IMAGE DENOISING USING DUALTREE COMPLEX WAVELET TRANSFORM BASED THRESHOLDING METHODS

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Abstract: Image denoising is one important objective in image processing and its applications. Image denoising methods are used to eliminate the noise from images without changing its characteristics and content. In all image processing applications, images are contaminated with the processing noise or channel noise. This contamination results in image quality degradation in both objective and subjective manner. To overcome this, image denoising approaches were suggested. In the advancement of image denoising in transform domain, dual tree complex wavelet transformation is observed to be an optimal upcoming solution. The advantage of processing the image in real and imaginary domain simultaneously gives the advantage of noise minimization in two domains. This complex wavelet transform process on two domains and perform the operation of denoising based on a thresholding process. This paper represents an comparative analysis of applying different threshold methods for image denoising on different images under variant noise condition using 2D dual tree complex wavelet transform and 2D discrete wavelet transform in terms of PSNR, MSE.

Index Terms - Dual Tree Complex wavelet Transform, Discrete wavelet Transform, Image Denoising, Threshold, Sure Shrink, Neigh Shrink, Block Shrink.

I. Introduction

Images are generally contaminated with noise during acquisition, transmission, or retrieval from storage media. Current application in image processing has lead to two principal needs: enhancement of picture information for human interpretation; and processing of image data effectively for storage, transmission, and representation. In various applications the transformation process is applied for its finer resolution details to improve the efficiency. During Transformation one object from a given domain is translated to another to represent some important implicit information which can be used for its recognition. The Transformations do not modify content of image/signal [1].

The discrete wavelet transform (DWT) is mostly used Transform Technique for a large scope of signal and image processing problems. Wavelet denoising techniques remove the noise present in the image without changing its characteristics, regardless of its frequency content. De-noising of natural images corrupted by noise using wavelet techniques is very effective because of its ability to capture the energy of a signal in few energy transform coefficients known as energy compaction. But it has disadvantages of shift-sensitivity and no phase information[2]. To eliminate these problems[3] analytic filters are used by complex wavelet transform(CWT). These filters form Hilbert Transform (HT) pair which provide real and imaginary parts for magnitude-phase representation [4] also secure shift invariance and no aliasing. Kingsbury in 1998 introduced the dual - tree complex wavelet transform(DTCWT) in which perfect reconstruction also achieved along with shift invariance, good directional selectivity and limited redundancy of CWT[5]. In denoising process based on wavelet transform or based on complex wavelet transform techniques threshold of wavelet coefficients plays an important role. A Proper selection of threshold leads to higher denoising performance [6]. There are two of threshold approach have been observed in DTCWT denoising [7,8], the soft threshold and the hard threshold approach. Even though different literature illustrates the application of this thresholding approach for denoising, some other different shrinkage methods also available for more efficient denoising. This paper is structured as: first discussed about dual tree complex wavelet transform in section 2, next different wavelet thresholding methods for image denoising in third section and in section 4 results are presented.

II. DUAL TREE COMPLEX WAVELET TRANSFORM

The limitations of wavelet transform listed are overcome in complex wavelet domain.

- *Oscillations* of the pixel values at a singularity (at zero crossings).

- *Shift variant*, where the effect on output is dominantly observed with a small change in input.
- *Aliasing*, observed due to the sampling process in the filtration operation.
- *Lack of directional selectivity*, the variation in the directions eg. +15 and -15 degree orientation variation could not be explored[9]

Dual Tree Complex Wavelet transform is an excellent analytic wavelet transform implemented by Kingsbury. This DTCWT design idea is simple that it has two real DWTs in it. The first DWT provides the real part and the second DWT provides imaginary part of the transform as shown in Fig 1. Real DWT structure is considered as Tree1 and imaginary DWT considered as Tree 2 so total transform is referred as Dual Tree Complex Wavelet Transform. These two trees are orthonormal or Biorthogonal with each other. Each of these real wavelet transforms satisfies the perfect reconstruction conditions. To make overall transform approximately analytic the two sets of filters are jointly designed. In the upper filter bank the low pass/high pass filter pair is represented by $h_0\,(n)$, $h_1\,(n)$ respectively, and in lower filter bank low pass/high pass filter pair is denoted by $g_0\;(n)$, g_1(n) respectively[10].

