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Wavelet Based Color Image Denoising through a Bivariate Pearson Distribution

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***Abstract*- In this paper we proposed an efficient algorithm for Color Image Denoising through a Bivariate Pearson Distribution using Wavelet Which is based on Bayesian denoising and if Bayesian denoising is used for recovering image from the noisy image the performance is strictly depend on the correctness of the distribution that is used to describe the data. In the denoising process we require a selection of proper model for distribution. To describe the image data bivariate pearson distribution is used and Gaussian distribution is used to describe the noise particles in this paper. For gray scale image lots of extensive works has been done in this field but for colour image denoising using bivariate pearson distribution based on baysian denoising gives us tremendous result for analysing coloured images which can be used in several advanced applications. The bivariate probability density function (pdf) takes into account the Gaussian dependency among wavelet coefficients. The experimental results show that the proposed technique outperforms several exiting methods both visually and in terms of peak signal-to-noise ratio (PSNR).**

***Key words* – Bivariate Pearson distribution, Bayesian denoising, wavelet transforms.**

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I. INTRODUCTION

In signal processing it is a classical problem to denoised of natural image corrupted by Gaussian noise. If the wavelet transform and shrinkage technique are used for this downside, the answer needs a priori information concerning however the wavelet coefficients distributed. Therefore, two issues arise: 1) What varieties of distributions represent the wavelet coefficients? 2) what's the corresponding estimator (shrinkage function)?

In this paper, we have a tendency to planned the bivariate Pearson type distribution . The Pearson model is chosen due to its flexibility, i.e. by adjusting some parameter it will converge to either Cauchy or Gaussian distribution [4]. While the image is suffering from Gaussian noise, a great tool of 2-D wavelet is applied during this paper that provides us an efficient technique of denoising. We use thresholding technique [6] and a Bayesian shrinkage function [2] to denoised an image that is corrupted by Gaussian noise. The rest of this paper is organized as follows. when a short review on the fundamental plan of Bayesian denoising we have a tendency to acquire a shrinkage function using bivariate Pearson distribution with local variance specifically, the proposed model is applied for wavelet-based denoising of many images corrupted with additive Gaussian noise in numerous noise levels.

The simulation results for color image denoising as compared 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. BAYESIAN DENOISING

In this section, the denoising of an image corrupted by additive independent white Gaussian noise with variance σn2 are going to be considered. For a wavelet coefficient x1, let x2 represent its parent, i.e. x2 is the wavelet coefficient at an equivalent position because the wavelet coefficient x1 , however at succeeding coarser scale. We tend to suppose these coefficients are contaminated by additive white Gaussian noise, that is:

$$y1 = x1 + n1 \qquad (1)$$

and

$$y2 = x2 + n2 \qquad (2)$$

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:

$$\mathrm{y} = \mathrm{x} + \mathrm{n} \qquad (3)$$

Where $\mathbf{y} = [\, y_1 , y_2\,]$, $\mathrm{x} = [x_1 , x_2\,]$, and $\mathrm{n} = [n_1, n_2\,]$.

The standard MAP estimator for x given to corrupted observation y is

$$x(\hat{y}) = \arg\max_x f_{(x|y)}\,(x|y)$$

In this paper we proposed the following bivariate Pearson distribution for coefficients and his parent. We assume that the noise is white Gaussian noise.

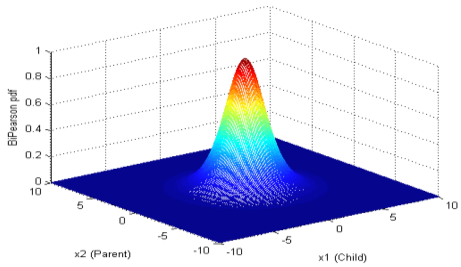

Figure 1: bivariate Pearson distribution with $m = 4$, $\sigma^2 = 4$

III. WAVELET TRANSFORM

In this paper we tend to use 2-Dimensional discrete wavelet transform (DWT) of the available two different wavelet transform techniques by that we will decompose the image by many parts principally range image and domain image contain LL2 and HL2, LH2, HH2 respectively.

