Comparative Analysis of Wavelet and Contourlet Transform in Digital Image Processing

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***Abstract*— Digital Image Processing is an interesting and broad field for research. Many research been done in this field and many more are running. In this work we have done image denoising using Wavelet transform and Contourlet transform and compare the results. Contourlet transform use directional filter for denoising. In this work we observe that results for Contourlet transform is better than Wavelet transform.**

***Keywords*— Directional Filter bank (DFB), Laplacian Pyramid(LP), SVD, Directional subband.**

I. INTRODUCTION

In digital Image processing, we study the basic process of image, a digital image contains large amounts of information that require much storage capacity for storing an image, required large transmission bandwidths and long transmission times for transmission. Hence, it is beneficial in this to compress the original image by loading only the necessary information needed to recreate the image. An image can be held off as a matrix of pixel values. In order to reduce the image, delicacy must be exploited, for example arena where there is tiny or no variation between pixel values. Therefore pictures having large amount of uniform color will have large delicacy. Wavelet and contourlet analysis is based on the division of information into approximation sub signals [5][6]. The approximation sub signal shows the general trend of pixels, and three sub signals that shows the diagonal, vertical and horizontal variations in the image. If these specifics are negligible then they can be set to 0 without changing the original image. The pixel significance which specifics are considered small enough to be set to 0 is known as the threshold. The larger the number of zeros the larger the compression that can be found. The amount of information contained by an image subsequently compression and decompression is recognized as the energy contained.

II. IMAGE PROCESSING

Noise

Noise is nothing but the unwanted signal. During the transmission some unwanted signal mixes with the original picture and create noisy signal.

Type of noises

However, there are three standard noise models which model well the types of noise encountered in most images: additive, multiplicative, and impulse noise. Additive noise is a type of noise that added with the original signal, multiplicative noise is a type of noise that multiply with original signal.

Denoising techniques

All digital images have certain amount of noise, different types of noise according their own characteristics are inherent in images in dissimilar behaviors. These noises may be internal or external depend on the condition, some basic noise are Gaussian noise, Impulsive noise and speckle noise etc. Gaussian noise also known as amplifier noise, this noise depend on the color, according the variety of colors effect of this noise is less or more, for digital color camera, blue colour are more amplified, therefore blue colour channel generate more noise than the other colour channels [2]. Impulsive Noise, this noise also called spike noise, this noise is usually available on images, it consists according the analysis of white and black pixels of image, it is also depend on the brightness of the image (bright and dark regions). Speckle Noise, Speckle noise is known as granular noise that commonly exists in radar signal, in the analysis and synthesis of active radar images, this noise increase the mean grey level of a image. It is produce due to the coherent processing of backscattered signals. Noise analysis, in the methods of image denoising, it is required to restore the original image, image restoration methods developed by immense construction of digital images and pictures of different types. A digital image is consisting as a matrix of grey-level or color standards. Digital image may be one dimensional and multidimensional according their conditions, in movies the image matrix has three dimensional, in grey level image are two dimensional. All denoising methods based on the analysis of filtering parameter [8], this parameter measured the degree of filtering in the processed image, filtering parameter depend on the estimation of noise variance. In this research multi resolution methods of image denoising are developed for recover the original image at the receiver, quality of denoise image compare for the value of PSNR for better quality.

III. RESEARCH METHODOLOGY

Types of Wavelet Transform

Basically two types of wavelet transform are discuss in this section, these transform are continuous wavelet transform and discrete wavelet transform.

Continuous Wavelet Transform

To overcome the limitation and resolution problem of short time Fourier transforms continuous wavelet transform was established. Continuous wavelet transform is defined according to the relationship as [11].

$$CWT_x\Psi(\tau,s) = \Psi_x\Psi(\tau,s)$$

$$=1/\sqrt{s}\int x(t)\Psi^*(t-\tau \; f \; s)\, dt$$

Discrete Wavelet Transform

It is practically impossible to evaluate a signal using all wavelet coefficients [15], so any one phenomenon which is satisfactory to select a discrete subset of the upper half plane to be able to recreate a signal from the corresponding wavelet coefficients will be taken as consideration. The relative discrete subclass of the half plane consists of all the points (a^m, $na^m b$) with (m, n) in ‘Z’. The corresponding baby wavelets are now given as [16].

$$\Psi_{m,n}(t) = a^{-m/2}\Psi\left(a^{-m}t-nb\right)$$

A necessary form for the restoration of any signal ‘x’ of a finite energy by the formula:

$$X(t) = \sum\sum\left(x,\ \Psi_{m,n}\right).\ \Psi_{m,n}(t)\ \ where\ m,n \in z$$

From Wavelet to Contourlet

As plot in the presentation, in spite of the fact that the DWTs have set up a great notoriety as an apparatus for scientific examination and flag preparing, it has the detriment of poor directionality, which has undermined its utilization in numerous applications. Noteworthy advance in the improvement of directional wavelets has been made as of late. The perplexing wavelet change is one approach to enhance directional selectivity. Be that as it may, the unpredictable wavelet trans-frame has not been broadly utilized as a part of the past, since it is hard to outline complex wavelets with flawless reproduction properties and great channel attributes. One well known procedure is the double tree complex wavelet change proposed by Kingsbury, which included (nearly) consummate reproduction to the next appealing properties of complex wavelets, including rough move invariance, six directional selectivities, constrained repetition and proficient O 1 N 2 calculation.[4]

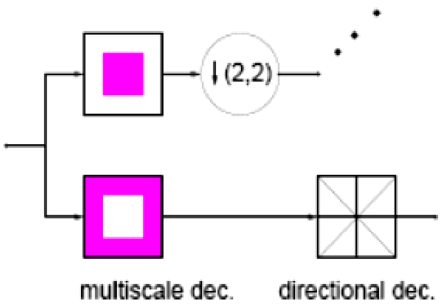

Fig. 3.1 Block diagram of CT (Contour-let transform)

CT (Contour-let Transform) With SVD

The CT (Contour-let Transform) (CT) is another picture differentiate upgrade conspire. CT is more successful in speaking to smooth forms in various headings of a picture than the Discrete Wavelet Transform. The CT can be separated into two fundamental strides: Laplacian Pyramid (LP) deterioration and Directional Filter Banks (DFB) disintegration.

