mathrm{t}),x_{j2}(\mathrm{t}),...x_{jd}(\mathrm{t})\}$ according to formula (10).

$$x_{jk}^{'}=\begin{cases}v_{jk},\text{if} \quad \mathrm{rand}b(k)\le CR \quad \text{or} \quad k=\mathrm{rand}r(j)\\ x_{jk},\text{if} \quad \mathrm{rand}b(k)\ge CR \quad \text{or} \quad k\ne \mathrm{rand}r(j)\end{cases} \tag{10}$$

Where, $k\in\{1,2,...d\}$, $0\le \mathrm{rand}b(k)\le 1$ is the k th value of the same random number generator. $CR(0\le CR\le 1)$ is the mutation probability. $\mathrm{rand}r(j)\in\{1,2,...,d\}$ is the random selection index,It ensures that $A_i(t)'$ gets at least one argument from $v_i(t)$.

(3) Selection operation: adopt the greedy strategy shown in equation (11).

$$A_j(t+1)=\begin{cases}A_j(t)', \text{ if } \Phi\left(A_j(t)'\right)<\Phi\left(A_j(t)\right)\\ A_j(t), \text{otherwise}\end{cases} \tag{11}$$

Where, $\Phi\left(A_j\right)$ is the fitness function.

3.3 Differential Evolution Particle Swarm Optimization

Comparing and analyzing the characteristics of the particle swarm optimization algorithm and the differential evolution algorithm, it can be found that the memory capability of the differential evolution algorithm enables it to track the current search situation to adjust its search strategy, and has strong global convergence ability and robustness. Awesome. The particle swarm optimization algorithm has the characteristics of simple algorithm, fast operation speed and strong search ability. The new particle swarm optimization algorithm, differential evolution algorithm, utilizes the respective advantages of the two algorithms and combines them organically. The essence of the hybrid algorithm is based on a dual population strategy, in which the individuals in one population operate and evolve according to the particle swarm optimization algorithm, and the individuals in the other population operate and evolve according to the differential evolution algorithm. In the evolution process, an information exchange is introduced. The mechanism enables information to be transmitted between the two populations, which helps individuals avoid erroneous information judgments and fall into local optimal points. The nonlinear dynamic adaptive inertia weight strategy is used to improve the performance of the algorithm, and its update equation is shown in Equation (12).

$$w(t) = w_{end} + (w_{start} - w_{end}) \times \exp\left(-k \times \left(\frac{t}{t_{\max}}\right)^2\right) \tag{12}$$

Where, k is the control factor,Controls the smoothness of the change curves of w and t, usually 3.

The implementation steps of the differential evolution particle swarm algorithm designed in this paper are as follows:

Step1: Divide the group into two groups equally $\mathrm{POP}^{\mathrm{PSO}}$ and $\mathrm{POP}^{\mathrm{DE}}$,The optimization objectives of $\mathrm{POP}^{\mathrm{PSO}}$ and $\mathrm{POP}^{\mathrm{DE}}$ are the same, but the initialization positions are located in different regions.

Step2: Basic parameter settings: M is subgroup size, $n_{\max}$ is the maximum number of iterations, ε is solution accuracy, w_{start} is maximum inertia weight, w_{end} is minimum inertia weight, k is control factor, c_1 and c_2 is acceleration factor, σ is scaling factor, CR is mutation probability.

Step3: Initialize the population separately $\mathrm{POP}^{\mathrm{PSO}}$ and $\mathrm{POP}^{\mathrm{DE}}$.

Step4: According to formula (10), formula (11) and formula (15), speed and position update are performed for all individuals in $\mathrm{POP}^{\mathrm{PSO}}$ group. Among them, the standard selected for each update is the optimal fitness value of the particle fitness function. According to equations (10), (11) and (15), speed and position updates are performed for all individuals in the population. Among them, the standard selected for each update is the optimal fitness value of the particle fitness function.The fitness function fitness value calculation method: adopt the serial scheduling generation scheme to obtain the scheduling scheme of the particles in the $\mathrm{POP}^{\mathrm{PSO}}$ group.

Step5: According to formula (12), formula (13) and formula (14), mutation, crossover and selection operations are performed on all individuals in $\mathrm{POP}^{\mathrm{DE}}$ population. Among them, when performing the selection operation, the selection criterion is that the fitness value of the particle fitness function is optimal.The fitness function fitness value calculation method: adopt the serial scheduling generation scheme to obtain the scheduling scheme of the particles in the $\mathrm{POP}^{\mathrm{DE}}$ group..

Step6: According to the fitness value, the best individual $\mathrm{G}_{\mathrm{BEST}}^{\mathrm{PSO}}$ in the $\mathrm{POP}^{\mathrm{PSO}}$ group is selected.

Step7: According to the fitness value, the best individual $\mathrm{G}_{\mathrm{BEST}}^{\mathrm{DE}}$ in the $\mathrm{POP}^{\mathrm{DE}}$ group is selected.

Step8: Compare the pros and cons of $\mathrm{G}_{\mathrm{BEST}}^{\mathrm{PSO}}$ and $\mathrm{G}_{\mathrm{BEST}}^{\mathrm{DE}}$,The best individual is selected as the evolutionary basis for the next generation of $\mathrm{POP}^{\mathrm{PSO}}$ and $\mathrm{POP}^{\mathrm{DE}}$.

