Classified denoising method for laser point cloud data of stored grain bulk surface based on discrete wavelet threshold

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Abstract: Surfaces of stored grain bulk are often reconstructed from organized point sets with noise by 3-D laser scanner in an online measuring system. As a result, denoising is an essential procedure in processing point cloud data for more accurate surface reconstruction and grain volume calculation. A classified denoising method was presented in this research for noise removal from point cloud data of the grain bulk surface. Based on the distribution characteristics of cloud point data, the noisy points were divided into three types: The first and second types of the noisy points were either sparse points or small point cloud data deviating and suspending from the main point cloud data, which could be deleted directly by a grid method; the third type of the noisy points was mixed with the main body of point cloud data, which were most difficult to distinguish. The point cloud data with those noisy points were projected into a horizontal plane. An image denoising method, discrete wavelet threshold (DWT) method, was applied to delete the third type of the noisy points. Three kinds of denoising methods including average filtering method, median filtering method and DWT method were applied respectively and compared for denoising the point cloud data. Experimental results show that the proposed method remains the most of the details and obtains the lowest average value of *RMSE* (Root Mean Square Error, 0.219) as well as the lowest relative error of grain volume (0.086%) compared with the other two methods. Furthermore, the proposed denoising method could not only achieve the aim of removing noisy points, but also improve self-adaptive ability according to the characteristics of point cloud data of grain bulk surface. The results from this research also indicate that the proposed method is effective for denoising noisy points and provides more accurate data for calculating grain volume.

Keywords: point cloud data, denoising, grid method, discrete wavelet threshold (DWT) method, 3-D laser scanning, stored grain

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1 Introduction

Research of grain storage is an important component in the field of agriculture[1-3], and the measurement of grain volume is a key issue in these researches[4]. An online measuring system for stored grain based on a 3-D laser scanning technology has been proposed by Shao et al.[5] Point cloud data should be pre-processed in order to reconstruct the grain bulk surface to calculate the grain volume. Thus, the denoising of point cloud data is an important step in the data processing process[6]. The result of the denoising process would influence the performance of the post processing and precision of the measuring system. Therefore, it is meaningful to propose more adaptive method to denoise the point cloud data obtained by the 3-D laser scanner in the measuring system.

The traditional denoising methods of point cloud data include average filtering, median filtering, Gaussian filtering, and so on[7-9]. Some researchers have tried to

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improve those denoising methods. Huang et al.[10] proposed a method for 3-D unorganized point cloud data denoising by making full use of depth information of unorganized points and space analytic geometry theory. Zhang et al.[11] presented a new approach to simultaneously denoise and parameterize unorganized point cloud data by minimizing an appropriate energy function. Rosman et al.[12] put forward a new framework to extract most of the noise points by patch-collaborative spectral analysis. Those improved denoising methods focused on the unorganized and scattered point cloud data. However, the data used in the online measuring system for stored grain were organized, unclosed, and distributed in scanning lines. According to the organized point cloud data, Song[13] presented a two-stage point clouds data denoising method, which combined the ellipsoid criterion with the mean shift filtering approach. Lai and Zheng[14] proposed an improved λ/μ iltering algorithm based on median filtering method and proved the effectiveness of the proposed algorithm by several experiments. Sun et al.[15] presented an anisotropic point cloud data denoising method using L_0 minimization, which could recover sharp features while smoothing the remaining regions. However, there were always some remained sparse noisy points and small noisy points in the above studies, which could not delete noisy points effectively and would further affect the reconstruction results. To solve this problem, Li and Li[16] divided the noisy points into two types using distance-based algorithm. However, the denoising performance of mixed noise needs to be improved. Alternatively, some researchers have tried to use a projection method to deal with the organized and unclosed point cloud data. Lü and Wan[17] presented a denoising method by layering slices in an elevation direction, and the discrete grid noises were filtered by a digital image processing method. Cheng et al.[18] projected tunnel point cloud data onto the horizontal and vertical planes respectively to delete the noise. These researchers tried to use the projection method to deal with the unclosed point cloud data, but their denoising methods were fundamental and general, and the results were not so ideal. Furthermore, Ram et al.[19] proposed a new redundant wavelet transform for point cloud data and image denoising. Smigiel et al.[20] applied wavelet analysis and a “non-local means” algorithm to denoise terrestrial laser scanner data, but many parameters associated with this method led to heavy processing costs.

