PERFORMANCE ANALYSIS OF IMAGE DENOISING WITH WAVELET THRESHOLDING METHODS FOR DIFFERENT LEVELS OF DECOMPOSITION

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ABSTRACT

Image Denoising is an important part of diverse image processing and computer vision problems. 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. One of the most powerful and perspective approaches in this area is image denoising using discrete wavelet transform (DWT). In this paper, comparison of various Wavelets at different decomposition levels has been done. As number of levels increased, Peak Signal to Noise Ratio (PSNR) of image gets decreased whereas Mean Absolute Error (MAE) and Mean Square Error (MSE) get increased . A comparison of filters and various wavelet based methods has also been carried out to denoise the image. The simulation results reveal that wavelet based Bayes shrinkage method outperforms other methods.

KEYWORDS

Denoising, Filters, Wavelet Transform, Wavelet Thresholding

1. INTRODUCTION

Applications of digital world such as Digital cameras, Magnetic Resonance Imaging (MRI), Satellite Television and Geographical Information System (GIS) has increased the use of digital images. Generally, data sets collected by image sensors are contaminated by noise. Imperfect instruments, problems with data acquisition process, and interfering natural phenomena can all corrupt the data of interest [1]. Various types of noise present in image are Gaussian noise, Salt & Pepper noise and Speckle noise. Image denoising techniques are used to prevent these types of noises while retaining the important signal features [2]. Spatial filters like mean and median filter are used to remove the noise from image. But the disadvantage of spatial filters is that these filters not only smooth the data to reduce noise but also blur edges in image. Therefore, Wavelet Transform is used to preserve the edges of image [3]. It is a powerful tool of signal or image processing for its multi-resolution possibilities.

This paper is organized as follows: Section 2 presents types of noise. Section 3 presents Filtering techniques. Section 4 discusses Wavelet based denoising techniques and various thresholding methods. Finally, simulated results and conclusions are presented in Section 5 and 6 respectively.

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2 .TYPES OF NOISE

Various types of noise have their own characteristics and are inherent in images in different ways.

2.1. Amplifier Noise (Gaussian Noise)

The standard model of amplifier noise is additive, Gaussian, which is independent at each pixel and independent of the signal intensity. In color cameras, blue colour channels are more amplified than red or green channel, therefore, blue channel generates more noise [4].

2.2. Impulsive Noise

Impulsive noise is also called as salt-and- pepper noise or spike noise. This kind of noise is usually seen on images. It consists of white and black pixels. An image containing salt and pepper noise consists of two regions i.e. bright and dark regions. Bright regions consist of dark pixels whereas dark regions consist of bright pixels. Transmitted bit errors, analog-to-digital converter errors and dead pixels contain this type of noise [5].

2.3. Speckle Noise

Speckle noise is a multiplicative noise. It is a granular noise that commonly exists in and the active radar and synthetic aperture radar (SAR) images. Speckle noise increases the mean grey level of a local area. It is causing difficulties for image analysis in SAR images .It is mainly due to coherent processing of backscattered signals from multiple distributed targets [4].

3. FILTERING TECHNIQUES

The filters that are used for removing noise are Mean filter and Median filter.

3.1. Mean Filter

The advantage of using this filter is that it provides smoothness to an image by reducing the intensity variations between the adjacent pixels [6]. Mean filter is essentially an averaging filter. It applies mask over each pixel in signal. Therefore, to make a single pixel each of the components of pixel which falls under the mask are average filter. The main disadvantage of Mean filter is that it cannot preserve edges.

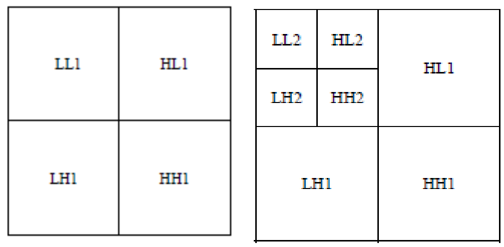
3.2. Median Filter

One type of non linear filter is Median filter. By firstly finding the median value and then replacing each entry in the window with the pixel's median value, median filtering is done [7]. Median is just the middle value after all the entries made in window are sorted numerically, if window has an odd number of entries. There is more than one median when window has an even number of entries. It is a robust filter. To provide smoothness in image processing and time series processing, median filters are used.

