Application of Improved Median Filter on Image Processing

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Abstract—**Median filter is the most common method of clearing image noise. This paper proposes improved algorithm of median filter to remove sale and pepper noise of image. According to the characteristics of salt and pepper noise, the algorithm detects image noise, and establishes noise marked matrix, without processing the pixels marked as signal. The signal of the pixel is marked as not treated, labeled according to their pixel noise pollution in the neighborhood to take a different pixel weighted mean filter window size, weight pixel region by the noise points to determine the local histogram. Matlab experiments show that improved median filter can greatly reduce the time of clears image noise and it performs better than median filters on noise reduction while retaining edges of an image.**

Index Terms—**image processing; median filter; improved median filter; histogram**

I. INTRODUCTION

Images are often corrupted by noise because digital images are subject to a wide variety of distortions during acquisition, processing, compression, storage, transmission and reproduction, any of which may bring noise. Removing noise and restoring the original image is a fundamental task of image processing. Therefore, the problem of recovering an original image from noisy data has received ever increasing attention in recent years.

When transferring an image, sometimes transmission problems cause a signal to spike, resulting in one of the three point scalars transmitting an incorrect value. This type of transmission error is called "salt and pepper" noise due to the bright and dark spots that appear on the image as a result of the noise. The ratio of incorrectly transmitted points to the total number of points is referred to as the noise composition of the image. The goal of a noise removal filter is to take a corrupted image as input and produce an estimation of the original with no foreknowledge of the characteristics of the noise or the noise composition of the image.

The median filter is a best known to remove salt and pepper noise in image processing. It is also the foundation upon which more advanced image filters like unsharp masking, rank-order processing, and morphological operations are built. Higher-level applications include object segmentation, recognition of

speech and writing, and medical imaging.

Among all kinds of methods for impulse noise, the median filter is used widely because of its effective noise suppression capability and high computational efficiency. However, it uniformly replaces the gray-level value of every pixel by the median of its neighbors. Consequently, some desirable details are also removed, especially when the window size is large. These filters usually perform well, but as the noise level is higher than 30%, they tend to remove many features from the images, or retain too much impulse noise.

Median filter techniques abound in many image processing applications. Median filters, however, tend to blur sharp edges, destroy lines and other fine image details, fail to effectively remove heavy tailed noise, and perform poorly in the presence of signal-dependent noise. The research effort on nonlinear median-based filter has resulted in remarkable results, and has highlighted some new promising research avenues. On account of its simplicity, its edge preservation property and its robustness to impulsive noise, the standard median filter remains among the favorites for image processing applications. The median filter, however, often tends to remove fine details in the image, such as thin lines and corners. In recent years, a variety of median-type filters such as stack filters, weighted median [2], and relaxed median [3] have been developed to overcome this drawback.

In this paper, we propose an improved algorithm of median filter based on local histogram to clear image noise, and prove the effectiveness of the algorithm by the comparison of other median filter algorithms.

II. LOCAL HISTOGRAM

The histogram is the oldest and most widely used nonparametric density estimator. It is intuitively very plausible and easy to compute. The histogram requires a partition of the sample space into sets $B_k, k = 1, \cdots, m$ and is defined as [4]

$$\hat{f}(x) = \frac{1}{n\lambda(B_k)} \#\{i \mid X_i \in B_k\} \qquad (1)$$

For $x \in B_k$. Here $X_1, \cdots, X_n$ denotes the data, assumed to be independent observations of a random

variable X with unknown density f and n is the sample size. We consider only the case of one-dimensional observations, i.e. $B_k \subset IR$, with B_k some real interval whose Lebesgue measure is $\lambda(B_k)$. The simplest case is an equal bin size histogram. Then the B_k determined through the choice of an origin x_0 and a bin size or cell width h as $B_k = [x_0 + (k-1)h, x_0 + kh]$. The above formula (1) then takes the form

$$\hat{f}(x) = \frac{1}{nh} \#\{i \mid X_i \in [x_0 + (k-1)h, x_0 + kh]\} \qquad (2)$$

The shape of the histogram and its quality as estimator of the density f depends decisively on the choice of the bin size h. Is h too large then all data are smeared into one box and no further data structure is visible. The other extreme, a bin size tending to 0, leads to a histogram that approaches a sum of delta functions, i.e. narrow, high boxes located at the observations with zero values in between observations. Some users and data analysts may consider drawing many histograms of the same data of varying origins and bin sizes to highlight different features of the data. Their final choice then may be motivated by intuition, considerations of interpretability or aesthetics or the need to have a common scale across a number of histograms. However, an eyeball choice of the bin size in scientific studies may be considered too subjective and lacking reproducibility. In particular, in complex situations or when many histograms have to be drawn, a data-driven or automatic selection rule is desirable.