To extend this transform to more than one dimensional signals then filter bank is applied in all dimensions separably. A coefficient redundancy of 2^m:1 appear in DTCWT. To obtain a 2D transform, the 1D transform is first applied across all the rows and then across all the columns at each decomposition level. 2D DT-CWT gives six directional sub bands per level to represent the details of an image in $\pm 15°$, $\pm 45°$, and $\pm 75°$directions with 4:1 redundancy.

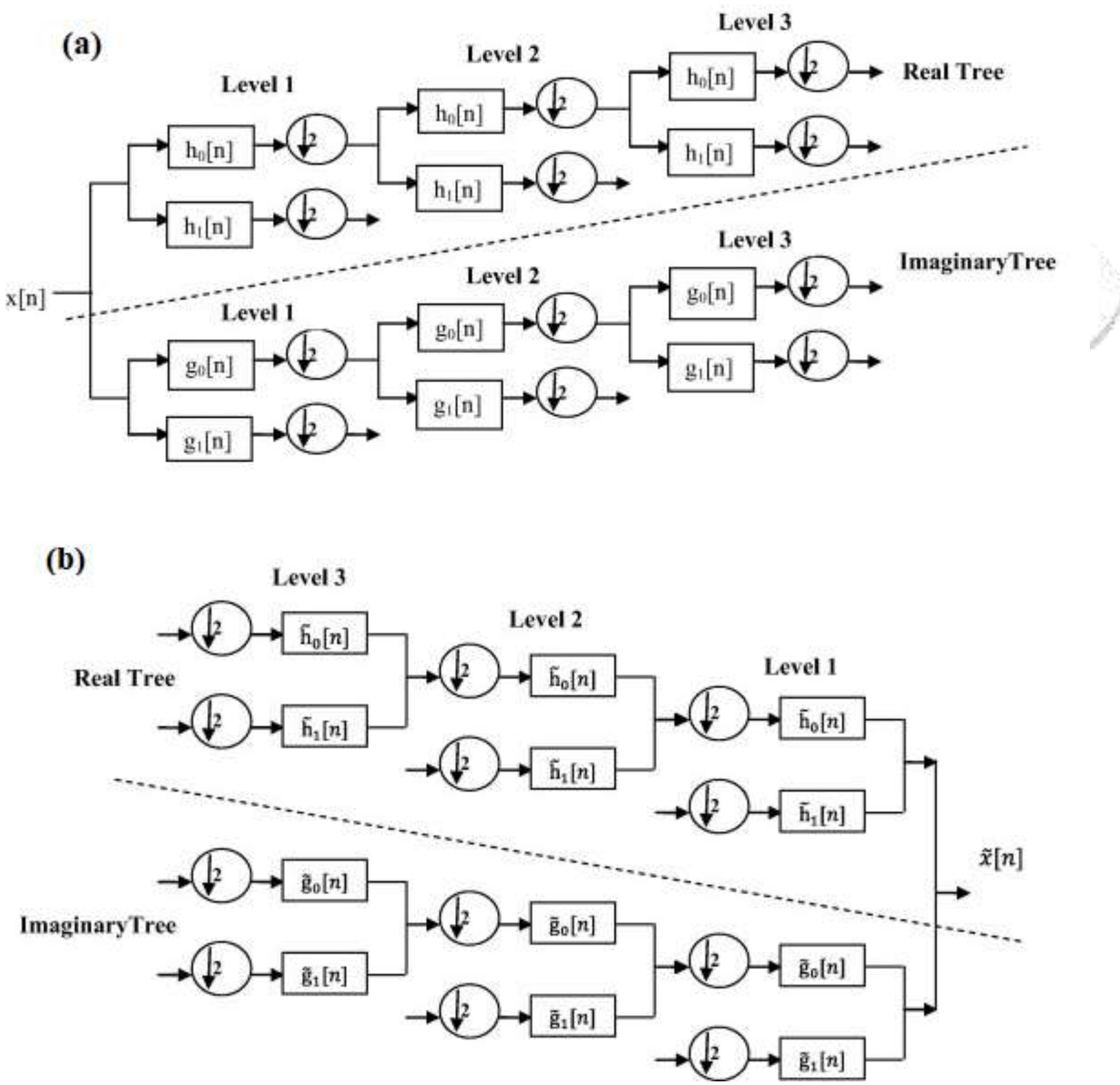


Fig 1: (a) Decomposition Structure of 1D DTCWT , (b) Reconstruction Structure of 1D DTCWT

