Point cloud simplification algorithm based on particle swarm optimization for online measurement of stored bulk grain

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Abstract: The simplification of 3D laser scanning point cloud is an important step of surface reconstruction and volume estimation of bulk grain in granary. This study presented an adaptive simplification algorithm based on particle swarm optimization (PSO). It introduced PSO into the average distance method, a conventional simplification method. The basic idea of this algorithm was to adaptively determine the optimal point reducing intervals of scanning lines according to original point cloud density by PSO. By using the 3D point cloud scanned from bulk grain surface in granary, the proposed algorithm was validated. Compared with the average distance method, the proposed algorithm obtained more evenly distributed point set, smaller reduction ratio (6.96%) and higher volume estimation accuracy (relative error was less than 3‰). The 3D laser scanner (GSLS003, Jilin University and SkyViTech Co., Ltd., Hangzhou, China) used in this study could scan the complete picture of the grain surface in a granary in one time, so the acquired point cloud data do not have to be jointed. For the good simplification performance and capability of updating the reducing interval at any moment, the proposed algorithm and the 3D laser scanner could be used to realize online real-time measurement of stored bulk grain volume in granary.

Keywords: point cloud, simplification algorithm, particle swarm optimization (PSO), 3D laser scanning, large object, stored grain

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1 Introduction

With the development of 3D laser scanning technique, point clouds are emerging as a new representation format of 3D shapes in many applications[1,2]. However, modern 3D laser scanner is capable of producing point cloud set that contains millions of sample points[3], which requires excessively large storage space and long time for post-processing. Therefore, it is necessary to simplify the redundant data to increase accuracy and efficiency of surface reconstruction and modeling. For this purpose, researchers have made great efforts to point cloud simplification. Generally, the point cloud simplification includes conventional and adaptive simplification method. Conventional simplification methods for scanning line type of point clouds mainly include average distance, minimum distance, angular deviation and chord deviation methods[4-7]; however, these methods may result in low efficiency and cannot express the detail of scanning lines.

Recently, 3D laser scanner has been used to scan large objects, such as granary, coal heap, mine and tree canopy[8]-[11]. The point cloud simplification methods for large objects are different from those for small or

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middle-sized objects, due to their surface characteristics, i.e., small curvature change and less detail variety. Moreover, it is impossible to use any single conventional method mentioned above to intelligently measuring these objects. Therefore researchers have focused on the study of the adaptive simplification method in recent years. Ferrari et al.[12] adopted a specified reduction ratio to automatically simplify the vectorized point cloud data, which is suitable for the point cloud data with relatively low space dimensionality. According to a specified reduction ratio, Song and Feng[13] simplified point cloud data by means of searching the subsets of original input data set. Yu et al.[14] proposed an adaptive 3D point cloud simplification algorithm based on fuzzy *k*-means clustering method. Shi et al.[15] presented an adaptive simplification algorithm that can guarantee the boundary integrity and distribution rationality of point cloud data. Wang et al.[16] put forward a simplification algorithm based on Akima spline interpolation to reduce point cloud data smoothly and steadily. In view of stored bulk grain, the simplification method of point cloud data remain to be studied.

Using laser scanning technology, researchers have done some work on the measurement system of stored grain volume. Li and Zhang[17] firstly used the independently developed 3D laser scanner to measure grain volume, but such an upright laser scanner made the scanning results have to be jointed. Liang and Sun[18] designed a multi-site laser scanning system for measuring grain volume, which needs to be reconstructed after re-sampling. Ren et al.[19] used a laser sensor to conduct non-contact measurement of stored grain, and their system could obtain grain volume through integration of actual measured data. The online measurement of grain volume emphasizes on efficiency and memory of footprint particularly[20]. In summary, the online measurement systems are generally installed in the granary, and the soft measurement technology is used to detect and feed back in time. The online measurement can better guide the grain inspection and reduce unnecessary waste of human and material resources. However, all the systems mentioned above need to be further improved to replace backward artificial measurement method[21], realize online measurement and supervision of stored grain[22].

