Edge-preserving Image Denoising using Wavelet Packets

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***Abstract*:** This paper presents performance enhancement of traditional image denoising techniques using wavelet packet decomposition. The wavelet packet based results are compared with Wiener filtering in wavelet domain. High quality images of different structures are taken and additive noise of some known standard deviations is induced in it. Then wavelet packet is used for noisy image decomposition. The noise standard deviation is calculated from the diagonal subband of first decomposition level to compute the threshold. The threshold values are computed for all terminal nodes of the wavelet packet tree. In this way, the edges of image are more preserved by using soft thresolding. The wavelet packet thresholding is evaluated and examines some improvements for different image contaminated by Gaussian noise of various densities.

***Index Terms*—Coefficient thresholding, Image denoising, edge preserving, wavelet packet transform.**

I. INTRODUCTION

The use of digital images is increased due to many applications of digital world such as digital cameras, medical images and many more. Generally, the images are contaminated by noise. Main reasons for producing noise in images are imperfect instruments, compression and transmission errors. Gaussian noise, salt-and-pepper noise and Speckle noise are different types of noise present in image. The image denoising is an important pre-processing in digital image processing [1-5].

There are so many kind of denoising procedures which provide the filtered images but the only a procedure is better which not only denoise the image but also preserves its features like edges, contrast level etc. Wavelet transform has been a powerful and wildly used tool in image denoising because of its different properties [15]. The limitations of Fourier transform is overcame by wavelet transform. Wavelet transform represents a function in frequency from time domain.

Discrete wavelet transform (DWT) is the critically sampled form of wavelet transform which provides most compact representation. The DWT is applied to the image for separation of details of image such as horizontal, vertical and diagonal [5-7]. It is the simplest of all wavelets and its operation is easy to understand. It also helps in multiresolution analysis. Wavelet transform decomposes image into sub bands and make easy to denoise the image.

In DWT, mathematical functions are applied to obtain further information from the image. The DWT of an image is calculated by passing it through a series of filters that are low pass filter and a high-pass filter [2, 3]. The outputs give the detail coefficients and approximation coefficients from the high-pass filter the low-pass filter respectively.

The DWT poses two major lacks in image denoising. The DWT coefficients provide different results under shifts of input images due to a problem that has large amounts of redundancy into DWT to make it shift-invariant. The DWT also has poor directional selectivity due to its three different spatial-feature orientations [10]. Shift sensitivity in an input image causes unaccepted changes in the output DWT coefficients. A small shift in the input images may cause a major change in the output images.

In image processing, wavelet packet transform are widely used now a days. It is a powerful tool of image processing for its different benefits [9]. They are able to recover the lacks of DWT in image processing. In, wavelet packet transform, all the features of the image are preserved after denoising. In wavelet domain, small wavelet coefficients represent the induced noise and large coefficients represent the important feature of an image. These small wavelet coefficients can be thresholded without affecting the significant features of the image [15]. Therefore, wavelet packets not only smooth the data to reduce noise but also preserve edges in an image.

The wavelet packet method is a better than wavelet decomposition because it offers a richer and better analysis of an image [11]. Wavelet packet atoms are indexed by three interpreted parameters i.e. position, scale and frequency. The wavelet packets can be used for transformation of a given image reconstructing exact features of an image.

In this paper work, high quality natural images are taken and some additive noise is added with some known standard deviation (std). These noisy images would then be given as input to the denoising system. Instead of standard discrete wavelet transform (DWT), wavelet packet decomposition is used along with each subband node until required levels. For each wavelet packet coefficient, a threshold value is calculated and applied using soft thresholding [8, 11]. Then inverse wavelet packet transform is used to reconstruct the original image. which produces an image close to the original high quality image. The performance of the algorithms is evaluated by computing the Peak Signal-to-Noise Ratio (PSNR).

This paper is organized as follows. Section II explains the DWT used in image denoising and gives brief descriptions of the wavelet based image denoising, which are the classical decimated image denoising algorithms. Section III and IV, describe the wavelet packets based image denoising system. Section V describes the experimental results and also shows some of the images and the measurements. Section VI presents the performance comparison with a graph. Finally, Section VII summarizes the results and the observations have been made while working on this paper.