4. WAVELET TRANSFORM

Wavelet domain is advantageous because DWT make the signal energy concentrate in a small number of coefficients, hence, the DWT of a noisy image consists of number of coefficients having high Signal to Noise Ratio(SNR) while relatively large number of coefficients is having low SNR. After removing the coefficients with low SNR, the image is reconstructed using inverse DWT [3]. Time and frequency localization is simultaneously provided by Wavelet transform. Moreover, wavelet methods represent such signals much more efficiently than either the original domain or fourier transform [8].

The DWT is same as hierarchical sub band system where the sub bands are logarithmically spaced in frequency and represent octave-band decomposition. Image is decomposed into four sub-bands and critically sampled by applying DWT as shown in Fig. 1(a). These sub bands are formed by separable applications of horizontal and vertical filters. Sub-bands with label LH1, HL1 and HH1 correspond to finest scale coefficient while sub-band LL1 represent coarse level coefficients [9] [3]. The LL1 sub band is further decomposed and critically sampled to find out the next coarse level of wavelet coefficients as shown in Fig. 1(b). It results in two level wavelet decomposition.



(a) One- Level (b) Two- Level

Figure1. Image Decomposition by using DWT

4.1 Wavelet Based Thresholding

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 irrelevant relative to some threshold [9] .Several studies are there on thresholding the Wavelet coefficients. The process, commonly called Wavelet Shrinkage, consists of following main stages:

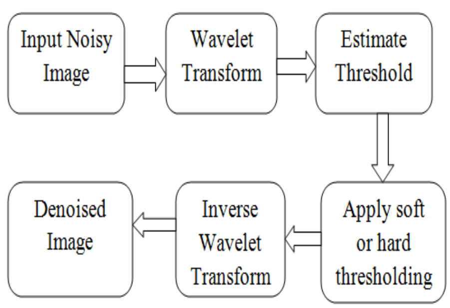


Figure2. Block diagram of Image denoising using Wavelet Transform

- Read the noisy image as input
- Perform DWT of noisy image and obtain Wavelet coefficients
- Estimate noise variance from noisy image
- Calculate threshold value using various threshold selection rules or shrinkage rules
- Apply soft or hard thresholding function to noisy coefficients
- Perform the inverse DWT to reconstruct the denoised image.

4.1.1. Thresholding Method

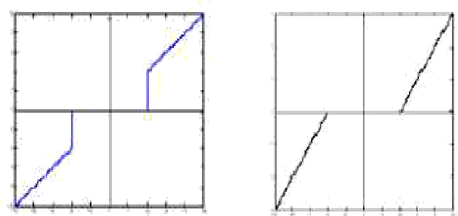
Hard and soft thresholding techniques are used for purpose of image denoising. Keep and kill rule which is not only instinctively appealing but also introduces artifacts in the recovered images is the basis of hard thresholding [10] whereas shrink and kill rule which shrinks the coefficients above the threshold in absolute value is the basis of soft thresholding [11]. As soft thresholding gives more visually pleasant image and reduces the abrupt sharp changes that occurs in hard thresholding, therefore soft thresholding is preferred over hard thresholding [12] [13].

The Hard Thresholding operator [14] is defined as,

$$D(U, \lambda) = U \text{ for all } |U| > \lambda$$
$$= 0 \text{ otherwise} \quad (1)$$

The Soft Thresholding operation the other hand is defined as ,

$$D(U, \lambda) = \operatorname{sgn}(U) * \max(0, |U| - \lambda) \quad (2)$$



(a) Hard Thresholding (b) Soft Thresholding [15]

Figure 3. Thresholding Methods

4.1.2. Threshold Selection Rules

In image denoising applications, PSNR needs to be maximized , hence optimal value should be selected [9]. Finding an optimal value for thresholding is not an easy task. If we select a smaller threshold then it will pass all the noisy coefficients and hence resultant images may still be noisy but larger threshold makes more number of coefficients to zero, which provides smoothness in image and image processing may cause blur and artifacts, and hence the resultant images may lose some signal values [16].

