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# Image Denoising Using Discrete Wavelet Transform

**Bobby Lukose**, Associate Professor,
Pg & Research Department Of Computer Science,
Hindusthan College Of Arts And Science,
Coimbatore, India
bobbylukose74@gmail.com

**P.Roobini**, Mphil Scholar,
Pg & Research Department Of Computer Science,
Hindusthan College Of Arts And Science,
Coimbatore, India
ruby.dharu@Gmail.Com

## ABSTRACT

Image Restoration is one of the major tasks in Image Processing which is used to recover or restore the original image when it is subjected to some sort of damage. There are a lot of Traditional methods which deal with the restoration of images. In this work, we propose a work which reduces the blocking artifacts to a great extent and allow the Ridglet transform along with the Radon transform to act on the image. Then the Discrete Wavelet Transform is applied to remove the artifacts. A new method of Mean Square Difference of Slope (MSDS) which involves the Horizontal, Vertical and Diagonal components of the image is used for effective restoration of the image. From the experimental results, it is evident that the new method is more effective in image restoration compared to that of the application of Discrete Cosine Transform over the image.

**Key words** : Ridgelet Transform, Radon Transform, Image restoration, blocking artifact reduction

## 1. INTRODUCTION

Image restoration refers to the process of recovering the original signal from its degraded form. Often, the terms Image Enhancement and Image Restoration are confused with one another. Image Enhancement is designed to emphasize the features of the image that make the image more pleasing to the observer, but not necessarily to produce realistic data from a scientific point of view. Image enhancement techniques provided by "Imaging packages" use no a priori model of the process that created the image. With image enhancement noise can be effectively be removed by sacrificing some resolution, but this is not acceptable in many applications. Recovering an Image object requires much advanced Image Processing Techniques. The main objective of image restoration is to remove defects which degrade an image. Degradation comes in many forms such as motion-blurs, noise etc. In cases like motion blur, it is possible to come up with a very good estimate of the actual blurring function and remove the blur to restore the original image. In cases where the image is corrupted by noise, the best approach is to compensate for the degradation it caused. In this work, we introduce and implement several of the methods used in the image processing world to restore images.

Ridgelet transform is a time-frequency and multi-resolution analysis tool which proves to be more powerful than any other wavelet analysis in the signal and image processing domain, especially in image restoration. Due to the strain to impart the types of noise formed by optical imaging equipment, this work use independent component analysis to separate the independent signals from overlapping signals. Ridgelet transform is applied to decompose overlapping signals. We introduce the Mean Square Difference of Slope filter to reduce the blocking artifacts and then apply the Ridgelet Transform to reconstruct the image to obtain a restoration image. It is provable that the efficiency of our method is better than other traditional filtering approaches.

## 2.RELATED WORKS

Hunt and Ktiblerb [l] presented that the restoration of a multichannel image is equivalent to the independent restoration of individual channels after assuming that the signal autocorrelation is separable. The multichannel minimum mean-square error (MMSE) restoration scheme and the Wiener filtering algorithm were proposed by Galatsanos and Chin [2]. By using both inter- and intra-channel correlations of the signal, the result is comparatively efficient. This algorithm does not require any separability assumption. Still, it assumes that the image signal is spatially motionless and the blur is space-invariant. It has been commonly recognized that the stationary assumption is restrictive and unrealistic. To remove this necessity, Galatsanos and Chin [3] developed a Kalman filtering algorithm for multichannel image restoration, which provides the possibility of handling space-variant degradation at the cost of complex implementation.

Later on, the various reduction methods were used for restoration of the image. Zakhor's CM-based method [4] smoothes all the pixels in a coded image by using a 5 × 5 space-invariant filter. In Yang's POCS-based method [5], a space-invariant filter, which provides the weighted sum of the two pixels as output, is applied at two adjacent pixels of each block boundary; the filtering is projections onto two convex sets that minimize the sum of the differences between horizontally adjacent block boundaries and that between vertically adjacent block boundaries. In Paek's POCS-based method [6], a space-variant filter is used in which a stop band in the 1-D DCT domain varies with the signal.

