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Implementation and Analysis of Image Denoising Technique

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Abstract: In this paper, a comparative analysis is performed on four different thresholding algorithms namely, Average filtering, Visu Shrink, Sure Shrink and Adaptive wavelet packet (WP) thresholding function for image de noising. These algorithms are implemented on different test images and for different amounts of noise intensities added to those images, and their performance are evaluated based on parameters like mean square error (MSE), peak signal-to-noise ratio (PSNR). On the basis of experimentally obtained result the best method is proposed. The proposed method applies multilevel WP decomposition to noisy images to obtain the optimal wavelet basis, using Shannon entropy. It selects an adaptive threshold value which is level and sub band dependent based on analyzing the statistical parameters of sub band coefficients. WP transform (WPT) along with optimal wavelet basis (OWB) for image decomposition is used. Next, a thresholding function is used to shrink small coefficients leading to calculate a modified version of dominant coefficients. The modification is done using optimal linear interpolation between each coefficient and the mean value of the corresponding sub band followed by reconstruction of de noised image from the corrected coefficients.

Keywords: Adaptive wavelet packet thresholding; Optimal wavelet basis (OWB) ; Shannon entropy; Wavelet packet transform(WPT),Discrete wavelet transform(DWT).

I. INTRODUCTION

Image processing is a general term for the wide range of techniques that exist for manipulating
and modifying images in various ways.

- Image Enhancement
- Image Restoration
- Image Reconstruction
- Feature Extraction and Recognition
- Compression

Visual information transmitted in the form of digital images is becoming a major method of communication in the modern age, but the image obtained after transmission is often corrupted with noise. The received image needs processing before it can be used in applications. Image de noising involves the manipulation of the image data to produce a visually high quality image. A very large portion of digital image processing is devoted to image restoration. This includes research in algorithm development and routine goal oriented image processing. Image restoration is the removal or reduction of degradations that are incurred while the image is being obtained. A noise is introduced in the transmission medium due to a noisy channel, errors during the measurement process and during quantization of the data for digital storage. Each element in the imaging chain such as lenses, film, digitizer, etc. contributes to the degradation.

In many applications, image denoising is used to produce a good estimate of the original image from noisy states. Image denoising techniques are necessary to eliminate as much random additive noise as possible while retaining important image features, such as edges and texture.

Wavelet transform, because of its signal representation with a high degree of sparseness and its excellent localization property, has rapidly become an indispensable image processing tool for a variety of applications, including compression, gray-level or color image denoising, object tracking and texture analyzing. In essence, wavelet denoising attempts to remove the noise presented in the image while preserving the image characteristics regardless of its frequency content. It involves the following three steps: 1) linear forward wavelet transform; 2) nonlinear thresholding; and 3) a linear inverse wavelet transform. [1]

II. DISCRETE WAVELET TRANSFORM (DWT)

In numerical analysis and functional analysis, a DWT is any wavelet transform for which the wavelets are discretely sampled. In addition to being an efficient, highly intuitive framework for the representation and storage of multi resolution image, the DWT provides powerful insight into an image's spatial and frequency characteristics. Wavelet series expansion maps a function of continuous variable into a sequence of coefficients. If the function being expanded is a sequence of numbers like samples of a continuous function f(x), the resulting coefficients are called the discrete wavelet transform of f(x).

- **Information content in DWT**

Discrete wavelet transform decomposes the input image into four different wavelet coefficients. The input image is first down sampled row wise by two. Out of these two coefficients one is called average and other is called

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difference. Now these two coefficients again down sampled by 2 but this time column wise. Now each intermediate coefficient yields two final coefficients. In this way after completion of whole process we have four coefficients

1. LPLP - This coefficient contain the low frequency image content in the reduced resolution.
2. LPHP -It contains Horizontal information.
3. HPLP - It contains vertical information.
4. HPHP - It contains diagonal information

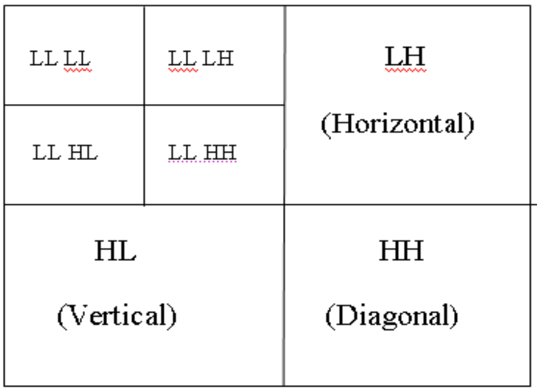

Fig 1. Sub band wise information content

III. WAVELET SHRINKAGE

Threshold process or wavelet shrinkage is main process responsible for de noising which depends on threshold selection and thresholding method. All de noising algorithm first find optimum threshold value. This threshold value can be computed in three ways shown in Fig.1. This value is applied using either of the threshold functions.

