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Overall Filtering Algorithm for Multiscale Noise Removal From Point Cloud Data

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ABSTRACT The multiscale noise in the 3D point cloud data of rock surfaces which collected by 3D scanners has a significant influence on the exploration of rock surface morphology. To this end, this paper proposes a multiscale noise removal overall filtering algorithm. The specific processing procedure of the algorithm is as follows. First, a weighted principal component analysis is performed on point cloud data, i.e., the neighboring point distance is used as a weight in the principal component analysis, the covariance feature matrix of the weighted point is estimated, and the eigenvector corresponding to the lowest eigenvalue is used as the normal vector of the point cloud data. Second, in the weighted principal component analysis, estimating three eigenvalues corresponding to the Eigen matrix of the point cloud data, the ratio of the eigenvalue corresponding to the normal vector to the sum of three eigenvalues is used as the surface change factor. For the sample point, if the surface change factor of one sample point is less than the average value of the surface change factor of all sample points in the neighborhood, the sample point belongs to a flat area; otherwise, it belongs to a mutation area. Finally, in order to achieve multiscale noise removal, statistical filtering algorithm is used to remove large scale noise in flat area, additionally bilateral filtering algorithm is adopted to remove small scale noise in mutation area. In the experiments, the improved principal component analysis is combined with the overall filtering algorithm to accurately estimate the eigenvalues of the point cloud data points. After that, the eigenvalues of the sample points are used to distinguish between flat area and mutation area, so as to consider large scale noise and small scale noise. From the experimental results, it can be seen that overall filtering algorithm can consider both large scale and small scale noise and can remove noise from the point cloud data of rock samples. Visual judgment, normal distribution and fractal distribution tests are employed on filtered rock sample point cloud data to verify the reliability of the filtering results.

INDEX TERMS 3D scanner, point cloud data, multiscale noise, statistical filtering, bilateral filtering.

I. INTRODUCTION

The 3D optical scanning method can be used to obtain the 3D point cloud data of the surface of an object. Then a complete, high precision 3D model is reconstructed based on the point cloud data [1]–[3]. However, because of the systematic error in 3D optical scanning instruments, the specular reflection on the surface of the observed object, and the accidental error in the measurement process [4], [5], the acquired 3D point cloud data contain noise and outliers, and consequently the reconstructed 3D model will be inaccurate. Therefore, it is necessary to denoise to accurately obtain the surface morphology of target samples [6], [7], and reconstruct a complete and high precision 3D model [8]. Given the uncertainty in the noise distribution state of acquired point cloud data of rock samples, it is essential to apply a robust algorithm to deal with the noise points.

Significant advancements have been made in developing a point cloud denoising algorithm. The extensive research conducted in this field can be broadly summarized into single algorithm denoising and multiple algorithms denoising. A single denoising algorithm removes noise from a noise

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source. A combination of multiple algorithms can remove noise points from different sources that are called multiscale noise. In the case of single algorithm, Wan *et al.* [9] achieved a good denoising of point cloud data based on the slope filtering algorithm, considering the number of filters and window size required for the filtering. Bian and Tong [10] classified the feature points of point cloud data and included a denoising method that relied on two feature weighting functions, which preserves the feature information of the point cloud data; however, this approach is unsuitable for processing multiscale noise. Yang *et al.* [11] proposed a two-way cloth simulation filtering algorithm that can consider terrain characteristics, sequentially calculate the regional terrain complexity and adaptive distance threshold, and perform partition filtering, which improves the efficiency of the filtering calculation; however, this method has poor adaptability to different noises. Lu *et al.* [12] estimated the initial mesh of a point cloud model, then completed feature detection through identification and connection, and finally updated the vertex position iteratively based on the constructed feature edge to complete the denoising process. Zeng and Li [13] used the Lagrangian interpolation method to fit a local surface and complete the filtering; however, this filtering algorithm cannot achieve an ideal filtering effect for unevenly distributed point cloud data. Rosman *et al.* [14] used the Laplace–Beltrami operator to generate a smooth surface to deal with high-frequency noise. However, it reduces the accuracy of object representation. Yang and Xiao [15] proposed a systematic smoothing algorithm to achieve point cloud denoising and better maintain the surface characteristics. In addition, statistical filtering is widely used in noise processing by analyzing the statistical characteristics of the data [16], mainly by calculating small neighborhood statistics, such as its mean, median, maximum, and minimum, to eliminate noise. Bilateral filtering was first proposed by Tomasi and Manduchi [17] for image noise processing. Shachar *et al.* [18] found bilateral filtering to be suitable for grid denoising and extended this algorithm to point cloud denoising. Although a single denoising method can realize denoising to a certain extent, it is difficult to accurately extract the morphological features of an object surface because of the poor denoising effect, inaccurate results, incomplete edge information, and many loopholes when applied to the surface of complex and discontinuous objects.

In view of the shortcomings of the above algorithms, some scholars have proposed multiscale noise processing algorithms. In this approach, point cloud data are divided into different regions, where different denoising algorithms are applied. Yuan *et al.* [19] divided point cloud noise into large-scale and small-scale noises, used statistical and radius filtering to process large scale noise, then estimated the point cloud data curvature, and used an improved bilateral filter to remove small scale noise. This method preventes over-smoothing and distortion while denoising. However, the accuracy is reduced in the noise processing of sparse point clouds. Based on the different curvature characteristics of a point cloud model, Gu *et al.* [20] proposed algorithms that used different filtering strategies for different curvature feature regions. Wu *et al.* [21] applied the conventional median filtering and bilateral filtering algorithms to different feature regions and applied the filtering algorithm based on the average curvature feature classification, thus effectively removing noise and maintaining the geometric features of the sharp regions. However, the noise processing connection issues under different scales requires further study. Li *et al.* [22] removed large-scale noise through statistical and radius filtering, and then smoothed small-scale noise through fast bilateral filtering. Their algorithm can effectively maintain the geometric characteristics of the scanned object; however, the relevant statistical and radius parameters need to be resolved. To a certain extent, these methods alleviate the drawbacks associated with the use of only one type of noise processing algorithm; however, the error in classifying the noise data affects the accuracy of noise processing. In other words, effective point cloud data are mistaken for noise data, yielding undesired results.

