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Adaptive Wavelet Packet Decomposition for Efficient Image Denoising By Using NeighSure Shrink Method

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***Abstract*— The search for efficient image denoising methods is still a valid challenge.This project presents adaptive wavelet packet(WP) decomposition along with the improved neighboring window method, which can determine neighbouring window size for every subband by using Stein's unbiased risk estimate (NeighSure) to remove the additive white Gaussian noise. WP decomposition is used to obtain Optimum wavelet basis by utilizing Shannon entropy. Experimental results on different test images under different noise intensities shows that this algorithm yields better peak signal to noise ratio compared to the other existing methods, and feature similarity for the proposed method is obtained.**

***Keywords*— wavelet packet decomposition, NeighSure, Shannon entropy, Optimum wavelet basis, Feature similarity.**

I. INTRODUCTION

Image denoising is a technique used to improve the visualizing quality of the noisy image. The noisy image produces undesirable visual quality; it also lowers the visibility of low contrast objects. Hence noise removal is essential in digital imaging applications in order to enhance and recover fine details that are hidden in the data. The goal of denoising is to remove the noise while retaining as much as possible the important signal features.

In many occasions, noise in digital images is found to be additive in nature with uniform power in the whole bandwidth and with Gaussian probability distribution. Such a noise is referred to as Additive White Gaussian Noise (AWGN) [2, 4]. It is difficult to suppress AWGN since it corrupts almost all pixels in an image.

Initially, AWGN is suppressed using linear spatial domain filters such as mean and wiener filters but Low-pass filters will not only smooth away noise but also blur edges in images. At the same time high-pass filters can make edges even sharper and improve the spatial resolution but will also amplify the noisy background. Linear filtering techniques possess mathematical simplicity but have the drawback of yielding blurring effect. They also do not perform well in the presence of signal dependent noise. Image denoising methods can be done either by transform domain methods or by spatial domain methods. Transform domain methods first transform an image from the spatial domain into a different domain and suppress noise in the transform domain. Hence to perform a meaningful and useful task, a suitable transform is used e.g. Discrete Fourier Transform (DFT), Discrete Cosine Transform, Discrete Hartley Transform (DHT), Discrete Wavelet Transform (DWT) [9] etc

The denoising of original image corrupted by additive white Gaussian noise [2] is a common problem in image processing. The important property of a good image denoising model is that it should completely remove noise as far as possible as well as preserve edges. The wavelet transform has become a powerfull tool for such problem. Wavelet denoising is used to remove the noise present in the image while preserving the image features such as edges and textures regardless of its frequency contents. 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.

Wavelet thresholding is one of the most popular denoising methods which apply the thresholding shrinkage upon the high frequency components after the wavelet decomposition. There are two basic thresholding methods, the hard thresholding and the soft thresholding, by which the threshold value is computed. Various threshold selection methods have been proposed, such as, VisuShrink, SureShrink and Bayes Shrink.

In this project, instead of standard wavelet decomposition wavelet packet decomposition is used along with optimal wavelet basis (OWB). Then, for each wavelet subband, an adaptive threshold value is calculated. Next modified neighShrink which uses stein's unbiased risk estimate rule is used to shrink the noisy coefficients. Then inverse transform is used to reconstruct the original image.

II. WAVELET AND WAVELET PACKET DECOMPOSITION

A 'wavelet'[7] is a small wave which has its energy concentrated in time. It has an oscillating wavelike characteristic but also has the ability to allow simultaneous time and frequency analysis and it is a suitable tool for transient, non-stationary or time-varying phenomena

Mathematical transformations are applied to image to obtain further hidden information from the image that is not readily available in the raw image. There are a number of transformations that can be applied, among which the Fourier transforms are probably by far the most popular.

Fourier transform based spectral analysis is the dominant analytical tool for frequency domain analysis. However, Fourier transform cannot provide any information of the spectrum changes with respect to time. In many cases, the most distinguished information is hidden in the frequency content of the signal. The frequency SPECTRUM of a signal is basically the frequency components (spectral components) of that signal. The frequency spectrum of a signal shows what frequencies exist in the signal.

To overcome the limitations of the standard FT, Gabor introduced the initial concept of Short Time Fourier Transform (STFT). The advantage of STFT is that it uses an arbitrary but fixed-length window for analysis, over which the actual nonstationary signal is assumed to be approximately stationary. STFT provides both time and frequency information. But the disadvantage is, frequency and time information of a signal at some certain point in the time-frequency plane cannot be known. In other words: We cannot know what spectral component exists at any given time instant. The best we can do is to investigate what spectral components exist at any given interval of time. This is a problem of resolution, and it is the main reason why researchers have switched to wavelet transform (WT) from STFT.

