An Adaptive Image De-noising Algorithm Based on Edge Preservation

Cheng Zhang, Haibo Gao, Wenjuan Zeng

College of Information Science and Engineering, Hunan International Economics University, Changsha 410205, Hunan, China

Abstract

Image is frequently polluted by noises in the acquisition and transmission. Noises have a significant impact on image quality. Therefore, inevitable image denoising has become an important technique for image analysis and processing. This paper proposes a new image denoising method for noise detection and edge preservation. By analyzing the noises, it detects local maximum and minimum values of image gray level of noise detection operator and integrates local energy information of pixel neighborhood. After determining the threshold range, it only uses the signal point within the window in the filtering process. In other words, after confirming certain pixel point as noise point, it is replaced with the filtering result of this point and the replaced result will affect further noise point detection and filtering. It greatly reduces the impact of noise points on the filtering result until the window is shifted to the bottom right corner. At that time, the entire image denoising process is completed. The experiment result shows that this algorithm can preserve the edge information and details of the image while it effectively removes noises and it has better performance than traditional denoising algorithms.

Key words: Image De-noising, Edge Preservation, Adaptive Filtering.

1. INTRODUCTION

Image is an important information source; however, the acquired image is always polluted by noises due to various reasons. Image denoising, also known as image filtering, is a kind of image restoration. It ultimately improves the given image and solves the image degradation caused by noise interference; therefore, image denoising has played an significant role in many fields. Different from image enhancement, image denoising is mainly an objective process. Edge information is the most fundamental characteristic of image and it includes important information of the image. It is not only the most important property on which image segmentation depends, but it is also a significant information source of texture features. It displays the signal salutation and it has such advantages that it can outline the shape of the region and that it can be defined locally (Ashish and Suman, 2015; Byungjin and Changhoon, 2014).

Denoising techniques can effectively improve the image quality, increases signal to noise ratio and better demonstrates the edge and detail information of the original image. Currently, there are already many image denoising methods and the traditional methods include spatial-domain synthesis method, frequency-domain synthesis method and optimal linear synthesis method (Eliahu and Ron et al., 2015; Wu and Hu, 2015). Correspondingly, many application methods have emerged, e.g. mean filter, median filter, low-pass filter, Wiener filter and minimum distortion. Although the image denoising methods have done well in the low-dimensional signals, they are not so good at processing high-dimensional ones. Some image denoising methods can achieve excellent denoising effect, but they have done harm to the edge information while some methods can detect the image edge information and preserve the details, but their processing results of the smooth regions are quite bad (Hamid and Rabha, 2015). The traditional mean filtering also has its own defect: because there are two different pixels in the image edge regions, to use the mean filter with the same weight will blur the image edge. Since the standard mean filter can have excellent smooth effect on the noises distributed at a long streaking probability and can preserve certain image detail, it has been widely applied in the image denoising. However, to remove the noises with standard mean filtering is greatly affected by the size of the filter window; therefore, there exists certain contradiction between noise suppression and detail preservation (Cong-Hua and Xiao-Wei, et al., 2014).

This paper firstly analyzes the image noise model and the principle of spatial-domain filtering. Then on this study, it provides a noise detection option, propose a noise detection removal algorithm based on edge preservation and realizes the accurate detection and filtering of noises. Finally, the simulation experiment shows that the algorithm of this paper can have ideal effect on image denoising.

2. IMAGE NOISES AND SPATIAL-DOMAIN FILTER

2.1. Image Noise Model
Image noise model describe the parameters of spatial properties of noises and their internal correlation with the spatial properties of the image. For example, in a black-and-white image, assume that its flat lightness distribution is \( f(x, y) \), the lightness distribution \( R(x, y) \) which interferes its reception is called image noise. It is suitable to see image noise as a multi-dimensional random process, therefore, the method to describe noises can totally borrow the description of the random process, namely to use its probability distribution function and probability density distribution function (Paras and Vipin, 2015; Zhuang and Xingbao, 2015). There are actually many kinds of noises and they come into being for different reasons. The common important noise models are indicated as follows.

