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Image De-noising using Contoulets (A Comparative Study with Wavelets)

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ABSTRACT

Although the wavelet transform is powerful in representing images containing smooth areas separated with edges, it cannot perform well when the edges are smooth curves. Wavelets are less effective for images where singularities are located both in space and directions. The contourlet transform is one of the new geometrical image transforms, which represents images containing contours and textures. New developments in directional transforms, known as contourlets in two dimensions, which have the property of capturing contours. The present paper is a discussion of image de-noised by wavelet and contourlet transform.
Contoulets, wavelets, Image de-noising

Keywords - Contoulets, Image de-noising, Wavelets

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1. Introduction

Presence of noise not only produces undesirable visual quality but also lowers the visibility of low contrast objects. Noise removal is essential in many imaging applications in order to enhance and recover fine details that may be hidden in the data. In the recent years there Has been more research on wavelets, curvelets, rigidlets, sparse representation for signal denoising. Wavelets are less effective for images where singularities are located both in space and directions. Shift invariance is very important in image denoising by thresholding. Contourlet transform[11] is a multidirectional and multiscale transform that is constructed by combining the Laplacian pyramid [12-13] with directional filter bank (DFB), can be used to capture geometrical properties of images. After contourlet decomposition feature like edges have higher contourlet coefficient in high frequency band however noise having small contourlet transformation coefficient. Therefore, eliminating noise is to eliminating the smaller coefficients.

A threshold is set to eliminate the noise from the image. The new multiresolution representation can be explained with painter work. The painter exploits effectively the smoothness of the contour by making brush strokes with different elongated shapes and in a variety of directions following the contour. This was formalized by Candes and Donoho in the *curvelet* construction [4] [5],

In multiresolution expansion. We identify following characteristics for image representation.

- **Multiresolution** The representation of image should allow successive approximation from coarse to fine resolutions.
- **Localization** The basic elements of the representation should be localized in both the spatial and the frequency domains.
- **Critical sampling** For some applications (e.g., compression), the representation should form a basis with less redundancy.
- **Directionality** The representation should contain basis elements oriented at a variety of that are separable by wavelets.
- **Anisotropy** To capture smooth contours in images, the representation should contain basis elements using a variety of elongated shapes with different aspect ratios.

There are many directional extensions of the 2-D wavelet transform that could be potentially examined that also

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possess directionality and anisotropy. The contourlet transform is a discrete extension of the curvelet transform that aims to capture curves instead of points, and provides for directionality and anisotropy.

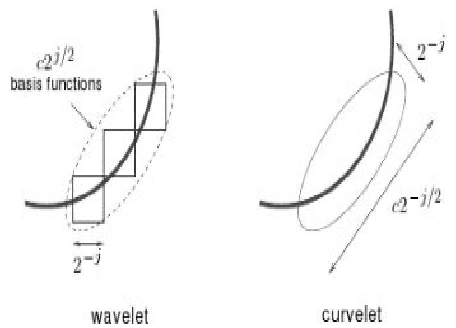

Figure 1: Conceptual visualization of curvelets/contourlets.

Contourlets are implemented by using a filter bank that decouples the multi-scale and the directional decompositions. In Figure 2, Do and Vetterli show a conceptual filter bank setup that shows this decoupling. We can see that a multiscale decomposition is done by a Laplacian pyramid, then a directional decomposition is done using a directional filter bank. This transform is suitable for applications involving edge detection with a high curve content[4].

2. Contoulet Transformations

Do and Vetterli proposed a multiscale and multidirectional image representation named contourlet transform [5, 6], which can effectively capture image edges and contours. The contourlet transform is constructed by Laplacian pyramid [4, 7, 10] (LP) and directional filter banks (DFB) [1, 2, 3, 9].

The Figure.2 illustrates the contourlet transformation, in which the input image consists of frequency components like LL (Low Low), LH (Low High), HL (High Low), and HH (High Low). The Laplacian Pyramid at each level generates a Low pass output (LL) and a Band pass output (LH, HL, and HH). The Band pass output is then passed into Directional Filter Bank, which results in contourlet coefficients [8].