Wavelets are mathematical functions that analyze data according to scale or resolution. They aid in studying a signal in different windows or at different resolutions. For instance, if the signal is viewed in a large window, gross features can be noticed, but if viewed in a small window, only small features can be noticed. STFT gives a fixed resolution at all times, whereas WT gives a variable resolution as follows: Higher frequencies are better resolved in time, and lower frequencies are better resolved in frequency. This means that, a certain high frequency component can be located better in time (with less relative error) than a low frequency component. On the contrary, a low frequency component can be located better in frequency compared to high frequency component. The finite scale multi resolution representation of a discrete function can be called as a discrete wavelet transform. DWT is a fast linear operation on a data vector, whose length is an integer power of 2. This transform is invertible and orthogonal, where the inverse transform expressed as a matrix is the transpose of the transform matrix.

Some Application of Wavelets:

Wavelets are a powerful statistical tool which can be used for a wide range of applications, namely

- Signal processing
- Data compression
- Smoothing and image denoising
- Fingerprint verification
- Biology for cell membrane recognition, to distinguish the normal from the pathological membranes
- DNA analysis, protein analysis
- Blood-pressure, heart-rate and ECG analyses
- Finance (which is more surprising), for detecting the properties of quick variation of values
- In Internet traffic description, for designing the services size
- Industrial supervision of gear-wheel Speech recognition

A. *Wavelet decomposition*

Wavelet transform is a time domain localized analysis method with the windows size fixed and forms convertible. There is quite good time differentiated rate in high frequency part of signals DWT transformed. Also there is quite good frequency differentiated rate in its low frequency part. It can distill the information from signal effectively. The basic idea of discrete wavelet transform (DWT) in image process is to multi-differentiated decompose the image into sub-images. After the original image has been DWT transformed, it is decomposed into 4 frequency districts which is one low-frequency district(LL) and three high-frequency districts(LH,HL,HH).

Wavelet decomposition produces three detailed sub-images also called as subband (HL, HL, HH) corresponding to three different directional-orientations (Horizontal, Vertical and Diagonal) and a lower resolution sub-image LL called as approximation. Decomposition is continued in a similar manner on the LL (approximation) to provide multilevel decomposition. Multilevel decomposition hierarchy of an image is illustrated in fig. 1.

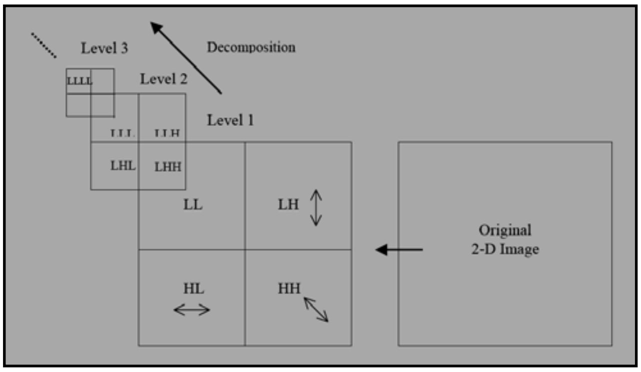

Fig.1 Multilevel decomposition hierarchy of an image with 2-D DWT

In wavelet analysis the use of a fully scalable modulated window solves the signal cutting problem. The window is shifted along the signal and for every position the spectrum is calculated. Then this process is repeated many times with a slightly shorter (or longer) window for every new cycle. In the end the result will be a collection of time-frequency representations of the signal, all with different resolutions. Therefore this is also called as multiresolution analysis.

Due to decomposition of only the approximation component at each level in a regular wavelet analysis the results of frequency resolution in higher-level DWT decompositions are less desirable (Figure 1). It may cause problems while applying DWT in certain applications which the important information is located in higher frequency components. The frequency resolution of the decomposition filter may not be fine enough to extract necessary information from the decomposed component of the signal. The necessary frequency resolution can be achieved by implementing a wavelet packet transform to decompose a signal further.

