Research on nondestructive measurement solving algorithm based on grid slice volume

Yong Gan, Junkai Luan¹, Qiufeng Zhang and Cuiyun Jia

School of Mechanical and Electrical Engineer, Guilin University of Electronic Technology, Guilin 541004, China

¹E-mail: 2545188670@qq.com

Abstract. In this paper, an improved discrete binary particle swarm optimization (BPSO) for large scale 0-1 integer programming is proposed. Firstly, a large-scale 0-1 integer programming model based on the multi-directional slice volume of the virtual grid element is constructed, and the optimization objective function is constructed to change the problem of solving the equations into the problem of seeking the optimal solution. Secondly, the 0-1 model intelligent solution algorithm based on the improved BPSO algorithm is designed, and the model solution system based on the grid slice volume measurement is designed. Finally, through the analysis of the experimental results, it shows that the improved discrete particle swarm optimization algorithm has a significant improvement on the convergence and calculation efficiency of the fitness function, which shows that the algorithm has a good optimization performance.

1. Introduction

Based on the three-dimensional nondestructive measurement method of grid slice volume measurement, it solves the problem that complex mechanical parts with internal through-hole are difficult to measure effectively, which has the advantages of fast speed and high precision [1]. As shown in Figure 1, it is the schematic diagram of the measuring device. The key technology lies in: using the layering principle, realizing the layering displacement through the layer by layer feeding of the precision motion platform, completing the measurement of the slice volume in different directions, establishing the three-dimensional mathematical model of the slice micro grid cell, processing and solving the measured data by the BPSO method, and finally writing the three-dimensional reconstruction method based on the ordered point cloud to recognize the inner contour and restore the solid.

Particle swarm optimization (PSO), as a swarm intelligence algorithm, has many advantages and is suitable for solving 0-1 integer programming problems. Many experts and scholars at home and abroad have carried out a series of research on this. Xu Yichun and others improved the particle swarm optimization algorithm to solve this problem by simplifying the probability calculation mode of the algorithm [2]. Shi Qiuhong et al. proposed to solve the 0-1 knapsack problem by artificial fish swarm algorithm [3]; You Xiaoliang and He Guangsheng et al. solved the 0-1 integer programming model in power system fault diagnosis by integrating firefly and particle swarm algorithm [4]; Li Fuqing et al. proposed a hybrid genetic tabu search algorithm to solve the 0-1 integer programming problem in the setting of special rail for traffic planning [5]. All the above algorithms have achieved
good results. But none of them involve the solution of the large-scale 0-1 integer programming model, nor the design and implementation of the solution system.

![Grid unit slice volume lossless measurement method.](image)

**Figure 1.** Grid unit slice volume lossless measurement method.

2. **Nondestructive measurement model for meshing layer volume**

In the space coordinate system, according to the requirements of measurement accuracy, the geometric parts to be measured are divided into several ordered micro grid cells, and each cell is a space cell with equal side length. Based on the space grid element method, the mathematical representation model of geometric parts is constructed. The description method based on binary mass is adopted. The volume value of the real grid body is 1, and the volume value of the virtual grid body is 0.

![Hierarchical schematic of virtual slice grid.](image)

**Figure 2.** Hierarchical schematic of virtual slice grid.

In order to realize the 3D non-destructive measurement and reconstruction of the measured geometry parts by meshing, the measured geometry parts are included by the minimum space inclusion with side length \( n \). Among them, the side length of the grid unit is taken as 1 (assuming the maximum length of the measured geometric part is \( L \) and the measurement accuracy is \( \Delta L \), then \( n = L / \Delta L \). In the measurement planning, \( \Delta L \) can be adjusted appropriately so that \( n \) is an integer).
Then the smallest containment body has a total of \( n^3 \) microgrids. As shown in Figure 2, immerse the liquid layer by layer in the z-axis direction, with each stroke of 1. Note that the volume of the grid body \( T_{(i,j,n)} \) is \( V_{(i,j,n)} \), and the volume of the \( n \)th layer in the Z direction is \( V_{Zn} \), then the mathematical model for calculating the volume of each layer can be established.

