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An image sharpening algorithm based on fuzzy logic

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ABSTRACT

This paper presents a solution to the problem of enhancing the spatial local contrast of images with nonlinear module. The proposed method that exploits the undecimated discrete fuzzy logic has much reduced noise sensitivity with respect to the linear unsharp masking technique and it permits to obtain perceptually pleasant results. The proposed method also compares favorably with other algorithms which recently have been studied to improve the behavior of the unsharp masking approach. And results are presented and discussed on different images.

1. Introduction

Sharpening is a basic measure in intensity or gray value in specified region of an image, such as details or edges. Although it is really very popular, in fact, it is a form of contrast enhancement and improving the acuity of details in the image included. And a large number of approaches have been devised to improve the perceived quality of an image [1], using point operators (for example, histogram modification), spatial operators (high emphasis filtering) and so on. Many of them aim at different objectives, such as to exploit the whole available dynamic range or to improve the local contrast; a wide class of algorithms aim at increasing the maximum luminance gradients which are achieved at the border between different objects or within textured areas. The algorithm proposed in the present paper belongs to this class. Useful information can be visible after application, and further processing works in obtaining the contemplated information [2]. The fundamental idea of unsharp masking is to subtract from the input signal a low-pass filtered version of the signal itself. The same effect can however be obtained by adding to the input signal a processed version of the signal in which high-frequency components are enhanced. Nevertheless, the linear high-pass filter makes the system extremely sensitive to noise, which often makes this method not usable in practice. In order to deal with this problem, many kinds of unsharp masking are improved: C. Matz studied an image contrast sharpening approach based on munsell's scale [3]. S.K. Mitr studied an image enhancement algorithm based on nonlinear filter [4]. G. Ramponi studied a nonlinear unsharp masking method for image contrast enhancement and a cubic unsharp masking technique for contrast enhancement [5,6]. S. Guillo studied adaptive nonlinear filters for 2D and 3D image enhancement [7]. The mentioned methods above can enhance the images and reduce noise, but there are still some unpleasant overshoot artifacts may appear in the output image. F. Russo studied an image enhancement system based on the Gaussian noise mode [8–10]. However, the type of image noise is not only Gaussian noise, so his method is not ideal. In this paper, a novel sharpening method based on fuzzy logic and nonlinear module is presented for image enhancement. The experimental results have proved the effectiveness of this method.

2. Background

2.1. Fuzzy logic

The various aspects of image processing and analysis problems where the theory of fuzzy set has so far been applied are addressed along with their relevance and applications. The reasons are as follows: firstly, in the field of image processing, people have to deal with many ambiguous situations, which caused by projecting a 3D object into a 2D image or digitizing analog pictures into digital images, with losing in-depth and non-visible part of the information. Secondly, the uncertainty related to boundaries and non-homogeneous regions are very common. Some of definitions, such as edges, contrast, enhancement, are fuzzy as well. Thirdly, image processing which lacks of information is always a ill-posed problem, and solving this problem needs some prior knowledge. But due to the complexity of the problem, we cannot completely clear all the reasons why the information is lack, which caused that we cannot describe the prior knowledge using classical mathematical language. On the contrary, the prior knowledge always can be described and concluded by human's language. But human natural language is imprecise and has a fuzzy nature. Take all the factors

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above into consideration; we can conclude that fuzzy set theory is a useful mathematical tool for handling the ambiguity or uncertainty. In the long run, the possibility of combining fuzzy set theory, neural network theory and genetic algorithms for improved performance will be further discussed.

2.2. Fuzzy set

The classical set A defined in the algebra is a collection of objects. Under this definition, each element x in the universal is either in the set or not.

Therefore, the membership $\mu_A(x_i)$ is 1 for those elements in the set ($x \in A$) and 0 for those out of the set ($x \notin A$).

However, a fuzzy set is defined as a collection of nation:

$$A = \frac{\mu_A(x_i)}{x_i} \quad i = 1, 2 \cdots N$$

where $\mu_A(x_i)$ is the membership function that maps x to the fuzzy domain [0,1] and N is the number of elements in the set. The value indicates the degree of the elements belong to the fuzzy set. Larger values denote higher degrees of the memberships.

