Image Denoising by Wavelet Based Thresholding Method

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***Abstract*— In the present day, visual data transferred in digital imageries is fetching a popular technique of communication, however the picture acquired after transfer communication is frequently distorted by noise. Before it can be used in applications, the received image must be processed. Picture denoising is the process of manipulating picture data in order to create a visibly excellent picture. We can characterize signals with a precise degree of scarcity using wavelet transforms. Wavelet thresholding is a signal estimating approach that uses the wavelet transform's ability to de-noise signals.**

Noise suppression in medical imaging is a very delicate and challenging endeavour. The trade-off between noise reduction and picture feature preservation must be adjusted in such a way that the diagnostically useful image content is enhanced. The wavelet thresholding method has been widely utilised to de-noise medical images. The goal is to convert the image information into a wavelet basis, where the large coefficients reflect the signal and the smaller coefficients indicate the noise. The noise in the data can be reduced by adjusting these coefficients appropriately. The goal of this thesis is to compare the performance of several thresholding strategies such as Sure Shrink, Visu Shrink, and Bayes Shrink.

Index Terms* — *Image denoising, Wavelet Thresholding, Image Enhancement, Sure Shrink, Visu Shrink and Bayes Shrink.

I. INTRODUCTION

Picture restoration takes up a significant percentage of digital image processing [1]. This involves work on algorithm creation and routine image processing with a goal in mind. Picture restoration is the process of removing or reducing image degradations [2] that occur during the acquisition of the image. Blurring and noise from electric and photo-metric resources cause degradation. Blurring is produced by an unsatisfactory image generation process such relative motion between the camera and the object or an out of focus visual system. Blurs are introduced to aerial images for faraway detecting reason by atmospheric disorder, irregularities of optical system, and relative motion between the camera and the object. The captured image is also distorted by noises, in adding to these blurring causes. Due to a blaring channel, inaccuracies throughout the operating procedure, and digitation of the image for digital storing, distortion is bringing together into the communication line. Lenses, film, digitizer, and other elements in the imaging chain all contribute to the degradation. When an image has been deteriorated but needs to be fixed before it can be printed, picture denoising is frequently utilised in the arena of shooting or printing. In order to design a model for this method of utilization, we need to understand the ruin procedure. When we have a model for the deterioration process, we may use the reverse procedure to restore the picture to its original state. The picture quality is also enhanced by histogram-equalization method [3].

II. METHODOLOGY

It offers the step-by-step, detailed methods for denoising images with wavelet transforms.

Step 1: Read the standard image in its entirety (Lena.jpg) [4].

Step 2: Convert the original RGB image to a grayscale version [5].

Step 3: The standard grey image is given a dose of Gaussian noise.

Step 4: Apply a discrete wavelet transform (WT) on the noisy image.

Step 5: After employing the WT to divide the corrupt image into approximation and detailed coefficients, it is subjected to the subsequent thresholding guidelines with varying threshold values.

A. ***Soft Thresholding: -*** *This thresholding process entails setting all input components with outright values which is lower compare to the specified threshold magnitude to zero and at that time scaling the nonzero coefficients toward zero. It eliminates visual discontinuities and produces more pleasing visuals given by equation 1&2.*

$$x = abs(y)$$
$$x - sign(y), * (x \geq thld), * (x - thld)$$

Where the Y is input, the threshold magnitude is thld, and the output is x.

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B. ***Hard Thresholding: -*** *The method where input items with absolute values less than the usual threshold values are fixed to zero is referred to as thresholding. It is discontinuous where it meets the noise energy and produces abrupt artefacts in the outcome picture, particularly at high noise energy.*

C. ***Visu Shrink****: - Donoho [6] first introduced Visu Shrink. It employs a threshold amplitude t which is proportional to the noise's SD (standard deviation). This is also known as the universal threshold, and given by equation 3.*

$$t = \sigma 2\sqrt{2l} \quad (3)$$

σ^2 is the signal's noise variance, and n is the signal's size, or the number of samples. The median absolute deviation [7] was used to calculate an approximation of the noise magnitude given by equation 4.

$$\sigma = \frac{(median(g(j-1,k)\,|:k=0,1,\ldots\ldots\,|(j-12)-1)}{0.67445} \quad (4)$$

In the wavelet transform where $g_{j-1,k}$, a coefficient. The detail of Visu Shrink is that it doesn't handle minimising the MSE [8]. It can be thought of as normal-purpose threshold pickers that have near best mini-max fault features and assure that the estimations are as fine as the genuine essential functions with a high likelihood [6].

