International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 3 Issue 11, November-2014

A New Hybrid Approach for Image Restoration using Wavelet Threshold

Richa Dhanda [1]
Post Graduate student,
Department of Electronics and Communication,
BGIET, Sangrur,India

Monika Aggarwal [2]
Assistant Professor,
Department of Electronics and Communication,
BGIET, Sangrur,India

Abstract- **Image restoration has become the field of interest these days due to its varied applications and proliferating requirements in the media world. Image restoration is the process of deducing the degradations which happen to occur while an image is recorded. In this paper, Hybrid image restoration method has been applied. Image denoising helps to retain the maximum possible features of the original image while eliminating the additive white Guassiannoise . One of the most popular and effective method for denoising of image such as different wavelets methods including Visu shrink, Bayes shrink and Sure shrink have been used in the paper. Combination of these aids in improved outcome.**

Keywords: Additive White Gaussian Noise, Hybrid, Peak signal to noise ratio (PSNR), Mean squared error(MSE),Bit error rate(BER).

1. INTRODUCTION

Image Restoration, which is essentially an image interpolation problem has wide applications in film and photo restoration, text removal, special effects in movies disocclusion, digital zoom-in, and edge-based image compression and coding. The objective is to improve the general quality of an image or remove defects. This includes research in algorithm development and routine goal oriented image processing. Image restoration is the removal or reduction of degradations that are incurred while the image is being obtained. This degradation is the result of two phenomena. The first one is deterministic and is related to the mode of image acquisition, to possible defects of the imaging system orother phenomena such as atmospheric turbulence. The second phenomenon is a randomone and corresponds to the noise coming from any signal. For this type of application we need to know something about the degradation process in order to develop a model for it. When we have a model for the degradation process, the inverse process can be applied to the image to restore it back to the original form.

1.1 DiscreteWavelet Transform (DWT) – Principles

Wavelets are mathematical functions that analyze data according to scale or resolution [10]. They aid in studying a signal in different windows or at different resolutions. Wavelets provide a good job in approximating signals with sharp spikes or signals having discontinuities. DWT is a fast linear operation on a data vector, whose length is an integer power of 2. This transform is invertible and orthogonal, where the inverse transform expressed as a matrix is the transpose of the transform matrix.

1.2 Wavelet Thresholding

Donoho and Johnstone [8] pioneered the work on filtering of additive Gaussian noise using wavelet thresholding. The term wavelet thresholding is explained as decomposition of the data or the image into wavelet coefficients, comparing the detail coefficients with a given thresholdvalue, and shrinking these coefficients close to zero to take away the effect of noise in thedata. The image is reconstructed from the modified coefficients. This process is also known as the inverse discrete wavelet transform. During thresholding, a wavelet coefficient is compared with a given threshold and is set to zero if its magnitude is less than the threshold; otherwise, it is retained or modified depending on the threshold rule.

2. DENOISING METHODS

In this section we introduce three known denoising methods and propose one new.Visu shrink, Bayes shrink and Sure shrink are the well-known wavelet filters that are well suited for image denoising.Results have shown that visu shrink is dealing with additive noise only and uses hard thresholding method. Goal of Sure shrink is to minimize mean square error and it follows soft thresholding rule. The goal of Bayes shrink method is to minimize the Bayesian risk, and hence its name, BayesShrink. It uses soft thresholding and is subband-dependent.Using these three methods, we proposed a new hybrid approach to get the best possible outcome.

2.1 Visu shrink

VisuShrink was introduced by Donoho [9]. It uses a threshold value *t* that isproportional to the standard deviation of the noise. It follows the hard thresholding rule. Itis also referred to as universal threshold and is defined as

$$t = \sigma\sqrt{(2\log n)}$$

$\sigma^2$is the noise variance present in the signal and *n* represents the signal size or number ofsamples. An estimate of the noise level $\sigma$was defined based on the median absolute deviation given by

$$\hat{\sigma} = \frac{median\left(\left\{|g_{j-1,k}| : k = 0,1,\ldots,2^{j-1}-1\right\}\right)}{0.6745}$$

where$g_{j-1,k}$corresponds to the detail coefficients in the wavelet transform.