Aimed at an intelligent and practical point cloud simplification algorithm for online measuring stored bulk grain volume, an adaptive point cloud simplification algorithm based on Particle Swarm Optimization (PSO) was proposed in this research. Specifically, PSO was introduced into average distance method to adaptively determine the point reducing intervals of scanning lines according to the density of original points. By using the 3D point cloud scanned from stored grain surface in granary, the proposed algorithm was verified.

2 Materials and methods

2.1 Measurement principle of 3D laser scanner

The 3D laser scanner (GSLS003, Jilin University and SkyViTech Co., Ltd., Hangzhou, China) designed for granary is composed of level regulation module, data acquisition unit, central control unit, rotation control module and scanning unit. A first-class safety laser device with a wave length of 905 nm is installed on the laser scanner, which has a scanning error of 7 mm/50 m, and a scanning diameter of 100 m. The laser scanner installed on the beam of granary, scanned the bulk grain surface from above. In addition, the motor can drive the scanner to make 270° rotation, so the scanner can scan the complete picture of the grain surface in a granary in one time without jointing point cloud data. After the laser scanner transmits a laser signal to a measured object, the beam of diffuse reflection occurring on the measured object goes back to receiver immediately. On the basis of the time required for the above-mentioned process, the scanner can calculate the distance (S_p) from the scanner itself to the scanned point (p). Synchronously, it can measure the horizontal scanning angle (φ) and the vertical scanning angle (ω) of each laser pulse (Figure 1). By using the above variables, the 3D coordinates (x_p, y_p, z_p) of a scanned point (p) can be calculated in accordance with Equation (1).

$$\begin{cases} x_p = S_p \cos\omega \sin\varphi \\ y_p = S_p \cos\omega \cos\varphi \\ z_p = S_p \sin\omega \end{cases} \tag{1}$$

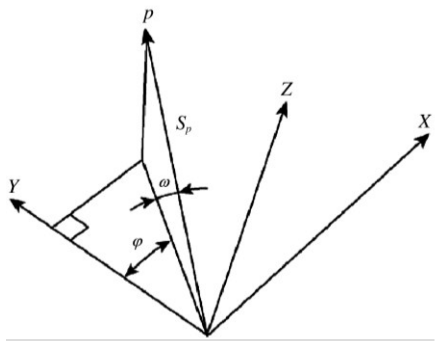


Figure 1 Schematic diagram of measurement principle inside 3D laser scanner

2.2 Data collection

The experiment was conducted in a maize granary in Jilin Province, China. The height of the stored grain in the granary was 6.13 m, the environmental temperature was 16ºC, and the temporal humidity was 61%.

The laser scanner was installed on the beam in the middle of the granary (Figure 2). The scanner was balanced by level regulation module in order to avoid the intersection angle between the build-in coordinate system of the scanner and the true coordinate system of the granary, and then to avoid the decrease of the scanning accuracy. The initial scanning point was returned to zero that was the default setting of the scanner so as to guarantee that the measured grain volume can be compared and analyzed according to the same standard. Scanning speed and motor subdivision set were selected according to the experiment result of the point cloud data that had least noise and best quality. The specific scanning parameters are shown in Table 1. The scanner communicated with long-distance host computer, and the scanned data were stored in the buffer memory of an upper computer after scanning the whole granary.

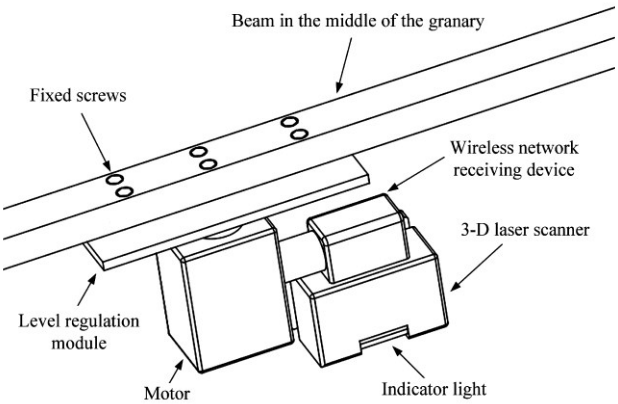


Figure 2 Installation position and system composition of 3D laser scanner

Table 1 Scanning parameters of 3D laser scanner

Scanning parameters	Server address	Scanning speed/(°)·s^{-1}	Scanning initial position	Motor subdivision set	Scanning angle of rotation/(°)
Parameters value	192.168.0.1	10	zero position	1/4	270

