IMAGE DENOISING USING WAVELET BASED CONTOURLET TRANSFORM

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Abstract: *The Contourlet transform consists of two modules: the Laplacian Pyramid and the Directional Filter Bank. When both of them use perfect reconstruction filters, the contourlet expansion and reconstruction is a perfect dual. Therefore, the contourlet transform can be employed as a coding scheme. The contourlet coefficients derived above can be transmitted through the wireless channel in the same way as transmitting the original image, where the transmission is prone to noise and block loss. However, the reconstruction at the receiver performs differently if the image is transmitted directly or coded by the contourlet transform. This paper studies the performance of the contourlet coding in image recovery and denoising. The simulation results show that for general images the contourlet transform is quiet competitive to the wavelet transform in the SNR sense and in the visual effect. Further, the contourlet transform can be used in a wireless face recognition system to extract the unique feature that other transforms cannot discover, For face recognition system, the recovery of the original image is not essential anymore; therefore, the resources on the image reconstruction from the contourlet coefficient can be saved.*

Key words: *Contourlet, wavelet, WBCT, denoising, PSNR.*

1. Introduction

The papers should include an even number of pages (at least 6). The wavelet transform has been widely used in image denoising. In image compression, the wavelet transform produces much less blocking artifacts than the DCT under the same compression ratio. The wavelet transform also performs quite well in image de-noising. In particular, the stationary wavelet transform (SWT) and the translation invariant wavelet transform (TIWT) produce smaller mean- square -errors than the regular wavelet transform, and the SWT or TIWT based image reconstruction are perceptually more delicate and smoother with much less observable artifacts than the regular wavelet transform. However, the 2D wavelet transform used in image processing is, intrinsically, a tensor-product implementation of the 1D wavelet transform, therefore it does not work well in retaining the directional edges in the images, and it is not efficient in representing the contours not horizontally or vertically.

As an attempt to represent the curves more efficiently, Starck, Candes and Donoho developed the continuous curvelet transform [7] in the discrete form is not a trivial issue. However, in practice, the complex polar sampling is usually simplified by nearest neighbor substitution, and the mathematical properties may not be preserved.

Then Minh. N. Do and M. Vetterli developed the contourlet in the discrete form [2], which is defined on the regular grids instead of the polar coordinate and more “digital-friendly”. Another difference between the contourlet and the curvelet is that the contourlets have the 2D frequency partition on the centric-squares, but the curvelets have the 2D frequency partition on the centric circles. The contourlet construction provides a space domain multiresolution scheme that offers flexible refinement for both spatial resolution and angular resolution. In short the contourlet transform is an efficient directional multiresolution image representation, which differs from the wavelet transform in that the contourlet transform uses non-separable filter banks developed in the discrete form; thus it is a true 2D transform, and it overcomes the difficulty in exploring the geometry in digital images due to the discrete nature of the image data.

Noise commonly present in an image which is undesired information that contaminates the image. In the image denoising process, information about the type of noise present in the original image plays a significant role. Noise in imaging systems is usually either additive or multiplicative. The Gaussian additive white noise has a frequency spectrum that is continuous and uniform over a specified frequency band. It is spatially uncorrelated, and the noise for each pixel is independent and identically distributed.

Additive and Multiplicative Noises

Typical images are corrupted with noise modeled with either a Gaussian, uniform, or salt & pepper distribution. Another typical noise is a speckle noise, which is multiplicative in nature. Noise is present in an image either in an additive or multiplicative form. An additive noise follows the rule which is given in the equation (1).

$$W(x,y) = s(x,y)+n(x,y) \qquad \text{--- (1)}$$

The multiplicative noise follows the rule as it is given in equation (2).

$$W(x,y) = s(x,y) * n(x,y) \qquad \text{--- (2)}$$

Where s(x,y)→ original signal
n(x,y) → noise introduced into the signal
W(x,y) →corrupted image
(x , y) → pixel location
Image addition also finds applications in image morphing. By image multiplication, the mean of brightness of the image is varied. The digital image acquisition process converts an optical image into a continuous electrical signal and then sampled. At every step in the process there are fluctuations caused by natural phenomena, adding a random value to the exact brightness value for a given pixel.

Gaussian Noise

Gaussian noise is evenly distributed over the signal. This means that each pixel in the noisy image is the sum of the true pixel value and a random Gaussian distributed noise [10], value. As the indicates, this type of noise has a Gaussian distribution, which has a bell shaped probability distribution function given in equation (3).

$$F(g) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-(g-m)^2/2\sigma^2} \qquad \text{--- (3)}$$

Where g →gray level ,
m→ mean or average of the function,
σ → standard deviation of the noise.
When introduced into an image, Gaussian noise with zero mean and variance as 0.05 would look as in Figure 1.

