Image Denoising Based on Contourlet Technique

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Abstract— In this paper to restore the original image corrupted by salt and pepper noise, Gaussian noise, Speckle noise and the Poisson noise Contourlet based image denoising algorithm is proposed. By applying contourlet transform, the noisy image is decomposed in to sub bands 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. From the simulation results it is observed that the proposed algorithm can remove Poisson and speckle noises effectively. It is well suited for images containing more curves. Our proposed threshold function gives better edge perseverance, background information, contrast stretching, in spatial domain.

Key words: Image Denoising, Contourlet Technique

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 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, 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. Contourlet is used to represent the curves more efficiently. The implementation of the curvelet transform in the discrete form is possible. Contourlet transform is proposed as an image denoising technique. If the image includes lots of edges, the contourlet transform performs better at retaining this edge information and the output is better compared to the wavelet and contourlet transform. Contourlet transform is implemented with Laplacian pyramid and two-dimensional directional filter banks that can simultaneously hold multi resolution localisation, nearly critical sampling, flexible directionality and anisotropy. The Image denoising algorithm for an input signal x(t) and noisy signal n(t) follows the following steps.

Add these components to get noisy data y(t) i.e.

$$y(t) = x(t) + n(t).$$

If the noise is Gaussian, Poisson's, speckle and Salt and pepper, then apply Contourlet transform to get c (t).

$$y(t)\,\frac{contourlet}{transform} = c(t)$$

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

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

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

II. NOISE MODEL

A. Gaussian Noise

This noise has a probability density function [PDF] of the normal distribution. It is also known as Gaussian distribution. It is a major part of the read noise of an image sensor that is of the constant level of noise in the dark areas of the image.

In other words, the values that the noise can take are on Gaussian-distribution. 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

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

Where x is a length-n vector, K is 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.

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

Where vi^{l} represents the phase noise component, z denotes amplitude component, ρ denotes the coherence and na1 is the zer0 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

Using a Poisson distribution the Poisson Integer Generator block generates random integers. 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.

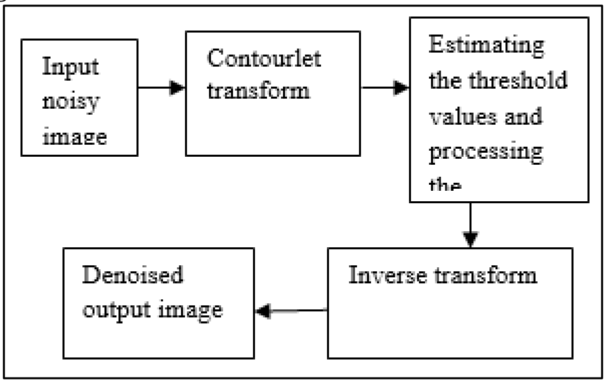


Fig. 1: Block Diagram of Image Denoising By Using Contourlet Transform

A. Contourlet Transform

Decomposed image coefficients are produced for the noisy image by applying contourlet transform. 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. These point discontinuities are linked into linear structures using directional filter bank (DFB). Similar to wavelet, contourlet decomposes the image into different scales. Contourlet decomposes each scale into arbitrarily power of two's number of directions as given by,

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

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. The number of directional filter bank decomposition levels are represented as l at different scales j. Thus the output of contourlet transform is the decomposed image coefficients.

B. Thresholding Functions

Image is decomposed in to 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,

1) Bayes Shrink
2) Visu Shrink
3) New threshold function

1) Bayes Shrink

The aim of this method is to minimize the Bayesian risk, and hence it is known as Bayes Shrink.The Bayes threshold is defined as

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

Where σ^2 is the noise variance and σ_s 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.

2) 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,

$$\acute{\sigma} = \frac{median(\{|g_{j-1,}k|; k = 0,1,\dots.2^{j-1}-1\})}{.6745}$$

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

3) New Threshold Function

This function is calculated by,

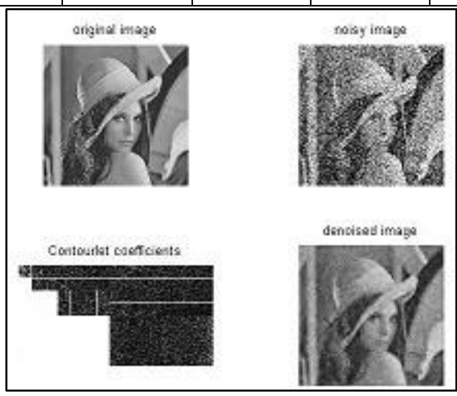
$$\mathbf{newth} = \sqrt{\mathbf{2m \times \log(M)}}$$

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.