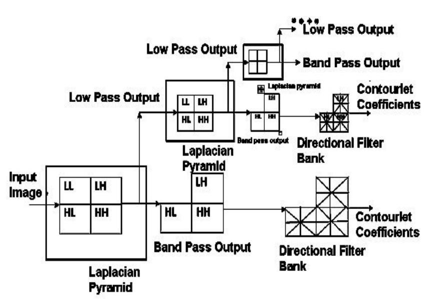

Figure 2: Diagram showing the countourlet transformation.

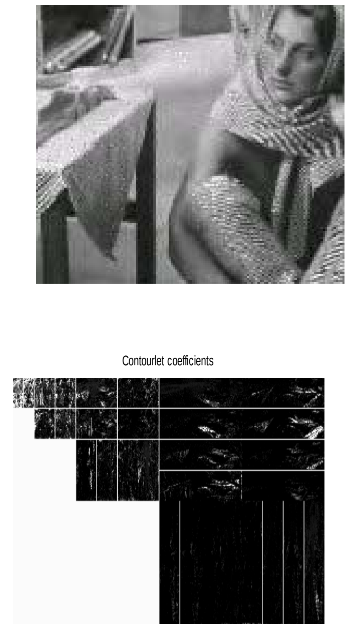

Figure: 3(a): Input of barabara image; 3(b):Contoulet deformation of barabara images.

3. Methodology

3.1 Laplacian Pyramid

The basic idea of the Laplacian Pyramid is the following. First, derive a coarse approximation of the original signal, by lowpass filtering and down sampling. Based on this coarse version, predict the original (by up sampling and filtering) and then calculate the difference as the prediction error.

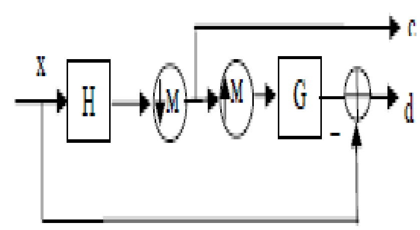

Figure 4: Laplacian pyramid construction

the outputs are a coarse approximation c and a difference d between the original signal and the prediction. The process can be repeated by decomposing the coarse version repeatedly.

3.2 Directional filter bank (DFB)

In 1992, Bamberger and Smith [12] introduced a 2-D directional filter bank (DFB) that can be maximally decimated while achieving perfect reconstruction. The DFB is efficiently implemented via an l-level tree

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structured decomposition that leads to 2l sub bands with wedge-shaped frequency partition as shown in Figure2

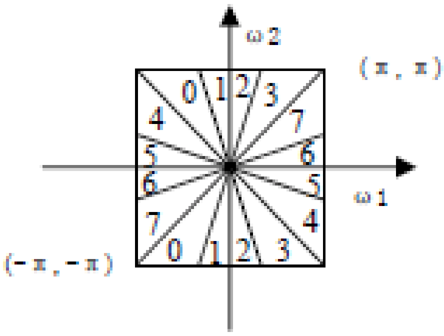

Figure 5: Directional filter construction.

The original construction of the DFB in involves modulating the input signal and using diamond-shaped filters. Furthermore, to obtain the desired frequency partition, an involved tree expanding rule has to be followed

Figure (5) shows a multiscale and directional decomposition using a combination of a LP and a DFB. Band pass images from the LP are fed into a DFB so that directional information can be captured. The scheme can be iterated on the coarse image. The combined result is a double iterated filter bank structure, named contourlet filter bank, which decomposes images into directional sub bands at multiple scales.

The contourlet transform is shift-variant and the lack of shift invariance causes pseudo-Gibbs phenomena around singularities. To achieve the shift-invariance, the Non subsampled contourlet transform is applied which built upon nonsubsampled pyramids and nonsubsampled DFB. A *double filter bank* structure are used for obtaining sparse expansions for typical images having smooth contours.

In this double filter bank, the Laplacian pyramid [3] is first used to capture the point discontinuities, and then followed by a directional filter bank[4] to link point discontinuities into linear structures.

The overall result is an image expansion using basic elements like contour segments, and thus are named *contourlets*. In particular, contourlets have elongated supports at various scales, directions, and aspect ratios. This allows contourlets to efficiently approximate a smooth contour at multiple resolutions.