In the above two types of methods used for processing point cloud noise data, a single algorithm cannot achieve the corresponding accuracy requirements for the processing of noise points of different scales. Isolated noise, clustered noise in low-density area, and dense noise close to the object itself cannot be separated. Therefore, multiscale noise processing algorithms need to be used for filter noise of different scales, and the effectiveness of the convergence of applicable processing algorithms should be improved.

In this study, based on the 3D point cloud data of rock surfaces which obtained using a 3D optical scanner, the overall filtering algorithm is proposed to remove noise from the point cloud data. This algorithm fully considers the multiscale problem of the point cloud and divides the point cloud region into two areas based on the noise scale. The corresponding filter algorithms are used for denoising, thus effectively combining different scale noise processing algorithms to complete the denoising of sample point cloud data.

II. DATA

A. SAMPLE COLLECTION

To study the performance of the noise removal algorithm for 3D interferometric-scanned rock surface point cloud data, 14 samples of three types of rocks, namely exposed granite, marble, and sandstone, are collected from the Central Plains in China. The exposed surface of the rock is the weathered natural surface, which is the surface to be observed, as shown in Figure 1:

B. DATA ACQUISITION

Obtaining the 3D spatial information of a target object through 3D measurement technology can help restore the 3D characteristics of the measured target completely. For the experiment, we use the VTOP600T 3D optical scanner

FIGURE 1. Fourteen pieces of natural rocks.

produced by WeiShen Technology Company, which is mainly composed of raster projection equipment and a CCD camera, and the scanning method is non-contact structured blue light photography. The instrument has the advantages of good anti-interference, high automation performance, and high work efficiency [23]. The 3D scanner reconstructs the 3D model through phase grating projection. The grating transmitter projects the simulated sinusoidal fringes onto the surface of the measured target. The grating fringes are deformed under the influence of the height of the measured target surface. Two cameras placed at different projection angles are used for a simultaneous shooting. The grating is modulated by the height of the measured target, making the regular fringes to bend to different degrees. The phase information is obtained by demodulating the curved grating fringes, and finally, the height information of the measured target object is inverted on the basis of the phase distribution [24]. Figure 2 shows the working principle.

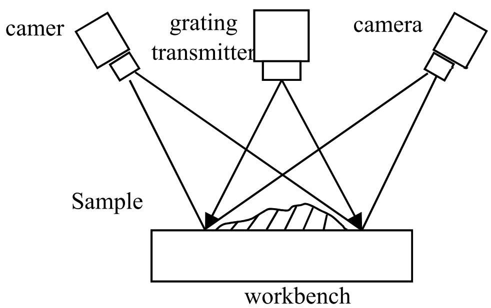

FIGURE 2. Working principle diagram of 3D scanner.

Based on the working principle of the 3D scanner, to improve the observation accuracy, the measured target can be observed from multiple angles, and the surface point cloud data measured from multiple angles can be matched and converted into the same coordinate system.

The 3D point cloud model of the rock surface is obtained by raster interferometry. The scanning sample range is approximately 10 cm $\times$ 10 cm $\times$ 10 cm, and the point cloud position accuracy is 5 μm. Figure 3 shows the 3D point cloud data.

As shown in Figure 3, the 3D scanner scans 14 natural rocks to obtain the point cloud model of the surface morphology. During the scanning process, the scanning points on the rock surface produce specular reflection of light, and the scanning of non-target objects produce noise points which is different from the effective points. Therefore, noise points include two parts: (1) the placement of the natural rock plane producing large scale noise points far from the main point cloud; (2) small scale noise points on the rock surface close to the effective point cloud. To improve the accuracy of the rock surface morphology, the noise should be removed. In this paper, these two scale noise are called multiscale noise and different denoising algorithms are used to deal with the noise.

III. METHODS

Many types of noise processing algorithms exist for point cloud data. However, it is difficult to adapt them to the removal of multiscale noise using a single denoising algorithm. Designing a new multiscale noise filtering algorithm for noise processing has become an urgent requirement. In this study, an improved principal component analysis (PCA) algorithm is used to estimate the normal vector and eigenvalues of point cloud data, a surface change factor composed of the eigenvalues is employed to distinguish the scale area of the point cloud noise, and a corresponding filter algorithm is applied to deal with the noise points located in different areas. Thus constituting a systematic overall filtering algorithm can perform multiscale denoising.

A. IMPROVED PRINCIPAL COMPONENT ANALYSIS METHOD FOR POINT CLOUD NORMAL VECTOR ESTIMATION

The process of point cloud data acquisition is constantly accompanied by missing point cloud data, uneven sampling of point cloud data, and missing point cloud sharp features. Therefore, the distribution characteristics of the point cloud normal vectors are the most important geometric properties of the point cloud data. Accurately estimating the cloud normal vector can help retain the detailed features of the point cloud model and provide basic data for reconstructing the real 3D surface. Most point cloud noise is directly processed by existing filtering algorithms, and the denoising effect is not good for missing point cloud data and incomplete expression information. In this paper, the neighborhood point weight value is added to the PCA, so that the improved PCA can accurately estimate the normal vector and eigenvalues of the point cloud, so that the subsequent filtering can achieve good results.