The calculation formula of the volume of the first layer along the z-axis direction is:

\[
V_{(1,1,1)} + V_{(2,1,1)} + \cdots + V_{(n,1,1)} + V_{(1,2,1)} + \cdots + V_{(n,n,1)} = V_{Z1}
\]  

(1)

The calculation formula of the volume of the second layer along the z-axis direction is:

\[
V_{(1,1,2)} + V_{(2,1,2)} + \cdots + V_{(n,1,2)} + V_{(1,2,2)} + \cdots + V_{(n,n,2)} = V_{Z2}
\]

(2)

The calculation formula of the volume of the third layer along the z-axis direction is:

\[
V_{(1,n,1)} + V_{(2,n,1)} + \cdots + V_{(n,n,1)} + V_{(1,1,n)} + \cdots + V_{(n,n,n)} = V_{Zn}
\]

(3)

For \( n \) linear equations along the z-axis, set

\[
f_1(V_{(1,1,1)}, V_{(2,1,1)}, \cdots, V_{(n,n,n)}) = V_{(1,1,1)} + V_{(2,1,1)} + \cdots + V_{(n,1,1)} + V_{(1,2,1)} + \cdots + V_{(n,n,1)} - V_{Z1} = \sum_{i=1}^{n} \sum_{j=1}^{n} V_{(i,j,l)} - V_{Z1}
\]

(4)

\[
f_2(V_{(1,1,1)}, V_{(2,1,1)}, \cdots, V_{(n,n,n)}) = V_{(1,1,2)} + V_{(2,1,2)} + \cdots + V_{(n,1,2)} + V_{(1,2,2)} + \cdots + V_{(n,n,2)} - V_{Z2} = \sum_{i=1}^{n} \sum_{j=1}^{n} V_{(i,j,2)} - V_{Z2}
\]

(5)

\[
f_n(V_{(1,1,1)}, V_{(2,1,1)}, \cdots, V_{(n,n,n)}) = V_{(1,n,1)} + V_{(2,n,1)} + \cdots + V_{(n,n,1)} + V_{(1,1,n)} + \cdots + V_{(n,n,n)} - V_{Zn} = \sum_{i=1}^{n} \sum_{j=1}^{n} V_{(i,j,n)} - V_{Zn}
\]

(6)

Among them, the \( X = (x_1, x_2, \cdots, x_n) = (V_{(1,1,1)}, V_{(2,1,1)}, \cdots, V_{(1,n,1)}, V_{(2,1,1)}, \cdots, V_{(n,n,n)}) \)

Then there are

\[
\begin{align*}
  f_1(x_1, x_2, \ldots, x_n) &= 0 \\
  f_2(x_1, x_2, \ldots, x_n) &= 0 \\
  \cdots \\
  f_n(x_1, x_2, \ldots, x_n) &= 0
\end{align*}
\]

(7)

In Cartesian coordinate system, \( 9n \) equations can be listed when measuring along X, Y, Z axis and 6 diagonal directions respectively. According to the definition of micro grid body, if the volume of micro grid body is known to be \( V \), then there are only two kinds of micro grid bodies in space, either the real grid body, the volume is \( V \), for the convenience of research, the unit volume is 1; or the virtual grid body, the volume is 0; then the volume value of grid body is only 1 or 0, including:

\[
V_{(i,j,n)} \cdot (V_{(i,j,n)} - 1) = 0
\]

(8)

In the formula, \( V_{(i,j,n)} \) is the equivalent volume of tiny mesh \( T_{(i,j,n)} \), \( i = 1,2,\ldots,n \), \( j = 1,2,\ldots,n \). Therefore, after the mesh volume normalization process, there are \( n^3 \) non-linear equations of \( V_{(1,1,1)} \cdot (V_{(1,1,1)} - 1) = 0 \), \( V_{(2,1,1)} \cdot (V_{(2,1,1)} - 1) = 0 \), \ldots \( V_{(n,n,n)} \cdot (V_{(n,n,n)} - 1) = 0 \).

\[
\begin{align*}
  f_1(x_1, x_2, \ldots, x_n) &= 0 \\
  f_2(x_1, x_2, \ldots, x_n) &= 0 \\
  \cdots \\
  f_{9n}(x_1, x_2, \ldots, x_n) &= 0 \\
  x_i &= \{0,1\} (i = 1,2,\ldots,n^3)
\end{align*}
\]

(9)
By using BPSO algorithm to solve the equations, we can get the $n^3$ unknowns, so that we can get the mass of any grid element entity, and reconstruct the 3D entity model of the mechanical parts to be tested by using the mass of all grid element entities.

