SPECKLE NOISE SMOOTHING USING AN MODIFIED MEAN CURVATURE DIFFUSION FILTER

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ABSTRACT : This paper presents a modified mean curvature diffusion filter to smooth speckle noise in images. Mean curvature diffusion filter has already shown good results in reducing noise in images while preserving fine details. In the mean curvature diffusion, the rate of smoothing is controlled by the local value of the diffusion coefficient chosen to be a function of the local image gradient magnitude. In this paper, the diffusion coefficient is modified to be controlled adaptively by local image surface slope and heterogeneity. The local surface slope contributes to preserving details (e.g. edges) in image and the local surface heterogeneity helps the smoothing filter consider the amount of noise in both edge and non-edge area. The proposed filter's performance is demonstrated by quantitative experiments using speckle noised aerial image and TerraSAR-X satellite image.

KEY WORDS: Mean curvature diffusion, surface normal, speckle noise, diffusion coefficient.

1. INTRODUCTION

Smoothing of speckle noise is an important pre-processing step in synthetic aperture radar (SAR) imagery analysis such as feature extraction, classification and registration. The speckle noise smoothing algorithm is required to smooth the noise in homogeneous areas while preserving edges and details in image. Various adaptive speckle filters have been proposed to smooth noise using local statistics (Lee, 1980; Lee, 1983; Kuan and Sawchuk, 985; Frost et al, 1982). These filters update central pixel using statistical measures in a small window area. The degree of smoothing is adaptively determined by the homogeneity of the window area. If the window area is heterogeneous, the filter has to use only some pixels in the window. This means the contribution of neighbour pixels in smoothing noise has to be different according to the similarity between each neighbour pixel and central pixel.

The adaptive weight of neighbour pixels is successfully controlled by diffusion coefficient in anisotropic diffusion filtering [5]. The diffusion coefficient is a kind of non-linear weighting coefficient controlling the amount of smoothing by each neighbour pixel based on image gradient. In mean curvature diffusion (MCD) filtering [6] related to the anisotropic diffusion model, image surface itself is diffused at a rate equal to twice the mean curvature. For the mean curvature of edge is very small, the pixel value on edge location remains almost unchanged while other non-edge pixels are smoothed during diffusion filtering. The diffusion coefficient, however, uses only image gradient magnitude computed using center pixel and neighbour pixel. As a result, noise effect is not considered in computing the diffusion coefficient, although the noise is gradually reduced by repeated iteration process.

This paper presents how the amount of noise can be estimated and used in computing diffusion coefficient to reduce speckle noise.

2. MEAN CURVATURE DIFFUSION

Image intensity can be viewed as a surface S in three dimensional coordinate system whose x, y, z coordinates represent row, column and gray level at each pixel location, respectively, as follows:

$$S : f(x,y,z) = z - I(x,y) = 0.$$

Mean curvature diffusion of f is modelled by

$$\frac{\partial f}{\partial t} = \nabla \cdot (C \nabla f)$$

where

$$C = \frac{1}{|\nabla f|} = \frac{1}{\sqrt{|\nabla I|^2 + 1}}.$$

When MCD local filter kernel M of the size 3x3 is given by

$$M = \begin{bmatrix} C_4 & C_3 & C_2 \\ C_5 & C_0 & C_1 \\ C_6 & C_7 & C_8 \end{bmatrix}$$

where $C_0 = 1 - \sum_{i=1}^{8} C_i$, the updated center pixel value $I(n+1)$ is

$$I(n+1) = \sum_{k=0}^{8} C_k I_k(n).$$

where $I_k(n)$ is the intensity of the pixel associated with diffusion coefficient C_k.

Note that the diffusion coefficient C_0 is determined by those of neighbour pixels. When the gradient of neighbour pixel is high, diffusion coefficient of the pixel becomes low and the updated center pixel value is more affected by the previous center pixel than the neighbour pixel. If the neighbour pixel is, however, affected by noise, the diffusion coefficient of center pixel becomes incorrect. Therefore, the diffusion coefficient needs to be determined by not only gradient magnitude but also the amount of noise.