D. ***Sure Shrink:-*** *Sure Shrink is a threshold selector created on Stein's Unbiased Risk Estimator introduced by Donoho and Johnstone [9]. It's the MSE result of combining the universal and SURE thresholds represented by equation 5.*

$$MSE = \frac{1}{n^2}\sum_{x,y=1}^{n}\left(z(x,y) - s(x,y)\right)^2 \quad (5)$$

Where z(x, y) is the signal's estimation, s(x, y) is the signal's actual signal short of noise & 'n' is the signal's magnitude. Sure Shrink reduces noise by using empirical wavelet coefficients to set a threshold. The Sure Shrink threshold t* is calculated by equation 6:

$$t = \min(t, \sigma\sqrt{2logn} \quad (6)$$

Where t represents the magnitude that diminishes Stein's Unbiased Risk Estimator, n is the size of image, and is the noise variance obtained using Equation (2.4). The gentle thresholding rule is followed by Sure Shrink.

E. ***Bayes Shrink: -*** *Chang, Yu, and Vetterli proposed Bayes Shrink [10]. The purpose of this strategy is to reduce Bayesian risk, which is why it's called Bayes Shrink. It is smoothness adaptable, just as the Sure Shrink method. The Bayes threshold, t_B, is calculated by equation 7:*

$$\boldsymbol{t_B} = \frac{\sigma^2}{\sigma_s^2} \quad (7)$$

Where σ^2 represent signal variance in absence of noise and where σ_s^2 represent variance of noise shown by equation 8 & 9.

$$w(x,y) = s(x,y) + n(x,y) \quad (8)$$

Because the noise and the signal are unrelated, it is possible to say that

$$\sigma_w^2 = \sigma_s^2 + \sigma^2$$

σ_w^2 can be computed by equation 10 as shown below:

$$\sigma_w^2 = \frac{1}{n^2}\sum_{x,y=1}^{n} w^2(x,y)$$

The variance of the signal, σ_s^2 is computed as shown by equation 11.

$$\sigma_s = \sqrt{\max(\sigma_w^2 - \sigma^2 . 0)}$$

Equation computes the Bayes threshold with σ^2 and Equation computes the Bayes threshold with σ_s^2 . The wavelet coefficients are threshold at each band using this threshold. For the corrupted image, this function produces wavelet coefficients.

Step 6: The de-noised picture is rebuilt consuming (IDWT) inverse discrete wavelet transforms after the mixed picture coefficients are thresholded by means of the three threshold magnitude signposted above for every thresholding method.

Step 7: Then, for each of the denoised images, their two parameters, peak signal to noise ratio, are calculated.

III. Experimental Results

The outcomes of the denoising algorithms for various techniques are discussed in this chapter. Denoising is performed after adding Gaussian noise to the original image using a two-level discrete wavelet transform. For each approach, the PSNR and MSE are calculated and compared. The results are collated and shown as a line chart and bar graph at the end. For the global and adaptive thresholding strategies, the figures and PSNR are compared. The findings are given for thresholds chosen using Visu Shrink methods as well as thresholds chosen using the default universal threshold soft thresholding. The Visu Shrink, Sure Shrink, and Bayes Shrink algorithms were used to generate the results. It is furthermost typically employed as a calculation of reconstruction eminence in picture compression and other applications. The following formula shown in equation 12 & 13 is used to compute it:

$$MSE = \frac{1}{mn}\sum_i (i=0)(m-1) = \sum (j-1)(n-1) = |I(i,j) - k(i,j)| \quad (12)$$

$$PSNR = 10 * log_{10}\frac{max_I^2}{MSE}$$

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The original and denoised images are represented by I and K, respectively. This is comparable to 255 when the pixels are characterised by means of eight bits for every sample.

