

An Improved Infrared Denoising Algorithm Based on Propagation Filter

Jingqi Fu^a, Yichun Jiang^b and Ziwei Cui^c

Changchun University of Science and Technology, National Demonstration Center for Experimental Electrical and Electronic Technology ChangChun, JiLin, 130022, China.

^a525706946@qq.com, ^b931645699@qq.com, ^c321918448@qq.com

Abstract

Due to the influence of material limitation, immature process and environmental factors, the infrared image has the problems of poor contrast and low signal-to-noise ratio, which reduces the quality of infrared image and affects the ability to extract useful information from infrared images. In order to solve this problem, the traditional propagation filter is improved in this paper. The propagation mode is perfected to eight-neighborhood, and the method to judge the propagation along the inclined direction is added. The method of nonlinear transformation can better protect the edge information of infrared image, suppress isolated noise points and improve the quality of infrared image. Experimental results show that the proposed algorithm improves both subjective vision and objective evaluation.

Keywords

Infrared image; Denoising; Marginal propagation; Eight-neighborhood.

1. Introduction

With the extensive application of infrared imaging system in military and civil fields, the quality requirements of infrared image in various occasions are gradually improved, among which the denoising of infrared image is one of the problems to be solved[1]. In the process of infrared image acquisition and transmission, the influence of external noise and the noise of the sensor system itself will make the infrared image quality poor, and part of useful information will be lost, which will seriously affect people's understanding and analysis of the scene[2]. Therefore, it is of great significance to denoise infrared image.

At present, infrared image denoising methods are mainly divided into two categories: the methods based on spatial domain mainly includes mean filtering and non-local mean filtering[3], etc.; The method based on transform domain mainly includes wavelet threshold denoising [4,5], multi-scale morphological filtering, etc. There are also methods that combine the spatial domain and the transform domain, such as the three-dimensional block matching filter[6]. Many scholars have also proposed a denoising method based on sparse decomposition[7], such as orthogonal matching tracking[8]. With the rise of neural network, many scholars have boldly proposed many denoising methods based on neural network[9]. At present, some methods with good denoising effect have a large amount of computation and cannot meet the requirement of real-time performance. How to minimize the loss rate of image information while suppressing the noise is still the focus of image denoising. Therefore based on edge information as a starting point, aimed at containing gaussian noise of infrared image noise suppression processing, the traditional filter method [10] is improved, which can better keep the edge in the image texture details, reasonably improve the visual comfort of human

eyes, provide guarantee for late infrared image enhancement processing, also can further improve the target detection in infrared image recognition rate.

2. Basic Principles

Propagating filter is a kind of edge preserving filter, which can be considered as robust estimator to minimize the difference between the image to be filtered and the desired image [10]. The propagating filter can alleviate the problem of cross-region mixing and better distinguish the image regions with different context information. The filtering denoising is carried out by selecting the local center point as the center and propagating outwards according to the direction of the pixel points in the four neighboring areas. The filter weight factor is affected by the weight of the previous point and is related to the pixel difference between each pixel point. As a result, the filtering denoising of the transmission filter requires not only the calculation of the similarity between the point and the center point, but also the consideration of the similarity between the point and the previous point. Moreover, the point can only propagate in four directions, up, down, left and right, and the skew edge cannot be accurately judged [10]. The specific propagation path diagram is shown in Figure 1.