3. Solution of meshing layer volume nondestructive measurement model

3.1. Standard particle swarm optimization

Particle swarm optimization is a parallel algorithm based on population intelligence. Any optimization particle in the population may be a feasible solution of the problem to be solved, and it has a random optimization speed. Through information interaction with other individuals, it can obtain organization information and adjust the optimization strategy of particles in the population [6, 7].

Assuming that the population GM consisting of $M$ particles is optimized in $D$-dimensional continuous space, where $X = (x_1, x_2, \cdots, x_D)$, each particle is represented by a $D$-dimensional vector, that is $x_i = (x_{i1}, x_{i2}, \cdots, x_{iD})$, $i = 1, 2, \cdots, M$,

$$v_{id}^{t+1} = wv_{id}^t + c_1r_1(t)(p_{id}^t - x_{id}^t) + c_2r_2(t)(p_{gd}^t - x_{id}^t)$$

(10)

$$x_{id}^{t+1} = x_{id}^t + v_{id}^{t+1}$$

(11)

Where, $t = 1, 2, \cdots$ is the number of iterations; $d = 1, 2, \cdots, D$; $i = 1, 2, \cdots, M$; $w$ is the inertia weight; $c_1, c_2$ is the acceleration constant, which indicates the step length to guide the optimization particles to $p_{id}^t$ and $p_{gd}^t$; $r_1, r_2$ is the random number in the $[0,1]$ interval; $v_{id}^t$ and $x_{id}^t$ is the speed and position of particle $i$ after $t$ times of searching and solving, while $v_{id}^{t+1}$ and $x_{id}^{t+1}$ are the speed and position of $i$ after $t + 1$ times of updating iteration, and $v_{id}$ is set by the user to limit the speed of particle. $p_{id}^t$ is the best position of particle $i$ in the $t$ times search; $p_{gd}^t$ is the best solution of all particle $p_{id}^t$ in the population in the $t$ times search, which is called the position of the global optimal solution.

3.2. Discrete binary particle swarm optimization

In order to solve the limitation of traditional particle swarm optimization (PSO) in solving discrete space, Kenney and Eberhart proposed BPSO algorithm based on PSO algorithm. The location update equation of the BPSO algorithm is as follows:

$$x_{id}^{t+1} = \begin{cases} 1 & r < s(v_{id}^{t+1}) \\ 0 & \text{other} \end{cases}$$

(12)

Where $r$ is a random number generated from the $U(0,1)$ interval.

The inertia weight value has an important influence on the global and local optimization ability of BPSO algorithm. In view of that the algorithm pays attention to the comprehensiveness of optimization search in the early stage of operation, and needs to improve the convergence rate in the later stage, the linear decreasing dynamic adjustment is carried out for $w$, and the adjustment method is shown in Equation (13):

$$w = w_{max} - (w_{max} - w_{min}) \cdot \frac{t}{T_{max}}$$

(13)

In the formula, $w_{max}, w_{min}$ are the maximum and minimum values of particle velocity respectively. Generally, 1.2 and 0.9 are taken respectively; $t$ is the current iteration number; $T_{max}$ is the maximum iteration number.
3.3. Designing algorithm
Based on the improved discrete particle swarm optimization algorithm, this paper designs a solution algorithm suitable for this project.

1. Fitness function design:
   In order to ensure that the minimum fitness function is the optimization objective, the design fitness function is

   \[
   F(x) = \sum_{i=1}^{n} f_i(x_1, x_2, \ldots, x_n)
   \]

   (14)

   The problem of solving equations is equivalent to the optimization problem of solving \( \min_f(x) \).