4.1.2.1. Universal Threshold

$$T = \sigma\sqrt{2\log M} \quad (3)$$

where σ^2 being the noise variance and M is the number of pixels [17] .It is optimal threshold in asymptotic sense and minimizes the cost function of difference between the function. It is assumed that if number of samples is large, then the universal threshold may give better estimate for soft threshold [18].

4.1.2.2. Visu Shrink

Visu Shrink was introduced by Donoho [19]. It follows hard threshold rule. The drawback of this shrinkage is that neither speckle noise can be removed nor MSE can be minimized .It can only deal with additive noise [20]. Threshold T can be calculated using the formulae [21],

$$T_v = \hat{\sigma}\sqrt{2\log N} \quad (4)$$

$$\hat{\sigma}^2 = \left[\frac{median(|X_{ij}|)}{0.675}\right]^2, X_{ij} \in HH1 \quad (5)$$

Where σ is calculated as mean of absolute difference (MAD) which is a robust estimator and N represents the size of original image.

4.1.2.3. Bayes Shrink

The Bayes Shrink method has been attracting attention recently as an algorithm for setting different thresholds for every sub band. Here sub-bands refer to frequency bands that are different from each other in level and direction [22]. Bayes Shrink uses soft thresholding. The purpose of this method is to estimate a threshold value that minimizes the Bayesian risk assuming Generalized Gaussian Distribution (GGD) prior [13]. Bayes threshold is defined as [23],

$$t_B = \sigma^2 / \sigma_s \tag{6}$$

Where σ^2 is the noise variance and σ_s is signal variance without noise.

From the definition of additive noise we have,

$$w(x, y) = s(x, y) + n(x, y) \tag{7}$$

Since the noise and the signal are independent of each other, it can be stated that ,

$$\sigma_w{}^2 = \sigma_s{}^2 + \sigma^2 \tag{8}$$

$\sigma_w{}^2$ can be computed as shown below:

$$\sigma_w{}^2 = \frac{1}{n^2} \sum_{x,y=1}^{n} w^2(x, y) \tag{9}$$

The variance of the signal, $\sigma_s{}^2$ is computed as

$$\sigma_s = \sqrt{\max(\sigma_w{}^2 - \sigma^2, 0)} \tag{10}$$

5. SIMULATION RESULTS

Simulated results have been carried on Cameraman image by adding two types of noise such as Gaussian noise and Speckle noise. The level of noise variance has also been varied after selecting the type of noise. Denoising is done using two filters Mean filter and Median filter and three Wavelet based methods i.e. Universal threshold, Visu shrink and Bayes shrink. Results are shown through comparison among them. Comparison is being made on basis of some evaluated parameters. Also the comparison of wavelet thresholding methods at different decomposition level has been discussed. The parameters are Peak Signal to noise Ratio (PSNR), Mean Square Error (MSE) and Mean Absolute Error (MAE).

$$\text{PSNR} = 10 \log_{10}\left(\frac{255^2}{MSE}\right) \text{ db} \tag{11}$$

$$\text{MSE} = \frac{1}{MN} \sum_{i=1}^{M}(\text{x}, \text{y}) \sum_{j=1}^{N}(\text{X}(\text{i}, \text{j}) - P(i, j))^2 \tag{12}$$

$$\text{MAE} = \frac{1}{MN} \sum_{i=1}^{M}(\text{x}, \text{y}) \sum_{j=1}^{N}|\text{X}(\text{i}, \text{j}) - P(i, j)| \tag{13}$$

Where, M-Width of Image, N-Height of Image
P- Noisy Image , X-Original Image

Table 1 and Table 2 show the comparison of PSNR and MSE for cameraman image at various noise variancies. Figure 4 and Figure 5 shows that bayes shrinkage has better PSNR and low MSE than filtering methods and other wavelet based thresholding techniques.