In this study, eight groups of experiments were conducted. Each group was scanned three times, and totally 24 point cloud data were obtained. Figure 3 shows original picture of the experimental granary. The instantaneity, integrity and veracity of the data collected satisfied the requirement of the technical manual for grain storage.

Figure 3 Picture of the experimental granary

3 Description of simplification algorithm based on PSO

In general, the scanner installation position, granary shape and bulk grain surface did not change in each scanning progress, the differences of distances and angles between scanner and the measured point might bring about a fact that the distributions of point cloud data were sparse in two sides and dense in center of the grain surface. Nevertheless, for the large objects, such as the grain surface, the average distance method was unable to change the reducing interval of points in accordance with the density of original point cloud data. Therefore, this research introduced the PSO into the average distance method.

PSO is a population based evolutionary optimization algorithm developed by Kennedy and Eberhart[23], inspired by social behavior of bird flocking or fish schooling. It has a simple mode of optimization and global searching method, so it is easy to be combined with other algorithms and will not fall into local optimal value in practical problems. The simplification algorithm based on PSO can adaptively determine whether the reducing interval of a scanning line decided by average distance method needs to be re-determined or not through optimization by PSO. It can update the reducing interval of scanning lines in accordance with the density of point cloud data at any moment, and finally output the point cloud data set after simplifying. The main steps of the proposed algorithm are as follows:

Step 1: Extract the coordinate information of point cloud data (x_i, y_i, z_i), i=1,2,3, …m.

Step 2: Determine the number of total scanning lines $k=\frac{m}{721}$ ($k=1, 2,\cdots \cdots$) according to the fact that the 3D laser scanner scans 721 points each line, and then calculate the line-to-line average distance (δ_k) by

$$\delta_k = (|y_{1k} - y_{1k+1}| + |y_{2k} - y_{2k+1}| + \cdots \cdots + |y_{721k} - y_{721k+1}|)/721$$

Step 3: Select scanning line k, then decide its point reducing interval threshold (η_k) ($3\delta_k > \eta_{k-1} > 0.3\delta_k$), finally judge whether the average reducing interval exceeds the interval threshold or not. If it exceeds the threshold, go to step 4 to determine the optimal average reducing interval by PSO; if it does not exceed the threshold, go to step 7, and follow the initial average reducing interval decided by average distance method or by last iteration.

Step 4: Determine the optimal average reducing interval by PSO; take coordinate information of point cloud data x_i, y_i, z_i as the design variables of optimization; let N be particle swarm scale, $t_{\max}$ be number of iterations, ω be weighting function; establish optimally mathematical model according to the position scope and upper velocity limit of each particle ($v_{\max}$).

Step 5: Start iteration; calculate fitness value of each particle according fitness function; judge whether the fitness value of particle's position is better than its best known position *pbest* or not; if it is better, update the *pbest* to the fitness value, otherwise, retain original *pbest*; and update the swarm's best known position *gbest* in accordance with the particle's best known position.

Step 6: Update inertial weight coefficient and particle velocity; if the velocity exceeds maximum velocity $v_{\max}$, let it equal to $v_{\max}$; if it satisfies the terminal conditions, output optimal solution η_{kbest}, otherwise, go to step 5.

Step 7: Reduce points on scanning line using adaptively optimal reducing interval, and output point cloud data after reduction.

Step 8: If the scanning lines are all simplified, exit program, otherwise, go to step 2.

The flowchart of point cloud simplification algorithm based on PSO is shown in Figure 4.

