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Research on mixed noise removal algorithm for ore images based on fusion filtering technique

Introduction

In the ore crushing process to obtain ore image information, ore image information through the digital image system for acquisition, transmission, storage, and other processing transformations is often subject to a variety of noise contamination. This makes the original image information biased and distorted, reducing the quality of the image and affecting the subsequent image processing work. Therefore, in order to improve the quality effect of the image, it is necessary to effectively remove the image noise and retain the useful information of the image.

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Traditional image denoising is mainly processed in both the null and frequency domains. Frequency domain enhancement techniques include low-pass filtering, high-pass filtering, wavelet filtering, and other methods (Somvanshi et al. 2018; Hu et al. 2022). Sun et al. (Sun et al. 2018) extracted various types of wavelet features from high-frequency to low--frequency images by wavelet transform, combined with local binary patterns to analyze and extract the noise features. Sun Chang (Sun 2019) of Anhui University of Technology proposed an improved wavelet soft threshold function on the basis of c, selecting the soft threshold function of the appropriate object as the improved object and adding the number of wavelet decomposition layers as an adjustment parameter, the experimental effect shows that the denoising effect of the algorithm has been improved to a certain extent. In the current null domain algorithm, Su Kangyou et al. (Su et al. 2022) proposed an improved Retinex algorithm for light uneven image enhancement to eliminate the effect of light unevenness on the image so as to realize the image enhancement. Chuanyi Liu et al. (Liu et al. 2021) used cosine similarity to improve the similarity of similar sub-blocks in the non-local-means (NL-means) algorithm, which utilizes the image structure information and is able better to maintain the edge structure information of CT images.

In addition to traditional image-denoising methods, image-denoising algorithms based on deep learning have been a popular research direction in the field of image-denoising in recent years. These include self-encoder, Generative Adversarial Network (GAN), Convolutional Neural Network (CNN), etc. (Lielāmurs et al. 2023). These methods recover high-quality images by learning a large amount of image data. Mei et al. (Mei et al. 2023), in order to make full use of shallow pixel-level features, extract image features by layering and use self-similarity to balance semantic and pixel features to retain more image details. Kim et al. (Woo et al. 2018; Kim et al. 2019), by using the Convolutional Attention Module (CBAM), focus on learning between noisy image and clear image differences and thus removing the noise by the deep network. Xu et al. (Xu et al. 2023) considered the process of image denoising in deep feature space and proposed the depth-expanded multiscale regularizer network DUMRN for image denoising. Saeed Anwar (Saeed et al. 2019; Li et al. 2020; Muhammad et al. 2019) proposed a feature attention module inserted into the denoising model, and by increasing the number of modules instead of the depth of the network, a single-blind denoising network with only one stage is realised, which solves the synthetic and real noise problems faced in image processing and gives good experimental results.

The above methods improve the noisy images to some extent. However, the noise suffered by ore images in the acquisition and transmission process is not a single one but is contaminated by a variety of noises. Therefore, this paper proposes a novel wavelet + non-local mean (NL-means) fusion algorithm for the problem of ore images containing a variety of mixed noises and then carries out the wavelet transform twice on the ore pictures with mixed noises and then carries out the NL-mean denoising process for the reconstructed pictures. Wavelet transform, and then the reconstructed image is subjected to NL-mean noise removal process; the method combines the advantages of wavelet and non-local mean and has an obvious effect on the removal of mixed noise in ore images.

1. Noise analysis of ore images

When taking ore images, due to the complexity of site conditions, ore image noise mainly comes from the following aspects:

1) The complexity of the ore image acquisition site environment, which has a significant impact on dust noise and may introduce irregular noise.
2) The possible reflection of the belt interferes with the data in the ore image and consequently affects the ore picture's quality.
3) Prolonged operation generates high temperature, which impacts the image capture stability of the camera.
4) The dimly lit, intricate shooting location produces shadows from the light source.

Noise can be differentiated into Gaussian noise, pepper noise, Rayleigh noise, gamma noise, and exponential noise based on the varying probability density function distributions in the spatial domain.

Gaussian noise (Ma et al. 2021) is a prevalent type of noise generated by the high temperature produced by the camera during extended image acquisition, as well as the interaction of circuit components' inherent noise. Its probability density function can be expressed mathematically.

$$p(z) = \frac{1}{\sqrt{2\pi\sigma}} e^{\frac{-(z-\mu)^2}{2\sigma^2}} \tag{1}$$

z – represents the pixel value,
μ – represents the mean (expectation) of Gaussian noise,
σ – is the standard deviation of Gaussian noise
σ^2 – denotes the variance of Gaussian noise.