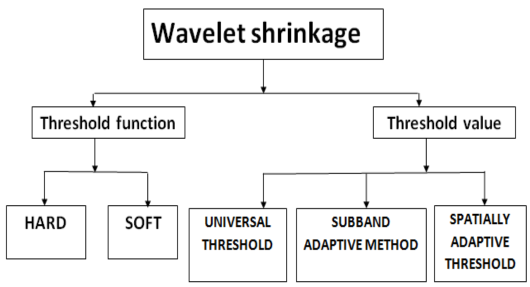

Fig 2. Block diagram of wavelet shrinkage and its different methods

WP and OWB

For the purpose of input image decomposition an OWB is employed because of its dynamic decomposition nature in forming the sub bands.

The threshold value is then picked up based on analyzing the statistical parameters of each subband coefficient. A fast method for extracting OWB, which was introduced by Kaur et al [3], is employed.

In this algorithm, we use Shannon entropy to produce the optimal wavelet basis.

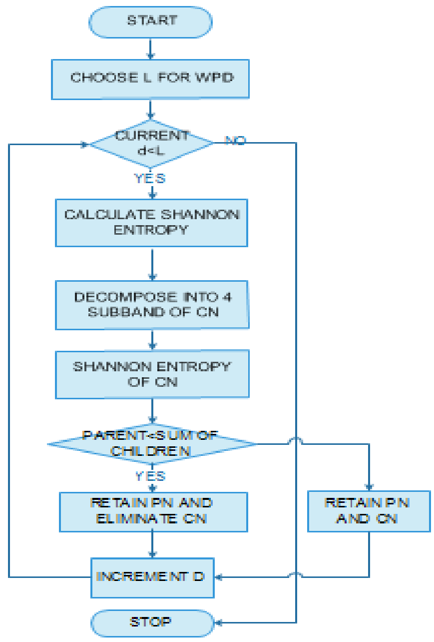

Fig 2 Algorithm of Fast OWB Extraction

WP and OWB:

For the purpose of input image decomposition an OWB is employed because of its dynamic decomposition nature in forming the sub bands. The threshold value is then picked up based on analyzing the statistical parameters of each sub band coefficient. A fast method for extracting OWB, which was introduced by Kaur [3], is employed. In this algorithm, we use Shannon entropy to produce the optimal wavelet basis.

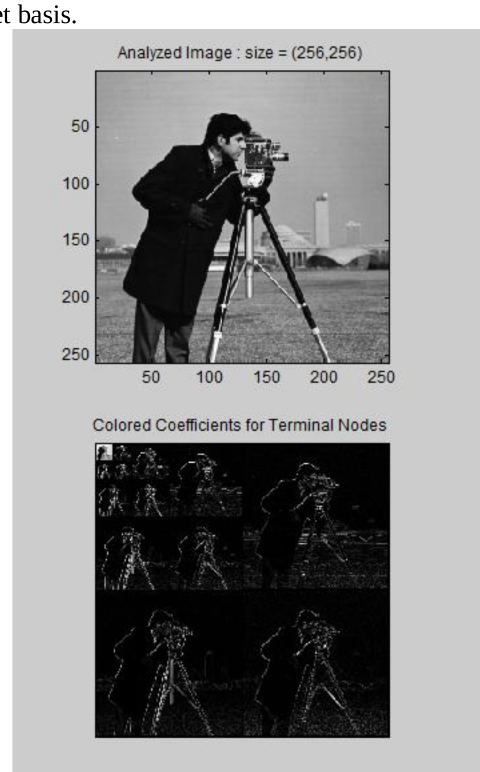

Fig 3 Decomposition of image into sub bands

Originally known as Optimal Subband Tree Structuring (SB-TS) also called Wavelet Packet Decomposition

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(WPD) (sometimes known as just Wavelet Packets or Subband Tree) is a wavelet transform where the discrete-time (sampled) signal is passed through more filters than the discrete wavelet transform (DWT).