II. IMAGE DENOISING USING WAVELET DECOMPOSITION

The past decade has witnessed the development of *wavelet analysis*, a new tool that emerged from mathematics and was quickly adopted by diverse fields of science and engineering. DWT help to reduce noise from a noisy image. When an image is decomposed using DWT, the resultant is a set of data called the wavelet coefficients. These coefficients are divided into approximation and detailed components. If the details are small, they are removed by thresholding. If the coefficients below a certain threshold are removed the output image will be a denoised image [13]. So, in thresholding all coefficients that are less than a particular threshold are set to zero. The image is reconstructed by thresholded wavelet coefficients.

The steps of image denoising using wavelet decomposition are: In the first level of decomposition, the image is decomposed into four subbands which can be denoted by HH, HL, LH and LL subband [15]. The HH subband gives the diagonal details of the image, the HL subband gives the horizontal features and the LH subband represents the vertical structures of an image. The LL subband is the low resolution residual consisting of low frequency components. Similarly, LL coefficient is further split into four subbands at next levels of decomposition [2, 5].

Image denoising using wavelet decomposition involved three steps: Linear forward wavelet transform, soft thresholding and linear inverse wavelet transform [2]. Wavelet thresholding is a nonlinear method, and denoising purpose can be achieved according to the wavelet coefficients in the wavelet domain. Principal of thresholding is that the wavelet coefficient with larger magnitude is mainly contain the image data and wavelet coefficient with smaller magnitude is mainly obtained from the noise image transformed. Hence, the thtresholding is done to the wavelet subbands [7]. Wavelet multilevel decomposition hierarchy of an image is illustrated in figure 1:

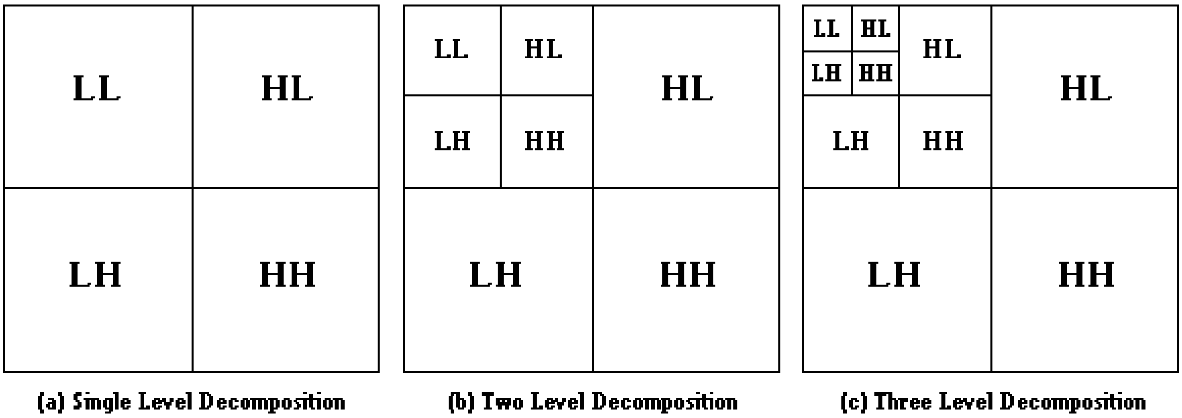


Figure1: Discrete Wavelet Transform

III. IMAGE DENOISING USING WAVELET PACKETS

A wavelet packet transform (WPT) is a simple generalization of a wavelet transform and provide superior performance than DWT [10]. Unlike wavelet transform, the WPT decomposes both approximation and detail subbands. Thus wavelet packet decomposition consists of more subbands than corresponding wavelet decomposition. At every decomposition level, all the subbands are subdivided [8, 9]. The primary advantage of such a hierarchical decomposition is that a minimal representation can be obtained by suitably choosing which subbands to split and thus a choice can be made between several possible combinations of subbands.