## 3. PROPOSED SOLUTION

### 3.1 Application of Gaussian Noise

For a 2-dimensional image, we initially apply the Gaussian Noise, whose noise density follows a Gaussian Normal Distribution $G(\bar{x},\sigma)$ defined by the mean $\bar{x}$ and standard deviation $\sigma$. Usually, this process is done to evaluate the filtering, segmentation and restoration algorithms. For each input voxel $v_{in}$, a sample is taken from the normal variate distribution $G(d)$ and is added to the image.

$$v_{out} = v_{in} + \bar{x} + \sigma G(d) \qquad (1)$$

For some mean noise $\bar{x}$ and standard deviation $\sigma$. $d$ is an arbitrary number to start the pseudo random sequence.

Let the outcome of the Gaussian Noise application over the image be $f(n)$ which is considered as a bivariate function since the image is two dimensional.

### 3.2 Application of Finite Ridgelet Transform.

The Finite Ridgelet Transform is an invertible and non-redundant algorithm which acts fast to create orthonormal bases for the images. The Ridgelet Transform is represented as

$$CRT_f(a,b,\theta) = \int_{R^2} \psi_{a,b,\theta}(n) f(n) dn \qquad (2)$$

where the ridgelets $x\cos\theta + y\sin\theta =$ constant in 2-D and the wavelet type function in $\psi(n)$ in 1-D is denoted as

$$\psi_{a,b,\theta}(x) = \sqrt{a}\psi((x\cos\theta + y\sin\theta - b)/a) \qquad (3)$$

In 2-D, the points and lines are related through the Radon Transform. Thus it is associated to the Wavelet Transform. The Radon Transform is denoted as

$$R_f(\theta,t) = \int_{R^2} f(x,y)\delta(x\cos\theta + y\sin\theta - t)dxdy \qquad (4)$$

Where R denotes the real line.

The Ridgelet transform is the application of 1-D wavelet transform to the slices of the Radon Transform and is defined as

$$CRT_f(a,b,\theta) = \int_R \psi_{a,b}(t) R_f(\theta,t) dt \qquad (5)$$

The finite Radon Transform is redundant and not orthogonal. The redundancy can be reduced by applying 1-D Discrete Wavelet Transform on the projections of the Finite Radon Transform. Let us assume that there are (p+1) 1-D orthonormal transforms on $R^p$, one for each projection $k$ of the finite Radon Transform that have bases as $\{W_m^k : m \in Z_p\} k = 0,1,....p$, where $p \times p$ is the size of the image.

Therefore, the Finite Ridgelet Transform can be indicated as

$$FRIT_f[k,m] = FRAT[k,..], w_m^{(k)}[.] \qquad (6)$$

On application of Discrete Wavelet Transform, decomposition of Radon Transform projections, the non-orthogonality and redundancy of the FRAT is shifted into the scaling co-efficient. When the Discrete Wavelet is taken to the maximum number of levels, it results in orthonormal Finite Ridgelet Transform.

Let the outcome of the input image $f(n)$ be transformed using the Finite Ridgelet Transform to $x(n)$.

### 3.3 Application of Discrete Wavelet Transform.

The pixel or signal $x(n)$ is processed by passing it through a series of filters. First, it is passed through a low pass filter with impulse response $g(n)$ giving the approximation co-efficient.

$$y_{high}[k] = \sum_n x[n].g[2k-n] \qquad (7)$$

The signal is decomposed simultaneously using a high pass filter $h(n)$ as a result of which the detailed co-efficient is obtained.

$$y_{low}[k] = \sum_n x[n].h[2k-n] \qquad (8)$$

Since an image is a 2-dimensional signal, it is represented as $x(N,M)$. Each row is filtered and sampled to obtain two $(N, M/2)$ images. Then each column is filtered and down sampled to obtain four $(N/2, M/2)$ images. The resultant is one dimensional scaling function $\varphi(x,y)$ and two dimensional wavelet functions $\psi^H(x,y), \psi^V(x,y) and \psi^D(x,y)$ which represent the sub bands of the image.

