Denoising of images using Thresholding Based on Wavelet Transform Technique

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Abstract — This paper presents an efficient method based on thresholding for images that are corrupted due to Gaussian noise. In order to achieve this task, wavelet transforms and various thresholding techniques have been applied. But the selection of the thresholding technique is restricted due to their widespread use in image denoising application. In this paper, a more efficient thresholding scheme named as neigh shrink sure is studied by incorporating the neighboring wavelet coefficients. Different thresholding techniques like Bayes shrink and Neigh shrink sure algorithms are applied to different images. The results are obtained using 3 different wavelets db⁴, sym⁴, and coif⁴. It has been observed that the use of coif⁴ transform produces better results as compared to other wavelet transforms. Further, it has been analyzed that Neigh Shrink sure method performs better in de-noising of corrupted images in comparison to Bayes shrink thresholding technique by possessing higher Peak Signal-to-Noise Ratio (PSNR) and lower Mean Square Error (MSE).

Keywords — Image denoising, Gaussian noise, Wavelet transforms, Bayes shrink thresholding, Neigh shrink thresholding

1. Introduction

Image denoising operation can be treated as a process itself, and as a component in other processes. There is a large number of methods to de-noise [1, 2] an image or a set of data exist. The key property of an efficient image de-noising representation is that it will eradicate noise while preserving edges. Image denoising is not an easy task to do. While performing the enhancement of image, there exists a trade-off between the process of noise removal image and preservation of real attributes of the image. Noise reduction has always been a challenging job in image processing. It is assumed that each resource of noise makes a distinct set of noises thus several techniques have been offered to eradicate it. Denoising is essential to minimize the noise and to help the revival of functions of that detected signal. Under standard assumptions, the most of the procedures are applied in a better way. An improved version of wavelet expansion has been recommended to tackle this situation. Wavelet transformation can further divide into two types: continuous and discrete [3,4]. Discrete wavelet transform (DWT) [5-7] of an image generate its non-redundant representation. In comparison with additional multi-scale representations like Laplacian pyramid etc. This representation provides better spatial and spectral localization of image formation. Random variation of color information or brightness in images generated by different devices like camera, sensor, etc. is termed as image noise. This noise leads to different undesirable effects such as unseen lines and corners; disturbs background scenes, and blur different objects. So, different de-noising techniques are studied for the removal of this noise from the image. Nigam et al. [8] presented a comparative analysis of different thresholding methodologies for denoising of images. Arun et al.[9] reviewed the various image denoising techniques based on wavelet thresholding. Iram Sami et al. [10] proposed a methodology to perform image denoising operation for Gaussian noise corrupted images using discrete wavelet transform.
The paper is structured as follows: Section 2 shows the research methodology of the proposed work. Section 3 presents the results of proposed method for image denoising and calculates parameters like Peak signal to noise ratio. Finally, the conclusion of the paper is presented in section 4.

2. Proposed Methodology
This segment portrays the various steps used for the denoising of images. The main components of research methodology are loading of image, the addition of noise, wavelet transform, thresholding technique, and calculation of parameters as shown by figure 2.1. The description of each component of the research methodology is presented in the coming sub-sections.

![Figure 2.1. Flow Chart of Proposed Methodology](image)

2.1. Load the Image
Initially, the image to be denoised is loaded into the system. In our proposed work, Lena image, Barbara image, and House image are chosen for simulation purpose as shown by figure 2.2. The format of images is PNG and the size of each image is 512 x 512.

![Figure 2.2. Original image (a) Lena.png (b) Barbara.png (c) House.png](image)

Different noises used in image processing are Gaussian noise, Quantization noise, Speckle noise, Fractal noise, Periodic noise, Salt & Pepper noise, Poisson noise, White noise, Poisson-Gaussian noise, Gamma noise, Rayleigh noise, and Structured noise. The three common types of image noise are Gaussian noise, Salt & Pepper noise, and Speckle noise. In our proposed work, Gaussian noise is added to the loaded images because in various imaging systems a better representation is provided by this noise. When the Gaussian noise is added to any digital image it shakes the gray values of that particular image. Image after the addition of Gaussian noise with mean equal to 0 and standard deviation (σ) equal to 20 is shown by figure 2.3.
2.3. Apply Thresholding Technique Based on Wavelet Transform