The wavelet packet decomposition is represented as a tree. The original image is the root of the tree. The first level of the tree is the result of one step of the wavelet packet transform. Next levels in the tree are constructed by applying the wavelet transform step to the low and high pass filter results of the previous nodes of the tree [11].

Wavelets are very effective for denoising of noisy image. However, wavelets are not very efficient in representing complex images like medical images, finger print images. The reason is that, complex images are mainly described by smaller scale wavelet coefficients. These smaller scale coefficients carry very little energy [5, 12].

i). Wavelet Packet Decomposition

WPT is always an efficient tool for analysis of an image. It provides a richer range for image processing. Unlike basic wavelet transformation, it has special ability in which the higher frequency domains of a image also decomposed [10, 12]. The frequency domains divided by the wavelet packet provides better processing of subbands. So the wavelet packet is more suitable and better than DWT in image processing. Wavelet packet has much wider applications such as image compression and denoising [8]. Wavelet packet transform uses a pair of low pass and high pass filters to split a image matrix into roughly a low and a high frequency component. In wavelet decomposition we leave the high-frequency part alone and keep splitting the low-frequency part. In wavelet packet decomposition, unlike wavelet decomposition, we split the high-frequency part also [9].

The set of wavelet packets collectively make up the complete family of possible decompositio. If only the low-pass filter is decomposed, the result is the wavelet decomposition. If all low-pass and high-pass filters are iterated, the result is wavelet packet decomposition [11]. The top level of the wavelet packet tree is the original image. As each level of the tree is traversed there is trade-off between time and frequency domain. The bottom level of a tree is the frequency representation of the image.

The following figure shows the decomposition using wavelet packet transform.

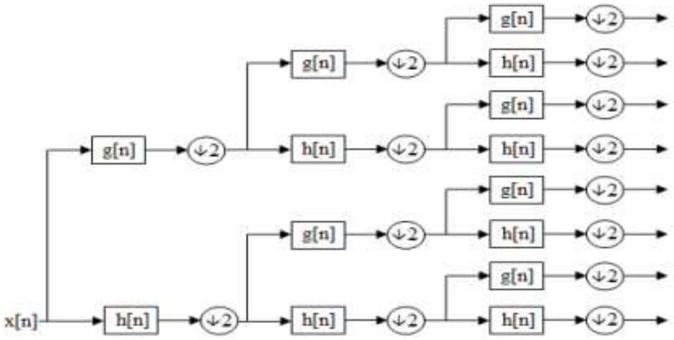


Figure 2: Wavelet Packet decomposition over 3 levels

So, wavelet packet decomposition divides the frequency space into various parts and allows better decompostion of image. This offers the richest analysis of the image and the complete binary tree is produced. As given in Fig. 3, the wavelet packet decomposition is represented as a tree. The original noisy image is the root of the tree. The first level of the tree is the result of one step of the wavelet transform. Next levels in the tree are constructed by applying the wavelet transform step to the previous nodes result of the tree. Similarly the inverse wavelet packet can reconstruct the original image from the wavelet packet tree. The difference between wavelet packet denosing and wavelet denoising is that first one is more complex and flexible [9]. The wavelet packets decompose both low-frequency part and high-frequency part and with more subband. The same steps for wavelet packet decompsition are used. These are the wavelet decomposition levels, the optimal tree calculation, thersholding to wavelet packet coefficients and finally wavelet packet reconstruction [11].

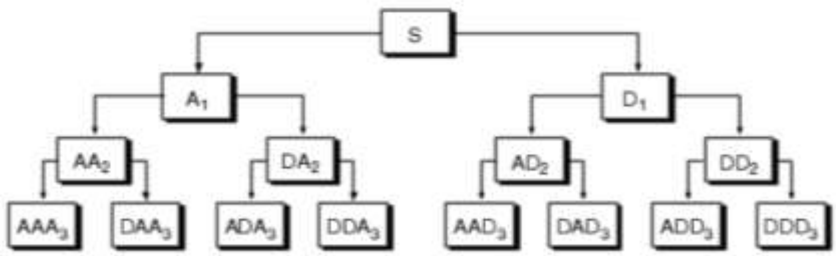


Figure 3: Wavelet Packet decomposition in approximate A and detail D part

It can be seen in figure 3 that based on the above analysis that wavelet packet analysis can provide a more precise frequency resolution than the wavelet analysis bacause both the approximation and details at a certain level are further decomposed into the next level in wavelet packet decomposition.

