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Underground Image Denoising

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Abstract

A Mixed Window Shrink and BayesShrink Image Denoising Algorithm Based on Curve let Transform is proposed in this paper. Curve let transform is effective in presenting line and surface property of image. In the proposed algorithm, Curvelet transform is employed for the first stage, then according the theory of image demising method based on Wavelet transform, we combine Window Shrink and BayesShrink denoising algorithm to perform noise reduction. Experiment results show that the proposed algorithm is competitive to Wavelet transform in terms of Peak Signal to Noise Ratio (PSNR) and denoising image quality.

Keywords: *curvelet transform, image denoise, hard threshold, adaptive coefficient*

1. Introduction

Wavelet transform has been widely used in the traditional methods to remove noise from image .Though the wavelet transform have the best bases when it represents target functions which has dot singularity [1], it can hardly get the best bases when it present the singularity of line and hyper-plane. This makes the traditional two-dimensional wavelet transform in dealing with the image have some limitations. To overcome the above-mentioned shortcomings that Wavelet transform has, Donoho, and some other people promote Curvelet transform theory. The anisotropy of Curvelet transform theory is very conducive to present the edge of the image.

2. Research Method

Cruvelet Transform was developed on the basis of Ridegelet Transform, and Ridgelet transform is introduced first.

2.1. Ridgelet Transform

Ridge let transform (RIT) overcomes the weakness of wavelet transform representing in two or higher dimensions [2]. Ridgelet transform can be defined as follows [4]. Set satisfying the conditions:

$$\int \frac{|\psi(\xi)|^2}{|\xi|^2} d\xi < \infty \tag{1}$$

Ridgelet function $\psi_{a,b,\theta} : R^2 \to R^2$ of the two-dimensional space is defined as:

$$\psi_{a,b,\theta}(x) = a^{1/2}\psi(x_1 \cos\theta + x_2 \sin\theta - b) / a \tag{2}$$

And, a represents the Ridgelet scale; b stands for Ridgelet position; θ represents Ridgelet direction. Given the dual integral function $f(x)$, we can define continuous Ridgelet transform (CRT) in the R^2 as:

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$$CRT_f(a,b,\theta) = \int_{R^2 \psi_{A,B,\theta}} f(x)dx \tag{3}$$

For a straight line with the singular multi-variable function, Ridgelet transform has a good approximation performance [6].

2.2. Radon Transform

Ridgelet transform is achieved by Radon transform in the domain of one-dimensional wavelet transform. For the function $f(x,y)$ in $(x,y) \in R^2$ plane, the Radon transform is the function at all angles on a straight line projection, [7, 8] as:

$$R_f(\rho,\theta) = \iint f(x,y)\delta(\rho - x\cos\theta - y\sin\theta)d\rho d\theta \quad (\rho,\theta) \in [0,2\pi) \times R \tag{4}$$

δ is the unit pulse function, and the Ridgelet transform coefficient $R_f(a,b,\theta)$ of $f(x,y)$ can be carried out on its Radon transform coefficients of wavelet transform to be:

$$R_f(a,b,\theta) = \int R_f(\rho,\theta) a^{-1/2} \psi[(\rho - b)/a] d\rho \tag{5}$$

According to the Fourier Projection Theorem:

$$f(\lambda\cos\theta, \lambda\sin\theta) = \int R_f(\rho,\theta) e^{-i\lambda t} dt \tag{6}$$

2.3. Curvelet Transform

The edges of natural image are almost in curve, so the Ridgelet analysis of the images of the entire single-scale is not very effective. To singular curve with the multi-variable function, its performance is only close to the equivalent of wavelet transform. In order to solve the singular curve with the multi-variable function of the sparse approximation problem, we can turn to Curvelet transform. The basic steps as shown in Figure 1:

a) Sub-band Decomposition. Through the wavelet transform it divided into a number of sub-band components [3]. For the $N \times N$ image f, the first break will be:

$$f = P_0 f + \sum_{i=1}^{I} \Delta_i f_0 \tag{7}$$

$P_0 f$ is for the low-frequency components, and $\sum_{i=1}^{I} \Delta_i f$ are for the high frequency components.

b) Smooth Partitioning [5]. Each sub-band high-frequency sub-divided into a number of pieces, with different sub-component division of the sub-block size can be different.

$$\Delta_s f \to (w_Q \Delta_S f)_{Q \in Q_S} \tag{8}$$

w_Q represented in binary box as:

$$Q = [k_1/2^s, (k_1+1)/2^s] \times [k_2/2^s, (k_2+1)/2^s] \tag{9}$$

And it is the set of smooth function. This step allows each sub-band was smoothed by window function block.

Ridgelet decomposition [9]. Each sub-band smooth partition of the sub-block is for Ridgelet transform.