In proposed work, initially, DWT [11, 12] is used for simulation purpose. A DWT is any wavelet transform for which the wavelets are discretely sampled. With the help of these wavelets, the data is divided into distinct frequency components, and later all the components are examined with a resolution matched to its scale. These mathematical functions are short waves with limited duration; as a consequence, the name ‘wavelets’ is used. According to frequency, several functions of the wavelet transform are scaled up. There are massive numbers of wavelets that can be used as dissimilar functions; a few of them are db4, sym4, and coif4.

![Figure 2.3. Image produced after addition of Gaussian noise in (a) Lena.png (b) Barbara.png (c) House.png](image)

![Figure 2.4. Bayes Shrink by soft thresholding on denoised Lena with (a) db4 (b) sym4 (c) coif4](image)

![Figure 2.5. Bayes Shrink by soft thresholding on denoised Barbara with (a) db4 (b) sym4 (c) coif4](image)
Figure 2.6. Bayes Shrink by soft thresholding on denoised House with (a) db4 (b) sym4 (c) coif4

Figure 2.7. Neigh Shrink sure by soft thresholding on denoised image Lena with (a) db4 (b) sym4 (c) coif4

Figure 2.8. Neigh Shrink sure by soft thresholding on denoised image Barbara with (a) db4 (b) sym4 (c) coif4
Figure 2.9. Neigh Shrink sure by soft thresholding on denoised image House with (a) db4 (b) sym4 (c) coif4

For image de-noising [13-15], diverse types of thresholding techniques are available in the wavelet domain. Bayes shrink and Neigh shrink sure [16,17] are the two thresholding techniques that are used in proposed work for thresholding of transformed image. Finally, Inverse Discrete Wavelet Transformation (IDWT) is used to reconstruct the original image. The final denoised Lena, Barbara, and House images obtained using Bayes Shrink method are shown by figure 2.4, 2.5, and 2.6 respectively. Similarly, the denoised Lena, Barbara, and House images obtained by using Neigh Shrink sure method are shown by Figure.2.7,2.8, and 2.9, respectively.

2.4. Evaluation of Performance Metrics
For the comparison of compression quality, two error metrics Mean Square Error (MSE) and the Peak Signal to Noise Ratio (PSNR) [18] are used. The MSE represents the cumulative squared error between the compressed and the original image as shown by equation 1, whereas PSNR represents the quality of image as shown by equation 2.

\[
MSE = \frac{1}{N \times N} \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} (x_{i,j} - \hat{x}_{i,j})^2 
\]

\[
PSNR = 10 \times \log_{10} \left( \frac{255^2}{MSE} \right) 
\]

Here, the size of the squared image is represented by N x N, the pixel value of an original image and de-noised image is represented by \(x_{i,j}\) and by \(\hat{x}_{i,j}\) respectively. The PSNR is measured in terms of bits per sample or bits per pixel. If the PSNR will be greater the image quality and noise suppression of an image will also be better.

3. Results and Discussion
Simulation is performed on various Gaussian noisy images [19] like Lena image, Barbara image and House image using Bayes shrink and Neigh shrink sure thresholding techniques. These three different images are contaminated with Gaussian white noise at different standard deviations (\(\sigma\)). The Effect of different wavelets on PSNR and MSE for the different thresholding methods are also analyzed by varying the value of \(\sigma\).

3.1. Bayes Shrink Thresholding
Table 3.1, 3.2 & 3.3 shows the effect of different wavelets on PSNR and MSE by varying the \(\sigma\) for the Bayes Shrink thresholding on Lena image, House image and Barbara image. This table shows that by varying the \(\sigma\), there is a change in PSNR and MSE respectively. It has been observed that a low value of \(\sigma\) produces lesser MSE and more PSNR. It has also been analyzed that, the coif4 wavelet produces maximum PSNR and minimum MSE in comparison with other wavelets.