Effect of Different Threshold Techniques on Image Quality: - The methods for denoising images utilised here include Visu Shrink, Sure Shrink, and Bayes Shrink. The impact of various strategies on image [11] quality is demonstrated here with photographs created using the methods. Figure 1 depicts the original image [12].

Fig. 1. Original lena image(lena.jpg(512x512))

A. Visu shrink: The following are the results of employing the Visu Shrink method shown by Figure 2- Figure 19.

Fig. 2. Noisy Image - Gaussian Noise (Mean=0,Variance=0.01)

Fig. 3. Visu Shrink (Soft Threshold with haar)

Fig. 4. Visu Shrink (Soft Thresholding with db1)

Fig. 5. Visu Shrink (Soft Thresholding with db2)

Fig. 6. Visu Shrink (Soft Thresholding with db3)

Fig. 7. Visu Shrink (Soft Thresholding with bior3.7)

Fig. 8. Noisy Image (Gaussian Noise) (Mean=0,Variance=0.05)

Fig. 9. Visu Shrink (Soft Thresholding with haar)

Fig. 10. Visu Shrink (Soft Thresholding with db1)

Fig. 11. Visu Shrink(Soft Thresholding with db2)

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Fig. 12. Visu Shrink (Soft Thresholding with db3)

Fig. 13. Visu Shrink (Soft Thresholding with bior3.7)

Fig. 14. Noisy Image -Gaussian Noise (Mean=0,Variance=0.10)

Fig. 15. Visu Shrink (Soft Thresholding with haar)

Fig. 16. Visu Shrink(Soft Thresholding with db1)

Fig. 17. Visu Shrink (Soft Thresholding with db2)

Fig. 18. Visu Shrink (Soft Thresholding with db3)

Fig. 19. Visu Shrink(Soft Thresholding with bior3.7)

B. Sure Shrink: The results obtained by using the Sure Shrink method sgown by Figure 20 to Figure 37.

Fig. 20. Noisy Image -Gaussian Noise (Mean=0,Variance=0.01)

Fig. 21. Sure Shrink (Soft Thresholding with haar)

Fig. 22. Sure Shrink (Soft Thresholding with db1)

Fig. 23. Sure Shrink (Soft Thresholding with db2)

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Fig. 24. Sure Shrink (Soft Thresholding with db3)

Fig. 25. Sure Shrink (Soft Thresholding with bior3.7)

Fig. 26. Noisy Image - Gaussian Noise (Mean=0,Variance=0.05)

Fig. 27. Sure Shrink (Soft Thresholding with haar)

Fig. 28. Sure Shrink (Soft Thresholding with db1)

Fig. 29. Sure Shrink (Soft Thresholding with db2)

Fig. 30. Sure Shrink (Soft Thresholding with bior3.7)

Fig. 31. Sure Shrink (Soft Thresholding with db3)

Fig. 32. Noisy Image -Gaussian Noise (Mean=0,Variance=0.10)

Fig. 33. Sure Shrink (Soft Thresholding with haar)

Fig. 34. Sure Shrink (Soft Thresholding with db1)

Fig. 35. Sure Shrink (Soft Thresholding with db2)

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Fig. 36. Sure Shrink (Soft Thresholding with db3)

Fig. 37. Sure Shrink (Soft Thresholding with bior3.7)

C. Bayes Shrink: The results acquired by applying the Bayes Shrink technique are presented by Figure 38- Figure 55.

Fig. 38. Noisy Image -Gaussian Noise (Mean=0,Variance=0.01)

Fig. 39. Bayes Shrink (Soft Thresholding with haar)

Fig. 40. Bayes Shrink (Soft Thresholding with db)

Fig. 41. Bayes Shrink(Soft with db2)

Fig. 42. Bayes Shrink (Soft Thresholding with bior3.7)

Fig. 43. Bayes Shrink (Soft Thresholding with db3)

Fig. 44. Noisy Image - Gaussian Noise (Mean=0,Variance=0.05)

Fig. 45. Bayes Shrink (Soft Thresholding with haar)

Fig. 46. Bayes Shrink (Soft Thresholding with db1)

Fig. 47. Bayes Shrink (Soft Thresholding with db2)

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Fig. 48. Bayes Shrink (Soft Thresholding with db3)