III. WAVELET THRESHOLDING AND WAVELET BASED DENOISING

Image denoising methods eliminates unwanted noise present in the images without changing their important features like preserving edges, sharp areas etc. regardless of its frequency content. General frame work for image denoising using wavelet transform is as follows and also shown in Fig 2:

Step 1: Get the input image and add any type of noise to it.
Step 2: Apply Dual Tree Complex Wavelet Transform and then decompose to different subbands of Wavelet Coefficients.
Step 3: By using suitable non linear shrinkage function compute threshold value.
Step 4: Apply soft /hard thresholding.
Step 5: Find inverse DTCWT .
Step 6: Then we get the image which is free from noise i.e denoised one.
Step 7: Calculate the output image quality in terms of performance matrices.

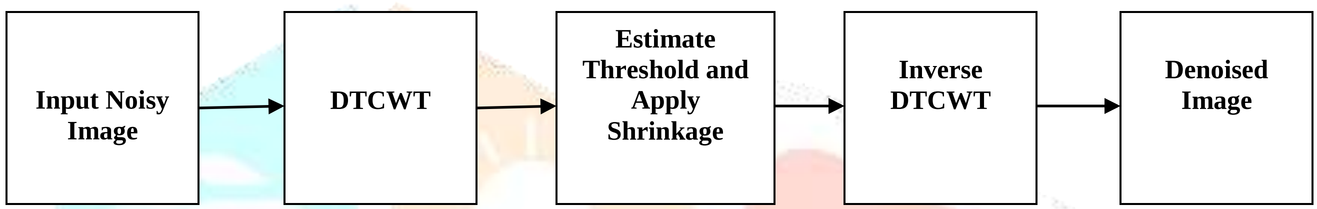


Fig 2: Basic structure of Wavelet Based Image Denoising Algorithm

Denoising is carried out using the thresholding method. The two types of thresholding are the hard and soft thresholding operation. The wavelet band coefficient derived after decomposition is processed for filtration using thresholding, where a given threshold work as a limiting tolerance from a user perspective or compute from the content of processing is taken as a limiting value to denoise the contaminations.

a) Hard Thresholding Method

This threshold operation is operated as hard decision logic. This type of thresholding is hard fixed around a limiting value and directly truncated to 0 when condition satisfies. In this process**,** the wavelet coefficients below the threshold value λ are treated zero and other are not changed. Mathematically it is represented as [11]:

$$\widehat{M} = \begin{cases} X, & if \ |X| \geq \lambda \\ 0, & otherwise \end{cases} \qquad (1)$$

Where the unchanged noisy coefficients are denoted by X , the threshold value is represented by λ , and the estimated coefficients are represented by $\widehat{M}$.

b) Soft Thresholding Method

Hard threshold result in ringing / Gibbs effect. To overcome this, another threshold known as soft threshold method was suggested. In this method the wavelet coefficients are shrunk towards zero by an offset λ. This computation is represented as :

$$\widehat{M} = \begin{cases} X - \lambda, & if \ X \geq \lambda \\ X + \lambda, & if \ X < -\lambda \\ 0, & otherwise \end{cases} \qquad (2)$$

This method has some artifacts like it removes the discontinuity, but maintains the smoothness. These two threshold approaches are limited by the usage of noise effect. As the practical approach of image coding has a dynamic noise effect, a fixed threshold approach is limited. It is required to have a optimal threshold value derived analytically under variant noise effect and variance value to explore the relation of noise effect over threshold selection.

3.1 WAVELET-THRESHOLDING METHODS

Choosing optimal threshold is a one important step in the process of denoising. If we take large threshold then noisy components may not eliminated. If we take small threshold value then image details may loss resulting in much smoothed images. So threshold must be chosen properly.

The different types of wavelet Threshold methods are (i) Sure Shrink, (ii) Neigh Shrink, (iii) Block Shrink. These methods vary only in calculation of the threshold value and strategy how it is operated.