The PCA first introduces an orthogonal transformation, which converts the component-related random point cloud vector into a new random point cloud feature vector with uncorrelated components. The mutual influence between the neighboring points in the point cloud data can be eliminated, thus yielding a more accurate result in the subsequent normal vector estimation [25]. The normal vector estimation of point cloud data involves estimating the principal component that retains most of the point cloud information as a feature vector [26]. The specific estimation method is to estimate a plane in its neighborhood for each point, at the same time the point and normal vector are required to determine the

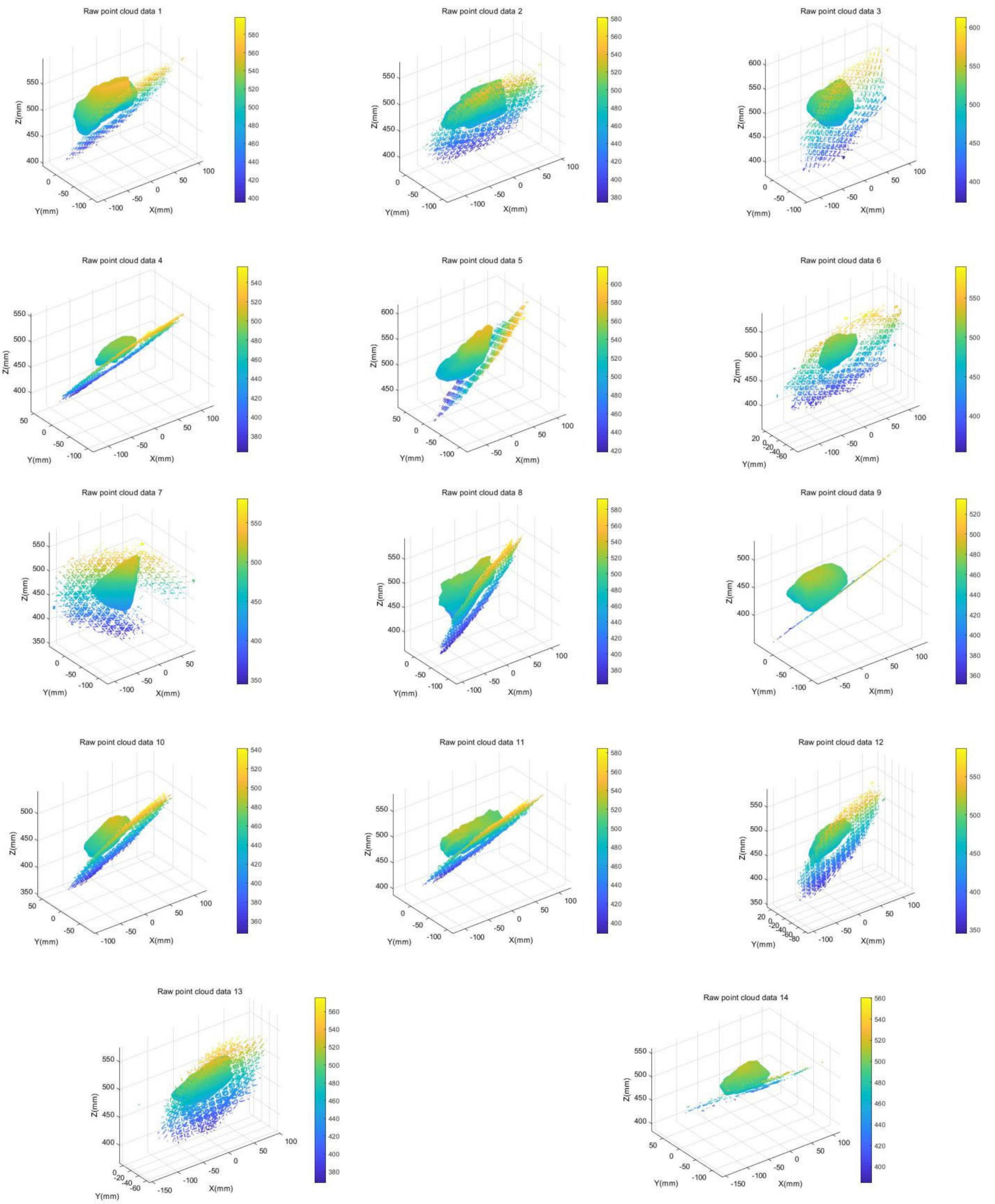

FIGURE 3. Raw point cloud data of 14 pieces of natural rock.

plane. In the direction of the normal vector, the projection distribution of all the neighborhood points of the estimated plane is the most concentrated, and the projection variance is the lowest. At this time, the eigenvalue corresponding to the principal component is also the lowest, i.e., the eigenvector corresponding to the eigenvalue is the normal vector of the point cloud. This method uses the neighborhood point distance as weight information in the original PCA algorithm. If the neighborhood point is far from the sample point, the weight is low, i.e., the contribution rate of the neighborhood point to the sample point is low. If the neighborhood point is close to the sample point, the weights are high, i.e., the contribution rate of the neighboring points to the sample points is high. Since the position information of each point in the neighborhood of the point cloud is considered, an accurate estimation of the normal vector of the point cloud for the data points on the segmented plane and the curved surface has a good effect.

