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High Resolution Image Denoising Method Based on Vector Neighbor Domain

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Abstract

It is assumed in the traditional total variation(neighbor domain, ND) algorithm that the pixel points are located at the edge and an edge-preserving model is set up. In the algorithm, pixels in flat regions of the image diffuse along the edge direction, leading to insufficient noise suppression and even presence of false edges. To carry on the edge-saving feature of neighbor domain algorithm and to make up its deficiency in omitting the image edge direction, this paper introduces direction neighborhood to the total variation algorithm so that edge points diffuse along the direction neighborhood. It changes the mode where edge points in the traditional ND algorithm diffuse along the multi-neighborhood, maximizing the smoothness along the edge direction and minimizing that at the vertical edge direction. The experimental results show that the image denoising method based on vector neighbor domain effectively addresses the drawbacks existing in the traditional ND algorithm and provides faster convergence efficiency, achieving both denoising and edge-preserving and improving PSNR and visual effects of the image.

Keywords: *Image denoising; Dictionary; Edge direction; High Spectral Image; vector neighbor domain*

1. Introduction

The processes of image acquisition, transmission and saving are subject to noise jamming, which may lead to degradation of the image quality and inconvenience in subsequent feature extraction and edge detection. Too much noise may result in false detection or detection omission of the image’s structure information and even misunderstanding or misinterpretation of the image [1]. For this reason, an image shall be denoised before analysis [2]. Noise achieves higher variation of the image pixel than that of a sharp image. The traditional NEIGHBOR DOMAIN algorithm establishes a denoising model of l_1 pattern approximation [12]. It is assumed in the algorithm that the image pixels are located at the edge and iterated denoising is achieved with the multi-neighborhood pixel gradient magnitude. This algorithm does not allow for the direction information of the image edges, resulting in insufficient noise suppression in flat regions of an image [13] and even presence of false edges, based on which staircasing effect occurs. To carry on the edge-saving feature of NEIGHBOR DOMAIN algorithm for deficiency make-up [14], a denoising algorithm based on directional total variation is proposed according to the gradient magnitude and direction information of the pixel: first, the gradient magnitude and direction of an image is analyzed according to the optics principle of forming the image edges; second, the image pixels are divided into edge region and non-edge region according t o the gradient magnitude of edges [15-16]. For the edge region, multi-neighborhood pixels close to the edge are selected according to the gradient direction; for the non-edge region, the spatial multi-neighborhood pixels are selected; third, the iterated function of the image NEIGHBOR DOMAIN is analyzed based on the multi-neighborhood pixel gradient. The experimental results show that the

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algorithm in this paper is edge-preserving for image edges. Smooth region has low residual noise and eliminates false edges, thus improving PSNR and visual effects of the image. However, small edges and textures in the image are eliminated as noise.

2. Extraction of Direction Neighborhood

As shown in the optics principle of forming the image edges, image edges are results of discontinuous gray. This paper induces the image edge according to gray saltation and describes the rate of pixel variation by using the spatial gradient magnitude $|\nabla I(x,y)|$:

$$|\nabla I(x,y)| = \sqrt{\left[\frac{\partial I(x,y)}{\partial x}\right]^2 + \left[\frac{\partial I(x,y)}{\partial y}\right]^2} \tag{1}$$

This paper calculates the gradient of the image with Sobel edge detection operator in order to suppress the impact of noise on the gradient magnitude of the image (Formula (1)). Such gradient operator is featured with local smoothing and may suppress the impact of noise on the gradient to much extent. The template is as follows:

$$Sg = \begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix} \tag{2}$$

The gradients of the image at both horizontal and vertical directions are:

$$\begin{cases} \dfrac{\partial I(x,y)}{\partial x} = Sg * I(x,y) \\ \dfrac{\partial I(x,y)}{\partial y} = Sg^T * I(x,y) \end{cases} \tag{3}$$