IV. THRESHOLDING TECHNIQUES

Threshold selection is important when de noising. A small threshold may yield a result close to the input, but the result may still be noisy. A large threshold on the other hand, produces a signal with a large number of zero coefficients. This leads to a smooth signal. Paying too much attention to smoothness, however, destroys details and in image processing may cause blur and artefacts'. Thresholding distinguishes between the coefficients due to noise and the ones consisting of important signal information. There are two main ways of thresholding the coefficients :
1) Hard thresholding method
2) Soft thresholding method

The hard threshold removes coefficients below a threshold value T. This is sometimes referred to as the "keep or kill" method. If the absolute value of a coefficient is less than a threshold, then it is assumed to be 0, otherwise it is unchanged. Mathematically it is

$$X = \begin{cases} p, & p \geq T \\ 0, & otherwise \end{cases} \qquad (1)$$

Where p is the approx wavelet coefficient and T is threshold value. The soft threshold shrinks the coefficients above the threshold in absolute value. It is a shrink or kill rule. It is the method where the coefficients greater than or equal to the threshold are subtracted from threshold and the coefficients which are smaller than threshold are added with threshold after comparing them to a threshold value. It is mathematically given as

$$X = \begin{cases} p - T, & p \geq T \\ p + T, & p \leq -T \end{cases} \qquad (2)$$

Where p is the approximate wavelet coefficient and T is threshold. It has been observed that the soft thresholding method is much better and yields more visually pleasant images than hard thresholding.

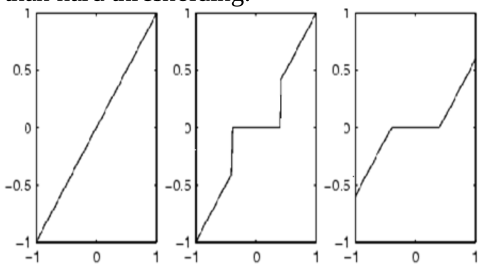

Fig 4 Original signal, hard threshold & Soft threshold

THRESHOLD VALUE DETERMINATION

- **AVERAGE FILTER**

An average filter acts on an image by smoothing it; that is, it reduces the intensity variation between adjacent pixels. The average filter is nothing but a simple sliding window spatial filter that replaces the center value in the window with the average of all the neighbouring pixel values including itself. It is implemented with a convolution mask, which provides a result that is a weighted sum of the values of a pixel and its neighbours. It is also called a linear filter. The mask or kernel is a square. Often a 3× 3 square kernel is used. If the coefficients of the mask sum up to one, then the average brightness of the image is not changed. If the coefficients sum to zero, the average brightness is lost, and it returns a dark image. The mean or average filter works on the shift-multiply-sum principle. It is effective when the noise in the image is of impulsive type. The averaging filter works like a low pass filter, and it does not allow the high frequency components present in the noise to pass through. In other words, the mean filter is useful when only a part of the image needs to be processed.

1/9	1/9	1/9
1/9	1/9	1/9
1/9	1/9	1/9

Fig 5 A constant weight 3× 3 filter mask

- **VISUSHRINK**

Visu Shrink uses a threshold value t that is Proportional to the standard deviation of the noise. It follows the hard thresholding rule. It is also referred to as universal threshold and is defined as

$$t = \sigma\sqrt{2logn} \qquad (3)$$

σ^2 is the noise variance present in the signal and n represents the signal size or number of samples. An estimate of the noise level σ was defined based on the median absolute deviation given by

$$\hat{\sigma} = \frac{median\ (\{|g_{j-1,k}|: k=0,1,2,\ldots\ldots,2^{j-1}-1\})}{0.6745} \qquad (4)$$

Visu Shrink it is known to yield recovered images that are overly smoothed because it removes too many coefficients. Another disadvantage is that it can only deal with an additive noise. It follows the global thresholding scheme where there is a single value of threshold applied.