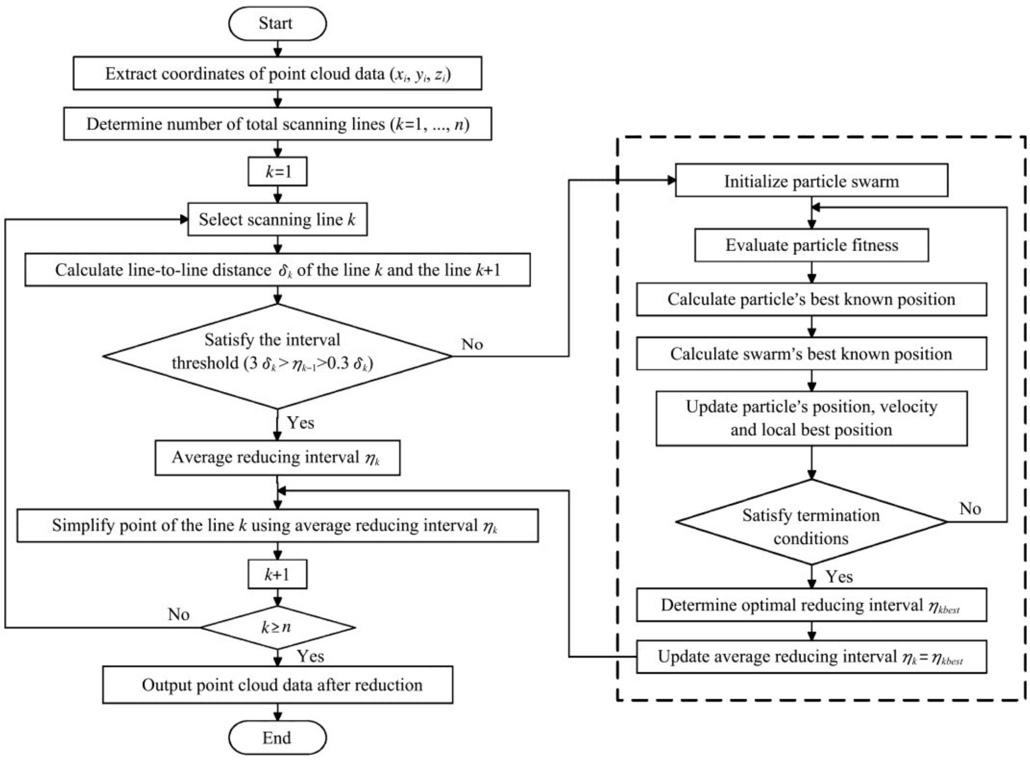


Figure 4 Flowchart of point cloud simplification algorithm based on PSO

Taking coordinate information of point cloud data x_i, y_i, z_i as the design variables of optimization, the optimized fitness function is expressed as

$$Fit(X)=\frac{\sum_{i=1}^{m}(x-x_{ik})+\sum_{i=1}^{m}(y-y_{ik})+\sum_{i=1}^{m}(z-z_{ik})}{[\sum_{i=1}^{m}(x-x_{ik})^2+\sum_{i=1}^{m}(y-y_{ik})^2+\sum_{i=1}^{m}(z-z_{ik})^2]^{1/2}} \tag{2}$$

The initial parameters of the proposed algorithm are shown in Table 2.

Table 2 Initial parameters of simplification algorithm based on PSO

Initial parameter	Value
Particle swarm scale N	40
Initial inertial weight ω_0	1
Accelerated constant c_1, c_2	2, 2
Maximum number of iterations t_{max}	500
Maximum running time T_{max}	∞
Maximum particle′s velocity v_{max}	10
Initial reducing interval η_0/mm	0.1