In the frequency domain, the contourlet transform provides a multiscale and directional decomposition.

4. Properties of the discrete contourlet

The main properties of the discrete contourlet transform are stated in the following theorem.

Theorem 1: In a contourlet filter bank, the following hold:

1) If both, the LP and the DFB use perfect-reconstruction filters, then the discrete contourlet transform achieves perfect reconstruction, which means it provides a frame operator.

2) If both, the LP and the DFB use orthogonal filters, then the discrete contourlet transform provides a tight frame with frame bounds equal to 1.

3) The discrete contourlet transform has a redundancy ratio that is less than 4/3.

4) Suppose an l_j -level DFB is applied at the pyramidal level j of the LP, then the basis images of the discrete contourlet transform (i.e. the equivalent filters of the contourlet filter bank) have an essential support size of width ≈ $C2_j$ and length ≈ $C2_j+l_j-2$.

5) Using FIR filters, the computational complexity of the discrete contourlet transform is O(N) for N-pixel images.

5. Experimental Techniques

A 256*256 with 32 bit depth input image has taken. The input image has corrupted with poisons, Gaussian noise, and uniform noise respectively shown in (Fig. 6(a), 6(b) and 6(c) respectively.

Figure 6. Canonicals Images having noise (a) poisson noise; (b) Gaussian noise; (c) Uniform noise

In experimental process, there are many kinds of orthogonal wavelets and biorthogonal wavelets, we can apply 'Daubechies 9/7', '5/3', 'Burt', 'haar' and 'pkvaN' them in Contourlet transformation[5]. we chose the optical images ‘barabara.png’ of size of 256*256. The noise is the results of different image de-noising algorithm with the same directional filter (DF) ‘pkva’ under different pyramid filter (PF) combination. The combinations of pyramid filter ‘9/7’ and the directional filter ‘pkva’ gain good result (Hong Jun Hi, Zhi Min Zhang).

Biorthogonal wavelet has the linear phase, so it gains good image de-noising result. So the filter we will construct needs to be biorthogonal at least.

Figure 7: De-noised image 7(a), 7(b), 7(c) using wavelet transform of noisy image figure 6(a),6(b),6(c) respectively ; De-noised image 6(d), 6(e), 6(f) using contourlet transform of noisy image figure 6(a),6(b),6(c) respectively.

6. Salt and pepper noise

Represents itself as randomly occurring white and black pixels. An effective noise reduction method for this type of noise involves the usage of a median filter or a contra harmonic mean filter. barabara.png image has corrupted with salt and pepper noise density 0.01, 0.05 ,0.1 ,0.5. Noisy images are shown in Fig 8(a-d).

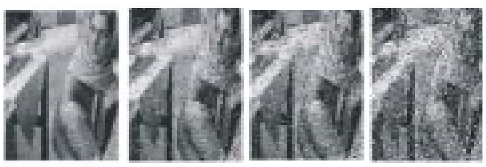

Figure 8: Barbara image was made noisy with salt and pepper noise with noise distribution (a) 0.01; (b) 0.05; (c) 0.1; (d) 0.2

Spackle Noise				
Expt No.	Noise Density	SNR dB Of Noisy images	SNR dB De-noise Images By Wavelets	SNR dB De-noised Image By Contourlets
EXPT 1	0.01	12.51 dB	13.51 dB	13.37 dB
EXPT 2	0.05	5.74 dB	7.81 dB	9.51 dB
EXPT 3	0.10	2.95 dB	4.20 dB	5.53 dB
EXPT 4	0.20	0.22 dB	0.90 dB	1.69 dB

Table 1: Image corrupted with different noise type

Salt & Pepper				
Expt No.	Noise Density	SNR dB Noisy Images	SNR dB De-noised image wavelets	SNR dB De-noised image by Contourlets
EXPT 1	0.01	11.83 dB	10.63 dB	13.15 dB
EXPT 2	0.05	5.86 dB	5.59 dB	8.84 dB
EXPT 3	0.10	1.84 dB	2.53 dB	4.30 dB
EXPT 4	0.20	-1.15 dB	-0.75 dB	-0.01 dB

Table 2: (different experiment performed with salt and pepper corrupted images with varying noise density)

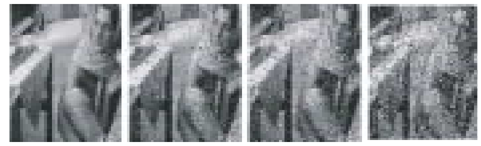

Figure 9: removal of noise from corrupted image with different noise distribution using wavelet transformation. 9(a), 9(b), 9(c) and 9(d) are de-noised image of Figure 8(a), 8(b), 8(c), 8(d) in the same order.

