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A slicing parameter optimization method using group search optimization algorithm in STL model for 3D printing application

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ABSTRACT. *In order to improve the accuracy and efficiency of 3D printing, a slicing direction and thickness optimization method based on group search optimization (GSO) algorithm is proposed. Firstly, according to the geometric characteristics of STL data model, the relationship between volume error, production time and layered direction and thickness in 3D printing is analyzed, and a weighted objective function is constructed. Then, the GSO algorithm is used to optimize the solution space to obtain the optimal slicing parameters. The experimental results show that this method can effectively reduce the volume error and improve the printing efficiency.*

KEYWORDS: *3D printing; slicing parameter optimization; volume deviation; group search optimization algorithm*

1. Introduction

In recent years, 3D printing technology is a hot topic in Additive Manufacturing (AM). STL model, as the file format of rapid prototyping technology service, is adopted by 3D printing technology [1-3]. Among them, how to extract the two-dimensional cross section of STL 3D model is always the basic problem in the research of 3D printing. The same STL 3D model will produce different two-dimensional cross-section information with different layering algorithms, and the gradient effect and printing efficiency of the printed entity will be different [4,5].

The factors that determine the results of slicing are the direction of slicing and the thickness of slicing [6]. The direction of slicing is the normal direction of the slice plane, and the thickness of slicing refers to the longitudinal distance between two adjacent slices. Layer thickness is limited by the hardware condition of printer.

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The smaller the layer thickness is, the more delicate the model is, and the longer the construction time is. In rapid prototyping process and forming system, the direction and thickness of layers are mainly selected according to experience, with strong subjectivity [7].

Several types of slicing algorithms commonly used are [8,9]: direct slicing algorithm, adaptive slicing algorithm and slicing algorithm based on Intelligent search. Direct Slicing is the most basic slicing algorithm in 3D printing. It directly divides the triangular patches of STL files. Users define the thickness of the layer to determine all the information of the two-dimensional contours after the layering. Based on the ratio of relative area deviation, adaptive layering (AAD) is used to calculate whether the ratio of area deviation between two continuous layers is less than a specific threshold to set the layer thickness adaptively. However, it is difficult to judge the model with many facets and complex structure, and the optimal slicing direction must be determined according to certain criteria. With the development of intelligent optimization algorithms, some intelligent slicing algorithms have been formed. However, most of them are single-objective optimization, that is to say, single factor such as volume deviation or surface smoothness is the objective function to obtain the optimal direction.

In order to solve the above problems, the relationship between volume deviation, fabrication efficiency and layering direction and thickness was established, and a weighted multi-objective optimization model was constructed. In addition, group search optimization (GSO) has good local search ability and is better at searching in a relatively small local search area. For this reason, this paper optimizes the objective function by GSO algorithm to realize the intelligent selection of layered direction and thickness.

2. Optimization model

2.1 optimization objective model

In 3D printing or other rapid prototyping technology, the volume deviation of the model is defined as the difference between the material used to construct the model and the material needed for the theoretical model. Volume deviation mainly affects the accuracy of the model. The smaller the volume deviation, the closer the surface of the model is to that of the theoretical model, the higher the surface accuracy of the model entity will be. The step effect on the surface of the model is the direct cause of the error volume of the model [11,12].

Layering direction (θ_1, θ_2) and thickness h were taken as design variables, and surface volume error ΔV and manufacturing time T were taken as objective

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functions. Setting the weight coefficients of k_1 and k_2 corresponding to ΔV and T respectively, the optimal mathematical models of the layering direction and thickness of 3D printing process are expressed as follows:

$$\begin{aligned} &Find: X=[\theta_1,\theta_2,h] \\ &Min: Y=k_1\Delta V+k_2T \end{aligned} \tag{1}$$

2.2 Volume error expression

The total volume error ΔV produced by the slicing processing can be expressed as the sum of the volume errors produced by each layer.

Hypothesis: In the i layer, the volume error caused by intersecting with one of the triangular patches j is ΔV_{ij}. The angle between triangular patch j and layered direction $P=[x_p,y_p,z_p]$ is θ_j, while the unit vector in the normal direction of triangular patch j is N_i, as shown in Figure 1. Fig. 1 (a) is the slicing of layer i, and Fig. 1 (b) is the slicing of a triangular surface.

