Problem of Colour Image Denoising and Technique using Wavelet Soft Thresholding

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Abstract- **Color image is made up of three primary colors red, green and blue called RGB color scale. Image Denoising is one of the most important parts of diverse image processing and computer image problems. The important property of a good image denoising model is that it should completely remove noise as far as possible as well as preserve edges. In this paper a new approach is proposed for color Image denoising using wavelet thresholding. For gray scale image lots of extensive works has been done by using bivariate Pearson distribution algorithm, so in this paper the gaussiasn noise is removed from the colour image using bivariate Pearson distribution.**

Keywords- Bivariate Pearson distribution, Bayesian denoising, wavelet transforms

I. INTRODUCTION

In recent year Color Image Denoising technique has been emerged as a challenging task for the scientists to remove noise from a multichannel data set. Previously a vital experiment has been done in order to remove noise from a gray scale image. Noises in natural colour photos have special characteristics that are substantially different from those that have been added artificially.

Various methodologies and algorithms have been proposed in the field of gray scale image but in the field of color image denoising there is a broad scope of research is yet to done. A color image denoising having multichannel set of data while in gray scale image single channel data is available that is why color image denoising is somewhat complex than the gray scale image since color image has three channels: red, green and blue. There are three channels which roughly follow the color receptor . Each channel of a color image is separated as the grayscale image of the same size as a color image, which is made up of one of the primary colors. Hence we can apply the gray image denoising scheme to resize each color channel separately and at last the three denoised channels are merged. Not only in case of gray scale image, removing noise with edge preservation is an important task but in Color image denoising the same must be followed.

The denoising of natural image corrupted by Gaussian noise is a classical problem in signal processing. If the wavelet transform and shrinkage technique are used for this problem, the solution requires a priori knowledge about how the wavelet coefficients distributed.

In this paper, we proposed the bivariate Pearson type distribution. After a brief review on the basic idea of Bayesian denoising we obtain a shrinkage function using bivariate Pearson distribution with local variance namely, the proposed model is applied for wavelet-based denoising of several images corrupted with additive Gaussian noise in various noise levels.

Color Image Denoising are digital images that include color information for each pixel. For proper visualization by the viewers, always there is a need to provide three color channels for each pixel. These color channels are interpreted as coordinates in some color space. The RGB color space is commonly used in computer displays. However, there still exist some other spaces such as YCbCr, HSV, which are often used in other context.

II. NOISE MODELS

Noise is a common problem which affects each imaging system. Noise reduces the brightness and contrast of image resulting blurring the edges and defects its size and shape. There are several reasons of occurring noise in an image.

Additive and multiplicative are the two basic models of noise. The noise which is systematically distributed is additive noise and the noise which is complex and distribution is based on image is known as multiplicative noise.

A. Additive Noise

Additive noise is continuous and symmetric in nature. Additive noise is independent in nature and evenly distributed throughout the image

- Gaussian Noise: Gaussian noise is a type of additive noise since it is symmetric in nature and continuous and has smooth probability distribution i.e. it is evenly distributed all over the image which gives each pixel in any image corrupting by Gaussian noise is the sum of random Gaussian distributed noise and true pixel value. And since it is an additive type of noise it is independent of image. As this is an additive type of noise it is also termed as additive white Gaussian noise (AWGN

- Poisson noise:Poisson noise is also a type of additive noise and it is generated from the data instead of adding artificial noise in the data. In this noise, the original image, is double precision, then input pixel values are interpreted as means of Poisson distributions scaled up by 1e12.If I is uint8 or uint16, then input pixel values are used directly without scaling. Poisson noise generates a noise sequence of integer numbers having a Poisson probability distribution.

B. *Multiplicative Noise*

Multiplicative noise is dependent on image. This type of noise is randomly distributed through the image. By multiplicative noise the brightness of image is varied.