The generalized fuzzy set is defined similarly except that the fuzzy domain is $[-1,1]$ comparing [0,1] in general fuzzy domain.

2.3. Image representation in fuzzy set nation

We suppose that an image I of size $M \times N$ having gray levels ranging from $L_{\min}$ to $L_{\max}$. A fuzzy characteristic matrix is defined as follows:

$$X = \begin{bmatrix} \mu_{11}/x_{11} & \mu_{12}/x_{12} & \cdots & \mu_{1N}/x_{1N} \\ \mu_{21}/x_{21} & \mu_{22}/x_{22} & \cdots & \mu_{2N}/x_{2N} \\ \vdots & \vdots & \vdots & \vdots \\ \mu_{N1}/x_{N1} & \mu_{N2}/x_{N2} & \cdots & \mu_{NN}/x_{NN} \end{bmatrix}$$

Or $$X = \frac{\bigcup_{i=1}^{M} \bigcup_{j=1}^{N} \mu ij}{x_{ij}}$$

where μ_{ij}/x_{ij} in this matrix denotes the degree of the brightness possessed by the gray level intensity x_{ij} of the (i,j) the pixel.

2.4. Membership function

Membership function characterizes the fuzziness in a fuzzy set. It essentially embodies all fuzziness for a particular fuzzy set, and its description is essence of fuzzy property or operation.

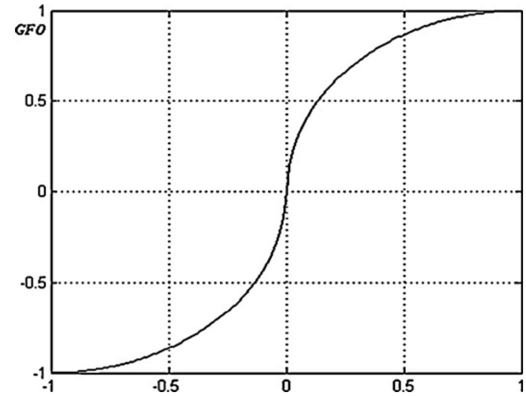

Fig. 1. *GFO* ($r = 0.5$).

	−1	
−1	5	−1
	−1	

−1	−1	−1
−1	9	−1
−1	−1	−1

Fig. 2. Four neighboring operator (on the left) and 8 neighboring operator (on the right).

The common *GFO* is defined as follows, which we use in this paper, and is described in Fig. 1:

$$\mu'_A(x) = GFO\,[\mu A(x)] = \begin{cases} -\left[-(2 * \mu A(x) + \mu A(x)^2)\right]^r & -1 \le \mu A(x) < 0 \\ \left[(2 * \mu A(x) - \mu A(x)^2)\right]^r & 0 \le \mu A(x) \le 1 \end{cases} \tag{1}$$

3. Proposed sharpening algorithm

Two of the most common unsharp masking operators are shown in Fig. 2. The 4 neighboring operator is on the left and the 8 neighboring operator is on right. We take the 8 neighboring operator for example. Suppose that the output image is $g(m,n)$. In the linear unsharp masking algorithm, the enhanced image $g(m,n)$ is obtained from the input image $f(m,n)$, the formula is as follows:

$$\begin{aligned} g(m, n) = {} & 9 * f(m, n) - f(m-1, n-1) - f(m-1, n) \\ & - f(m-1, n+1) - f(m, n-1) - f(m, n+1) \\ & - f(m+1, n-1) - f(m+1, n) - f(m+1, n+1) \end{aligned} \tag{2}$$

Eq. (2) can be rewritten in the following form:

$$\begin{aligned} g(m, n) = {} & f(m, n) + [f(m, n) - f(m-1, n-1)] + [f(m, n) - f(m-1, n)] \\ & + [f(m, n) - f(m-1, n+1)] + [f(m, n) - f(m, n-1)] + [f(m, n) - f(m, n+1)] \\ & + [f(m, n) - f(m+1, n-1)] + [f(m, n) - f(m+1, n)] + [f(m, n) - f(m+1, n+1)] \end{aligned} \tag{3}$$

Selecting the fuzzy region of membership function is a fundamental and important task. In order to apply the fuzzy theory, most researchers use a predetermined approach. The selection of membership function is dependent on the applications. The *S*-function and π-function are most commonly used. Other membership functions can be found in [11]. And in generalized fuzzy set, we use the generalized fuzzy operation (*GFO*) for enhancement.