Taking the distribution characteristics of point cloud data of grain bulk surface into consideration, we proposed a classified denoising method in this study. This method divided the noisy points into three types: The first and second types were deleted by a grid method. Then, the point cloud data with the third type of noisy points were projected into a horizontal plane. Finally, an image denosing method, discrete wavelet threshold (DWT), was applied to delete the third type of noisy points.

2 Materials and methods

2.1 Data collection

The experiment was conducted in a maize granary in Jilin Province, China (43.88°N, 125.88°E) on July 17, 2013. The dimension of the stored grain in the granary was 53.50 m × 30.00 m × 6.13 m ($X \times Y \times Z$). The environmental temperature was 16ºC, and the temporal humidity was 61%. The internal environment of the granary is shown in Figure 1. The 3-D laser scanner (GSLS003, Jilin University and SkyViTech Co., Ltd., Hangzhou, China) was installed on the beam in the middle of the granary. The point cloud data of grain bulk surface were acquired by the online measuring system[5]. Then, the scanner communicated with a long-distance host computer, and the scanned data were stored in the buffer memory of an upper computer. Eight groups of experiments were conducted. Each group was scanned three times, and the total 24 sets of point cloud data were obtained. Then, the coordinates of the point cloud data measured by the scanner were transformed to the calculative coordinate by bursa model[21]. The data were stored in .xyz format, which is a type of point cloud data memory form. Only one set that had the most complete data was chosen from each group, and the total eight sets of point cloud data were selected. These sets of point cloud data were simplified[22], denoised and reconstructed[5] in order to calculate the grain volume. The denoising process in this study was conducted in MATLAB in the workstation DELL M6800 (Dell Computer Corporation One Dell Way Round Rock, Texas 78682 USA).

Figure 1 Internal environment of the granary

2.2 Grid method for denoising the first and second types of the noisy points

There are always noisy points included in the point cloud data obtained from 3-D laser scanner. They could be produced by the vibration of instruments, the interference from outside light, or the extra data from the surrounding temperature sensors. Consequently, the noisy points were distributed around the main body points irregularly. Some researchers divided those noisy points into three types[23]. This classification method was adopted in this study. The first type was the sparse points deviating and suspending from the main point cloud data. This type had no relationship with the main body of the point cloud data, and they could be basically considered as mistake points. The second type of noisy points was the small and dense point cloud data, which were far from main point cloud data. The third type of noisy points was mixed with the main body points.

The third type was different from the first and second types, and it could not be denoised by the same method. Furthermore, the noisy points of the third type were most difficult to be denoised. Therefore, we dealt with the first and second types by a grid method to prepare for the denoising procedure of the third type.

Firstly, a 3-D grid model was established. The model was composed of a series of cubes that were perpendicular to X, Y and Z axes. The spatial relation of the point cloud data could be determined roughly according to the location of the points. The schematic diagram of the grid model is shown in Figure 2.

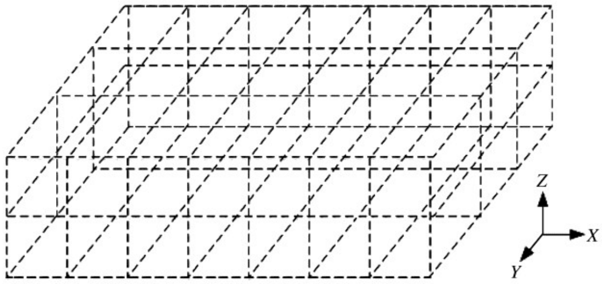


Figure 2 Schematic diagram of the grid model

The point cloud data in the .xyz format were saved in an array. The maximum (x_{max}, y_{max}, z_{max}) and minimum (x_{min}, y_{min}, z_{min}) value of the X, Y and Z coordinates could be found after a search for the array. A bounding box according to the maximum and minimum value was established to surround all the data points. According to the density of the point cloud data, the bounding box would be divided into small cubes. The numbers of these small cubes in X, Y, Z coordinates are:

$$\begin{aligned} A &= \operatorname{int}\left[\frac{1}{L}(x_{max}-x_{min})\right]+1 \\ B &= \operatorname{int}\left[\frac{1}{L}(y_{max}-y_{min})\right]+1 \\ C &= \operatorname{int}\left[\frac{1}{L}(z_{max}-z_{min})\right]+1 \end{aligned} \tag{1}$$

where, x_{min}, y_{min}, z_{min} are the minimum coordinate values of the bounding box; x_{max}, y_{max}, z_{max} are the maximum coordinate values of the bounding box; L is the length of the cubes.

If the coordinates of a certain point P are Px, Py, Pz, the index functions of the small cubes are:

$$\begin{aligned} D &= \operatorname{int}\left[\frac{1}{L}(P_x-x_{min})\right] \\ E &= \operatorname{int}\left[\frac{1}{L}(P_y-y_{min})\right] \\ F &= \operatorname{int}\left[\frac{1}{L}(P_z-z_{min})\right] \end{aligned} \tag{2}$$

where, D, E, F are the key numbers of the cube in X, Y, Z axes. There is another array to record the serial numbers of the points in each cube and the element number of the array is $A \times B \times C$.

Afterwards, the first type of the noisy points could be denoised by judging the number of the points in each small cube. The small cubes were divided into 100 mm× 100 mm×100 mm size according to the density of the point cloud data. Each line in Y direction had 721 points on the basis of the scanner settings, and the point number of the cubes in main body should be more than two. If the number was not larger than two, the points in the cube were deleted. By doing this, all the sparse and suspended noisy points could be found and deleted.

Finally, if the number was greater than two, this cube was set as the center to inspect other cubes orderly by a region growing concept. Specific method was as follows: If a certain cube satisfied the condition, this cube was set as the center to inspect the cubes around it. If the points of these cubes were also greater than two, they would continue to be set as the centers in sequence until all the cubes were checked. The cubes belonging to the same point cloud data could be found out after the inspection. The point cloud data that owned the most cubes could be found by judging the cubes number of each point cloud data. The point cloud data that did not have the most cubes were the second type of noisy points, and they should be deleted.

2.3 Discrete wavelet threshold method for denoising the third type of noisy points

The noisy points of the third type were mixed with main body points, and they were most difficult to be deleted. The outline of the point cloud data of the grain bulk surface were similar to an unclosed plane, and the first and second types of noisy points had already been deleted. Therefore, the remained point cloud data of grain bulk surface could be projected to a horizontal plane, X-Y coordinate plane, for the unique value of the Z axis. By the same way, the point cloud data of the granary walls were projected to a vertical plane, X-Z coordinate plane or Y-Z coordinate plane.

Point cloud data could be regarded as a 3-D data array that was constituted by the coordinate values of X, Y and Z axes. An arbitrary point of point cloud data contained its 3-D coordinate information. This information could be recoded to the memory format of a gray image. The X, Y coordinates were used as a 2-D information index, and the Z coordinate of this point was the index value. The 3-D data array could be translated into a 2-D matrix after all the points had been recoded. The gray image was also expressed in a 2-D matrix in computer processing. Therefore, a conversion relationship was established between the point cloud data and gray image. The elements of the matrix were the pixel of the gray image as well as the Z coordinate value of point cloud data. The Z coordinate values were transformed into integral form. The conceptual diagram of the conversion relationship is shown in Figure 3.

