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Design Approach of Colour Image Denoising Using Adaptive Wavelet

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Abstract—*In modern age, visual information transmitted in the form of digital images is becoming a major method of communication, but the image obtained after transmission is often corrupted with noise. For obtaining the high quality image from original noisy image data manipulation is required. In this paper noise is remove by wavelet based approach & it is proved that wavelet based approach is best when the image is corrupted by Gaussian noise, salt and pepper noise, speckle noise and Brownian noise. Quantitative measures of comparison are provided by the signal to noise ratio of the image. In this paper colour image is denoise by using wavelet based approach & also improve the peak signal to noise ratio of the colour image.*

Keywords— *Image denoising, Problems Formation, Noise categories, Wavelet Thresholding, Proposed Method.*

I. INTRODUCTION

A very large portion of digital image processing is devoted to image restoration, image acquisition & enhancement. This includes research in algorithm development in image processing. Degradation comes from blurring as well as noise due to electronic, camera and photometric sources. Transmission medium introduces a noise due to errors during the measurement process, storage and noisy channel during quantization of the data for digital storage.

II. IMAGE DENOISING

In digital imaging, quality of image degrades due to contamination of various types of noise during the process of acquisition, transmission and storage. Noise introduced in an image is usually classified as substitutive (impulsive noise: e.g., salt & pepper noise, random-valued impulse noise, etc.), additive (e.g., additive white Gaussian noise) and multiplicative (e.g., speckle noise). Reducing the noise is very essential tool in medical area also. Among the currently available medical imaging modalities, ultrasound imaging is considered to be best one since it is noninvasive, practically harmless to the human body, portable, accurate, and cost effective. Unfortunately, the quality of medical ultrasound is generally limited because of Speckle noise, which is an inherent property of medical ultrasound imaging, and this noise generally tends to reduce the image resolution and contrast, which reduces the diagnostic value of this imaging modality. So reduction of speckle noise is an important preprocessing step, whenever ultrasound imaging model is used for medical imaging.

From many methods that have been proposed to perform this preprocessing task, as we know that speckle noise & gaussian noise is multiplicative & additive in nature we can take advantage of the logarithmic transformation in order to convert multiplicative speckle noise into additive noise. The common assumption to be taken here is additive noise samples are mutually uncorrelated and these samples obey a Gaussian distribution. Now the noise became AWGN. Many spatial-Domain filters such as Mean filter, Median filter, Alpha- trimmed mean filter, Wiener filter, Anisotropic diffusion filter, Total variation filter, Lee filter, Non-local means filter, Bilateral filter etc. are in literature for suppression of AWGN. Also many Wavelet-domain filters such as Visu Shrink, Sure Shrink, Bayes Shrink.

III. PROBLEM FORMATION

The basic idea behind this paper is the estimation of the uncorrupted image from the distorted or noisy image, and is also referred to as image “denoising”. There are various methods to help restore an image from noisy distortions. Selecting the appropriate method plays a major role in getting the desired image. The denoising methods tend to be problem specific. In order to quantify the performance of the various denoising algorithms, a high quality image is taken and some known noise is added to it. This would then be given as input to the denoising algorithm, which produces an image close to the original high quality image. The performance of each algorithm is compared by computing Signal to Noise Ratio (SNR) besides the visual interpretation.

IV. WAVELET THRESHOLDING

Wavelet Thresholding is a simple non-linear method, which operates on one wavelet coefficient at a time. In its basic form, each coefficient & threshold is compared each other , if the threshold is higher than coefficient, set to zero, otherwise it is kept as it is & other coefficient is modified & replace the small noisy coefficients by zero. Inverse wavelet transform may lead to reconstruction with the essential signal characteristics and with less noise. There are three steps of Wavelet thresholding i) linear discrete wavelet transform ii) nonlinear thresholding Step iii) a linear inverse wavelet transform.

Let us consider a signal $\{ x_{ij}, i, j = 1,2\ldots M\}$ denote the M X M matrix of the original image to be recovered and M 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 z_{ij} *with* standard deviation σ i.e. $z_{ij} \sim N(0, \sigma 2)$ as follows.

$$y_{ij} = x_{ij} + z_{ij}$$

From this noisy signal *y*, we want to find an approximation $x_{ij.}$ The goal is to estimate the signal x_{ij} from noisy observations y_{ij} such that Mean Squared error (MSE) is minimum. I.e.