From Eq. (3), we can see that the pixel value of $g(m,n)$ is equal to the center pixel value of the location (m,n) of $f(m,n)$ plus the sum of the difference of gray values within 3×3 window. In addition, we can see that traditional unsharp masking uses the same sharpening intensity for the different deviation, therefore noise increase when the image is sharpening. Instead, in the new method, the sharpening intensity is varying with the different of gray values within 3×3 window. If the deviation is bigger, it means that the high frequency is richer, and then the sharpening intensity should be lower, or else

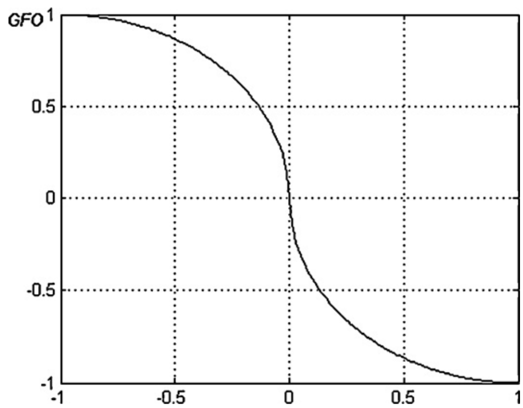

Fig. 3. The curve of sharpening operator.

Table 1
The associated indices of the images in Fig. 4.

Filter	Variance	Entropy	DV	BV	DV/BV
LUM	63.04	7.66	1894	54	35.1
Method in [7]	55.76	7.69	1384	165	8.4
Our method	52.5	7.57	932	14	66.6

noise will increases; on the contrary, the different is smaller means that the sharpening intensity should be higher. The algorithm is described as follows:

Suppose that an image $f(i,j)$ of size $M \times N$ having gray levels ranging from $L_{\min}$ to $L_{\max}$. Let $f_{i,j}$ be the value of the pixel at set (i,j) in the original image. Let W briefly denote the set of 8 neighboring pixels:

$$W = \{f_{i-1,j-1}, f_{i-1,j}, f_{i-1,j+1}, f_{i,j-1}, f_{i,j+1}, f_{i+1,j-1}, f_{i+1,j}, f_{i+1,j+1}\}$$

The output $g_{i,j}$ is defined as follows:

$$g_{i,j} = f_{i,j} + 255 * \sum_{x_{m,n} \in W} - GFO\frac{(\mu(m,n))}{8} \tag{4}$$

where $\mu(m,n) = (x_{mn} - x_{ij})/\max\{\left|x_{mn} - x_{ij}\right|\}$, and the sharpening operator is shown in Fig. 3.

Sharpening aims at highlighting the image edges. Suppose that m stands for the center pixel of the 3×3 window, and s means the other pixel. if $m > s$, namely $\mu > 0$, we set $\mu' < 0$. On the contrary, if $m < s$, we set $\mu' < 0$. The shape of the function controls the effect of the sharpening. When the difference of the gray $|m-s|$ is zero, no sharpening is performed in order to avoid any noise increase. On the contrary, when $|m-s| > 0$, the effect of the sharpening will be changed with the difference of the gray. To avoid the artifacts along contours, when the difference of the gray becomes bigger, the sharpening should be weakened. From Fig. 3 and Eq. (4), we know that the shape of the sharpening operator is determined by the chosen r. Then, we can adjust r to change the shape of the operator.

