"Enhancement of Image Denoising PSNR by using Discrete Wavelet Transform Methodology"

Sanchesh Gautam, Electrical Department, Jabalpur Engineering College Jabalpur,India
Guided By:- Mr. HemantAmhia, Electrical Department, Jabalpur Engineering College Jabalpur,India

***Abstract*-** Removing noise from the original signal is still a challenging problem for researchers. There have been several published algorithms and each approach has its assumptions, advantages, and limitations. This paper presents a review of some significant work in the area of image de noising. After a brief introduction, some popular approaches are classified into different groups and an overview of various algorithms and analysis is provided. Wavelet algorithms are very useful tool for signal processing such as image compression and image de noising. The main aim is to show the result of wavelet coefficients in the new basis, the noise can be minimize or removed from the data. Insights and potential future trends in the area of de noising are also discussed. Due to the increasing requirements for transmission of images in computer, mobile environments, the research in the field of image compression has increased significantly. Image compression plays a crucial role in digital image processing, it is also very important for efficient transmission and storage of images. When we compute the number of bits per image resulting from typical sampling rates and quantization methods, we find that Image compression is needed. Therefore development of efficient techniques for image compression has become necessary .This paper is a survey for lossy image compression using Discrete Wavelet Transform, it covers JPEG all format of image compression algorithm which is used for full-colour still image applications and describes all the components of it.

***Keyword*-** Wavelet transforms, MATLAB, DWT, De noising.

I. INTRODUCTION

Digital images play an important role both in daily life applications such as satellite television, magnetic resonance imaging, computer tomography as well as in areas of research and technology such as geographical information systems and astronomy [1]. Data sets collected by image sensors are generally contaminated by noise. Imperfect instruments, problems with the data acquisition process, and interfering natural phenomena can all degrade the data of interest. Furthermore, noise can be introduced by transmission errors and compression. Thus, denoising is often a necessary and the first step to be taken before the images data is analyzed. It is necessary to apply an efficient denoising technique to compensate for such data corruption. Image denoising still remains a challenge for researchers because noise removal introduces artifacts and causes blurring of the images. This paper describes different methodologies for noise reduction (or denoising) giving an insight as to which algorithm should be used to find the most reliable estimate of the original image data given its degraded version. Noise modeling in images is greatly affected by capturing instruments, data transmission media, image quantization and discrete sources of radiation. Different algorithms are used depending on the noise model. Most of the natural images are assumed to have additive random noise which is modeled as a Gaussian. Speckle noise is observed in ultrasound images whereas Rician noise affects MRI images. The scope of the paper is to focus on noise removal techniques for natural images [1].

II. IMAGE DENOISING AND COMPRESSION

Image de noising is one of the important and essential components of image processing. Many scientific data sets picked by the sensors are normally contaminated by noise. It is contaminated either due to the data acquisition process, or due to naturally occurring phenomenon. There are several special cases of distortion. One 2 of the most prevalent cases is due to the additive white gaussian noise caused by poor image acquisition or by communicating the image data through noisy channels. Other categories include impulse and speckle noises. The goal of de noising algorithm is to remove the unwanted noise while preserving the important signal features as much as possible. Noise elimination introduce artifacts and blur in the images. So image de noising is still a challenging task for the investigators. Several methods are being developed to perform de noising of corrupted images. The two fundamental approaches of image de noising are the spatial filtering methods and transform domain filtering methods. Spatial filters operate a low-pass filtering on a set of pixel data with an assumption that the noise reside in the higher region of the frequency spectrum. Spatial low-pass filters not only provide smoothing but also blur edges in signals and images. Whereas high pass filters improve the spatial resolution, and can make edges sharper, but it will also intensify the noisy background. Fourier transform domain filters in signal processing involve a trade-off between the signal-to-noise ratio (SNR) and the spatial resolution of the signal processed. Using Fast Fourier Transform (FFT) , the de noising method is basically a low pass filtering procedure, in which edges of the de noised image are not as sharp as it is in the original image . Due to FFT basis functions the edge information is extended across frequencies, which are not being localized in time or space. Hence low pass-filtering results in the spreading of the edges. Wavelet theory, due to the advantage of localization in time and space, results in de noising with edge preservation. The success of de noising technique is ensured by the ability of de-correlation (separation of noise and useful signal) of the different discrete wavelet 3 transform coefficients. As the signal is contained in a small number of coefficients of such a transform, all other coefficients essentially contain noise. By filtering these coefficients, most of the noise is eliminated. Currently there is a large proliferation of digital data. Multimedia is an evolving method of presenting many types of information. Multimedia combines text, sound, pictures and animation in a digital format to relate an idea. In future multimedia may be readily available as newspapers and magazines. The multimedia and other types of digital data require large memory for storage, high bandwidth for transmission and more communication time. The only means to get better on these resources is to compress the data size, so that it can be transmitted quickly and followed by decompression at the receiver. Another most significant and booming applications of the wavelet transform is image compression. More popular and efficient existing wavelet based coding standards like JPEG2000 can easily perform better than conventional coders like Discrete Cosine Transform (DCT) and JPEG. Unlike in DCT based image compression, the effectiveness of a wavelet based image coder depends on the choice of wavelet selection [2-3].