2. The algorithm flow is as follows:
   (1) The structural data of quality information is established by inputting the overflow quality and virtual grid parameter information corresponding to each direction slice entity.
   (2) Selecting the improved BPSO algorithm, initializing the particle size \( m \), learning factor \( c_1, c_2 \), the maximum value \( w_{\max} \) and minimum value \( w_{\min} \) of inertia weight, and the maximum number of iterations \( T_{\max} \).
   (3) Initializing the velocity \( v \), position \( p \), and number of iterations \( t \) of the population particle.
   (4) According to the fitness function formula, the optimal fitness value of each individual particle is calculated.
   (5) According to the historical optimal fitness values of individuals and populations, the individual and global optimal positions of particles are updated.
   (6) Iteratively updating the speed and position of particles.
   (7) Performing boundary condition processing.
   (8) Judging termination condition: if \( t < T_{\max} \), skipping to step (4) to continue the optimization; if \( t = T_{\max} \), terminating the optimization and outputting the calculation results.

3.4. Architecture of system and implementation of mechanism
The whole solution system is realized by MATLAB language, and the architecture of the solution system is shown in Figure 3. The user can input the slice volume mass through the human-computer interaction module, and input the initialization parameters of the discrete particle swarm optimization algorithm, and realize the slice volume input through the formula calculation transformation. In the process of discrete particle swarm optimization (DPSO), the solution process is displayed dynamically, and the results is displayed finally.

![Figure 3. Architecture of solving system.](image)

The improved inertia weight part realizes the improved mechanism of discrete particle swarm, while the fitness function realizes the fitness function proposed in this paper, and the improved discrete particle swarm algorithm part realizes the intelligent solution of the established model.
4. Case verification and simulation

4.1. Function analysis of inertia weight
Considering the influence of inertia weight on the optimization ability of BPSO algorithm, this paper compares different inertia weight BPSO algorithm to obtain the optimal inertia weight. In the simulation experiment, particles of different sizes are used to test every dimension of the objective function, and the method of random generation is used for the initial population, the acceleration factor \( c_1 = c_2 = 2.0 \), the fixed inertia weight is 0.8, and the definition domain of the linearly decreasing inertia weight is \([1.2, 0.4]\). When the number of iterations of particle optimization \( T > T_{max} \), the optimization operation will be terminated automatically.

It can be seen from the experimental results in the Tables 1 and 2 that, compared with the traditional fixed inertia weight BPSO algorithm, the performance of linear continuous decline of inertia weight BPSO algorithm is significantly improved, the average optimization result is also significantly improved, and the algorithm achieves the expected effect of improving the convergence speed. Moreover, the BPSO algorithm with decreasing inertia weight also has good stability in the process of objective function optimization.

| Population size | Dimension | Maximum algebra | Average fitness value | Maximum fitness value | Minimum fitness value | Time     |
|-----------------|----------|-----------------|-----------------------|-----------------------|-----------------------|----------|
| 100             | 27       | 1000            | 0.35                  | 4.0                   | 0                     | 3.114039 |
| 125             | 64       | 2000            | 25.85                 | 41.5                  | 17.5                  | 11.674363|
| 300             | 125      | 3000            | 550.575               | 671.5                 | 336.5                 | 17.655086|
| 500             | 27       | 1000            | 0.20                  | 4.0                   | 0                     | 9.370245 |
| 125             | 64       | 2000            | 15.85                 | 22.5                  | 11.5                  | 26.486483|
| 300             | 125      | 3000            | 409.075               | 486.0                 | 270.5                 | 52.878015|
| 500             | 27       | 1000            | 0.15                  | 3.0                   | 0                     | 15.549277|
| 125             | 64       | 2000            | 14.25                 | 19.0                  | 7.5                   | 46.418156|
| 300             | 125      | 3000            | 423.525               | 469.5                 | 160.5                 | 89.301516|