- **SURESHRINK**

A threshold chooser based on Stein's Unbiased Risk Estimator (SURE) was proposed by Donoho and John stone and is called as Sure Shrink. It is a combination of the universal threshold and the SURE threshold. This method specifies a threshold value tj for each resolution level j in the wavelet transform which is referred to as level dependent thresholding . The goal of Sure Shrink is to minimize the mean squared error. Sure Shrink suppresses noise by thresholding the empirical wavelet coefficients. The Sure Shrink threshold t* is defined as

$$t^* = \min(t, \sigma\sqrt{2logn}) \qquad (5)$$

where t denotes the value that minimizes Stein's Unbiased Risk Estimator, σ is the noise variance, and n is the size of the image. Sure Shrink follows the soft thresholding rule.

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The thresholding employed here is adaptive, i.e., a threshold level is assigned to each dyadic resolution level by the principle of minimizing the Stein's Unbiased Risk Estimator for threshold estimates. It is smoothness adaptive, which means that if the unknown function contains abrupt changes or boundaries in the image, the reconstructed image also does.

- **ADAPTIVE WAVELET PACKET THRESHOLDING**

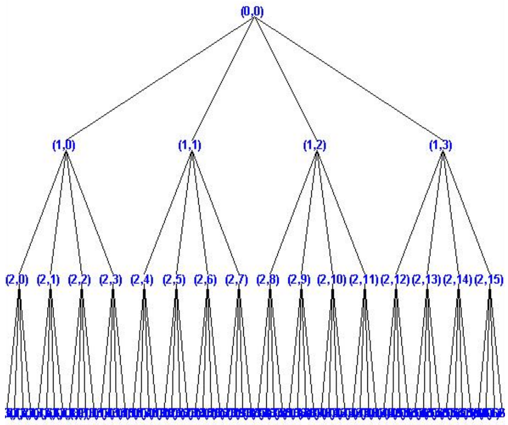

Fig 8 Wavelet Packet tree

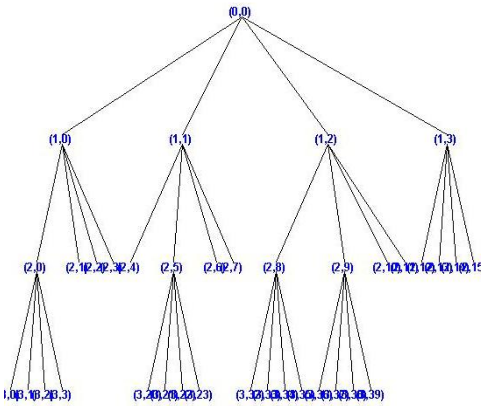

Fig 9 Best tree

In this algorithm, an adaptive threshold value λs for each sub band S at level d is calculated as

$$\lambda_s = \alpha_{d,s}\left(\frac{\sigma_\eta^2}{\sigma_{X,s}}\right) \qquad (6)$$

Where σ^2_η and $\sigma^2_{X,s}$ are the variances of noise and clean image coefficients in the sub band S, respectively.

The image noise is assumed to be an additive Gaussian white noise. The value of the input noise variance is known by applying the robust median estimator on the HH1 sub band's coefficients $(Y_{i,j}^{HH1})$

$$\hat{\sigma}_\eta^2 = \left[\frac{median\left(\left|Y_{i,j}^{HH\,1}\right|\right)}{0.6745}\right]^2 \qquad (7)$$

Equation (13) was adopted to estimate the image noise variance. Since the noise is additive, the observation model can be written as below

This method is a top-down search algorithm for selecting the optimal basis. The algorithm starts at the root and generates the optimal basis using algorithm shown in fig (2). An optimum threshold value, which is adaptable to each sub band characteristics, is desired to maximize the signal and minimize the noise. This method uses an optimum threshold selection algorithm proposed by Chang [2].

Extraction of OWB

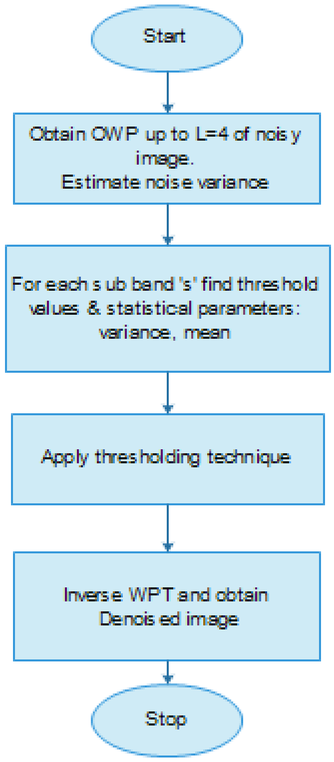

Fig 10 Proposed Denoising Algorithms

$$. Y_{i,j}^S = X_{i,j}^s + \eta_{i,j}^s \qquad (8)$$

Where $Y_{i,j}^S$ are the noise coefficients of subband S, $X_{i,j}^S$ are the coefficients of the clean sub band, and $\eta_{i,j}^S$ are noise coefficients. We assume that $Y_{i,j}^S$, $X_{i,j}^S$ and $\eta_{i,j}^S$ have generalized Gaussian distribution models. Since the coefficients of the clean image and the noise are independent, implies