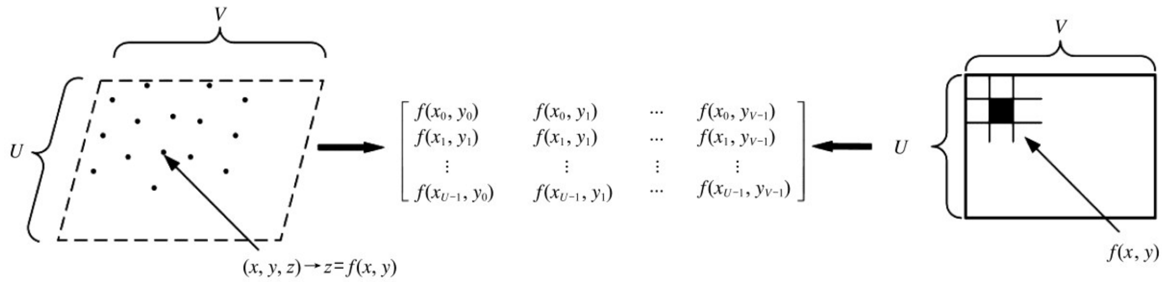


Figure 3 The conceptual diagram of the conversion relationship

The DWT method, an image denoising method, could be used on this point cloud data to filter the third type of noisy points after the conversion. Generally, the noise in the practical project was not smooth and regular. The traditional denoising method was difficult to deal with this kind of noise. The wavelet analysis was known as a new denoising method[24], which could provide an effective way to separate the main data and non-stationary noise. The image data could be decomposed into high frequency and low frequency parts. Low frequency part reflects the outline of the image data, and high frequency part embodies the details of the image data and noise. Therefore, the high frequency part needed to be removed selectively in order to delete the noise.

The point cloud data with noisy points were $f(i, j)=s(i, j)+n(i, j)$, $s(i, j)$ was the point cloud data without the noisy points, and $n(i, j)$ was the noisy points. The point cloud data with the noisy points was transformed by the DWT method. The wavelet coefficient $\omega_{i,j}$ comprised two parts for the linear behavior of the wavelet transform.

One part of the coefficient, $\mu_{i,j}$, corresponded with the main body points $s(i, j)$, and the other part, $\upsilon(i, j)$, represented the noisy points $n(i, j)$. Thus the wavelet coefficient $\omega_{i,j}$ could be described as:

$$\omega_{i,j} = \mu_{i,j} + \upsilon_{i,j}$$

A regular threshold method included hard and soft threshold estimation methods was proposed by Donoho and Johnstone[25]. The hard threshold estimation method was defined as:

$$\hat{\omega}_{i,j} = \begin{cases} \omega_{i,j}, & |\omega_{i,j}| \geq \lambda \\ 0, & |\omega_{i,j}| < \lambda \end{cases}$$

And the soft threshold estimation method was defined as:

$$\hat{\omega}_{i,j} = \begin{cases} \mathrm{sgn}(\omega_{i,j}) \cdot (|\omega_{i,j}| - \lambda), & |\omega_{i,j}| \geq \lambda \\ 0, & |\omega_{i,j}| < \lambda \end{cases}$$

Both of the two methods could denoise the noisy points to a certain degree. However, the hard threshold estimation method was not continuous at point λ. It could lead to the vibration of the reconstruction data. The soft threshold estimation method had better continuity, but there was always deviation between $\hat{\omega}_{i,j}$ and $\omega_{i,j}$, when $|\omega_{i,j}| \geq \lambda$. It could influence the denoising effect. Thus, it was important to select an appropriate threshold λ in DWT method. The selection principle of the threshold was λ just more than the maximum amplitude of the wavelet coefficients corresponding to the noisy points. We used the threshold $\lambda = \sigma\sqrt{2\ln N}$, which was proposed by Donoho and Johnstone in 1994[25], where, σ was the estimated variance of the noise; N was the number of all the points. The steps of the DWT denoising method were as follows (decomposition level: 3, wavelet basis function: sym2), and the flow chart of proposed method is shown in Figure 4.

Step 1: Three levels were decided as the decomposition level of the wavelet transform. The point cloud data with the noisy points were denoised by the DWT method and a set of the wavelet coefficients $\omega_{i,j}$ was obtained.