Particle swarm scale N, initial inertial weight ω_0, accelerated constant c_1, c_2 and maximum particle's velocity v_{max} are given as the experience values. Maximum number of iterations t_{max} and maximum running time T_{max} are set to terminate the program. Initial reducing interval η_0 is set according to the density of the point cloud data. $X_i\,(x_{i1}, x_{i2}, \ldots, x_{id})$ is the current position of particle q (q = 1, 2, …, N); $V_i(v_{i1}, v_{i2}, \ldots, v_{id})$ is the current velocity of particle i; $P_i\,(p_{i1}, p_{i2}, \ldots, p_{id})$ is particle's best known position; $P_g\,(p_{g1}, p_{g2}, \ldots, p_{gd})$ is swarm's best known position. When the particle q at the generation t is iterated to the generation t+1, its l-dimension velocity and position can be described as:

$$\begin{aligned} v_{ql}(t+1) = \omega\, v_{ql}(t)\ + c_1\, r_1\, [p_{ql}(t)-x_{ql}(t)] + \\ c_2\, r_2\, [p_{gl}(t)-x_{ql}(t)] \end{aligned} \tag{3}$$

$$x_{ql}(t+1)=x_{ql}(t)+v_{ql}(t+1) \tag{4}$$

where, q = 1, 2, …, N, l-dimension $(1\leq l\leq d)$. r_1, r_2 are random numbers between (0, 1). Weight function ω can be calculated by the following equation:

$$\omega=\omega_{max}-\frac{\omega_{max}-\omega_{min}}{t_{max}}t \tag{5}$$

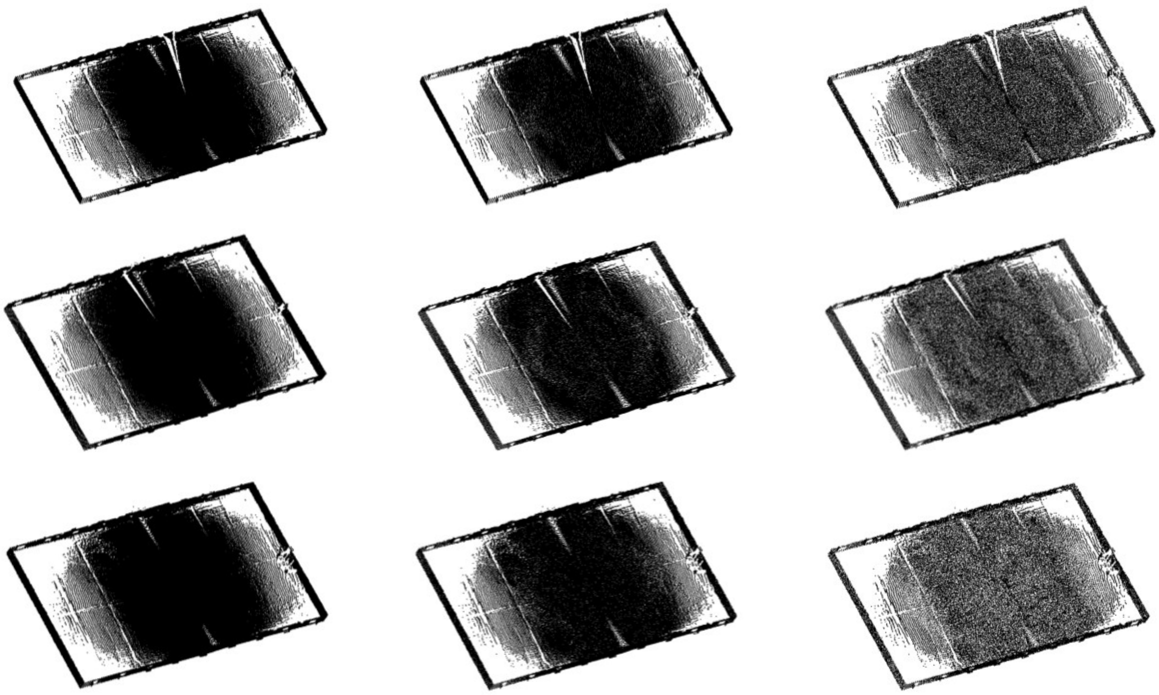
where, ω_{max} and ω_{min} are maximum and minimum of ω. The linear reduction of the weight function ω with the iteration could make the PSO algorithm have strong exploration ability in the initial stage of iteration and good convergence in the later period. Generally the weight function ω is a constant between 0.8 and 1.2, so we choose $\omega_{max}\in[2,3]$, $\omega_{min}\in[0.8,1.2]$, initial inertial weight ω_0 is 1.