Figure 1 illustrates the comparison graph of the original image and the image after Gaussian noise has been added.

Fig. 1. Adding Gaussian noise

Rys. 1. Dodawanie szumu gaussowskiego

Pepper and salt noise (Huang 2019) is an image distortion phenomenon that causes randomly appearing black and white dots. This is caused by two types of noise: pepper noise, which appears as low gray noise with a value of 0, and salt noise, which appears as high-gray noise with a value of 255. Generally, both types of noise appear simultaneously, resulting in an image that resembles black and white sprinkled dots akin to pepper and salt. Pepper and salt noise mainly stem from environmental conditions during image acquisition and the quality of the sensor device. Equation (2) displays its probability density function.

$$P(z) = \begin{cases} P_a, & z = a \\ P_b, & z = b \\ 0, & \text{other} \end{cases} \tag{2}$$

The average and variation of this disturbance are demonstrated in Equations (3) and (4) correspondingly.

$$m = aP_a + bP_b \tag{3}$$

$$\sigma^2 = (a - m)^2 P_a + (b - m)^2 P_b \tag{4}$$

↳ a and b are the two gray values of noise that appear in the image, and the probability of these two gray values appearing is P_a and P_b, respectively.

The image comparison of the ore with the addition of pretzel noise is presented in Figure 2.

In the process of image acquisition of ore, complex working conditions and noisy environments will produce a variety of redundant and complex noise. Hence, this paper uses the ore pictures with added mixed noise for analysis. The images used are Gaussian noise

Fig. 2. Adding salt and pepper noise

Rys. 2. Dodawanie szumu „sól i pieprz”

Fig. 3. Adding mixed noise

Rys. 3. Dodawanie szumu mieszanego

and pretzel noise, two of the most likely to occur in the mine acquisition images of the noise fusion redundant ore images, in order to simulate the real mine production shot in the ore images. The ore image after adding mixed noise is shown in Figure 3.

2. Ore image denoising algorithm implementation

2.1. Two-wavelet filtering algorithm

The time-frequency properties of wavelet filtering facilitate the usage of nonlinear denoising techniques. Wavelet transform (Wang et al. 2020) effectively denoise signals due to their inherent characteristics, which include:

- Low Entropy. The sparse distribution of wavelet coefficients reduces the entropy after transforming the image. Once the signal (i.e., image) is decomposed, more wavelet basis coefficients tend to noise, and the main part of the signal becomes concentrated in certain wavelet bases. The use of threshold denoising can preserve the original signal more effectively.
- Multi-resolution properties. Multi-resolution methods can effectively capture the signal's non-smoothness, such as mutations and breakpoints, and overcome the limitation that Fourier transforms cannot precisely represent them. Furthermore, signal and noise distributions allow for efficient noise suppression at different resolutions, ultimately enhancing noise processing efficiency.
- Decorrelation. The wavelet transform is capable of de-correlating the signal, leading to white noise after the transformation. Therefore, the wavelet domain is more suited for denoising than the time domain. The wavelet transform provides flexibility in choosing the basis function by selecting from multi-band wavelet, wavelet packet,

and other wavelet basis functions based on signal characteristics and denoising requirements. The effect of the signal is related to the regularity of the wavelet function and the degree of structural similarity between the waveform of the basis function and the data. Wavelets with good symmetry do not produce phase distortion, and wavelets with good regularity make it easy to obtain smooth reconstructed curves and images. Choosing a wavelet system with better symmetry and regularity for denoising can result in a better denoising effect.

Secondary wavelet filtering decomposes the image into low-frequency approximation signals and detailed signals of different frequencies through multi-scale decomposition. It carries out targeted processing for noise components of different frequencies. Compared with the traditional filtering methods, quadratic wavelet filtering can well protect the edge and detail information of the image to avoid blurring and distortion. Meanwhile, quadratic wavelet filtering has good flexibility and can be adjusted according to different wavelet functions and decomposition layers, thus adapting to different types and intensities of noise.