Fig. 49. Bayes Shrink (Soft Thresholding with bior3.7)

Fig. 50. Noisy Image - Gaussian Noise (Mean=0,Variance=0.10)

Fig. 51. Bayes Shrink (Soft Thresholding with haar)

Fig. 52. Bayes Shrink (Soft Thresholding with db1)

Fig. 53. Bayes Shrink (Soft Thresholding with db2)

Fig. 54. Bayes Shrink (Soft Thresholding with db3)

Fig. 55. Bayes Shrink (Soft Thresholding with bior3.7)

Effect of various Wavelets on PSNR by changing the Noise Variance for the Different Methods tabulated in Table 1 – Table 3 and expressed by Figure 56- Figure 58.

TABLE I. PSNR VS. VARIANCE FOR VISU SHRINK METHOD

	0.01 (Variance)	**0.02 (Variance)**	**0.05 (Variance)**	**0.08 (Variance)**	**0.10(Variance)**
haar	25.99	24.93	23.07	21.96	21.33
db1	26.02	24.96	23.13	21.99	21.35
db2	27.21	25.97	23.76	22.36	21.70
db3	27.45	26.13	23.82	22.46	21.78
bior3.7	28.06	26.43	23.87	22.39	21.71

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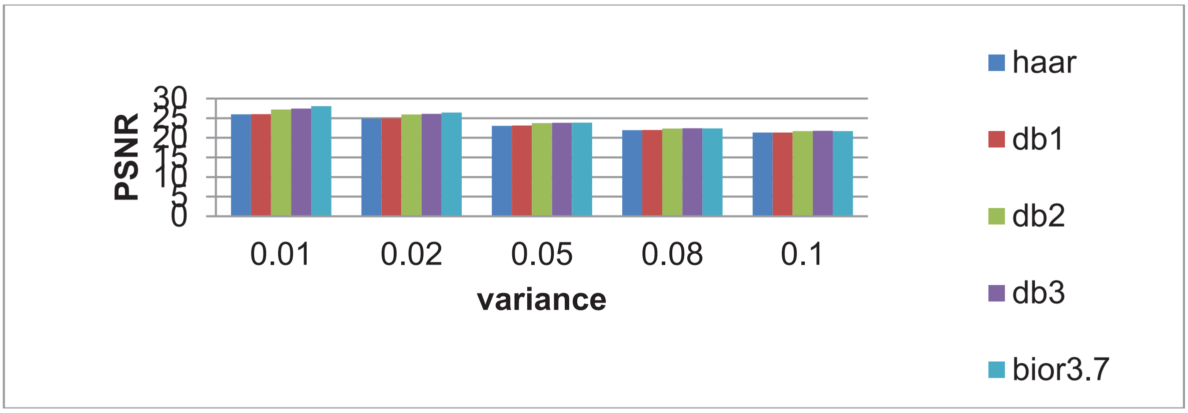

Fig. 56. Bar graph of PSNR vs. Variance for Visu Shrink method

TABLE II. PSNR VS. VARIANCE FOR SURE SHRINK METHOD

	0.01 (Variance)	0.02 (Variance)	0.05 (Variance)	0.08 (Variance)	0.10(Variance)
haar	27.41	25.58	23.24	21.88	21.25
db1	27.47	25.67	23.38	21.85	21.29
db2	28.22	26.40	23.78	22.21	21.46
db3	28.33	26.56	23.79	22.34	21.54
Bior3.7	28.13	26.29	23.48	21.92	21.27