Table1. Comparison of PSNR for Cameraman image corrupted with Gaussian and Speckle noise at different Noise variances using db1 (Daubechies Wavelet)

PSNR (PEAK SIGNAL TO NOISE RATIO)						
NOISE	NOISE VARIANCE	MEAN FILTER	MEDIAN FILTER	UNIVERSAL THRESHOLD	VISU SHRINK	BAYES SHRINK
GAUSSIAN NOISE	0.001	24.0598	25.4934	27.2016	28.2978	33.7031
	0.002	23.2251	24.3480	25.1748	26.1439	29.9001
	0.003	22.5261	23.4147	24.0062	24.8430	27.7650
	0.004	21.9796	22.6049	23.1590	23.8149	26.0865
	0.005	21.4536	22.0205	22.5099	23.0527	25.1235
	0.01	19.5569	19.7703	20.3580	20.5660	22.0446
SPECKLE NOISE	0.001	24.8274	26.6157	28.4073	32.6526	44.0220
	0.002	24.5114	26.1260	26.8834	30.4768	40.0535
	0.003	24.2207	25.6708	25.9557	29.3585	38.3935
	0.004	23.9316	25.2771	25.3274	28.1881	35.6827
	0.005	23.7015	24.8599	24.8691	27.5283	34.3460
	0.01	22.6357	23.4053	23.3231	25.1853	30.9207

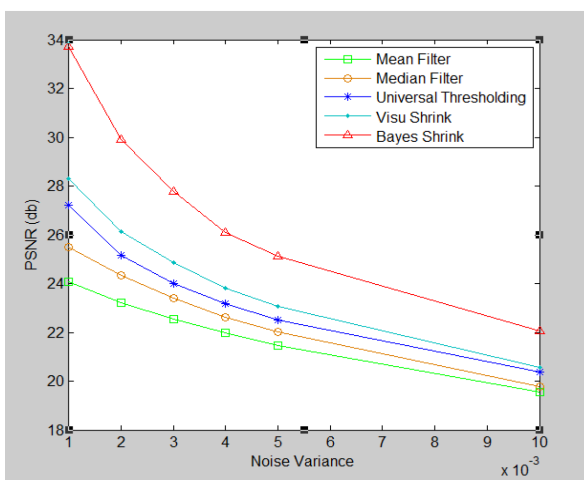


Figure4. Comparison of PSNR for cameraman image (corrupted with Gaussian noise) at different noise variance

Table2. Comparison of MSE for Cameraman image corrupted with Gaussian and Speckle noise at different Noise variances using db1

MSE (MEAN SQUARE ERROR)						
NOISE	NOISE VARIANCE	MEAN FILTER	MEDIAN FILTER	UNIVERSAL THRESHOLD	VISU SHRINK	BAYES SHRINK
GAUSSIAN NOISE	0.001	255.3265	183.5446	123.8560	96.2288	27.7188
	0.002	309.4321	238.9368	197.5136	158.0136	66.5377
	0.003	363.4693	296.2178	258.5006	213.1975	108.7875
	0.004	412.2133	356.9362	314.1828	270.1428	160.1160
	0.005	465.2894	408.3482	364.8271	321.9641	199.8629
	0.01	720.1005	685.5656	598.8007	570.7912	406.0842
SPECKLE NOISE	0.001	213.9645	141.7451	93.8319	35.3036	2.5756
	0.002	230.1138	158.6638	133.2721	58.2642	6.4229
	0.003	246.0413	176.1971	165.0083	75.3748	9.4130
	0.004	262.9796	192.9158	190.6971	98.6903	17.5716
	0.005	277.2851	212.3693	211.9193	114.8823	23.9047
	0.01	354.4109	296.8613	302.5347	197.0393	52.6035