2.2 Bayes shrink

BayesShrink was proposed by Chang, Yu and Vetterli. It uses soft thresholdingand is subband-dependent,which means that thresholding is done at each band of resolution in the wavelet decomposition. Like the SureShrink procedure, it is smoothness adaptive. The Bayes threshold, tB, is defined as

$$t_B = \sigma^2 / \sigma_s$$

where $\sigma^2$is the noise variance and σ_s^2 is the signal variance without noise. The noise variance $\sigma^2$is estimated from the subbands by the median estimator's equation

$$\hat{\sigma} = \frac{median\left(\left\{|g_{j-1,k}| : k = 0,1,\ldots,2^{j-1}-1\right\}\right)}{0.6745}$$

The variance of the signal, σ_s^2 is computed as

$$\sigma_s = \sqrt{\max(\sigma_w^2 - \sigma^2, 0)} \quad \sigma_w^2 = \frac{1}{n^2}\sum_{x,y=1}^{n} w^2(x,y)$$

Where $\sigma_w^2 = \sigma_s^2 + \sigma^2$ and $W^2(x,y)$ represents the wavelet coefficient corresponding to vertical, horizontal and diagonal bands.

2.3Sure Shrink

A threshold chooser based on Stein's Unbiased Risk Estimator (SURE) wasproposed by Donoho and Johnstone [8] and is called as SureShrink. It is acombination of the universal threshold and the SURE threshold. The goal of SureShrink is to minimize the meansquared error

$$mse = \frac{1}{n^2}\sum_{x,y=1}^{n}(z(x,y) - s(x,y))^2$$

where z(x,y) is the estimate of the signal while s(x,y) is theoriginal signal without noise and n is the size of the signal.

3. PROPOSED WORK

Proposed method is the newly designed hybridized one. Hybrid threshold is a combination of visu shrink, Bayes shrink and sure shrink. From the above mentioned method, we have analyzed that Bayes shrink has better results than other two. In the proposed one, we are using bayes method on the final output to get the more refined image. First of all, decompositionof noisy image is done at level1.It gives four coefficients i.e. Approximation,Horizontal, Vertical and Diagonal. Approximation coefficient is threshold using using sure shrink and remaining three are using Visu shrink. Output from approximation and other three levels are combined to get the output image. Bayes shrink is applied to output image to get the final refined image. After wavelet thresholding,inverse discrete wavelet transform is applied to reconstruct the image.

4. RESULTS AND DISCUSSIONS

To see the qualitatively performance of the proposed algorithm, the experimental study has been performed on several RGB test images. The noisy images are denoised with the three methods: Bayes shrink,Visu shrink and proposedmethod. The results are compared using quality measures PSNR, BER andMSE. The Images are corrupted using additive white guassian noise. The PSNR, MSE and BER values obtained for two different images are given in table 1 and table 2 respectively. Table 1 shows the results of quality metrics on baby.jpeg and table 2 on bird.jpeg.From the mathematical and experimental results it can be concluded that overall proposed method gives better results than other methods.