Wavelet denoising implementation steps:

- The signal is decomposed from S to N layers and then soft-threshold quantised for the high-frequency coefficients in each layer.
- Process the frequency characteristics of a signal and calculate its frequency characteristics.
- The process of soft-threshold quantisation employs a layer-by-layer selection of a threshold value from 1 to N to quantize high-frequency coefficients for achieving more precise outcomes.

2.2. Non-local means denoising

Non-local-means (NL-means) (Du et al. 2017) is a denoising technique that was proposed in recent years and is based on utilising image redundancy information to denoise while preserving detailed image features. The estimate for the current pixel is obtained by a weighted averaging of pixels in the image that share a similar domain structure. The non-local mean denoising method effectively reduces noise through weighted estimation of the surrounding pixels. This principle is akin to that of Gaussian denoising and bilateral denoising, illustrated in Figure 4.

The left figure illustrates the features of Gaussian filtering, which uses the proximity degree of image pixel points to estimate weights for performing image processing. The middle figure illustrates the features of the bilateral filter. Meanwhile, the dual-wave filter considers not only the similarity of values among pixel points but also the distance of similar pixel points from the estimated pixel point. In this case, closer similar pixel points receive a higher weight. The figure on the right exhibits the traits of non-local mean filtering. Unlike local mean filtering, non-local means searching for similar blocks of pixels within a window to assign weights. The centroids in the closest blocks of pixels are combined based on weighting

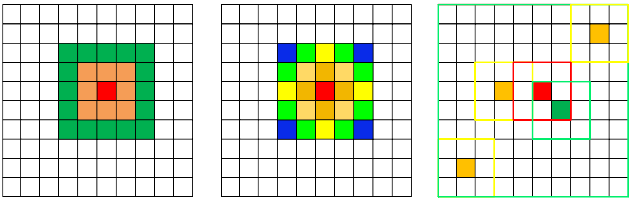


Fig. 4. Schematic diagram of the nonlocal mean algorithm

Rys. 4. Schematyczny diagram algorytmu średniej nielokalnej

to estimate the true value. The area to be searched is located within the green box, with the yellow window indicating the searched block of the image. The points to be de-noised are found within the centroids of the sepia window.

Non-local means (NLM) is a spatial noise reduction algorithm that differs from local filtering methods like median and Gaussian filtering. Instead, NLM is a global algorithm that replaces the gray value of the current pixel with the gray value of similar pixels throughout the entire image. This process is calculated using Equation (5).

$$\hat{u}_i(p) = \frac{1}{C(p)} \sum_{q \in B(p,r)} u_i(p) w(p,q) \tag{5}$$

$u_i(q)$ – is the gray value of pixel q of the noisy image;
$\hat{u}_i(q)$ – is the gray value of pixel p of the image after noise reduction;
$w(p,q)$ – is the weight between pixel p and q;
$B(p,r)$ – is the region in the noisy image, centered on pixel p, with a width of $2r + 1$,
$C(p)$ – is the weight normalisation coefficient, which is calculated as shown in Equation (6).

$$C(p) = \sum_{q \in B(p,r)} w(p,q) \tag{6}$$

The weights must depict the resemblance between two pixels, and that resemblance is usually quantified by the Euclidean distance amid the pixels neighboring these two pixels, as presented in Equation (7).

$$d^2\left(B(p,f), B(q,f)\right) = \frac{1}{3(2f+1)^2} \sum_{i=1}^{3} \sum_{j \in B(0,\Omega)} \left(u_i(p+j) - u_i(q+j)\right)^2 \tag{7}$$

In this case, the three times summation is for the color image, $B(p,r)$ is the region in the noise image, centered on pixel p, with a width of $2f + 1$. Based on this, the exponential kernel function is added to compute the weights, as shown in Equation (8).

$$w(p,q) = e^{-\frac{\max(d^2, 2\sigma^2, 0, 0)}{h^2}} \tag{8}$$

↳ σ and h are human-set parameters.

2.3. Mixed noise denoising algorithm

To eliminate the intricate noise from ore images, we put forth a wavelet + non-local means (NL-means) fusion algorithm. Refer to Figure 5 for the detailed procedure. First, convert the input original noisy image to a grayscale image and fill it so that its size is a power-of-two integer. Then, use the wavelet function to perform a two-dimensional wavelet transform on the filled image to separate its high-frequency and low-frequency information. Set up a threshold vector, threshold the high-frequency wavelet coefficients, and perform a two-dimensional wavelet inverse transform. Finally, resynthesize the wavelet coefficients to obtain the original noisy image. The first reconstructed image of the wavelet is obtained by restoring the details and texture information of the image. Next, the two-dimensional wavelet inverse transform of the second image is performed. Then, the second reconstructed image undergoes non-local mean noise removal. This method utilises non-local similarity in the image to obtain better estimates of the true pixel values through pixel-level similarity comparisons and weighted averages. As a result, it achieves the best noise removal effect and removes the complex mixed noise present in the image to the maximum degree possible.