B. *Wavelet Packet Decomposition*

Wavelet Packet Transform (WPT) [9] is now becoming an efficient tool for signal analysis. The wavelet packet method is a generalization of wavelet decomposition that offers a richer range of possibilities for signal analysis. Compare with the normal wavelet analysis, it has special abilities to achieve higher discrimination by analyzing the higher frequency domains of a signal. The frequency domains divided by the wavelet packet can be easily selected and classified according to the characteristics of the analyzed signal. So the wavelet packet is more suitable than wavelet in signal analysis and has much wider applications such as signal and image compression, denoising and speech coding.

Wavelet packet transform uses a pair of low pass and high pass filters to split a signal into roughly a low-frequency and a high frequency component. In wavelet decomposition [7] we leave the high-frequency part alone and keep splitting the low-frequency part. In wavelet packet decomposition, we can choose to split the high-frequency part also into a low frequency part and a high-frequency part. So in general, wavelet packet decomposition divides the frequency space into various parts and allows better frequency localization of signals [9]. This offers the richest analysis: the complete binary tree is produced as shown in the following Fig. 2.

As shown in Fig. 2, the wavelet packet transform can be viewed as a tree. The root of the tree is the original data set. The next level of the tree is the result of one step of the wavelet transform. Subsequent levels in the tree are constructed by recursively applying the wavelet transform step to the low and high pass filter results from the previous wavelet transform step. Similarly the inverse wavelet packet can reconstruct the original signal from the wavelet packet decomposition spectrum.

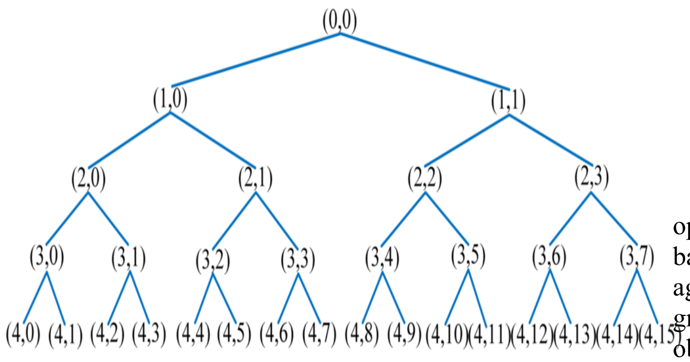

Fig. 2 Wavelet packet decomposition tree.

Wavelet packet denosing and wavelet noise reduction are basically the same in principle. The difference between them is that wavelet packet analysis is more complex and flexible than wavelet analysis. The wavelet packet analysis decompose both low-frequency part and high-frequency part and with more accurate local analysis capacity. Specific steps are as follows:

1. Wavelet decomposition: Determine the level of wavelet decomposition, select the appropriate wavelet basis.
2. Calculate the optimal tree;
3. Do thersholding to wavelet packet coefficients;
4. Wavelet packet reconstruction of the low-frequency coefficients and the treated high-frequency coefficients.

III. COST FUNCTION

In wavelet packet transform, the optimal representation basis of the input signal is selected by optimizing a function known as "cost function" in each subband. The cost function will determine the cost value for each node and its children in the obtained full binary tree. The algorithm starts with computing the cost values from the deepest level nodes. If the sum of the cost values for two children nodes is lower than the cost value of their parent node, then the children are retained, otherwise, they are eliminated. For example, in Fig. 1, four such decisions are made: either a pair of blocks in the bottom row or the block immediately above them (dotted boxes) may be selected.

This cost value computation process is recursively repeated up to the tree's root. The result is a basis that has the least cost among all the possible bases in this tree, so called best basis or optimal basis. In this project Shannon entropy cost function is selected and implemented.

$$SE(S) = -\sum S_i^2 \log (S_i^2) \qquad (1)$$

Where S_i is the subband in WPD tree and i = 1, 2, 3......

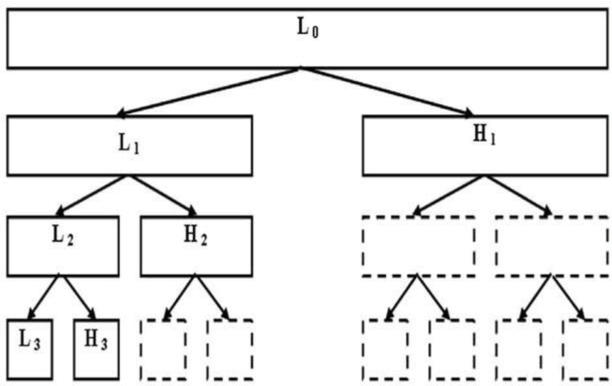

Fig. 3 Wavelet packet decomposition

IV. THRESHOLDING

Thresholding [6] is a simple non-linear technique, which operates on one wavelet coefficient at a time. In its most basic form, each coefficient is thresholded by comparing against threshold. thresholding is a process of converting gray scale input image into binary image.it segment the objects from their backgrounds dependind on pixel intensity.

