



Contourlet Based Image Denoising Using New-Threshold Function

Sakthivel K.

PG scholar, Paavai College of Engineering, Namakkal, Tamilnadu, India¹

ABSTRACT: In this paper contour let based image denoising algorithm which can restore the original image corrupted by salt and pepper noise, Gaussian noise, Speckle noise and the poisson noise is proposed. The noisy image is decomposed into sub bands by applying contour let transform, and then a new thresholding function is used to identify and filter the noisy co efficient and take inverse transform to reconstruct the original image. The simulation result of the proposed method is compared with other simulation results which used the various thresholding functions namely Bayes Shrink and Visu Shrink. From the simulation results it is observed that the proposed algorithm can remove poisson and speckle noises effectively.

KEYWORDS: Salt & pepper noise, Poisson noise, Speckle noise, Contourlet Transform, Threshold function, new threshold function

I. INTRODUCTION

Digital images are often corrupted by many types of noise including salt and pepper noise, Gaussian noise, Poisson noise, Speckle noise which are normally acquired during image acquisition and transmission. Salt and pepper noise is nothing but the random occurrences of black and white pixels in the images, Gaussian noise is statistical noise that has its probability density function equal to that of the normal distribution, which is also known as the Gaussian distribution, Speckle noise is a multiplicative noise i.e. it is direct proportion to the local grey level in any area. It is essential to estimate and remove these noises in the image. The wavelet transform performs quite well in image denoising. 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 art if acts than the regular wavelet transform. However, the 2D wavelet transform used in image processing is, basically, 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 (curves) not horizontally or vertically. As an attempt to represent the curves more efficiently curvelet is developed. But the implementation of the curvelet transform in the discrete form is not a trivial issue. Thus to overcome this new algorithm by using contour let transform is proposed for the denoising of images. If the image includes lots of edges, the contour let transform performs better at retaining this edge information and the output is better compared to the wavelet and contour let transform. Contourlet transform is implemented by Laplacian pyramid and two-dimensional directional filter banks that can simultaneously hold multi resolution, localisation, nearly critical sampling, flexible directionality and anisotropy. Image denoising algorithm consists of few steps; consider an input signal $x(t)$ and noisy signal $n(t)$. Add these components to get noisy data $y(t)$ i.e. $y(t)=x(t)+n(t)$.

Here the noise can be Gaussian, Poisson's, speckle and Salt and pepper, then apply Contourlet transform to get $c(t)$.

$$y(t) \xrightarrow[\text{transform}]{\text{contourlet}} c(t).$$

Modify the contour let coefficient $c(t)$ using different threshold algorithm and take inverse wavelet transform to get denoising image $\hat{x}(t)$



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$$c(t) \frac{\text{inverse}}{\text{transform}} \hat{x}(t)$$

Image quality was expressed using signal to noise ratio of denoised image.

II. NOISE MODEL

A. Gaussian Noise

Gaussian noise is statistical noise that has its probability density function equal to that of the normal distribution, which is also known as the Gaussian distribution. In other words, the values that the noise can take on are Gaussian-distributed. A special case is white Gaussian noise, in which the values at any pairs of times are statistically independent (and uncorrelated). In applications, Gaussian noise is most commonly used as additive white noise to yield additive white Gaussian noise. The probability density function of n-dimensional Gaussian noise is

$$f(x) = ((2\pi)^n \det K)^{-1/2} \exp(-(x - \mu)^T K^{-1} (x - \mu) / 2)$$

Where x is a length-n vector, K is the n-by-n covariance matrix, μ is the mean value vector, and the superscript T indicates matrix transpose.

B. Speckle Noise

Speckle noise is a multiplicative noise i.e. it is direct proportion to the local grey level in any area.

$$\text{var}\{zvi^l\} = \rho^2 \text{var}\{na1\} = 1/2\rho^2(1 - |\rho^2|)^{1.64}$$

Where vi^l represents the phase noise component, z denotes amplitude component, ρ denotes the coherence and na1 is the zero mean random variable.

C. Salt and Pepper Noise

Salt and pepper noise is nothing but the random occurrences of black and white pixels in the images

D. Poisson Noise

The Poisson Integer Generator block generates random integers using a Poisson distribution. The probability of generating a nonnegative integer k is

$$\lambda^k \exp(-\lambda) / (k!)$$

Where λ is a positive number known as the Poisson parameter. You can use the Poisson Integer Generator to generate noise in a binary transmission channel. In this case, the Poisson parameter Lambda should be less than 1, usually much less.