Table 3.1: Effect of different wavelets on PSNR and MSE by varying the \(\sigma\) for the Bayes Shrink Thresholding on Lena Image

| Bayes Shrink Thresholding | Gaussian noise |
|--------------------------|----------------|
| Lena                     |                |
| db4                      | MSE | PSNR | MSE | PSNR | MSE | PSNR |
| 10                       | 29.8075 | 33.4215 | 29.8356 | 33.4175 | 28.5136 | 33.6143 |
| 15                       | 45.7645 | 31.5595 | 43.7048 | 31.5652 | 43.9004 | 31.7401 |
| σ  | MSE   | PSNR  | MSE   | PSNR  | MSE   | PSNR  |
|----|-------|-------|-------|-------|-------|-------|
| 20 | 61.3984 | 30.2832 | 61.1830 | 30.2985 | 58.8018 | 30.4705 |
| 25 | 75.3252 | 29.3954 | 76.4306 | 29.3321 | 72.5165 | 29.5604 |
| 30 | 90.7737 | 28.5852 | 90.8027 | 28.5838 | 87.3295 | 28.7532 |
| 35 | 105.951 | 27.9137 | 105.4346 | 27.9350 | 100.837 | 28.1226 |
| 40 | 120.347 | 27.3604 | 120.4300 | 27.3575 | 118.863 | 27.4143 |
| 45 | 137.061 | 26.7957 | 136.1562 | 26.8244 | 132.379 | 26.9466 |
| 50 | 152.498 | 26.3322 | 153.042 | 26.3167 | 148.951 | 26.4344 |

Table 3.2: Effect of different wavelets on PSNR and MSE by varying the σ for the Bayes Shrink Thresholding on Barbara Image

| σ  | MSE   | PSNR  | MSE   | PSNR  | MSE   | PSNR  |
|----|-------|-------|-------|-------|-------|-------|
| 10 | 52.0462 | 31.0092 | 53.5943 | 30.8736 | 49.5918 | 31.2107 |
| 15 | 89.9725 | 28.6237 | 89.7709 | 28.6334 | 83.0674 | 28.9705 |
| 20 | 123.722 | 27.2403 | 122.444 | 27.2854 | 115.101 | 27.5540 |
| 25 | 158.146 | 26.1742 | 157.574 | 26.7900 | 150.075 | 26.4017 |
| 30 | 194.412 | 25.2776 | 192.616 | 25.3179 | 182.997 | 25.5404 |
| 35 | 229.694 | 24.5533 | 228.414 | 24.5776 | 217.773 | 24.7848 |
| 40 | 261.201 | 23.9950 | 262.258 | 23.9775 | 253.429 | 24.1262 |
| 45 | 290.671 | 23.5308 | 293.788 | 23.4845 | 281.539 | 23.6694 |
| 50 | 322.187 | 23.0703 | 323.634 | 23.0643 | 315.538 | 23.1743 |
| Average | 191.3391 | 25.9416 | 191.5659 | 26.0047 | 183.2346 | 26.1591 |

Table 3.3: Effect of different wavelets on PSNR and MSE by varying the σ for the Bayes Shrink Thresholding on House Image

| σ  | MSE   | PSNR  | MSE   | PSNR  | MSE   | PSNR  |
|----|-------|-------|-------|-------|-------|-------|
| 10 | 32.3407 | 33.0673 | 31.1194 | 33.2345 | 31.3251 | 33.2059 |
| 15 | 51.1761 | 31.0741 | 50.6493 | 31.1191 | 49.8323 | 31.1897 |
| 20 | 69.9418 | 29.7174 | 67.1508 | 29.8943 | 65.2394 | 30.0197 |
| 25 | 87.5932 | 28.7401 | 84.0734 | 28.9182 | 83.3564 | 28.9554 |
| 30 | 102.561 | 28.0550 | 98.4815 | 28.2313 | 98.6987 | 28.2217 |
| 35 | 117.939 | 27.4482 | 115.517 | 27.5384 | 112.621 | 27.6486 |
| 40 | 135.864 | 26.8338 | 129.588 | 27.0391 | 134.895 | 26.8648 |
| 45 | 155.768 | 26.2400 | 149.026 | 26.4322 | 152.013 | 26.3460 |
| 50 | 172.176 | 25.8051 | 174.320 | 25.7513 | 162.278 | 26.0622 |
| Average | 102.8178 | 28.5534 | 99.99171 | 28.68427 | 98.91766 | 28.72378 |
3.2. Neigh Shrink Sure Thresholding