$$\sigma_{Y,s}^2 = \sigma_{X,s}^2 + \sigma_\eta^2 \qquad (9)$$

Where $\sigma_{Y,s}^2$ is the variance of coefficients $(Y_{i,j})$ in sub band S. From this, the value of can be $\sigma_{X,s}^2$ derived as:

$$\sigma_{X,s}^2 = max\left(\sigma_{Y,s}^2 - \sigma_\eta^2, 0\right) \qquad (10)$$

$SWF_{H/V}(i) = \frac{i^2}{2^{2L}}$ for i=1,2,……. 2^L

Based on the premise that noise is majorly present in the high frequency components and information in the low frequency components, we introduced the term αd,s to increase the threshold value in high-frequency sub bands based on their level of decomposition and their positions at corresponding levels.

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$$\alpha_{d,s} = \sum_i SWF_H\,(i) + \sum_j SWF_V\,(j) \qquad (12)$$

A thresholding algorithm (OLI-Shrink) is implemented that uses optimal linear interpolation between each coefficient and corresponding subband mean in the modification of dominant coefficients.

$$\delta_{\lambda S}^{OLI}\left(Y_{i,j}^{S}\right) = \begin{cases} 0, & \left|Y_{i,j}^{S}\right| \le \lambda s \\ Y_{i,j}^{S} - \beta\left(Y_{i,j}^{S} - \mu s\right), & \left|Y_{i,j}^{S}\right| > \lambda s \end{cases} \qquad (13)$$

where μs is the mean value of the coefficient of subband s and β is computed as follows:

$$\beta = \frac{\sigma_\eta^2}{(\sigma_{X,s}^2 + \sigma_\eta^2)} \cong \frac{\sigma_\eta^2}{\sigma_{Y,s}^2} \qquad (14)$$

The performance of the proposed noise reduction algorithm is measured using quantitative performance measures such as peak signal noise ratio (PSNR) and mean square error(MSE) and results are tabulated and analysed by means of tables and charts

$$\text{PSNR}\,(X, \hat{X}) = 10 \log_{10}\left(\frac{255^2}{\text{MSE}}\right)\text{ dB} \qquad (15)$$

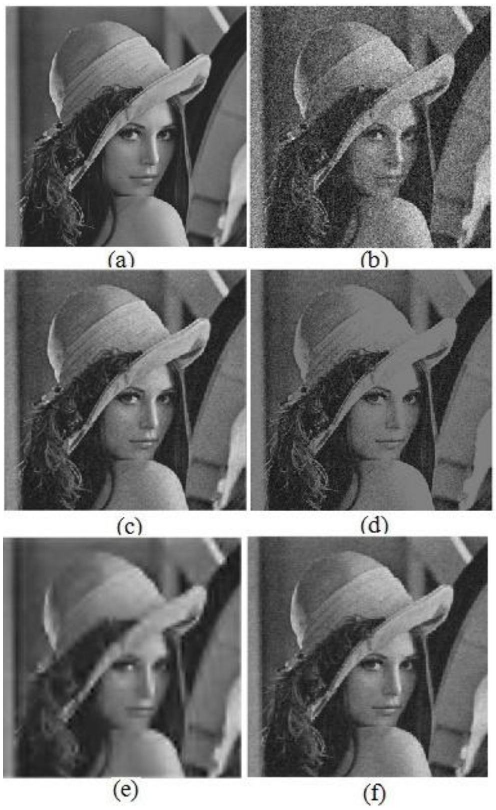
$$\text{MSE} = \left(\frac{1}{MN}\right) \sum_{i=1}^{M} \sum_{j=1}^{N} \left(X(i,j) - \hat{X}(i.j)\right)^2 \qquad (16)$$

where M and N are the width and height of the image, respectively.