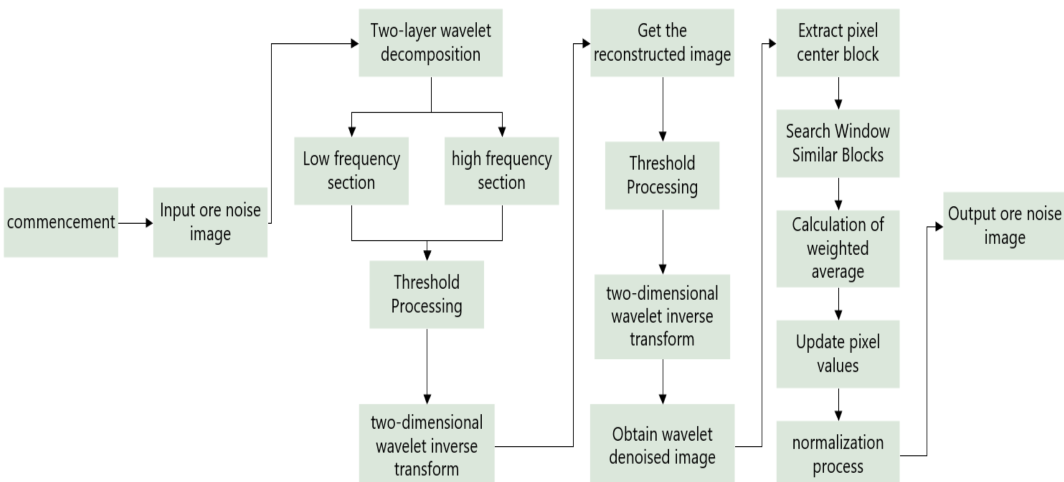
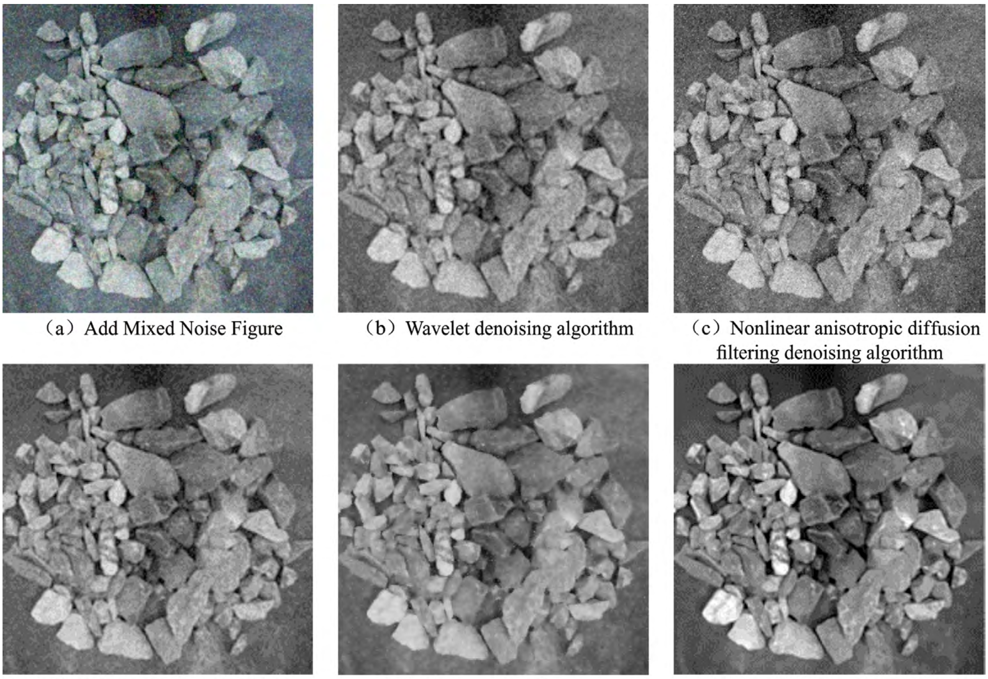


Fig. 5. Wavelet + Non-Localised Means (NL-means) fusion algorithm flow

Rys. 5. Przebieg algorytmu fuzji falki + średnich nielokalnych (NL-means)

3. Experimental results and analysis

To verify the effectiveness of the wavelet + NL-mean fusion algorithm proposed in this paper, this paper adds Gaussian noise and pretzel noise to the ore image and conducts comparative experiments using different single filtering methods and hybrid filtering methods. The results of the experiments are shown in Figure 6.



