COMPARATIVE ANALYSIS OF DIFFERENT THRESHOLD ESTIMATORS FOR NOISE REDUCTION

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ABSTRACT

The choice of threshold in wavelet based image denoising is very important.It has been seen that wavelet thresholding methods had better results than classical methods. However estimation of threshold and selection of thresholding function are still the challenging tasks .Threshold determination depends on the pixel characteristics and not on the size of image to be denoised. Different Threshold estimators are applied to image corrupted with Gaussian , poisson & speckle noise.Finally all the images are compared on the basis of PSNR & MSE.

Keywords: *Wavelet transforms, AWGN, Threshold, image denoising, wavelet thresholding*

I. INTRODUCTION

Noise in an image is a very critical problem. Estimation of threshold is very important in image denoising . Noise may be classified as substitutive noise and additive white Gaussian noise. In this paper, White Gaussian , Poisson & Speckle Noise are applied to different images.Wavelet domain based noise removal techniques need some threshold value for removing small coefficients because small coefficients are usually noisy and large coefficients contains main features of image. Therefore, estimating threshold and determining thresholding rules are still challenging problems in wavelet denoising. Removal of noise is very important area of research. An image gets corrupted with different types of noise during the processes of transmission, reception, and storage &retrieval. Image denoising is usually required to be performed before display of image or further processing like image analysis, image recognition, image segmentation etc. Recently, various nonlinear and various adaptive filters have been suggested for the purpose. The objectives of wavelet schemes are to reduce noise as well as to retain the edges and fine characteristics of the original image in the restored image as much as possible.Thus we have developed a adaptive threshod determination technique based on spatial context modeling of different wavelet coefficients. Here the image has been broken down into different blocks of images .Noise of different variance level has been added and it is passed to wavelet denoising techniques for noise suppression. The proposed algorithm is evaluated in terms of mean square error, peak signal to noise ratio and processing time.

II. PREVIOUS WORK

Turgay Celik [1] proposes a novel technique for unsupervised change detection in multi temporal satellite images using principal component analysis and k-means clustering. The image is partitioned into different blocks. Ortho normal eigen vectors are extracted through PCA of n*n non overlapping block set to create an eigenvector space Simulation results show that the proposed algorithm performs quite well on combating both the zero-mean Gaussian noise and the other noise, which is quite attractive for change detection in optical and SAR images. S.Sudha, G.R.Suresh and R.Sukanesh [2] presents a wavelet-based thresholding scheme for noise suppression in ultrasound images. The results obtained by the proposed method with the results achieved from the other speckle noise reduction techniques demonstrate its higher performance for speckle reduction. T.Ratha Jeyalakshmi and K.Ramar [3] they described and analyzed an algorithm for cleaning speckle noise in ultrasound medical images. Mathematical Morphological operations are used in this algorithm.This algorithm is based on Morphological Image Cleaning algorithm (MIC). The algorithm uses a different technique for reconstructing the features that are lost while removing the noise. For morphological operations it also uses arbitrary structuring elements suitable for the ultrasound images which have multiplicative noise. Pierrick Coup´e, Pierre Hellier, Charles Kervrann and Christian Barillot [4] proposed a Bayesian Non Local Means-Based Speckle Filtering In their proposal, a new version of the Non Local (NL) Means filter adapted for US images is proposed. Originally developed for Gaussian noise removal, a Bayesian framework is used to adapt the NL means filter for noise. Experiments were carried out on synthetic data sets with different speckle simulations. Nonlocal Means-Based Speckle Filtering for Ultrasound Images is presented by [5] In this method, an adaptation of the nonlocal (NL) means filter is proposed for speckle reduction in ultrasound (US) images. Originally developed for additive white Gaussian noise, we propose to use a Bayesian framework to derive a NL-means filter adapted to a relevant noise model. Results on real images demonstrate that the proposed method is able to preserve accurately edges and structural details of the image. M. I. H. Bhuiyan, M. Omair Ahmad, Fellow, IEEE, and M. N. S. Swamy [6] presented Wavelet-Based Despeckling of Medical Ultrasound Images with The Symmetric Normal Inverse Gaussian Prior In their proposal, an efficient wavelet-based method is proposed for despeckling medical ultrasound images. A simple method is presented for obtain-ing the parameters of the SNIG prior using local neighbors. Thus, the proposed method is spatially adaptive. Jeny Rajan and M.R. Kaimal [7] In their paper they discuss the speckle reduction in images with the recently proposed Wavelet Embedded Anisotropic Diffusion (WEAD) and Wavelet Embedded Complex Diffusion (WECD). Both these methods are improvements over anisotropic and complex diffusion by adding wavelet based bayes shrink in its second stage. Both WEAD and WECD produce excellent results when compared with the existing speckle reduction filters. Philip Langley proposed a denoising method for hyperspectral data cubes .Experimental results demonstrated that the proposed denoising methods produces better denoising results in terms of PSNR. Ioana Firoiu, Corina Nafornita [11] proposes the use of a recently introduced hyperanalytic WT (HWT), in association with filtering techniques already used with the discrete wavelet transform. The result is a very simple and fast image denoising algorithm. Lei Zhan& Rastislav Lukac [12] proposes a principle component analysis based spatially-adaptive denoising algorithm, which works directly on Colour Filter Array data using a supporting window to analyze the local image statistics. By exploiting the spatial and spectral correlations existed in the CFA image, the proposed method can effectively suppress noise while preserving color edges and details. Experiments using both simulated and real CFA images indicate that the proposed scheme outperforms many existing approaches, including those sophisticated demosaicking and denoising schemes, in terms of both objective measurement and visual evaluation.

