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A New Non-local Mean Method for the Image Denoising of Coal Dust

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Abstract. In the process of coal dust image collecting and transmitting, it is inevitable that it will be interfered by noise. The denoising effect of image is crucial for the segmentation and recognition of image behind. The denoising effect of image is better based on the non-local mean denoising algorithm. However, the exponential weighted kernel function is used in the traditional non-local mean filtering algorithm, which tends to cause the image details to be blurred due to excessive smoothing. Therefore, according to the exponential weighted kernel function, a new non-local mean image denoising algorithm is designed by using the Gaussian kernel function of weighted of cosine coefficient, and applied to the weighting coefficient calculation. The experimental results show that the denoising performance of the algorithm is better than the traditional algorithm and can better preserve the details of coal dust image.

1. Introduction

The noise of coal dust image mainly comes from three aspects: (1) scratches on the glass tube for sampling; (2) coal dust particles attached to the glass tube; (3) random noise during image acquisition and transmission. The first two kinds of background noise are static and can be controlled by a suitable background suppression algorithm, which is not studied in this paper. The third type of noise is generally considered to be a random variable represented by a probability density function (PDF). Common types are: Gaussian noise, Rayleigh noise, exponential noise, and uniform noise. Therefore, for Gaussian noise, this paper has a good effect with the non-local mean algorithm.

In 2005, Buades A et al proposed a non-local Means (NLM) denoising algorithm[1], and proved that the NLM algorithm is superior to other denoising algorithms[2], such as bilateral filtering[3] and total variation filtering[4],[5]. The basic idea is to use a large amount of redundant information in the image, and use the non-local self-similarity in the process of denoising image. A pixel weighted average of all structural similarities to the current pixel in the image yields the value of this pixel. The weighting coefficients are determined by the similarity to the neighboring blocks of each pixel. For each pixel point weight, it is determined by the Gaussian weighted Euclidean distance between the image block centered on the current pixel point and the image block centered at each pixel point.

The core problem of non-local mean filtering algorithm is to determine the weighted kernel function. In the original non-local mean denoising, the exponential kernel function is used to denoise the image. In this paper, we focus on the establishment of weighted kernel function and propose an improved non-local mean denoising algorithm.

2. Noise model and non-local mean filtering

Assuming the noise is additive white Gaussian noise, the noise image model is:

$$V(i) = X(i) + N(i) \tag{1}$$

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Where $V(i)$ is denoted to the noise image; $X(i)$ is denoted to the original image; $N(i)$ is the Gaussian white noise of zero mean and variance σ^2. Consider a given discrete noise image $v = \{v(i)|i \in I\}$, I is denoted to the image area. For any pixel in the image, the NLM algorithm calculates the estimated value of the point after denoising by calculating the weighted average of all pixel values in the image, ie

$$NL[v](i) = \sum_{j \in I} w(i,j)v(i) \tag{2}$$

Where the weight $w(i,j)$ is determined by the similarity between pixels i and j , and $0 \le w(i,j) \le 1$, $\sum_{j \in I} w(i,j) = 1$. The degree of similarity between the pixels i and j depends on the similarity of the matrices N_i and N_j, where N_i represents the image block centered on the pixel i . The weight $w(i,j)$ between the gray matrix of each neighborhood is measured by Gaussian weighted Euclidean distance, ie

$$d(i,j) = \left\| N_i - N_j \right\|_{2,a}^2 \tag{3}$$

Where a>0 is denoted to Gaussian weighted standard deviation; Function $\|\cdot\|_2$ is the L^2 norm. So the higher the neighborhood similarity (lower), the smaller the distance (large). The weight $w(i,j)$ is defined as:

$$w(i,j) = \frac{1}{C(i)} f_k\big(d(i,j)\big) \tag{4}$$

Where $C(i) = \sum_j f_k\big(d(i,j)\big)$ is the normalized parameter. The core problem of non-local mean filtering given by equation (3) is to determine the kernel function $f_k(\cdot)$ in equation (5). It plays an important role in the denoising performance of the algorithm[6],[7][8][9][10]. The ONLM algorithm uses an exponential kernel function, defined as:

$$f_k\big(d(i,j)\big) = \exp\left(-\frac{d(i,j)}{h^2}\right) \tag{5}$$

Where the parameter h is the attenuation factor of the exponential function, which controls the decay rate of the exponential function, and also affects the degree of filtering and the denoising performance of the algorithm. If it is $i = j$, the excessive weighting will occur. Taking this issue into consideration,

$$w(i,j) = \max\big(w(i,j)\big) \ , \forall j \ne i \tag{6}$$

3. A new non-local mean denoising algorithm

In the traditional non-local mean filtering algorithm, an exponential function is used as the weighted kernel function, and the weighted kernel function plays a decisive role in the degree of denoising effect. The kernel function should be able to obtain greater weight for neighborhoods with high similarity, and less weight for neighborhoods with lower similarity.