(1) Gaussian Noise
Due to the mathematical tractability of Gaussian noise in spatial and frequency domain, this kind of noise (normal noise) model has been frequently used in practice. Gaussian model is always used in the critical condition. PDF of Gaussian random variable \( z \) is given by the following formula.

\[
P(z) = \frac{1}{\sqrt{2\pi\sigma}} \exp\left[-\frac{(z-u)^2}{2\sigma^2}\right]
\]

Here, \( z \) is gray level, \( u \) is the mean value of \( z \), \( \sigma \) is the standard deviation of \( z \) and the square of the standard deviation is called the variance of \( z \).

(2) Gamma Noise
The PDF of Gamma noise is provided by the following formula.

\[
p(z) = \begin{cases} a^b z^{b-1} e^{-az} \frac{e^{-az}}{(b-1)!}, & z \geq 0 \\ 0, & z < 0 \end{cases}
\]

Here, \( a > 0 \), \( b \) is the positive integer and “!” is factorial. The mean value and variance of its density is given by the following formula.

\[
\mu = \frac{b}{a}, \quad \sigma^2 = \frac{b}{a^2}
\]

(3) Salt-and-Pepper Noise
Salt-and-pepper noise (impulse noise) is black-and-white bright dark point noise produced in image sensor, transmission channel and decoding process. It refers to two noises: salt noise and pepper noise. The former is high gray-level while the latter is low gray-level. Generally, these two noises appear at the same time and they are black and white points in the image. The PDF of impulse noise is given by the following formula.

\[
p(z) = \begin{cases} P_a, & z = a \\ P_b, & z = b \\ 0, & \text{others} \end{cases}
\]

If \( P_a \) of \( P_b \) is 0, then the impulse noise is called unipolar pulse. If \( P_a \) and \( P_b \) are not 0, the impulse noise are similar to the pepper and salt particles randomly distributed in the image, especially when they are also the same. The simulation diagrams of several common noises are indicated as Fig.1.
2.2. Spatial-Domain Filtering of Image

Spatial-domain filtering directly conducts data operation on the original image, processes the gray-level value of the pixel and uses the image processing (convolution operation) of the spatial-domain template. The template itself is called spatial-domain filter. The common spatial-domain image denoising algorithms include neighborhood averaging method, median filter and low-pass filter (Malini and Moni, 2015; Vijaykumar and Santhana Mari, et al., 2014).

In the $M \times N$ image $f$, the $m \times n$ filter is used.

$$g(x, y) = \sum_{s=a}^{b} \sum_{t=-b}^{b} w(s, t) f(x + s, y + t)$$

$$m = 2a + 1, n = 2b + 1$$

The simplifying form of spatial filter is as follows.

$$R = w_1 z_1 + w_2 z_2 + \cdots + w_m z_m$$

Here, $w$ is the filter coefficient, $z$ is the corresponding image gray-level value to this coefficient and $mn$ is the sum of the pixel points included in the filter. The diagram of the spatial-domain template filter is shown in Figure 2.

![Diagram of spatial-domain template filter](image)

Figure 2. Diagram of spatial-domain template filter

The output of the above Fig.2 template is $R = k_0 s_0 + k_1 s_1 + \cdots + k_8 s_8$. Several common filter techniques can be seen below.

1. Mean Filtering

Mean filtering algorithm is a simple algorithm which suppresses Gaussian noise well and it mainly uses neighborhood averaging method. Mean filtering is very sensitive to impulsive noise, fundamentally because of the mean operation. The weights of every pixel are the same. When there is a singular point in the filtering window, that point greatly affects the filtering effect and the existence of the singular point will also be spread to its surrounding pixels after affected by mean filter. Its basic principle is to replace each pixel value with the mean value, namely to choose a template for the current pixel point $(x, y)$ to be processed. This template is formed by several neighborhood pixels. Seek the mean value of all pixels in the template and give the mean
value to the current pixel point \((x, y)\) as the gray level \(g(x, y)\) of this point of the processed image. Its formula is as follows.

\[
g(x, y) = \frac{1}{M} \sum_{s \in S} f(s, x, y)
\]

(8)

Here, \(s\) is the template and \(M\) is the total pixels (including the current pixel) in the template.

