Image Denoising using Discrete Wavelet transform

Article · January 2008

Perumal Arumuga
S.T. Hindu College

Mohamed Sathik
Sadakathullah Appa College

Image De-noising using Discrete Wavelet transform

S.Kother Mohideen[†] Dr. S. Arumuga Perumal[††], Dr. M.Mohamed Sathik[†††]
[†]Head, IT & PG Dept. of Comp.sc, Sadakthullah Appa College, Tirunelveli-627 011
[††] Prof & Head, Dept. of Computer Science, St. Hindu College, Nagarcoi
[†††]Reader Dept. of Computer Science Sadakathullah Appa College Tirunelveli-627011

Summary
The image de-noising naturally corrupted by noise is a classical problem in the field of signal or image processing. Additive random noise can easily be removed using simple threshold methods. De-noising of natural images corrupted by Gaussian noise using wavelet techniques are 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. In this paper, it is proposed to investigate the suitability of different wavelet bases and the size of different neighborhood on the performance of image de-noising algorithms in terms of PSNR.

Key words:
Image, De-noising, Wavelet, Transform

1. Introduction

This paper investigates the suitability of different wavelet bases and the size of different neighborhood on the performance of image de-noising algorithms in terms of PSNR. Over the past decade, wavelet transforms have received a lot of attention from researchers in many different areas. Both discrete and continuous wavelet transforms have shown great promise in such diverse fields as image compression, image de-noising, signal processing, computer graphics, and pattern recognition to name only a few. In de-noising, single orthogonal wavelets with a single-mother wavelet function have played an important role. De-noising of natural images corrupted by Gaussian noise using wavelet techniques is very effective because of its ability to capture the energy of a signal in few energy transform values. Crudely, it states that the wavelet transform yields a large number of small coefficients and a small number of large coefficients. Simple de-noising algorithms that use the wavelet transform consist of three steps.

- Calculate the wavelet transform of the noisy signal.
- Modify the noisy wavelet coefficients according to some rule.
- Compute the inverse transform using the modified coefficients.

One of the most well-known rules for the second step is soft thresholding. Due to its effectiveness and simplicity, it is frequently used in the literature. The main idea is to subtract the threshold value T from all wavelet coefficients larger than T, arising from the standard discrete wavelet transform and to set all other coefficients to zero.

The problem of Image de-noising can be summarized as follows. Let A(i,j) be the noise-free image and B(i,j)the image corrupted with independent Gaussian noise Z(i,j),

$$B(i,j)= A(i,j)+\sigma\, Z(i,j) \;\ldots\ldots(1)$$

where Z(i,j) has normal distribution N(0,1). The problem is to estimate the desired signal as accurately as possible according to some criteria. In the wavelet domain, if an orthogonal wavelet transform is used, the problem can be formulated as

$$Y(i,j)= W(i,j)+N(i,j)\;\ldots\ldots(2)$$

where Y(i,j) is noisy wavelet coefficient; W(i,j) is true coefficient and N(i,j) noise, which is independent Gaussian. . In this paper, it is proposed to investigate the suitability of different wavelet bases and the size of different neighborhood on the performance of image de-noising algorithms in terms of PSNR.

2. Discrete Wavelet transform

The Discrete Wavelet Transform (DWT) of image signals produces a non-redundant image representation, which provides better spatial and spectral localization of image formation, compared with other multi scale representations such as Gaussian and Laplacian pyramid. Recently, Discrete Wavelet Transform has attracted more and more interest in image de-noising. The DWT can be interpreted as signal decomposition in a set of independent, spatially oriented frequency channels. The signal S is passed through two complementary filters and emerges as two signals, approximation and Details. This is called decomposition or analysis. The components can be assembled back into the original signal without loss of information. This process is called reconstruction or synthesis. The mathematical manipulation, which implies analysis and synthesis, is called discrete wavelet transform