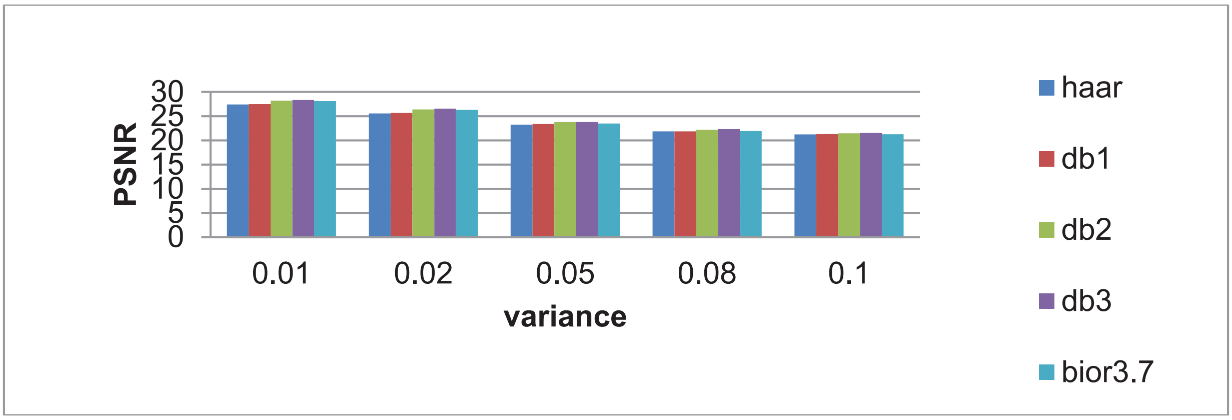

Fig. 57. Bar graph of PSNR vs. Variance for Sure Shrink method

TABLE III. PSNR VS. VARIANCE FOR BAYES SHRINK METHOD

	0.01 (Variance)	0.02 (Variance)	0.05 (Variance)	0.08 (Variance)	0.10 (Variance)
haar	27.41	25.71	23.27	21.95	21.31
db1	27.56	25.73	23.34	21.99	21.30
db2	28.24	26.44	23.96	22.45	21.82
db3	28.48	26.68	24.04	22.53	21.87
bior3.7	28.47	26.46	23.54	22.38	21.49

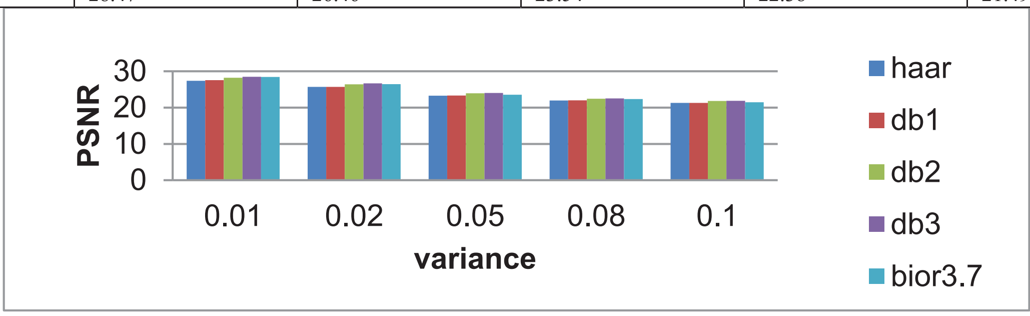

Fig. 58. Bar graph of PSNR vs. Variance for Bayes Shrink method

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Effect of various methods on PSNR by changing the Noise Variance for The Different Wavelets tabulated in Table 4 – Table 7 and represented by Figure shown by Figure 59 to Figure 62.

TABLE IV. PSNR VS. VARIANCE FOR HAAR WAVELET

	0.01 (Variance)	0.02 (Variance)	0.05 (Variance)	0.08 (Variance)	0.10(Variance)
Visu Shrink	25.99	24.93	23.07	21.96	21.33
Sure Shrink	27.41	25.58	23.24	21.88	21.25
Bayes Shrink	27.41	25.71	23.27	21.95	21.31