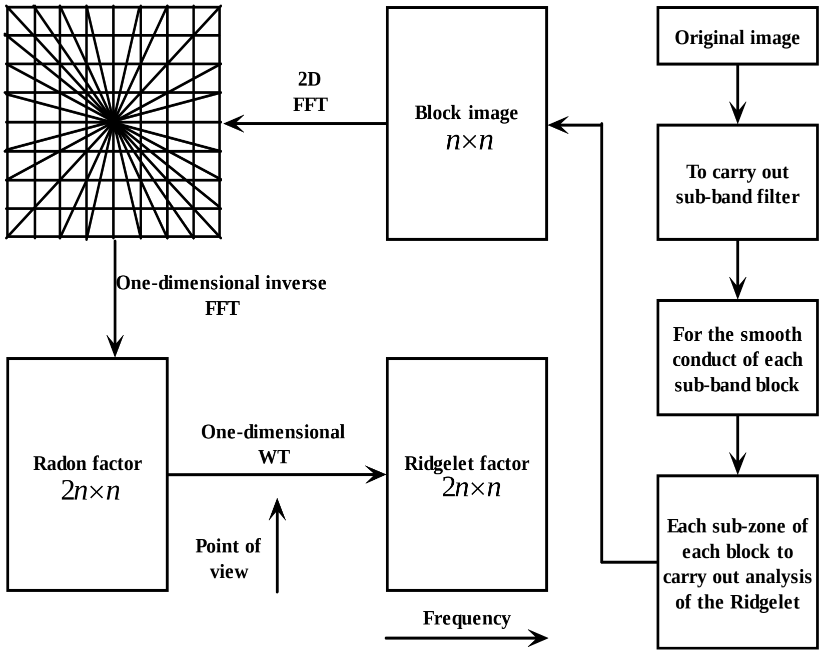


Figure 1. Curvelet Transform Flow Chat

3. Curvelet Transform Used in Image Noise-removing

The method of Window Shrink-image-removing noise is very important in the theories of wavelet. Through the adaptive processing to the parameter of wavelet, it can achieve the goal of removing noise. This article applies the theory in Curvelet parameter processing for removing noise.

Set $d_{i,j}$ is the parameter which is from curvelet-transformed noise-image, choose a $d_{i,j}$ centered window of n×n as the processing subject. Figure 2 indicate the windowShink when n is 3. Each of $d_{i,j}$ following the processing below (If $d_{i,j}$ is in the edge of the parameter-matrix, then ignore it):

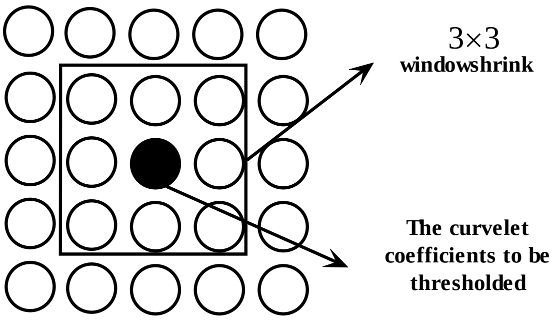


Figure 2. Illustration of the Neighborhood Window and Curvelet Coefficient

Firstly, we can get the sum of all the parameter's square in the n×n-window [12].

$$S_{i,j}^2 = \sum_{p=i-(n-1)/2}^{i+(n-1)/2} \sum_{q=j-(n-1)/2}^{j+(n-1)/2} d_{p,q}^2 \quad (10)$$

$$\mathrm{I}(X) = \begin{cases} X, & X \geq 0 \\ 0\ , & X < 0 \end{cases} \quad (11)$$

Set Symbolic function:

$$\eta = \sqrt{2\sigma^2 \log n^2}\ . \quad (12)$$

σ is the variance of Gaussian white noise in the image, then shrinking-processing parameter is:

$$\alpha_{i,j} = \mathrm{I}\left(1 - \eta^2 / S_{i,j}^2\right) \quad (13)$$

After removing noise, the parameter can be calculated as:

$$d_{i,j}^{'} = d_{i,j} \times \alpha_{i,j} \quad (14)$$

The method of WindowShink depends on the window's scale. If the window is too small, it fails to remove noise. While if the window is too big, then it causes reconstructed image distorted. Usually the window will be set at 3×3, 5×5,or 7×7 scale.

3.1. Summarize of BayesShrink-removing Noise Method

We set σ_D^2 as the variance of an image containing noise, σ^2 is the variance of noise, and σ_X^2 is the Original image's variance. We also that noise variance:

$$\sigma = \frac{Median\left|d_{i,j}\right|}{0.6745} \quad (15)$$

$Median\left|d_{i,j}\right|$ is median in the parameters of the low-frequency sub-band after the transformation . We can get the variance of a noise contained M×N image through the formula:

$$\sigma_D^2 = \frac{1}{MN}\sum_{i,j} d_{i,j}^2 \quad (16)$$

The variance of original image:

$$\sigma_X = \sqrt{\left|\sigma_D^2 - \sigma^2\right|} \quad (17)$$

Setting Threshold is σ^2 / σ_X , then begin the processing of removing noise [9].

