IMAGE DENOISING USING CURVELET TRANSFORM AND EDGE DETECTION IN IMAGE PROCESSING

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ABSTRACT

Image usually have different kind of noise in the process of coding receiving and transmission. Curvelet transform is used for denoising of image. Noise removed belong to image restoration in digital image processing. A satisfying result cannot be found if processing method such as edge extraction, registration or image fusion is carried out on image with noise. So removing noise is absolutely necessary for image. The major objective of this paper is how to remove noise present in image using non-linear technique such as curvelet transform and edge detection in image processing.

KEYWORDS:

Visual information send in the form of digital images is becoming a major method of exchanging information by speaking or writing in this modern age, but this image obtained after transmission is often corrupted with noise. So, the given image needs to be processed before it can be used in any sort of application. The noise which is created due to improper modeling of product and capturing system of signals so, the real world signal usually contain deviations from the ideal signal that is accepted.

A large portion of digital image processing is concerned with the image denoising. A noise can occur in transmission medium due to channel, or error during the measurement process and during quantization of data for digital storage.[Bala;2014] et al.

Edge detection is an important work in image processing as it is the most important tool for pattern recognition, image segmentation and scene analysis. One of the most important characteristic in an image is the feature extraction, edges which can be described as a discontinuity in local domain of the image. Edge detection is a pre-processing step towards high level image analysis away of improving the accuracy and quality of edge detection of noisy contaminated image is to preserve edge details while removing noise. In recent year, one kind of new multiscale transform based on wavelet transform has developed.[singh] et al.

E.J.Candes in 1999 developed the structural element of curvelet transform include the parameter of dimension and location, and orientation parameter more which let it has good orientation characteristic. Therefore the curvelet transform is superior to wavelet in the expression of image edges, such as geometry characteristic of curve, which already obtained good research result in image denoising. This paper put forward a improve method based on curvelet transform because certain regions of image have the ringing and radial strip after curvelet transform. [starck;2003] et al

RELATED WORK

Although the DWTs have established an impressive reputation as a tool for mathematical analysis and signal processing, it has the disadvantage of poor directionality, which has undermined its usage in many applications. Significant progress in the development of directional wavelets has been made in recent years. The complex wavelet transform have improved directional selectivity. However, the complex wavelet transform has not been widely used in the past, as it is difficult to design complex wavelets with perfect reconstruction properties and good filter characteristics. The dual-tree complex wavelet transform (DT CWT) proposed by Kingsbury, which added perfect reconstruction to the other attractive properties of complex wavelets.

The 2-D complex wavelets are essentially constructed by using tensor-product one-dimensional (1-D) wavelets. The directional selectivity provided by complex wavelets (six directions) is much better than that obtained by the classical DWTs (three directions), but is still limited.
In 1999, an anisotropic geometric wavelet transform, named ridgelet transform, was proposed by Candès and Donoho. The ridgelet transform is optimal at representing straight-line singularities. Unfortunately, global straight-line singularities are rarely observed in real applications. To analyze local line or curve singularities, a natural idea is to consider a partition of the image, and then to apply the ridgelet transform to the obtained sub images. This block ridgelet-based transform, which is named curvelet transform, was first proposed by Candès and Donoho in 2000. [candes;2005] et al.

The structural elements of curvelet transform include the parameters of dimension and location, and orientation parameter more, which let it has good orientation characteristic. Therefore, curvelet transform is superior to wavelet in the expression of image edge, such as geometry characteristic of curve and beeline, which has already obtained good research results in image denoising.

Figure 1: Curvelet transform flow block diagram

The curvelet decomposition is the sequence of the following steps.

Sub-band decomposition:

The object is decomposed into subbands. Let us consider ‘f’ is an original image

\[ f \mapsto (P_0f, \Delta_1f, \Delta_2f, \ldots) \]

Figure 2: Original image

Figure 3: Subband images

Smooth Partitioning :

Each subband is smoothly windowed into “square” of an appropriate scale.

\[ h_{ij} = w_{ij} \cdot \Delta_s f \]

The windowing function \( w \) is a nonnegative smooth function.

Partition of the intensity:

The intensity of certain pixel \((x_1, x_2)\) is divided between all sampling windows of the grid.

\[ \sum_{k_1, k_2} \Delta(x_1 - k_1, x_2 - k_2) = 1 \]

Figure 4: Smooth Partitioning
Renormalization:

Each resulting square is renormalized to unit scale

$$g_Q = T_Q^{-1} h_Q$$

Ridgelet analysis:

Each square is analyzed in the orthonormal system.

$$\alpha_{(Q,l)} = \langle g_Q, \rho_s \rangle$$

Ridgelet are an orthonormal set \( \{\rho_s\} \) for \( L^2(\mathbb{R}^2) \).

$$h_Q = w_Q \cdot \Delta_s f$$

![Figure 5: Ridge in Square](image)

The ridgelet element in the frequency domain.

$$\hat{\rho}_s(\hat{\xi}) = \frac{1}{2} \| \hat{\psi}_{j,k} \|_2 \cdot \alpha_{(j,l)}(\theta) + \hat{\psi}_{j,l}(\hat{\xi}) \cdot \alpha_{(l,j)}(\theta + \pi)$$

Where,

\( \omega_{ij} \) are periodic wavelets for \([-\pi, \pi)\).

‘i’ is the angular scale.

\( \psi_{j,k} \) are wavelets for \( \mathbb{R} \).

‘j’ is the ridgelet scale and k is the ridgelet location.

Image Reconstruction

The Inverse of the Curvelet Transform:

- Ridgelet Synthesis
  
  $$g_Q = \sum \alpha_{(Q,l)} \cdot \rho_s$$

- Renormalization
  
  $$h_Q = T_Q g_Q$$

- Smooth Integration
  
  $$\Delta_s f = \sum_{\hat{Q} \in \hat{Q}} w_{\hat{Q}} \cdot h_{\hat{Q}}$$

- Sub-band Reconstruction
  
  $$f = \sum_{\hat{Q}} \hat{f}_\hat{Q} + \sum_{\hat{Q}} \Delta_s \hat{f}_\hat{Q}$$

Expected Results

1. Gaussian Noise with mean (m) = 0 and variance (v) = 0.01

![Figure 6: Removal of Gaussian noise](image)

PSNR (Peak Signal to Noise Ratio) = 28.5961

2. Salt & Pepper Noise with noise density (D) = 0.02.

![Figure 7: Removal of salt and pepper noise](image)

3. Speckle Noise variance (v) = 0.02

![Figure 8: Removal of Speckle noise](image)

PSNR = 29.1945

4. Removal of Poisson noise

![Figure 9: Removal of Poisson noise](image)

PSNR = 29.6584

Conclusions and Discussion

The best result are obtained with denoising the test images corrupted by random noise, spackelnoise, Gaussian noise and salt and pepper noise in terms of PSNR it is noticed that the lowest PSNR gain is obtained for biomedical images when compared to satellite images. We also have shown that the gain is not only in terms of PNSR but, the
related work can also retrain the edges with better accuracy.

REFERENCES


JIANG Tao and ZHAO Xin,” Research and application of image denoising method based on curvelet transform”, Commission II, WG II/2,363-368