It can be seen from the above analysis of mean filtering algorithm that the traditional mean filtering algorithm can be realized by optimizing weight and mean filtering doesn’t fully use the correlation between the pixels of the image and the position information of the pixel (Amala and Helen, 2015; Ching-Ta, 2014).

(2) Median Filtering

Standard median filter can smoothen the noises distributed at a long streaking probability and protect certain details of the image; however, there is certain contradiction between noise suppression and detail preservation. If the filtering window is small, it can better protect the image details, but its capacity to filter and remove noises will be restricted and if the window is big, the noise suppression ability can be enhanced, but too many image details (i.e. image edge, corner and fine lines) will be lost, causing image blurring.

The definition of median is as follows: for a group of number \(x_1, x_2, \ldots, x_n\), they can be arranged in the order of size.

\[
x_1 \leq x_2 \leq x_3 \leq \cdots \leq x_n, \quad y = \text{Med}(x_1, x_2, x_3, \ldots, x_n)
\]

(9)

Here, \(y\) is called the median of the sequence \(x_1, x_2, x_3, \ldots, x_n\).

If \(n\) is an odd number, then the median \(y\) is the \((\frac{n+1}{2})\)th number and if \(n\) is an even number, then the median is the mean value of the sum of the \(\frac{n}{2}\)th number and the \((\frac{n}{2} + 1)\)th number (Jin, 2013; Defa and Zhuang, 2015).

(3) Non-Local Mean Filter (NLM)

There are plenty of redundant information and many similar image blocks in the natural image. the adjacent pixels points usually have similar neighborhood while the non-adjacent points may also have similar neighborhood. For instance, the neighborhood of the pixel point which has the same x-coordinate as the pixel point \(p\) is similar to that of \(p\). Non-local mean image denoising method uses this image property and suppresses noise with the self-similarity of non-local image. NLM divides the image into several blocks, every of which can find many image blocks which are similar to them. Determine the weight coefficient by comparing the similarity of each pixel neighborhood block and obtain the current templateing central pixel by weighting the central pixel of the similar blocks, as indicated by the following formula.

\[
NL(V)(p) = \sum_{q \in V} w(p, q) V(q)
\]

(10)

Here, \(V\) is the noisy image, \(w(p, q)\) is the weight and \(0 \leq w(p, q) \leq 1, \sum_q w(p, q) = 1\). Every pixel of the denoised image is the result of weighting and averaging the noisy image. The weight is related to the similarity of the neighborhoods of pixels \(p\) and \(q\). For the pixel point, since point \(p\) and point \(q_i\) have similar neighborhood, the neighborhoods of point \(p\) and point \(q_i\) are quite different, therefore, weight \(w(p, q_i)\) is much bigger than \(w(p, q_2)\). The similarity calculation conducted in the neighborhood. Assume that \(N_i\) is the square neighborhood of the central pixel \(i\) . Generally, Euclidean distance is used to measure the similarity of two neighborhood, namely

\[
d(p, q) = \|V(N_p) - V(N_q)\|_2
\]

(11)

The weight can be calculated by the following formula.

\[
w(p, q) = \frac{1}{Z(p)} e^{-\frac{d(p, q)}{h}}
\]

(12)
Here, \( Z(p) \) is the normalized constant and \( Z(p) = \sum_{q} e^{-\frac{d(p,q)}{h}} \), \( H \) is weight decay factor, which controls the decay rate of the weight and affects the denoising performance of NLM filtering algorithm (Saroj and Brijra, 2014; and Yuan and Wen, et al., 2013).

The above-mentioned combinational methods are non-linear and the common spatial filtering differential operators include Sobel operator, Prewitt operator and Guass-Laplacian operator. The sharpening results are shown in Figure 3.

![Figure 3. Non-linear sharpening filter](image)

### 3. THE ALGORITHM REALIZES NOISE DETECTION AND REMOVAL BASED ON EDGE PRESERVATION

1. Assume \( S \) is a noisy \( M \times N \) 256-color gray-scale image, \( W_{ij} \) is the window of \( M \times N \) with the coordinate of \((i, j)\) as its central point and \( x \) is the central pixel point of window \( W_{ij} \). Filter the noisy image according to the following step. The matrix \( f_{i,j} \) is the noisy image to be detected with a size of \( M \times N \).