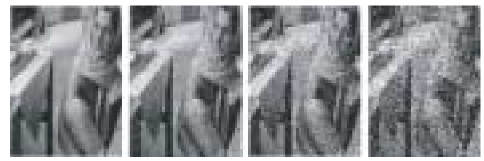

Figure 10: removal of noise from corrupted image with different noise distribution using Contourlet transformation. 10(a), 10(b), 10(c) and 10(d) are de-noised image of Figure 8(a), 8(b), 8(c), 8(d) in the same order.

7. Spackle Noise

Speckle noise is a granular noise that inherently exists and degrades the quality of the active images. Speckle noise in a *multiplicative* noise, i.e. it is in direct proportion to the local grey level in any area. Signal and the noise are statistically independent of each other. The sample mean and variance of a single pixel are equal to the mean and variance of the local area that is centred on that pixel. barabara.png image has corrupted with multiplicative noise density 0.01, 0.05 ,0.1 ,0.5 shown in Fig. 11(a-d)

Table 3: (different experiment performed with spackle corrupted images with varying noise density)

Noise Type	PSNR of Noisy Image	Wavelets	Contourlets
Poisson	10.9 dB	13.56 dB	13.64 dB
Gaussian	6.71dB	9.95 dB	11.58 dB
Uniform	9.53 dB	12.63 dB	13.07 dB

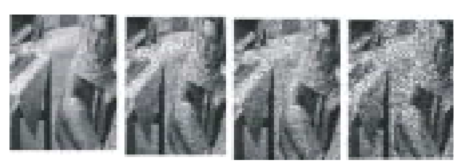

Figure 11: Barbara image was made noisy with spackle with noise distribution (a) 0.01; (b) 0.05; (c) 0.1; (d) 0.2

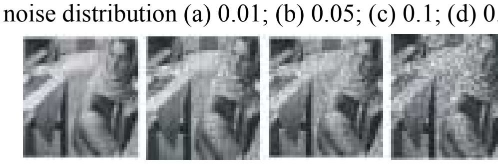

Figure 12: removal of noise from corrupted image with different noise distribution using wavelet transformation. 12(a), 12(b), 12(c) and 12(d) are de-noised image of Figure 11(a), 11(b), 11(c), 11(d) in the same order.

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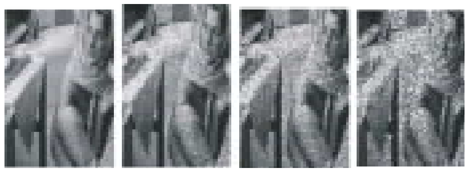

Figure 13: removal of noise from corrupted image with different noise distribution using Contourlet transformation. 13(a), 13(b), 13(c) and 13(d) are de-noised image of Figure 11(a), 11(b), 11(c), 11(d) in the same order.

8. Conclusion

The contourlet transform is one of the new geometrical image transforms, which represents images containing contours and textures Although the wavelet transform is powerful in representing images containing smooth areas separated with edges, it cannot perform well when the edges are smooth curves. New developments in directional transforms, known as contourlets in two dimensions, which have the property of capturing contours. We have performed four experiment using spackle and salt and pepper noise at different noise density 0.01, 0.05, 0.1, 0.2. We observed that SNR noise is higher in de-noised image is always higher in contoulets as compare to wavelets. for wavelet transform, the entropy of subbands in contourlet transform is much less than that of wavelet transform. Besides, the contourlet preserves better the edges than wavelet causing better PSNR. So, these two facts cause that the overall performance of contourlet transform is better for the compression of CT images.

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