(a) Add Mixed Noise Figure
(b) Wavelet denoising algorithm
(c) Nonlinear anisotropic diffusion filtering denoising algorithm
(d) Non-local mean denoising algorithm
(e) Bilateral filter denoising algorithm
(f) Wavelet + NL-mean fusion algorithm

Fig. 6. Comparison of denoising effects of five different methods for adding mixed noise to images

Rys. 6. Porównanie efektów odszumiania pięciu różnych metod dodawania szumu mieszanego do obrazów
a) Dodaj mieszany szum, b) Algorytm odszumiania falkowego, c) Algorytm odszumiania filtrowania dyfuzyjnego anizotropowego nieliniowego, d) Algorytm odszumiania średniej nielokalnej, e) Algorytm odszumiania filtru dwustronnego, f) Algorytm łączenia falkowego + NL-średniej

As can be seen from Figure 6, the image is processed by wavelet denoising, although the black and white pixel dots on the picture are much less, still not completely removed. It is not possible to determine whether the noise is high-frequency noise or low-frequency noise and to classify and target the removal of noise, which leads to the loss of some useful signals; the image processed by nonlinear anisotropic diffusion filtering (NADF), the ore image is clearer than the original image, but the removal of black and white pixel points on the image is not obvious; the image processed using the non-local mean algorithm, compared to the image after two wavelet denoising, the pretzel noise in the ore image has been eliminated. The ore image is clearer, with higher contrast between the edges of the image and the ore. However, it has not yet reached the expectation that the pretzel noise, Gaussian noise, and various types of noise in the ore image have been completely removed, and the contrast between the ore and the background is higher; the image processed by bilateral filtering denoising algorithm has obvious denoising effect compared to the previous three denoising algorithms, but the contrast of the ore edge of the image decreases, and the ore image becomes fuzzy. In contrast, the wavelet + NL-mean fusion algorithm not only removes the noise more effectively but also maintains more detailed information so that its denoised image is closer to the un-noised original image.

To more precisely evaluate the denoising impact of mixed noise in ore images, this study utilises Mean Squared Error (MSE) and Peak Signal to Noise Ratio (PSNR) (Boppudi 2022) as the criteria for assessment according to the following formula:

$$MSE = \frac{1}{H \cdot W} \sum_{i=1}^{H} \sum_{j=1}^{W} \left(X(i,j) - Y(i,j) \right)^2 \tag{9}$$

$$PSNR = 10 \log_{10} \left(\frac{(2^n - 1)^2}{MSE} \right) \tag{10}$$

Where W and H are the height and width of the image, respectively, is the number of bits per pixel, generally taken as 8, i.e., the number of pixels in grayscale is 256. The unit of PSNR is dB, and the larger the value indicates that the smaller the distortion is, the better the denoising effect is.

Structural similarity (SSIM) (Tong et al. 2006) is an image quality metric used to assess the similarity between two images, measuring image similarity in terms of brightness, contrast, and structure respectively; SSIM is defined as:

$$SSIM(X,Y) = \mathrm{l}(X,Y) \cdot c(X,Y) \cdot s(X,Y) \tag{11}$$

$$l(X,Y) = \frac{2\mu_X \mu_Y + C_1}{\mu_X^2 + \mu_Y^2 + C_1} \tag{12}$$

$$c(X,Y) = \frac{2\sigma_X \sigma_Y + C_2}{\sigma_X^2 + \sigma_Y^2 + C_2} \tag{13}$$

$$s(X,Y) = \frac{\sigma_{XY} + C_3}{\sigma_X + \sigma_Y} \tag{14}$$

μ_X and μ_Y – denote the mean of image X and Y respectively,
σ_X and σ_Y – denote the variance of image X and Y respectively,
σ_{XY} – denotes the covariance of image X and Y.
C_1, C_2 and C_3 – are constants, and in order to avoid the denominator of 0, $C_1 = (K_1 \cdot L)^2$, $C_2 = (K_2 \cdot L)^2$, $C_3 = C_2/2$ is usually taken and $K_1 = 0.01$, $K_2 = 0.03$, $L = 255$. SSIM takes a value in the range of [0,1]; the larger its value, the smaller the image distortion, and the better the result.