Now, we use the concept of Mean Square Difference of Slope (MSDS) to remove the artifacts. We have two MSDS namely $MSDS_1$ and $MSDS_2$ of which $MSDS_1$ is comprised of vertical and horizontal blocks.

$$MSDS_1 = \varepsilon(\psi^H(x,y)) + \varepsilon(\psi^V(x,y)) = \varepsilon_H + \varepsilon_V \qquad (9)$$

Similary, the $MSDS_2$ involves the usage of the diagonal components.

$$MSDS_2 = \varepsilon(\psi^D(x,y)) = \varepsilon_D \qquad (10)$$

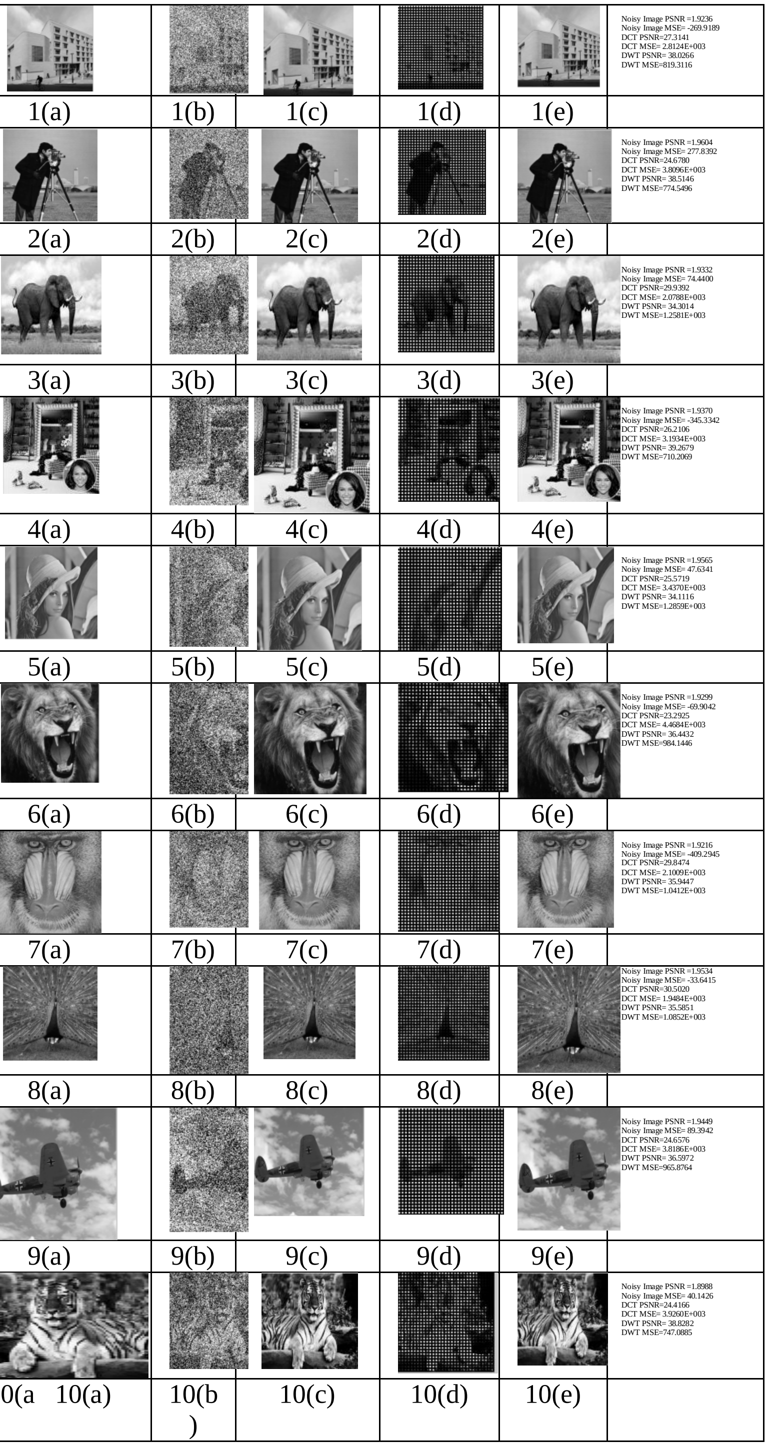
The intensity slopes of all adjacent blocks is