4. Experimental results

We have applied the proposed algorithm to a variety of images. Here, we present a few of the experimental results to demonstrate the performance of the proposed method. Figs. 4(a)–7(a) are the original images, and Figs. 4(b)–7(b) are the results obtained by LUM method, respectively. Figs. 4(c)–7(c) are the results obtained by CUM method, respectively, and Figs. 4(d)–7(d) are the results obtained by the proposed method, respectively. And the differences of sharpening algorithms are shown in Tables 1–4.

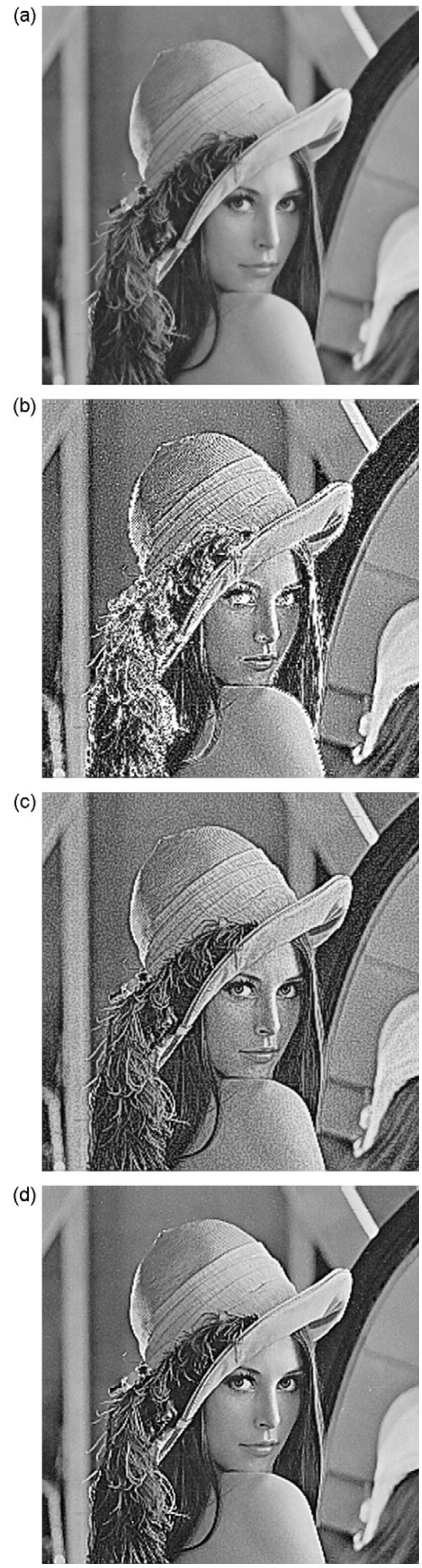

Fig. 4. (a) Original image, (b) enhanced image with LUM, (c) enhanced image with CUM and (d) enhanced image with the proposed method.

