Image Denoising by NAM-based Detection and Median Filter

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Abstract
Image denoising is a very important issue in image processing, which is encountered in many practical applications. The traditional median filter based method was to replace the center point by the median value of its 4 or 8 neighborhood points. However this method haven't considered whether the point is the noise point or not, which cannot achieve satisfied results. In this paper, we proposed an improved median filter method—homogeneous blocks based median filter based method. The homogeneous block is used to detect the noise point as it is sensitive to the salt & pepper noise. And then the median filter is used to remove the noise detected by the homogeneous blocks. The experimental results show that the proposed method achieves much better denoising results than the popularly used median filter and mean filter method with low computational complexity.
Key words: NAM-BASED DETECTOR; MEDIAN FILTER; IMAGE DENOISING

Introduction

Image denoising is a very challenage task in the field of image processing [1-3], which aims to recover a clean image from a noised one. In the literature, many methods have been proposed to remove the noise, such as filter based method, wavelet based method, and variational-based method.

The wavelet based method [4-6] is to remove the noise in the wavelet space, where the noise is consisted in the high-frequency part. Usually, the authors found a threshold and remove the high-frequency part and retain the lowfrequency part. By using this kind of method, a great amount of useful information is also removed while some noise in lower-frequency part is still retained.

The variational-based method [7-9] is to remove the noise by using the following equation:

$$f = \arg\min\{\frac{1}{2}\|f-g\|_2^2 + \lambda R(f)\} \qquad (1)$$

where $\frac{1}{2}\|f-g\|_2^2$ is the data fidelity item, which stands for the fidelity between the observed image and the original image, g is the observed degraded image. $R(f)$ is the regularization item, which gives a prior model of the original image f, and λ is the regularization parameter, which controls the trade-off between the data fidelity and prior items. However, this kind of method needs a great much more computational complexity than other methods. Also, the prior knowledge is different for different kind of images.

The filter based method [10-12], such as median filter, mean filter, removes the noise by using its 4 or 8 neighborhood information. However, this method is a kind of global method. All the points in the image will be filtered including the points without degraded.

In this paper, we are focus on the pepper & salt noise. Our aim is to locate each noise and then apply the median filter to remove the noise. The main contribution of our method includes: (1) our method is first to locate each noise in order to decrease the efficiency of the filter to the noise-free points and (2) the low computational complexity.

The rest of the paper is organized as follows: in section II, we introduce our method in detail. Section III gives the computational complexity analysis and the experimental results are presented in section IV. Section V concludes the paper.

The Proposed method

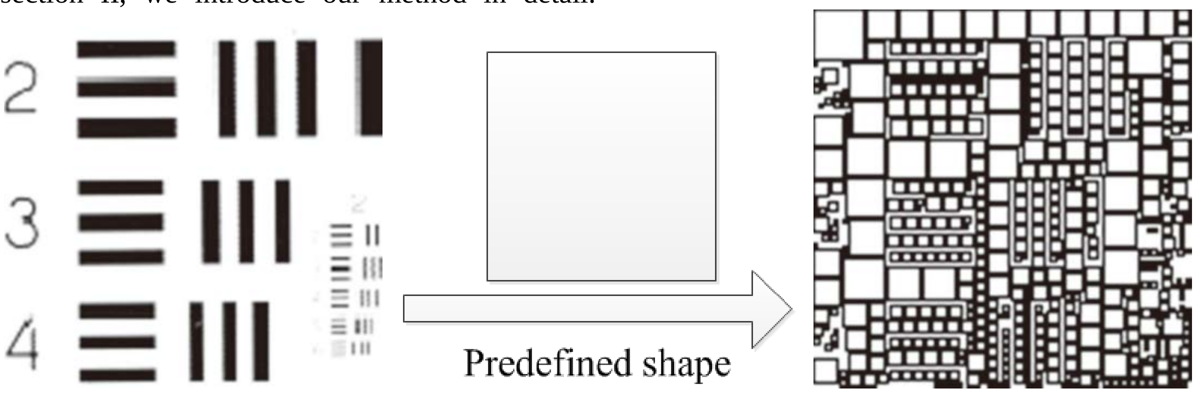
In this section, we introduce our method in detail. In subsection A, we will introduce the noise detection method, and the noise removing method is presented in subsection B.

A. Detection Method

In our proposed method, one or more shapes are predefined. In our work, for convenience, just one predefined shape is defined. Then, by using this predefined shape, the observed image is partitioned into numbers of homogeneous blocks. These homogeneous blocks are in the same gray value interval. As for the pepper & salt noise is a kind of impulse noise with great gradient error between its neighborhood points. Removing the homogeneous blocks, most of the rest points are the noise.

In this work, the predefined shape is square. Then the images could be partitioned by this predefined into small blocks. Also, the image could be approximated by these homogeneous blocks (see Fig 1).

Fig. 1 is an simple example of image partition by using the predefined shape. Fig. 1 (a) is the input image, Fig. 1 (b) is the predefined shape, and Fig. 1 (c) is the partitioned image. From this figure, we can notice that, in the smooth region, the homogeneous block is large, and the homogeneous block is discontinued in the large gradient region.



(b) (c)

Figure 1. An example of image partition by using the predefined shape. (a) is the input image, (b) is the predefined shape, and (c) is the partitioned image

In our work, the gray value scale used in this paper is the uniform length (i.e., [0, 32), [32, 64), [64, 96), [96, 128), [128, 160), [160, 192), [192, 224), and [224, 256)). The adjacent points in the same gray value scale will be partitioned in the same homogeneous block under the shape constraint. The same homogeneous block will be stopped when coming across the larger gradient.