Baby.jpeg corrupted by additive white guassian noise

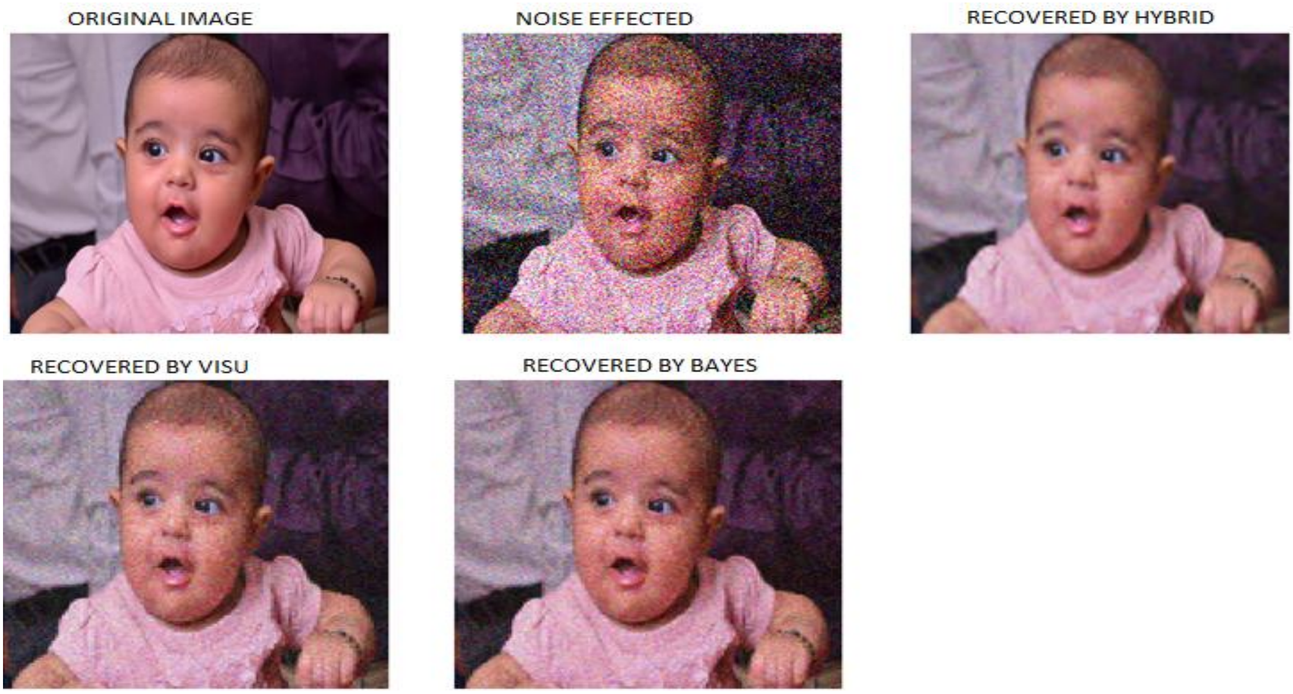

Table 1
Results of quality metrics on baby.jpeg corrupted with guassian white noise

Wavelets	PSNR	MSE	BER	TIME(in secs)
Visu shrink	34	24.9	2.5	0.7
Bayes shrink	34.6	18.7	0.8	1.25
Hybrid	35.4	18.25	0.75	1.1

Bird.jpeg corrupted by additive white Guassian noise

Table 2
Results of quality metrics on bird .jpeg corrupted with guassian white noise

Wavelets	PSNR	MSE	BER	TIME(in secs)
Visu shrink	34.1	22	1.8	0.5
Bayes shrink	34.3	16.5	0.6	0.7
Hybrid	35.2	16.2	0.5	0.8

5. CONCLUSION AND FUTURE SCOPE

From the data elicited in the tables, we conclude with the application of hybrid methods for denoising, the three quality metrics parameters showed improvement along with the reduction in the execution time as compared to the older hybrid methods. In future, we try to extend this hybrid method with bilateral filter and normal shrink [3] [4].

6. REFERENCES

[1] Donoho, D.L. (1995), "De-noising by soft-thresholding", IEEE Transactions on Information Theory, Vol. 41, No. 3, 1995, pp. 613-627.

[2] S. Grace Chang, Bin Yu and M. Vattereli.(2000). Wavelet Thresholding for Multiple Noisy Image Copies.IEEE Transaction.Image Processing, vol. 9, pp.1631- 1635.

[3] Sudipta Roy, NidulSinha&Asoke K. Sen, "A New Hybrid Image Denoising Method", International Journal of Information Technologyand Knowledge Management, July-December 2010, Volume 2, No. 2, pp. 491-497.

[4] LakhwinderKaur, Savita Gupta and R.C. Chauhan, "Image Denoising using Wavelet Thresholding", Proceedings of the third IndianConference on Computer Vision, Graphics and Image processing, Dec 2002, Space Application Center (ISRO), Ahmedabad, India.

[5]. Chang, S. G., Yu, B., Vetterli, M.: Adaptive Wavelet Thresholding for Image Denoisingand Compression, IEEE Trans. on Image Processing, Vol. 9, No. 9 (2000) 1532-1546

[6] Gonzalez, Rafael C. and Woods, Richards E. (2006) "Digital Image Processing", Pearson Prentice Hall, New Delhi.

[7] Rajesh Kumar Rai, Trimbak R. Sontakke "Implementation of Image Denoising using Thresholding Techniques" , IJCTEE, Vol 1 issue 2

[8] David L. Donoho and Iain M. Johnstone, "Adapting to UnknownSmoothness via Wavelet Shrinkage," Journal of American StatisticalAssociation, 90(432):1200-1224, December 1995.

[9] David L. Donoho, "De-noising by soft-thresholding," http://citeseer.nj.nec.com/cache/papers/cs/2831/http:zSzzSzwwwstat.stanford.eduzSzreportszSzdonohozSzdenoiserelease3.pdf/donoho94denoising.pdf, Dept of Statistics, Stanford University, 1992.

[10] Amara Graps, "An Introduction to Wavelets," IEEE Computational Science and Engineering, summer 1995, Vol 2, No. 2.