III.WAVELET THRESHOLDING

Here we have considered different threshold estimation algorithm . Different Gaussian ,Poisson and speckle noise is applied to different threshold estimators such as rigrsure, heursure minimaxi & Sqtwolog.Comparision of different threshold estimators have done on classical grey scale lena image and the results have been compared on the basis of Peak signal to Noise Ratio and Mean Square Error. Sure shrink method is widely used as orthonormal wavelet transform for wavelet thresholding. The idea behind SUREshrink is to set to zero all coefficients below a certain threshold value T, while shrinking the remaining ones by this same value; this technique is thus also called soft thresholding.

(y) = sign(y)(|y| – T)+

The soft thresholding function has been shown to be near optimal value. The threshold value T is then selected so as to minimize the risk level. The mean squared error (MSE) in the image domain is preserved in the wavelet domain. Hence, we can write it as follows:

$$\text{MSE(Image Domain)} = \frac{1}{N}\sum_{i=1}^{N}(\square i - fi)^2 \qquad (1)$$

$$= \frac{1}{N}\sum_{j=1}^{j}\sum_{i=1}^{N_j}(\square_i^j - x_i^j)^2 \qquad (2)$$

$$= \text{MSE (Wavelet Domain)}$$

Where N is the number of samples;

J is the number of channels;

NJ is the number of samples in the channel j.

I is the it sample of the jet channel.

As the non-noisy wavelet coefficients are unknown, we need to estimate the MSE using Stein's unbiased risk estimator (SURE).Its minimization according to our particular estimator ˆx = ▼ (y) leads to:

$$\text{SURE}_j(t,y) = \sigma^2 - 1/Nj\,(2\,\sigma^2.\#\{i:|yi| <= t\}$$
$$+ \sum_{i=1}^{Nj}\min(|yi|, t^2) \qquad (3)$$

The resulting threshold is thus:

$$T_j = \text{argmin}\,(\text{SURE}_j(t,y)) \qquad (4)$$

To better adapt to image discontinuities, we need to select a new threshold for each wavelet sub-band of successive scales, except the low-pass residual. This method is thus known as adaptive with respect to the sub-bands.The SURE principle can also be used to optimize the (_α, ▼)-parameters of the fractional B-spines. To estimate the noise variance σ_n^2 from the noisy wavelet

coefficients, a robust median estimator is used from the finest scale wavelet coefficients.

$$\sigma_n^2 = \text{Median}\,(|y_i|) / 0.6745 \quad (5)$$

Where $\mathbf{y_i}$ is element of sub band HH_1 .

Donoho's has proposed the fixed thresholding based reduction of noise in images . Here, the value of threshold (t) is computed as:

$$t=\sigma\sqrt{2\log(n)}\,/n \quad (6)$$

where σ=MAD/0.6745 where MAD is the median of wavelet coefficients and *n* is the total number of wavelet coefficients.

(a) Global Thresholding (wt_q)

This is known as fixed threshold or global thresholding method and it is calculated as:

$$wt_q = \sqrt{2\log(n)} \quad (7)$$

where n is the total number of wavelet coefficients.