The approach in this change begins with the discrete area development and after that inadequate extension in the constant space. The fundamental contrast amongst Contour-let and different changes are that, in this new change Laplacian pyramid alongside the Directional Filter Banks are utilized. Accordingly, this recognizes the edge discontinuities, as well as believers every one of these discontinuities into constant area. A picture is initially decayed into low pass picture and band pass picture by LP deterioration. Each band pass picture is further deteriorated by DFB step. A DFB is intended to catch the high recurrence content like smooth shapes and directional edges as shown in fig3.2. In Contour-let, the quantity of directional sub bands at every level is set to 2n where n is a positive whole number.

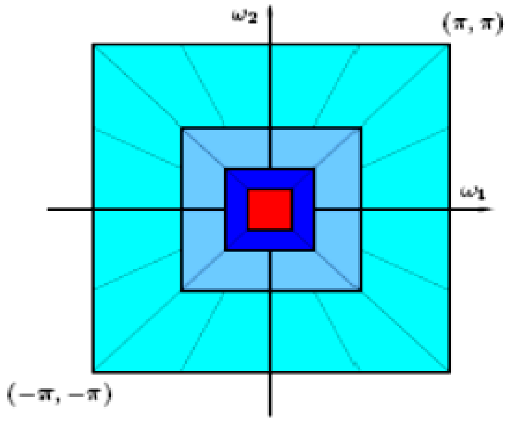

Fig.3.2 Frequency partition of Directional Filter Banks

IV. RESULT ANALYSIS

In the previous section we have discussed about the research methodology, in this section we will validate the expected result. We have used different images (“lena”, “Barbara”) for experiments and results shown in tabular form.

Fig 4.1 Lena.jpg original, noisy and denoised image for σ=0.1 by wavelet transform

Fig 4.2 Lena.jpg original, noisy and denoised image for σ=0.1 by contourlet transform

Table 4.1 Wavelet & contourlet comparison of Lena .jpg for N=512 and standard deviation 0.1

Transform	Input Image	Value of N	Standard deviation (σ)	RMSE	PSNR	SSIM
DWT	Lena.jpg	512	.1	8.00	30.10	0.993
Contourlet	Lena.jpg	512	.1	6.3759	32.04	0.997

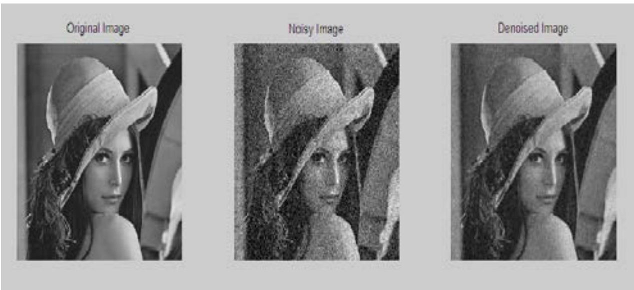

Fig 4.3 Lena.jpg original, noisy and denoised image for σ=0.25 by wavelet transform

Fig 4.4 Lena.jpg original, noisy and denoised image for σ=0.25 by contourlet transform

Table 4.2 Wavelet & contourlet comparison of Lena .jpg for N=512 and standard deviation .25

Transform	Input Image	Value of N	Standard deviation (σ)	RMSE	PSNR	SSIM
DWT	Lena.jpg	512	.25	11.20	26.00	0.9889
Contourlet	Lena.jpg	512	.25	9.92	28.19	0.9937

Fig 4.5 Barbara.jpg original, noisy and denoised image for σ=0.1 by wavelet transform

Fig 4.6 Barbara.jpg original, noisy and denoised image for σ=0.1 by contourlet transform

Table 4.3 Wavelet & contourlet comparison of Barbara.jpg for N=512 and standard deviation .1

Transform	Input Image	Value of N	Standard deviation(σ)	RMSE	PSNR	SSIM
DWT	barbara.jpg	512	.1	15.70	24.30	0.9880
Contourlet	barbara.jpg	512	.1	14.20	25.08	0.9890

Fig 4.7 Barbara.jpg original, noisy and denoised image for σ=0.25 by wavelet transform

Fig 4.8 Barbara.jpg original, noisy and denoised image for σ=0.25 by contourlet transform

Table 4.4Wavelet & contourlet comparison of Barbara.jpg for N=512 and standard deviation .25

Transform	Input Image	Value of N	Standard deviation(σ)	RMSE	PSNR	SSIM
DWT	barbara.jpg	512	.25	18.92	21.62	0.9848
Contourlet	barbara.jpg	512	.25	15.03	24.58	0.9865

V. CONCLUSION

In this work we have implemented Discrete Wavelet Transform and Contourlet Transform for image denoising and compare result. In this implementation we observe that results for Contourlet are better than Wavelet. In this implementation we have used different images (“lena”, “Barbara”).

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