ii). Edge preserving with Wavelet Packet Decomposition

Edge-preserving is required in many real life applications such as medical or satellite imaging. The edges are important features and must be preserved well in image denoising using wavelet packet decomposition. Edge-preserving techniques are the mathematical tools which are designed to automatically restrict the smoothing at edges in images [10].

The edge-preserving techniques are formulated in each basic context of image processing, where the adjacency matrix, using the differential structure of the image, is first determine, then the graph Laplacian is formulated and finally the low-pass filter is formed to boost the Eigen vectors of the graph related to its smallest values.

Since one method of the edges preserving is by using the method of edge-preserving filters, a typical method used in this paper is by wavelet packet decomposition by soft thresholding in which image is decomposed into it's smallest components or subbands using low-pass filters band high-pass filters [6]. The subbands are treated and noise is reduced by using soft threholding method. During this process edges of the images are preserved well. Finally, the image is reconstructed using inverse wavelet transform and the edges or sharp transition of the images are preserved [15].

Thus, the restored image contains less noise than the input image still keeping the sharp transitions or edges by using wavelet packet decomposition along with soft thresholding.

IV. WAVELET PACKET COEFFICIENTS THRESHOLDING

Thresholding in packet decomposition is a simple technique in which each wavelet coefficient is thresholded by comparing against threshold value [11]. Thesholding is non- linear technique which operates on one wavelet coefficient at one time. Thresholding also converts gray scale input image into binary image. The purpose of thresholding is to extract those pixels from the image which represent that image. Wavelet thresholding is a image processing technique that exploits the capabilities of wavelet packet decomposition for image denoising. It reduces noise by killing coefficients that are insignificant related to some threshold. It is very simple and effective which depends majorly on the choice of a thresholding parameter or threshold value. The choice of this threshold determines the productivity of denoising to a great extent [15]. Threshold determination is a major in image denoising. A small threshold yields an image close to the input, but the result may still be noisy. On the other hand, a large threshold value, produces an denoised image with degraded of its basic information, details or features and can cause blur and artefacts. There are two types of thresholding schemes, namely global thresholding and local or adaptive thresholding.

Traditionally, it was proposed by different researchers that the global threshold applied uniformly throughout the entire wavelet decomposition tree is more efficient than any other thresholding technique. Although thresholding with a uniform threshold at each subband is more efficient due to its simplicity, the performance is limited and the denoising quality is often not very satisfactory [8, 10]. Thus, the method using separate threshold in each subband is used for efficient thresholding. This method is also called wavelet shrinkage or adaptive thresholding. In general, adaptive thresholding is found to be more effective than global thresholding.

i). Threshold Selection

Threshold value selection is the most determining task in the process of wavelet packet denoising. Before thresholding of the wavelet coefficient, the value of threshold is calculated. The adaptive threshold value is evaluated by analysing the statistical parameters diagnal subband coefficient of the first level of wavelet packet tree. The threshold is not at all a constant value and is therefore calculated for all terminal nodes of the wavelet packet tree. Due to this varying nature of threshold, the denoising algorithm becomes adaptive.

Threshold determination is a major in image denoising. A small threshold yields an image close to the input, but the result may still be noisy [15]. On the other hand, a large threshold, produces an image which is denoised but may get deprived of its basic information, details or features and may cause blur and artifacts. Therefore, an optimum threshold value is desired to minimize noise, which is adaptable also to each terminal nodes of wavelet packet tree. A constant value will not give good result since the value suitable for one subband or level may not be the right choice for some other subband or level [9, 3]. Hence an optimal threshold value which is adaptable to each subband is desired to maximise the features of the image and minimize the noise.

