COMPARATIVE ANALYSIS OF FILTERS AND WAVELET BASED THRESHOLDING METHODS FOR IMAGE DENOISING

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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 comparative analysis of filters and various wavelet based methods has been carried out. The simulation results show that wavelet based Bayes shrinkage method outperforms other methods in terms of peak signal to noise ratio (PSNR) and mean square error(MSE) and also the comparison of various wavelet families have been discussed in this paper.

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) have 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. Transmission errors and compression can also introduce noise [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 as much as possible 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 multiresolution possibilities. Wavelet Transform is good at energy compaction in which small coefficients are more likely due to noise and large coefficients are due to important signal feature. These small coefficients can be thresholded without affecting the significant features of the image.

Dhinaharan Nagamalai et al. (Eds) : ACITY, WiMoN, CSIA, AIAA, DPPR, NECO, InWeS - 2014
pp. 137–148, 2014. © CS & IT-CSCP 2014 DOI : 10.5121/csit.2014.4515

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

2. FILTERING TECHNIQUES

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

2.1. Mean Filter

This filter gives smoothness to an image by reducing the intensity variations between the adjacent pixels [4]. Mean filter is also known as averaging filter. This filter works by applying mask over each pixel in the signal and a single pixel is formed by component of each pixel which comes under the mask. Therefore, this filter is known as average filter. The main disadvantage of Mean filter is that it cannot preserve edges [5].

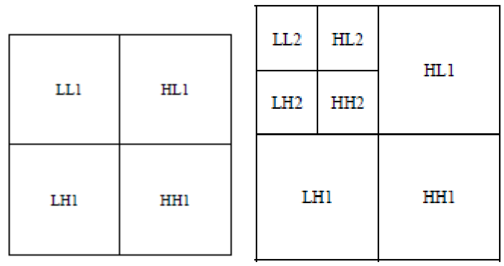
2.2. Median Filter

Median filter is a type of non linear filter. Median filtering is done by, firstly finding the median value across the window, and then replacing that entry in the window with the pixel's median value [6]. For an odd number of entries, the median is simple to define as it is just the middle value after all the entries are made in window. But, there is more than one possible median for an even number of entries. It is a robust filter. Median filters are normally used as smoothers for image processing as well as in signal processing and time series processing [5].

3. WAVELET TRANSFORM

In Discrete Wavelet Transform (DWT) , signal energy is concentrated in a small number of coefficients .Hence, wavelet domain is preferred. DWT of noisy image consist of small number of coefficients having high SNR and large number of coefficients having low SNR. Using inverse DWT, image is reconstructed after removing the coefficients with low SNR [3]. Time and frequency localization is simultaneously provided by Wavelet transform. In addition, Wavelet methods are capable to characterize such signals more efficiently than either the original domain or transforms such as the Fourier transform [7].

The DWT is identical to a hierarchical sub band system where the sub bands are logarithmically spaced in frequency and represent octave-band decomposition. When DWT is applied to noisy image, it is divided into four sub bands as shown in Figure 1(a).These sub bands are formed by separable applications of horizontal and vertical filters. Finest scale coefficients are represented as sub bands LH1, HL1 and HH1 i.e. detail images while coarse level coefficients are represented as LL1 i.e. approximation image [8] [3]. The LL1 sub band is further decomposed and critically sampled to obtain the next coarse level of wavelet coefficients as shown in Fig. 1(b).



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

Figure1. Image Decomposition by using DWT

LL1 is called the approximation sub band as it provides the most like original picture. It comes from low pass filtering in both directions. The other bands are called detail sub bands. The filters L and H as shown in Fig.2 are one dimensional low pass filter (LPF) and high pass filter (HPF) for image decomposition. HL1 is called the horizontal fluctuation as it comes from low pass filtering in vertical direction and high pass filtering in horizontal direction. LH1 is called vertical fluctuation as it comes from high pass filtering in vertical direction and low pass filtering in horizontal direction. HH1 is called diagonal fluctuation as it comes from high pass filtering in both the directions. LL1 is decomposed into 4 sub bands LL2, LH2, HL2 and HH2. The process is carried until some final scale is reached. After L decompositions a total of D (L) = 3 *L +1 sub bands are obtained .The decomposed image can be reconstructed using are construction filter as shown in Figure 3. Here, the filters L and H represent low pass and high pass reconstruction filters respectively.