Table 1 and Table 2 present the PSNR and SSIM values for the wavelet + NL-means fusion algorithm, as well as other single and hybrid filtering methods, for images of ores with added hybrid noise.

Table 1. PSNR and SSIM values of a single filtering method

Tabela 1. Wartości PSNR i SSIM pojedynczej metody filtrowania

Indicators/ /Pictures	The image to be denoised	Mean filtering	Median filtering	Gaussian filtering	Wavelet deno1sig	NL-Noise removal	Bilateral filtering	NADF
PSNR	15.2597	21.59270	22.2341	22.61430	21.88410	19.6977	27.5172	26.0433
SSIM	0.14672	0.44077	0.4225	0.27463	0.22986	0.1573	0.4745	0.5102

Table 2. Comparative of PSNR and SSIM of hybrid filtering method

Tabela 2. Porównanie PSNR i SSIM hybrydowej metody filtrowania

Indicators/ /pictures	The image to be denoised	Mean filter + + NL	Median filter + + NL	Gaussian filter + NL	Wavelet denoising + NL
PSNR	15.25970	26.53450	25.98760	27.33410	31.01810
SSIM	0.14672	0.34563	0.34769	0.45327	0.59913

According to the PSNR values and SSIM values in Table 1 and Table 2 drawing the histogram shown in Figure 7, the X-axis is the number of the graph to be denoised, the single filter denoised graph, and the hybrid filter denoised graph, of which No. 10 is the wavelet + NL-means fusion algorithm used in this paper. As depicted in the figure, the wavelet + NL-means fusion algorithm outperforms all other filtering algorithms in terms of PSNR and SSIM values, exhibiting a PSNR value of 31.0181 dB – 15.7584 dB higher compared to the pre-denoising period – and an SSIM value of 0.59913, a 0.45241 increase from

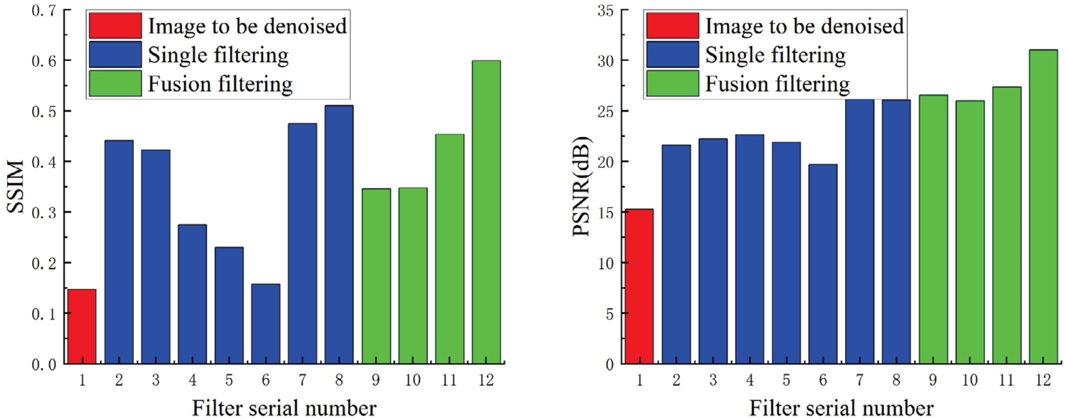


Fig. 7. PSNR and SSIM values after removal of hybrid noise

Rys. 7. Wartości PSNR (*Peak Signal to Noise Ratio*)
i SSIM (*Structural Similarity*) po usunięciu szumu hybrydowego

the pre-denoising period. To summarize, the wavelet + NL-means fusion algorithm utilised in this study displays greater improvement than other algorithms.