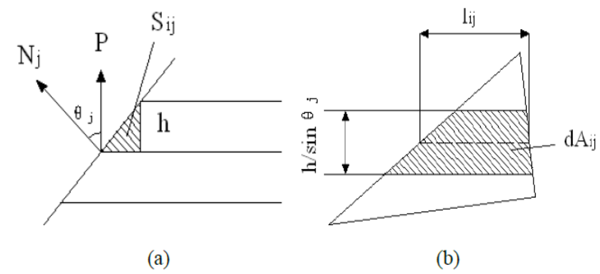

Fig. 1 Geometric diagram of volume error generated by layer i and triangular facet j

From Fig. 1 (b), it can be seen that the i TH layer intersects with the triangle patch j to form an intersection line, thus forming a shadow part with an area of dA_{ij}, of which l_{ij} is the median line of the two intersections on the triangle patch j. Then, the volume ΔV_{ij} of the step formed by layer i and triangle j can be regarded as the integral of the area S_{ij} of the shadow part in Figure 1 (a) in l_{ij} directions, that is:

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$$\Delta V_{ij} = \int_0^{l_{ij}} S_{ij} dS_{ij} \tag{2}$$

$$S_{ij} = \frac{h^2 \cos\theta_j}{2\sin\theta_j} \tag{3}$$

Then, the total volume error caused by step effect of layer i is as follows:

$$\Delta V_i = \sum_j \Delta V_{ij} = \sum_j \frac{h^2 \cos\theta_j}{2\sin\theta_j} l_{ij} \tag{4}$$

The total volume error caused by step effect of each layer is as follows:

$$\Delta V = \sum_i \Delta V_i = \sum_j \sum_i \frac{h^2 \cos\theta_j}{2\sin\theta_j} l_{ij} = \sum_j \Delta V_j \tag{5}$$

Because the thickness of the layer is very small, it can be considered that the two intersecting lines produced by the intersection of layer i and triangle j are equal in length. Thus, the two intersecting lines form a rectangle with the edges of the triangular surface, whose length and height are l_{ij} and $h/\sin\theta_j$, respectively.

$$dA_{ij} = \frac{h}{\sin\theta_j} l_{ij} \tag{6}$$

Substituting Formula (6) into Formula (5) obtains:

$$\Delta V_j = \sum_i \frac{h\cos\theta_j}{2} dl_{ij} = \frac{h\cos\theta_j}{2} A_j \tag{7}$$

Among them, A_j is the area of triangle j . Assuming that $(x_{ja}, y_{ja}, z_{ja}), a = 1,2,3; j = 1,2\cdots s$ is the coordinates of the three vertices of triangular patch j and s is the number of triangular patches, the total volume error of the whole model is:

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$$\Delta V=\sum_{j}\frac{h\cos\theta_j}{2}A_j,\ j=1,2\cdots s \tag{8}$$

It is noteworthy that when the angle between the layered direction P and the normal phase vector N_j of the triangle patch is $\theta_j\in[\frac{\pi}{2}+2k\pi,\pi+2k\pi]$. When k is taken as an integer, the volume error is negative. In this case, the absolute value of the volume error should be taken. When $\theta_j=0,\pi$, that is, the normal vector of the triangular patch is perpendicular to the vector of the stratified direction, the step effect will not appear after the model is stratified, so the volume error will be zero. So there are:

$$\cos\theta_j=\begin{cases}0 & ,\theta_j=0,\pi\\ \left|P\cdot N_j\right| & ,\theta_j\neq 0,\pi\end{cases} \tag{9}$$

2.3 Making Time Expressions

In 3D printing process, in order to reduce the production time, we only need to find a better layered direction, so that the height of the model in the Z axis direction of the working slot is minimum. In this way, the total number of slices of the model will be reduced, and the total time of making the model will also be reduced [13].

The total number of slices of the model is determined by two parameters, the thickness of slices and the height of the model on Z axis. Therefore, according to experience, when the thickness of slices is constant, the height of the model in the direction of placement can be minimized to reduce the production time. That is to say, by projecting all vertices n in the STL model in the given layered direction, and dividing the minimum value obtained by subtracting the projection length by the slice thickness, the minimum height of the model in the layered direction can be obtained. Let $m_i(x_i,y_i,z_i),i=1,2,\cdots n$ be a vertex coordinate of the surface in the model and n be the number of vertices. Then the production time expression is:

$$T=\frac{\max(P\cdot m_i)-\min(P\cdot m_i)}{h} \tag{10}$$

Among them, P is a slicing directional vector: $P=(\sin\theta_1\cos\theta_2,\sin\theta_1\sin\theta_2,\cos\theta_1)$

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3. GSO algorithm

The GSO algorithm consists of three operations: discoverer operation, searcher operation and rogue operation. In the iteration process, the member with the best fitness value is selected as the discoverer. Several members whose fitness value is higher than threshold are selected as searchers. A number of members whose fitness value is below the threshold are selected as wanderers [14].