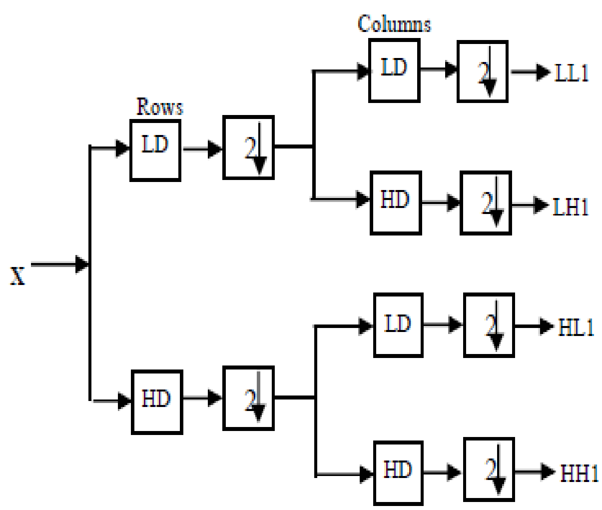


Figure2. Wavelet Filter bank for one-level Image Decomposition

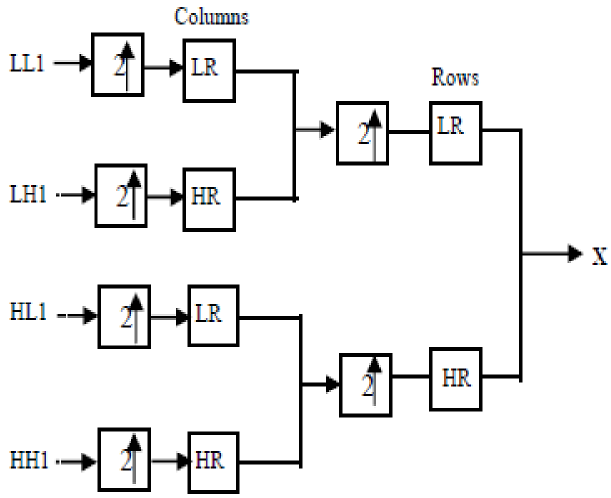


Figure3. Wavelet Filter bank for one-level Image Reconstruction

3.1 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 [8] .Several studies are there on thresholding the Wavelet coefficients. The process, commonly called Wavelet Shrinkage, consists of following main stages:

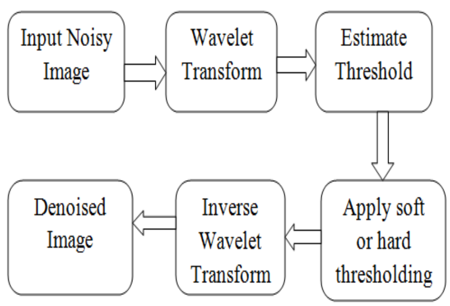


Figure 4. Block diagram of Image denoising using Wavelet Transform

- 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.

3.1.1 Thresholding Method

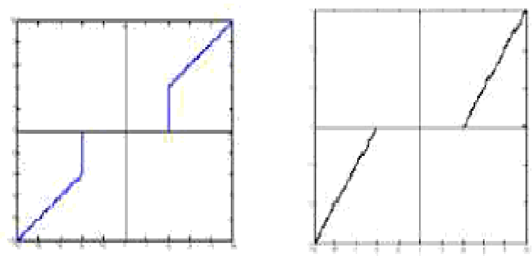
Hard and soft thresholding is one of the thresholding techniques which are used for purpose of image denoising. Keep and kill rule which is not only instinctively appealing but also introduces artifacts in the recovered images is the basis of hard thresholding [9] whereas shrink and kill rule which shrinks the coefficients above the threshold in absolute value is the basis of soft thresholding [10]. 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 [11] [12].

The **Hard Thresholding** operator [13] 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 [14]

Figure 5. Thresholding Methods

3.1.2 Threshold Selection Rules

In image denoising applications, PSNR needs to be maximized , hence optimal value should be selected [8]. 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 [15].

3.1.2.1 Universal Threshold

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

where σ^2 being the noise variance and M is the number of pixels [16] .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 [17].

3.1.2.2 Visu Shrink

Visu Shrink was introduced by Donoho [18]. 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 [19]. Threshold T can be calculated using the formulae [20],

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

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

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

3.1.2.3 Bayes Shrink

The Bayes Shrink method has been attracting attention recently as an algorithm for setting different thresholds for every sub band. Here subbands refer to frequency bands that are different from each other in level and direction [21]. 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 [12]. Bayes threshold is defined as [22],

$$t_B = \sigma^2 / \sigma_s \quad (6)$$

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

From the definition of additive noise we have,

$$w(x, y) = s(x, y) + n(x, y) \quad (7)$$

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

$$\sigma_w{}^2 = \sigma_s{}^2 + \sigma^2 \quad (8)$$

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

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

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

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

4. 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. The parameters are Peak Signal to noise Ratio (PSNR) and Mean Square Error (MSE).