Conclusion

In this paper, for the mixed noise in ore images, the image is decomposed into frequency bands of different scales using two wavelet transforms. The high-frequency coefficients of the wavelet transforms are processed using adaptive thresholding to remove some of the noise. Then, on the basis of wavelet denoising, the NL-means algorithm is adopted to compute the distances between the image to be weighted and the search block. The distance weighting kernel is used to compute the weighting factor. The denoising is computed through weighted average pixel values to realize the removal of the remaining noise, which improves the detail protection and denoising effect of the image. The wavelet+NL-means that the fusion algorithm is compared with other single filter and hybrid filter methods, and the experimental results show that the PSNR value of the wavelet + NL-means the fusion algorithm is improved by 15.7584dB and the SSIM value is improved by 0.45241 compared with the denoising. It shows that the wavelet + NL-means fusion algorithm proposed in this paper not only effectively preserves the details of the ore image but also improves the image quality. Effectively retain the details of the ore image, and at the same time, can effectively remove the mixed noise.

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RESEARCH ON MIXED NOISE REMOVAL ALGORITHM FOR ORE IMAGES BASED ON FUSION FILTERING TECHNIQUE

Keywords

denoising algorithm, mixed noise, complex operating conditions, image processing

Abstract

To meet the requirements of the image processing process on image quality, as the ore image contains Gaussian noise, pepper noise, Rayleigh noise, and other kinds of mixed noise is easy to destroy the real information of the image combined with the advantages of wavelet and non-local mean filtering, a new wavelet + non-local mean (NL-means) fusion denoising algorithm is proposed. Taking the ore image with mixed noise obtained from a mine as the research object, the wavelet function is used to carry out a two-dimensional wavelet transform on the filled image, separating the high and low-frequency information, setting the threshold vector to deal with the high-frequency wavelet coefficients, inverting the transform to get the first reconstructed image, followed by the second inverse transform. Then, the second reconstructed image is subjected to NL-mean denoising to remove the complex mixed noise in the ore image to the maximum extent. The experimental results show that the noise reduction performance of the fusion denoising algorithm has a greater improvement compared with the single filter and several other fusion algorithms. The peak signal-to-noise ratio of the denoised image is 31.0181dB. The structural similarity is 0.59913, which is 15.7584dB and 0.45241, respectively, compared with that before denoising. It has an obvious effect on the removal of the mixed noise in the ore image, which provides strong technical support to improve the noise removal of the ore image.

BADANIA NAD ALGORYTMEM USUWANIA SZUMU MIESZANEGO DLA OBRAZÓW RUDY W OPARCIU O TECHNIKĘ FILTROWANIA FUZYJNEGO

Słowa kluczowe

algorytm odszumiania, szum mieszany, złożone warunki działania, przetwarzanie obrazu

Streszczenie

Aby spełnić wymagania procesu przetwarzania obrazu dotyczące jakości obrazu, ponieważ obraz rudy zawiera szum Gaussa, szum pieprzowy, szum Rayleigha i inne rodzaje szumu mieszanego, łatwo jest zafałszować rzeczywiste dane obrazu w połączeniu z zaletami filtrowania falkowego i średniej nielokalnej, zaproponowano nowy algorytm odszumiania fuzji falkowej + średniej nielokalnej (NL-means). Biorąc obraz rudy z szumem mieszanym uzyskany z kopalni jako obiekt badawczy, funkcja falkowa jest używana do przeprowadzenia dwuwymiarowej transformacji falkowej na wypełnionym obrazie, oddzielając informacje o wysokiej i niskiej częstotliwości, ustawiając wektor progowy w celu radzenia sobie ze współczynnikami falkowymi o wysokiej częstotliwości, odwracając transformację w celu uzyskania pierwszego zrekonstruowanego obrazu, a następnie drugiej odwrotnej transformacji. Następnie drugi zrekonstruowany obraz jest poddawany odszumianiu NL-mean w celu usunięcia złożonego szumu mieszanego w obrazie rudy w maksymalnym stopniu. Wyniki eksperymentów pokazują, że wydajność redukcji szumu algorytmu odszumiania fuzji jest większa w porównaniu z pojedynczym filtrem i kilkoma innymi algorytmami fuzji. Szczytowy stosunek sygnału do szumu odszumionego obrazu wynosi 31,0181 dB. Podobieństwo strukturalne wynosi 0,59913, co stanowi odpowiednio 15,7584 dB i 0,45241 w porównaniu z tym przed odszumianiem. Ma to oczywisty wpływ na usuwanie szumu mieszanego w obrazie rudy, co zapewnia silne wsparcie techniczne w celu poprawy usuwania szumu obrazu rudy.