Step 2: The wavelet coefficients were processed by the threshold, and the coefficient of low frequency a_3 and coefficients of high frequency d_1, d_2 and d_3 were extracted. The coefficients of high frequency part were processed by the threshold to obtain a set of new coefficients. The new coefficients and low frequency coefficient comprised the new wavelet coefficients $\hat{\omega}_{i,j}$, and they led the $\|\hat{\omega}_{i,j} - \mu_{i,j}\|$ to the minimum value.

Step 3: The point cloud data were reconstructed by the new coefficient $\hat{\omega}_{i,j}$ and point cloud data without noisy points $f(i, j)$ were obtained.

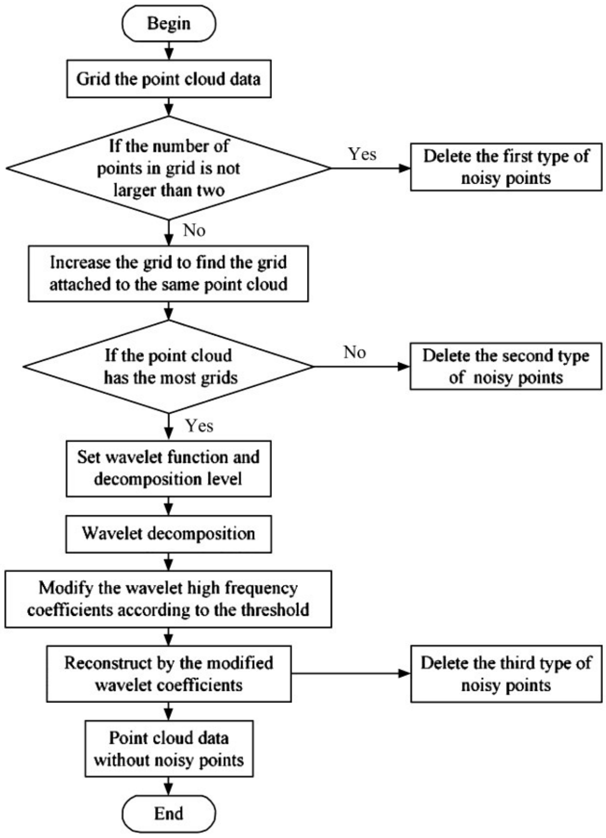


Figure 1 Flow chart of the proposed denoising method

2.4 Evaluation standards of the denoising effect

The denoising effect should reach some certain standards after the denoising process. These standards generally include the subjective standard and objective standard. The subjective standard is the most appropriate standard for the evaluators. However, same point cloud data might have different evaluation results according to different evaluators. In general, the denoising procedure might lead to missing details. Therefore, the subjective standard of this research was to remain more details and reduce more noise at the same time.

A proper analysis should also satisfy the objective standard according to different evaluation indexes.

These evaluation indexes include root mean square error (*RMSE*), signal noise ratio (*SNR*), peak signal to noise ratio (*PSNR*), computation time and so on. *RMSE* is described in Equation (3):

$$RMSE=\sqrt{\frac{1}{U\times V}\sum_{i=1}^{u}\sum_{j=1}^{v}(f(i,j)-n(i,j))^2} \qquad (3)$$

where, $f(i, j)$ is the Z coordinate values of the original point cloud data; and $n(i, j)$ is the Z coordinate values of the noisy point cloud data deleted in the denoising processing; $U\times V$ is the projected point cloud data size. The bigger *RMSE* is, the poorer the denoising effect is. It reflected that the denoised point cloud data were seriously deviated from the original point could data. Otherwise, the denoising effect was better.