The specific mathematical expression of the improved PCA is given below. Assuming there is a sample point p with $\mathrm{d_i}$ representing the distance between the sample point and the neighboring point, the weight formula can be expressed in Equation (1):

$$\mathrm{w_i} = \begin{cases} 1 & \mathrm{d_i} = 0 \\ \dfrac{1}{\mathrm{d_i}^2 \sum_{\mathrm{i}=1}^{\mathrm{k}} \mathrm{d_i}^2} & \mathrm{d_i} \neq 0 \end{cases} \tag{1}$$

The weighted average of the coordinate values in the neighborhood points can be calculated using Equation (2), where $\mathrm{p_i}$ indicates the coordinate information of the neighboring point, and the weighted covariance matrix can be calculated using Equation (3):

$$\overline{p_w} = \frac{\sum\limits_{i=1}^{k} w_i p_i}{\sum\limits_{i=1}^{k} w_i} \tag{2}$$

$$C_W = \frac{1}{k} \sum_{\mathrm{i}=1}^{k} \sqrt{w_i}(p_i - \overline{p_w})(p_i - \overline{p_w})^T \tag{3}$$

After the weighted matrix is estimated, the characteristic polynomials of the matrix are listed and three eigenvalues of the sample point are calculated to accurately distinguish the noise points of different scales. When the eigenvalue of the sample point is the lowest, the corresponding eigenvector is used as the normal vector and applied to bilateral filtering to smoothen the noise point cloud.

B. USE OF EIGENVALUE CORRESPONDING TO THE NORMAL VECTOR TO DISTINGUISH DIFFERENT-SCALE NOISE

To filter the noise information in the point cloud model and retain the detailed features of the point cloud data, based on the location and density of the noise in the point cloud model, it is necessary to divide the point cloud into two regions in terms of the distance from the noise: one is a flat area where the noise points are scattered and far away from the target point cloud, and the other is a mutation area of the surface where the points and the target point cloud are closely connected [27]. In this study, different areas are distinguished on the basis of the different surface change factors of the point cloud, and the three eigenvalues of the sample point are calculated using the improved PCA. Among them, the eigenvalue corresponding to the normal vector is the lowest eigenvalue, and the ratio $\sigma(\mathrm{p})$ of the eigenvalue to the sum of the three eigenvalues is used as the surface change factor, and finally, the average $\overline{\sigma(\mathrm{p})}$ of all the sample points in the neighborhood is calculated. Different scale noise can be distinguished on the basis of the relationship between the surface change factor of the sample point and the mean surface change factor. If the sample point $\sigma(\mathrm{p})$ is less than $\overline{\sigma(\mathrm{p})}$, the point belongs to a flat area, and the noise point in the flat area is the large scale noise; on the contrary, if the sample point $\sigma(\mathrm{p})$ is greater than $\overline{\sigma(\mathrm{p})}$, the point belongs to a mutation region, and the noise point in the mutation region is the small scale noise.

The surface change factor of the sample point is expressed in Equation (4).

$$\sigma\,(p) = \frac{\lambda_0}{\lambda_0 + \lambda_1 + \lambda_2} \tag{4}$$

where λ_0 is the eigenvalue corresponding to the normal vector of the sample point, λ_1 and λ_2 are the remaining two eigenvalues of the sample point.

The average surface change factor of all the sample points in the k-neighborhood is expressed in Equation (5).

$$\overline{\sigma\,(p)} = \frac{1}{k} \sum\nolimits_{i=1}^{k} \sigma\,(p_i) \tag{5}$$

The surface change factor $\sigma(\mathrm{p})$ describes whether the local k-neighborhood of the sampling point forms an approximate smooth plane patch. In the smooth area with a low curvature, the surface change factor is relatively low, whereas in the area with a high curvature and sharp features, the surface change factor is higher. This information can be used to determine the area where the point cloud data are located. If the sample point p surface change factor $\sigma(\mathrm{p})$ is less than the average surface change factor $\overline{\sigma(\mathrm{p})}$ in the neighborhood, the sample point belongs to a flat area; on the contrary, if the sample point p surface change factor $\sigma(\mathrm{p})$ is greater than the average surface change factor $\overline{\sigma(\mathrm{p})}$ in the neighborhood, the sample point belongs to a mutation area. Since the noise data include points mixed in the effective point cloud and discreted around the effective point cloud, the area where the sample point is located can be clarified, and the noise data in the different areas can be processed on the basis of the applicable range of the different denoising algorithms.

C. DIFFERENT SCALE NOISE REMOVAL

Most of the existing denoising algorithms can only remove one kind of point cloud noise. A single algorithm cannot effectively remove the noise points of different scales generated in the process of point cloud data acquisition. Different denoising algorithms are used on the basis of the area where the noise points are located, which can effectively remove the noise points and restore the real spatial geometric characteristics of the point cloud data. Using the relationship between the surface change factors of the sample points and the average surface change factor, we find that the sample points are located in the flat area and the sudden change area. In the flat area, the statistical filtering algorithm is adopted to process large scale noise points, and the bilateral filtering algorithm is used to process small scale noise points in the mutation area.

1) STATISTICAL FILTERING

The signal and noise in the point cloud data are randomly distributed, and their characteristics can often only be described in a statistical sense. The distance between each point in the point cloud model and the neighboring point obeys a certain statistical distribution law [28]. For sample point p, the large scale noise in the flat area, where the surface change factor is less than the average surface change factor, is removed by statistical filtering. Each point in the point cloud, based on the k-nearest neighbor search in the KD-tree, selects the appropriate neighborhood and calculates the average distance d_i from the center point to all the neighboring points. The Gaussian distribution is used to determine the distribution status of the data points, and the k-neighborhood average distance of all the sample points is weight- averaged to obtain the mean μ, and finally, the average distance d_i and the mean μ of all the sample points are used to obtain the standard deviation σ. In the statistical filtering algorithm, the threshold parameter λ of the multiple of the standard deviation is set, and the given global distance formula is expressed in Equation (6).

$$d_i' = u \pm \lambda\sigma \tag{6}$$

By performing a statistical analysis in the flat area and synthesizing the global distance as the judgment criteria, we can define points whose average distance is outside the standard range as outlier noise points and remove them from the data. After processing the large scale noise, the small scale noise points in the point model should be processed. In this study, bilateral filtering was used to denoise the small scale noise.

