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An Improved Method of Removing Gaussian Noise for a Gray Scale Image using Multiresolution Technique

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ABSTRACT

This paper proposes a new image denoising algorithm using wavelets. It utilizes the pertinence of the neighbor wavelet coefficients by using the block thresholding scheme. Proposed enjoys a number of advantages over the other conventional image denoising methods. The aim of this paper is to investigate a multiresolution technique and the corresponding thresholding methods for image denoising. Consideration may also be given to applying some enhancement techniques to the existing methods so as to achieve both noise reduction and feature preservation. The noise acceptance and rejections rates have been computed for the existing techniques and the newly developed technique. The proposed technique provides better results with the soft thresholding and block thresholding based on parameters, MSE and PSNR

General Terms

Gray Scale Image, Multiresolution Technique

Keywords

Image Denoising, Wavelet Transform, Soft Thresholding, Block Thresholding, and Noise Variance.

1. INTRODUCTION

Digital images play an important role in today's life. In the applications, such as satellite television, magnetic recourse imaging, ultrasound imaging, geographical information systems, astronomy and computer tomography, scientists face the problem of recovering original images from incomplete, indirect and noisy images. Generally, data sets received by image sensors are corrupted by noise. This degradation of data sets is due to imperfect instruments like charge coupled device (CCD) camera, problems with the data acquisition processes and with the interfering natural phenomena. One of the most prevalent cases is distortion due to additive white Gaussian noise, which can be caused by poor acquisition or by transferring of the image data in noisy communication channels. Other types of noises include impulse and speckle noises.Images may be corrupted during transmission processes and compression.

Image denoising is the first necessary step to be taken before the image data is analysed. It is necessary to apply an efficient denoising technique to compensate to such corruption. Image denoising is still a challenge for researchers because noise removal techniques introduce airtifacts and cause blurring of the images. Denoising of electronically distorted images is an old but still a relevant industrial problem. Denoising of natural images corrupted by noise using wavelet techniques is very effective because of its ability to capture the energy of a signal in few energy transform values.

2. DISCRETE WAVELET TRANSFORM

The wavelet transform describes a multi-resolution decomposition process in terms of expansion of an image onto a set of wavelet basis functions[4]. Discrete Wavelet Transformation has its own excellent space frequency localization property. Applying DWT in 2D images corresponds to 2D filter image processing in each dimension. The input image is divided into 4 non-overlapping multi-resolution sub-bands by the filters, namely LL_1 , LH_1 ,HL_1 and HH_1[2],named Approximation coefficients, vertical details, horizontal details, diagonal details respectively. The subband(LL_1) is processed further to obtain the next coarser scale of wavelet coefficients, until some final scale "N" is reached. When "N" is reached, we'll have 3N+1 sub-bands consisting of the multi-resolution sub-bands (LL_N) and (LH_x), (HL_x) and (HH_x) where "X" ranges from 1 until "N". Generally most of the Image energy is stored in these sub-bands

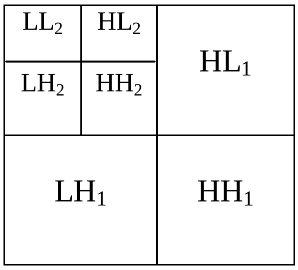

Fig1: Subbands of 2D DWT

Let us consider a signal { p_{ij} , $i, j = 1,2\ldots N$} denote the N X N matrix of the original image to be recovered and N is some integer power of 2. During transmission the signal is corrupted by independent and identically distributed (i.i.d) zero mean, white Gaussian Noise q_{ij} *with* standard deviation σ i.e. $q_{ij} \sim M(0, \sigma^2)$ as follows.

$$y_{ij} = p_{ij} + q_{ij} \quad (1)$$

From this noisy signal y, we want to find an approximation p_{ij}. The goal is to estimate the signal pij from noisy observations yij such that Mean Squared error (MSE) is minimum.

Let W and W^{-1} denote the two-dimensional orthogonal discrete wavelet transform (DWT) matrix and its IDWT respectively i.e.

$$d_{ij} = c_{ij} + \varepsilon_{ij} \quad (2)$$

With d=Wy, c =Wp, ε =Wq .Since W is orthogonal transform, £j is also an i.i.d Gaussian random variable with ij ε~(0, σ2).Now T (.) be the wavelet thresholding function then the wavelet thresholding based Denoising scheme can be expressed as $X = W^{-1}(T(Wy))$ wavelet transform of noisy signal should be taken first and then thresholding function is applied on it.

