Iterative Adaptive Median Filter for Impulse Noise Cancellation

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Abstract – Based on the characteristics of impulse noises, the authors establish a new filter, Iterative Adaptive Median Filter (IAMF). According to the characteristics of images polluted by impulse noises, they establish weight function combined with iterative algorithm to eliminate noises. In IAMF filter process, because the noise spots do not participate in the computation, they do not influence the normal points in the image, therefore IAMF can retain the detail well, maintain the good clarity after processing image, and simultaneously reduce the computation. Experiments showed that IAMF have ideal denoising effect for the images polluted by the impulse noises; especially when the noise rates are more than 0.5, IAMF is more prominent, even when the noise rates are more than 0.9, IAMF can achieve a satisfactory results.

Key words – *iterative adaptive median filter*; *impulse noise*; *image processing*

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1 Introduction

Median filter is put forward by famous scholar J. W. Tukey in 1971, whose essence is image pixels' neighborhood operation. That is, all the pixels which lie in a processing pixel's neighborhood will be sorted according to the grey value, and then choose the middle value to replace the gray value pixel which will be processed. It is generally accepted that median filter can protect the image details well after filtering out the image noise. But, in fact, the filter effect of the median filter is affected by the following two aspect factors: 1) noise intens. When impulse noise intensity increases, the filter effect will be worse; 2) neighborhood template's size and shape. The different shape's neighborhood template will obtain different filter effect[1-2].

The filtering ability of conventional median filter is mostly limited, especially for the high noise intensity. For example, when the impulse noise intensity is bigger than 0.5, regardless of how to select the neighborhood template, the filter effect of the median filter is not really ideal[2-3]. Obviously, we must try to reduce the noise spots' influence in the filter window, and automatic control the size and the shape of neighborhood template. However, in the traditional filter design, how to choose the size and the shape of the neighborhood template, it is still unable to eliminate the influence of the noise spots to the normal pixels in the template window.

At present, some scholars proposed a lot of improved methods[2-5], these filters have improved in the filtering performance compared with the traditional filters, but the most unconditionally filter all input sample. so the operand becomes larger, and the speed becomes also quite slow. For a noisy image, only a part of pixels are polluted by the noise, and the remaining pixels often keep original values. That each pixel is unconditionally filtered is bound to lead to lose some original image's information, increase the operand, and reduce the speed of image processing. Therefore, this paper presented a new Iterative Adaptive Median Filter(IAMF) algorithm. The experiment proved that not only this algorithm can effectively extinguish the impulse noise, but also its denoising effect obviously surpassed other traditional algorithms, especially when the image noise rates surpassed 0.5.

2 Iterative adaptive median filter algorithm

2.1 The characteristics of impulse noise image

In the images, when a pixel polluted by the impulse noise, its gray value will be very larger different from around points' gray value. When the impulse noise gray is positive, the isolated bright spots are presented in the image, and when impulse noise gray is negative, the isolated dark spots are presented in the image. The character of the impulse noise image is that the noise spots are uniformly distributed in the entire image. That is, the spots of the original image are substituted by the noise spots on equal probability and all noise spots value are 0 or 255, which lead to that pixel values between 1 and 254 reduce on equal probability. Therefore, the noise image histogram has the following nature: Fig. 1(a) is the original Lena image's histogram, Fig. 1(b) is the image histogram of the Lena image polluted by impulse noise, and Fig. 1(c) is the Lena image's histogram polluted by impulse noise and removed the gray values 0 and 255. From the following image we can see that the extreme points of the Lena image's histogram which polluted by impulse noise and removed the gray values 0 and 255 and the extreme points of original image histogram are basically invariable.

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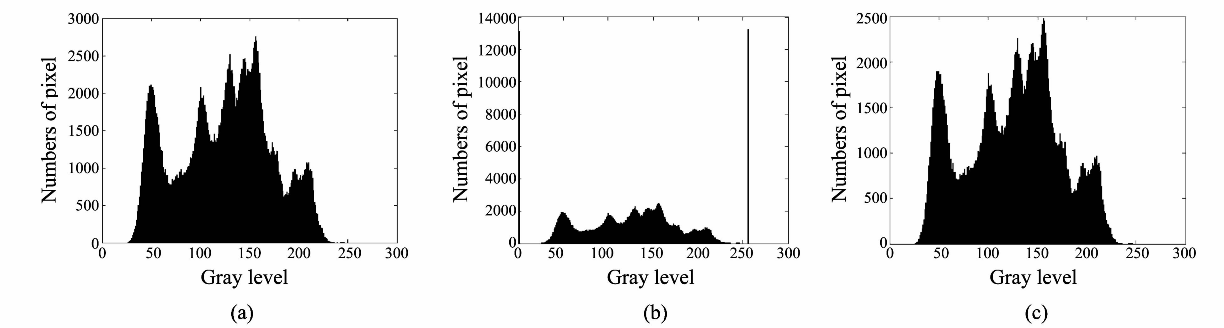