Suppose $w(i,j)$ is $n \times m$ windows of i as the center on image f, statistics appears of gray value x_k in the window $w(i,j)$ is called local histogram $p_{ij}(x_k)$, defined as $p_{ij}(x_k) = n_{wk}$. Where n_{wk} is number of pixels with gray value in windows $w(i,j)$.

Local histogram can reflect the frequency of each gray level in the local image. When an image is contaminated by sale and pepper noise, and each pixel in the image is the same as the probability of noise pollution. Therefore, noisy images also reflect the local histogram of each gray level occurring in the relative frequency of local image.

III. FILTERING ALGORITHM

Impulse noise is caused by malfunctioning pixels in camera sensors, faulty memory locations in hardware, or transmission in a noisy channel. See [7] for instance, two common types of impulse noise are the salt-and-pepper noise and the random-valued noise. For images corrupted by salt-and-pepper noise (respectively random-valued noise), the noisy pixels can take only the maximum and the minimum values (respectively any random value) in the dynamic range.

Different remedies of the median filter have been proposed, e.g. the adaptive median filter [8], the multi-state median filter [9], or the median filter based on homogeneity information [10], [12]. These so-called "decision-based" or "switching" filter first identify possible noisy pixels and then replace them by using the median filter or its variants, while leaving all other pixels unchanged. These filters are good at detecting noise even at a high noise level. Their main drawback is that the noisy pixels are replaced by some median value in their vicinity without taking into account local features such as the possible presence of edges. Hence details and edges are not recovered satisfactorily, especially when the noise level is high.

Denote by $\tilde{y}$ the image obtained by applying an adaptive median filter to the noisy image y. Noticing that noisy pixels take their values in the set $\{s_{min}, s_{max}\}$, we define the noise candidate set as [6]

$$N = \{(i,j) \in A : \tilde{y}_{i,j} \neq y_{i,j} \quad and \quad y_{i,j} \in \{s_{min}, s_{max}\}\}$$

The set of all uncorrupted pixels is $N^c = A \setminus N$.

Since all pixels in N^c are detected as uncorrupted, we naturally keep their original values, i.e., $\hat{x}_{i,j} = y_{i,j}$ for all $(i,j) \in N^c$. Let us now consider a noise candidate, say, at $(i,j) \in N$. Each one of its neighbors $(m,n) \in V_{i,j}$ is either a correct pixel, i.e., $(m,n) \in N^c$ and hence $\hat{x}_{m,n} = y_{m,n}$; or is another noise candidate, i.e. $(m,n) \in N$, in which case its value must be restored. The neighborhood $V_{i,j}$ of (i,j) is thus split as $V_{i,j} = (V_{i,j} \cap N^c) \bigcup (V_{i,j} \cap N)$. Restricted to the noise candidate set N:

$$F_y|_N(u) = \sum_{(i,j) \in N} [\,|u_{i,j} - y_{i,j}| + \frac{\beta}{2}(S_1 + S_2)] \qquad (3)$$

Where

$$S_1 = \sum_{(m,n) \in V_{i,j} \cap N^c} 2 \bullet \varphi(u_{i,j} - y_{m,n}),$$

$$S_2 = \sum_{(m,n) \in V_{i,j} \cap N} \varphi(u_{i,j} - u_{m,n}).$$

The restored image $\hat{x}$ with indices $(i,j) \in N$ is the minimize of (3) which can be obtained. The regularization term $(S_1 + S_2)$ performs edge-preserving smoothing for the pixels indexed by N.

Let us emphasize our method can be realized by any reliable impulse noise detector, such as the multi-state median filter [9] or the improved detector [12], etc. Our choice, the weighted mean filter, is motivated by the fact that it provides a good compromise between simplicity and robust noise detection, especially for high level noise ratios.