By choosing a threshold value and multiplying with the standard deviation of the random noise, the noise in the denoised image is removed by thresholding the wavelets transform coefficients [6]. The noise in the denoised image is additive Gaussian white noise. Input noise variance of the Gaussian noise is estimated by applying the median estimator on the HH1 subband's coefficients by using the formula as:

$$\hat{\sigma}_{noise} = \frac{median(|HH_{cor}|)}{0.6954} \qquad (1)$$

ii). Hard Thresholding

If the absolute value of the coefficient is smaller than than the threshold then absolute value is assumed to be zero, otherwise it will remain same [3]. Hard thresholding works on the procedure of "keep or kill". This process is known as hard thresholding [7]. Hard thresholing is not suitable for noise removal as it creates discontinuities. It is given by:

$$\mathrm{T(X)} = \begin{cases} \mathrm{X}, & \text{if } |\boldsymbol{X}| \geq \lambda \\ 0, & \text{otherwise} \end{cases} \qquad (2)$$

where, λ is the threshold value.

From Figure 4, we can see that hard thresholding can create discontinuities, and thus greatly magnify small differences in the transform value which are near the threshold value λ. If the value is only slightly less than λ, then this value is set equal to zero, while a value whose magnitude is only slightly greater than λ remains same. Therefore, hard thresholding is not fit for most noise removal.

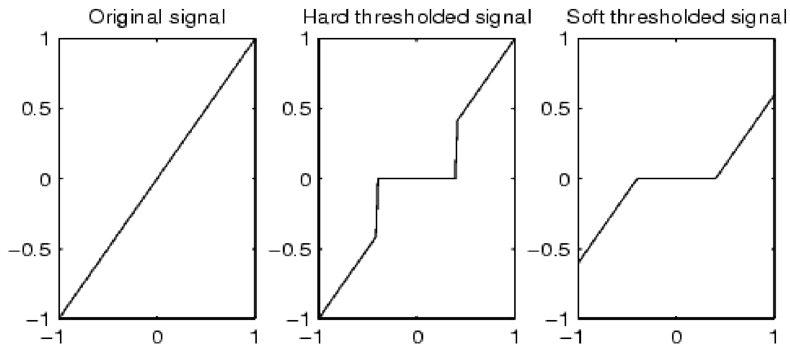


Figure 4: Hard vs. soft thresholding

iii). Soft Thresholding

To avoid the limitations of hard thresholding, soft thresholding is used. Unlike hard thresholding, in soft thresholding, if the absolute value of a coefficient is less than a threshold, then the value is set equal to zero, otherwise its value is decreased by threshold itself (λ) . This also removes the discontinuity, but reduce all the other coefficients which might blur the image.

$$T(X) = \begin{cases} X - \lambda \;\; if\; X \geq \lambda \\ \;\; 0,\; otherwise \end{cases} \qquad (3)$$

Where, λ is the threshold value.

V. EXPERIMENTAL RESULTS

After denoising by thresholding of the image, the image is reconstructed using wavelet packet reconstruction. Six images of different complexities and format are considered namely cameraman.tif, barbara.png, peppers.png, parrot.jpg, house.png, coins.png. Different images are used which are contaminated by additive Gaussian white noise of different standard deviations that are: σ = 5, 10, 15, 20, 25, 30, 35, 40, 45 and 50. The results are shown for low, medium and high noise densities for cameraman.tif and barbara.png images with their PSNR values.

i). Objective Results Analysis

PSNR is the quantitative performance measurement technique by which the quality of the image is measured. PSNR is used to measure feature similarity of original and denoised image. Comparison of PSNR values for existing method and wavelet packet for proposed method is stated in table 1 and table 2. The formula of PSNR is given as:

$$\text{PSNR} = 10 \log_{10}(255^2/\text{MSE}) \text{ dB} \tag{4}$$

Where the MSE between the original and denoised images given as:

$$MSE = \frac{1}{NM}\sum_{n=1}^{N}\sum_{m=1}^{M}\left[f(n,m) - \hat{f}(n,m)\right]^2 \tag{5}$$

Where N and M are the lengths of images, and f and $\hat{f}$ are the original and reconstructed intensities.
All the techniques implemented are compared by finding the MSE and then PSNR in dB using wavelet type 'db5', as it is more suitable in image denoising. Following Table 1 and 2 illustrates the comparison with Wiener filtering in wavelet domain.