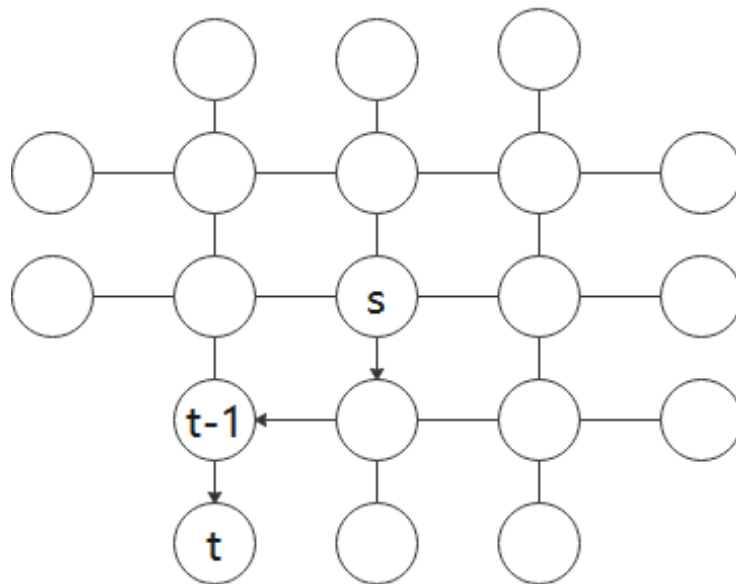


Figure 1. A schematic diagram of the propagation path of a two-dimensional propagation filter

First, it is assumed that pixel s and pixel t have only one propagation path, so the propagation mode is linear connection. Secondly, if pixel s and pixel t have multiple propagation paths, then propagation paths can be determined according to Manhattan distance formula. If the distance is odd, then the propagation mode of pixel t and the previous pixel $t-1$ is connected in the vertical direction; otherwise, the propagation mode is connected in the horizontal direction.

The weight calculation of the propagating filter does not depend on the spatial kernel function, but on the probability theory and the distance between pixels. The weight formula is as follows[10]:

$$\omega_{s,t} = g(p_{PF}^a(I_s, I_t); \sigma_a) g(p_{PF}^r(I_s, I_t); \sigma_r) \quad (1)$$

Where, the terms on the right side of the equation are expressed as:

$$p_{PF}^a(I_s, I_t) = \sqrt{\sum_{x, x+1 \in \phi} \|I_{x+1} - I_x\|^2} \quad (2)$$

$$p_{PF}^r(I_s, I_t) = \sqrt{\sum_{x \in \phi} \|I_x - I_s\|^2} \quad (3)$$

$$P(x, y) = g(\|I_x - I_y\|; \sigma_a) = \exp\left(\frac{-\|I_x - I_y\|^2}{2\sigma_a^2}\right) \quad (4)$$

In the above equation, $P(x, y)$ represents the probability that pixel x and pixel y are adjacent to each other in terms of photometric correlation. I_x denotes the gray value of pixel x , and $\|I_x - I_y\|$ denotes the Euclidean distance between the gray value difference of pixel x and pixel y . Φ denotes pixels propagation path between s and pixel point t . The probability estimation between adjacent pixel points $p_{PF}^a(I_s, I_t)$ is used to represent the weight contribution of the photometric distance.

3. Algorithm in this paper

In order to solve the problem of limited detection edge of traditional propagation filter, an improved image denoising method is proposed in this paper, which mainly includes the selection of propagation path and the calculation of weight factor. On the basis of the traditional four neighborhood propagation filter, the denoising method in this paper improves the propagation path into the eight-neighborhood direction. First, the center pixel points are selected and propagated in the direction of the eight-neighborhood pixel points. Similar edge points are determined through calculation, and the filtering weight of each point is more reasonably distributed. This method can effectively suppress isolated noise points and achieve good smoothing and denoising effect on the region without edges. The propagation path diagram of the improved propagation filter is shown in Figure 2:

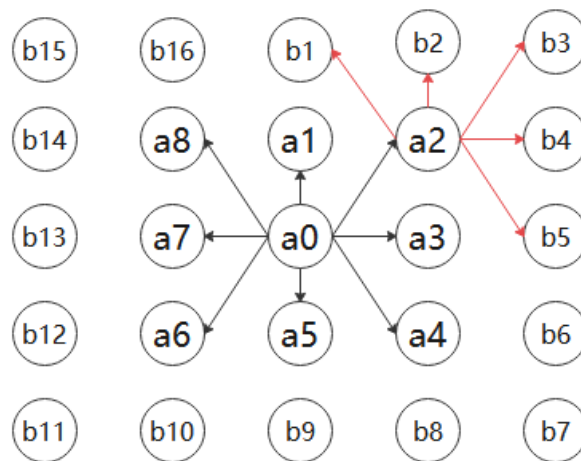


Figure 2. Schematic diagram of the propagation path of the improved propagation filter

The specific operation steps are as follows: (1) Select a pixel point as the central pixel point a_0 from the pixel point of the original image; (2) Calculate the maximum difference value between the center pixel Point a_0 and each pixel point a_i in the eight-neighborhood region; (3) Calculate the weight of a_i of each pixel in the eight-neighborhood region according to the maximum difference value; (4) Normalize the weight of the center pixel a_0 and the a_i of each pixel in the neighborhood; (5) Filter a_0 according to the weight processed in the previous step and obtain the denoised pixel value of a_0 ; (6) Take each pixel point as the center pixel point and perform the first five steps successively to obtain the denoised image.