3.2. Images Denoising by the Combination of WindowShrink and BayesShrink

Though the Window Shrink theory have shrink factors to dispose the coefficient to clean noise using a adaptive way, the theory have a disadvantage that the noise must be the Gauss Noise and we should know the Variance first [11]. This makes the method have some limits.The BayesShrink theory can conclude the Variance by the transformed factors, but it uses a very simple hard threshold value method to clean noise, which means it uses the same threshold to deal with all factors, and it can't deal with the noise very well [10]. In order to overcome the disadvantages of the two methods above, we accept both the advantages of WindowShrink and BayesShrink to filter the noise.

Firstly, we estimate Variance σ_X^2 of the original picture using BayesShrink theory, then we calculate η using σ_X^2 instead of the noise Variance σ^2, such as:

$$\eta = \sqrt{2\sigma_X{}^2 \log n^2} \tag{18}$$

At last we can get shrink factors $\alpha_{i,j}$ and figure out the noise coefficient by taking advantage of $\alpha_{i,j}$.

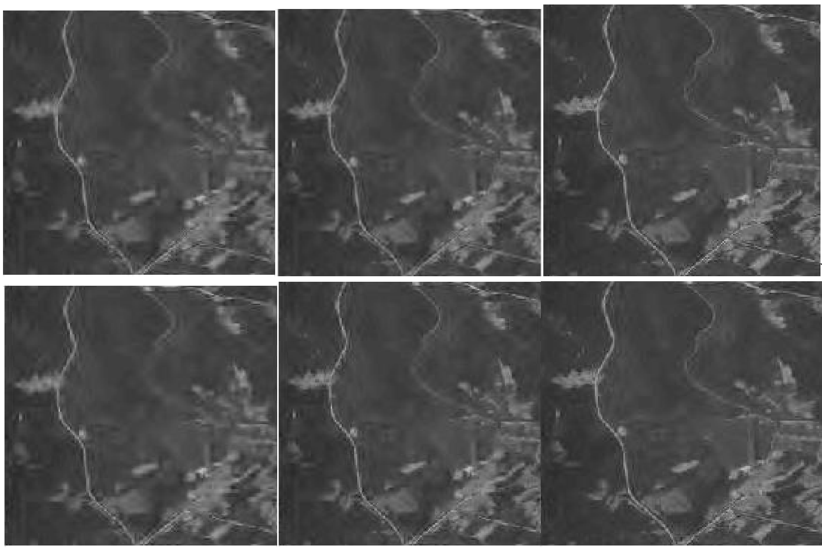
4. Simulation

We can use the method described in the paper to dispose image Lena and Pepper to see the validity of the method, and we can also compared the result of it to the result of the wavelet method. We adopt a 5/3 Double Quadrature Wavelet Filter and 5×5 windows of Window Shrink filter. The result as the following table:

Table 1. The Result of PSNR of Disposing Various Noises in Different Ways

Transform methods		σ =20	σ =30
Wavelet transform (PSNR)	WindowShrink	27.0654	26.5289
	BayesShrink	28.3811	27.6625
	Proposed method	29.6792	29.0285
Curvelet Transform (PSNR)	WindowShrink	27.8318	26.9634
	BayesShrink	28.9546	28.1325
	Proposed method	30.0965	29.5694

From Table 1, we can see that the results of the method described in the article are better than results of WindowShrink and BayesShrink. Though WindowShrink Theory have adopt adaptive way to remove noise, it only considered the trait of noise rather than that of the image to calculate and dispose the coefficient by noise Variance; it can't remove the noise of each image of their own trait. BayesShrink make use of the Variance of the image, but it uses the same hard threshold to the transform coefficients to remove noise and it can't deal with the transform coefficient based on their different frequency band coefficient, which can lead to key information coefficient lost in small area and make image distortion. The method described in the paper use the Variance of original image to calculate, but the Variance of original image comes from the estimation of Variance of noise contained image and the Variance of noise image. It includes both the information of the image and noise, so it can reach a better result by using adaptive threshold to remove noise. We can also see that whichever method we chose, the PSNR of Curvelet transform are higher than Wavelet transform. This is partly because Curvelet transform not only inherit the multiple resolving rate and dot odd character of Wavelet transform, but also represent the line and plane, so it can do closer to the image. The Figure 3 have shown different methods in σ =20. We can see that the result of noise removing are as the same as what we said above.



wavelet

curvelet

Window shrink Bayes shrinksPromoted method

Figure 3. Disposed Images

5. Conclusion

In this paper, a new method of combination of the WindowShrink and BayesShrink based on Curvelet transform is used to remove noise from image. By experiment, we can see it has better PSNR and we can also get a more distinct image. So the image we get by our method is better and that of the traditional Wavelet methods.

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