The edge point of the image is where the maximum local gradient occurs. Considering such nature, this paper determines whether the pixel point is located at the edge with the non-maximal suppression principle. For pixel points not on the edge, the spatial multi-neighhborhood variation is slow and the relevance is high. In this paper, the spatial multi-neighborhood linearity is used to express such pixel value. Neighboring pixels on the edge show slight variation. To protect the saltation of edge pixels in the course of denoising, pixel points on the edges will be expressed in linearity according to the edge neighborhood pixels. Neighboring pixel points on image edges has a feature that it shows slight variation (except for angular points) at the edge direction in order to extract the pixel neighborhood on the edges. The pixel neighborhood on the edge is extracted by using the gradient direction as follows:

$$\theta(x,y) = \arctan\left(\frac{\partial I(x,y)}{\partial y} \Big/ \frac{\partial I(x,y)}{\partial x}\right) \tag{4}$$

The edge direction is divided into 4 regions (8 directions). The edge direction of pixel points is perpendicular to the gradient direction, as shown in Figure 1:

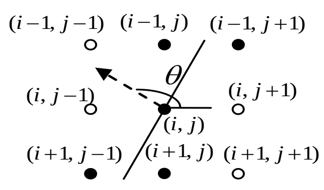

Figure 1. Edge Direction and Neighborhood

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Assuming that point O is on the edge, the direction neighborhood of such point relies on the gradient direction. The direction neighborhood is expressed in $S_{i,j}$:

$$S_{i,j} = \begin{cases} \{(i, j-1),(i, j+1)\}, if\ \theta(i,j)=0 \\ \{(i-1, j-1),(i-1, j),(i+1, j),(i+1, j+1)\}, if\ 0<\theta(i,j)<\frac{\pi}{4} \\ \{(i-1, j+1),(i+1, j-1)\}, if\ \theta(i,j)=\frac{\pi}{4} \\ \{(i-1, j-1),(i, j-1),(i, j+1),(i+1, j+1)\}, if\ \frac{\pi}{4}<\theta(i,j)<\frac{\pi}{2} \\ \{(i-1, j),(i-1, j)\}, if\ \theta(i,j)=\frac{\pi}{2} \\ \{(i-1, j+1),(i, j+1),(i, j-1),(i+1, j-1)\}, if\ \frac{\pi}{2}<\theta(i,j)<\frac{3\pi}{4} \\ \{(i-1, j-1),(i+1, j+1)\}, if\ \theta(i,j)=\frac{3\pi}{4} \\ \{(i-1, j),(i-1, j+1),(i+1, j+1),(i+1, j)\}, if\ \frac{3\pi}{4}<\theta(i,j)<\pi \end{cases} \tag{5}$$

For the neighborhood of pixel points on the edge, pixels close to the edge should be selected so that edge points go smoothly along the image edge direction and the edge information will be protected in the course of denoising.

3. Total Variation Denoising of Direction Neighborhood

Image denoising is a very basic and important part of image analysis. However, some key edge details are missing in denoising. The edge is a key feature to represent the image content. On this account, the edge feature of an image should be preserved during image denoising. Supposed that $I(\mathbf{x})$ is an original shape image signal and $I^0(\mathbf{x})$ is a noise-polluted image signal,

$$I^0(\mathbf{x}) = I(\mathbf{x}) + n(\mathbf{x}) \tag{6}$$

In Formula (6), $n(x)$ denotes the random noise when the zero mean variance is σ^2. Noise intensifies the variation of image pixels, leading to higher variation of the overall image gradient than that of a sharp image. To eliminate the noise and protect the edge, the traditional NEIGHBOR DOMAIN algorithm establishes the denoising model of l_1 pattern approximation according to the structure information:

$$I(\mathbf{x}) = \arg\min_I \left\{ \iint_\Omega |\nabla I(\mathbf{x})| \, d\Omega \right\} \tag{7}$$

The extremum of the objective function (Formula (7)) is addressed based on the statistical property of noise. Lagrangian multiplier λ is introduced to define a new energy function $F[I(x),\lambda]$:

$$F[I(\mathbf{x}),\lambda] = \iint_\Omega |\nabla_{\mathbf{x}} I(\mathbf{x})| + \frac{\lambda(I(\mathbf{x})\text{-}I^0(\mathbf{x}))^2}{2} d\Omega \tag{8}$$

Euler-Lagrange Equation is obtained by analyzing the energy function with descent algorithm:

$$-\nabla \cdot \left(\frac{\nabla I}{|\nabla I|} \right) + \lambda (I - I^0) = 0 \tag{9}$$