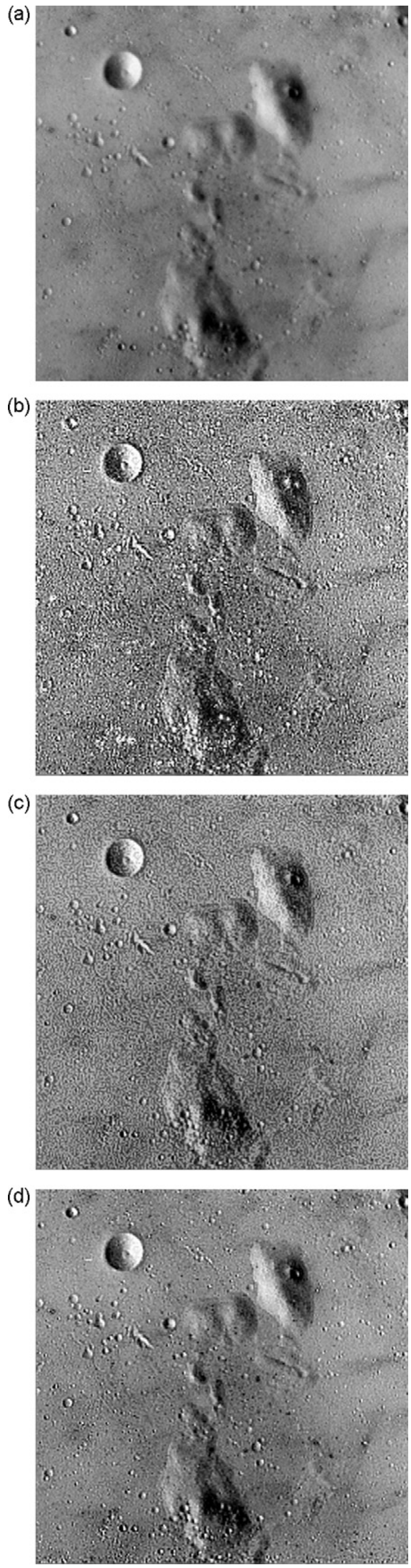

Fig. 5. (a) Original image, (b) enhanced image with LUM, (c) enhanced image with CUM and (d) enhanced image with the proposed method.

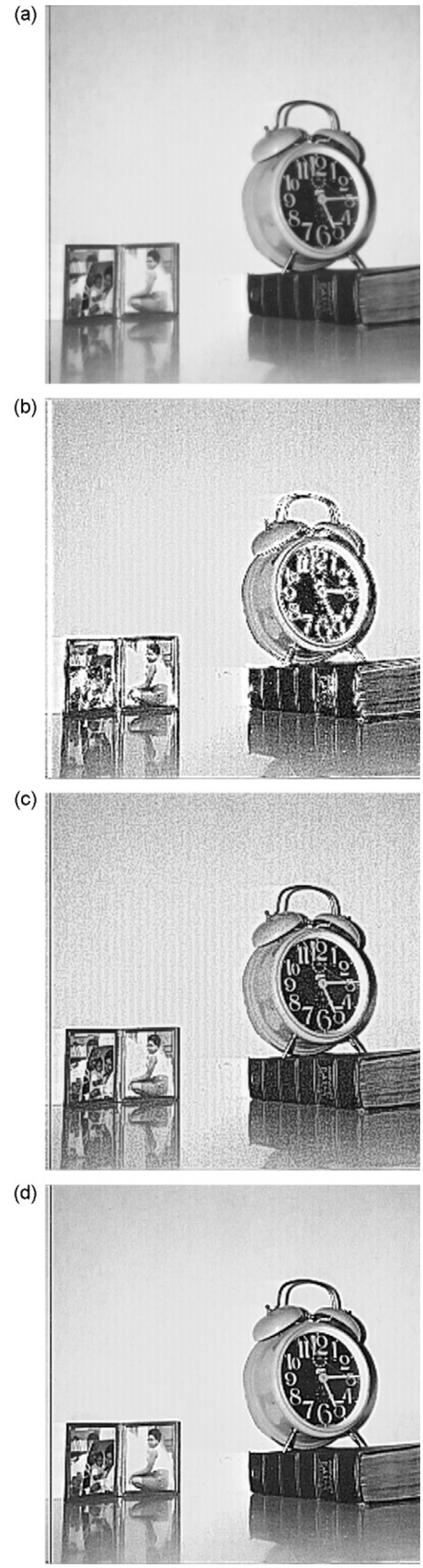

Fig. 6. (a) original image, (b) enhanced image with LUM, (c) enhanced image with CUM and (d) enhanced image with the proposed method.