3.1.1 SURE SHRINK

In Sure Shrink distinct threshold value is allotted to each sub band of each level of wavelet tree using recursive process. This achieves adaptivity. Along with adaptivity of threshold this sure shrink minimizes the mean squared error.

$$\text{MSE}=\frac{1}{n^2}\sum_{X,Y-1}^{n}(Z(X,Y)-S(X,Y))^2 \qquad (3)$$

Where the estimate of the signal is $Z(X,Y)$, the original signal without noise is $S(X,Y)$ and n is the size of the signal. Sure Shrink eliminates noise by threshold the wavelet coefficients. The Sure Shrink threshold t* is defined as:

$$t^* = \min\left(t, \sigma\sqrt{2\log n}\right) \qquad (4)$$

Where t^* denotes the value that minimizes Stein's Unbiased Risk Estimator, σ is the noise variance and an estimate of the noise level is defined based on the median absolute deviation given by

$$\hat{\sigma} = \frac{\text{median}(\{|g_{j-1,k}|:k=0,1.....2^{j-1}-1\})}{0.6745} \qquad (5)$$

here n is the size of the image. It is smoothness adaptive, which means that if the unknown function contains abrupt changes or boundaries in the image, the reconstructed image also does.

3.1.2 Neigh Shrink

In this the wavelet coefficients are threshold according to the magnitude of the squared sum of all the wavelet coefficients within the neighborhood window as shown in Fig 3. The window sizes may be 3×3, 5×5, 7×7, 9×9 etc [12].

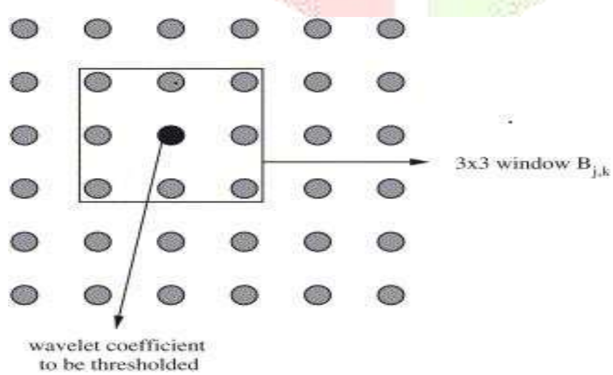


Fig 3: The neighboring window of size 3x3 and the center coefficient is the wavelet coefficient to be shrinked.

The Shrinkage function for Neigh Shrink of any 3x3 window centered at (i, j) is expressed as:

$$\Gamma_{i,j} = \left[1-\frac{T_{i,j}^2}{S_{i,j}^2}\right]+ \qquad (6)$$

where the universal threshold is $T_{i,j}$ and the squared sum of all wavelet coefficient in the given window is .$S_{i,j}$ i.e.,

$$S_{i,j}^2 = \sum_{n=j-1}^{j+1} \sum_{m=i-1}^{i+1} Y_{m,n}^2 \quad (7)$$

Here "+" sign at the end of the formula it means keep the positive values while setting it to zero when it is negative. The estimated center wavelet coefficient $\mathrm{F}_{i,j}$ is then calculated from its noisy counterpart $Y_{i,j}$ as

$$\mathrm{F}_{i,j} = \Gamma_{i,j} \, . \, \mathrm{Y}_{i,j} \quad (8)$$

3.1.3 BLOCK SHRINK

Block Shrink is a data-driven block threshold approach. It uses the pertinence of the neighbor wavelet coefficients by using the block shrinkage. It can decide the optimal block size and threshold for every wavelet sub band by minimizing Stein's unbiased risk estimate (SURE). The block thresholding simultaneously keeps or kills all the coefficients in groups rather than individually.

The block thresholding increases the estimation precision by utilizing the information about the neighbor wavelet coefficients. Unfortunately, the block size and threshold level play important roles in the performance of a block thresholding estimator[13]. The local block thresholding methods mentioned above all have the fixed block size and threshold and same thresholding rule is applied to all resolution levels regardless of the distribution of the wavelet coefficients.