III. MOTIVATION FOR THE RESEARCH WORK

After the development of continuous wavelet transform by Morlet and Grossman, many wavelet transforms (WT) have been extended their usage in image processing applications like de-noising. Wavelets are mathematical tools that decompose the data into number of different frequency components, and then studying each component with good resolution, matched to its scale. Wavelet transforms have advantages over traditional Fourier methods in analyzing the signal containing discontinuities and sharp spikes. Basically wavelet transforms are classified into continuous wavelet transform and discrete wavelet transform. The digital signal processors and computes are discrete in nature, image processing algorithms use discrete wavelet transform. Wavelets perform a better-quality in image de noising, due to the sparsity and multiresolution properties. Each wavelet based image de noising method follow three steps: o computing a linear forward wavelet transform of the image to be de noised, o filtering with nonlinear thresholding in the wavelet domain. o Computing a linear inverse wavelet transform. In signal de noising, wavelet thresholding suggested by Donoho, is a signal identification technique that make use of the properties of wavelet transform. Coefficients that are insignificant relative to some threshold can be eliminated by thresholding. The choice of a thresholding parameter determines the effectiveness of de noising algorithm. Even though the Discrete Wavelet Transform (DWT) is a powerful tool, it suffers with three limitations (shift sensitivity, poor directionality and absence of phase information), which decreased its usage in many applications. DWT is shift sensitive because it produce unpredictable changes in DWT coefficients, if input signal is shifted [3]. Next, the DWT undergo poor directionality because DWT 5 coefficients unveil only three orientations(horizontal, vertical and diagonal). Last, absence of phase information because DWT investigation of non-stationary signals lacks the phase information. Prof N. Kingsbury proposed a redundant complex wavelet transform to avoid the above limitations in standard DWT. A Dual-Tree Wavelet Transform (DTWT) with good directionality, approximate shift sensitivity and explicit phase information perform in excellence where redundancy is acceptable. In DTWT a pair of filter banks operate simultaneously on the input signal and furnish two wavelet decompositions. The wavelets related with filter banks form a Hilbert Transform(HT) pair and provides shift insensitivity, good directionality and explicit phase information. However, the design of DTWT filters is complex, because it requires an iterative optimization over the space of ideal reconstruction filter banks. A thorough study and interest in later years showed pathway for usage of complex wavelets, and complex analytic signals particularly in signal processing and statistical applications. Further it is linked to the expansion of complex valued discrete wavelet filters and intelligent dual filter banks. Finally, the complex wavelet transforms, directional wavelet transforms, analytic wavelets, steerable pyramids, curve lets and contour lets are intelligent and powerful redundant tools applied to signal and image analysis. Based on the above study, it is inferred that the transform domain is better suited for image analysis. A novel complex wavelet transform (CWT) can be used for analyzing and identifying the objects in image processing applications like image de noising, compression and segmentation. Investigation results illustrate that complex wavelet transforms outperform the standard real wavelet transforms in the sense of shift-insensitivity, directionality and anti-aliasing [4-5].