The purpose of thresholding is to extract those pixels from some image which represent an object.object of binarization is to mark pixels that belong to true foreground and background regions with different intensities. Wavelet thresholding is a signal estimation technique that exploits the capabilities of wavelet transform for signal denoising. It removes noise by killing coefficients that are insignificant relative to some threshold and turns out to be simple and effective which depends heavily on the choice of a thresholding parameter. The choice of this threshold determines the efficacy of denoising to a great extent.

Threshold determination is an important question when denoising. 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 artifacts.

There are two types of thresholding, they are

- Global thresholding
- Local or adaptive thresholding.

Originally, Donoho and Johnstone proposed the use of a global threshold uniformly throughout the entire wavelet decomposition tree which was found to be more efficient. Although thresholding with a uniform threshold per subband is attractive due to its simplicity, the performance is limited and the denoising quality is often not satisfactory. Thus wavelet shrinkage methods using separate threshold in each subband have been developed over recent years. Some methods of selecting thresholds that are adaptive to different spatial characteristics have been recently proposed and investigated. In general, adaptive approaches have found to be more effective than their global counterparts.

The difficult task in wavelet thresholding is the selection of threshold. Various threshold selection methods have been proposed, such as, VisuShrink, SureShrink and Baye'sShrink. In the VisuShrink method, a universal threshold which is a function of the noise variance and the number of samples is developed based on the minimal error measure. The threshold value in the Sure Shrink approach is optimal one in terms of the Stein's unbiased risk estimator. The Baye's Shrink approach determines the threshold value in a Bayesian rule, through modeling the distribution of the wavelet coefficients as Gaussian. These shrinkage methods have further improved with the help of interscale and intrascale correlations of the wavelet coefficient. Originally, Donoho and Johnstone proposed the use of a universal threshold method uniformly throughout the whole wavelet decomposition. Then the implementation o f the wavelet tree was found to be more effective. An adaptive wavelet threshold method is applied with the help of Baye's Shrink for wavelet thresholding method. In Neigh Shrink threshold is the wavelet coefficients according to the magnitude of the squared sum of all the wavelet coefficients, i.e., the local energy, within the neighborhood window. The neighborhood window size may be 3×3, 5×5, 7×7, 9×9, etc.

V. METHODOLOGY

Image denoising procedure which is used in this project is as shown in the form of block diagram in fig.3.From the block diagram we can say that, when noise is add to the image such image called noisy image. In this work we are adding additive white Gaussian noise with different noise variance.

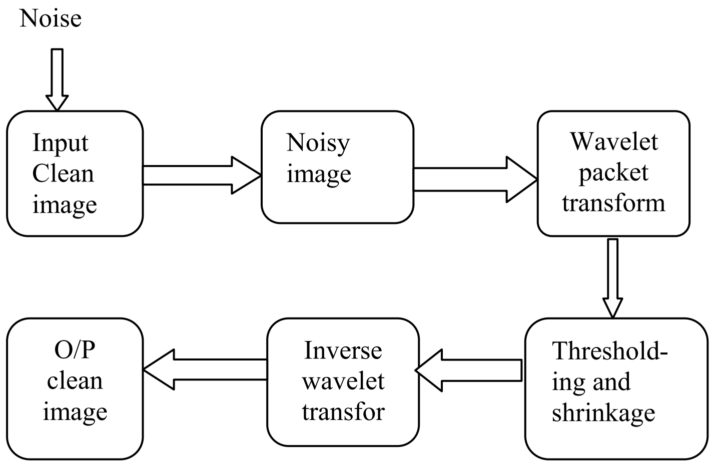

Fig. 4 Wavelet packet decomposition

Once the noisy image is obtained, a mathematical transformation is applied on this image to extract the hidden information from that image. In this work we are using wavelet packet transform for rich analysis and it also preserve important features of an image effectively compared to the other transforms like Fourier and STFT after denoising.

Then optimum wavelet basis or best tree basis is found using OWB algorithm. The result is a basis that has the least cost among all the possible bases in this tree, so called best basis or optimal basis. In this paper Shannon entropy cost function is selected and implemented. Then modified neighbouring window method is applied for shrinking the noisy coefficients. Next inverse wavelet transform is applied to get the original image.