Therefore, the key to the non-local mean denoising algorithm is to determine the weighted kernel function. The traditional non-local mean algorithm uses an exponential kernel function for weighted denoising, such as (5). A new weighted kernel function can be obtained by improving the exponential kernel function. Tian Jing.etc proposed Various forms of weighted kernel functions, including Gaussian. And it was analyzed and compared[11].The Gaussian kernel function is defined as:

$$f_k\big(d(i,j)\big) = \exp\left(\frac{d^2(i,j)}{h^2}\right), d(i,j) \le h \tag{7}$$

The cosine type kernel function is defined as:

$$f_k\big(d(i,j)\big) = \begin{cases} \cos\left(\frac{\pi d(i,j)}{2h}\right), 0 < d(i,j) \le h \\ 0, \ \text{else} \end{cases} \tag{8}$$

When the noise intensity is weak, it is better than the ONLM. However, due to the excessive weighting of the cosine-type kernel function and the insufficient weighting of the Gaussian kernel function, the denoising performance is degraded when the signal strength is increased. a new cosine Gaussian kernel function is proposed by comparing and analyzing the exponential cosine and Gaussian kernel functions, which is defined as:

$$f_k(d(i,j)) = \begin{cases} \exp\left(\frac{d^2(i,j)}{{h_1}^2}\right)\cos\left(\frac{\pi d(i,j)}{2h_2}\right), 0 < d(i,j) \le h_2 \\ 0, \quad \text{else} \end{cases} \tag{9}$$

Where h_1, h_2 is filtering parameter. The cosine-type Gaussian kernel function adds a cosine coefficient to the Gaussian kernel function, so that the improved algorithm maintains good denoising performance in different noise levels. Comparing these weighted kernel functions, the response curve is shown in the figure. 1 is shown.

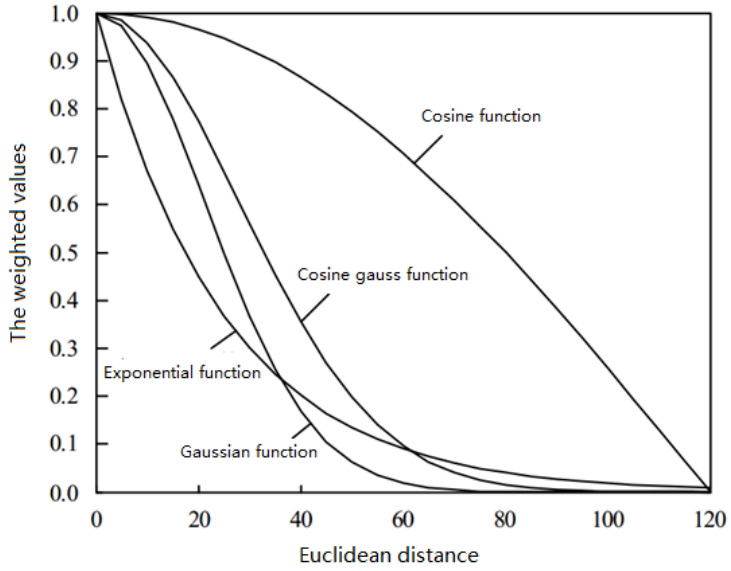
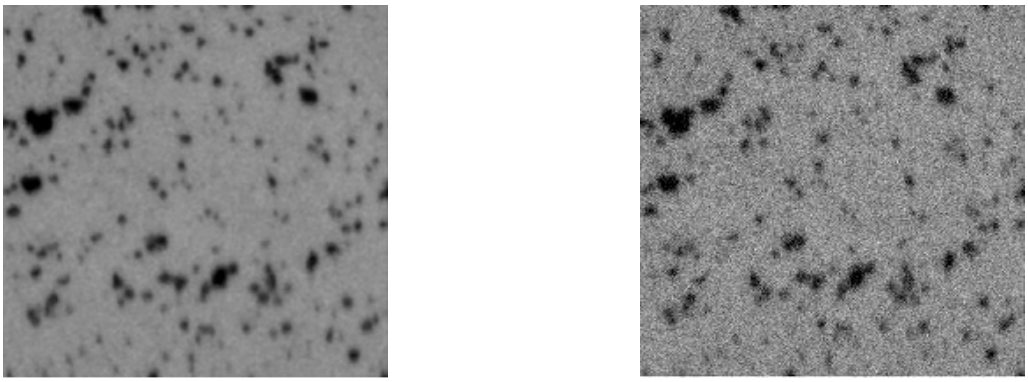


Figure 1 Kernel function response curve

It can be seen from the observation of Fig. 1 that the response curve of the Gaussian kernel function is flatter when the pixel neighborhood distance is larger than the exponential kernel function of the ONLM, and decreases rapidly as the distance increases; The response curve of the cosine kernel function is relatively flat throughout the region; The improved cosine Gaussian kernel function combines their advantages, and has a larger weight when the distance is smaller, and the weight decreases as the distance increases, avoiding excessive weighting and weighting deficiency, so that the similarity is high. The neighborhood filters out noise, effectively reducing interference with low similarity and dissimilar neighborhoods. Experimental results show that the denoising performance is excellent ONLM algorithm.