Manuscript received January 5, 2008
Manuscript revised January 20, 2008

and inverse discrete wavelet transform. An image can be decomposed into a sequence of different spatial resolution images using DWT. In case of a 2D image, an N level decomposition can be performed resulting in 3N+1 different frequency bands namely, LL, LH, HL and HH as shown in figure 1. These are also known by other names, the sub-bands may be respectively called a^1 or the first average image, h^1 called horizontal fluctuation, v^1 called vertical fluctuation and d^1 called the first diagonal fluctuation. The sub-image a^1 is formed by computing the trends along rows of the image followed by computing trends along its columns. In the same manner, fluctuations are also created by computing trends along rows followed by trends along columns. The next level of wavelet transform is applied to the low frequency sub band image LL only. The Gaussian noise will nearly be averaged out in low frequency wavelet coefficients. Therefore, only the wavelet coefficients in the high frequency levels need to be thresholded.

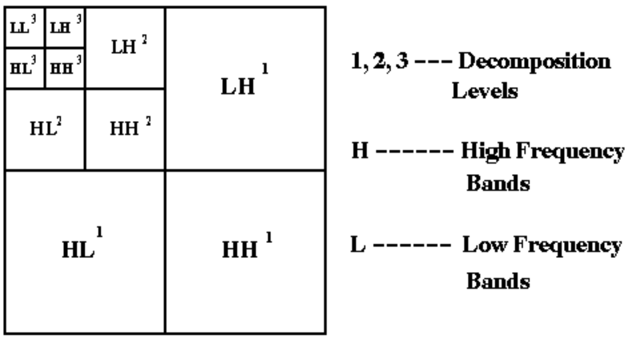

Figure 1: 2D-DWT with 3-Level decomposition

3. Wavelet Based ImageDe-noising

All digital images contain some degree of noise. Image de-noising algorithm attempts to remove this noise from the image. Ideally, the resulting de-noised image will not contain any noise or added artifacts. De-noising of natural images corrupted by Gaussian noise using wavelet techniques is very effective because of its ability to capture the energy of a signal in few energy transform values. The methodology of the discrete wavelet transform based image de-noising has the following three steps as shown in figure 2. 1. Transform the noisy image into orthogonal domain by discrete 2D wavelet transform. 2. Apply hard or soft thresholding the noisy detail coefficients of the wavelet transform 3. Perform inverse discrete wavelet transform to obtain the de-noised image. Here, the threshold plays an important role in the de-noising process. Finding an optimum threshold is a tedious process. A small threshold value will retain the noisy coefficients whereas a large threshold value leads to the loss of coefficients that carry image signal details. Normally, hard thresholding and soft thresholding techniques are used for such de-noising process. Hard thresholding is a keep or kill rule whereas soft thresholding shrinks the coefficients above the threshold in absolute value. It is a shrink or kill rule.

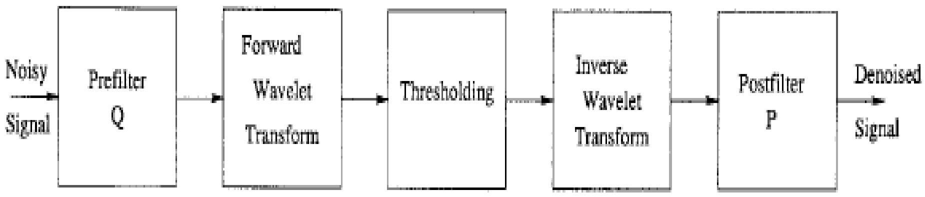

Figure2: Diagram of wavelet based image De-noising

The following are the methods of threshold selection for image de-noising based on wavelet transform

Method 1: Visushrink

Threshold T can be calculated using the formulae,

$T=\sigma\sqrt{2\log n^2}$ …….(3)

This method performs well under a number of applications because wavelet transform has the compaction property of having only a small number of large coefficients. All the rest wavelet coefficients are very small. This algorithm offers the advantages of smoothness and adaptation. However, it exhibits visual artifacts.