Step9: Determine whether the particles are stagnant during the optimization iteration process. If so, mutate the particles according to the following mechanism:

IF $\left(x_i(t)=x_i(t+1)=x_i(t+2)=...=x_i(t+p)\right)\&\left(\sigma\left(x_i(t+p)\right)\neq\sigma^*\right)$

THEN

$x_i(t+p+1)=X_{\min}+rand\left(0,1\right)\times\left(X_{\max}-X_{\min}\right)$

END

Where, σ^* represents the global minimum value of the fitness function, p is the maximum number of iterations allowed to stall, $\left(X_{\max}-X_{\min}\right)$ is the defined allowable search boundary.

Step10: Record the best individual in the current whole population. If the accuracy requirement is met or the entire evolution has reached the maximum number of iterations, the algorithm is terminated; otherwise, go to Step 4.

Experimental results and analysis

The experimental platform is ArcGIS 10.2, the programming language version is Python 2.7, the SciPy software package is used for numerical calculation, the matplotlib software package is used for the drawing library, and the radial basis function model is used for the decompression model. PSO, GA, ABC and ICABC algorithms are used for deciphering calculation respectively. The deciphering object is 2 square kilometers in the area of Hunan Technology and Business University in China. For information security, this paper does not use the vector map of the land department, but uses the vector map obtained from the Internet. Non-confidential map, the original data is shown in Figure 1:

Figure 1 Raw data to be decrypted

When comparing the models, a certain number of control points are selected, the parameters are obtained through calculation, and the parameters are substituted into the control points to compare the precise transformation characteristics of the control points. The model sets the maximum limit distance to 50 meters and the minimum limit distance to 30 meters. The number of control points selected in this section is 12, with 120 degrees east longitude as the central meridian. After de-densification by the differential evolution particle swarm algorithm, it is roughly evenly distributed in the data area. As shown in Table 1, the de-densification transformation of the control points is the smallest. It is 39.16 meters and the maximum is 45.82 meters.

Table 1: Decryption calculation data using differential evolution particle swarm algorithm

point number	source coordinates	target coordinates	Disturbance distance
A	10358009.75 ,2532503.82	10358042.14,2532529.25	41.18
B	10357995.68 ,2532170.65	10357955.73,2532177.05	40.46
C	10357937.48 ,2531734.22	10357963.64,2531770.23	44.51
D	10357810.76 ,2531688.63	10357846.81,2531665.93	42.60
E	10357692.34 ,2531528.12	10357668.76,2531559.39	39.16
F	10357506.84 ,2531551.61	10357539.07,2531526.79	40.67
G	10357773.83 ,2532044.90	10357799.03,2532014.61	39.40
H	10357859.89 ,2532343.39	10357888.25,2532377.09	44.05
I	10357633.64 ,2531999.33	10357667.18,2531968.11	45.82
J	10357729.57 ,2532378.22	10357767.84,2532388.64	39.67
K	10357817.28 ,2532653.73	10357850.07,2532676.75	40.07
L	10357652.05 ,2532550.77	10357611.08,2532565.33	43.48

The GA, ABC, FA and DEPSO swarm algorithms are used to decrypt the map shown in Figure 1, respectively. The four dimensions of calculation time, topology retention, disturbance distance deviation, and average disturbance distance are shown in Table 2. Among them, the topological maintenance row adopts manual evaluation and is divided into five grades: A, B, C, D, and E, of which grade A is the highest.

Table 2 PSO, GA, ABC and ICABC evaluation data

	GA	ABC	FA	DEPSO
Computation time (seconds)	2.514	2.312	2.148	2.057
topology retention	B	B	C	A
Average disturbance distance (m)	35.67	38.46	39.81	41.76
Average overrun deviation (m)	2.13	1.97	1.61	1.57

It can be seen from Table 2 that the FA algorithm has the worst topology retention, the DEPSO algorithm has the best topology retention, the GA calculation takes the longest time, and the DEPSO has the highest calculation efficiency. The DEPSO algorithm is the best among the four algorithms both in terms of average disturbance distance and average out-of-limit deviation.

The algorithm in this paper greatly increases the search breadth through differential evolution and particle swarm parallel search mechanism; in addition, by implementing the mutation mechanism when the stagnation phenomenon occurs in the optimization iteration process, the inertia weight factor of the dominant particle is adjusted nonlinearly to make it It can change rapidly in the early stage of search to improve the efficiency of the search, so that the particles can easily jump out of the local optimum. Through these measures, the algorithm in this paper enhances the diversity of the population, so that it can easily avoid premature convergence and obtain a global optimal solution in a wider search range, thus obtaining a better optimization effect than the literature algorithm.

4. Conclusion

This paper proposes a differential evolution particle swarm optimization algorithm, which can ensure that the entire particle swarm can quickly and effectively deviate from the local optimum and avoid premature convergence, so it has a strong global optimization ability. The algorithm is applied to the vector map desecration problem, and it outperforms the GA, ABC and FA algorithms in four aspects: computation time, topology preservation, average disturbance distance and average out-of-limit deviation.

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