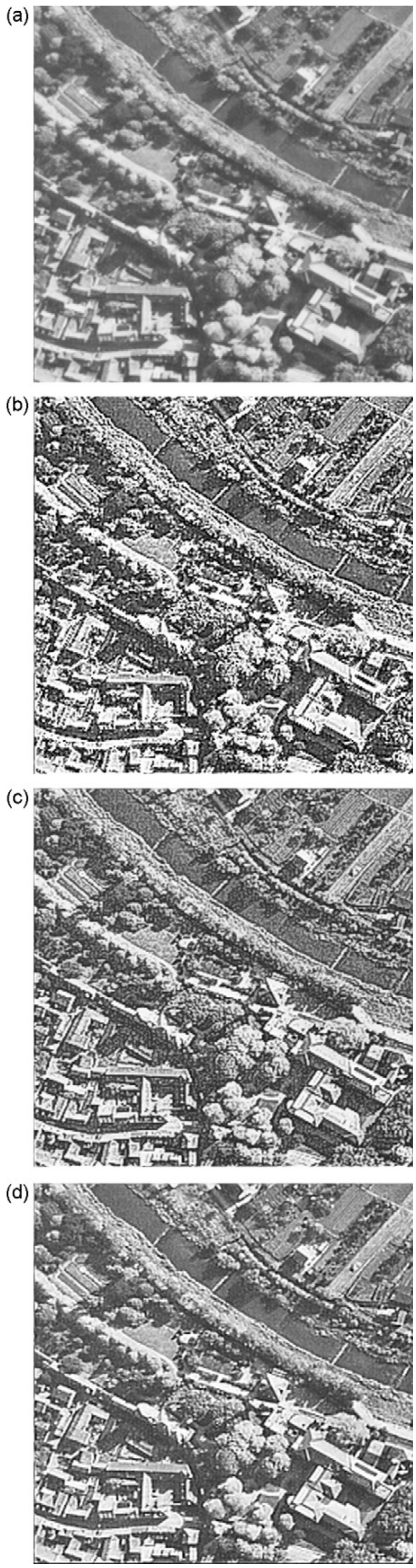

Fig. 7. (a) original image, (b) enhanced image with LUM, (c) enhanced image with CUM and (d) enhanced image with the proposed method.

Table 2
The associated indices of the images in Fig. 5.

Filter	Variance	Entropy	DV	BV	DV/BV
LUM	64.01	9.91	1315	5	263
Method in [7]	63.06	7.14	1146	54	21.2
Our method	48.52	6.83	858	0.7	1225

Table 3
The associated indices of the images in Fig. 6.

Filter	Variance	Entropy	DV	BV	DV/BV
LUM	64.01	9.91	13615	5	263
Method in [7]	63.06	7.14	1146	54	21.2
Our method	48.52	6.83	858	0.7	1225

Table 4
The associated indices of the images in Fig. 7.

Filter	Variance	Entropy	DV	BV	DV/BV
LUM	91.44	7.59	1510	546	2.8
Method in [7]	64.65	7.63	2432	283	8.7
Our method	58.98	7.58	1468	21	70.8

From a quantitative point of view, we can resort to a measure of the quality of the enhancement which has recently been proposed [12]. They are detail variance (DV) and background variance (BV), parameters that have already been used to assess the performance of enhancement operators, finding that it is in good agreement with the perceived image quality. It is based on the evaluation of the local image variance using a 3×3 or 5×5 window scanning the image. To this purpose, first of all, each pixel of the original image is assigned a label according to the local measured variance: if this variance is below a threshold which is determined by [13], the pixel is deemed to belong to a background area, otherwise to a detail. In this way, a binary reference map is created. Then, the local variance is measured again in the processed images (and even in the original one, if contemplated). Each variance sample is accumulated as 'detail' variance (DV) or 'background' variance (BV) according to the label assigned to that pixel, and the two average values for DV and BV are obtained for each image. Qualitatively, it can be stated that a good enhancement method should yield a DV/BV value significantly larger than other methods.

As is shown in tables, DV/BV in the proposed method is maximum, which demonstrates that the proposed method is possessed of strong capacity for detail enhancement and noise suppression. In addition, the variance in our method is minimum, and the entropy which represents the remaining information is also minimum. As we know that, the entropy is smaller, the information of the image is more. Therefore, the proposed algorithm is more practical, and can improve the quality of the image and suppress noise of the image.

5. Conclusion

An image sharpening algorithm based on nonlinear module and fuzzy logic was presented to improve the image quality while reducing the noises. The key idea of the proposed method is given as follows: the images were sharpened to different levels according to the differences between the center pixel value and the 8 neighboring pixel values. The sharpening intensity varies with the difference, i.e., the bigger the difference is, the lower the intensity is. The experimental results have shown that the algorithm yields promising results in sharpening images as well as refraining noises.

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