Table 1: Comparison of PSNR values for different images

Standard Deviation σ	***Cameraman***		***Barbara***		***Peppers***	
	Wiener Filter in Wavelet Domain	Edge Preserving using WP	Wiener Filter in Wavelet Domain	Edge Preserving using WP	Wiener Filter in Wavelet Domain	Edge Preserving using WP
5	34.3102	36.3206	35.6433	37.5163	32.2533	36.9081
10	31.9532	34.6464	32.2334	35.9062	31.3884	34.5245
15	30.6952	33.2973	28.3995	33.9234	28.1901	31.2776
20	28.3402	31.5315	27.8323	32.6045	26.5772	28.9266
25	26.4412	30.1842	26.3457	31.5481	23.4108	26.8587
30	24.8991	28.0307	24.0229	30.5812	22.2209	25.9999
35	22.6227	27.0187	23.7908	29.9265	21.6134	25.0251
40	21.5108	25.9864	22.2130	28.2832	20.2099	24.2592

45	20.5591	24.2457	21.8560	26.6371	19.9878	23.5503
50	19.7386	23.6312	21.2009	25.7664	18.1912	22.9376

Table 2: Comparison of PSNR values for different images

Standard Deviation σ	*Parrot*		*House*		*Coins*	
	Wiener Filter in Wavelet Domain	Edge Preserving using WP	Wiener Filter in Wavelet Domain	Edge Preserving using WP	Wiener Filter in Wavelet Domain	Edge Preserving using WP
5	33.4465	37.4095	33.2871	36.3201	34.1094	37.7011
10	30.9315	33.5836	29.2907	32.2395	30.5123	33.4443
15	28.9803	31.4282	27.6889	29.9217	27.9217	31.2229
20	27.4315	29.929	25.5319	28.4664	26.4994	29.6626
25	25.0272	28.9008	23.9956	27.3427	24.0859	28.5865
30	23.9218	27.9894	23.3214	26.4561	22.4301	26.679
35	22.9895	27.3613	22.1413	25.7434	21.4335	25.9448
40	21.9089	26.7311	21.1442	25.0707	20.5104	24.4291
45	20.5051	25.8409	20.1129	24.5542	19.8035	23.8165
50	18.6111	25.5769	19.0433	23.4439	18.8155	23.1567

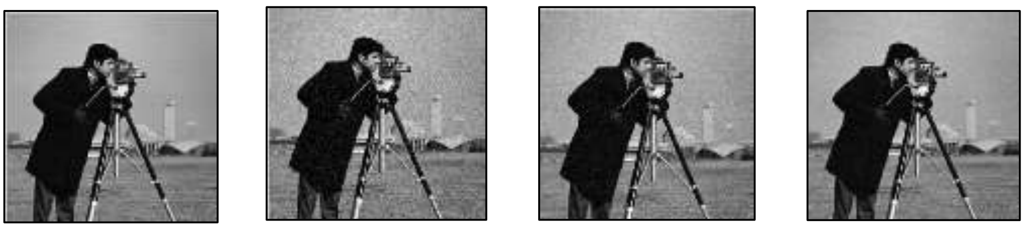
ii). Subjective Results Analysis

Subjective evaluation is done by visual perception, which is a quality measurement between original and denoised image by visually judging it.

The results of the wavelet packet decomposition are shown for low, medium and high noise densities for all the images with their PSNR values. The wavelet packet algorithm restores the most of the image details at the high noise standard deviation and avoids the artifacts in the image of different intensities.