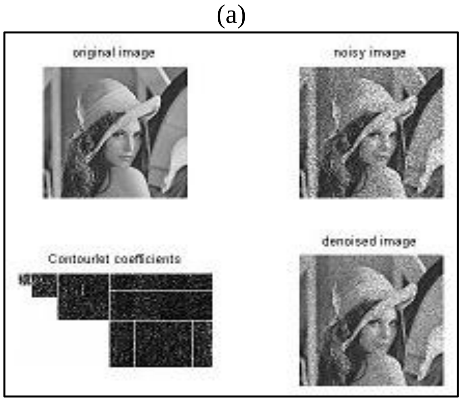
IV. RESULT

In this paper threshold function in spatial domain is calculated. For implementation purpose Lena image is used. Thus the proposed algorithm is used to preserve the image details such as contrast, brightness, edges and gray level n 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'.

METHODS	DENOISED IMAGE PSNR			
	Gaussian noise	Speckle noise	Poisson noise	Salt& pepper noise
Bayes shrink	17.7620	18.5983	47.3452	13.1295
Visu shrink	18.1030	19.5674	29.4532	15.3674
New threshold	16.0123	15.9635	16.7647	13.1476

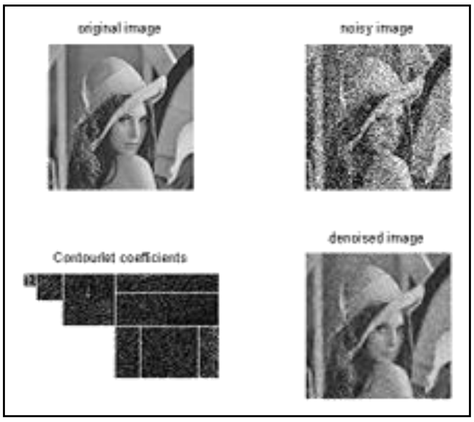


(a)

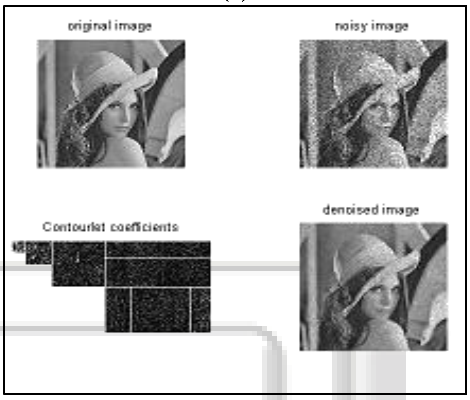


(b)

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

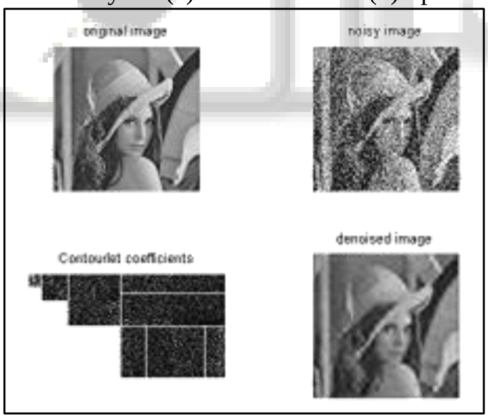


(a)

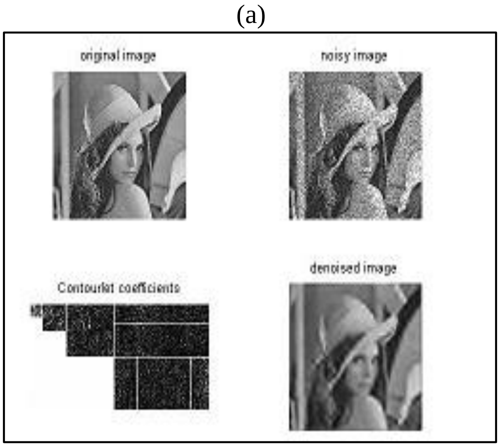


(b)

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



(a)



(b)

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

V. CONCLUSION

The proposed contourlet technique is computationally faster and gives better results compared to the existing wavelet technique. Some aspects that were analyzed in this paper are 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. The proposed method is highly suitable 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 this technique for medical images as well as texture images to get image denoising with improved performance parameter.

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