| Population size | Dimension | Maximum algebra | Average fitness value | Maximum fitness value | Minimum fitness value | Time     |
|-----------------|----------|-----------------|-----------------------|-----------------------|-----------------------|----------|
| 100             | 27       | 1000            | 5.405                 | 10.5                  | 4.0                   | 6.245139 |
| 125             | 64       | 2000            | 84.845                | 234.0                 | 7.0                   | 22.615580|
| 300             | 125      | 3000            | 944.75                | 1575.0                | 507.5.5               | 60.233644|
| 500             | 27       | 1000            | 3.075                 | 6.5                   | 0                     | 36.186785|
| 125             | 64       | 2000            | 32.385                | 108.5                 | 4.0                   | 156.621177|
| 300             | 125      | 3000            | 494.025               | 940.5                 | 117.0                 | 431.652887|
| 500             | 27       | 1000            | 1.40                  | 4.0                   | 0                     | 89.697922|
| 125             | 64       | 2000            | 13.875                | 31.5                  | 6.0                   | 394.985474|
| 300             | 125      | 3000            | 341.525               | 785.5                 | 108.0                 | 1160.657559|

4.2. Validation of the algorithm
The dimension of the data in the experiment is 125. The dimension of the particle is 500 and other factors don’t change. When the number of iterations of the particle optimization is \( t > 5000 \), the optimization operation will be terminated automatically.
Table 3. Experimental results of two BPSO algorithms.

| Algorithm                              | Optimum Solution | Average Fitness Value | Number of Optimal Solutions |
|----------------------------------------|------------------|-----------------------|----------------------------|
| Traditional Fixed Inertial             | 0                | 6.705                 | 7                          |
| Inertial Weight Linear Decline         | 0                | 0.934                 | 22                         |

Through the analysis of the experimental results, it is found that the experimental results of the two BPSO algorithms in solving the problem of grid slice volume measurement are shown in Table 3. In 30 experiments, both algorithms get the known optimal solution of the problem, and the error of the solution is 14.9% and 6.2% respectively. However, the calculation time of the linear decreasing inertia weight BPSO algorithm is almost 1/3 of that of the traditional fixed inertia weight BPSO algorithm. The performance of the algorithm is better than that of the traditional algorithm.

5. Conclusions
In this paper, based on the mesh slice volume nondestructive measurement method to simplify the analysis, mainly from improving the inertia weight, fitness function design and other aspects to optimize the discrete particle swarm optimization algorithm based on mesh slice volume nondestructive measurement. The results show that the convergence accuracy and computational efficiency of the adaptive function of the improved discrete particle swarm algorithm based on the grid-layer volume lossless measurement model are obviously improved compared with the traditional discrete particle swarm algorithm, the error of the solution is reduced by 8.7%, and the calculation speed is increased by more than 2/3. The algorithm has good optimization performance and the system has good practicability.

Acknowledgement
This work is supported by National Natural Science Foundation of China (Grant No. 51665005).

References
[1] Gan Yong 2012 3D homogeneous solid measurement method based on static equilibrium principle[J]. China Mechanical Engineering 23(11) 1350-1353
[2] Xu Yichun and Xiao Renbin 2007 An improved binary particle swarm algorithm[J]. Pattern Recognition and Artificial Intelligence 20(06) 788-793
[3] Shi Qiuhong 2010 study on the improvement and application of artificial shoal algorithm[D]. Gansu Agricultural University
[4] You Xiaoliang, He Guangjun, Tian Dewei and Li Penang 2015 A study of firefly and particle swarm hybrid algorithms for power system fault diagnosis[J]. Computer Measurement and Control 23(10) 3342-3346353
[5] Li Fuqing 2016 Study on the Modeling and Solving of Special Channel Setting in Traffic Planning[D].
[6] Hu Jin 2011 Grid task scheduling algorithm based on improved PSO algorithm[D]. Central South University
[7] Li Xun, Gong Qingwu and Guan Qinyue 2013 Application of PSO - based modal atomic method in time - dependent tracking of low frequency oscillation mode[J]. Chinese Journal of Electrical Engineering 2013(10) 14108-118