The weight calculation formula of each pixel a_i in the eight-neighborhood of the central pixel a_0 is as follows:

$$\omega_{ai} = \omega_{a0} * \left[1 - \left(\frac{|ai - a0|}{diff_max} \right)^{\gamma_1} \right] * \left[1 - \left(\frac{|ai - (a(i-1))|}{diff_max} \right)^{\gamma_2} \right] \quad (5)$$

Among them, ω_{a0} is the weight of the central pixel $a0$. $|ai - a0|$ is the absolute value of the difference value between the pixel ai and the central pixel $a0$. $|ai - (a(i-1))|$ is the absolute value of the difference value between pixel ai and the pixel value of the previous point $(a(i-1))$ with the largest weight in the propagation path. γ_1, γ_2 is the parameter values. $diff_max$ is the maximum difference value, including the comparison of the absolute value of the difference between $a0$ and ai pixels and the absolute value of the difference between any two adjacent (eight-neighborhood) pixel ai pixels.

The weight was normalized twice, and the threshold value was set to judge the weight obtained after the first processing. If the weight was greater than the threshold value, it was set as 0, while if the weight was less than the threshold value, it was retained. At this point, the second normalization process is performed to obtain the final weight of all pixel points, thus generating the propagation filter of the central pixel point $a0$.

4. Simulation results and Parameter analysis

In order to verify the validity and feasibility of the algorithm in this paper, two scenes are selected for comparative experiments. The experimental platform uses Intel Core i5-4258u CPU, runs Windows10 PC, and programming software is MATLAB 2018b. First, imnoise function was used to add gaussian noise with mean value of 0, variance of 0.02 and 0.04 to the two scenes respectively to generate 4 scenes containing noise. For each scene containing noise, Gaussian filter, Butterworth filter, bilateral filter, non-local mean filter NLM, traditional propagation filter denoising algorithm and the algorithm presented in this paper are used respectively. Finally, the advantages and disadvantages of the algorithm are analyzed from two aspects of subjective visual effect and objective evaluation criteria. The subjective standard takes human as the observer and human eyes as the observation tool to evaluate the quality of the scene and strive to reflect the visual perception of human eyes. PSNR and structural similarity SSIM were selected as objective evaluation criteria to reflect the real image quality[11,12].

In the case of Gaussian noise with different variances, denoising results of each algorithm are shown in Figure 3-6, and objective indicators are shown in Table 1:

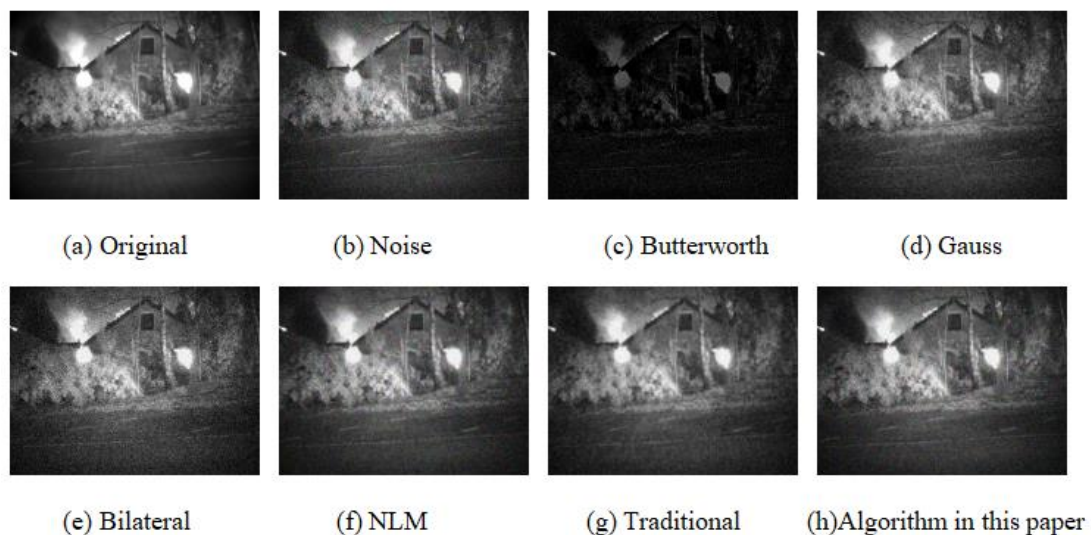


Figure 3. Denoising effects of each method in Scene 1 when the variance is 0.02

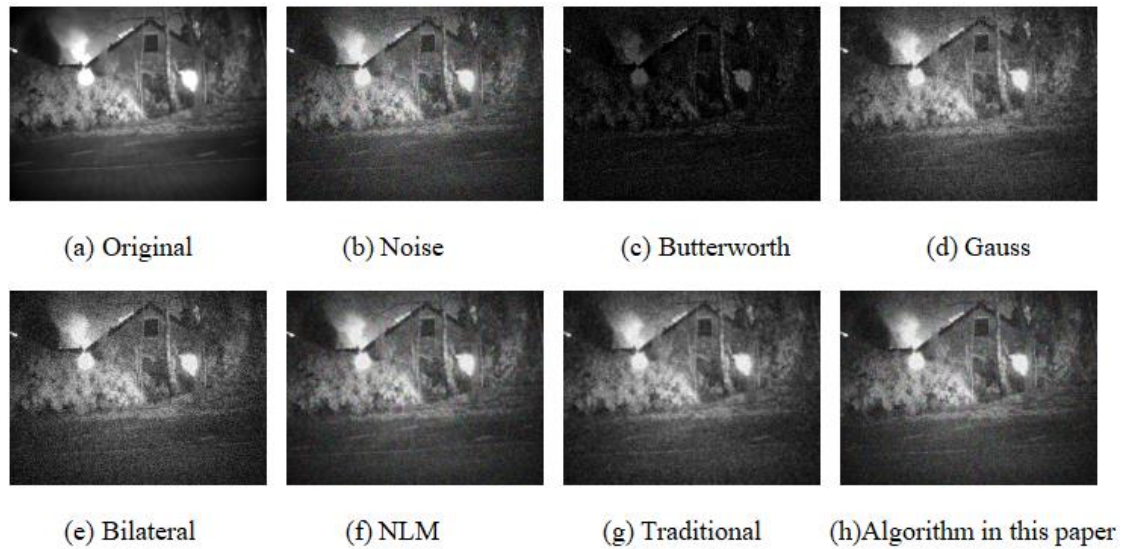


Figure 4. Denoising effects of each method in Scene 1 when the variance is 0.04

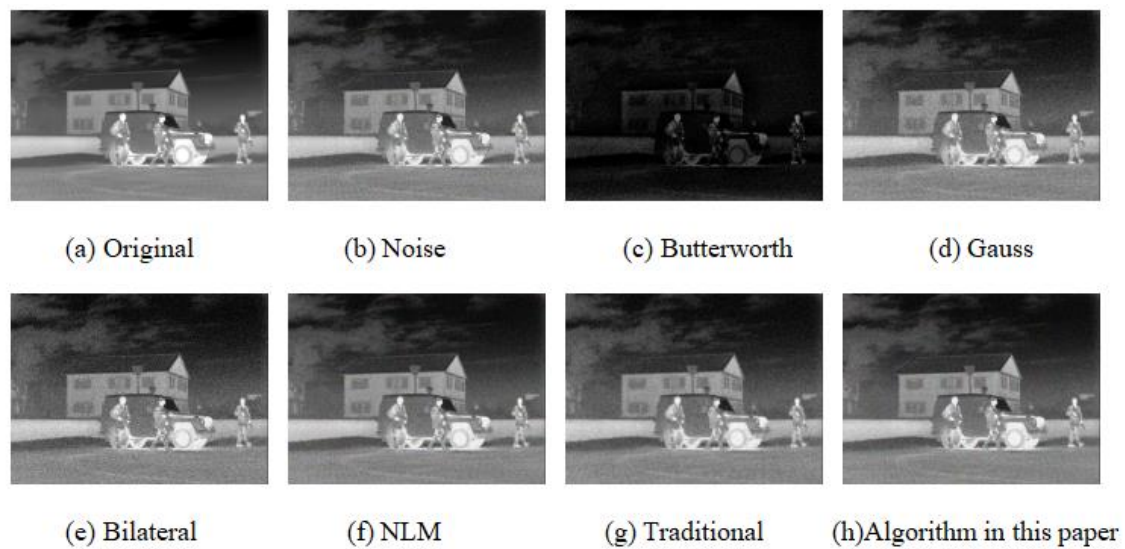


Figure 5. Denoising effects of each method in Scene 2 when the variance is 0.02

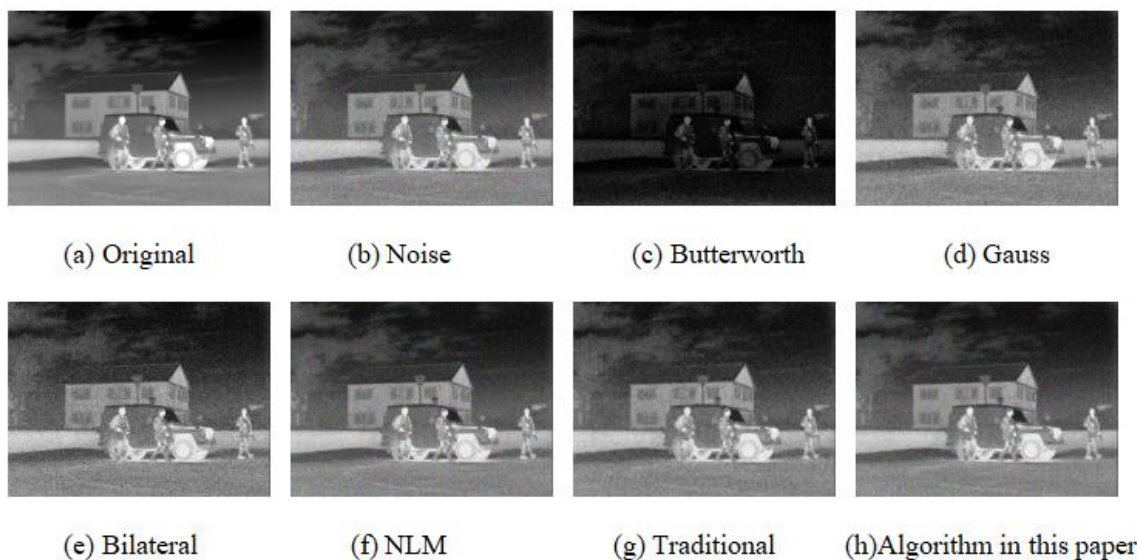


Figure 6. Denoising effects of each method in Scene 2 when the variance is 0.04

Table 1. Objective indexes of each method in the two scenarios

Indicators		Scene 1		Scene 2	
		$\sigma=0.02$	$\sigma=0.04$	$\sigma=0.02$	$\sigma=0.04$
Butterworth	PSNR	10.7386	10.8176	8.6302	8.7682
	SSIM	0.2088	0.2016	0.1846	0.1973
Gauss	PSNR	18.8411	16.2903	18.8090	16.1276
	SSIM	0.3417	0.3074	0.3256	0.2979
Bilateral	PSNR	20.5076	19.7361	17.9015	18.1254
	SSIM	0.3951	0.3865	0.3362	0.3431
NLM	PSNR	24.5607	25.1749	22.1283	23.7746
	SSIM	0.4058	0.4686	0.4325	0.4516
Traditional	PSNR	27.5493	21.8111	27.9521	25.1282
	SSIM	0.5809	0.4989	0.5472	0.5144
Algorithm in this paper	PSNR	29.0398	26.5742	29.4053	26.4903
	SSIM	0.7309	0.6393	0.7123	0.5977