- Salt & Pepper Noise: Salt-and-Pepper noise is a type of multiplicative noise since it is dependent on the image on which it is applied. It is caused by bit errors in image transmission and retrieval as well as in analog-to-digital converters. Salt and pepper noise is an intensity spikes, which is impulse type of noise. It occurs due to data transmission error. Salt and pepper noise generally contains two possible values a and b. Each having less than 0.1 probabilities. The term “salt and pepper” denote that the corrupted pixels which are set one by one having minimum or maximum value, because of it image looks like “salt and pepper”. Black and white pixels denote (0) and (1) respectively. Where D is the density of noise which has to be applied. Normal value of D is taken 0.9.

- Speckle Noise: Speckle noise is a multiplicative noise and occurs in coherent imaging system like laser, acoustics and SAR (Synthetic Aperture Radar) image. This type of noise is dependent on image. It is a multiplicative noise.

III. WAVELET TRANSFORM

In image denoising it is necessary to preserve the actual image discontinuities when noise separation is done but there is always a tradeoff between the two. So for removing noise without excessive smoothing of important details, a denoising algorithm needs to be spatially adaptive. Wavelet transform is a very useful mathematical tool for image processing. The wavelet representation, due to its edge detection and multi-resolution properties, naturally facilitates such spatially adaptive noise filtering. The scaling coefficients are usually kept unchanged, unless in certain cases of signal dependent noise.

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 contain LL2 and HL2, LH2, HH2 respectively.

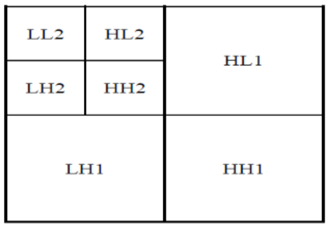

Figure 1. Image Decomposition by using DWT

IV. WAVELET DCOMPOSITION AND RECONSTRUCTION

The Decomposition process is accomplished by the following method is shown in Fig.2 and fig.3 are one-dimensional Low Pass Filter (LPF) and High Pass Filter (HPF) respectively for image decomposition. To obtain the next level of decomposition, sub band LL1 alone is further decomposed.

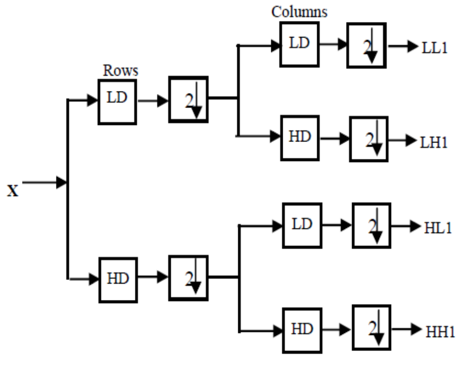

Figure 2 Wavelet filter bank of one level image-decomposition

This process continues until some final scale is reached. The decomposed image can be reconstructed using a reconstruction filter as shown in Fig. 3. Here, the filters LR and HR represent low pass and high pass reconstruction filters respectively. Here, since the image size is not changed after decomposition this DWT is called critically sampled transform without having any redundancy.[18]

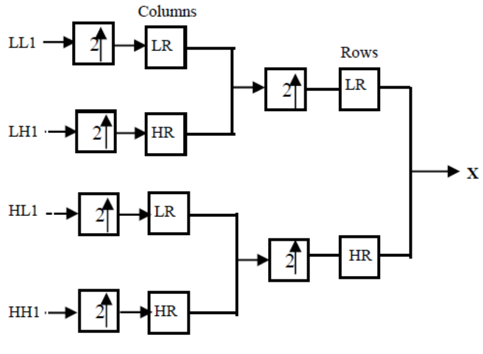

Figure 3 Wavelet filter bank of one level image-Reconstruction

V. SHRINKAGE TECHNIQUES

There are various shrinkage methods are present in the field of image denoising. Shrinkage methods are used to calculate the threshold level or the threshold value against which the wavelet coefficients are compared in thresholding techniques in wavelet transform method. In this paper we are using Bipearson shrink but we have to discuss sure shrinkage technique along with Bipearson shrink. Noise reduction in wavelet domain is usually results from wavelet shrinkage.