A. *OPTIMUM WAVELET BASIS (OWB) EXTRACTION*

The algorithm discussed in chapter 3(under the title of cost function) uses the bottom up procedure to extract the optimal basis from the full WP tree of an input image. This algorithm starts at the deepest level of the tree and eliminates quads of nodes that have higher cost than their parent node at each level while working back toward the root.

Instead of the above highly computational complex algorithm, an alternative fast method for extracting OWB, which was introduced by Kaur et al. [1], is employed. This method is a top-down search algorithm for selecting the optimal basis. The algorithm starts at the root and generates the optimal basis tree without growing the tree to full depth. In this algorithm, we use Shannon entropy to produce the optimal wavelet basis.

OWB extraction algorithm starts with choosing the maximum number of levels (L) for WP decomposition. While the current level (d) of decomposition is less than L, compute the subband's Shannon entropy as cost function. Again decompose the each and every suband and find the cost function of each by using Shannon entropy.

If cost function of parent node is less than the sum of the cost function of all their children nodes then only retain the parent node and eliminate the children nodes, otherwise retain the parent and children nodes. Repeat this process recursively until current level (d) of decomposition is greater than L.

B. Modified NighShrink Algorithm

NeighShrink is an efficient image denoising algorithm based on the decimated wavelet transform (DWT). Its disadvantage is to use a suboptimal universal threshold and neighbouring window size in all wavelet subbands. In this project an improved method is used, which can determine an optimal threshold and neighbouring window size for every subband by Stein's unbiased risk estimate (SURE).

VI. EXPERIMENTAL RESULTS

The code is simulated by using MATLAB tool. We used different images contaminated by Gaussian white noise at different standard deviations: σ = 5, 10, 15, 20, 30, 40, and 50 are used.

The quality of the image is measured by using quantitative performance measures such as peak signal to noise ratio (PSNR) and feature similarity of original and denoised image is measured.comparision of PSNR values with existing method and FSIM for proposed method is given in table I and table II respectively.

$$PSNR=(X, \hat{X}) = 10\log_{10}(255^2/MSE)db \qquad (2)$$

Where X and X^ are the original and denoised image respectively. And the MSE between the original and denoised images given as,

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(X(i,j) - X^{\wedge}(i,j))2 \qquad (3)$$

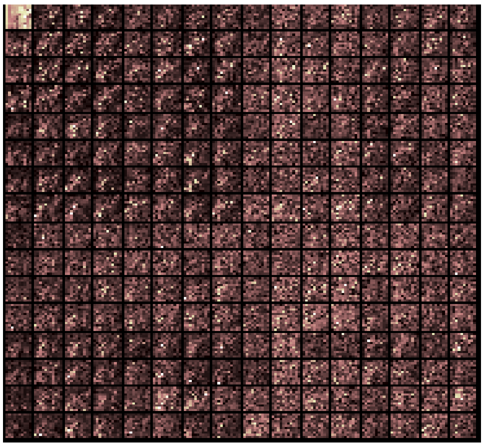

Fig. 4 Wavelet packet decomposition of Lena image.

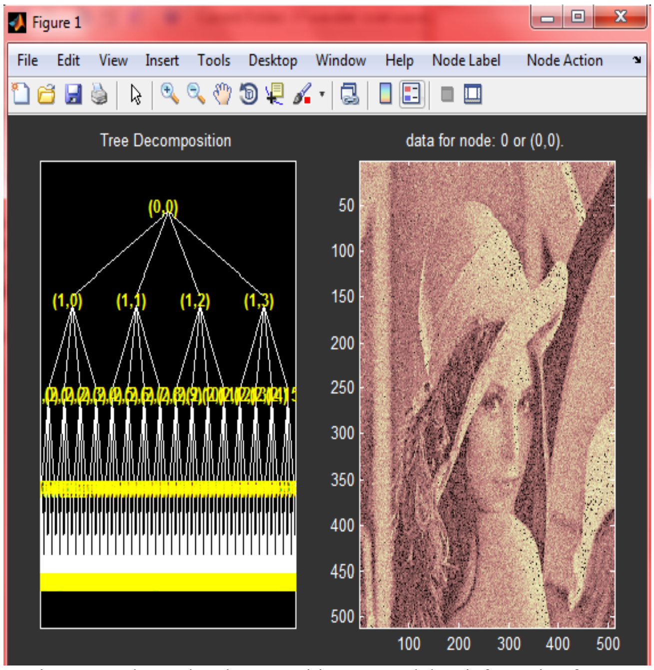

Fig. 5 Wavelet packet decomposition tree and data information for node (0, 0) of Lena image with noise intensity 30.

