ISSN No. 0976-5697

Volume 3, No. 3, May-June 2012

International Journal of Advanced Research in Computer Science

RESEARCH PAPER

Available Online at www.ijarcs.info

Comparison of BayesShrink and SureShrink for image denoising using DWT

Sandeep Kaur*
Computer Science and Engineering
Mtech student BBSBEC
Fatehgarh Sahib, India
sandeeptiwana@yahoo.com

Ranjit Singh
Computer Science and Engineering
Assistant Professor BBSBEC
Fatehgarh Sahib, India
jitbhatthal@yahoo.com

Abstract: Removing noise from image is still a challenging problem for the researchers .An image is often corrupted by noise during various processes of transmission. Image denoising is used to remove the noise while preserving the important details. In this paper a frequency domain technique of discrete wavelet transform is discussed with various thresholding techniques and is compared by PSNR and MSE parameters.

Keywords: Discrete wavelet Transform, Gaussian noise, Salt & pepper noise, Speckle noise, Haar, Daubechies, VisuShrink, BayesShrink, SureShrink.

I. INTRODUCTION

Image denoising is the process of removing noise from the images. In broad, denoising techniques can be divided into two[1] main categories-

(a) Spatial domain filtering
(b) Transform domain filtering

A. ***Spatial domain filtering***-A traditional way to remove noise is by using the spatial filters means by working in the same space of co-ordinates. There are further two categories:-

- **a.** ***Linear filters***- where output image pixels have linear relationship with the input image pixels. Examples of linear filter include means filter which replaces the central pixel by the mean of the neighborhood pixels. Another one is wiener filter [2] which requires information about nature of signal as well as noise.
- **b.** ***Nonlinear filters***- are those in which output pixels don't have linearity constraint with input pixels. Examples include median filter [3], alpha trimmed median filters etc.

Generally these filters remove noise to a certain extent but at the cost of blurring edges.

B. ***Transform domain filtering***-means the image pixels values are transformed in other coordinates for evaluation and then thresholding is applied to reject noise and again image is converted into same coordinates .In this paper a wavelets based transform domain filtering is applied.

II. NOISE

Noise is basically random variation in brightness or change in pixel value of an image. Different types of noise [4] are-

a. ***Salt and pepper noise***- also known as binary noise or impulse noise. An image containing this noise will have dark pixels in bright region and bright pixels in dark region.

Let S (t) is the original image and N (t) is the noisy image.

The observed gray level at pixel (i, j) by impulse noise is given by

$$I(t) = (1 - e)S(t) + eN(t)$$

Where e= {0, 1} with probability P.

b. ***Gaussian noise***- It is basically additive noise i.e. each pixel in noisy image is the sum of true pixel value and a random Gaussian distributed noise value given by F (g) as

$$F(g) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-(g-m)^2/2\sigma^2}$$

Where g represents gray level, m is the mean/average value that is most probable and σ known as variance to show how these values are spread.

Figure 1(a) Figure 1(b)

Figure 1 (a) Salt and pepper noise
b) Gaussian noise with mean 0 and variance 0.1

c. ***Speckle noise***- Whereas Gaussian noise is an additive noise, Speckle noise is a type of multiplicative noise, means random values are multiplied by pixel value.

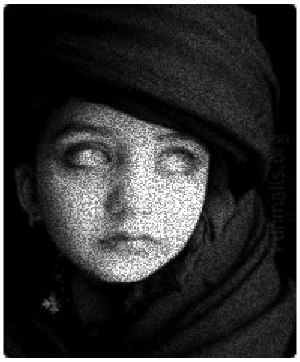

Figure 1(c) Speckle noise

Rayleigh distribution is the most popular model for speckle. Other models such as gamma distribution etc. can be employed.

III. DISCRETE WAVELET TRANSFORM

The theory of discrete wavelet transform has become a new signal processing theory in recent years. De-noising of images corrupted by noise using wavelet techniques [5] is very effective because of its ability to capture the energy of a signal in few energy transform values. The wavelet de-noising scheme thresholds the wavelet coefficients arising from the standard discrete wavelet transform.

The image is first divided into four sub-bands i.e. LL1 (Approximation sub band), LH1 (Horizontal detail sub band), HL1 (vertical detail sub band) and HH1 (Diagonal detail sub band) by cascading horizontal and vertical two channels critically sub-sample filter bank. To obtain the next coarse scale wavelet coefficient, the sub-band LL1 is further decomposed and critically sub-sampled. This process continues depending on the level specified. In this paper DWT is discussed at level 2.

There is no. of parameters on which wavelet based denoising depends-

a. Wavelet Basis-which wavelet is used for image denoising such as haar, daubechies etc.
b. Level of decomposition-means decomposition of image using DWT is done upto which level.
c. Thresholding method-by which wavelet coefficients are rejects or accepted.