4 Results and discussion

4.1 Simplification results and analyses

Three typical point cloud data were selected from the above experiment in the maize granary in Jilin Province to discuss the performance of the proposed algorithm. Figure 5a shows the 3D original point cloud sets of grain surface. Figures 5b and c are the simplified data point sets by average distance method and the simplification algorithm based on PSO proposed in this research, respectively. Macroscopically saying, there were obvious differences between the simplification results by the two algorithms. The data points by the proposed algorithm were evenly distributed, and had clear margin and small noise, which indicated that the simplification results by the proposed algorithm were better than those by average distance method.

The performance of the two algorithms using eight different point cloud data is listed in Table 3. The original point clouds of stored grain surface were simplified to 11.69% of their original size by average distance method and to 6.96% by the proposed algorithm, which was 5.12% lower than that by average distance method. Compared with the Figure 5b, the dense point cloud in center region had larger simplification amplitude, which reduced the redundancy of point cloud data; the sparse point cloud in two sides had smaller simplification amplitude, which would not lose the important information to describe the basic forms in Figure 5c. So the distribution of point cloud data simplified by the proposed algorithm was more uniform on the whole. Thus it cloud be seen that the proposed algorithm not only adaptively increased the evenness of simplified data points, but also greatly reduced the data size, which made the surface reconstruction and grain volume calculation more convenient and faster.



a. Original point cloud data b. Simplification by average distance method c. Simplification by algorithm based on PSO

Figure 5 Spatial distribution of original point clouds and simplified point clouds by different algorithms

Table 3 Comparison of reduction performance of different algorithms

Group No.	Number of original points	Number of points by ADM	Number of points by SA-PSO	Reduction ratio by ADM/%	Reduction ratio by SA-PSO/%
1	1 159 887	978 96	65 572	8.440	5.653
2	747 669	100 368	67 019	13.424	8.964
3	877 047	112 623	69 756	12.841	7.954
4	882 989	96 832	45 664	10.966	5.172
5	889 326	115 529	61 759	12.991	6.944
6	855 678	98 842	63 475	11.551	7.418
7	886 096	103 530	61 736	11.684	6.967
8	890 099	104 182	59 188	11.705	6.650
Average	898 599	103 725	61 771	11.700	6.965

Notes: ADM represents average distance method; SA-PSO represents simplification algorithm based on PSO; reduction ratio means the ratio of the number of points after simplification to the number of original points.

4.2 Grain volume estimation results and analyses

The point cloud data of the grain surface simplified by the algorithm based on PSO was evenly and the data could regularly reflect the actual characteristics of the grain surface. After dealing with the denoising and smoothing, this study used the Delaunay triangulation method to reconstruct the point cloud data in order to get the grain surface. The Delaunay triangulation method uses a series collection of connected but not overlapping triangles to reconstruct the surface, so this method can be adapted to a variety of distribution density of data and it has high storage efficiency and small data redundancy. Then the surface was used to calculate the space volume above the grain and the space volume was used to get the volume of the grain by subtraction.

The average CPU time was 1523 s when the point cloud data simplified by the PSO simplification method were denoised, smoothed and reconstructed to calculate the volume on a PC with 3.20 GHz CPU and 8 GB physical RAM. However, the average CPU time of the point cloud data simplified by the average simplification method was as much as 5871 s. It showed that the simplification performance of the point cloud data had great influence on the later surface reconstruction, especially the data were enormous. The less data and more evenly distributed the point cloud data were, the shorter CPU time and the better performance of the surface reconstruction will be got. This clearly confirmed the need to develop a more efficient simplification algorithm for the intensive point cloud data.