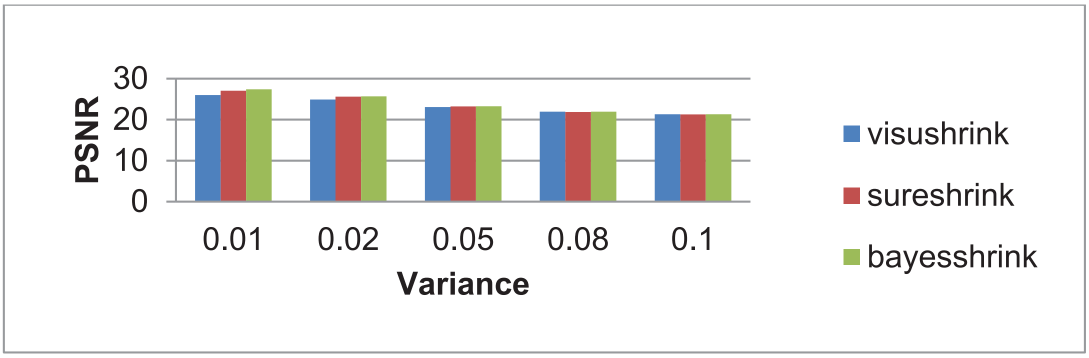

Fig. 59. Bar graph of PSNR vs. Variance for Haar Wavelet

TABLE V. PSNR VS. VARIANCE FOR DB1 WAVELET

	0.01 (Variance)	0.02 (Variance)	0.05 (Variance)	0.08 (Variance)	0.10(Variance)
Visu Shrink	26.02	24.96	23.13	21.99	21.35
Sure Shrink	27.47	25.67	23.38	21.85	21.29
Bayes Shrink	27.56	25.73	23.34	21.99	21.30

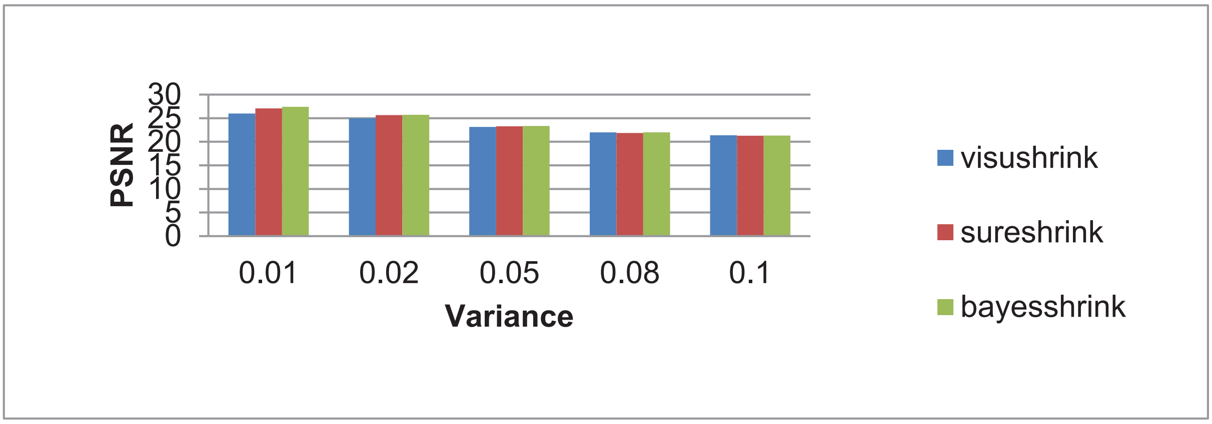

Fig. 60. Bar graph of PSNR vs. Variance for db1 Wavelet

TABLE VI. PSNR VS. VARIANCE FOR DB2 WAVELET

	0.01 (Variance)	0.02 (Variance)	0.05 (Variance)	0.08 (Variance)	0.10(Variance)
Visu Shrink	27.21	25.97	23.76	22.36	21.70
Sure Shrink	28.22	26.40	23.78	22.21	21.46
Bayes Shrink	28.24	26.44	23.96	22.45	21.82

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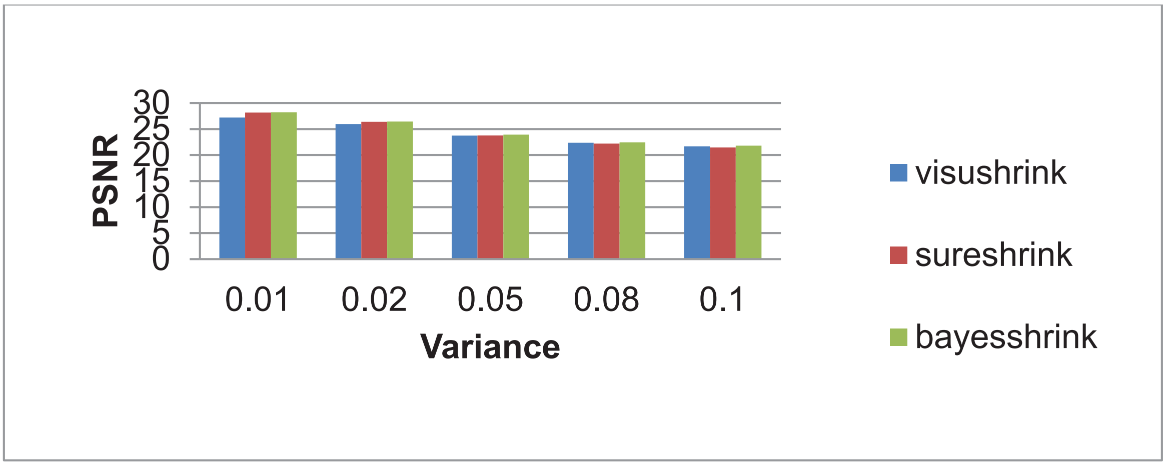