Similarly, Table 3.4, 3.5 & 3.6 shows the effect of different wavelets on PSNR and MSE by varying the $\sigma$ for the Neigh shrink sure thresholding on Lena image, House image, and Barbara image. This table shows that by varying the $\sigma$, there is a change in PSNR and MSE respectively. It has been observed that a low value of $\sigma$ produces lesser MSE and more PSNR. It has also been analyzed that, the coif4 wavelet produces maximum PSNR and minimum MSE in comparison with other wavelets.

**Table 3.4: Effect of different wavelets on PSNR and MSE by varying the $\sigma$ for the Neigh Shrink Sure Thresholding on Lena Image**

| Neigh Shrink Sure Thresholding | Gaussian noise |
|-------------------------------|----------------|
| Lena                          |                |
| $\Sigma$                      |                |
| 10 22.6749 34.6093 22.8906 34.5682 21.9470 34.7510 |                |
| 15 35.6875 32.6396 35.5195 32.6601 34.1482 32.8311 |                |
| 20 48.9989 31.2630 48.9916 31.2636 46.4550 31.4945 |                |
| 25 62.2536 30.2232 62.3131 30.2190 59.2694 30.4362 |                |
| 30 74.6010 29.4374 75.4164 29.3901 72.1341 29.5834 |                |
| 35 89.7443 28.6347 90.9898 28.5749 85.8731 28.8262 |                |
| 40 106.724 27.8822 104.071 27.9915 99.3946 28.1912 |                |
| 45 120.606 27.3511 121.994 27.3014 115.882 27.5246 |                |
| 50 136.762 26.8051 136.679 26.8078 126.923 26.9171 |                |
| Average 77.56136 29.87173 77.65167 29.86407 73.55849 30.0617 |                |

**Table 3.5: Effect of different wavelets on PSNR and MSE by varying the $\sigma$ for the Neigh Shrink Sure Thresholding on Barbara Image**

| Neigh Shrink Sure Thresholding | Gaussian noise |
|-------------------------------|----------------|
| Barbara                      |                |
| $\Sigma$                      |                |
| 10 34.4324 32.7951 34.5311 32.7827 32.2586 33.0783 |                |
| 15 59.0890 30.4497 59.4393 30.4241 54.7180 30.7835 |                |
| 20 85.4662 28.8469 85.1896 28.8609 79.3281 29.1705 |                |
| 25 111.933 27.6752 111.553 27.6900 103.889 27.9991 |                |
| 30 137.593 26.7788 137.383 26.7855 128.561 27.0737 |                |
| 35 164.191 26.0113 164.263 26.0094 154.521 26.2749 |                |
| 40 193.636 25.2949 191.698 25.3386 180.603 25.5975 |                |
| 45 219.952 24.7415 219.342 24.786 209.117 24.9606 |                |
| 50 248.634 24.2092 249.904 24.1871 240.172 24.3596 |                |
| Average 139.4363 27.42251 139.2559 27.42632 131.4631 27.69974 |                |
Table 3.6: Effect of different wavelets on PSNR and MSE by varying the $\sigma$ for the Neigh Shrink Sure Thresholding on House Image

|        | Neigh Shrink Sure Thresholding | Gaussian noise |
|--------|--------------------------------|----------------|
|        | House                          |                |
|        | db4   | sym4 | coef4 | db4   | sym4 | coef4 | db4   | sym4 | coef4 |
| $\Sigma$ | MSE   | PSNR | MSE   | PSNR | MSE   | PSNR | MSE   | PSNR | MSE   | PSNR |
| 10     | 23.8835 | 34.3838 | 24.1610 | 34.3337 | 23.3512 | 34.4817 |
| 15     | 38.5809 | 32.3011 | 38.4536 | 32.3154 | 37.0373 | 32.4784 |
| 20     | 52.8313 | 30.9359 | 52.7365 | 30.9437 | 50.7047 | 31.1143 |
| 25     | 67.5051 | 29.8714 | 66.9689 | 29.9061 | 65.6194 | 29.9945 |
| 30     | 84.1793 | 28.9127 | 84.4594 | 28.8983 | 81.2787 | 29.0650 |
| 35     | 99.0660 | 28.2058 | 97.6743 | 28.2670 | 99.0102 | 28.2080 |
| 40     | 115.929 | 27.5229 | 116.998 | 27.4830 | 108.046 | 27.8287 |
| 45     | 130.381 | 27.0127 | 125.243 | 27.1872 | 129.227 | 27.0513 |
| 50     | 147.882 | 26.4656 | 149.128 | 26.4292 | 152.594 | 26.3294 |
| Average| 84.4709 | 29.51243 | 83.9803 | 29.52929 | 82.98539 | 29.61681 |