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

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

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 noisevariancies. Figure6 and Figure 7 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

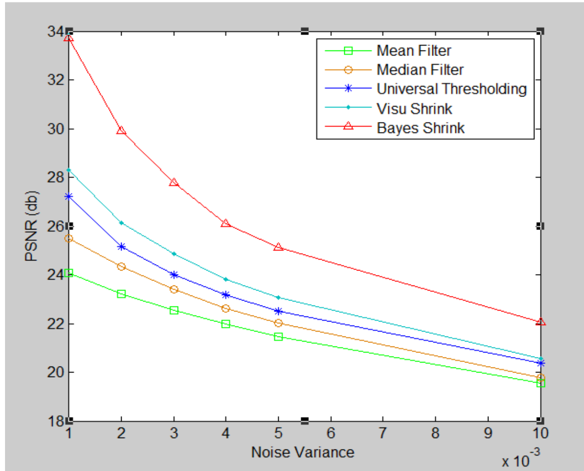


Figure6. Comparison of PSNR for cameraman image (corrupted with Gaussian noise) at different noise variance

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

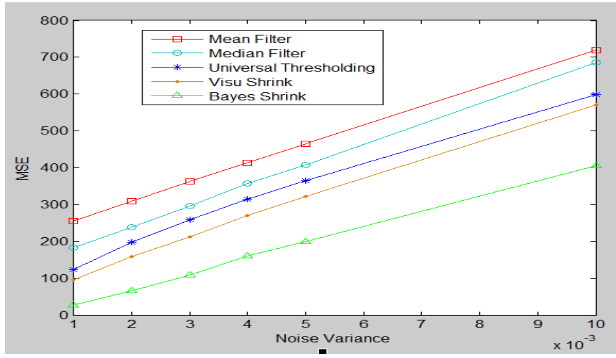


Figure 7. Comparison of MSE for cameraman image (corrupted with Gaussian noise) at different noise variances

The cameraman image is corrupted by gaussian noise of variance 0.01 and results obtained using filters and wavelets have been shown in Figure 8.

(a)

(b)

(c)

(d)

(e)

(f)

(g)

Figure 8. 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

A Comparative study of various wavelet families viz. Daubechies, Symlet, Coiflet, Biorthogonal and Reverse Biorthogonal using the Matlab Wavelet Tool box function *wfilters* is done and results have been tabulated in Table 3. Almost all the wavelet families perform in a much similar fashion.

Table3. Comparison of MSE and PSNR for Cameraman image (with Gaussian noise of variance 0.001) using various Wavelet families namely Daubechies, Symlet, Coiflet, Biorthogonal and Reverse Biorthogonal.

Wavelet Families		**MSE**			**PSNR**		
		Universal Threshold	**Visu Shrink**	**Bayes Shrink**	**Universal Threshold**	**Visu Shrink**	**Bayes Shrink**
DAUBECHIES	db2	118.9888	92.7006	27.8870	27.3757	28.4600	33.6768
	db5	116.0008	91.0493	29.1175	27.4862	28.5380	33.4893
	db7	114.5742	93.8306	32.3802	27.5399	28.4074	33.0280
	db9	117.1231	96.3611	33.6797	27.4444	28.2918	32.8571
	db10	117.7054	97.1057	33.8515	27.4228	28.2584	32.8350
Symlets	sym2	118.9952	93.2712	30.7511	27.3755	28.4333	33.2522
	sym4	114.9689	91.2290	29.3524	27.5250	28.5295	33.4544
	sym6	113.4957	92.9196	30.9472	27.5810	28.4497	33.2246
	sym7	112.3352	89.5128	29.1537	27.6256	28.6120	33.4839
	sym8	111.7177	90.6427	30.6893	27.6496	28.5575	33.2609
Coiflet	coif1	119.0472	93.1594	27.9323	27.3736	28.4385	33.6697
	coif2	113.9656	89.6841	29.1131	27.5631	28.6036	33.4899
	coif3	112.4675	92.3045	29.8983	27.6205	28.4786	33.3743
	coif4	112.3909	91.2025	31.0492	27.6235	28.5307	33.2103
	coif5	112.2086	90.1873	30.9109	27.6305	28.5794	33.2297
Biorthogonal	bior1.3	124.8644	99.1098	28.1472	27.1664	28.1696	33.6365
	bior2.2	125.0148	79.3262	22.2066	27.1612	29.1366	34.6660
	bior3.1	145.9058	85.0012	28.1984	26.4901	28.8366	33.6286
	bior4.4	114.5491	88.4300	29.0607	27.5409	28.6648	33.4977
	bior6.8	114.2567	88.5645	29.8665	27.5520	28.6582	33.3790
REV ERS	rbio1.5	117.1884	98.8170	35.9098	27.4420	28.1825	32.5787

	rbio2.4	106.7042	109.6627	47.6843	27.8490	27.7302	31.3470
	rbio3.3	104.6786	155.5353	75.9330	27.9322	26.2125	29.3265
	rbio5.5	119.0634	82.0170	22.4013	27.3730	28.9918	34.6281
	rbio6.8	111.1183	94.8413	31.7120	27.6729	28.3608	33.1186

5. 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. From the simulation results, it is evident that Bayes shrinkage method has high PSNR at different noise variance and low MSE. This concludes that this method performs better in removing Gaussian noise and Speckle noise than filters and other wavelet methods.

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