3. LOCAL SURFACE CHARACTERISTICS FOR NOISE ANALYSIS

Let $\vec{n}_A$ and $\vec{n}_B$ be unit normal vectors at two adjacent pixels, respectively, as shown in Figure 1. Unit normal vector $\vec{n}$ on the image surface S is given by

$$\vec{n} = \frac{f_x \times f_y}{\|f_x \times f_y\|} = \frac{1}{\sqrt{1+I_x^2+I_y^2}}\begin{bmatrix}-I_x & -I_y & 1\end{bmatrix}^T.$$

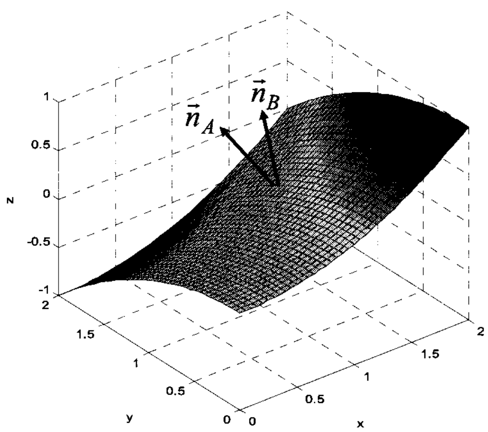


Figure 1. Unit normal vectors on image surface.

If the angle $\theta(\vec{n}_A, \vec{n}_B)$ between $\vec{n}_A$ and $\vec{n}_B$ is zero, the two adjacent pixels are located on a same tangent plane. This means that the angle $\theta(\vec{n}_A, \vec{n}_B)$ between two normal vectors of two adjacent pixels describes local surface heterogeneity. For the vectors $\vec{n}_A$ and $\vec{n}_B$ have unit length, the area $A(\vec{n}_A, \vec{n}_B)$ between two the normal vectors and a given part of an unit circle is given as follows :

$$A(\vec{n}_A, \vec{n}_B) = \pi \cdot \left(\|\vec{n}_A\|^2\right) \cdot \frac{\theta(\vec{n}_A, \vec{n}_B)}{2\pi} = \frac{\theta(\vec{n}_A, \vec{n}_B)}{2} = \frac{\cos^{-1}(\vec{n}_A \bullet \vec{n}_B)}{2}$$

From the above equation, the area $A(\vec{n}_A, \vec{n}_B)$ is equal to half the angle $\theta(\vec{n}_A, \vec{n}_B)$. Now, we define local surface heterogeneity $H_S(x,y)$ as follows:

$$H_S(x,y) = \sum_{(i,j)\in W} A(\vec{n}_M(x,y), \vec{n}(x+i, y+j)) = \sum_{(i,j)\in W} \frac{\theta(\vec{n}_M(x,y), \vec{n}(x+i, y+j))}{2}$$

where $W = \{(i,j) \mid -1 \le i, j \le 1,\ i, j\text{:integer}\}$ represents a local area defined by 3×3 moving window and $\vec{n}(x+i, y+j)$ is unit normal vectors in the local area. We define mean normal vector $\vec{n}_M(x,y)$ as follows :

$$\vec{n}_M(x,y) = \frac{1}{|W|} \sum_{(i,j)\in W} \vec{n}(x+i, y+j).$$

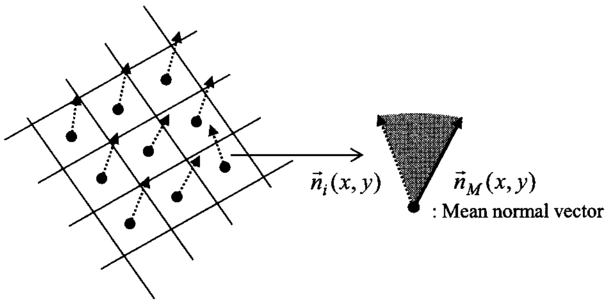
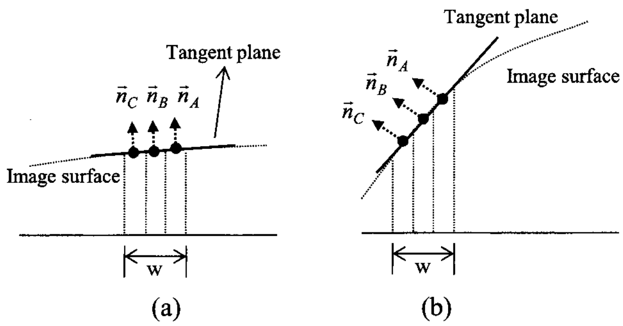


Figure 2. Local surface heterogeneity computation.