SNR explains whether the denoised point cloud data has less noisy points according to the original point cloud data (Equation (4)). The bigger *SNR* is, the better denoising effect is:

$$SNR=10\cdot\lg[\sum_{i=1}^{u}\sum_{j=1}^{v}\frac{f(i,j)^2}{(f(i,j)-n(i,j))^2}] \qquad (4)$$

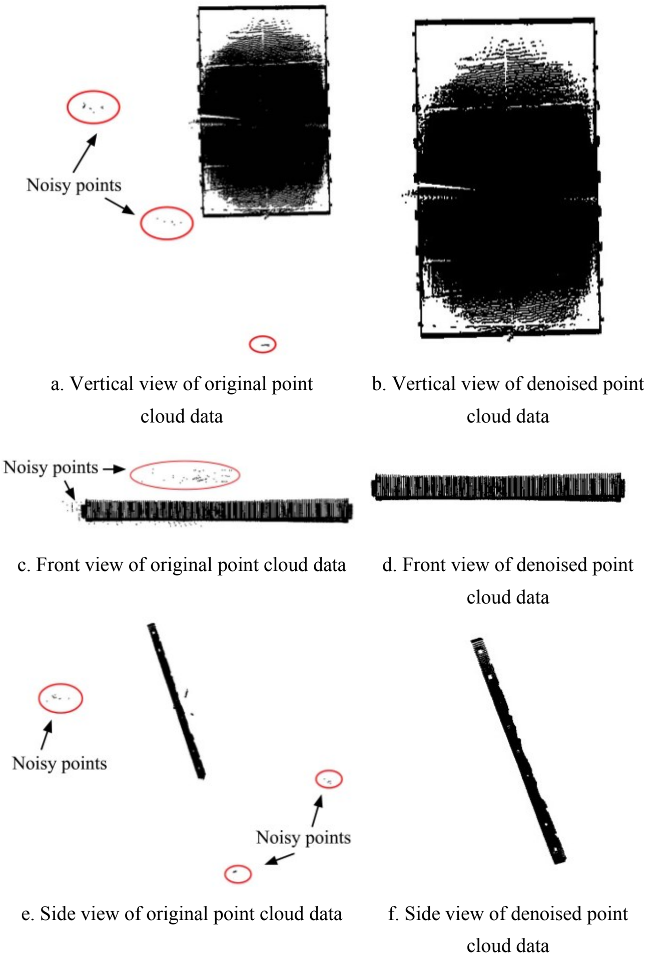
PSNR (Equation 5) is the ratio of the maximum Z coordinate value and *RMSE*. The bigger *PSNR* is, the better denoising effect is, and the more information kept.

$$PSNR=10\cdot\lg\frac{z_{\max}^2}{MSE} \qquad (5)$$

The average filtering method and median filtering method were introduced to compare with the proposed denoising method according to the subjective and objective standards. The average filtering method was also known as the linear filter. The main denoising thought was neighborhood average method, and it used the average value instead of each value. The median filtering method was a nonlinear smoothing filter for denoising processing technology based on the rank statistical theory. It defined a point as the center of the neighborhood. Then, the points in the neighborhood were ranked according to the value of center point, and finally the median value was selected as the new point value.

3 Results and discussion

Total eight sets of the point cloud data were selected from the experiment. These sets of point cloud data were denoised by different algorithms to evaluate the denoising effect. However, only one set was provided here to discuss the subjective standard due to length limitations. The point cloud data denoised by the grid method are shown in Figure 5. It could be found that the marked first and second types of noisy points were deleted by comparison of the three view points of the point cloud data. Therefore, the grid method is effective, which could denoise the sparse points and small point clouds data deviating from the main point cloud data and prepare for dealing with the mixed noisy points.



a. Vertical view of original point cloud data

b. Vertical view of denoised point cloud data

c. Front view of original point cloud data

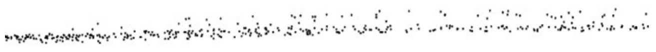
d. Front view of denoised point cloud data

e. Side view of original point cloud data

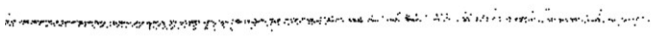
f. Side view of denoised point cloud data