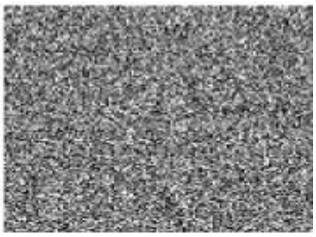


Fig. 1. Gaussian noise with Mean = 0 and Variance = 0.05

Salt and Pepper Noise

Salt and pepper noise is an impulse type of noise, which is also referred to as intensity spikes. This is caused generally due to errors in data transmission. It has only two possible values, a and b. The probability of each is typically less than 0.1. The corrupted pixels are set alternatively to the minimum or to the maximum value, giving the image a "salt and pepper" like appearance. Unaffected pixels remain unchanged. For an 8-bit image, the typical value for pepper noise is 0 and for salt noise 255. The salt and pepper noise is generally caused by malfunctioning of pixel elements in the camera sensors, faulty memory locations, or timing errors in the digitalization process. The salt and pepper noise with a variance of 0.05 is shown in Figure 2.

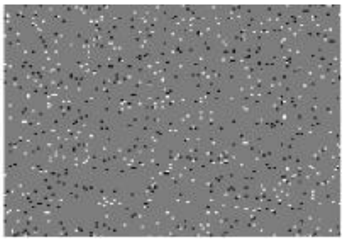


Fig. 2. Salt and Pepper noise with Variance = 0.05

Speckle Noise

Speckle noise is a multiplicative noise. This type of noise occurs in almost all coherent imaging systems such as laser, acoustics and SAR(Synthetic Aperture Radar) imagery. The source of this noise is attributed to random interference between the coherent returns. Fully developed speckle noise has the characteristic of multiplicative noise. Speckle noise follows a gamma distribution and is given as in equation (4).speckle noise with variance 0.05 shown in the Figure 3.

$$F(g) = \frac{g^{\alpha-1}}{(\alpha-1)!a^2} e^{-g/a} \qquad \text{--- (4)}$$

Where a^2 α → variance , g → gray level

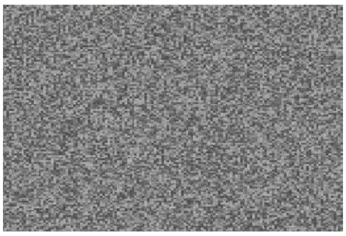


Fig. 3.Speckle noise with Variance 0.05

Poisson Noise

Poisson noise is frequently present in an image. It is not an additive noise rather than pixel-intensity dependent. Due to this noise, bright pixels in an image are statistically corrupted with noise than dark pixels. These causes a fluctuation in a pixel values of an image which leads to a complication in denoising process.

3. Image Denoising

Removing noise from the original image or signal is still a challenging problem for researchers. The general image denoising procedure is shown in Figure 5. The purpose of image denoising is to maintain the main features of the original image and remove noise from the image.
Image denoising also has wide application domain in medicine diagnosis. Medical images have different species such as CT, MRI etc. These different images have their respective application ranges medical denoise image is to get the clear information without

noise. The image s(x , y) is blurred by a linear operation and noise n(x , y) is added to form the degraded image w(x , y). This is convolved with the restoration procedure g(x , y) to produce the restored image z(x , y). The denoising concept is shown in Figure 5.

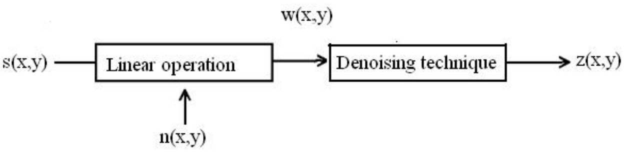


Fig. 5.Denoising concept

4. Discrete Wavelet Transform

As with wavelet transforms, a key advantage it has over Fourier transforms is temporal resolution i.e., it captures both frequency and location information. The wave and wavelet represented in Figure 6.

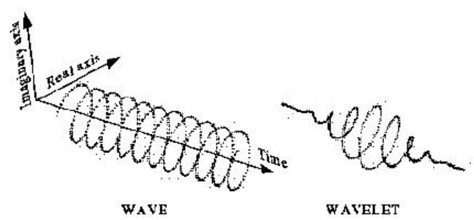


Fig. 6.Representation of wave and wavelet

Repeating the filtering and decimation process on the low-pass branch outputs make multiple levels or scales of the wavelet transform only. The decomposition levels are shown in Figure 8. The process is typically carried out for a finite number of levels K, and the resulting coefficients are called wavelet coefficients.