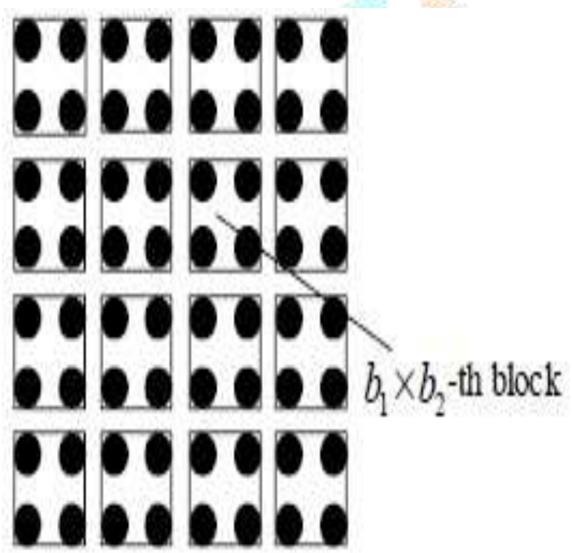


Fig 4: 2x2 Block Partition for a wavelet sub band.

As shown in Fig 4, there are a number of sub bands produced when we perform wavelet decomposition on an image. For every sub band, we need to divide it into a lot of square blocks. Block Shrink can select the optimal block size and threshold for the given sub band by minimizing Stein's unbiased risk estimate.

IV.RESULTS AND ANALYSIS

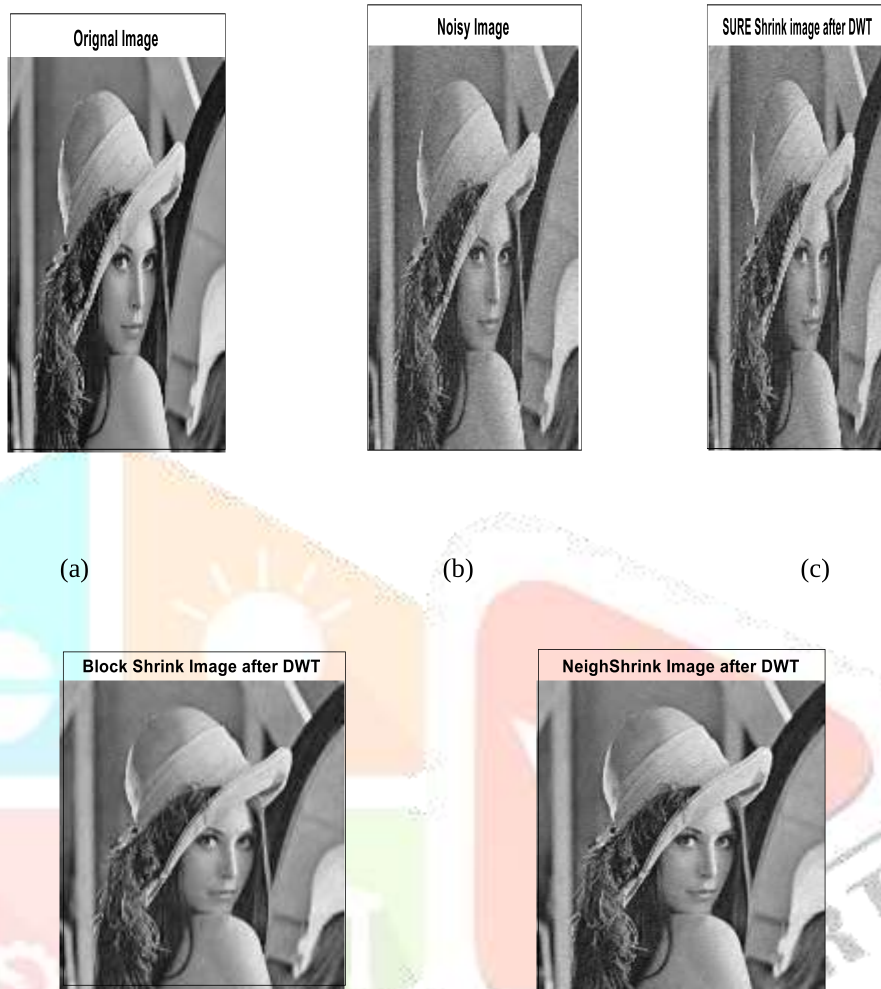
The performance of DWT based denoising and DT- CWT based denoising are compared with Sure shrink, Block shrink, Neigh Shrink threshold selection methods by considering two standard test images Lena , Barbara.