III. PROPOSED ALGORITHM

The block diagram for the proposed algorithm is shown in the figure1.

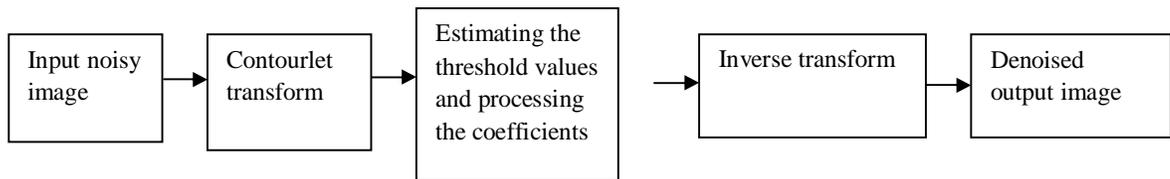


Figure1: Block Diagram of Image Denoising By Using Contourlet Transform

A. Contourlet Transform

The contourlet transform is applied for the noisy image to produce decomposed image coefficients. Basically Contourlet transform is a double filter bank structure. It consists of a Laplacian pyramidal filter followed by a directional filter bank. First the Laplacian pyramid (LP) is used to capture the point discontinuities. Then directional filter bank (DFB) used to link point discontinuities into linear structures. Similar to wavelet, contourlet decomposes the image into different scales. Unlike the wavelet contourlet decomposes each scale into arbitrarily power of two's number of directions.

The contourlet transformation expression is given by,

$$\lambda_{j,k}^{(l)}(t) = \sum_{i=0}^3 \sum_{m \in \mathbb{Z}^2} d_k^{(l)}[2m+k_i] \left(\sum_{m \in \mathbb{Z}^2} f_i[m] \phi_{j-1,2m+m} \right)$$

Where $\lambda_{i,j}^{(l)}(t)$ represents the contourlet transformation of the image. The $d_k^{(l)}$ and $f_i(m)$ represents the directional filter and the band pass filter in the equation. Thus j, k and n represent the scale direction and location. Therefore l represents the number of directional filter bank decomposition levels at different scales j. Thus the output of contourlet transform is a decomposed image coefficients.

B. THRESHOLDING FUNCTIONS

After the decomposition of the image in to the image coefficients, this image coefficient gets processed by using the thresholding for the restoration of noiseless image coefficients. Here we use three types of thresholding functions they are,

- Bayes Shrink
- Visu Shrink
- New threshold function

a. Bayes Shrink

The goal of this method is to minimize the Bayesian risk, and hence its name, Bayes Shrink .The Bayes threshold is defined as

$$t_R = \sigma^2 / \sigma_s$$



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Where σ^2 is the noise variance and σ_s^2 is the signal variance without noise. The noise variance σ^2 is estimated from the sub band HH by the median estimator shown in the above equation.

b. Visu Shrink

It uses a threshold value t that is proportional to the standard deviation of the noise. It follows the hard threshold rule. An estimate of the noise level σ was defined based on the median absolute deviation given by,

$$\hat{\sigma} = \frac{\text{median}(|g_{j-1,k}|; k = 0, 1, \dots, 2^j - 1)}{0.6745}$$

Where $|g_{j-1,k}|$ corresponds to the detail coefficients in the contourlet transform.

c. New Threshold Function

This function is calculated by,

$$\text{newth} = \sqrt{2m \times \log(M)}$$

Where, M is the total number of pixel of an image, m is the mean of the image. This function preserves the contrast, edges, background of the images. This threshold function calculated at different scale level.

IV. RESULT

In this image parameters had not to be disturbed while denoising. In this paper calculating threshold function in spatial domain, and Lena image is used for implementation. Thus the proposed algorithm is used to preserve the image details such as contrast, brightness, edges and gray level tonalities in the image. Hence the table given below shows the results of the proposed technique for the 50% noise density using various threshold levels for 'Lena image'.