Method 2: Neighshrink

Let $d(i,j)$ denote the wavelet coefficients of interest and $B(i,j)$ is a neighborhood window around $d(i,j)$. Also let $S^2=\sum d^2(i,j)$ over the window $B(i,j)$. Then the wavelet coefficient to be thresholded is shrinked according to the formulae,

d(i,j)= d(i,j)* B(i,j) ….(4)

where the shrinkage factor can be defined as $B(i,j) = (1- T^2/ S^2(i,j))_+$, and the sign + at the end of the formulae means to keep the positive value while set it to zero when it is negative.

Method 3: Modineighshrink

During experimentation, it was seen that when the noise content was high, the reconstructed image using Neighshrink contained mat like aberrations. These aberrations could be removed by wiener filtering the reconstructed image at the last stage of IDWT. The cost of additional filtering was slight reduction in sharpness of the reconstructed image. However, there was a slight improvement in the PSNR of the reconstructed image using wiener filtering. The de-noised image using Neighshrink sometimes unacceptably blurred and lost some details. The reason could be the suppression of too many detail wavelet coefficients. This problem will be avoided by reducing the value of threshold itself. So, the shrinkage factor is given by

$B(i,j) = (1- (3/4)*T^2/ S^2(i,j))_+$ …….(5)

4. Evaluation Criteria

The above said methods are evaluated using the quality measure Peak Signal to Noise ratio which is calculated using the formulae,

PSNR= 10log 10 (255) 2/MSE (db) … (6)

where MSE is the mean squared error between the original image and the reconstructed de-noised image. It is used to evaluate the different de-noising scheme like Wiener filter, Visushrink, Neighshrink and Modified Neighshrink.

5. Experiments

Quantitatively assessing the performance in practical application is complicated issue because the ideal image is normally unknown at the receiver end. So this paper uses the following method for

experiments. One original image is applied with Gaussian noise with different variance. The methods proposed for implementing image de-noising using wavelet transform take the following form in general. The image is transformed into the orthogonal domain by taking the wavelet transform. The detail wavelet coefficients are modified according to the shrinkage algorithm. Finally, inverse wavelet is taken to reconstruct the de-noised image. In this paper, different wavelet bases are used in all methods. For taking the wavelet transform of the image, readily available MATLAB routines are taken. In each sub-band, individual pixels of the image are shrinked based on the threshold selection. A de-noised wavelet transform is created by shrinking pixels. The inverse wavelet transform is the de-noised image.

6. Results and Discussions

For the above mentioned three methods, image de-noising is performed using wavelets from the second level to fourth level decomposition and the results are shown in figure (3) and table if formulated for second level decomposition for different noise variance as follows. It was found that three level decomposition and fourth level decomposition gave optimum results. However, third and fourth level decomposition resulted in more blurring. The experiments were done using a window size of 3X3, 5X5 and 7X7. The neighborhood window of 3X3 and 5X5 are good choices.