Finder operation:

During the discoverer's operation, animals rotate sensory receptors to capture information from the environment. In the s -dimensional search space, the position of the i -member of the z th search round (iteration) is expressed as $y_i^z \in R^s$, the search angle is expressed as $\lambda_i^z = (\lambda_{i1}^z, \ldots, \lambda_{i(s-1)}^z) \in R^{s-1}$, and the corresponding search direction is expressed as $F_i^z(\lambda_i^z) = (f_{i1}^z, \ldots, f_{is}^z) \in R^{s-1}$. It can be calculated by polar coordinate transformation according to λ_i^z . The expression is as follows:

$$\begin{cases} f_{i1}^z = \prod_{p-1}^{s-1} \cos(\lambda_{ip}^z) \\ f_{ij}^z = \sin(\lambda_{i(j-1)}^z) * f_{i1}^z \\ f_{is}^z = \sin(\lambda_{i(j-1)}^z) \end{cases} \tag{11}$$

Assuming that the location of the finder is y_p at the z TH iteration, the finder will choose three different angles for visual scanning at the current location, that is, first scan at zero, then scan to the right and then to the left. The maximum search angle of vision is $\omega_{\max}$ and the maximum distance of vision scanning is $d_{\max}$. The expression is as follows:

$$d_{\max} = \|U_i - L_i\| = \sqrt{\sum_{i=1}^{s} (U_i - L_i)^2} \tag{12}$$

In the formula, U_i and L_i are the upper and lower bounds of the range of design variables. Then, the three different locations found by the discoverer through scanning are as follows:

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$$\begin{cases} y_{zero} = y_p^z + r_1 d_{\max} F_p^z(\lambda^z) \\ y_{right} = y_p^z + r_1 d_{\max} F_p^z(\lambda^z + r_2 \frac{\omega_{\max}}{2}) \\ y_{left} = y_p^z + r_1 d_{\max} F_p^z(\lambda^z - r_2 \frac{\omega_{\max}}{2}) \end{cases} \quad (13)$$

In the formula, y_{zero} represents zero scan, y_{right} represents right scan, y_{left} represents left scan, $r_1 \in R^1$ is normal distribution random number with mean value of 0 and variance of 1, and $r_2 \in R^{s-1}$ is a random sequence.

Then, the fitness of the three new locations searched by the discoverer is calculated and moved to the location with the best fitness. If the new position is not as good as the current position, turn its head to a new angle as follows:

$$\lambda^{z+1} = \lambda^z + r_2 \gamma_{\max} \quad (14)$$

In the formula, $\gamma_{\max}$ represents the maximum steering angle. If the finder fails to find a better location after a iterations, the search process is stopped and remains motionless, that is:

$$\lambda^{z+a} = \lambda^z \quad (15)$$

Searcher operation:

The searcher operates as a follower of the discoverer and searches the area around it. At the z -th iteration, the i th searcher performs a region search [15] based on the location information shared by the discoverer, and the location updates are as follows:

$$y_i^{z+1} = y_i^z + r_3(y_p^z - y_i^z) \quad (16)$$

In the formula, $r_3 \in R_s$ represents the random number in the interval.

Rover operation:

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Wanderers operate only random walks to explore new locations. If the i th member of the group is chosen as the wanderer of the z th iteration, it will generate a random angle λ_i, which is expressed as follows:

$$\lambda_i^{z+1} = \lambda_i^z + r_2\gamma_{\max} \quad (17)$$

Similarly, a random distance is chosen, which is expressed as follows:

$$d_i = a \cdot r_1 d_{\max} \quad (18)$$

Then move to a new position according to the following pattern:

$$y_i^{z+1} = y_i^z + d_i F_i^z(\lambda^{z+1}) \quad (19)$$

4. Experimental results and analysis

4.1 Parameter setting

The standard Stanford Bunny model, Bottle model and MakeRobot model are used for experimental analysis. Stanford Bunny's STL model includes 69630 triangular facets, Bottle model 1240 triangular facets and MakeRobot model 1166 triangular facets.

The allowable minimum thickness is 0.07 mm, the allowable maximum thickness is 1.9 mm and the allowable limited cutting depth is 0.07 mm. For the weighted objective function in this paper, since the volume error ΔV is more important than the production time T, the weight coefficient k_1 = 0.6, k_2 = 0.4 is set. For the GSO algorithm, the maximum number of iterations is 200 and the population number is 20. The initial search angle λ^z is $\pi/4$, the maximum search angle $\omega_{\max}$ is π/a^2, the maximum steering angle $\gamma_{\max}$ is $\pi/2a^2$, and the constant a is an integer of approximately $\sqrt{s+1}$.