Finally the output should be undergone inverse wavelet transformation to obtain the estimate p.

In the experiments, soft thresholding has been used over hard thresholding because it gives more visually pleasant images as compared to hard thresholding; reason being the latter is discontinuous and yields abrupt artifacts in the recovered images especially when the noise energy is significant.

3. PROBLEM FORMULATION

Traditionally linear filters such as mean, median and wiener filtering are used for image denoising, but it leads to blurred and smoothed image with incomplete noise suppression. To overcome this shortcoming, non linear techniques have been proposed. In nonlinear techniques such as wavelets based image denoising have focused due to their multiresolution nature. Researchers have employed various approaches to nonlinear denoising: In one approach, a hard threshold function keeps a coefficient if it is larger than a threshold and sets it to zero otherwise, in another approach, a soft threshold function shrinks the coefficient by an amount equal to the value of the threshold and sets it to zero otherwise. Wavelet technique provides more detailed information of the image by decomposing image into various subbands at each resolution level or scale

3.1Proposed Algorithm

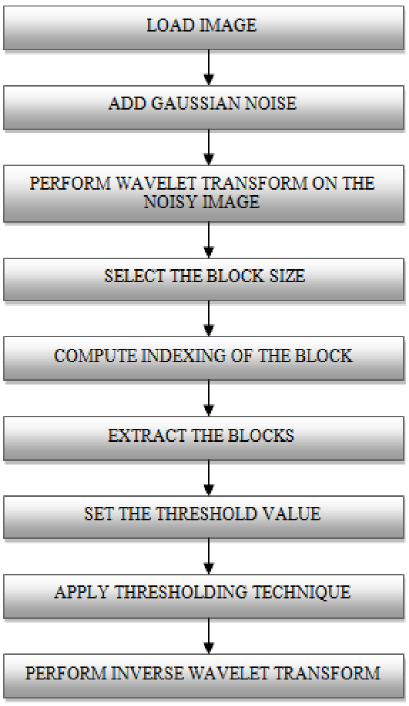

Fig2:proposed algorithm

4. EXPERIMENTAL RESULTS

The quality of reconstructed image is specified in terms of MSE and PSNR. The MSE values are calculated using the following expression:

$$MSE = \frac{1}{N^2}\sum_{i,j=1}^{N}\left(X(i,j)-\hat{X}(i,j)\right)^2 \qquad (3)$$

where X(i,j) is original image and X(i,j) is the denoised image.The PSNR values are calculated using the following expression:

$$PSNR=10\log_{10}\frac{255^2}{MSE}\ (dB) \qquad (4)$$

The experiments are conducted on natural gray scale images like Lena.bmp, Barbara.bmp Boat.bmp of size 512 x 512 with Gaussian noise level of standard deviations 10,15,20,25,30,35.

Experimental results show that MSE and PSNR with proposed algorithm are better soft thresholding and Block thresholding. The denoised images obtained after reconstruction are visually more sharper and also free of artifacts along edges.

Table1:PSNR results of various Test images

	Soft Thresholding	Block Thresholding	Proposed Method
	PSNR	PSNR	PSNR
Lena.bmp			
σ=10	31.2707	32.7214	**34.1384**
σ=15	29.1056	30.4595	**31.7789**
σ=20	27.5348	28.9432	**30.2188**
σ=25	26.3692	27.7004	**28.9433**
σ=30	25.5239	26.9336	**28.0775**
σ=35	24.7068	26.0796	**28.1806**
Barbara.bmp			
σ=10	30.66	32.0654	**33.2162**
σ=15	28.5898	29.8204	**30.9109**
σ=20	27.2014	28.428	**29.4758**
σ=25	26.0192	27.2861	**28.2596**
σ=30	25.2443	26.5602	**27.4916**
σ=35	24.4737	25.8825	**26.7245**
Boat.bmp			
σ=10	30.3817	31.76591	**32.9734**
σ=15	28.1722	29.358	**30.553**
σ=20	26.6982	27.7331	**28.8796**
σ=25	25.6228	26.6766	**27.7614**
σ=30	24.6562	25.694	**28.8284**
σ=35	23.9614	25.0234	**26.0889**