2. If the gray scale of any pixel \((i, j)\) in the image \( X \) is \( x_{i,j} \), then the set \( W_{i,j} \) formed by the gray scales of all pixels of the detection window with a center of \((i, j)\) is as follows.

   \[
   W_{i,j} = \{ x_{i+k,j+r} \mid -n \leq k \leq n, -n \leq r \leq n, (i,j) \in X \} \quad (13)
   \]

   Search the maximum and minimum gray scales from \( W_{i,j} \) and mark them as \( S_{\text{max}}, S_{\text{min}} \).

3. Determine the candidate noise points and determine the value of \( f_{i,j} \) according to the gray scale \( x_{i,j} \) of the pixel to be detected under the following rule.

   \[
   f_{i,j} = \begin{cases} 
   1 & x_{i,j} = S_{\text{min}} \text{ or } x_{i,j} = S_{\text{max}} \\
   0 & S_{\text{min}} < x_{i,j} < S_{\text{max}} 
   \end{cases} \quad (14)
   \]

   Calculate the joint probability distribution \( P(I,J) \) of the image.

   \[
   P(I,J) = \sum_{i,j} s_{i,j} \quad (15)
   \]
Among

\[
    s = \begin{cases} 
    1 & \text{if } x = I, \text{med}(W_{ij}) = J \\
    0 & \text{others} 
    \end{cases} 
\] (16)

In this formula, \( I \in [0, 225] \), \( J \in [0, 225] \) and \( \text{med}(W_{ij}) \) is the median filtering result of window \( W_{ij} \). Actually, \( P(I, J) \) reflects the distribution relationship between every gray scale of the image and the possible median result.

(4) For all the candidate noise points which meet the condition of \( f_{ij} = 1 \), select a and mark 3×3 neighborhood with the candidate noise point \( x_{ij} \) to be classified as the center and calculate its neighborhood mean value.

\[
    \mu = \frac{1}{3 \times 3} \sum_{i,j \in h} x_{ij} 
\] (17)

In the meanwhile, define the local energy of the candidate noise point \( x_{ij} \) as follows:

\[
    E(x_{ij}) = \max(E_i(x_{ij}), E_j(x_{ij})) 
\] (18)

Here,

\[
    E_i(x_{ij}) = \left( (x_{ij} - \mu)^2 - (x_{i+1,j} - \mu)^2 - (x_{i,j+1} - \mu)^2 - (x_{i-1,j} - \mu)^2 - (x_{i,j-1} - \mu)^2 \right) 
\] (19)

\[
    E_j(x_{ij}) = \left( (x_{ij} - \mu)^2 - (x_{i+1,j+1} - \mu)^2 - (x_{i-1,j-1} - \mu)^2 - (x_{i+1,j-1} - \mu)^2 - (x_{i-1,j+1} - \mu)^2 \right) 
\] (20)

Then calculate the local threshold.

\[
    \varepsilon_t = \frac{1}{t} \sum_{i=1}^{t} E_i 
\] (21)

In the above formula, \( E_n \) is the local energy value of the \( n \)th pixel of the \( t \)th neighborhood pixel of the window.

(5) Move the window \( W_{ij} \) to the upper left corner of the image. Rank the \( n \times n \) pixels of the image by order of the gray scales. Find the corresponding gray scale to the central position \((n \times n + 1) / 2 \). Compare the local energy \( E(x_{ij}) \) of the candidate noise point \( x_{ij} \) which meets the condition of \( f_{ij} = 1 \) with the threshold \( \varepsilon_t \). If \( E(x_{ij}) \) is bigger than \( \varepsilon_t \), it is taken as the real noise point, otherwise, it is deemed as the edge detail signal point, namely

\[
    f_{ij} = \begin{cases} 
    1 & E(x_{ij}) > \varepsilon_t \text{ and } f_{ij} = 1 \\
    0 & \text{otherwise} 
    \end{cases} 
\] (22)

(6) Move the window \( W_{ij} \) one bit to the right. If it doesn’t exceed the lower right corner of the image, then turn to Step 2, otherwise, the entire filtering process will be finish. Finally, the matrix \( f_{MN} \) is the detection result. Its element value is 1 or 0.1 means that the corresponding pixel point is the impulse noise point while 0 means that the pixel point is the signal point.