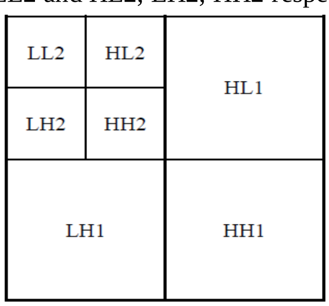

Figure 2 Image Decomposition by using DWT

IV. WAVELET DCOMPOSITION AND RECONSTRUCTION

The Decomposition method is accomplished by the subsequent technique is shown in Fig.3 and fig.4 are one-dimensional Low Pass Filter (LPF) and High Pass Filter (HPF) respectively for image decomposition. to get succeeding level of decomposition, sub band LL1 alone is further decomposed.

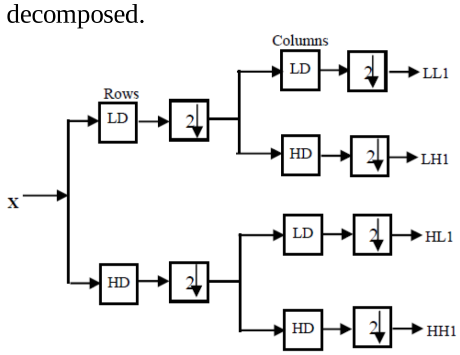

Figure 3: Wavelet filter bank of one level image-decomposition

This method continues until some final scale is reached. The decomposed images are often reconstructed employing a reconstruction filter as shown in Fig. 3. Here, the filters LR and hour represent low pass and high pass reconstruction filters respectively. Here, since the image size isn't modified after decomposition this DWT is named critically sampled transform while not having any redundancy.[18]

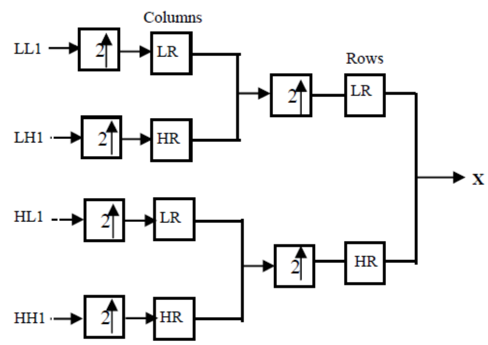

Figure 4: Wavelet filter bank of one level image-Reconstruction

V. THRESHOLD ESTIMATION PROCESS

As we have a tendency to discussed earlier that we are employing a Bayesian Denoising dependent on bivariate pearson distribution supported bayes Shrink the function of Bayes Shrink is represented as below: beside Bayes shrinkage function we have a tendency to are using hard and Soft Thresholding method for comparison of threshold estimation. Bayes Shrink Bayes Shrink is AN adaptative data-driven threshold for image denoising via wavelet soft-thresholding. the threshold is driven in a bayesian framework, and that we assume generalized gaussian distribution (GGD) for the wavelet coefficients in each detail sub band and try to search out the threshold T that minimizes the bayesian Risk. bayes Shrink performs better than sure Shrink in terms of MSE. The reconstruction using bayes Shrink is power tool and a lot of visually appealing than one obtained using sure Shrink [22, 32].

Hard-Thresholding

$$Y = T_{hard}(X, Y) = \begin{cases} X & \text{where } |X| \geq \lambda \\ 0 & |X| < \lambda \end{cases} \quad (4)$$

In the hard thresholding scheme given in equation (4), the input is kept if it's larger than the threshold λ; otherwise it is set to zero. The hard thresholding procedure removes the noise by thresholding solely the wavelet coefficients of the elaborated sub bands, whereas keeping the low-resolution coefficients unchanged.