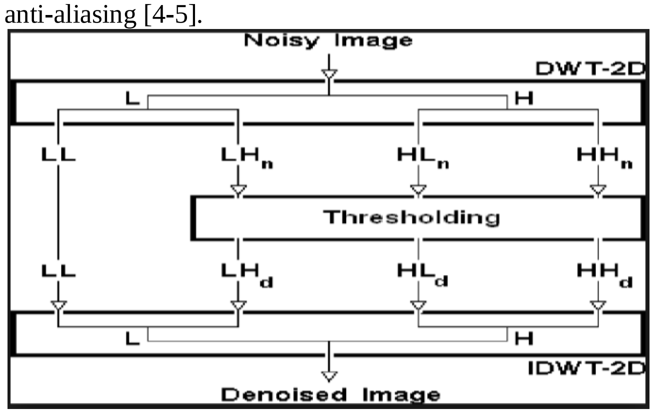

Fig.1: De-Noising Compression in Wavelets

IV. DWT DECOMPOSITION

In Fourier analysis, the Discrete Fourier Transform (DFT) decompose a signal into sinusoidal basis functions of different frequencies. No information is lost in this transformation; in other words, we can completely recover the original signal from its DFT (FFT) representation. In wavelet analysis, the Discrete Wavelet Transform (DWT) decomposes a signal into a set of mutually orthogonal wavelet basis functions. These functions differ from sinusoidal basis functions in that they are spatially localized – that is, nonzero over only part of the total signal length. Furthermore, wavelet functions are dilated, translated and scaled versions of a common function φ, known as the mother wavelet. As is the case in Fourier analysis, the DWT is invertible, so that the original signal can be completely recovered from its DWT representation. Unlike the DFT, the DWT, in fact, refers not just to a single transform, but rather a set of transforms, each with a different set of wavelet basis functions. Two of the most common are the Haar wavelets and the Daubechies set of wavelets. For example, Figures 1 and 2 illustrate the complete set of 64 Haar and Daubechies-4 wavelet functions (for signals of length 64), respectively. Here, we will not delve into the details of how these were derived; however, it is important to note the following important properties [5-6]:

1. Wavelet functions are spatially localized;
2. Wavelet functions are dilated, translated and scaled versions of a common mother wavelet; and
3. Each set of wavelet functions forms an orthogonal set of basis functions.

DWT in two dimensions In this section, we describe the algorithm for computing the two-dimensional DWT through repeated application of the one-dimensional DWT. The two-dimensional DWT is of particular interest for image processing and computer vision applications, and is a relatively straightforward extension of the one-dimensional DWT discussed above.

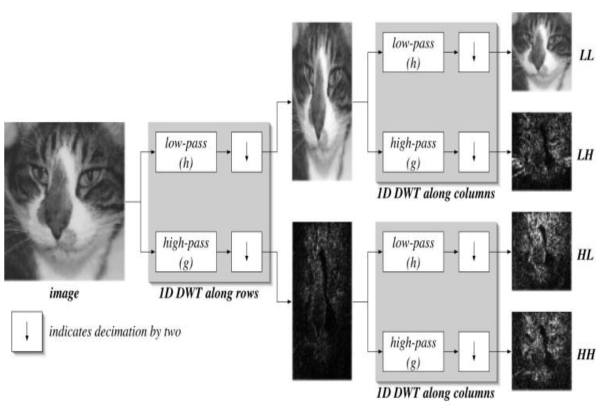

Fig.2: One-level, two-dimensional DWT.

First, the one-dimensional DWT is applied along the rows; second, the one-dimensional DWT is applied along the columns of the first-stage result, generating four sub-band regions in the transformed space: LL, LH, HL and HH [6-7].