4. EXPERIMENTAL RESULT AND ANALYSIS

In order to prove the effectiveness of the algorithm, this paper take the mean square error (MSE) and the peak signal-to-noise ratio (PSNR) of the output image as the objective standards to evaluate the filtering performance. MSE and PSNR are defined respectively as follows.

\[
    MSE = \frac{1}{M \times N} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} \left| x_{ij} - y_{ij} \right|^2 
\] (23)

\[
    PSNR = 10 \log \left( \frac{(M \times N) \max(x_{ij})^2}{\sum_{i,j} (x_{ij} - y_{ij})^2} \right) 
\] (24)
In the above formulas, \( x \) is the original image with a size of \( M \times N \) and \( y \) is the denoised image.

In order to prove that the algorithm of this paper can effectively filter and remove the Gaussian noises with different densities and protect the image detail information, this paper has taken image Tire and Mandi with gray scale of 256 as the experiment objects and perform denoising processing on them. Fig.4 and Fig.5 are the images of Tire which have been put in the Gaussian noises with densities of 5% and 50% and the output images after being filtered by the algorithm of this paper respectively. Fig.6 and Fig.7 show the images of Mandi with the Gaussian noises of the densities of 5% and 50% as well as the output images after being processed by the algorithm of this paper.

![Tire with 5% Gaussian noise and filtered result](image1)

(a) Tire with 5% Gaussian noise  
(b) Filtered result

**Figure 4.** Tire with 5% Gaussian noise and filtered result by algorithm of this paper

![Tire with 50% Gaussian noise and filtered result](image2)

(a) Tire with 50% Gaussian noise  
(b) Filtered result

**Figure 5.** Tire with 50% Gaussian noise and filtered result by algorithm of this paper

![Mandi with 5% Gaussian noise and filtered result](image3)

(a) Mandi with 5% Gaussian noise  
(b) Filtered result

**Figure 6.** Mandi with 5% Gaussian noise and filtered result by algorithm of this paper
Figure 7. Mandi with 50% gaussian noise and filtered result by algorithm of this paper

See the objective evaluation of the filtering results of Fig.4, 5, 6 and 7 in Table 1.

<table>
<thead>
<tr>
<th>Evaluation Criteria</th>
<th>Tire 5%</th>
<th>Tire 50%</th>
<th>Mandi 5%</th>
<th>Mandi 50%</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSE</td>
<td>0.626</td>
<td>0.545</td>
<td>0.809</td>
<td>0.446</td>
</tr>
<tr>
<td>PSNR</td>
<td>53.415</td>
<td>47.951</td>
<td>49.052</td>
<td>52.425</td>
</tr>
</tbody>
</table>

It can be seen from the above results that with a lower noise density, this algorithm can filter and remove noises thoroughly. Lots of detail information hasn’t lost in the denoising and the image edge is clearly. This means, the algorithm of this paper can not only reduce the image noises, but it can also preserve the image edge information better. When it comes to serious noises, this algorithm basically can effectively remove noise. It doesn’t smoothens much edge information, the image the edge won’t blur and the phenomenon of “ringing” won’t also occur. Besides, the algorithm of this paper only uses the signal points within the window to participate in the filtering, so it greatly reduces the impact of noise points on the filtering result. Additionally, it better preserves most edge information of the image and it protects the detail information, as well.

5. CONCLUSIONS

This paper has proposed an image denoising algorithm based on noise point detection. Firstly, it conducts noise detection to the image according to the extremum and confirms the candidate noise point. Since the noise is usually isolated and closed to the local part of the image, it may be the point with the maximum of the minimum gray level. Then, based on the relationship between the detected point and the neighborhood pixel, it further classifies the candidate noises and sorts the pixels in the window by size. The noise point usually ranks in the most front or end of the sequence and it is significantly different from the gray level of the central pixel of the sequence. However, the useful information of the image usually is usually closed to the position of the central point of the sequence and it is only slightly different from the gray level of the central point of the sequence. In accordance with the above principle, this paper has realized this algorithm and proven that even with high noise density, this algorithm can also make satisfactory effect, which has demonstrated the effectiveness and superiority of the algorithm of this paper in an objective perspective.

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