From the description above, we can notice that the homogeneous block is sensitive to the pepper & salt noise, when the homogeneous block comes across the noise, it would be discontinued and another new homogeneous block will be set up automatically to cover another part of the image until the image is wholly covered by homogeneous blocks. The detail algorithm is presented below.

Algorithm 1: Noise detection	
Input:	The noised image, the predefined shape.
Output:	The partitioned image.
1:	Set a new stack, set the start point;
2:	**Do**
3:	Search the largest homogeneous blocks under the constraint of the predefined shape and the gray scale;
4:	When find the homogeneous block, record its location and size and put it into the stack;
5:	Set a new start point from top-left to right-down, which is not marked;
6:	**Until** the image is finished partitioned;
7:	Remove all the homogeneous blocks and record all the single points.

Note that, after the process described in Algorithm 1, all the pepper & salt noise point are detected. However, some noise-free points would also be detected, which are usually texture point according to our experiments. A histogram of each single point and its 8 neighborhood region is set up to solve this problem.

B. Noise Removing

Since the noise points are detected by using the method described in subsection A, in the following, we will remove these points by using a very simple but efficient and effective method, median filter. By using the process described in subsection A, many noise free points are removed, and it could avoid the false positives.

Commonly, the noise could be described in the following equation:

$$g = f + \varepsilon \qquad (2)$$

where f is the noise free image, g is the observed noised image, and ε is the noise, in this paper, we set it as pepper & salt noise.

For the points in the stack g’ which record the single noise points, we locate it in the original noised image g, and its 3×3 neighborhood region, noted as S. Then, in this region, we find its median value as follows:

$$\bar{f}(x,y) = \frac{1}{2}[\max_{(s,t)\in S} g(s,t) + \min_{(s,t)\in S} g(s,t)] \qquad (3)$$

where (x, y) is current noise point, S is its 3×3 neighborhood region. (s, t) is the point in the neighborhood region. By using this method, we can calculate the estimated value. It should be noted that, this kind of method is a combination method of statistics and mean, which is stable to the stochastic noise.

Thus, we can obtain the denoised image. The whole denoising process can be described as following Algorithm 2.

Algorithm 2: Image denoising	
Input:	The noised image, the predefined shape, the stack g’.
Output:	Denoised image.
1:	Set g’ as empty
2:	Find the homogeneous blocks by using the predefined shape;
3:	Filter the single points by using a histogram to ensure the noise points and put them into the stack;
4:	For each points in the stack, do the median filter;
5:	Obtain the final denoised image.

Computational Complexity Analysis

In this section, we will analyze the computational complexity of our proposed method. Suppose that the input noised image is a $M \times N$ matrix, for the homogeneous process, the computational complexity is $M \times N$.

For the histogram process and denoise process, the computational complexity is with the noise points, its much smaller than the size of the image, depending on the strength of the noise.

Thus the whole computational complexity is as follows:

$$O(T)=O(detection)+O(denoising)<=20(M \times N)$$

where $M \times N$ is the size of the observed image g.

Experimental results

In this section, we will show our experimental results in detail, the images used for this section is presented in Fig.2, which are the popularly used images. Also, the noise used in this work is pepper & salt noise, the noised images are presented Fig.3. In Fig.3 (a) is in weak noise and (b) is in strong noise.

We will compare our proposed method with original median filter method, mean value filter method in visual quality and numerical standard which is defined as follows:

where (x,y) is the coordinate of the image point, M and N are the length and width of the image. μ is the mean value of line x or column y, and σ is the covariance of line x or column y.

(a) (b) (c)

Figure 2. The images used in our experiments.

(a)noise strength 0.02 (b) noise strength 0.06 (c) noise strength 0.1

Figure 3. An example of the strength of noise used in this paper

(a)median filter (b) mean value filter (c) our methods

Figure 4. The denoised image of "lena" under the noise strength 0.06.

(a)median filter (b) mean value filter (c) our methods

Figure 5. The denoised image of "Babara" under the noise strength 0.1.

Table 1. The numerical results of the denoised images by using different methods

	Noise strength 0.02			Noise strength 0.06			Noise strength 0.1		
	median	mean	ours	median	mean	ours	median	mean	ours
Lena	28.45	26.11	30.43	28.49	24.05	29.59	27.94	22.60	28.39

	0.8626	0.6645	0.9453	0.8552	0.5282	0.9247	0.8478	0.4556	0.9026
Boats	29.33	26.33	31.34	28.80	24.26	30.13	28.42	22.87	28.80
	0.8399	0.5886	0.9400	0.8317	0.4641	0.9077	0.8219	0.4091	0.8821
Babara	27.23	25.16	28.92	26.96	23.51	28.09	26.46	22.08	27.05
	0.8559	0.7240	0.9310	0.8498	0.6206	0.9066	0.8396	0.5492	0.8817

Conclusions

In this paper, an improved detection based image denoising method is proposed. Just a predefined shape is used to partition the images into homogeneous blocks. Because these blocks are very sensitive to the noise, it could be used to detect the pepper & salt noise. In order to decrease the false positives, a local region histogram based method is used to test the single points are the textures or the noise. Then for each noise points detected, the median filter is used to remove these noise by using the median value of its small region. The experimental results showed that the proposed method is much more superior than the original median filter based method with just a few more computational complexity cost.

Acknowledgements

This study was supported in part by the National Natural Science Foundation of China (Grant No. 61401242), China Postdoctoral Science Foundation(Grant No.2015M572143), the Research Foundation for Advanced Talents of Nanyang Normal University (Grant No.ZX2014058), Technology Research and Development Program of Lianyungang (Grant No.SH1223), the Research plan for Basic and frontier Research of Henan (Grant No. 142300410044), and the Key Programs of Education Department of Henan Province (Grant No. 14A520057).

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