Figure 2 illustrates the basic, one-level, two-dimensional DWT procedure. First, we apply a one-level, onedimensional DWT along the rows of the image. Second, we apply a one-level, one-dimensional DWT along the columns of the transformed image from the first step. As depicted in Figure 2 (left), the result of these two sets of operations is a transformed image with four distinct bands:

(1) LL,
(2) LH,
(3) HL and
(4) HH. Here, L stands for low-pass filtering, and H stands for high-pass filtering. The LL band corresponds roughly to a down-sampled (by a factor of two) version of the original image. The LH band tends to preserve localized horizontal features, while the HL band tends to preserve localized vertical features in the original image. Finally, the HH band tends to isolate localized high-frequency point features in the image.

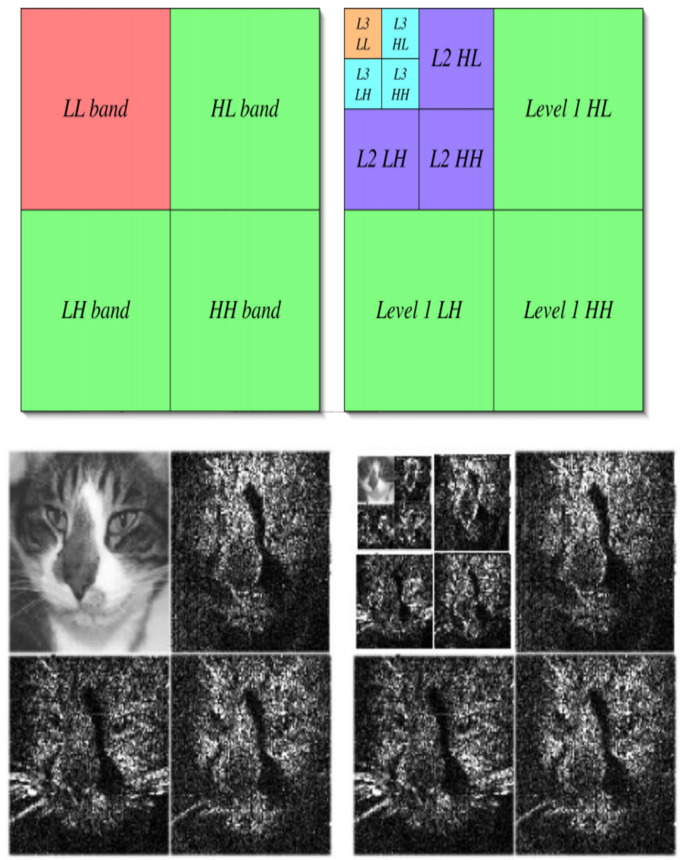

Fig.3: Two-dimensional wavelet transform: (left) one-level 2D DWT of sample image, and (right) threelevel 2D DWT of the same image. Note that the LH bands tend to isolate

horizontal features, while the HL band tend to isolate vertical features in the image.

V. INVERSE DWT

To understand the procedure for computing the one-dimensional inverse DWT, consider Figure 2, where we illustrate the inverse DWT for a one-level DWT of length 16 (assuming filters of length four). Note that the two filters are now h^{-1} and g^{-1} where,

$$h_k^{-1} = \begin{cases} h_k & k \in \{1,3,\dots\} \\ h_{n-k-1} & k \in \{0,2,\dots\} \end{cases}$$

and g^{-1} is determined from h^{-1} using equation (1). To understand how to compute the one-dimensional inverse DWT for multi-level DWTs, consider Figure 3. First, to compute w2 from w3, the procedure in Figure 5 is applied only to values L3 and H3. Second, to compute w1 from w2, the procedure in Figure 2 is applied to values L2 and H2. Finally, to compute x from w1, the procedure in Figure 5 is applied to all of w1 – namely, L1 and H1 [7-8].

VI. PROPOSED DWT FEATURE EXTRACTION ALGORITHM

Initially, it is verified that the digitized flaw data are available in the powers of 2 for making the effective decomposition. The various steps involved in the feature extraction algorithm are as follows:

Step 1: The ultrasonic flaw data are decomposed into four detail subbands using Discrete Wavelet Transform (DWT). The subbands are high frequency detail band coefficients and low frequency approximation band coefficients [9-10].