The mean normal vector $\vec{n}_M(x,y)$ is a normal vector computed by averaging the normal vectors in the moving window. The local surface heterogeneity $H_S(x,y)$ is sum of each area computed by the mean normal vector $\vec{n}_M(x,y)$ and unit normal vectors $\vec{n}(x+i, y+j)$ in the local area (Figure 2). The local surface heterogeneity $H_S(x,y)$ becomes zero if all unit normal vectors are same. If some pixels in local area have been affected by noise, the local surface heterogeneity $H_S(x,y)$ becomes large. This means that the local surface heterogeneity $H_S(x,y)$ is proportional to the amount of noise in the local area.



(a) (b)

Figure 3. Normal vectors and tangent plane (a) homogeneous intensity area (b) strong edge area.

Conventional noise removal algorithms using local statistics (e.g. mean and variance) in a local window area are successful when applied into homogeneous area, but their performance becomes low if the local area contains edge or noise, which causes incorrect local statistics. However, the local surface heterogeneity $H_S(x,y)$ can measure the amount of noise in both homogeneous intensity area and strong edge area because the local surface heterogeneity uses only normal vectors instead of using directly pixel intensity itself (Figure 3). This property makes the local surface heterogeneity more useful when strong local edge area contains noise.

4. SPECKLE NOISE REMOVAL USING MODIFIED MEAN CURVARTURE DIFFUSION

The proposed modified mean curvature diffusion filter has the following diffusion coefficient:

$$C(x,y)=\frac{1}{\sqrt{k_1\cdot N(x,y)^2+k_2\cdot H_S(x,y)^2+1}}$$

where local surface slope $N(x,y)=\theta(\vec{n}_M,\vec{n}_V)$ is the angle between the mean normal vector $\vec{n}_M$ and the unit vector $\vec{n}_V(x,y)=[0\ \ 0\ \ 1]^T$. The constants k_1 and k_2 are weighting factors controlling the contribution of $N(x,y)$ and $H_S(x,y)$ in the diffusion coefficient.

The local surface slope is proportional to image gradient and the local surface heterogeneity is a kind of smoothing factor controlled by the amount of noise. The diffusion coefficient of the neighbour pixel with high local surface heterogeneity becomes small in computing center pixel's diffusion coefficient.

Let $g(x,y)$ and $s(x,y)$ are observed image, original image, respectively and then speckle noise is modelled by multiplicative noise $v(x,y)$ as follows :

$$g(x,y)=s(x,y)v(x,y).$$

By applying logarithm operator to the above equation, we can obtain the following equation:

$$G(x,y)=S(x,y)+V(x,y)\,.$$

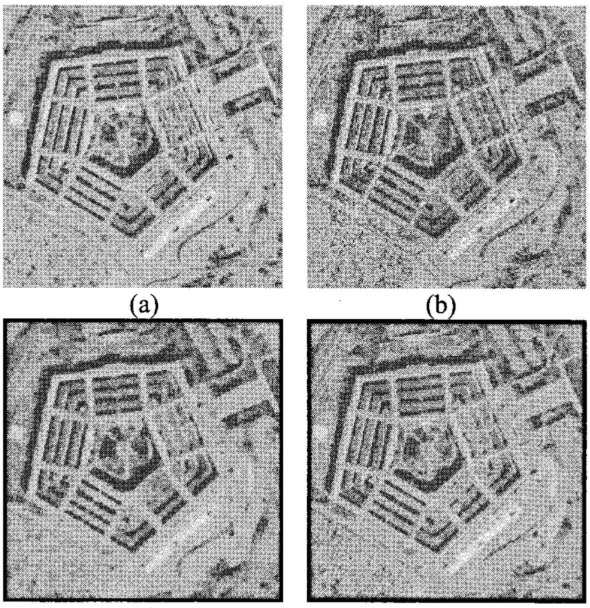
After smoothing $G(x,y)$ by applying the proposed diffusion filtering, original image is finally recovered by applying exponential operator to the smoothing result.

5. EXPERIMENTAL RESULTS

The proposed algorithm was tested using Pentagon aerial image and TerraSAR-X satellite image. We compared our algorithm with the original MCD algorithm.