5. Contourlet Transform

In the recent years, Do and Vetterli proposed a multiscale and multidirectional image representation method named contourlet transform [5], which can effectively capture image edges and contours. The contourlet transform is constructed by Laplacian Pyramid [4,7] (LP) and Directional Filter Bank (DFB) [2,3]. The Figure 5 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 High). 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 coefficient. The Low pass output is again passed through the Laplacian Pyramid [8] to obtain more coefficients and this is done till the fine details of the image are obtained.

6. The Wavelet Based Contourlet Transform

The contourlet transform is a true 2D transform defined in the discrete form to capture the contour information in all directions; therefore it's very suited for image processing. The idea of the wavelet transform shown in Figure 10 (on the left) is to square shaped brush strokes along the contour to paint the contour, with different brush sizes corresponding to the multi-resolution structure of the wavelets. As the resolution becomes finer, the wavelet transform must use many fine dots i.e. small squares to capture the contour. On the other hand, the contourlet transform shown in Figure 10 (on the right) uses different elongated shapes in a variety of directions following the contour to paint the contour with more flexibility. The contourlet transform uses contour segments to realize the local, multi-resolutional and directional image expansion, hence it's named the contourlet transform. The efficiency of a representation is defined as the ability of it to capture the information of an object in interest using fewer descriptors. Figure 10 shows that with parabolic scaling and sufficient directional vanishing moments, the contourlets achieve the optimal.

In the wavelet based contourlet transform, the operation of Laplacian pyramid is replaced by the wavelet transform and then application of directional filter banks are used thus the wavelet transform uses the 2D level sub band decomposition in the wavelet based contourlet transform to perform the Laplacian pyramid operation.

7. Algorithm

Thresholding is a simple non-linear technique,[2] which operates on one wavelet coefficient at a time. The two types of thresholding are hard thresholding and soft thresholding. The hard thresholding is defined in equation (5).

$$\text{THR H}(\,dj(k),\ \delta\,) = \begin{cases} 0, \text{if } d_j(k) \le \delta \\ d_j(k), \text{if } d_j(k) > \delta \end{cases} \quad \text{----} \quad (5)$$

Here the hard thresholding algorithm is used for an image with the different noise. The soft thresholding technique is defined in equation (6).

$$\text{THR S}(dj(k),\ \delta\,) = \begin{cases} 0, \text{if } d_j(k) \le \delta \\ \text{sgn}\left(d_j(k)\right)\left|d_j(k) - \delta\right|, \text{if } d_j(k) > \delta \end{cases} \quad \text{--} \ (6)$$

The soft thresholding results in a smooth reduction of all coefficients toward zero and sets equal to zero those closest to the origin.

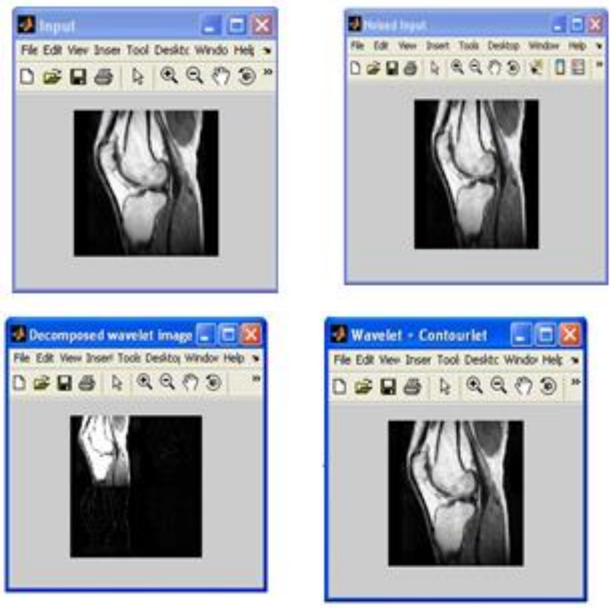
Procedure

1. Apply multiscale wavelet transform to the noisy image and get the scaling coefficients and multiscale wavelet coefficients.
2. Chose the threshold and apply thresholding to the multiscale wavelet coefficients (leave the scaling coefficients alone).
3. Reconstruct the scaling coefficients and the