Figure 5 Comparisons between the original and denoised point cloud data

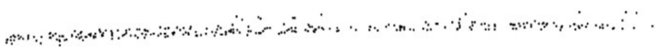
The proposed denoising method, average filtering method and median filtering method were used to compare the local and whole denoising results (Figures 6 and 7). The holes in Figure 7 were due to the blind area that the 3-D laser scanner could not scan, and they could be filled in reconstruction processing. The average filtering method could delete the points far away from the main point cloud data (Figure 6b), and the reconstruction surface using the denoised point cloud data by this method had less details of the features (Figure 7a). However, the heaves were quite apparent, which were due to the residual noisy points on the surface, and they would affect the calculation accuracy of grain volume. In an enlarged view of the reconstruction surface, the region around the heaves was too smooth, and it would reduce useful information provided by data. This method could restrain the additive noise effectively, but it might lead to the decline of calculation accuracy. The median filtering method could remain more details of local point cloud data (Figure 6c), but there were more denoising points affecting the reconstructed surface (Figure 7b). The heaves were obvious in the enlarged view. The traditional denoising methods had the contradiction between the denoising and details holding. These methods were simple, but they were not suitable for the point cloud data that had many lines and spires. These methods could not take effect in time domain, and they could not detect the local mutation and may lose the detail information while removing noisy points. The DWT denoising method had obvious advantages in comparison with the traditional methods for its feature of multiresolution. The DWT method could keep more details of local point cloud data and reduce noisy points (Figure 6d). The reconstructed surface by this method had clear outline and edge (Figure 7c). In the enlarged view, the non-anticipatory heaves were less and not obvious, and the region around them had more details of the features to reflect the real condition of the surface. As a result, this method satisfied the subjective standard and had better application value in the online measuring system for stored grain.



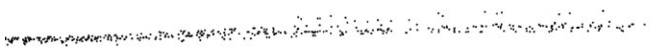
a. Original point cloud data



b. Average filtering method

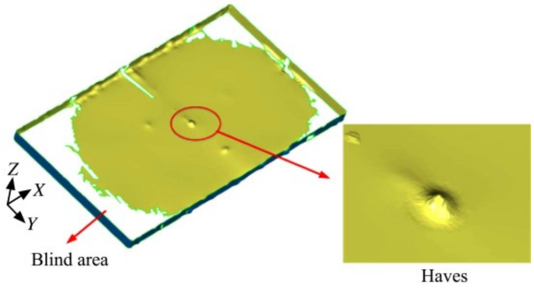


c. Median filtering method

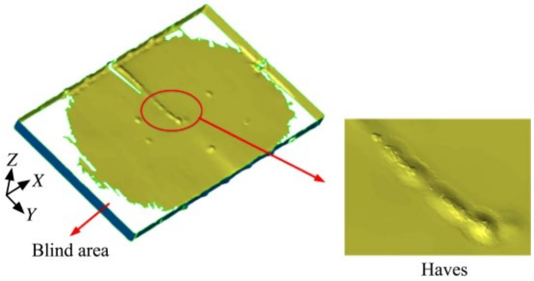


d. DWT method

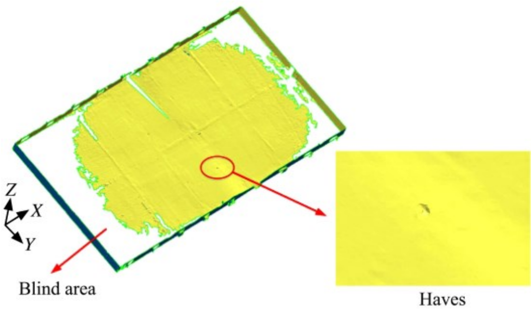
Figure 6 Local denoising results by different methods



a. Average filtering method



b. Median filtering method



c. DWT method

Figure 7 Reconstruction of surfaces by different methods

The objective standards of different methods were listed in Table 1. As for reducing *RMSE*, improving *SNR* and keeping the characteristic information of the point cloud data as much as possible, the DWT method had the better performance in all the sets compared with the traditional methods. Due to the multiresolution feature of this method, the non-stationary characteristics could be described very well during extracting and detail features could be protected.