$$MSDS_t = MSDS_1 + MSDS_2 \qquad (11)$$

On global minimization of $MSDS_t$, we can reduce the blocking artifacts. On de-quantization and application of Inverse Discrete Transform, the original image is restored.

## 4. EXPERIMENTAL RESULTS

To evaluate the performance of the proposed method, computer simulation has been performed with various images.



| | | | | | |
|---|---|---|---|---|---|
| 1(a) | 1(b) | 1(c) | 1(d) | 1(e) | Noisy Image PSNR =1.9236<br>Noisy Image MSE= -269.9189<br>DCT PSNR=27.3141<br>DCT MSE= 2.8124E+003<br>DWT PSNR= 38.0266<br>DWT MSE=819.3116 |
| 2(a) | 2(b) | 2(c) | 2(d) | 2(e) | Noisy Image PSNR =1.9604<br>Noisy Image MSE= 277.8392<br>DCT PSNR=24.6780<br>DCT MSE= 3.8096E+003<br>DWT PSNR= 38.5146<br>DWT MSE=774.5496 |
| 3(a) | 3(b) | 3(c) | 3(d) | 3(e) | Noisy Image PSNR =1.9332<br>Noisy Image MSE= 74.4400<br>DCT PSNR=29.9392<br>DCT MSE= 2.0788E+003<br>DWT PSNR= 34.3014<br>DWT MSE=1.2581E+003 |
| 4(a) | 4(b) | 4(c) | 4(d) | 4(e) | Noisy Image PSNR =1.9370<br>Noisy Image MSE= -345.3342<br>DCT PSNR=26.2106<br>DCT MSE= 3.1934E+003<br>DWT PSNR= 39.2679<br>DWT MSE=710.2069 |
| 5(a) | 5(b) | 5(c) | 5(d) | 5(e) | Noisy Image PSNR =1.9565<br>Noisy Image MSE= 47.6341<br>DCT PSNR=25.5719<br>DCT MSE= 3.4370E+003<br>DWT PSNR= 34.1116<br>DWT MSE=1.2859E+003 |
| 6(a) | 6(b) | 6(c) | 6(d) | 6(e) | Noisy Image PSNR =1.9299<br>Noisy Image MSE= -69.9042<br>DCT PSNR=23.2925<br>DCT MSE= 4.4684E+003<br>DWT PSNR= 36.4432<br>DWT MSE=984.1446 |
| 7(a) | 7(b) | 7(c) | 7(d) | 7(e) | Noisy Image PSNR =1.9216<br>Noisy Image MSE= -409.2945<br>DCT PSNR=29.8474<br>DCT MSE= 2.1009E+003<br>DWT PSNR= 35.9447<br>DWT MSE=1.0412E+003 |
| 8(a) | 8(b) | 8(c) | 8(d) | 8(e) | Noisy Image PSNR =1.9534<br>Noisy Image MSE= -33.6415<br>DCT PSNR=30.5020<br>DCT MSE= 1.9484E+003<br>DWT PSNR= 35.5851<br>DWT MSE=1.0852E+003 |
| 9(a) | 9(b) | 9(c) | 9(d) | 9(e) | Noisy Image PSNR =1.9449<br>Noisy Image MSE= 89.3942<br>DCT PSNR=24.6576<br>DCT MSE= 3.8186E+003<br>DWT PSNR= 36.5972<br>DWT MSE=965.8764 |
| 0(a 10(a) | 10(b ) | 10(c) | 10(d) | 10(e) | Noisy Image PSNR =1.8988<br>Noisy Image MSE= 40.1426<br>DCT PSNR=24.4166<br>DCT MSE= 3.9260E+003<br>DWT PSNR= 38.8282<br>DWT MSE=747.0885 |