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According to the pixel neighborhood, the iterative value of Formula (9) is calculated as follows with analysis of the pixel point α and the direction neighborhood S:

$$I_\alpha = \frac{\sum_{\beta \in S} \left(\frac{1}{|\nabla I|_\beta} + \frac{1}{|\nabla I|_\alpha} \right) I_\beta + \lambda I_\alpha^0}{\lambda + \sum_{\beta \in S} \left(\frac{1}{|\nabla I|_\beta} + \frac{1}{|\nabla I|_\alpha} \right)} \tag{10}$$

A noise image contains the structure image of the image. Formula (10) uses the pixel value of the noise image I_α^0. The pixel neighborhood is the direction neighborhood so that edges of the image will not be fuzzy. Iteration should be stopped when Formula (11) is met:

$$\sum \left| I^{(n)}(i,j) - I^{(n-1)}(i,j) \right| \le 2\% \sum \left| I^{(n)}(i,j) \right| \tag{11}$$

The direction neighborhood total variation image denoising referred to in this paper enables diffusion of the pixel on image edges along the edge direction. Pixels not on the edges diffuse along the spatial multi-neighborhood. The procedures are as follows:

1) The gradient magnitude and direction of each pixel points is calculated with Formulas (1), (2), (3) and (4);

2) Whether the pixel points are edge points shall be determined within the non-maximal suppression method: for edge points, the edge direction should be obtained by using the perpendicular direction of the gradient angle to select the direction neighborhood; for non-edge points, the spatial multi-neighborhood should be the direction neighborhood;

3) The diffused pixel value shall be calculated with Formula (10); and

4) Steps 1) through 3) shall be repeated till the end conditions in Formula (11) are met.

The procedures are shown in Figure 2:

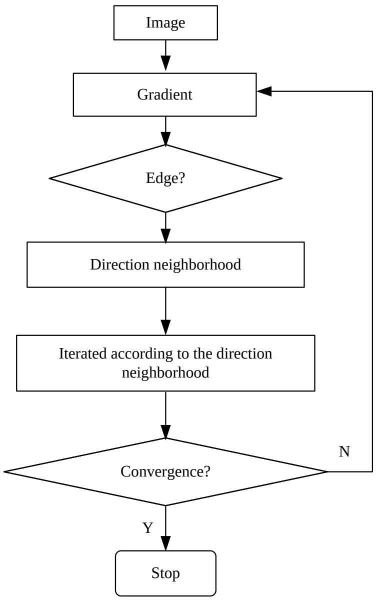

Figure 2. Algorithm Flow

The algorithm in this paper approaches to the original noise-free image through iteration. The image pixel value changes after each iteration. The gradient magnitude and

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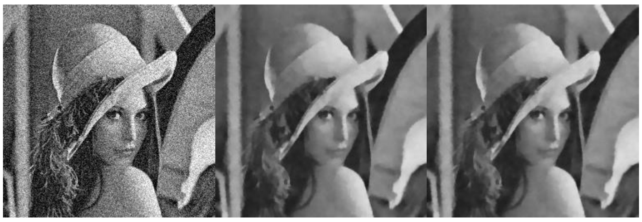
direction should be re-calculated after iteration to change the direction neighborhood. With more times of iteration, the direction neighborhood will be more accurate and more resemble the real image.

4. Analysis of Experimental Results

The traditional NEIGHBOR DOMAIN algorithm gives iterated denoising to pixel points with the gradient magnitude of the spatial multi-neighborhood pixels and does not allow for the edge direction information, which results in insufficient noise suppression in flat regions of an image and even presence of false edges and leads to relatively fuzzy edges. To carry on the strengths of NEIGHBOR DOMAIN algorithm for deficiency make-up, a denoising algorithm based on directional total variation is proposed according to the gradient magnitude and direction. The parameter λ is introduced to balance the smooth region and protect the image edges. The results from treatment of “Lena” image with gaussian noise (PSNR=19.36dB) by using varying λ are shown in Figure 3, when $\lambda = 1$, PSNR will be 24.36dB; with the increase of λ, the edge will be less fuzzy; when $\lambda = 2.5$, PSNR will be 27.86dB. In case of continuous increase, the edge will be better protected; however, there will be higher residual noise in smooth regions so that PSNR is reduced. When $\lambda = 4.0$, PSNR will be 24.71dB. As shown in Formula (10), when $\lambda = 0$, the algorithm in this paper is so smooth that the edge is severely fuzzy due to absence of the consideration for the structure information of the noise image. On the contrary, when $\lambda = \infty$, the algorithm in this paper wrongly takes noise as the structure information and protects such noise.