Step 2: The approximation co-efficients are further decomposed using DWT to extract localized information from the subband of detail coefficients. In this work, four levels of decomposition have been done using biorthogonal wavelet (bior 4.4). Four level approximation and detail coefficients of six classes of defect are graphically represented in Appendix 1 as Figures 3.

Step 3: For further analyzing and processing, all the four level detail band coefficients have been taken.

Step 4: The frequency vector (in radians/sample) is extracted for four detail subbands using periodogram function in MATLAB.

Step 5: The features are computed either by using syntax or by implementing the formulae. They are mean, variance, mean of energy, maximum amplitude, minimum amplitude, maximum energy, minimum energy, average frequency, mid frequency, maximum frequency, minimum frequency, half point of the function.

The M-file program for four level signal decomposition and features extraction using DWT are provided.

Step 6: Finally, the extracted features for the six classes of defects are tabulated and analyzed for classification.

VII. EXTRACTED FEATURES

In this work, twelve features are extracted from the discrete wavelet transform (DWT) coefficients of ultrasonic test signals obtained from the six classes of defect. The extracted features from the signal are as below:

1. Mean: It is nothing but an average value.

$$m = \left(\frac{1}{n}\right)\sum_{i=1}^{n} x_i$$

Parameter	First Decomposition	Second Decomposition	Third Decomposition
MSE	0.000001	0.000001	0.0001
PSNR	604.1514	608.44	608.743
Compression ratio	1.85	1.962	1.99
Enc_time	7.16	5.57	5.344
Dec_time	5.2	5.8	6.335

2. Variance: The variance is defined as the sum of square distances of each term in the distribution from the mean, divided by the number of terms in the distribution.

$$v \quad \frac{1}{n-1}\sum_{i=1}^{n}(x_i - m)^2$$

3. Mean of the energy: It is the average value of the energy.

$$m_e = \left(\frac{1}{n}\right)\sum_{i=1}^{n} x_i^2$$

Where

x Sequence, m Mean, n Number of Samples

4. Maximum Amplitude: It is the peak value of amplitude of the signal

5. Minimum Amplitude: It is the lowest value of amplitude of the signal.

6. Maximum Energy: It is the highest energy value obtained from the signal.

7. Minimum Energy: It is the lowest energy value obtained from the signal.

8. Average Frequency:

$$f_{avg} = \frac{\sum_{i=1}^{n} f_i x p_i}{\sum_{i=1}^{n} p_i}$$

9. Mid Frequency: It is the frequency value which is obtained when the power spectral density is at the maximum value.

10. Maximum frequency: It is the maximum frequency value of the energy in the spectrum.

11. Minimum frequency: It is the minimum frequency value of the energy in the spectrum.

12. Half Point of the energy (HaPo): It is a very valuable variable as it represents the frequency that divides up the spectrum into two parts of same area.

VIII. RESULT AND SIMULATION

1. Base paper result:-

Table (1) our base paper result.

MSE					PSNR			
Description Of the wavelet Packet used								
σ	0.0001	0.001	0.01	0.1	0.0001	0.001	0.01	0.1
Daubechies2 at level 2	6.28	61.56	594.73	4551.22	40.18	30.27	20.42	11.58
Daubechies4 at level 4	6.46	61.63	594.62	4551.19	40.06	30.27	20.42	11.58
Description Of the wavelet used								
Daubechies2 at level 2	64.22	154.64	322.50	777.23	30.09	26.27	23.08	19.26
Daubechies4 at level 4	76.90	195.27	448.86	925.66	29.31	25.26	21.64	18.50