2) BILATERAL FILTERING

First, bilateral filtering was applied to image noise processing, by comprehensively considering the two weighting mechanisms of the distance measurement and the gray-scale similarity measurement between the surrounding pixels and the center pixel, thus ensuring the reliability of the bilateral filtering results [29]. In this study, bilateral filtering of the 3D point cloud data is used to remove small scale noise in the sudden change area of the rock surface. Moreover, the improved PCA algorithm is applied to the bilateral filtering algorithm to analyze the eigenvector corresponding to the minimum eigenvalue of the sample point. Then the eigenvector is used as the normal vector of the point cloud to smoothen the point cloud containing noise. The bilateral filtering of point cloud data can be generally divided into five steps: establishing the k-neighborhood, estimating the normal vector estimation, defining the viewing plane, introducing the bilateral filtering algorithm, and correcting the point cloud noise coordinate value. Among them, the position p_i' of the sample point after denoising and moving is expressed in Equation (7):

$$p_i' = p_i + a * n \tag{7}$$

where p_i is the original position of the point cloud, α is the bilateral filter factor, which determines the distance adjusted by the neighboring points along the normal direction; n is the normal vector at the measuring point p_i, which is accurately estimated with the eigenvector corresponding to the lowest eigenvalue, contributing to bilateral filtering for better results, and α can be expressed as in Equation (8):

$$\alpha = \frac{\sum_{i=1}^{k} \omega_1(\|p-p_i\|)\omega_2(\langle p-p_i, n\rangle)\,\langle p-p_i, n\rangle}{\sum_{i=1}^{k} \omega_1(\|p-p_i\|)\omega_2(\langle p-p_i, n\rangle)} \tag{8}$$

where k is the number of sampling points in the k-neighborhood, and p_i is the projection of the neighborhood point in the viewing plane, ω_1 and ω_2 are the Gaussian filter functions on the tangent plane of the local neighborhood of the sampling point and on the normal height, which jointly determine the bilateral filter factor. The specific form is:

$$\omega_1(x) = e^{-\frac{(x-k)^2+(y-l)^2}{2\delta_1^2}} \tag{9}$$

$$\omega_2(x) = e^{-\frac{\|f(x,y)-f(k,l)\|^2}{2\delta_2^2}} \tag{10}$$

where δ_1 and δ_2 are respectively the Gaussian filter coefficient on the tangent plane in the local neighborhood of the sampling point and the Gaussian filter coefficient on the normal height. (x, y) are the coordinates of the sampling point, and (k, l) are the coordinates in the neighborhood of the sampling point.

Two filtering algorithms are combined to achieve double handling of large scale and small scale noise. Figure 4 below is a workflow of applying the overall filtering algorithm to remove the entire point cloud noise.

In summary, with regard to the denoising process proposed in this paper, the neighborhood point distance weight information of the point cloud data is used for PCA processing, thus accurately estimating the point cloud normal vector and eigenvalue, and the eigenvalue is used to form the surface change factor σ (p) to calculate the surface change factors average value $\overline{\sigma(p)}$ of all the sample points. Based on the relationship between the surface change factor and the average surface change factor, the scale area of all the point cloud data is determined, and the point cloud is divided into a flat area and a mutation area. If the sample point σ (p) is less than $\overline{\sigma(p)}$, the point belongs to a flat area; conversely, when the sample point σ (p) is more than $\overline{\sigma(p)}$, the point belongs to a mutation area. Statistical filtering is applied to remove the large scale noise in the flat area of the point cloud data; moreover, the bilateral filtering algorithm is used to smoothen the small scale noise in the mutation area. For the flat and mutation areas in the point cloud, an algorithm combining of statistical filtering and bilateral filtering is selected for denoising, and finally, a multiscale noise overall filtering

TABLE 1. **Point cloud distribution table of high frequency part.**

Rock number/before denoising	Points ratio/%			Rock number/after denoising	Points ratio/%		
	<1.00σ	<1.96σ	<2.58σ		<1.00σ	<1.96σ	<2.58σ
1	76.14	92.45	97.01	1	68.33	95.08	98.91
2	85.34	93.35	95.91	2	69.33	94.68	98.73
3	80.60	92.75	96.23	3	68.04	95.22	99.08
4	78.29	92.40	96.24	4	66.86	95.25	99.38
5	76.93	92.31	96.63	5	68.08	94.96	99.09
6	78.72	92.58	96.40	6	68.34	94.05	98.42
7	84.67	95.72	97.52	7	68.53	93.80	98.56
8	75.27	95.57	98.23	8	69.05	94.58	98.80
9	80.66	92.33	96.09	9	69.03	94.86	98.87
10	77.15	92.42	96.60	10	69.63	93.97	98.63
11	82.91	92.77	95.93	11	68.98	95.50	98.71
12	78.71	92.31	96.38	12	68.43	95.54	99.46
13	81.24	92.46	95.97	13	69.35	94.59	98.71
14	76.64	92.47	96.75	14	68.84	95.43	99.34