Window Size		3X3				5X5				7X7			
Wavelet	Variance	0.02	0.04	0.06	0.08	0.02	0.04	0.06	0.08	0.02	0.04	0.06	0.08
	NoisyImage	16.8601	14.1096	12.6435	11.6742	16.8309	14.0995	12.6717	11.681	16.8464	14.103	12.64	11.6592
	wiener	24.056	21.343	19.9475	19.0223	26.4167	24.1466	22.8984	21.98	26.6335	24.826	23.732	22.9097
Haar	Visushrink	22.2984	19.7787	18.3776	17.3849	22.2735	19.7681	18.3769	17.431	22.2856	19.807	18.332	17.4044
	Neighshrink	24.5738	23.3066	22.2924	21.5432	24.5822	23.2439	22.3749	21.555	24.5543	23.254	22.287	21.5715
	Mod. Nei	25.961	25.0158	24.1295	23.4049	25.9627	24.9922	24.2039	23.438	25.9576	24.988	24.093	23.3887
db16	Visushrink	22.6224	20.0023	18.4513	17.5362	22.6177	19.9746	18.4704	17.526	22.6147	19.97	18.508	17.5385
	Neighshrink	23.3646	22.3845	21.5909	21.0162	23.3556	22.4143	21.6199	21.04	23.366	22.359	21.629	21.0237
	Mod. Nei	24.332	23.7027	23.0889	22.5978	24.3175	23.7657	23.1492	22.627	24.3335	23.681	23.129	22.5932
sym8	Visushrink	22.6042	19.9785	18.5036	17.4728	22.5682	19.9576	18.5172	17.517	22.6058	19.984	18.454	17.498
	Neighshrink	23.4209	22.5088	21.6579	21.1155	23.464	22.4881	21.7313	21.053	23.4157	22.482	21.628	21.0469
	Mod. Nei	24.388	23.8718	23.2045	22.7326	24.4283	23.8263	23.2761	22.688	24.3611	23.833	23.159	22.6622
coif5	Visushrink	22.5678	19.9391	18.5022	17.5062	22.6137	19.9899	18.4535	17.497	22.6153	19.917	18.486	17.4952
	Neighshrink	26.0778	24.2732	23.1822	22.2243	26.0365	24.3298	23.0888	22.289	26.0615	24.278	23.123	22.2693
	Mod. Nei	27.2788	26.008	25.0155	24.1331	27.2752	26.0147	24.9283	24.161	27.2978	25.981	24.999	24.1564

Figure3: Results of various Image De-noising Methods

7. Conclusion

In this paper, the image de-noising using discrete wavelet transform is analyzed. The experiments were conducted to study the suitability of different wavelet bases and also different window sizes. Among all discrete wavelet bases, coiflet performs well in image de-noising. Experimental results also show that modified Neighshrink gives better result than Neighshrink, Weiner filter and Visushrink.

References

[1] D. L. Donoho, “Denoising by soft-thresholding,” IEEE Transactions on Information Theory, vol. 41, pp.613-627, 1995.

[2] Bui and G. Y. Chen, “Translation invariant de-noising using multi-wavelets,” IEEE Transactions on Signal Processing, vol.46, no.12, pp.3414-3420, 1998.

[3] L. Sendur and I. W. Selesnick, “Bi-variate Shrinkage with Local Variance Estimation,” IEEE Signal Processing Letters, Vol. 9, No. 12, pp. 438-441,2002.

[4] G. Y. Chen and T. D. Bui, “Multi-wavelet De-noising using Neighboring Coefficients,” IEEE Signal Processing Letters, vol.10, no.7, pp.211-214, 2003.

Prof. S. Kother Mohideen has been working as Head of the Department of Information Technology in Sadakathullah Appa College, Tirunelveli. He has completed his M.Sc. (Computer Science) in Jamal Mohamed College, Trichy and M.Phil. (Computer Science) in Manonmaniam Sundaranar University. He is a Member of IEEE. He has attended many national seminars and his research specialization is Image Denoising.

Dr.S.Arumuga Perumal has been working as Reader and Head of the Department of Computer Science in South Travancore Hindu College for the last 20 years. He has completed his M.S. (Software Systems) in BITS, Pilani, M.Phil Computer Science degree in Alagappa University, Karaikudi and Ph.D (Computer Science) in Manonmaniam Sundaranar University, Tirunelveli. He is a senior member of Computer Society of India, Member of IEEE, and also a Fellow of IETE. He has involved in various academic activities. He has attended so many national and international seminars, conferences and presented numerous research papers and also published research articles in national and international journals. He is a member of curriculum development committees of various universities and autonomous colleges of Tamilnadu and his area of research specialization is Digital Image compression.

Dr.M.Mohamed Sathik has been working as Reader in the Department of Computer Science, Sadakathullah Appa College, Tirunelveli. He has completed M.Phil., Computer Science and Ph.D (Computer Science) in Manonmaniam Sundaranar University, Tirunelveli. He has involved in various academic activities. He has attended so many national and international seminars, conferences and presented numerous research papers. He is a member of curriculum development committees of various universities and autonomous colleges of Tamilnadu and his area of research specialization is Virtual Reality.