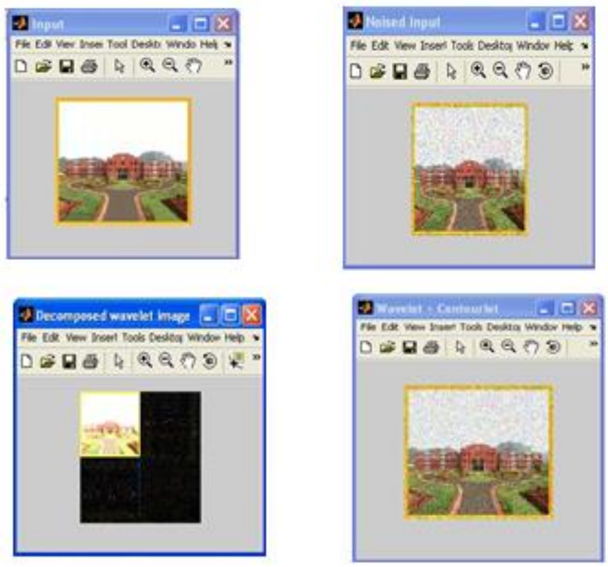
multiscale contourlet coefficients are thresholded and get the denoised image.
With the help of hard threshold algorithm in MATLAB tool, simulation results are given below in the Figure 11,12,13,14 for different noises and then the PSNR values for wavelet based Contourlet Transform are tabulated in Table I, II & III for clean understanding.

8. Simulation Results

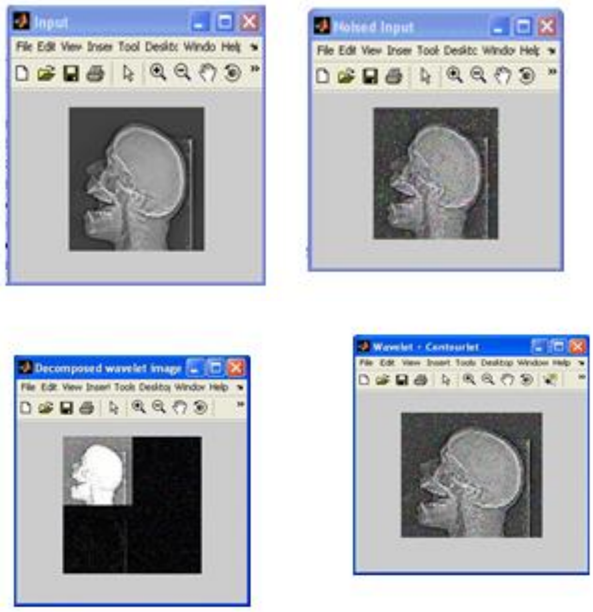
(a)



(b)



(c)



(d)

Fig. 7 (a) Gaussian Noise, (b) Poisson Noise (c) Speckle Noise, (d) Salt & Pepper Noise

Table 1
Performance of wavelet based contourlet transform for General images

Type of noise	PSNR (dB)			
	Building	Home	Mandril	Pepper
Poisson	26.9189	27.2825	26.6761	31.5222
Gaussian	20.0745	20.5928	19.9719	24.7886
Speckle	17.2837	19.4764	19.0505	23.4107
Salt and pepper	18.1569	17.6414	18.6312	23.0338

Table 2
Performance of wavelet based contourlet transform for Medical images

Type of noise	PSNR (dB)			
	MRI-Brain	**MRI-Heart**	**MRI-Knee**	**CT-Skull**
Poisson	34.7898	31.6785	33.5666	32.7422
Gaussian	26.0232	20.9448	25.9103	24.8358
Speckle	28.0844	23.9196	25.3379	25.0092
Salt and pepper	21.7350	22.0909	21.7865	21.9774

Table 3
Performance of wavelet based contourlet transform for colour images

Type of noise	PSNR (dB)			
	Bird	**Building**	**Elephant**	**College**
Poisson	31.7088	30.9608	30.5676	31.4462
Gaussian	25.0422	24.8752	24.8998	25.7184
Speckle	23.6893	22.3361	22.036	22.4335
Salt and pepper	22.6609	22.7623	22.6845	21.9774

6. Conclusion

Wavelets are powerful tools in the representation of signal and are good at detecting point discontinuities. However, they are not effective in representing the geometrical smoothness of the contours. This is because natural images consist of edges that are smooth curves, which cannot be efficiently captured by the wavelet transform. A wavelet based contourlet transform can be designed to a tight frame, which implies robustness against noise due to quantization and thresholding. Because of this property, contourlet can be used in image denoising and water marking. It provides a flexible multi-resolution, local and directional expansion for images as a band pass filter, pyramid construction tends to enhance image features such as edges, which are vital for image interpretation. The directional filter bank provides the flexibility to obtain good resolution both angularly and radially.

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