On a computer equipped with 64-bit Windows 10 system, Core i5-7400, 3.4 GHz frequency and 16GB memory, various layered algorithms are implemented by using MATLAB R2013a.

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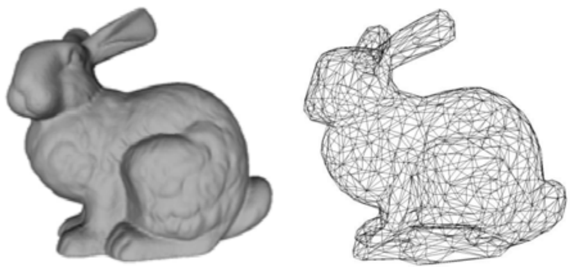
4.2 Layered effect

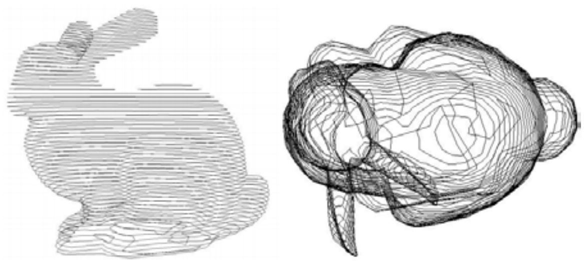
Figure 2 (a) shows the Stanford Bunny model and (b) the STL representation of the model. Figure 2 (a) shows the Stanford Bunny model and (b) the STL representation of the model.



(a)Stanford Bunny Model (b)STL Express

Fig.2 Stanford Bunny Model

Fig. 3 is based on Stanford Bunny model. The slicing results under the optimal slicing direction and thickness parameters are obtained by this method, (a) positive effect map, (b) overhead effect map. The optimal parameters obtained are layered direction (0 degree, 100 degree) and layered thickness (0.203 mm). The graph shows that the layered contour obtained by this algorithm is continuously closed and can be used as input data generated by 3D printing scanning line.



(a) Positive effects map (b) Overlooking effect map

Fig.3 Slicing contour

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4.3 Algorithm comparison

For AAD algorithm, the allowable threshold of relative area difference is 0.28 mm2, and the threshold of relative area deviation ratio is 5%.

From the analysis above, it can be seen that the volume error of the model is affected by both the thickness and direction of the layers. Therefore, the volume error is taken as a performance measure and a number of experiments are carried out. This method is compared with direct slicing (DS) algorithm, adaptive slicing (AAD) algorithm based on relative area deviation ratio and Non-dominated Sorting Genetic Algorithms (NSGA) slicing algorithm proposed in reference [10]. Table 1 shows the volume error under the optimal slicing parameters obtained by each algorithm. Table 2 shows the total number of slices obtained by various algorithms, which is used to represent the time of model making.

It can be seen that because of the simple structure of DS algorithm, it takes a long time to slice according to the minimum layer thickness, and the volume error is also large. Because NSGA only considers volume error to construct single objective optimization model, the number of layered slices is large, which leads to long production time. In addition, the convergence time of NSGA algorithm is longer, so the running time is also longer. In this paper, the GSO algorithm is used to improve the convergence efficiency to a certain extent, and the production time is taken into account in the construction of the objective function, so the comprehensive performance is better. Especially for the model with complex topological structure, the slicing algorithm in this paper has better effect and good stability.

Table 1 Volume Errors of Various Algorithms (mm3)

Model name	DS algorithm	AAD algorithm	NSGA algorithm	Algorithm in this paper
Stanford Bunny	1.05	0.26	0.25	0.21
Bottle	14.37	9.62	7.86	5.37
MakeRobot	23.63	17.83	13.91	11.35

Table 2 The total number of slices of various algorithms

Model name	DS algorithm	AAD algorithm	NSGA algorithm	Algorithm in this paper
Stanford Bunny	825	65	583	473
Bottle	517	105	342	326
MakeRobot	1062	367	499	306

5. Conclusion

In this paper, a layered direction and thickness optimization method based on GSO algorithm is proposed to improve the accuracy and efficiency of 3D printing. The objective function is constructed by weighting the volume error and production time, and the optimal layering parameters are obtained by using GSO algorithm. The simulation results show the effectiveness of the proposed method.

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