2. Our Proposed Method Result:-

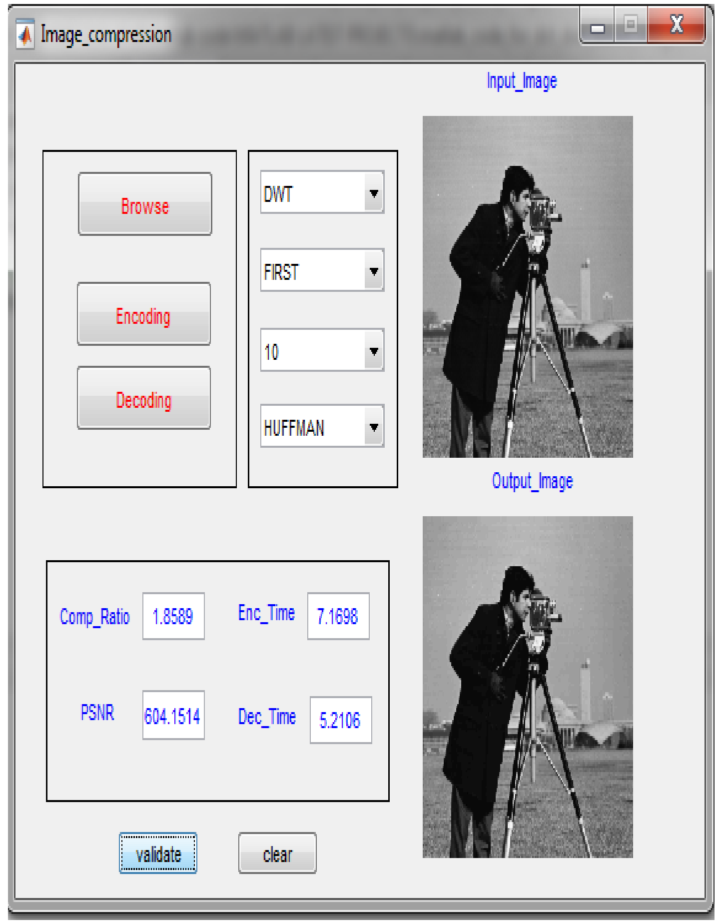

Fig.4: GUI two-dimensional DWT

Data sets 1:

Fig.5: Data set 1 Input and Output Denoising image.

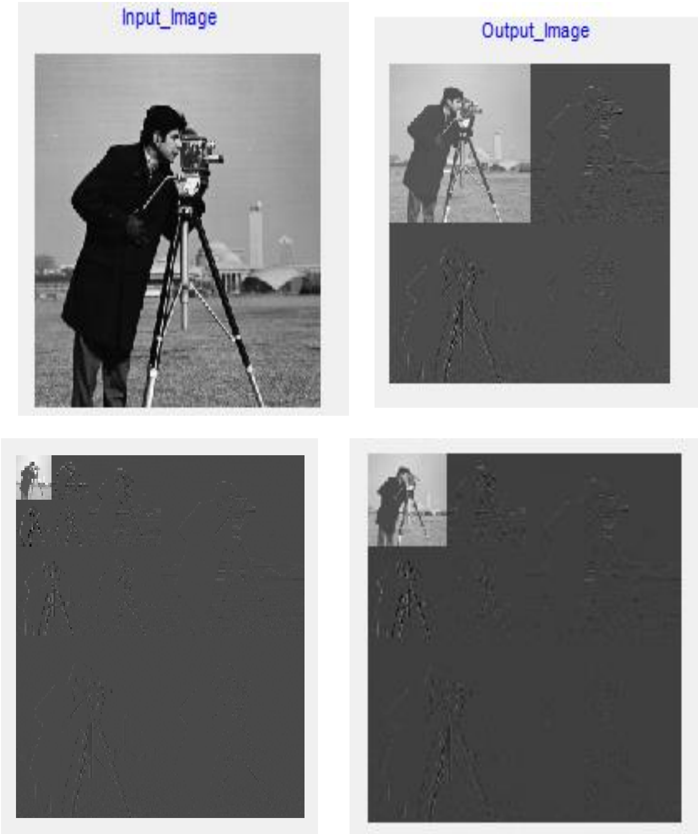

Fig.6: Data set 1 Input and Output Denoising image.