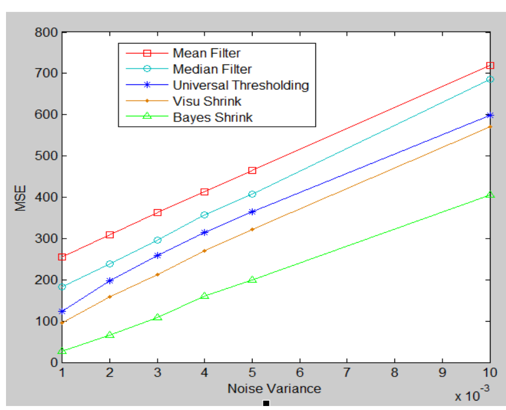
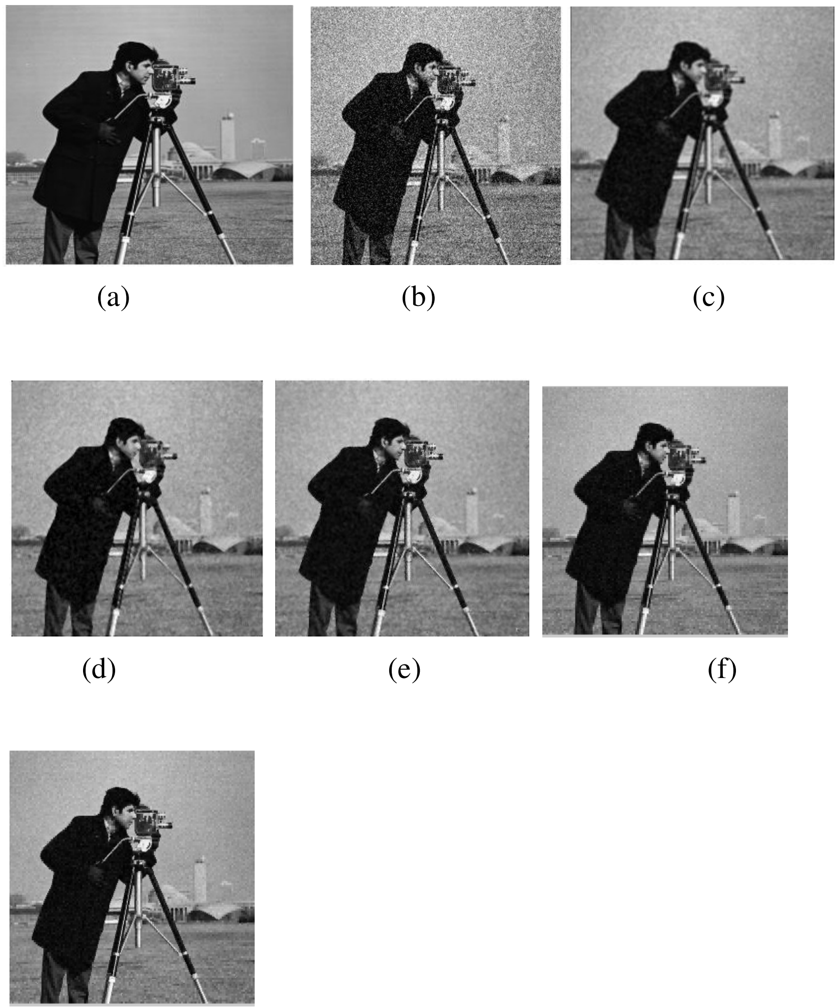


Figure5. Comparison of MSE for cameraman image (corrupted with Gaussian noise) at different noise variances

The cameraman image is corrupted by gaussian noise of variance 0.01 and results obtained using filters and wavelets have been shown in Figure 6.



(a) (b) (c)

(d) (e) (f)

(g)

Figure 6. Denoising of cameraman image corrupted by Gaussian noise of variance 0.01
(a) Original image (b) Noisy image (c) Mean Filter (d) Median Filter (e) Universal thresholding (f) Visu Shrink (g) Bayes shrink

Table 3. shows the comparison of PSNR, MSE and Mean Absolute Error (MAE) for cameraman image at different decomposition levels. As number of levels increased, PSNR gets decreased whereas MAE and MSE get increased. Figure 7, 8 and 9 show that decomposition level1 has high PSNR and low MSE and MAE than other decomposition levels.