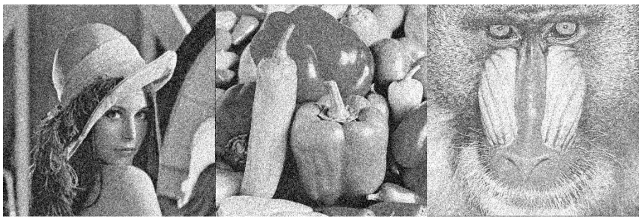


(a) Noise image (b) 1.0 (12.25dB) (c) 1.5 (13.24dB)

(d) 2.0 (14.57dB) (e)2.3 (14.28.31dB) (f)2.5 (16.88dB)

(g) 2.8 (18.22 dB) (h) 3.0 (18.91dB) (i) 4.0(18.78dB)

Figure 3. Denoising Results with Varying λ

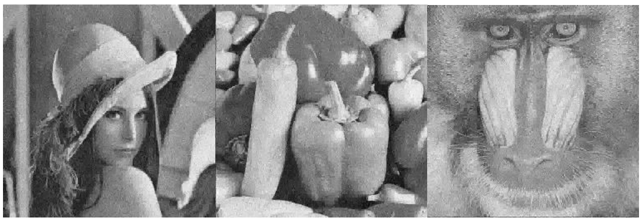


PSNR=13.14dB , PSNR=17.67dB , PSNR=18.38dB
(a) Noise Image

PSNR=28.24dB , PSNR=27.27dB , PSNR=27.18dB
(b) Algorithm in this Paper

PSNR=27.12dB, PSNR=25.15dB, PSNR=26.16dB
(c) Traditional NEIGHBOR DOMAIN algorithm

PSNR=27.12dB, PSNR=25.19dB, PSNR=26.13dB
(d) BM3D algorithm



PSNR=21.78dB , PSNR=21.26dB, PSNR=23.17dB
(e) Wavelet threshold

Figure 4. Comparison among Different Algorithms

The image overlaid with different gaussian noises is denoised with the algorithm in this paper ($\lambda = 2.5$), the traditional NEIGHBOR DOMAIN algorithm, BM3D [17] and the wavelet threshold denoising in order to validate the effectiveness of the algorithm in this paper. Partial results are shown in Figure 4. PSNR of the denoised image is included in Figure 5. The algorithm in this paper outweighs BM3D, the traditional NEIGHBOR DOMAIN algorithm and wavelet threshold in terms of PSNR. For the visual effect, both NEIGHBOR DOMAIN algorithm and BM3D are edge-preserving (as shown in Figure 4c&d). However, the wavelet threshold algorithm is subject to edge fuzziness to varying

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extents (as shown in Figure 4e). Residual noise occurs in the smooth region of the image for the traditional NEIGHBOR DOMAIN algorithm. The edges of BM3D denoised image is rather fuzzy; the algorithm reduces the contrast of the edge region. However, the direction neighborhood total variation image denoising algorithm reduces the residual noise in the smooth region to much extent and fuzziness of the edges. It yields higher overall quality of the treated image has higher overall quality and better improves the visual effects of images. However, for texture-rich images, such algorithm eliminates small edges and fine textures in the image as noise. For this reason, the treated texture region is too smooth (as shown in baboon image in Figure 4b).

Figure 5. Comparison of Visual Effects After Noise Reduction

5. Conclusion

A denoising algorithm based on vector neighbor domain is proposed according to the gradient magnitude and direction in order to make up the deficiency that traditional total variation (NEIGHBOR DOMAIN) omits the edge direction of an image. The algorithm in this paper divides image pixels into edge region and non-edge region by using gradient magnitude. It selects varying multi-neighborhood pixels for the pixel in different regions by using gradient direction. For different neighborhoods, the traditional NEIGHBOR DOMAIN algorithm is provided with a discrete analysis, which completes edge-preserving of an image. The experimental results show that this paper improves the neighborhood selection mode of the traditional NEIGHBOR DOMAIN algorithm based on the edge direction information, not only better preserving the image edge information and important details but also improving PSNR and visual effects of the image.

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