A. ***Wavelet Basis***-A wavelet [6] is a waveform of effectively limited duration that has an average value of zero. They are irregular and asymmetric in nature. Signal. There are different types of wavelets in wavelet family such as haar wavelet, daubechies, symlets, coiflets[7] etc. classified on the basis of filter length used and number of vanishing points. Vanishing moment refers to the ability of wavelet to represent polynomial behavior in the signal. Example Daubechies 4 with two vanishing moments[8] can easily encode constants and linear components. Similary db3 can also encode quadratic components. For a particular application i.e. for any signal the used wavelet function frequency should match the signal as closely as possible.

B. Thresholding-It basically means that a particular value among coefficients is chosen, known as threshold value, according to that threshold, the coefficients are accepted or rejected.
There are basically 2 types of thresholding.

a. ***Hard thresholding-*** In this type, all the coefficients whose magnitude is greater than the selected threshold value ' t' remains as they are and the others with magnitudes smaller than 't' are set to zero.

Th= {x for |x|≥t.
= 0 for all other regions}

b. ***Soft thresholding*** –In this the coefficients with value greater than the threshold't' are shrunk towards zero after comparing them to a threshold value.

Ts= {sign(x) (|x|-t) for |x|≥t.
=0 for all other regions}

Soft thresholding gives much better results as compared to hard thresholding [9].

There are various thresholding techniques[10] such as Visu Shrink Bayes shrink, Sure Shrink[11] etc. And can be implemented using any of wavelets such as haar, daubechies, coiflets, symlets etc.

a) ***Visu Shrink-*** It was given by Donoho. It uses a universal threshold that is proportional to standard deviation of noise.

$t=\sigma*\sqrt{2*\log(n)}$ ………………(1)

Where σ^2 is noise variance and n is size or number of pixels in image.

Noise level estimate is given as

σ =median (|gi| i=0, 1…..)/.6745 ……... (2)

Where gi denote the detail coefficients of wavelet domain.

It can be implemented as both hard and soft threshold, But as only one threshold is selected for all the coefficients so it doesn't give good performance.

b) ***SURE Shrink-*** It uses level dependent threshold means a different threshold is applied to each level. For example in this paper daubechies with 2 levels is used. So it computes 2 threshold one for each level. This method tries to minimize mean square error.

SURE Shrink threshold is given as

Ts=min (t, σ*√2*log (n) …………….(3)

Where σ is computed as given by equation

And t denotes the value that minimizes SURE (Stein's unbiased risk estimate.)

c) ***Bayes Shrink-*** It uses sub band dependent threshold means a different threshold for each sub band of image. It is based on Bayesian mathematical framework. The wavelet coefficients are modeled by Generalized Gaussian Distribution.

In this threshold Tb is computed as ratio of noise variance to signal variance without noise.

$Tb=\sigma^2/\sigma s^2$ …………… (4)

Where $\sigma s=\sqrt{\max(\sigma w^2-\sigma^2),0}$ ....(5)

and

$$\sigma w^2 = 1/n^2 \sum_{x,y}^{n} w^2(x,y) \qquad \text{………..(6)}$$

and σ is computed from equation (2).

Like the SUREShrink threshold, it is also smoothness adaptive.

IV. DWT BASED IMAGE DENOSING ALGORITHM

The methodology of the discrete wavelet transforms (DWT)[12] based image de-noising has the following steps [13],[14]as explained

a. Load the original noisy image.
b. Convert the noisy image from spatial domain to frequency domain by applying DWT.

Table 1 PSNR values using SUREShrink and BayesShrink Thresholding

Threshold Standard deviation	**SURE Shrink**			**Bayes Shrink**		
	Salt and Pepper noise	Gaussian Noise	Speckle noise	Salt and Pepper noise	Gaussian Noise	Speckle noise
Lena σ =10	31.01	28.23	31.36	33.90	28.54	36.51
Lena σ =15	30.65	28.17	31.09	30.66	28.55	34.12
Lena σ =20	30.28	28.10	30.74	27.73	28.44	32.33
Lena σ =25	29.92	27.95	30.30	25.94	28.30	30.87
Lena σ =30	29.47	27.69	29.81	25.93	28.02	29.72
Barbara σ =10	24.47	23.73	24.49	33.65	25.72	35.44
Barbara σ =15	24.40	23.71	24.45	30.21	25.74	32.51
Barbara σ =20	24.30	23.68	24.40	27.56	25.67	30.46
Barbara σ =25	24.17	23.63	24.30	25.66	25.61	28.84
Barbara σ =30	24.04	23.53	24.23	23.99	25.44	27.63

(Using db4 at level 2)

c. As DWT divides the image into high frequency and low frequency subparts as explained, So compute noise level estimate from equation (2) by diagonal (HH) sub band coefficients.
d. Apply soft thresholding on high frequency components(HH,LH,HL) by using either of the methods
   a) For SURE threshold compute threshold from (3).
   b) For Bayes threshold compute threshold from (4), (5) and (6).
e. Perform inverse discrete wavelet transform (IDWT) to obtain the de-noised image.