Table3. Comparison of PSNR, MSE and MAE for Cameraman image corrupted with Gaussian noise at different decomposition levels using db2

DECOMPOSITION LEVEL	NOISE VARIANCE	UNIVERSAL THRESHOLD			VISU SHRINK		
		PSNR (db)	**MSE**	**MAE**	**PSNR (db)**	**MSE**	**MAE**
LEVEL 1	0.001	27.417	117.864	7.9166	28.031	102.305	7.512
	0.002	25.483	183.956	10.070	26.028	162.286	9.622
	0.003	24.324	240.229	11.632	24.764	217.077	11.235
	0.005	22.775	343.185	14.090	23.087	319.419	13.763
	0.01	20.610	564.927	18.373	20.740	548.297	18.179
LEVEL 2	0.001	25.736	173.564	9.612	26.778	136.524	8.767
	0.002	23.834	268.933	12.177	24.667	222.007	11.343
	0.003	22.673	351.355	14.047	23.477	291.968	13.110
	0.005	21.144	499.579	17.007	21.769	432.649	16.135
	0.01	19.027	813.403	22.095	19.424	742.403	21.331
LEVEL 3	0.001	25.201	196.329	10.250	26.473	146.467	9.1091
	0.002	23.203	311.007	13.050	24.386	236.814	11.730
	0.003	22.037	406.731	15.079	23.109	317.751	13.722
	0.005	20.532	575.175	18.176	21.422	468.585	16.764
	0.01	18.443	930.519	23.619	19.091	801.536	22.171

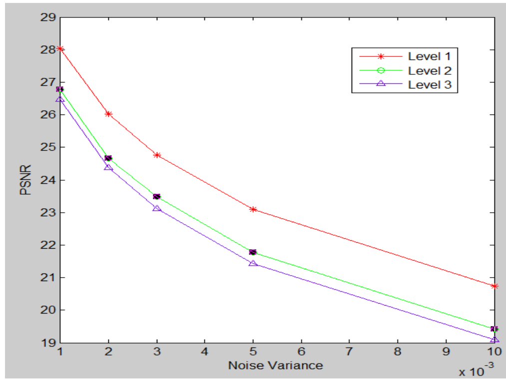


Figure 7. Comparison of Peak Signal to Noise Ratio (PSNR) for cameraman image (denoising using Visu Shrink) at different decomposition levels

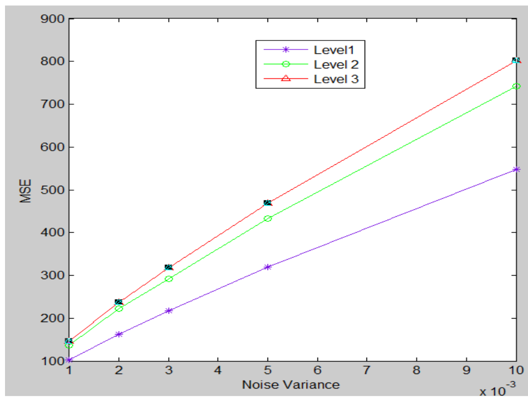


Figure 8. Comparison of Mean Square Error (MSE) for cameraman image (denoising using Visu Shrink) at different decomposition levels

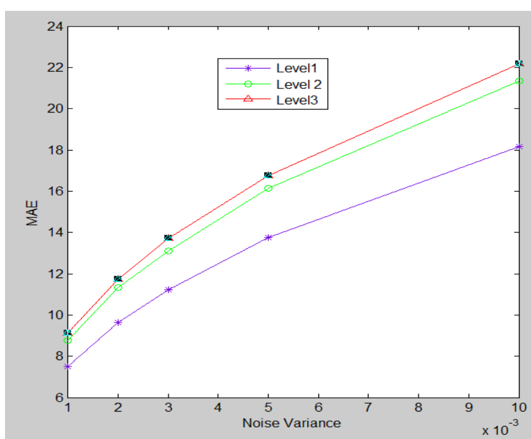


Figure 9. Comparison of Mean Absolute Error (MAE) for cameraman image (denoising using Visu Shrink) at different decomposition levels

6. CONCLUSION

In this paper, an analysis of denoising techniques like filters and wavelet methods has been carried out. Filtering is done by Mean and Median Filter. And three different wavelet thresholding techniques have been discussed i.e. Universal Thresholding, Bayes Shrink and Visu Shrink. The results conclude that Bayes shrinkage method has high PSNR at different noise variance and low MSE. Also the comparison of Wavelet thresholding methods at different decomposition level has been discussed. From simulation result, it is evident that decomposition level 1 has high PSNR and low MAE and MSE than other decomposition levels i.e. level 2 and level 3.This concludes that decomposition level 1 is better in removing Gaussian noise than other decomposition levels.

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