Table2:MSE results of various Test images

	Soft Thresholding	Block Thresholding	Proposed Method
	MSE	MSE	MSE
Lena.bmp			
σ=10	48.053	34.7486	**25.075**
σ=15	79.879	58.4965	**43.1704**
σ=20	114.7087	82.9402	**61.83**
σ=25	150.0227	110.4175	**82.9379**
σ=30	182.2598	131.7397	**101.2351**

σ=35	219.9892	160.3684	**124.4575**
Barbara.bmp			
σ=10	55.8571	40.4147	**31.0071**
σ=15	89.4711	67.7708	**52.7221**
σ=20	123.8616	93.3864	**73.3671**
σ=25	162.6153	121.4699	**97.0782**
σ=30	194.3807	143.5697	**115.8559**
σ=35	232.1178	167.8148	**138.2391**
Boat.bmp			
σ=10	59.554	43.3003	**32.7899**
σ=15	99.0504	75.385	**57.2502**
σ=20	139.0772	109.5897	**84.163**
σ=25	178.1568	139.7712	**108.8791**
σ=30	222.5648	175.2594	**134.9695**
σ=35	261.1792	204.5207	**160.0264**

Fig2: (a) Original Image (b) Noisy image with σ=10 (c) denoised with soft threshold (d) denoised with Block threshold (e) denoised with proposed algorithm

Figure2: (a) Original Image (b) Noisy image with σ=10 (c) denoised with soft threshold (d) denoised with Block threshold (e) denoised with proposed algorithm

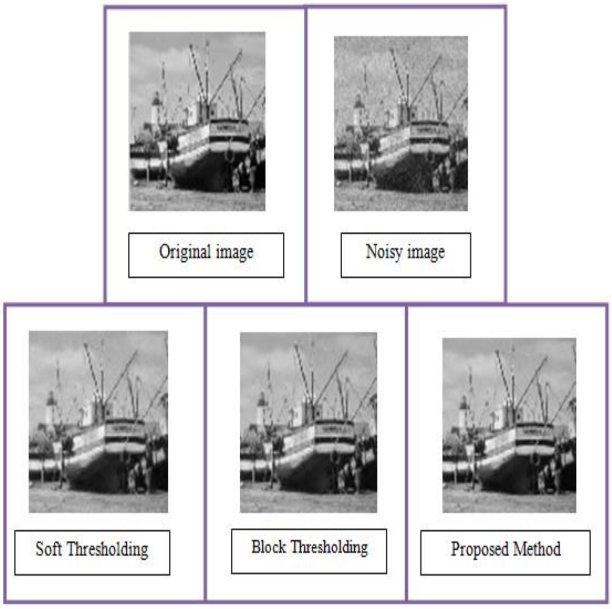

Figure2: (a) Original Image (b) Noisy image with σ=10 (c) denoised with soft threshold (d) denoised with Block threshold (e) denoised with proposed algorithm

5. CONCLUSION AND FUTURE SCOPE

In this paper, we developed a new image denoising method. This Method applies the block thresholding scheme which utilizes the information about the neighbor wavelet coefficients. Proposed Method is a completely data-driven approach. It can select the optimal block size and threshold for every wavelet subband by minimizing Stein's unbiased risk estimate. We compared proposed method with classic Soft Thresholding and Block thresholding. Experimental results showed that the proposed method gave better results as compared to Soft Thresholding and Block Thresholding

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7. REFERENCES

[1] Donoho, D. L.and Johnstone I. M. 1994. Ideal spatial adaptation by wavelet shrinkage, *Biometrika*,vol. 81, no. 3, pp. 425–455.

[2] Zhou, D. and Xiaoliu,S. 2008. Image Denoising Using Block Thresholding ,congress on image and signal processing

[3] Donoho D. L.1995. Denoising by soft-thresholding, *IEEE Trans. Inf. Theory*, vol. 41, no. 3, pp.613–627.

[4] Chang,S.G.,Yu,B. and Vetterli,M. 2000. Adaptive wavelet thresholding for image denoising and compression, IEEE. Image Process. 9(9), pp. 1532–1546.

[5]. Donoho,D.L 1993. De-Noising by Soft Thresholding, *IEEE Trans. Info. Theory 43*, pp. 933-936.

[6] Guo, L. and Jiaxue, L. 2009. Image Denoising using Adaptive Threshold based on Second Generation Wavelets Transform, IFCSTA, pp. 444-447.