A) Subjective results for *cameraman* image using wavelet packet:

a) Noise Standard Deviation=15, Value of PSNR= 30.6924, PSNR= 33.2973



Original image | Noisy image | Denoised image Wiener Filter | Denoised image Wavelet packet

b) Noise Standard Deviation=25, Value of PSNR=26.4236, PSNR=30.1842


Original image


Noisy image


Denoised image Wiener Filter


Denoised image Wavelet packet

c) Noise Standard Deviation=35, Value of PSNR= 22.6227, PSNR=27.0187


Original image


Noisy image


Denoised image Wiener Filter


Denoised image Wavelet packet

B) Subjective results for *barbara* image using wavelet packet

a) Noise Standard Deviation=15, Value of PSNR= 28.3995, PSNR= 33.9234


Original image


Noisy image


Denoised image Wiener Filter


Denoised image Wavelet packet

b) Noise Standard Deviation=25, Value of PSNR= 26.3457, PSNR=31.5418


Original image


Noisy image


Denoised image Wiener Filter


Denoised image Wavelet packet

c) Noise Standard Deviation=35, Value of PSNR= 23.7908, PSNR=29.9265


Original image

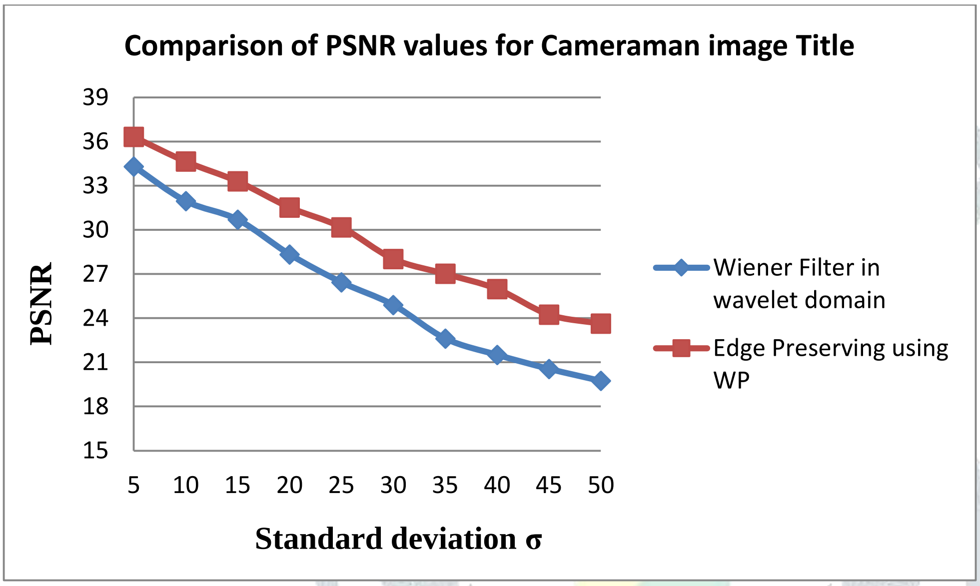

Noisy image


Denoised image Wiener Filter


Denoised image Wavelet packet

VI. PERFORMANCE ANALYSIS

i). Comparison of PSNR values for ***cameraman*** image



VII. CONCLUSIONS

In this paper, image denoising algorithm is analysed for noise reduction along with soft thresholding technique in wavelet packet decomposition along with edge-preserving using soft thresholding. Experimental results analysis are conducted on different test images of different structures in which additive Gaussian noise is induced and the performance of the proposed algorithms are evaluated objectively and subjectively. The Gaussian noise is reduced in the output denoised images with textures and other fine details such as edges are preserved as shown in denoised images.

The PSNR values given in Table 1 and 2 for all the methods have been considerably analyzed. The experimental results demonstrate the significance of the image denoising for visual perception of the images. This algorithm is based on the analysis of statistical parameters like standard deviation and variance. The proposed technique yields remarkably better image quality by preserving edges and have a better PSNR value.

It is also observed that the images corrupted with less noise densities shows a better results having a better PSNR and MSE values. Also, From the obtained results it can be seen that wavelet packet algorithm gives the better PSNR than Wiener filter in wavelet domain. The proposed algorithm may be extended in future to different images for lower frequency components which may improve image quality.

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