For further comparing the performance of the two algorithms, the grain surface was reconstructed, and the grain volume was estimated by using the reconstructed surfaces by the average distance method and the proposed algorithm. The actual maize volume in the granary was calculated of 4100 m^3 according to the real weight and unit weight of maize, which were measured when holding the maize in the granary. Compared to average distance method, the calculated grain volume was more approximate to the actual grain volume by the proposed algorithm (Table 4), with a relative error of less than 3‰, which satisfied the accuracy requirement of grain volume estimation. Then root mean square error (RMSE) was introduced to reflect the discrete degree of individual in the group as shown in Equation (6), which represented the error between the calculated volume and the actual volume. RMSE of grain volume estimation by the proposed algorithm was greatly less than that by average distance method (Table 4), indicating that the proposed algorithm not only reduced the redundant point cloud data, but also greatly raised the estimation accuracy of grain volume.

$$\mathrm{RMSE}=\sqrt{\frac{\sum_{i=1}^{p}(\hat{V}_i-V_r)}{p}} \tag{6}$$

where, p is the number of samples; V_i and V_r is the calculated volume and the actual volume.

Table 4 Comparison of performance in grain volume estimation by different algorithms

Algorithm	Group No.	Number of simplified points	Calculated volume of maize/m^3	Relative error/%	RMSE
SA-PSO	1	65 572	4093.401	0.171	5.852
	2	67 019	4106.935	0.146	
	3	69 756	4105.273	0.120	
	4	45 664	4091.359	0.220	
	5	61 759	4094.235	0.146	
	6	63 475	4103.227	0.073	
	7	61 736	4107.739	0.171	
	8	59 188	4097.522	0.073	
ADM	1	97 896	4079.032	0.512	15.910
	2	100 368	4113.257	0.317	
	3	112 623	4120.039	0.488	
	4	96 832	4089.711	0.268	
	5	115 529	4119.906	0.463	
	6	98 842	4088.021	0.293	
	7	103 530	4110.403	0.244	
	8	104 182	4117.401	0.415	

Notes: ADM represents average distance method; SA-PSO represents simplification algorithm based on PSO.

5 Conclusions

In this research, a 3D laser scanning point cloud simplification algorithm based on PSO for online measuring stored grain volume in granary was proposed. the proposed algorithm could adaptively determine whether the point reducing intervals of scanning lines decided by average distance method need to be re-determined or not through optimization by PSO. It solved the problems of massive data and uneven distribution of original point cloud, which resulted in more evenly and distributed simplified point set, and lower reduction ratio (6.96%) compared to the average distance method. By using the proposed algorithm, grain surface was reconstructed and grain volume was estimated. The relative error of grain volume estimation by the proposed algorithm was lower than that by the average distance method (less than 3‰). Due to the good performance of point cloud simplification and the capability of updating the reducing interval in accordance with the density of point cloud data at any moment, the proposed algorithm could be used as a simple and practical means for realizing online measurement of stored grain volume in granary to replace the average distance method.

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[References]

[1] Fleishman S, Cohen-Or D, Alexa M, Silva C T. Progressive point set surfaces. ACM Transactions on Graphics, 2003; 22(4): 997–1011. doi: 10.1145/944020.944023

[2] Amenta N, Kil Y J. Defining point-set surfaces. ACM Transactions on Graphics, 2004; 23(3): 264–270. doi: 10.1145/1015706.1015713

[3] Levoy M, Pulli K, Curless B, Rusinkiewicz S, Koller D, Pereira L, et al. The digital michelangelo project: 3D scanning of large statues. Proceedings of SIGGRAPH, 2000.

[4] Liu H, Tao Y L, Fu J W. Data processing of scanning beam point-cloud based measuring freeform surface. Modular Machine Tool & Automatic Manufacturing Technique, 2011; (5): 77－80. (in Chinese with English abstract)

[5] Fang Y M, Xia Y H, Chen J. Study on point cloudy data simplification of goal based on improved angular deviation method. Journal of Earth Sciences and environment, 2012; 34(2): 106–110. (in Chinese with English abstract)

[6] Wang G F, Lü Y M, Han N, Zhang D. Simplification method and application of 3D laser scan point cloud date. Journal of Micro-nanolithography MEMS and MOEMS, 2012; 266–268. doi:10.2991/mems.2012.166