Table 1: Result of Different Technique with Lena For 50% Noise Density

METHODS	DENOISED IMAGE PSNR			
	Gaussian noise	Speckle noise	Poisson noise	Salt & pepper noise
Bayes shrink	17.762	18.5983	47.3452	13.1295
Visu shrink	18.103	19.5674	29.4532	15.3674
New threshold	16.0123	15.9635	16.7647	13.1476

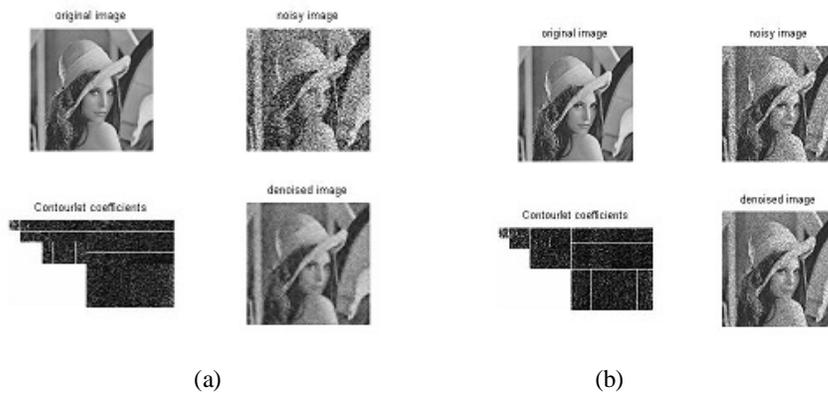


Figure 1: Results for proposed algorithm using Bayes Shrink for 50% noise density for (a) Gaussian noise (b) Speckle noise.

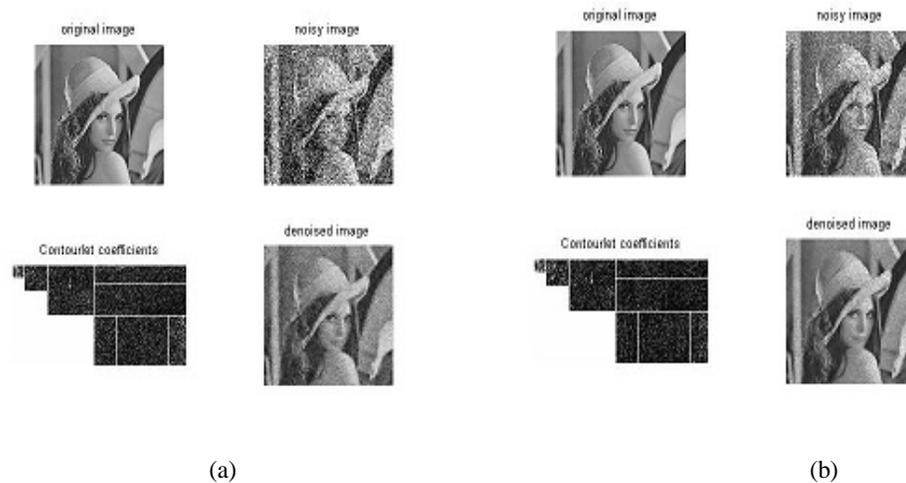


Figure 2: Results for proposed algorithm using Visu Shrink for 50% noise density for (a) Gaussian noise (b) Speckle noise.

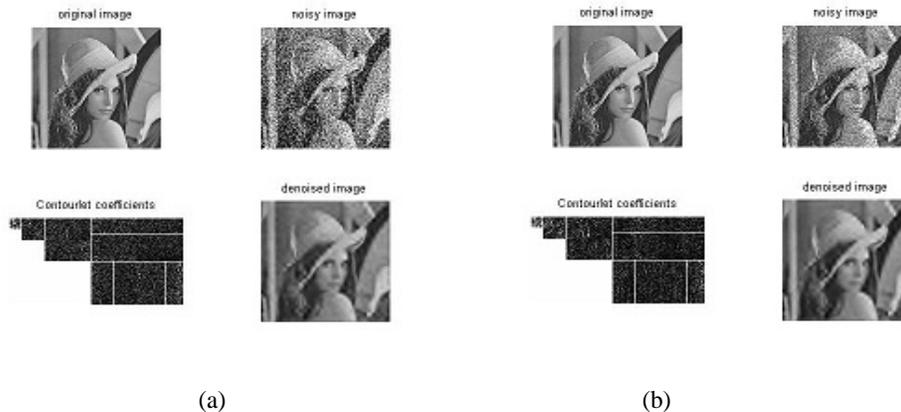


Figure 3: Results for proposed algorithm using New Threshold Function for 50% noise density for (a) Gaussian noise (b) Speckle noise.

VI. CONCLUSION

This contourlet technique is computationally faster and gives better results compared to the existing wavelet technique. Some aspects that were analyzed in this paper that contourlet transform is well suited for images containing more curves. This proposed method is not well suited for the removal of salt and pepper noise from the original image. Therefore the proposed method is highly suited for Gaussian noise and speckle noise. Our proposed threshold function gives better edge perseverance, background information, contrast stretching, in spatial domain. In future we can use same threshold function for medical images as well as texture images to get denoised image with improved performance parameter.

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