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Color Image denoising Based on Bi Pearson Shrinkage Method using Wavelet

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Abstract- ***Images are often ruined by noises. Noise is an undesired data which moderates the contrast and brightness of image resultant blurring the edges and defects its size and shape. Noise removal is a vital task in Image processing. In general the results of the noise removal have a strong outcome on the quality of the image processing technique. Several techniques for noise removal are familiar in gray image processing and very few works is done for color image processing. In the field of image noise fall several linear and nonlinear filtering methods have been offered.so in this paper wavelet technique have been proposed for denoising the color image based on bipearson shrinkage technique. The wavelet techniques are very effective to remove the noise also use of its capability to confine the power of a signal in tiny convert of energy values. Also this paper gives comparison between hard and soft threshold technique based on bipearson shrinkage method.***

Index Terms **– Noise, Filter, Bi Pearson shrinkage, wavelet transforms**

I. INTRODUCTION

Digital cameras, Magnetic Resonance Imaging (MRI), Satellite Television and Geographical Information System (GIS) have increased the use of digital images. Generally, data sets collected by image sensors are contaminated by noise. Imperfect instruments, during data acquisition process, and interfering natural occurrences can all corrupt the data of image. Noise in the image can be occurred in the sensor and circuitry of a scanner or digital camera [1]. Also Image noise can also originate in film grain and in the unavoidable shot noise of an ideal photon detector. Various types of noise present in image are Gaussian noise, Salt & Pepper noise and Speckle noise Traditionally, linear filters (mean, median, and wiener filter) are used for removing noise from images, but it blurs the data also arising artificial frequency problem .also filter domain cannot work in both the time and frequency domains simultaneously[2]. But in wavelet transform one can work in joint time-frequency domain at the same instant of time.

In this paper Bipearson shrinkage method have been proposed for denoising the color image. The Pearson model is chosen because of it flexibility, i.e. by adjusting some parameter it can converge to either Cauchy or Gaussian distribution. The simulation results for color image denoising in comparison with hard Thresholding and Soft Thresholding. The experimental results show that our algorithm achieves better performance visually and in terms of PSNR. Finally the concluding remarks are given in last Section.

II. BIPEARSON SHRINKAGE TECHNIQUE

In this section, the denoising of an image corrupted by additive independent white Gaussian noise with variance ${\sigma_n}^2$ will be considered. For a wavelet coefficient x_1, let x_2 represent its parent, i.e. x_2 is the wavelet coefficient at the same position as the wavelet coefficient x_1, but at the next coarser scale. We suppose the these coefficients are contaminated by additive white Gaussian noise, that is

$$y1 = x1 + n1 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

and

$$y2 = x2 + n2 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2)$$

Where $y1$ and $y2$ are noisy observations of $x1$ and $x2$; and $n1$ and $n2$ are noise samples. To take into account the statistical dependencies between a coefficient and its parent, we combine them into vector form
as follow:

$$\mathbf{y} = \mathbf{x} + \mathbf{n} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(3)$$

Where $\mathbf{y} = [\, y1 \, , y2 \,]$, $\mathbf{x} = [x1 \, , x2 \,]$, and $\mathbf{n} = [n1, n2 \,]$.

In this paper we proposed the following bi Pearson for coefficients and his parent. We assume that the noise is white Gaussian noise.[1]

III. WAVELET TRANSFORM

Wavelet transform has extensive range of application in signal processing as well as other fields. The wavelet expansion set is not unique. Wavelet systems a set of building blocks to signifies or construct a signal or function. The signals may be one-dimensional, two-dimensional and three dimensional. They convey useful information. Denoising (noise reduction) is the first step in many applications. Other applications include data mining, medical signal/image analysis (ECG, CT,etc.), radio astronomy image analysis etc. Motivation to the thresholding idea is based on the assumptions that the decorrelating property of a wavelet transform creates a sparse signal: most untouched coefficients are zero or close to zero. The noise level is not too high so that we can distinguish the signal wavelet coefficients from the noisy ones. [2][3][4]

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In this paper we use 2-Dimensional Discrete Wavelet Transform (DWT) of the available two different wavelet transform techniques by which we can decompose the image by several parts mainly range image and domain image containing LL2 and HL2, LH2, HH2 respectively.

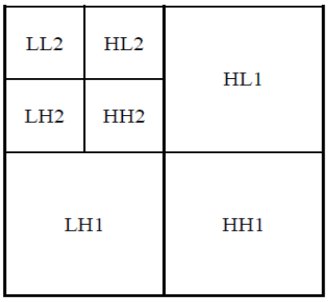


Figure 2 Image Decomposition by using DWT [2]

IV. THRESHOLD ESTIMATION PROCESS

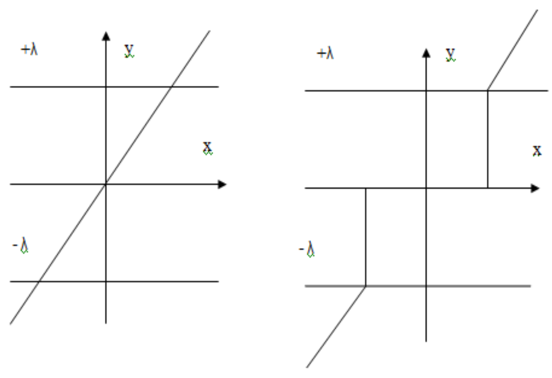
As we discussed earlier that we are using Bipearson shrinkage method and we are also using hard and Soft Thresholding process for comparision of threshold estimation.