Each test image is of size 256 x 256, the Mat lab results are shown in terms of performance metrics like PSNR and MSE. PSNR finds the ratio between the maximum possible value (power) of a image and the power of distorting noise that affects the quality of its representation where as MSE gives the mean squared error between the denoised and the original image.

PSNR Value is calculated as fallows

$$\mathrm{PSNR} = 10 \log_{10} \left(\frac{255^2}{MSE} \right) dB \quad (9)$$

Results obtained using Mat lab for various images are shown in below figures.



(a) (b) (c)

(d) (e)

Fig 5: DWT based Denoising on Lena Image (a) original Lena Image (b) Lena Image with Gaussian Noise of variance 10 (c) Denoised Image with sure shrink (d) Denoised Image with Block shrink (e) Denoised Image with Neigh shrink

(a)

(b)

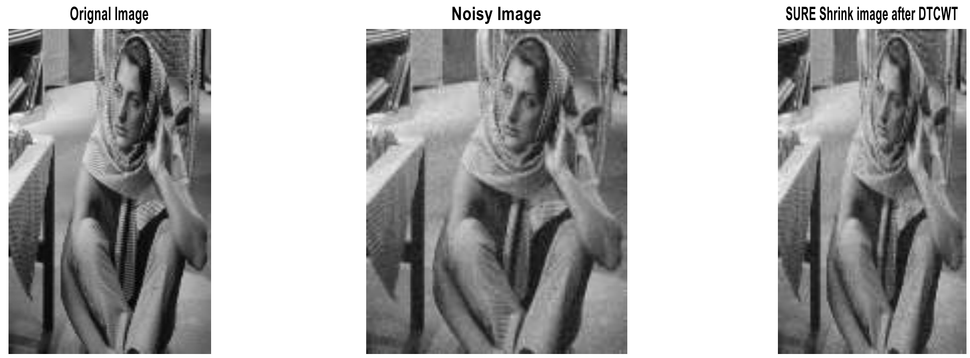
(c)

(d)

(e)

Fig 6: DWT based Denoising on Barbara Image (a) original Barbara Image (b) Barbara Image with Gaussian Noise of variance 10 (c) Denoised Image with sure shrink (d) Denoised Image with Block shrink (e) Denoised Image with Neigh shrink

Fig 7: DT - CWT based Denoising on Lena Image (a) original Lena Image (b) Lena Image with Gaussian Noise of variance 10 (c) Denoised Image with sure shrink (d) Denoised Image with Block shrink (e) Denoised Image with Neigh shrink



(a) (b) (c)

(d) (e)

Fig 8: DT-CWT based Denoising on Barbara Image (a) original Barbara Image (b) Barbara Image with Gaussian Noise of variance 10 (c) Denoised Image with sure shrink (d) Denoised Image with Block shrink (e) Denoised Image with Neigh shrink

Table 1:Denoising results for Lena Image 256x256 with Gaussian noise of variance 10

Thresholding Technique	DWT		DT-CWT	
	PSNR	MSE	PSNR	MSE
Sure Shrink	23.4719	292.3409	23.6522	280.4528
Block Shrink	26.3064	152.2074	26.6286	141.3247
Neigh Shrink	28.3969	94.0559	28.4808	92.2564

Table 2:Denoising results for Barbara Image 256x256 with Gaussian noise of variance 10

Thresholding Technique	DWT		DT-CWT	
	PSNR	MSE	PSNR	MSE
Sure Shrink	26.0663	160.8612	26.1371	158.2579

Block Shrink	**30.5268**	**57.5975**	**30.629**	**56.2548**
Neigh Shrink	**28.4650**	**92.5635**	**28.4809**	**92.2548**

V. Conclusion

The performance of Image denoising based on Threshold selection methods (sure shrink, block shrink, Neigh shrink) is comparatively performed, analyzed with 2d dual tee complex wavelet transform and 2d dual tree wavelet transform. While using DTCWT we have less artifacts and ringing artifacts for reconstruction of image which we observed in terms of PSNR, MSE. The result shows that Neigh shrink performs well in terms of improving visual quality for both smooth and detailed images among the shrinkage methods.

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