If a pixels detected as an impulse noise pixel, then we store the corresponding grayscale value in a histogram (e.g. Figure 1. (b)),and this histogram indicates the amount of noise detections (Y-axis) for each possible

grayscale value (X-axis). We use this histogram (which we simply call the noise histogram) to investigate the presence of impulse noise. If the noise histogram contains some peaks, then we conclude that the image contains impulse noise pixels otherwise we conclude that the image is free of impulse noise. Figure 1 Shows noise histograms for an image.
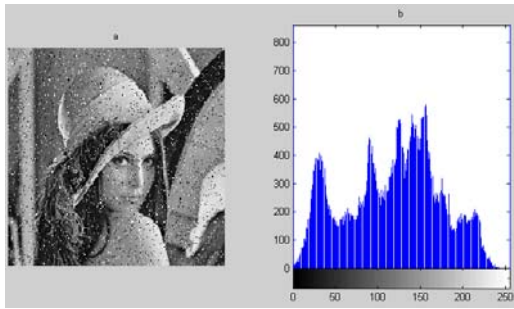

Figure 1. (a) A Lena image corrupted with 7% salt-and-pepper noise (b) The corresponding histogram of the detected noisy pixels.

IV. EXPERIMENTAL RESULTS

A Gray-scale images

Among the commonly tested 256b×256b×8b gray-scale images, the one with homogeneous region (Lena) and the one with high activity (Bridge) will be selected for our simulations. Their dynamic ranges are [0, 255]. In the simulations, images will be corrupted by "salt" (with value 255) and "pepper" (with value 0) noise with equal probability. Also a wide range of noise levels varied from 10% to 50% with increments of 10% will be tested.

For comparison purpose, the standard median filter, stack median filter, and the algorithm in this paper are tested. Restoration results of different filter are shown as in the Figure 2. - Figure 4.

Figure 2. Restoration Results of Different Filters of Corrupted Lena Image with 10% Salt-and-pepper Noise

Figure 3. Restoration Results of Different Filters of Corrupted Lena Image with 30% Salt-and-pepper Noise
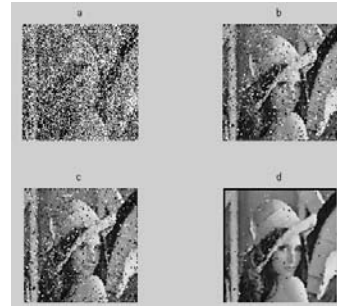

Figure 4. Restoration Results of Different Filters of Corrupted Lena Image with 50% Salt-and-pepper Noise

In the above three figures,(a) is corrupted Lena image with salt-and-pepper noise,(b) is restoration results of standard median filter,(c) is restoration results of stack median filter, and (d) is restoration results of the algorithm in this paper. The three figures show that restoration results of median filter in this paper is the best.

B color images

Based on the above-mentioned algorithm, the size of 384 × 512, 24 bit color image pixel has been tested; Figure 5 shows the results of test in MATLAB7.8 environment.
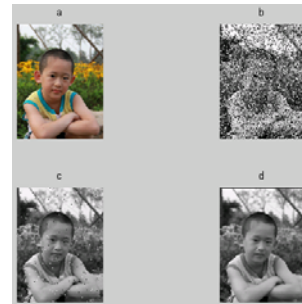

Figure 5. Restoration Results of Different Filters of Corrupted Color Image with 30% Salt-and-pepper Noise

In the above figure,(a) is original color image, (b) is corrupted color image with salt-and-pepper noise,(c) is restoration results of standard median filter, and (d) is restoration results of the algorithm in this paper. The figure shows restoration results of median filter in this paper is the best.

Examine the quality of original image and the quality of filtered image, we use the peak signal to noise ratio. The phrase peak signal-to-noise ratio, often abbreviated PSNR, is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Because many signals have a very wide dynamic range, PSNR is usually expressed in terms of the logarithmic decibel scale.