Fig. 61. Bar graph of PSNR vs. Variance for db2 Wavelet

TABLE VII. PSNR VS. VARIANCE FOR DB3 WAVELET

	0.01 (Variance)	0.02 (Variance)	0.05 (Variance)	0.08 (Variance)	0.10(Variance)
Visu Shrink	27.45	26.13	23.82	22.46	21.78
Sure Shrink	28.33	26.56	23.79	22.34	21.54
Bayes Shrink	28.48	26.68	24.04	22.53	21.87

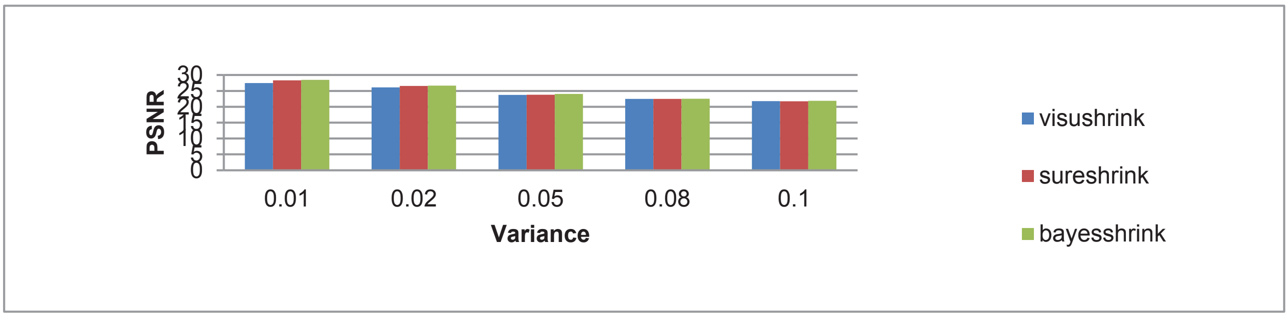

Fig. 62. Bar graph of PSNR vs. Variance for db3 Wavelet

IV. CONCLUSION

We compare the numerous input and output parameters that have been taken into account when applying wavelet transformations to de-noise images. Using wavelet transforms, we compare and contrast several image denoising strategies. Many different combinations have been tried in order to determine the most effective way for denoising intensity photographs. This method is also using in image based solar follower [13-15] now in present days. Solar follower is a way to harvest renewable of sustainable energy [16, 17].

Wavelet shrinkage denoising has been found to be almost ideal in the case of images affected by Gaussian noise. In comparison to Visu Shrink & Sure Shrink, Bayes Shrink produces the highest PSNR. However, unlike the other two approaches, the Bayes Shrink method produces an image that is considerably nearer to the best quality picture & has no blur effect. Unlike Bayes Shrink, Visu Shrink is unable to de-noise multiplying noise. It has been found to be ineffective for noise variances greater than 0.05. When compared to the other two approaches, Visu Shrink performs poorly. This is due to the circumstance that the threshold is examined by the size of the image rather than the content of the image. The performance of Bayes Shrink in terms of image quality and smoothness is better than Visu Shrink and Sure Shrink.

Daubechies wavelets are better than Haar wavelet. Within the Daubechies wavelets db2 appears to have produced the least flawless denoised image; that agrees db2 is being better in image denoising than db1 and Haar.

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