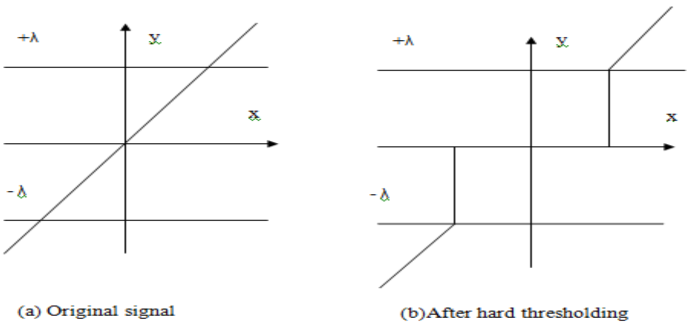

Figure 5: Hard Thresholding Scheme

Soft-Thresholding

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

$$\text{Where } |X| \geq \lambda,\ 0,\ |X|<\lambda \quad (5)$$

The soft thresholding scheme shown in equation (5) is associate extension of the hard thresholding. If absolutely the value of the input X is a smaller amount than or adequate to λ then the output is forced to zero. If absolutely the value of X is bigger than λ then the output is |y| = |x - λ|. When comparing each hard and soft shrinking schemes diagrammatically from Figures five and vi. It may be seen that tough thresholding exhibits some discontinuities at ±λ and might be unstable or additional sensitive to little changes within the data, whereas soft thresholding avoid discontinuities and is thus additional stable than hard thresholding. [30]

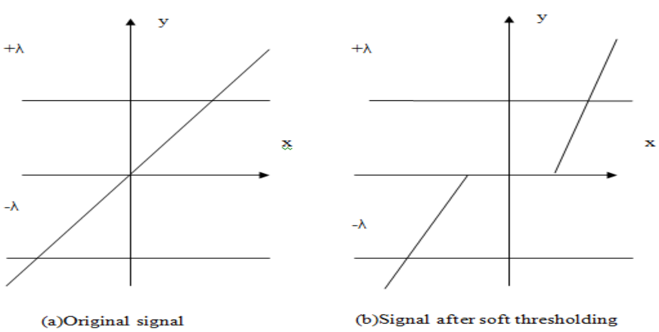

Figure 5: Soft Thresholding Scheme

VI. PROPOSED ALGORITHM

(1) Read the initial standard image.

(2) Check whether or not the image may be a color image or grey image.

(3) Size the loaded image to a typical size of 256 × 256. the images taken for rectification have lots of variation in their sizes and thus cannot be compared on identical basis. For giant sized images, like 512× 512, the computation time for denoising is found to be additional. And if the image size is taken smaller than 256× 256, then the information knowledge is susceptible to drift.

(4) Noise is added to the standard take a look at images using the subsequent kind of offered noise. during this work Gaussian image is employed.

(5) Make the noisy image to endure wavelet transform through DWT.MAP estimator is employed for corrupted y. Noise pdf is given by the equation:

$$f(n) = \frac{1}{2}\pi\sigma n^2 \exp(n12 + \frac{n22}{2}\sigma n2) \quad (6)$$

After the noisy image is decomposed into approximation and detail coefficients using wavelet transform, it's created to endure the subsequent thresholding rules having varied threshold values. Additionally, two cases are considered- one wherever the low pass components don't seem to be thresholded and therefore the different being the one wherever the low pass components are 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.

VII. EXPERIMENTAL RESULT AND DISCUSSIAN

Two parameters, PSNR (peak signal to noise ratio) and MSE (Mean sq. Error) are calculated for all the standard images with their noisy and denoised counterparts, severally. Hence, we have a tendency to get a good quantity of comparison between the noisy and denoised images keeping the set standard image intact.