Figure 1-10 (a)Original Image, (b) Noisy Image, (c) DCT Restored Image, (d) DWT image, (e) DWT Restored Image.

Figure 1-10 compares the Image Restoration Technique using Discrete Cosine Transform with that restored using the application of the combination of Ridgelet Transform and Discrete Wavelet Transform.

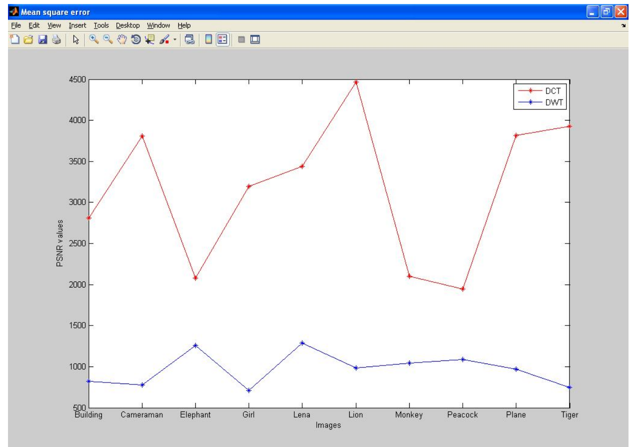



Figure 11. Comparison of Mean Square Error (DCT vs DWT)

The comparison of the image restoration using Discrete Wavelet Transform against Discrete Cosine Transform is shown in Figure 11. From the compariosn chart, it is clearly visualised that the Mean Square Error of DCT is much higher than that of DWT. Hence, it is evident that DWT is better than DCT.

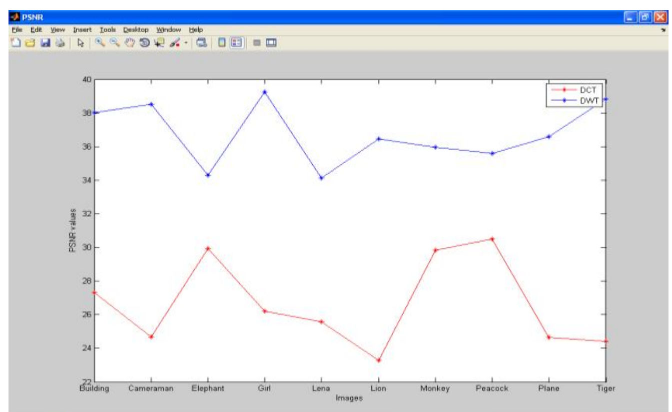



Figure 12. Peak Signal to Noise Ratio (DWT vs DCT)

Figure 12 clearly visualizes the variation in the Peak Signal to Noise Ratio (PSNR) between the Discrete Cosine Transform and the Discrete Wavelet Transform. The more is the PSNR value, the much efficient is the restoration algorithm. Here, it is found that the PSNR value is more for the DWT than DCT in each case. Hence it is proved that the DWT is better than the DCT.

## 5. CONCLUSION

The proposed algorithm introduces the novel and enhanced form of DWT which involves all neighboring blocks, including the diagonally located neighboring blocks using MSDS. This work presents not only a method for the removal of the blocking artifacts, but also increases the PSNR thereby provides a much efficient and non-redundant method of restoration.

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