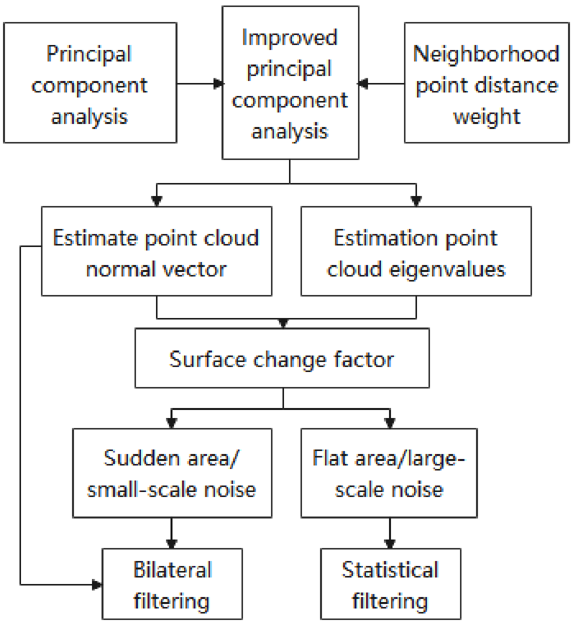

FIGURE 4. **Workflow of denoising.**

algorithm is established, which can remove multiscale noise and effectively obtain the true surface morphology of rocks.

IV. RESULTS AND DISCUSSION

A. EXPERIMENTAL RESULTS

In this study, the multiscale noise removal overall filtering algorithm is used to denoise 14 natural rock point cloud models and obtain a reasonable denoising result. The 14 natural rocks have different surface morphologies, so it is necessary to fully consider the influence of parameter sensitivity. In view of the similarity between the collected natural rock samples and the uniformity of the observation conditions, the same parameter setting method is used for the 14 rock samples. The tentative test method is adopted for sample 1, and the denoising result is used as the test standard to obtain the optimal denoising parameters. For statistical filtering, through tentative testing, when the neighborhood parameter k is set too small, the calculation efficiency is high; but the noise points cannot be completely filtered. When the parameter k is set too high, the calculation efficiency is low, whereas the real model points are filtered as noise points. Similarly, if the standard deviation multiple threshold parameter λ is set too low, the real model points are filtered as noise points. If the parameter λ is set too high, the noise points cannot be completely filtered. Taking model points conforming to normal and fractal distributions as the verification standard, it is concluded that when the parameter k is 20 and λ is 5, the denoising result of the rock sample 1 is the best, seeing Section B for the verification scheme and results. Similarly, the three parameters in bilateral filtering are tentatively tested, and the number of neighboring points, the spatial-domain weight filter coefficient, and the frequency-domain weight filter coefficient are 20, 5, and 10, respectively, in which case the denoising result is the best. The above-mentioned parameters setting method were used to complete the denoising of the 14 natural rocks, and real point cloud models are obtained.

By removing the point cloud noise using the overall filtering algorithm, a preliminary visual judgment of the point cloud image of the 14 natural rocks after denoising shows that the iron ore noise removal effect is better. The large scale noise has been completely removed, and the small scale noise is removed later, making the point cloud model more in line with the surface morphology of natural rocks. For the point cloud model, it is feasible to use the overall filtering algorithm depending on the different surface change factors.

B. RESULTS VERIFICATION

Multiscale noise overall filtering algorithm for denoising has a good visual effect. By checking whether the filtered point cloud conforms to the normal and fractal distributions, the five parameter settings of the overall filtering algorithm