3.3 Comparative Analysis
Comparative analysis of Lena Gaussian noisy image using Bayes Shrink thresholding and Neigh shrink sure thresholding techniques is also made by table 3.7. Average PSNR and average MSE of Gaussian noisy image for different wavelets db4, sym4, and coef4 are compared using different thresholding techniques. Graphical analysis of the comparison of average values is also represented by figure 3.1 and figure 3.2 respectively. It has been observed that Neigh shrink sure thresholding produces lower MSE and higher PSNR as compared to Bayes shrink sure thresholding technique which proves that use of Neigh shrink sure technique leads to better performance of the system.

Table 3.7: Comparative Analysis of average PSNR and average MSE of Gaussian noisy image for Different thresholding methods

| Lena Image | Gaussian Image |
|------------|----------------|
| Thresholding Method | PSNR Average | MSE Average |
| Bayes Shrink | db4 | sym4 | coef4 | db4 | sym4 | coef4 |
|              | 29.07187 | 29.07008 | 29.22849 | 90.99181 | 90.77994 | 88.0102 |
| Neigh Shrink Sure | 29.87173 | 29.86407 | 30.0617 | 77.56136 | 77.65167 | 73.55849 |
Figure 3.1. Column graph of average PSNR of Gaussian noisy image for Different thresholding methods

Figure 3.2. Column graph of average MSE of Gaussian noisy image for Different thresholding methods

Similarly, comparative analysis of HOUSE Gaussian noisy image and Barbara Gaussian noisy image is shown by table 3.8 and 3.9 respectively. Similarly, graphical analysis of comparison of average PSNR and MSE values for House image is shown by figure 3.3 and figure 3.4 respectively and for Barbara image is shown by figure 3.5 and figure 3.6 respectively

Table 3.8: Comparative Analysis of average PSNR and average MSE of Gaussian noisy image for Different thresholding methods

| Thresholding Method   | PSNR Average | MSE Average |
|-----------------------|--------------|-------------|
|                       | db4 | sym4 | coif4 | db4 | sym4 | coif4 |
| Bayes Shrink          | 28.55344 | 28.68427 | 28.72378 | 102.8178 | 99.99171 | 98.91766 |
| Neigh Shrink Sure     | 29.51243 | 29.52929 | 29.61681 | 84.4709 | 83.9803 | 82.98539 |
Figure 3.3 Column graph of average PSNR of Gaussian noisy image for Different thresholding methods

Figure 3.4 Column graph of average MSE of Gaussian noisy image for Different thresholding methods

Table 3.9: Comparative Analysis of average PSNR and average MSE of Gaussian noisy image for Different thresholding methods

| Thresholding Method | Barbara Image | Gaussian Image |
|---------------------|---------------|----------------|
|                     | PSNR Average  | MSE Average    |
|                      | db4          | sym4           | coif4          | db4    | sym4    | coif4    |
| Bayes Shrink         | 25.9416      | 26.00047       | 26.15911       | 191.3391| 191.5659| 183.2346 |
| Neigh Shrink sure    | 27.42251     | 27.42632       | 27.69974       | 139.4363| 139.2559| 131.4631 |
Figure 3.5. Column graph of average PSNR of Gaussian noisy image for different thresholding methods

Figure 3.6. Column graph of average MSE of Gaussian noisy image for different thresholding methods