V. RESULTS

A) DENOISED IMAGES

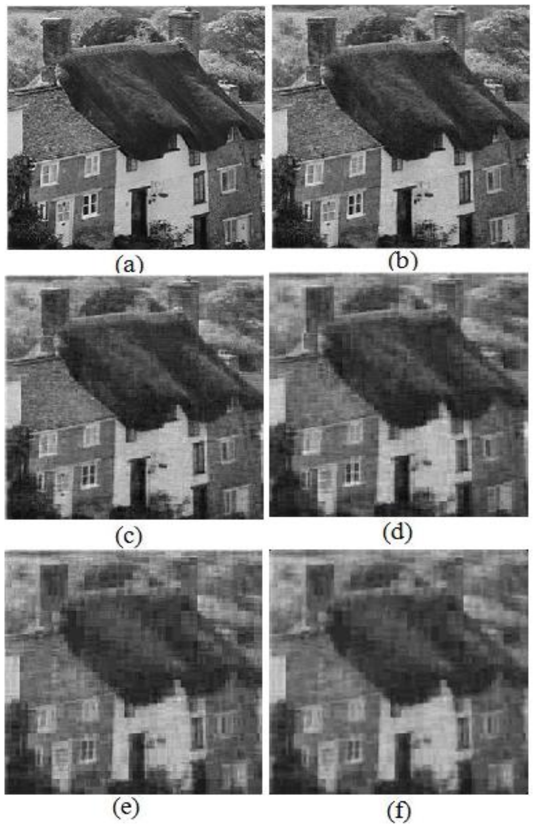
IMAGE LENA for σ=20



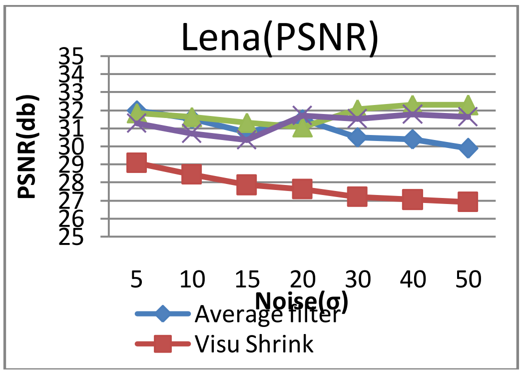
a)Original image, b) Noisy image, c) Average filter, d) VisuShrink, e) SureShrink, f)Adaptive thresholding

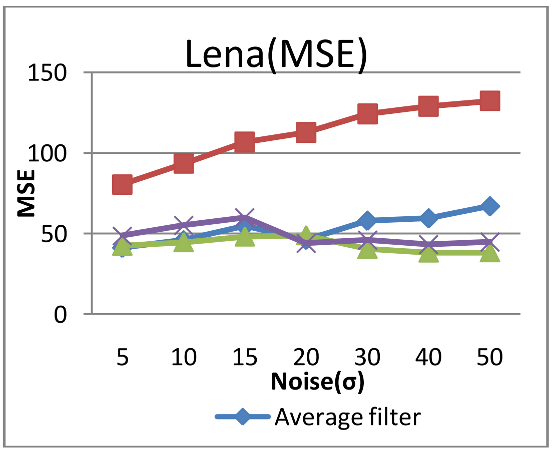
B) IMAGE GOLD HILL:

(a)Original Image (b) σ=10 (c) σ=20 (d) σ=30 (e) σ=40 (f) σ=50



A) GRAPHICAL REPRESENTATION OF EXPERIMENTAL OBSERVATION





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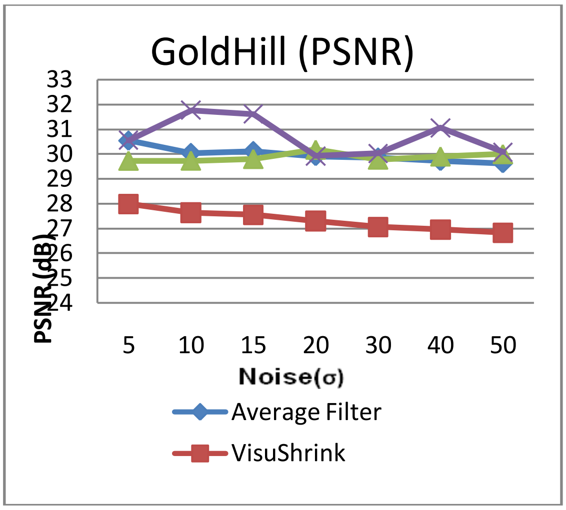