$$\| X - X\|^2 = \overline{1/N} \sum_{i=0}^{N-1} (X_i - X_i)^2$$

Let W and W^{-1} denote the two-dimensional orthogonal discrete wavelet transform (DWT) matrix and its inverse respectively. Then equation (1) can be written as

$$d_{ij} = c_{ij} + \varepsilon_{ij}$$

With $d=W y$, $c = W x$, $\varepsilon = W z$ .Since W is orthogonal transform, εj is also an i.i.d Gaussian random variable with ij $\varepsilon \approx (0, \sigma 2)$.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 *x*. There are two thresholds frequently used, i.e. hard threshold, soft threshold. The hard-thresholding function keeps the input if it is larger than the threshold; otherwise, it is set to zero. It is described as

$$f_h(x) = x \quad \text{if } x \geq \lambda$$
$$= 0 \quad \text{otherwise}$$

The hard-thresholding function chooses all wavelet coefficients that are greater than the given threshold λ and sets the others to zero. The threshold λ is chosen according to the signal energy and the noise variance (σ^2).

The soft-thresholding function has a somewhat different rule from the hard-thresholding function. It shrinks the wavelet coefficients by λ towards zero,

$$f(x) = x - \lambda \quad \text{if } x \geq \lambda$$
$$= 0 \quad \text{if } x < \lambda$$
$$= x + \lambda \quad \text{if } x \leq -\lambda$$

The soft-thresholding rule is chosen over hard-thresholding, for the soft-thresholding method yields more visually pleasant images over hard thresholding.

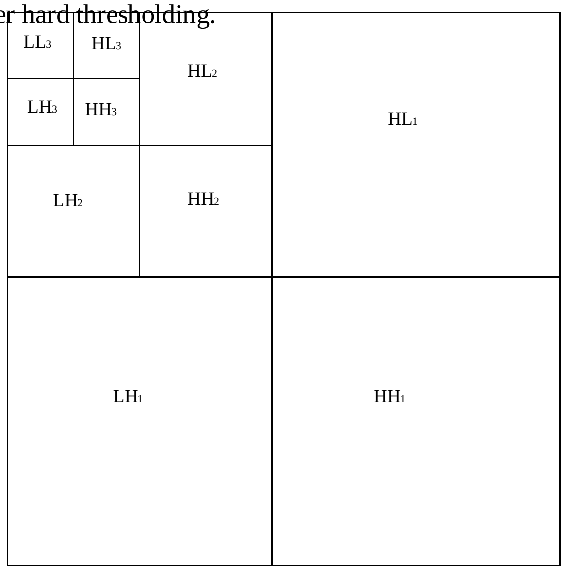

Fig1. Image Decomposion

V. NOISE CATEGORIES

In image denoising process, information about what type of noise present in the original image plays a significant role. Some of the typical noise is a speckle noise, which is multiplicative in nature & also Gaussian noise, which is additive in nature. Some are corrupted with salt & pepper noise or uniform distribution noise.

There are the five types of noise categories in image processing

1. Gaussian noise
2. Salt & pepper noise
3. Poison noise
4. Speckle noise
5. Brownian noise

VI. PROCESS OF DENOISING

In case of image denoising methods, the known characteristics of the degrading system and the noises are assumed. The image s(x,y) is blurred by a linear operation and noise n(x,y) is added to form the degraded image w(x,y). This is convolved with the restoration procedure g(x,y) to produce the restored image z(x,y).

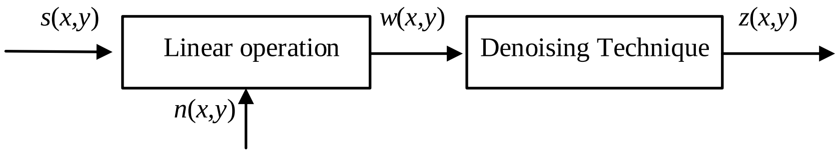

Fig 2. Denoising Concept

Noise is present in an image either in a multiplicative form or additive form.
A multiplicative noise follows the rule

$$w(x, y) = s(x, y) * n(x, y)$$

while additive noise satisfy this rule

$$w(x, y) = s(x, y) + n(x, y)$$

Where $s(x,y)$ is the original signal, $n(x,y)$ denotes the noise introduced into the signal to produce the corrupted image $w(x,y)$, and (x,y) represents the pixel location