Fig. 1 Histogram comparison of Lena original images, image by the noise pollution and image destinated noise: (a) Lena's original image; (b) Polluted by impulse noise; (c) Removed two sides

2.2 Realization of iterative adaptive median filter algorithm

Supposing the original image is X whose size is $N \times M$ (N is the number of rows, M is the number of columns), the impulse noise image is C, and the output image after filtering is Y.

1) Establishe the weighting function

Because the pixel values of the pulse noise spots are all 0 or 255, pixel values between 1 and 254 reduce on equal probability, and the extreme points of the image's histogram which polluted by impulse noise and removed the gray values 0 and 255 and the extreme points of original image's histogram are basically invariable. Therefore, suppose that the pixel $x(i,j)$ is the value of the processing image $X = [x(i,j)]_{N \times M}$, $x(i,j) \in \{0,1,\cdots,L-1\}$, $0 \leqslant i \leqslant N-1$, $0 \leqslant j \leqslant N-1$, and establishe the weighted function

$$f(x) = \begin{cases} 0 & x = 0, \\ 1 & 0 < x < 255, \\ 0 & x = 255. \end{cases} \quad (1)$$

2) process noise image with the function $f(x)$, and form a binary template image

After processed by the function $f(x)$, the noise image becomes a binary template image which the image pixels polluted by noise are 0 and others not polluted by noise are 1.

3) process the noise image from right to left and from top to bottom according to the following algorithm:

① Take the pixel $c(i,j)$ of noise image as the center and selecte $(2n+1) \times (2m+1)$ number pixels as a window (e.g. 3×3 window, such as formula 2 shows).

$$\underline{C(i,j)} = \begin{bmatrix} c(i-1,j-1) & c(i-1,j) & c(i-1,j+1) \\ c(i,j-1) & c(i,j) & c(i,j+1) \\ c(i+1,j-1) & c(i+1,j) & c(i+1,j+1) \end{bmatrix}. \quad (2)$$

Take the pixel $w(i,j)$ of binary template image which is correspond with the pixel $c(i,j)$ of noise image as the center and also selecte $(2n+1) \times (2m+1)$ number pixels as a window (e.g. 3×3 window, such as formula3 shows).

$$\underline{w(i,j)} = \begin{bmatrix} w(i-1,j-1) & w(i-1,j) & w(i-1,j+1) \\ w(i,j-1) & w(i,j) & w(i,j+1) \\ w(i+1,j-1) & w(i+1,j) & w(i+1,j+1) \end{bmatrix}. \quad (3)$$

② We make elements of the formula(3) multiply corresponding elements of the formula(2) in order to remove the noise spots of the formula(2) window and convert the value of noise spots (0 or 255) to 0 value.

If all the elements in the new window are 0 values, $c(i,j) = 0$. Otherwise, sort nonzero pixels according to the size of nonzero pixels value in the new window. For exemple, if the total of nonzero elements is n, $C(1) < C(2) < \cdots < C(n)$, 0 values in the window do not participate in the operation, and take the middle value to replace (i,j); when the number of nonzero element n is odd, take the middle value $C(n+1/2) = c(i,j)$; when the number of nonzero element n is even, take the average of the middle two elements $1/2(C(n/2) + C(n+1/2) = c(i,j)$.

4) we can get a very good result after above processing for the low rate noise images (such as noise rate less than 0.4). But for the high rate noise image (such as noise rate more than 0.6) some pixels value in noise image will be 0 value after above processing. Due to the noise rate is quite high, all pixels in the window which take the pixel of the noise image $c(i,j)$ as center are all noise points (for example the formula (4) shows); In this case, the weight value of every pixel in the calculation window of weight function is 0, so the output values are all 0; At this point, the noise of output image Y must mainly be pepper noise (0 value).

$$\underline{C(i,j)} = \begin{bmatrix} 0 & 255 & 0 \\ 255 & 255 & 0 \\ 255 & 255 & 0 \end{bmatrix}. \quad (4)$$

5) Take the output image as noise image and filter processing again through the steps 1~3. Due to the weight of pepper noise (0 values) and salty noise (255 values) is 0, it does not participate in the operation in the filter process. undergoe the iterative loop, gradually use the normal pixel value in the window to substitute the noise point $c(i,j)$ and "0 value points" which produce in the previous filter processing (as shown in Fig. 2); Because the noise point does not participate in the operation, it will not have large influence to the result in the filter processing, and the image detail information will be good preservation, therefore this algorithm for the high noise rate images, even the noise rates more than 0.9, is able to produce the very ideal results.