It can be seen from Figure 3 to Figure 6 that, to a certain extent, all the algorithms are effective in suppressing noise. The image contrast of butterworth filter after denoising is low, which is not good for human vision. The gaussian filter enhances the denoising contrast, but it is difficult to process the smooth part of the image, so the texture information of the image cannot be well retained. The denoising ability of bilateral filtering is slightly weak, and there is a phenomenon of "pseudo-contour". The NLM algorithm and the traditional propagation filter denoising algorithm retain the image structure information well. The algorithm in this paper has a better suppression effect on isolated noise points, a clearer judgment on the direction of image edges, and a better edge preservation effect, such as: the texture information of trees in Figure 3 and Figure 4, and the details of tires in Figure 5 and Figure 6 are clearer.

As can be seen from Table 1, when different noise variances are added, PSNR and SSIM of this algorithm are the largest. The larger the PSNR value, the smaller the ratio of noise content in the image, the less the distortion, and the better the denoising effect. SSIM value represents the degree of similarity between the denoised image and the original image. The larger the value is, the more similar the two images are. When the noise content increases, the denoising effect of other algorithms will be suppressed, but the index in this paper is still the best, indicating that the denoising effect of the algorithm in this paper is relatively stable. To sum up, the subjective feeling of this algorithm is consistent with the quantitative analysis results, and the denoising effect of this algorithm is better.

5. Conclusion

In order to improve the problem of noise in infrared image, a improved denoising algorithm based on traditional transmission filter is proposed in this paper that introduces the eight-neighborhood and adds oblique propagation path based on the original horizontal and vertical propagation path. The method adopts nonlinear transform to calculate the weighting factor of each pixel and sets weighting threshold to ensure the rationality of weight distribution. The experimental results show that the denoising method in this paper has a good denoising effect on the image containing Gaussian noise, and can better protect the image edge to some extent, and the subjective evaluation is consistent with the objective index.

References

- [1] Y. Shen, Y. Chen, Q. Liu, S.Q. Lou, et al. Improved Anscombe transformation and total variation for denoising of lowlight infrared images[J]. Infrared Physics and Technology, 2018,93.
- [2] Z. Fengbo, L. Changgeng, H.-q. Zhu, Research on threshold improved denoising algorithm based on lifting wavelet transform in UV-vis spectrum. Spectrosc. [J]. Spectr. Anal. 2(38),506–510 (2018)

- [3] Kuppusamy P G, Jayaraman S, Joseph J. A customized nonlocal restoration scheme with adaptive strength of smoothening for magnetic resonance images[J]. Biomedical Signal Processing and Control, 2019, 49: 160-172.
- [4] Binbin, Y. An improved infrared image processing method based on adaptive threshold denoising. [J]. J Image Video Proc.2019,5 (2019).
- [5] Z. Zhenfeng, W. Huan, B. Tan, An improved wavelet threshold denoising method. [J].Study Opt. Commun. 2(206), 75–78 (2018).
- [6] Jingyu Y, Xue Z, Huanjing Y, et al. IBM3D: Integer BM3D for Efficient Image Denoising[J]. Circuits, Systems, and Signal Processing, 2018.
- [7] Zeng M, Chen Z. SOSO Boosting of the K-SVD Denoising Algorithm for Enhancing Fault-Induced Impulse Responses of Rolling Element Bearings[J]. IEEE Transactions on Industrial Electronics, 2019.
- [8] Zhang, Z., Chen, X., Liu, L. et al. A sparse representation denoising algorithm for visible and infrared image based on orthogonal matching pursuit. [J].SIViP 14,737–745 (2020).
- [9] Zhang F, Cai N, Wu J, et al. Image denoising method based on a deep convolution neural network[J]. IET Image Processing, 2018, 12(4):485-493.
- [10] Xin Liu. Research on infrared Image Denoising Algorithm [D]. Xidian University,2019. (in Chinese)
- [11] Meng Jiang. Edge enhancement and noise suppression for infrared image based on feature analysis[J]. Infrared Physics and Technology, 2018, 91.
- [12] Li Liu, Luping Xu, Houzhang Fang. Infrared and visible image fusion and denoising via ℓ_2 - ℓ_p norm minimization [J]. Signal Processing, 2020,172.