(b) Rigrsure(wt_{su})

Steins unbiased risk estimator (SURE) or rigrsure is an adaptive thresholding method which is proposed by Donoho and Jonstone .

(c) Heursure (w_{th})

Heursure threshold is a combination of SURE and global thresholding method. If the signal-to noise ratio of the signal is very small, then the SURE method estimation will account for more noises. In this kind of situation, the fixed form threshold is selected by means of global thresholding method. *Minimax* (w_{tm}) Minimax threshold is also used fixed threshold and it yields minmax performance for Mean Square Error (MSE) against an ideal procedures. Because the signal requiredthe denoising can be seen similar to the estimation of unknown regression function, this extreme value estimator can realize minimized of maximum mean square error for a given function.

IV. COMPARATIVE ANALYSIS OF IMAGE FOR DIFFERENT THRESHOLD ESTIMATORS

Gaussian Noise								
Variance	Rigrsure		Heur sure		Sqtwolog		Minimaxi	
	PSNR	MSE	PSNR	MSE	PSNR	MSE	PSNR	MSE
0.005	27.3	86.2	25.4	133.1	133	25.5	25.6	144
0.003	28.8	75.5	28	77.5	27.5	77.9	27.3	85.6
0.001	28.1	68.7	33.1	23.7	32.9	23.77	32.4	26.7
0.02	21.6	321.2	19.2	558	19.1	557	19.01	585
0.01	25.7	125.1	22.2	275	22.3	276	22	293

Table I: Comparison of different threshold estimators for classical *Lena* image distorted by Gaussian Noise

Poisson Noise								
Variance	Rigrsure		Heur sure		Sqtwolog		Minimaxi	
	PSNR	MSE	PSNR	MSE	PSNR	MSE	PSNR	MSE
0.005	28.2	69.9	29.8	48.8	29.9	48.9	29.4	53.5
0.003	28.4	67.7	29.8	48.4	29.6	48.1	29.3	54
0.001	28.3	68.4	29.6	47.6	29.8	48	29.4	53.1
0.02	28.3	68.9	29.9	47.6	29.8	48	29.3	53.2
0.01	28.36	68.01	29.91	47.8	29.7	47.1	29.4	54.5

Table II: Comparison of different threshold estimators for classical Lena image distorted by Poisson Noise

Speckle Noise								
Variance	Rigrsure		Heur sure		Sqtwolog		Minimaxi	
	PSNR	MSE	PSNR	MSE	PSNR	MSE	PSNR	MSE
0.005	28.6	63.6	31.4	33.5	31.2	33.1	30.9	37.5
0.003	28.9	59.4	33.7	19.7	33.5	25.1	33.27	21.4
0.001	29.2	55.8	38.8	7.14	38.1	10.1	38.15	7.14
0.02	26.8	96.4	24.9	147.9	24.91	151	24.6	159.9
0.01	27.9	74.2	28.8	71.2	29.3	76	27.8	77.1

Table III: Comparison of different threshold estimators for classical Lena image distorted by Speckle Noise

V. EXPERIMENTAL RESULTS

The algorithms are programmed in MATLAB and the simulated results for PSNR(Peak signal to noise ratio) & MSE(Mean Square Error) are compared with different threshold estimators With Gaussian , poisson & speckle noise.Table I,II & III shows the values of PSNR and MSE for different threshold estimators. Different wavelet functions and four threshold rules have considered in analyzing the performance of denoising the images using soft thresholding method. From the literature, we have seen that, wavelet transform shows a good performance on denoising classical lena images.However, the selection of appropriate wavelet functions and number of wavelet different decomposition level is still an important issue to remove the various kinds of noises from the images.

VI. CONCLUSION AND FUTURE PROSPECTS

In this work, different wavelet estimators are compared for noise reduction. Four thresholds estimators rigrsure, heursure,sqtwolog and minimaxi are respectively used in the process of wavelet denoising . Simulation results show that different selection of the wavelet thresholds estimators have significant impact on the de-noising results. The evaluation indexes include Peak signal to noise ratio (PSNR), and mean square error (MSE). As future work, we would like to work further on the comparison of different denoising techniques. We would also like to reduce mean square error with less processing time.Besides, the complexity of the algorithms we would also like to improve Signal to Noise ratio. These points would be considered as an extension to the present work done.

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