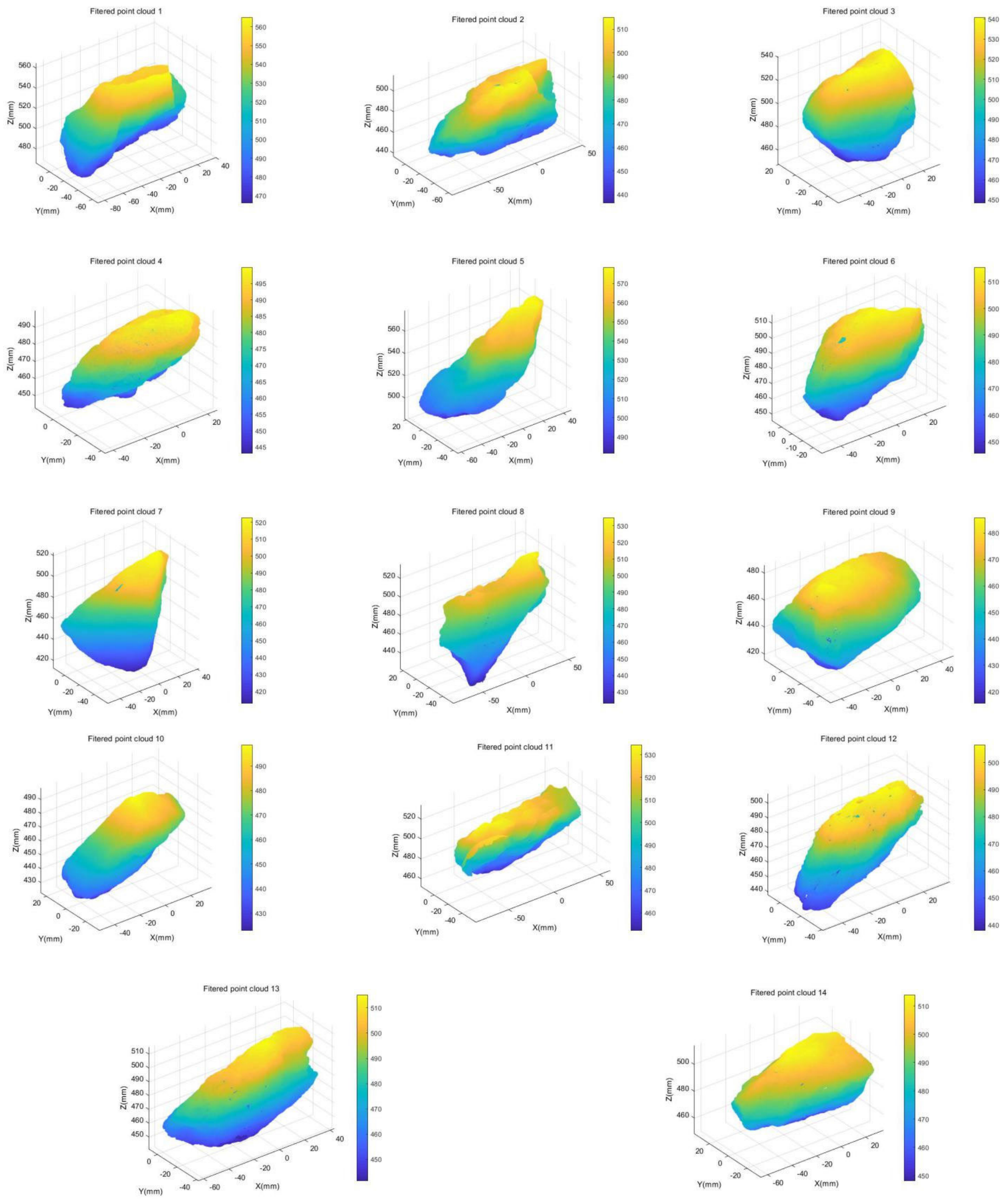

FIGURE 5. Point cloud diagram of 14 pieces of natural rock after denoising.

for the point cloud model of this experiment could be determined. Since the sample point cloud can be decomposed into low frequency information representing mutation and high-frequency information representing roughness, the point cloud conforming to the normal and fractal distributions can only be tested for indicating the roughness, which is high frequency information. The high-frequency information can be extracted using wavelet decomposition [30] to process natural rock point cloud data. Subsequently, the parameters of the overall filtering algorithm can be determined by judging

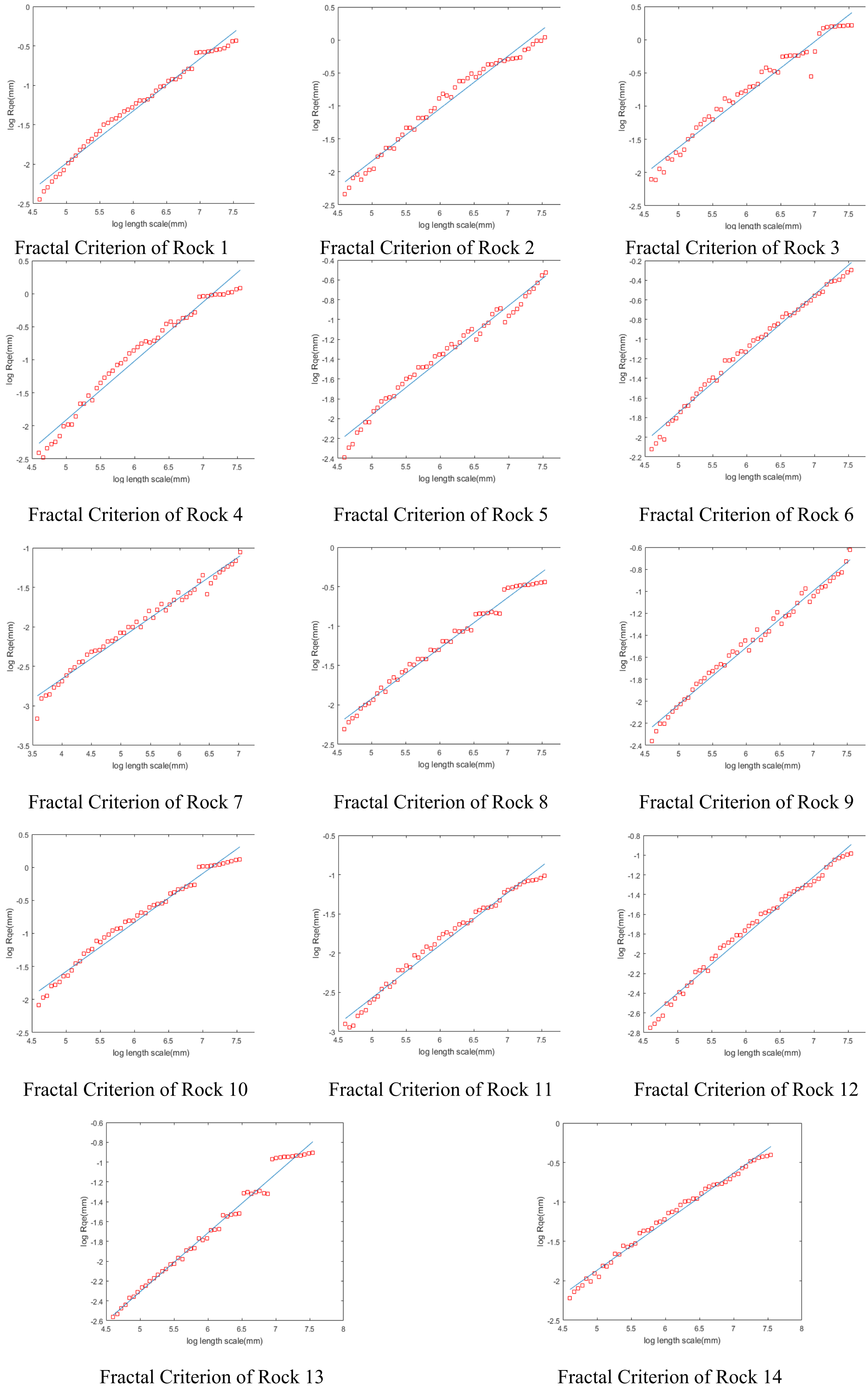

FIGURE 6. **Fractal criterion of high-frequency information of 14 pieces of iron ore samples.**

whether the high-frequency information conforms to the normal and fractal distributions. The 3D point cloud data of 4 cm $\times$ 4 cm on the natural rock surface before and after denoising was subjected to wavelet decomposition. Table 1 lists the normal distribution of the point cloud on the surface of the 14 natural rock samples.