The PSNR is most commonly used as a measure of quality of reconstruction of lossy compression codecs (e.g., for image compression). The signal in this case is the original data, and the noise is the error introduced by compression. When comparing compression codecs it is used as an approximation to human perception of reconstruction quality, therefore in some cases one reconstruction may appear to be closer to the original than another, even though it has a lower PSNR (a higher

PSNR would normally indicate that the reconstruction is of higher quality). One has to be extremely careful with the range of validity of this metric; it is only conclusively valid when it is used to compare results from the same codec (or codec type) and same content. [13]

It is most easily defined via the mean squared error (MSE) which for two $m \times n$ monochrome images I and K where one of the images is considered a noisy approximation of the other is defined as:

$$MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [I(i,j) - K(i,j)]^2$$

The PSNR is defined as:

$$PSNR = 10 \cdot \log_{10}(\frac{MAX_I^2}{MSE}) = 20 \cdot \log_{10}(\frac{MAX_I}{\sqrt{MSE}})$$

Here, MAX_I is the maximum possible pixel value of the image. When the pixels are represented using 8 bits per sample, this is 255. More generally, when samples are represented using linear PCM with B bits per sample, MAX_I is $2^B - 1$. For color images with three RGB values per pixel, the definition of PSNR is the same except the MSE is the sum over all squared value differences divided by image size and by three. Alternately, for color images the image is converted to a different color space and PSNR is reported against each channel of that color space, e.g., YCbCr or HSL.

We tested four cases of both algorithms on a living image. In the following table, the PSNR values are listed.

Table 1 PSNR Value ofEach Method in Under Different Noise Ratio

algorithm	noise ratio		
	0.1	0.3	0.5
Corrupted image	15.41	10.69	8.48
standard median filter	38.35	35.43	32.67
stack median filter	38.71	35.76	32.89
the algorithm in this paper	41.21	37.68	33.59

It can be seen that the algorithm in this paper provides the best results in PSNR.

V. CONCLUSIONS

Image denoising is a hard nut to crack in image analysis. There is not an efficient method to remove the random noise yet. We presented a method of usingimproved median filter to image denoising. The experiment image contains salt and pepper noises as well as random noises. Experiments obtained a satisfactory result. It is proved that improved median filter denoising algorithm can not only greatly reduce the program running time, but also maintain the image detail better, so it is more suitable for ordinary computer image denoising.

REFERENCES

[1] Perona,P., Malik,J.: Scale Sapce and Edge Detection Using Anisotropic Diffusion. IEEE Transactions on Pattern Analysis and Machine Intelligence 12,629-639(1990).

[2] Yiqiu Dong and ShufangXu. A New Directional Weighted Median Filter for Removal of Random-Valued Impulse Noise. Signal Processing Letters, IEEE, 2007

[3] A. Ben Hamza, P. Luque, J. Martinez, and R. Roman, "Removing noise and preserving details with relaxed median filters," J. Math. Imag. Vision, vol. 11, no. 2, pp. 161–177, Oct. 1999.

[4] JOACHIM ENGEL .The multiresolution histogram. Metrika (1997) 46:41-57

[5] S. Schulte, M. Nachtegael, V. D. Witte, D. V. der Weken, and E. E.Kerre, "Fuzzy impulse noise reduction methods for color images," in Computational Intelligence, Theory and Applications International Conference 9th Fuzzy Days in Dortmund. Springer Verlag , 2006, pp. 711–720.

[6] Raymond H. Chan, Chung-Wa Ho, and Mila Nikolova.Salt-and-Pepper Noise Removal by Median-type Noise Detectors and Detail-preserving Regularization.

[7] A. Bovik, Handbook of Image and Video Processing, Academic Press, 2000.

[8] H. Hwang and R. A. Haddad, "Adaptive median filters: new algorithms and results," IEEE Transactions on Image Processing, 4 (1995), pp. 499–502.

[9] T. Chen and H. R. Wu, "Space variant median filters for the restoration of impulse noise corrupted images," IEEE Transactions on Circuits and Systems II, 48 (2001), pp. 784–789.

[10] H.-L. Eng and K.-K. Ma, "Noise adaptive soft-switching median filter," IEEE Transactions on Image Processing, 10 (2001), pp. 242–251.

[11] G. Pok, J.-C. Liu, and A. S. Nair, "Selective removal of impulse noise based on homogeneity level information," IEEE Transactions on Image Processing, 12 (2003), pp. 85–92.

[12] S. Zhang and M. A. Karim, "A new impulse detector for switching median filters," IEEE Signal Processing Letters, 9(2002), pp. 360–363.

[13] Huynh-Thu, Q.; Ghanbari, M. (2008). "Scope of validity of PSNR in image/video quality assessment". Electronics Letters 44 (13): 800–801.

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