4. Conclusion
Comparative analysis of different image denoising algorithms using different wavelets has been presented in this paper. Different combinations have been performed to find the best suitable technique which can be used for denoising of intensity images. Many experiments are conducted on three different standard images Lena, Barbara, and House with Gaussian noise using Bayes Shrink and Neigh Shrink sure algorithms. The experiments are conducted using 3 different wavelets db-4, coif-4, and sym-4. Bayes Shrink is faster than Neigh Shrink sure but it has been analyzed that Bayes Shrink is not effective for denoising of images because it produces more PSNR and less MSE as compared to Neigh shrink sure method. After computations, it has been analyzed that there is 2.76%, 3.03%, 5.55% increase in PSNR and 16.4%, 16.1%, and 28.2% decrease in MSE of Neigh shrink sure method as compared to Bayes shrink method for Lena, House, and Barbara images respectively which proves that Neigh shrink sure thresholding technique is an efficient scheme producing accurate results.
References

[1] Bopardikar, A. S. (1999). Wavelet transforms: introduction to theory and applications. Pearson Education.

[2] Tania, S., & Rowaida, R. (2016). A comparative study of various image filtering techniques for removing various noisy pixels in aerial image. *International Journal of Signal Processing, Image Processing and Pattern Recognition, 9*(3), 113-124.

[3] Ruikar, S. D., & Doye, D. D. (2011). Wavelet based image denoising technique. *IJACSA) International Journal of Advanced Computer Science and Applications, 2*(3).

[4] Kumar, N., & Nachamai, M. (2017). Noise removal and filtering techniques used in medical images. *Orient J. Comp. Sci and Technol, 10*(1).

[5] Gnanadurai, D., & Sadasivam, V. (2006). An efficient adaptive thresholding technique for wavelet based image denoising. *International Journal of Signal Processing, 2*(2), 114-119.

[6] Cho, D., Bui, T. D., & Chen, G. (2009). Image denoising based on wavelet shrinkage using neighbor and level dependency. *International journal of wavelets, multiresolution and information processing, 7*(03), 299-311.

[7] Chen, G. Y., Bui, T. D., & Krzyzak, A. (2005). Image denoising using neighbouring wavelet coefficients. *Integrated Computer-Aided Engineering, 12*(1), 99-107.

[8] Nigam, V., Luthra, S., & Bhattachar, S. (2010, September). A comparative study of thresholding techniques for image denoising. In 2010 International Conference on Computer and Communication Technology (ICCCT) (pp. 173-176). IEEE.

[9] Dixit, A., & Sharma, P. (2014). A comparative study of wavelet thresholding for image denoising. *IJ Image, Graphics and Signal Processing, 12*, 39-46.

[10] Sami, I., & Thakur, A. (2013). Image Denoising for Gaussian Noise Reduction in Bionics Using DWT Technique 1.

[11] Mohideen, S. K., Perumal, S. A., & Sathik, M. M. (2008). Image de-noising using discrete wavelet transform. *International Journal of Computer Science and Network Security, 8*(1), 213-216.

[12] Cai, T. T., & Silverman, B. W. (2001). Incorporating information on neighbouring coefficients into wavelet estimation. *Sankhyā: The Indian Journal of Statistics, Series B, 127-148.

[13] Jaiswal, A., Upadhyay, J., & Somkuwar, A. (2014). Image denoising and quality measurements by using filtering and wavelet based techniques. *AEU-International Journal of Electronics and Communications, 68*(8), 699-705.

[14] Shrestha, S. (2014). Image denoising using new adaptive based median filters. *arXiv preprint arXiv:1410.2175*.

[15] Gupta, K., & Gupta, S. K. (2013). Image Denoising techniques-a review paper. *IJITEE, 2*, 6-9.

[16] Mahalakshmi, B. V., & Anand, M. J. (2014). Adaptive wavelet packet decomposition for efficient image denoising by using neighsure shrink method. *Int. J. Comput. Sci. Inf. Technol., 5*(4), 5003.

[17] Dirami, A., Hammouche, K., Difaf, M., & Siarry, P. (2013). Fast multilevel thresholding for image segmentation through a multiphase level set method. *Signal processing, 93*(1), 139-153.