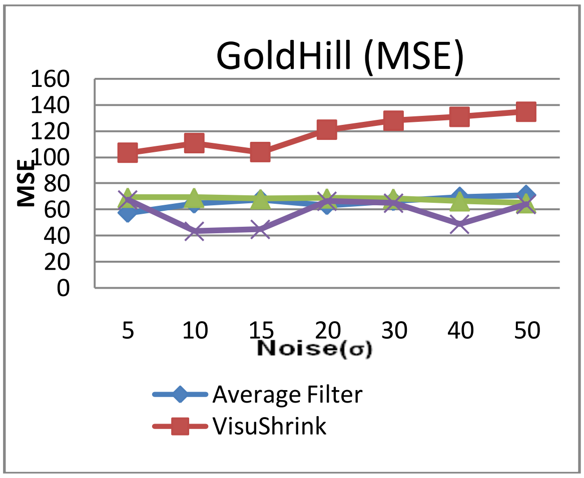

B) OBTAINED RESULTS OF DIFFERENT METHODS ON IMAGE LENA

Table 1: PSNR

Noise(σ)	5	10	15	20	30	40	50
Average filter	31.9731	31.5110	30.7485	31.4824	30.4884	30.3752	29.8625
VisuShrink	29.0674	28.4239	27.8434	27.6080	27.1888	27.0265	26.9152
SureShrink	31.8448	31.6228	31.2923	31.0418	32.0460	32.2947	32.2741
Proposed Method	31.2632	30.6982	30.3501	31.6999	31.5117	31.7748	31.6117

Table 2 : MSE

Noise(σ)	5	10	15	20	30	40	50
Average filter	41.2820	45.9177	54.7301	46.2208	58.1077	59.6427	67.1163
VisuShrink	80.6009	93.4735	106.8395	112.7904	124.2210	128.9526	132.3002
SureShrink	42.5204	44.7511	48.2890	49.0650	40.5961	38.3361	38.5182
Proposed Method	48.6130	55.3677	59.9885	43.9638	45.9101	43.2118	44.8655

C) OBTAINED RESULTS OF DIFFERENT METHODS ON IMAGE GOLDHILL

Table 3 : PSNR

Noise(σ)	5	10	15	20	30	40	50
Average filter	30.5399	30.0360	30.1134	29.9108	29.8479	29.7102	29.6208
VisuShrink	27.9852	27.6383	27.5499	27.3055	27.0576	26.9612	26.8327
SureShrink	29.7254	29.7300	29.7968	30.1759	29.7712	29.8989	29.9952
Proposed Method	30.5499	31.7564	31.6106	29.9165	30.0198	31.0458	30.0634

Table 4 : MSE

Noise(σ)	5	10	15	20	30	40	50
Average filter	57.4240	64.4784	67.3420	63.3490	66.3744	69.5123	70.9585
VisuShrink	103.4000	110.8400	104.0000	121.0000	128.0000	131.0000	135
SureShrink	69.2700	69.1960	68.1397	68.7358	68.5423	66.5571	65.0973
Proposed	67.312	43.3955	44.8769	66.2876	64.7299	48.9268	64.0827

VI. CONCLUSION

In this project various thresholding algorithms for recovering an image affected with Gaussian Noise are evaluated, implemented and compared. These algorithms are so chosen that each represents one of the three methods of selecting the threshold value, namely – Global threshold, spatially adaptive threshold and sub band adaptive threshold. The local thresholding methods work on the coefficients obtained by best tree based decomposition of an image using wavelet packet model. The results obtained from different methods are compared on the basis of image parameters PSNR (peak signal to noise ratio) and MSE (mean square error). Based on the statistical and visual results obtained the proposed algorithm is the most effective method. VISU shrink employs a global thresholding hence tends to remove too many coefficients which is not desirable. Conventional method of Mean (Average) filtering provides a better PSNR than the other methods but it gives a smoothening or blurring effect, which implies the edges (detailing) of the image is lost. SURE shrink although provides a PSNR comparable to the proposed method by the virtue of its sub band dependent threshold selection, but the visual appearance is highly distorted. Thus the proposed Algorithm by employing sub band dependent adaptive wavelet packet thresholding is the most effective de noising method.

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