Based on the normal distribution theory [31], the probability of the statistics at $<1.00\sigma$, $<1.96\sigma$, and $<2.58\sigma$ are 68.26%, 95.45%, and 99.73%, respectively, which is completely consistent with the normal distribution. From Table 1, we find that the probability ranges of the roughness, which is at $<1.00\sigma$, $<1.96\sigma$, and $<2.58\sigma$, are respectively 75.27%–85.34%, 92.31%–95.72%, and 95.91%–97.52%, which do not satisfy the normal distribution. After denoising the point cloud data using the overall filtering algorithm, the high-frequency information obtained by wavelet decomposition is close to the normal distribution. To further determine the distribution position of the discrete point cloud, the fractal distribution method is used to verify the acquired high-frequency information [32], as shown in Figure.

In Fig. 6, the abscissa is the natural logarithm of the series length interval within the sampling length, i.e., log length scale (mm), and the ordinate is the natural logarithm of the root-mean-square height, i.e., log Rqe (mm). The high-frequency information obtained by wavelet decomposition also conforms to the law of fractal distribution, which helps determine the parameters of the overall filtering algorithm and also verifies the reliability and effectiveness of the denoising algorithm.

C. DISCUSSION

For the overall filtering algorithm to remove noise in the 14 natural rock point cloud models, in addition to the algorithm itself, a part of the theory needs to be further tested. The evaluation of whether the five filtering parameters are worthy of optimal selection and the effectiveness of the denoising result test method are key factors influencing the point cloud denoising effect.

(1) Rationality of using the normal vector corresponding eigenvalue to distinguish different scale noise. The average surface change factor $\overline{\sigma(p)}$ of all the sample points in the k-neighborhood is used to distinguish flat and mutation areas. The filtering effect is achieved by visual judgment of the filtered point cloud, the normal and fractal distributions of the point cloud roughness; however, the rationality of this method requires further research, and the universality requires further testing.

(2) Evaluation mechanism for filter parameter optimization. The overall filtering algorithm designed in this study has five main filtering parameters, namely the number of statistical filtering neighborhood points k, the standard deviation multiple threshold λ and the number of bilateral filtering neighborhood points k, the Gaussian filter coefficients in the tangent plane of the local neighborhood of the bilateral filtering sampling points, the point cloud normal Gaussian filter coefficient. The setting of these parameter values directly affects the filtering effect. The setting of the optimal values of the five filter parameters is determined by the distribution characteristics of the sample point cloud. There is no theoretical or analytical relationship between the filter parameters and the point cloud distribution characteristics. This study adopts the method of tentative testing, sets multiple combined values for the five filtering parameters, and determines the optimal combined values through visual inspection of the filtering results and inspection of the normal and fractal distributions of the roughness. Whether it is visual inspection or the conformity of the normal and fractal distributions, it is artificially judged by visual observation, which brings errors to the selection of the optimal combination of the five filter parameters.

(3) Effectiveness of the denoising results test method. After the sample point cloud model is filtered by overall filtering, the point cloud is visually judged for the filtering effect, and the visual judgment is further utilized to verify whether it conforms to the normal and fractal distributions. It is necessary to further study the reliability of the point cloud visual judgment filtering effect and the visual judgment regarding whether the point cloud conforms to the normal and fractal distributions to form a new judgment theory. In addition, the use of the normal and fractal distributions in judging the point cloud denoising effect requires further research and improvement.

V. CONCLUSION

In this study, we developed an overall filtering algorithm for removing multiscale noise point cloud data pertaining to 14 natural rock samples, completed the denoising work of the point cloud model, and verified the rationality of the denoising results. The following conclusions can be drawn from the results:

(1) An improved principal component analysis algorithm was proposed to accurately estimate the normal vector of the point cloud. In view of the lack of point cloud data obtained, uneven sampling, lack of sharp features, etc., and considering the position information of each point in the neighborhood of the point cloud, an improved principal component analysis was proposed and the point cloud normal vector was accurately estimated for the data points. Eigenvalues were used to distinguish between large scale and small scale noise, which lied a data foundation for point cloud filtering.

(2) An innovative overall filtering algorithm was developed to complete point cloud noise removal. To remove multiscale noise in the point cloud, an innovative overall filtering algorithm was established, which combined statistical filtering for flat area and bilateral filtering for mutation area to remove

large scale and small scale noise close to the rock surface, respectively, thus completing the point cloud multiscale noise removal process.

(3) A scientific test standard was put forward for the filtering results of the point cloud model. For the selection of the filtering parameter values in the overall filtering algorithm and the inspection of the denoising results of the point cloud model, in addition to visual judgments, a test plan with normal and fractal distribution results were devised, providing a scientific basis for the reliability of the filtering results as inspection standards.

Therefore, the filtering method of the overall filtering algorithm designed in this study can complete the task of removing multiscale noise from data pertaining to natural surfaces obtained using a 3D scanner. The denoised rock surface has a real shape, so the algorithm proposed in this paper has important value for accurately studying the surface shape information of rock and mine.

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