PSNR – PSNR stands for the height signal to noise ratio. it's accustomed calculate the ratio between the most attainable signal power and therefore the power of corrupting noise that affects the fidelity of its representation. as a result of several signals have a very wide dynamic range, PSNR is typically expressed in terms of the index dB scale. it's most commonly used as a measure of quality of reconstruction in compression etc. it's calculated because the following:

$$PSNR = 10\ \log(\frac{255}{MSE})^2 \quad (7)$$

At just once, we have a tendency to calculate PSNR for original with noisy image and refer it as PSNR (O/N). Once the image is denoised, it's calculated for original with denoised image and is then referred as PSNR (O/D). Hence, it shows the advance within the noisy image once denoising, if any. An even image to the initial can yield an undefined.

NOISY IMAGE	Variance	0.005	0.01	0.015	0.02	0.025
	MSE	318.0046	614.3486	621.0403	628.4504	639.3689
	PSNR(dB)	23.1115	20.2554	20.2122	20.165	20.0896
Proposed Algorithm with Soft Throslding	MSE	150.1946	294.0938	297.5801	301.0309	306.396
	PSNR(dB)	24.9235	22.0089	21.9616	21.9162	21.8388
	TIME	3.2827	2.0592	2.0597	2.1604	2.058
Proposed Algorithm with Hard Throslding	MSE	146.2732	288.2421	291.7945	295.319	300.5907
	PSNR(dB)	25.0385	22.0964	22.0471	21.9997	21.9221
	TIME	0.54704	0.51893	0.49953	0.53111	0.50578

Table.1 PSNR values and MSE for LENA image

PSNR because the MSE can become adequate zero due to no error. during this case the PSNR worth is thought of as approaching infinity because the MSE approaches zero; this shows that the next PSNR worth provides the next image quality.

MSE -MSE indicates average error of the pixels throughout the image. In our work, a definition of the next MSE doesn't indicate that the denoised image suffers a lot of errors instead it refers to a larger distinction between the initial and denoised image. this suggests that there's a big speckle reduction. The formula for the MSE calculation is given in equation.

$$MSE = \frac{1}{N}\sum_{j=0}^{N-1}(X_j - \overline{X}_j)^2 \qquad (8)$$

where I and K are the original and noisy/ denoised image, respectively. I MAX is the maximum possible pixel value of the image. When the pixels are represented using 8 bits per sample, this is equivalent to 255, and in this work as well it is 255.

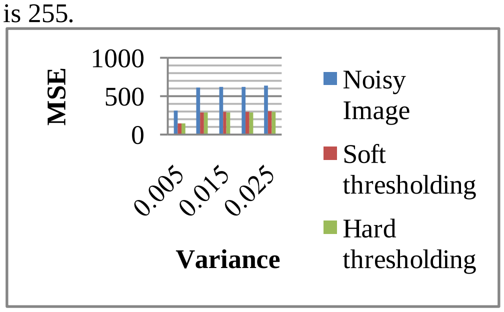

Figure 6: Graph Variance vs MSE for LENA Image

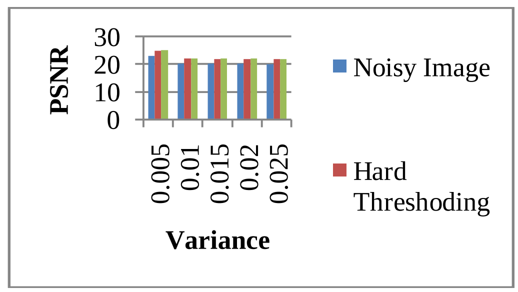

Figure 7: Graph Variance vs PSNR for LENA Image

VII. CONCLUSION

Since the proposed threshold estimation method is based on the analysis of statistical parameters like arithmetic mean, geometrical mean and standard deviation of the subband coefficients, it is more subband adaptive. Experiments are conducted on different natural images corrupted by Gaussian noise levels to access the performance of proposed thresholding method in comparison with BayesShrink using Hard and Soft Thresholding Method. Since the denoising of images which is effected through the proposed thresholding technique has possessed better PSNR, this method find its' application in denoising images those are corrupted during transmission, which is normally random in nature.

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