V. PERFORMANCE METRICS

Performance is evaluated by calculating Peak Signal to noise ratio (PSNR) and MSE (Mean Square error) between the original image and denoised image. Better denoising requires ratio (PSNR) to be high and MSE to be low. The formulas of all these parameters are as follow:

a) $$\text{PSNR} = \frac{10 * \log 10 (\max((x(i,j))^2))}{\text{MSE}}$$

b) $$\text{MSE} = \frac{\sum\sum ((x(i,j) - y(i,j))^2}{M*N}$$

Where x (i, j) is the original image, y (i, j) is the denoised image. And M* N is the size of image.

VI. RESULTS AND DISCUSSION

Results and discussion Two images 'Lena' and 'Barbara' of size 512*512 are taken, and then various noises such as salt and pepper, speckle and Gaussian noise of mean 0 and of varying variance are added. Wavelets transform using

Daubechies db4 wavelet at level 2 decomposition is used in all thresholding methods. Then sub band adaptive thresholding using SUREShrink and BayesShrink is applied.

PSNR values are computed for both the thresholding methods using 2 different thresholds, by applying the initial same db4 wavelet with level 2 of discrete wavelet transformation (DWT) as shown in table 1 Though SUREShrink gives better performance than VisuShrink, But BayesShrink outperforms it in all aspects.

VII. CONCLUSION

It is found that BayesShrink threshold gives better PSNR values as compared to SureShrink threshold method due to better threshold selection so accordingly noisy coefficients are removed in more efficient way in it. It provides better threshold for each type including salt & pepper, Gaussian and speckle noise.

VIII. FUTURE SCOPE

Image denoising based on other mutiresolution methods such as curvelets and ridgelets etc. can be employed for better PSNR.

In DWT based denoising more optimal threshold selection can be done based on other parameters such as neighbor coefficients.

IX. REFERENCES

[1]. Mukesh C. Motwani, Mukesh C. Gadiya, Rakhi C. Motwani," Survey of Image Denoising Techniques," International Journal of Information Technology and Knowledge Management.,2004

[2]. Mr. Salem saleh Al –Amri, Dr. N.V Kalyankar and Dr, Khamitkar S.D,"A comparative study of removal noise from remote sensing images, "International journal of computer science issues ,vol. 7,Issue 1,No. 1,January 2010.

[3]. D. Maheshwari and Dr. V Radhe," Noise removal in compound image using median filter," International journal of computer science & engineering, vol. 2,no. 4,2010.

[4]. Pawan Patidar, Manoj Gupta, Sumit Srivastava,"Image denoising by various filters for different noise."International journal of computer applications ,Volume 9,No. 4 ,Novenber 2010.

[5]. S.Sudha, G.R.Suresh and R.Sukanesh,"Speckle noise reduction in ultraviolet image by wavelet thresholding based on weighted variance", International Journal of Computer Theory and Engineering, Vol. 1, No. 1, April 2009.

[6]. Sachin D Ruikar and Dharmpal D Doye,"Wavelet based image denoising techniques", International Journal of Advanced Computer Science and Applications, Vol. 2, No.3, March 2011.

[7]. Daniel T. L Joe and Akio Yamamoto,"Wavelet Analysis & theory & Applications,"Hewelett-Packard Journal, December 1994.

[8]. Mohamed I. Mahmoud, Moawad I. M. Dessouky, Salah Deyab, and Fatma H. Elfouly,"Comparison between Haar and Daubechies Wavelet Transformions on FPGA Technology,"World Academy of Science, Engineering and Technology 2007.

[9]. Mahesh S. Chavan and Nikos Mastorakis ," Studies on Implementation of Harr and daubechies Wavelet for Denoising of Speech Signal", International Journal of Circuit system and signal processing, Issue 3, volume 4, 2010.

[10]. Raghuram Rangarajan,Ranjit Venkataramanan Siddharth shah," Image denoising using wavelets ,December 16,2002.

[11]. S.S Patil,A.B Patil,"Wavelet Shrinkage techniques for images," International journal of computer applications,volume-7,No.-1,September 2010.

[12]. S. Kother Mohideen, Dr. S. Arumuga, "Image denoising using discrete wavelet transform", International Journal of Computer Science and Network Security, Vol. 8, No. 1, January 2008.

[13]. J.N Ellinas,T. Mandadelies,"Image Denoising using Waveletes, T.E.I of Piraeus, Department of electronic computer systems2004.

[14]. Xiwen Qin , Yang Yue, Xiaogang Dong, Xinmin Wang , ZhanSheng Tao," An Improved Method of Image Denoising Based on Wavelet Transform", International Conference on Computer, Mechatronics, Control and Electronic Engineering (CMCE), 2010.