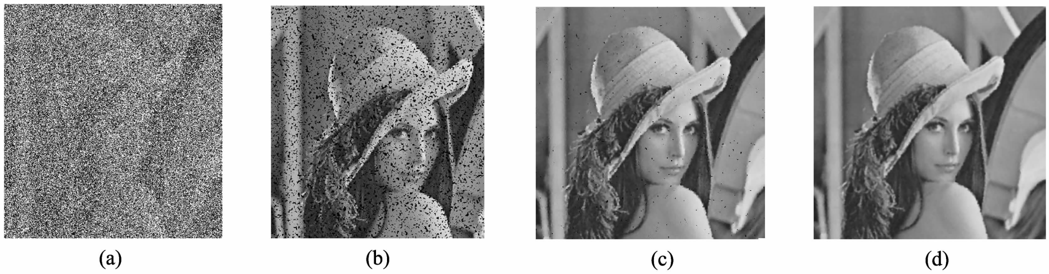

Fig. 2 Reduction process of the noise rate of 0.8 of the Lena image noise: (a) 0.8 noise image; (b) the first iterative; (c) the second iterative; (d) the third iterative

6) The output effect is closely related with the number of iterations. Because the latter iteration base on the preceding results, the output image will become fuzzy with the iterations increasing. For the noise image whose noise rate is more than 0.6, the output image which is ideally filtered the impulse noise can be got through 2-3 iterations.

In order to correctly estimate the number of iterations for variety noise images, before the filtering the noise rate R of images should be estimated, and the estimate formula is

$$R = 1 - \frac{n_i}{n}. \tag{5}$$

Where, n_i is the number of pixels whose gray value equal 0 and 255, and n is the total number of pixels for the image X.

The experimental results show that the numbers of iterations, as follows, can make the majority of images which polluted by impulse noise obtain the optimum filtering results:

$$N = \begin{cases} 1 & 0 \leqslant R \leqslant 0.5 \\ 1 & 0.5 \leqslant R \leqslant 0.7, \\ 3 & 0.7 \leqslant R \leqslant 0.8, \\ 4 & 0.8 \leqslant R \leqslant 0.9, \\ 6 & R \geqslant 0.9. \end{cases} \tag{6}$$

3 Verification tests

In order to verify the effectiveness of this algorithm, this paper selects the Lena image and a gorilla facial image, and chooses the size of 3×3 filter template. Respectively filter the impulse noise image that the noise rates are 0.3, 0.5, 0.7, 0.9, 0.95 Lena image and the noise rates are 0.2, 0.4, 0.6, 0.8 gorilla facial image by using IAMF. Estimate the number of iterations according to formula (6). In order to confirm the superiority of IAMF, meanwhile use adaptive median filter (adpmedian) and the standard median filter (median) of 3×3 and 5×5 template to respectively filter Lena image which polluted by 0.5 and 0.7 rates' impulse noise. Partial experimental results are shown in Fig. 3.

In the experiment, the mean square error (MSE), the mean average absolute error (MAE) and peak noise signal to noise ratio (PSNR) values of restored images under the different noise rates are gave. As shown in Tab. 1.

$$MSE = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}[y(i,j) - x(i,j)]^2}{\sum_{i=1}^{M}\sum_{j=1}^{N}x(i,j)^2}, \tag{7}$$

$$MAE = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}|y(i,j) - x(i,j)|}{\sum_{i=1}^{M}\sum_{j=1}^{N}|x(i,j)|}, \tag{8}$$

$$PSNR = 10 \times \log_{10}\frac{(L-1)^2}{\frac{1}{M \times N}\sum_{i=1}^{M-1}\sum_{j=1}^{N-1}[y(i,j) - x(i,j)]^2}. \tag{9}$$

The experiment indicates that when the noise rates are less than 0.5, IAMF can achieve the ideal effect after the first iteration; when the noise are higher than 0.5 and less than 0.8, IAMF can eliminate the noise through two times iterative processing; When the noise rates are 0.8, 0.9, the results shown in the above Figure can be got through three times and four times iterations. When the noise rates surpasses 0.9, after many times iteration IAMF can also achieve the ideal results. The experiment also discovers that when the noise rates surpass 0.5, no matter how to take the templates, the denoising effect of adaptive median filter (adpmedian) and the staodard median filter (median) are all not ideal. Such as in Fig. 3(13)～(15), partial processing results are shown using 3×3 and 5×5 templates to filter the noise images respectively.