4. Application of algorithm to coal dust image and result analysis

The improved non-local mean algorithm was applied to the coal dust image denoising experiment, and the simulation experiment was carried out with Python3, which was tested from three aspects: denoising effect, method noise and peak signal to noise ratio. During the experiment, both the algorithm and the NLM algorithm use the similar window 5*5 and the search window 11*11. The coal dust image used in the experiment is shown in Figure 2. The coal dust image adds noise with a mean of 0 and a standard deviation of $\sigma = 20$.

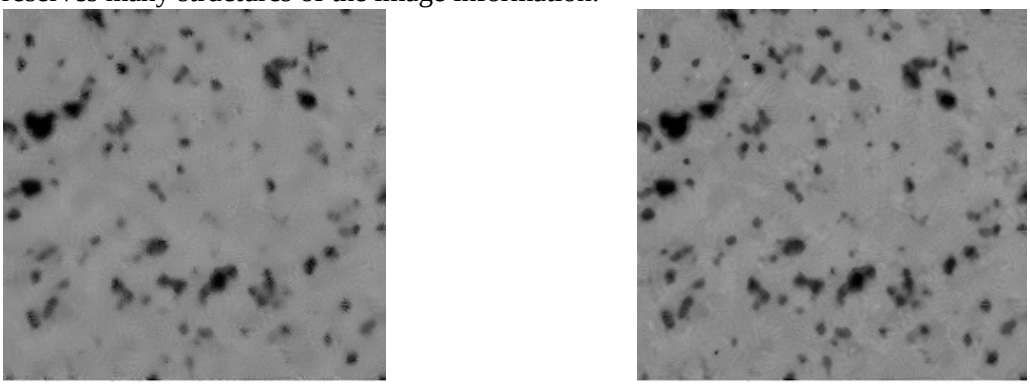


(a) The image of coal dust (b) The image of noise-added coal dust

Figure 2 Test image and noise image

4.1 Comparison of experimental results

It can be seen from the analysis of Fig. 3 that the proposed algorithm is better than the classical non-local mean denoising algorithm. The image is well protected, and the image denoising effect is better, which preserves many structures of the image information.



(a) NLM denoising (b) The algorithm denoising

Figure 3 Denoising effect diagram

4.2 Peak signal to noise ratio comparison experiment

In this paper, the signal-to-noise ratio (SNR) is used to determine the denoising effect of the algorithm. The formula is:

$$\mathrm{PSNR} = 10 \times \log_{10}\left(\frac{\mathrm{MAX_I^2}}{\mathrm{MSE}}\right) = 20 \times \log_{10}\left(\frac{\mathrm{MAX_I}}{\sqrt{\mathrm{MSE}}}\right) \quad (10)$$

Where MSE is the mean square error between the original image and the processed image, MAX_I represents the maximum value of the image color, and the 8-bit sample point is represented as 255.

In this paper, Gaussian white noise with a standard deviation of 5, 10, 15, 20, 25 and an average value of 0 is added to the coal dust image. The peak signal noise obtained by the original image, the NLM algorithm and the improved algorithm is shown in Table 1.

Table 1 Performance comparison of coal dust images under different noise levels

Noise standard deviation		5	10	15	20	25
Original image	PSNR /dB	33.00	32.22	31.20	31.25	29.45
NLM		37.11	34.18	32.51	32.49	29.96
improve algorithm		38.22	35.19	33.12	33.16	30.23

It can be seen from the analysis and comparison in Table 1. The peak signal-to-noise ratio of the improved algorithm is higher than the classical non-local mean denoising algorithm. It also proves that the denoising effect of the improved algorithm is better than the classical non-local mean denoising algorithm.

5. Conclusions

Based on the above experimental results and analysis, the proposed algorithm is applied to the denoising of coal dust image. Compared with the NLM algorithm, it can obtain better visual effects, and contains more details and texture images. The improved cosine Gaussian kernel function. It can effectively improve the processing of image detail and texture part of the algorithm, and the peak signal-to-noise ratio after denoising is higher than that of NLM algorithm.

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