There are many shrinkage techniques available in image denoising.

A. Sure Shrink

In this paper we are not using Sure-shrink method but it is also a very good method for threshold value calculation. Sure Shrink suppresses noise by thresholding the empirical wavelet coefficients. It is an ultimate procedure in which threshold is estimated from decomposition coefficients at certain level to minimize the unbiased estimate of MSE. This method uses the wavelet transform coefficients at each resolution level j to choose a threshold value λj with which to threshold the wavelet coefficients. The idea is to employ Stein's unbiased risk criterion to get an unbiased estimate of the L2 –risk. It is well suited for Haar thresholding technique. The Sure Shrink threshold t* is defined as [5] [31]

$$t^{*} = \min\left(t\sigma\sqrt{2\log n}\right) \ldots\ldots\ldots\ldots\ldots\ldots..1$$

Here t denotes the value that minimizes Stein's Unbiased Risk Estimator, σ is the noise variance, and n is the size of the image. Sure Shrink follows the soft thresholding rule. The thresholding employed here is adaptive. A threshold level is assigned to each dyadic resolution level by the principle of minimizing the Stein's Unbiased Risk Estimator for threshold estimates. This method is much better than Visu Shrink. The sharp features of image are retained and the MSE is considerably lower. This because Sure Shrink is sub band adaptive. Sure shrink method of threshold calculation gives a tremendous result for hard thresholding technique.

B. Bipearson Shrink

A Bayesian approach is also one of the shrinkage methods, which imposes a prior distribution of noise-free data. In Bayesian prior estimation of noise free data is done by assuming statistically independent data and relies on marginal statistics. And other prior knowledge about inter and/or intra scale dependencies among the wavelet coefficients is getting by use of bivariate or joint statistics, by employing Hidden Markov Tree (HMT) models or Markov Random Field (MRF) models, or alternatively, and by using some local (context) measurements calculated from a surrounding of each coefficient. Here in this paper we are using Bivariate Pearson distribution for distribution of wavelet coefficients and Bayesian shrinkage estimator is used for threshold selection and combining both it is called Bipearson shrink. It is a very effectual method of threshold calculation. It is a new shrinkage function which depends on both coefficient and its parent. [1][21][24]

Soft-Thresholding

$$Y = \mathrm{Tsoft}(X, Y) = \{\mathrm{sign}\{X\}\ (|X|-\lambda)$$

$$\text{where } |X| \geq \lambda,\ 0,\ |X|<\lambda \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots(2)$$

The soft thresholding scheme shown in equation (2) 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 .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 evade discontinuities and so soft thresholding is more stable than hard thresholding. [30]

VI. PROPOSED ALGORITHM

- Take different type of image as a experiment purpose.
- Check whether the image is a colour or gray .
- Image should be resize in a standard form i.e 256 × 256 in size, then the valuable data is likely to get lost.
- Noise should be added in the test image.Different types of noise is found as we explained earlier. But in this paper Guassian noise is used.
- Make the noisy image to undergo wavelet transform through DWT.
- 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 are used for this purpose.
- After the decomposed image coefficients are thresholded using the thresholding technique, the denoised image is reconstructed using inverse wavelet transforms- IDWT.
- Experiments are conducted on different natural images corrupted by Gaussian noise levels to access the performance of proposed thresholding method in comparison with Sure Shrink using Soft Thresholding Method.

VII. RESULT

We have find that the wavelet transform approach gives tremendous result in the field of image denoising. Many researchers had given lot of thresholding techniques and shrinkage estimators like bayes shrink, Bayesian shrink, sure shrink, visu shrink, neigh shrink, laplacian shrink etc. and also gave comparisons between the techniques, but in the field of gray scale image. Most of the work which had done in color scale image is done by filter domain approach, but we think that the transform domain approach give great result in the field of color image denoising. Since we have studied a lot of papers on image denoising using filters but when we compare those approaches with transform domain we find that transform domain give tremendous result.

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