VII. PROPOSED ALGORITHM

Bayes Shrink was proposed by Chang, Yu and Vetterli . The goal of this method is to minimize the Bayesian risk, and hence its name, Bayes Shrink. It uses soft thresholding and it is also subband-dependent,like Sure Shrink, which means that threshold level is selected at each band of resolution in the wavelet decomposition.. The Bayes threshold, , is defined as

$$t_b = \frac{\sigma^2}{\sigma_x} \text{ --------------------------- (1)}$$

where is the noise variance and is the signal variance without noise. The noise variance is estimated from the subband HH1 in the decomposition of wavelet by the median estimator.. From the definition of additive noise we have

$$w(x, y) = s(x, y) + n(x, y) \text{-----------------------(2)}$$

Since the signal and noise are independent of each other it can be stated that

$$\sigma_w^2 = \sigma_s^2 + \sigma^2 \text{ --------------------------- (3)}$$

σ_w^2 can be calculated as shown below

$$\sigma_w^2 = \frac{1}{\eta^2} \sum_{x,y=1}^{\eta} w^2(x, y) \text{ ---------------------------- (4)}$$

The variance of the signal σ^2 is computed as shown below

$$\sigma_s = \sqrt{\max(\sigma_w^2 - \sigma^2, 0)} \text{ ------------------------ (5)}$$

With these σ^2 and σ_w^2 the Bayes threshold is computed from the below equation

$$t_b = \frac{\sigma^2}{\sigma_x} \text{ -------------------------------------- (6)}$$

the wavelet coefficients are thresholded at each band

PEAK SIGNAL TO NOISE RATIO

Mean Square Error (MSE) and Root Mean Squared Error (RMSE) are defined as

$$\text{MSE} = \sum_{x=1}^{x} \sum_{y=1}^{y} (Z(x,y) - X(x,y))^2 \text{ ---------------------------------------} \mathbf{(7)}$$

$$\text{RMSE} = \sqrt{MSE} \text{ ---(8)}$$

Peak signal to noise ratio (PSNR) is defined in logarithmic scale, in dB. It is a ratio of peak signal power to noise power. Since the MSE represents the noise power and the peak signal power, the PSNR is defined as:

$$PSNR = 10 * \log_{10} \frac{1}{MSE} \text{ ---------------------------- (9)}$$

This image metric is used for evaluating the quality of a filtered image and thereby the capability and efficiency of a filtering process.

RESULTS

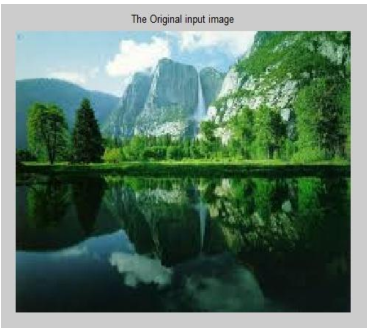

Fig 6a Original Image

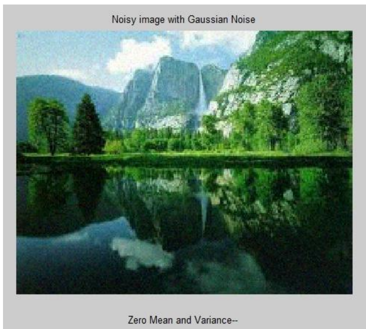

Fig 6b Noisy Image

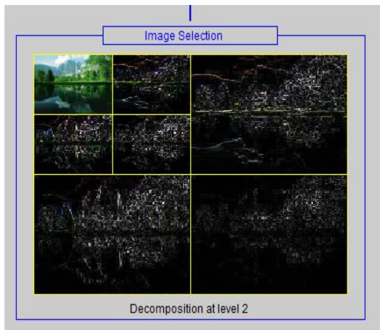

Fig 6c Decomposition of Image

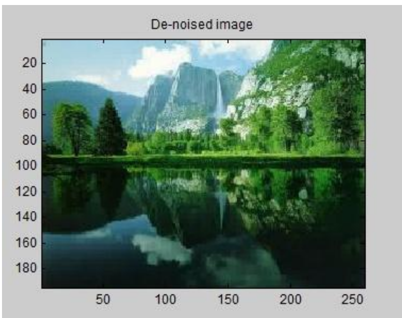

Fig 6d Denoising Image

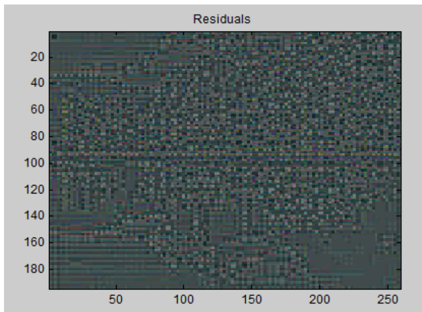

Fig 6e Residual

VIII. CONCLUSIONS

The main issues regarding image denoising were addressed in this paper. an adaptive threshold for wavelet thresholding images was proposed, based on the generalized Guassian distribution modelling of subband coefficients, and test results showed excellent performance . The results show that Proposed Shrink removes noise significantly. In this paper, we compare the results with soft thresholding, hard thresholding & proposed method

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