Fig. 6 from the left first is the original Lena image, second is with noise intensity 30, and third is the denoised image.

TABLE I
OBTAINED PSNR FOR DIFFERENT NOISE INTENSITIES BY USING MATLAB

Noise σ	**5**	**10**	**15**	**20**	**30**	**40**	**50**	**5**	**10**	**15**	**20**	**30**	**40**	**50**
Method	**Lena**							**House**						
Average filter[1]	35.9	31.3	28.1	25.5	22.2	20.2	18.4	33.2	30.2	27.6	25.5	22.3	20.1	18.3
VisuShrink[1]	34.3	28.2	24.6	22.1	18.7	16.4	14.6	33.8	28.2	24.7	22.2	18.8	16.4	14.7
SureShrink[1]	25.1	25.1	25.1	25.1	25.0	24.8	24.6	21.2	21.2	21.4	21.4	21.4	21.4	20.8
BayesShrink[1]	35.6	30.9	28.4	26.9	25.2	22.9	22.1	34.0	29.8	27.2	25.5	22.9	21.4	19.5
OLI Shrink[1]	36.2	32.5	30.9	29.8	28.5	27.2	26.5	33.12	30.6	28.8	27.4	25.2	24.4	23.6
NeighSure Shrink with WPD	**38.0**	**34.7**	**32.9**	**31.5**	**30.8**	**28.41**	**27.4**	**38.2**	**34.4**	**32.4**	**31.08**	**30.43**	**27.89**	**26.89**
Method	**Medical**							**Texture**						
Average filter[1]	37.2	31.8	28.4	25.9	22.6	20.2	18.5	35.6	31.2	28.1	25.8	22.5	20.4	18.6
VisuShrink[1]	32.5	30.9	30.0	29.5	28.6	27.8	26.9	27.4	25.6	24.5	23.6	22.7	22.2	21.8
SureShrink[1]	30.5	30.3	30.1	29.8	29.0	28.2	27.2	22.6	22.6	22.5	22.5	22.4	22.2	21.9
BayesShrink[1]	38.3	34.9	32.8	31.3	29.6	28.0	27.1	35.9	31.6	29.7	28.4	26.4	24.9	23.8
OLI Shrink[1]	39.6	36.0	33.9	32.7	**30.8**	28.7	27.2	36.1	32.6	30.8	29.3	27.6	26.2	24.7
NeighSure Shrink with WPD	**39.9**	**36.6**	**34.0**	**33.3**	30.6	**28.9**	**28.0**	**37.9**	**34.6**	**32.8**	**31.2**	**28.2**	**27.2**	**25.6**

TABLE II
OBTAINED FSIM FOR NEIGHSURE SHRINK METHOD BY USING MATLAB

Noise σ	**5**	**10**	**15**	**20**	**30**	**40**	**50**	**5**	**10**	**15**	**20**	**30**	**40**	**50**
Method	**Lena**							**House**						
NeighSure Shrink with WPD	0.9927	0.9649	0.9293	0.8932	0.8202	0.7624	0.7056	0.9627	0.8759	0.7964	0.7336	0.6316	0.5565	0.5028
Method	**Medical**							**Texture**						
NeighSure Shrink with WPD	0.9937	0.9849	0.9393	0.9320	0.8602	0.7920	0.7696	0.9674	0.8872	0.8096	0.7396	0.6272	0.5995	0.5158

VII. CONCLUSIONS

Based on wavelet packet analysis, its denoising effect is better than wavelet transform. In this work we compared the five denoising methods with the modified NeighShrink which uses WPD for denoising an image. An ideal denoising procedure requires a priori knowledge of the noise, whereas a practical procedure may not have the required information about the variance of the noise or the noise model. Thus, most of the image denoising algorithms consider known variance of the noise and the noise model to compare the performance with different image denoising algorithms. Gaussian Noise with different variance values is added in the natural images to test the performance of the image denoising algorithm.

From the obtained results it can be seen that NeighSure Shrink gives the better PSNR and VisuShrink gives the lowest PSNR, and FSIM for NeighSure Shrink is obtained which gives the feature similarity for the original and denoised image.

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