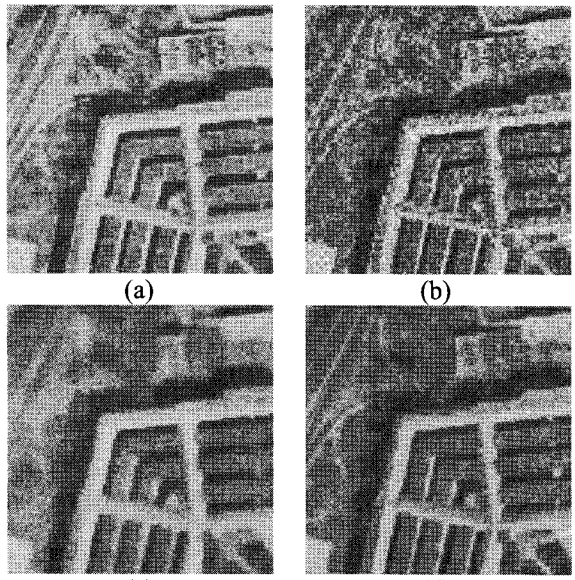
First, we took logarithm of original images and then multiflied the result by a normaliing constant $\frac{255}{\log 255}$. The normalizing constant makes the pixel have intensity value between 0 and 255. The filtered image is then multiflied by its inverse before applying exponential operator to the smoothing result. The original MCD algorithm oversmoothed the noised image with some details lost as shown in Figure 5(c). The proposed method preserved, however, details in the image as shown in Figure 5(d).

Figure 7 shows smoothing result of TerraSAR-X image using original MCD and proposed method, respectively. In the each experiment, we iterated the filtering 20 times. We can see that the proposed method more attenuated the bright pixels in original image than the original MCD.



(a) (b) (c) (d)

Figure 4. The result of noise filtering for Pentagon image (a) original image (b) speckle noised image (noise variance = 0.01) (c) recovered image by original MCD (iteration number =11) (d) proposed method ($k_1=1600$, $k_2=50$, iteration number =11).



(a) (b) (c) (d)

Figure 5. Enlarged images of Figure 4 (a) original image (b) speckle noised image (c) recovered image by original MCD (d) proposed method.

6. CONCLUSIONS

We proposed a new smoothing filtering method to reduce speckle noise. This method adaptively controls the smoothing level using local surface slope and local surface heterogeneity. The local surface slope in diffusion coefficient contributes to preserving details (e.g. edges) in image. The local surface heterogeneity helps the smoothing filter consider the amount of noise in both edge and non-edge area. The quantitative experiments are more required to evaluate correctly the performance of the proposed method.

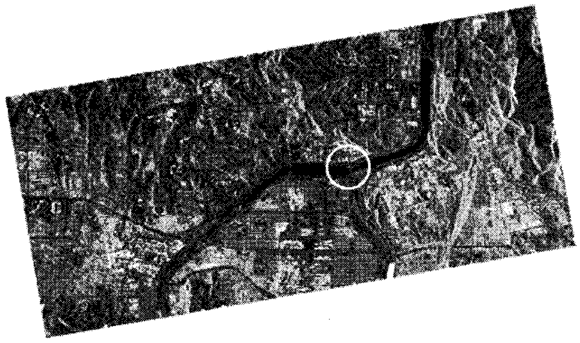
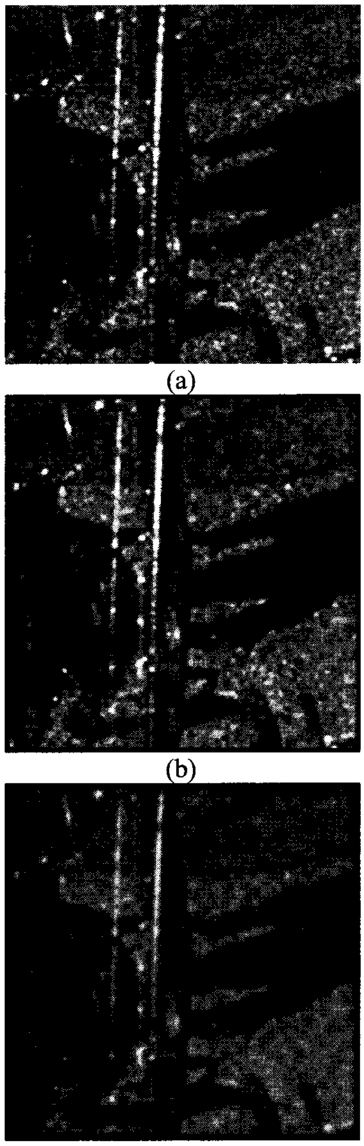


Figure 6. TerraSAR-X imagery taken on July 11, 2008 (Daejeon). The white circle is a test area containing a large bridge.



(a) (b) (c)

Figure 7. The filtering results of the area displayed in the circle in Figure 6 (a) original image (b) recovered image by original MCD (c) proposed method.

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