The following conclusions can be drawn from the characteristics reflected in Fig. 3 and Tab. 1.

1) IAMF has ideal denoising effect for the image polluted by impulse noise. As can be seen from the experiment, with the noise rates enhancing, especially the noise rates more than 0.5, IAMF can prove its superiority. and the restored images by IAMF can keep relative high clarity;

2) That IAMF has good stability when it restores the images polluted by a variety of size impulse noise rates. Due to the noise points do not participate in the operation, it dose not have large influence to the result in the filter processing, so image detail information can be preserved better, and the restored images can keep relatively high clarity.

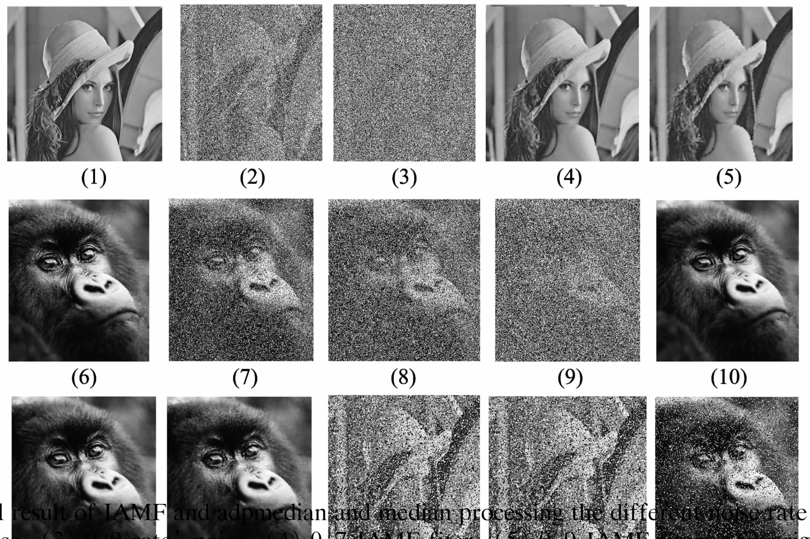

Fig. 3 The experimental result of IAMF and adpmedian and median processing the different noise rate image: (1) lena's original image; (2) 0.7 rate' noise; (3) 0.9 rate' noise; (4) 0.7 IAMF filter; (5) 0.9 IAMF filter; (6) original image; (7) 0.4 rate' noise; (8) 0.6 rate' noise; (9) 0.8 rate' noise; (10) 0.4 IAMF filter; (11) 0.6 IAMF filter; (12) 0.8 IAMF filter; (13) 0.7 adpmedian 3×3; (14) 0.7 median 3×3; (15) 0.6 median 5×5

Tab. 1 Comparison of restored Lena image with different noise rate

filter	Noise rate	PSNR(dB)	MSE	MAE
IAMF	0.3	32.9285	0.0019	0.028
IAMF	0.5	31.3521	0.0027	0.0325
IAMF	0.7	30.2366	0.0035	0.0350
IAMF	0.9	27.1075	0.0072	0.0495
IAMF	0.95	25.2923	0.0109	0.0609
adpmedian3×3	0.5	15.4280	0.1054	0.1213
adpmedian5×5	0.5	26.8270	0.0076	0.0384
median3×3	0.5	15.2999	0.1086	0.1365
median5×5	0.5	22.8631	0.0190	0.0568
adpmedian3×3	0.7	10.0471	0.3639	0.3735
adpmedian5×5	0.7	16.1668	0.0889	0.1163
median3×3	0.7	10.0201	0.3661	0.3823
median5×5	0.7	14.1663	0.1409	0.1785

4 Conclusion

According to the characteristics of impulse noise, this paper designed a new filter-iterative adaptive median filter (IAMF), and analyzed its principle. The experiment proved that IAMF has some advantages such as the simple principle, the stable property, and suitable processing all kinds of impulse noise rates' images. In addition, in filter operation, after the elements of formula(3) multiplied corresponding elements of the formula (2), using average value in the new window to replace middle value substituted the noise point $c(i,j)$, that is, $c(i,j)=\frac{1}{n}\sum_{i=1}^{n}c(i)$. This also got relative ideal effect. in other words, iterative adaptive mean filter was also effective. But experiments also discovered that IAMF did not restore these pixels whose grey value were 0 or 255.

Therefore, we attempt to apply fuzzy mathematics' principle, establishing fuzzy membership function which can describe the extent of the central pixel polluted by noise and determining the combination of fuzzy algorithms according to pollution degree of the central pixel in the window, to improve the IAMF filtering algorithm in the following research. And we attempt to filter the noise image polluted by Gauss noise and Stochastic noise by improved IAMF.

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