[7] Chen Z W, Da F P. 3D point cloud simplification algorithm based on fuzzy entropy iteration. Acta Optica Sinica, 2013; 33(8): 0815001-1–0815001-7. (in Chinese with English abstract)

[8] Mccafrey K J W, Rjones R, Holdsworth R E, Wison R W, Clegg P, Imber J, et al. Unlocking the spatial dimension: digital technologies and the future of geoscience fieldwork. Journal of the Geological Society, 2005; 162: 1–12. doi: 10.1144/0016-764905-017

[9] Qin J. Open access publishing of scientific scholarly journals in China. PhD dissertation. Tianjin: Tianjin University of Technology, 2011.63p. (in Chinese)

[10] Xu W H, Feng Z K, Su Z F, Xu H, Jiao Y Q, Deng O. An automatic extraction algorithm for individual tree crown projection area and volume based on 3D point cloud data. Spectroscopy and Spectral Analysis, 2014; 34(2): 465–471. (in Chinese with English abstract).

[11] Zhu L L, Juha H. The use of airborne and mobile laser scanning for modeling railway environments in 3D. Remote Sensing, 2014; 6(4): 3075–3100. doi: 10.3390/rs6043075

[12] Ferrari S, Ferrigno G, Piuri V. Reducing and filtering point clouds with enhanced vector quantization. IEEE Transactions on Neural Networks, 2007; 18(1): 161–176. doi: 10.1109/TNN.2006.886854

[13] Song H, Feng H Y. A global clustering approach to point cloud simplification with a specified data reduction ratio. Computer-Aided Design, 2008; 40(3): 281–292. doi: 10.1016/j.cad.2007.10.013

[14] Yu Z W, Wong H S, Peng H, Ma Q L. ASM: An adaptive simplification method for 3D point-based models. Computer-Aided Design, 2010; 42(7): 598–612. doi: 10.1016/j.cad.2010.03.003

[15] Shi B Q, Liang J, Liu Q. Adaptive simplification of point cloud using k-means clustering. Computer-Aided Design, 2011; 43(8): 910–922. doi: 10.1016/j.cad.2011.04.001

[16] Wang Y Q, Tao Y, Zhang H J, Sun S H. A simple point cloud data reduction method based on Akima spline interpolation for digital copying manufacture. International Journal of Advanced Manufacturing Technology, 2013; 69(9-12): 2149–2159. doi: 10.1007/s00170-013-5195-3

[17] Li K, Zhang A W. The Grain reserves quantity calculation method based on the laser point cloud. Bulletin of Surveying and Mapping, 2010; (supplement): 264–266. (in Chinese)

[18] Liang X H, Sun W D. A fast 3D surface reconstruction and volume estimation method for grain storage based on priori model. International Symposium on Photoelectronic Detection and Imaging, 2011; Vol.8192. doi: 10.1117/12.901036

[19] Ren G C, Yang Y, Guo H C. Intelligent grain storage measurement system design and research. FEMET, 2012; 430-432: 1881–1885. doi: 10.4028/www.scientific.net/AMR.430-432.1881

[20] Pauly M, Gross M, Kobbelt L P. Efficient simplification of point-sampled surface. In: Visualization, IEEE. Boston, MA, USA. 2002; pp.163–170. doi: 10.1109/VISUAL.2002.1183771

[21] Lu Z W, Wu J J, Sun F Y, Feng L M, He S J, Li W. Research and design of modern smart grain depot system. Journal of Henan University of Technology (Natural Science Edition), 2013; 34(5): 79–82. (in Chinese with English abstract)

[22] Qi G L, Wang W X, Yao G, Wang W J. The design of grain storage′s monitoring technology and system. Acta Agriculture Boreali-Occidentalis Sinica, 2006; 15(2): 167–169, 179. (in Chinese with English abstract)

[23] Kennedy J, Eberhart R. Particle swarm optimization. In: IEEE Int. Conf. Neural Network. Perth, Australia, 1995; 4: 1942–1948.