Hard-Thresholding

$Y = T_{hard}\,(X, Y) = \{X \quad where\ |X| \geq \lambda$

$\{0 \qquad |X| < \lambda$ …………………(4)

In the hard thresholding scheme given in equation (4), the input is kept if it is greater than the threshold λ; otherwise it is set to zero. The hard thresholding procedure removes the noise by thresholding only the wavelet coefficients of the detailed sub bands, while keeping the low-resolution coefficients unaltered.



(a) Original signal (b)After hard thresholding

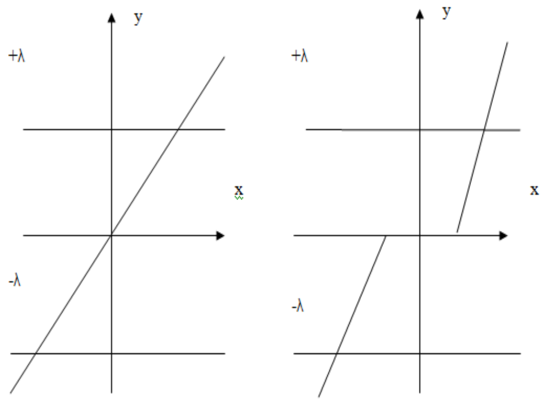
Figure 5 Hard Thresholding Scheme

Soft-Thresholding

$Y = T_{soft}(X, Y) = \{sign\{X\}\ (|X|-\lambda)$

Where $|X| \geq \lambda$, 0, $|X|<\lambda$ …………………(5)

The soft thresholding scheme shown in equation (5) is an extension of the hard thresholding. If the absolute value of the input X is less than or equal to λ then the output is forced to zero. If the absolute value of X is greater than λ then the output is |y| = |x - λ|. When comparing both hard and soft shrinking schemes graphically from Figures 5 and 6. It can be seen that hard thresholding exhibits some discontinuities at ±λ and can be unstable or more sensitive to small changes in the data, while soft thresholding avoid discontinuities and is therefore more stable than hard thresholding. [5]



(a)Original signal (b)Signal after soft thresholding

Figure 5 Soft Thresholding Scheme

V. PROPOSED ALGORITHM

(1) Read the original regular image.

(2) Check whether the image is a color image or gray image.

(3) Resize the loaded image to a standard size of 256 × 256. The images taken for rectification have a lot of variation in their sizes and hence cannot be compared on the same basis. For large sized images, such as 512× 512, the computation time for denoising is found to be more. And if the image size is taken smaller than 256× 256, then the useful data is liable to get lost.

(4) Noise is added to the standard test images using the following type of available noise. In this work Guassian noise is used.

(5) Make the noisy image to undergo wavelet transform through DWT.

MAP estimator is used for corrupted y. Noise pdf is given by the equation:

$$F_n(n)=1/2\ \pi\sigma_n^2\ \exp(n_1^2+n_2^2/2\sigma_n^2) \ldots\ldots\ldots\ldots(6)$$

After the noisy image is decomposed into approximation and detail coefficients using wavelet transform, it is made to undergo the following thresholding rules having various threshold values. In addition, two cases have been considered- one where the low pass components are not thresholded and the other being the one where the low pass components have been thresholded. Soft Thresholding and Hard Thresholding are used for this purpose.

(6)After the decomposed image coefficients are thresholded using the thresholding technique, the denoised image is reconstructed using inverse wavelet transforms-IDWT.

VI. EXPERIMENTAL RESULT AND DISCUSSIAN

Two parameters should be taken to calculate the image with their noisy and denoise counterparts, respectively. The parameter we are taken is PSNR (peak signal to noise ratio) and MSE (Mean Square Error) Hence, we get a good amount of comparison between the noisy and denoised images keeping the set standard image intact. Also we are reducing the time of denosing process.

Table.1 PSNR values and MSE for pepper image

	Variance	0.005	0.01	0.015	0.02	0.025
NOISY IMAGE	MSE	326.9179	640.448	945.6892	1238.2296	1525.973
	PSNR(dB)	22.9864	20.066	18.3733	17.2028	16.2953
Proposed Algorithm with Soft Thresholding	MSE	156.1983	308.6877	475.7685	601.2948	743.4503
	PSNR(dB)	24.8721	21.9137	20.2024	19.018	18.0964
	TIME	0.40123	0.75408	0.75408	0.73507	0.7124
Proposed Algorithm with Hard Thresholding	MSE	152.7369	303.4097	450.8902	593.1911	734.4558
	PSNR(dB)	24.9694	21.9877	20.2682	19.0769	18.1492
	TIME	0.14673	0.16042	0.16105	0.16295	0.6137

VII. CONCLUSION

For digital color images with real noise, based on the analysis of color space decomposition and noise distribution we proposed an efficient algorithm which significantly remove the noise in chrominance channels and keep the geometry and details well relying on the luminance channel. This method can be widely used together with almost any of the previous denoising methods but saves the number of iterations.
We noticed that how wavelet transforms provides us a tool to implement scales and translate a noisy image into noise free image. Lot of parameters and functions used to reduce noise like Gaussian at different resolution levels.
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