Data sets 2:

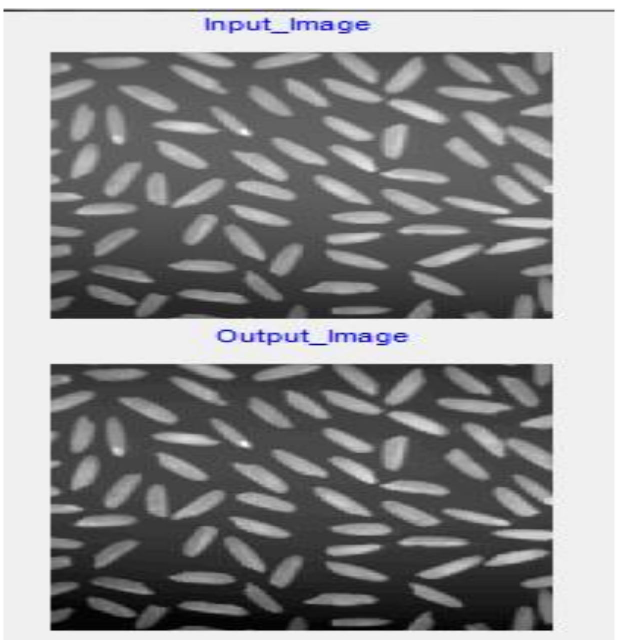

Fig.7: Data sets 2 input and output.

Table (2) our Proposed result.

Parameter	First Decomposition	Second Decomposition	Third Decomposition
MSE	0.000001	0.000001	0.0001
PSNR	613.9574	621.5812	622.6526
Compression ratio	2.0288	2.0022	1.9977
Enc_time	11.9528	11.6978	11.0246
Dec_time	12.3245	12.2741	11.8945

Hence shows that data sets 1 and 2 is better result as compare to old image denoising technique. With Find data sets 1 result show minimum MSE, maximum PSNR and image pixel quality.

IX. CONCLUSION

The comparative study of various de-noising techniques for digital images shows that wavelet filters outperforms the other standard spatial domain filters. Although all the spatial filters perform well on digital images but they have some constraints regarding resolution degradation. These filters operate by smoothing over a fixed window and it produces artifacts around the object and sometimes causes over smoothing thus causing blurring of image. Wavelet transform is best suited for performance because of its properties like sparsity, multi resolution and multi scale nature. Thresholding techniques used with discrete wavelet are simplest to implement.

X. REFERENCES

[1]. V. Nigam, S. Luthra and S. Bhatnagar, "A Comparative Study of Thresholding Techniques for Image Denoising," 2010 International Conference on Computer and Com-munication Technology, Allahabad, 17-19 September 2010, pp. 173-176.

[2]. Matlab6.1―ImageProcessingToolbox‖,http:/www.mathworks.com/access/helpdesk/help/toolbox/images/

[3]. Umbaugh, Computer Vision and Image Processing, Prentice Hall PTR, New Jersey, S. E. 1998

[4]. Gagnon, L. "Wavelet Filtering of Speckle Noise- ome Numerical Results, Proceedings of the Conference Vision Interface", Trois-Reveres.1999

[5]. Goodman, J. W. " Some fundamental properties of Speckle", J. Opt. Soc. Am., 66, pp. 1145–1150. 1976

[6]. Motwani, M.C., Gadiya, M. C., Motwani, R.C., Harris, F. C Jr. "Survey of Image Denoising Techniques".

[7]. Windyga, S. P., "Fast Impulsive Noise Removal", IEEE transactions on image processing, Vol. 10, No. 1, pp.173-178., 2001

[8]. Kailath, T., "Equations of Wiener-Hopf type in filtering theory and related applications, in Norbert Wiener: Collected Work" vol. III, P.Masani, Ed. Cambridge, MA: MIT Press, pp. 63–94, 1976.

[9]. V. Strela. “Denoising via block Wiener filtering in wavelet domain”. In 3rd European Congress of Mathematics, Barcelona, July 2000.

[10]. David L. Donoho and Iain M. Johnstone., “Adapting to unknown smoothness via wavelet shrinkage”, Journal of the American Statistical Association, vol.90, no432, pp.1200-1224, December 1995. National Laboratory, July 27, 2001.