The grain surface was reconstructed after the denoising process. Then, the grain volume was estimated by the reconstructed surfaces using a slicing method. The actual grain volume in the granary was calculated of 4100 m^3 according to the real weight and unit weight of maize. The calculated volume and volume relative error are listed in Table 2. The average value of the relative error by average filtering method, median filtering method and DWT method were 0.165%, 0.135% and 0.086%, respectively. The calculated grain volume by DWT method had the lowest average value of relative error, which would improve the precision of the online measuring system for stored grain. The average CPU time of average filtering method, median filtering method and DWT method were 6.85 s, 8.31 s and 22.17 s, respectively.

Table 1 The objective standard of different methods

Set No.	Average filtering method			Median filtering method			DWT method		
	RMSE	*SNR*	*PSNR*/m^2	*RMSE*	*SNR*	*PSNR*/m^2	*RMSE*	*SNR*	*PSNR*/m^2
1	0.631	45.093	20.253	0.492	45.469	22.405	0.237	46.256	28.774
2	0.570	45.195	21.314	0.482	45.993	23.762	0.179	46.344	29.935
3	0.546	45.269	21.484	0.476	45.454	23.835	0.199	46.412	30.542
4	0.694	45.019	20.087	0.524	46.040	21.910	0.342	46.214	28.537
5	0.574	45.140	20.663	0.488	45.356	22.893	0.243	46.280	29.286
6	0.532	45.476	22.738	0.465	46.138	24.504	0.150	46.560	31.365
7	0.681	45.041	20.103	0.522	45.375	21.932	0.235	46.138	28.978
8	0.540	45.373	22.451	0.470	46.120	24.100	0.163	46.415	31.010
Average	0.596	45.201	21.137	0.490	45.743	23.168	0.219	46.327	29.803

Table 2 Comparison of performance in grain volume estimation by different algorithms

Set No.	Average filtering method		Median filtering method		DWT method	
	Calculated volume/m^3	Volume relative error/%	Calculated volume/m^3	Volume relative error/%	Calculated volume/m^3	Volume relative error/%
1	4093.401	0.171	4094.235	0.146	4097.522	0.073
2	4093.645	0.155	4105.453	0.133	4103.239	0.079
3	4093.932	0.148	4105.330	0.130	4097.540	0.060
4	4091.062	0.218	4093.317	0.163	4093.645	0.155
5	4106.724	0.164	4094.301	0.139	4096.720	0.080
6	4094.629	0.131	4095.654	0.106	4102.050	0.050
7	4108.159	0.199	4105.945	0.145	4105.699	0.139
8	4105.617	0.137	4104.961	0.121	4102.091	0.051

4 Conclusions

Denoising method of point cloud data played an important role for reconstructing grain bulk surface in online measuring system for stored grain. The proposed method in this study was used to remove the noisy points and satisfying results were achieved. According to the simulated results, the following conclusions can be obtained:

1) A classified denoising method was proposed to denoise the noisy points based on two different methods. The first and second types of the noisy points were deleted by the grid method, which could prepare fundamental data for next denosing procedure. Then, the third type of the noisy points were deleted by an image denoising method, DWT method, which projected the point cloud data to a horizontal plane, and deleted the noisy points mixing with the useful data.

2) The performance of the denoising method proposed in this research was compared with the average filtering method and median filtering method. By comparing of the subjective standard and objective standard of the denoised point cloud data, the proposed method remained the most details and had higher average value of *SNR* (46.327), *PSNR* (29.803), and lower average value of *RMSE* (0.219). Therefore, the grain volume calculated by using the denoised data by the proposed method had the lowest average value of the relative error (0.086%), indicating that this method was advantageous for improving the accuracy of the online measuring system for stored grain.

3) The proposed method could also be applied to denoise the point cloud data of tunnels and tall buildings. In the future research, we aim to reduce the processing time of the denoising procedure.

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