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Novel Approach for Removal of Gaussian and Salt-n-Pepper Noise Simultaneously

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Abstract: Noisy image consist of unwanted data which may reduce the shape and size of objects in the image and blurring of edges or dilution of fine details in the image so eliminating such noise is an important pre-processing task. This process of removing noise is called Denoising. This paper presents a novel approach for simultaneously removing the Gaussian and Salt-n-pepper noise from a single image by using the proposed technique. In this paper, a new proposed technique using fast multidirectional filter bank and median filter is used which improves the radial frequency resolution of the image by addition decomposition in the high frequency band. Denoising performance of proposed technique will be compared with median and wiener filter. We analyze the performance of the proposed denoising technique using PSNR (Peak Signal to Noise Ratio) and Coc (Correlation coefficient).

Keywords: Denoising, FMDFB, Median Filter Threshold, Discrete Wavelet Transform.

I. INTRODUCTION

Denoising is one of the important pre-processing tasks for various image processing. Image noise is the random variation of brightness and color information in images produced by the s scanner and digital camera. Various noise types such as Gaussian and Salt & Pepper etc. are addressed in literature. A number of denoising algorithms have been proposed for removing various types of noises. The good property of image denoising is that to remove the noise completely and preserve the edges. Traditionally, there are two types of models i.e. linear model and non-liner model. Generally, linear models are used because noise removing speed is more but not able to preserve edges in efficient manner i.e. the edges, which are recognized as discontinuities in the image. On the other hand, Non-linear models can handle edges in a much better way than linear models. An image containing salt-and-pepper noise will have dark pixels in bright regions and bright pixels in dark regions. This type of noise can be caused by dead pixels, analog-to-digital converter errors, and bit errors in transmission. This error can be removed in large part by using dark frame Subtraction and by interpolating around dark/bright pixels. Salt-and-pepper noise can be best removed by median filter. Gaussian noise is an independent at each pixel and independent of the signal intensity. In color cameras where more amplification is used in the blue color channel than in the green or red channel, there can be more noise in the blue channel. Amplifier noise is a major part of the "read noise" of an image sensor, that is, of the constant noise level in dark areas of the image. Gaussian noise can be best removed by fast mutliscale directional filter bank and in this dissertation, we remove these both mentioned noise simultaneously with by proposed technique using the fast mutliscale directional filter bank and median filter.

This paper is organized as follows. Section 2 briefs about the filters for denoising. In Section 3 a detailed description of the BayesShrink and proposed technique. Section 4 is about the experimental results and Section 5 is about the conclusion and future work.

II. FILTERS USED FOR DENOISING

2.1 Median Filter

This filter finds the values of the surrounding pixels in an image to an orderly set and replaces the value of the center pixel with the middle value in the set.

$$\hat{f}(x,y) = \underset{(s,t)\in S_{xy}}{median}\{g(s,t)\}$$

Median filtering is a non-linear technique that works best with impulse noise (salt & pepper noise) whilst retaining sharp edges in the image. The main disadvantage of median filter is that it takes extra computation time to find the intensity value of each set.

2.2 Wiener Filter

This filter is to remove the noise that has corrupted a signal. It is based on a statistical approach. Various filters are designed for a desired frequency response but Wiener filter approaches filtering from a different angle. For this we have.

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to knowledge of the spectral properties of the original signal and the noise

J = wiener2 (I, [m n], noise) filters the image I using pixel wise adaptive Wiener filtering, using neighborhoods of size m-by-n to estimate the local image mean and standard deviation. The additive noise (Gaussian white noise) power is assumed to be noise.

2.3 Removal of Gaussian noise using Fast Multiscale Directional Filter Bank (FMDFB)

Fast multiscale filter banks is used to obtain the transformed coefficients. In this filter, multiscale decomposition is performed prior to the directional decomposition. In the first level of Laplacian Pyramid each sub bandis split into two radial frequency ranges by low pass filtering and subtraction. By using Wavelet filtering the decomposition of directional sub band can also be implemented. Further, Directional Filter Bank of desired level 'l' is applied to each band pass image which results in '2l' sub bands. This process can be iterated up to the desired level of decomposition. In the original MDFB, all the multi scale decomposition is performed prior to the directional decomposition. In the fast MDFB structure, the scale and decomposition processes are swapped in the first two scales. This fast structure results in less computation and retained the performance of the original Contourlet transform. First, the DFB with smaller decomposition is applied on the band pass image in the LP. Each sub band is then split into two different radial frequency bands using either a vertical or horizontal low pass filter depending upon the spectral region in which the directional sub band is located. [1]

III. PROPOSED TECHNIQUE USED BAYESSHRINK METHOD TO CALCULATE THE THRESHOLD VALUE

The goal of BayesShrink method is to minimize the Bayesian risk. It uses soft thresholding and is sub band-dependent, which means that thresholding is done at each band of resolution in the wavelet decomposition. This process is smooth as well as adaptive. The Bayes threshold is defined as

$$\sigma_x = \sqrt{\max\left(\frac{\sum X(i,j)^2}{length(X)} - \sigma^2, 0\right)}$$

$$Th2 = \begin{cases} \sigma_x = 0 & \max(abs(X)) \\ else & \sigma^2/\sigma_x \end{cases}$$

Where $\sigma^2$is the noise variance and σ_x is the standard deviation. The noise variance $\sigma^2$is estimated from the sub band HH1 by the median estimator.

3.1 Discrete Wavelet Transform

Discrete Wavelet Transform is identical to a hierarchical sub band system where the sub bands are logarithmically spaced in frequency and represent octave-band decomposition.

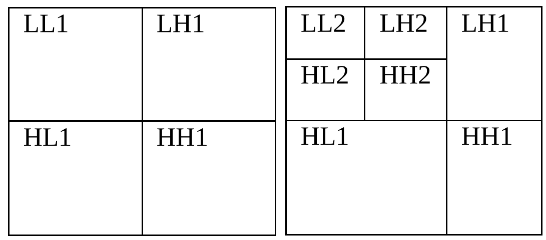

Fig 3.1 Two Level Image Decomposition

These four sub bands arise from separable applications of vertical and horizontal analysis filters for wavelet decomposition.

To obtain the next coarse level of wavelet coefficients, the sub band LL1 alone is further decomposed and critically sampled using similar filter bank shown in fig 3.1

Similarly, to obtain further decomposition, LL2 will be used. This process continues until some final scale is reached. The decomposed image can be reconstructed using a reconstruction (i.e., Inverse DWT).

3.2Thresholding

According to wavelet technique, the most effective ways to remove noises without smearing out the sharp edges of an image is to threshold only high frequency components while preserving most of the sharp features in the image. The approach is to shrink the high frequency coefficients whose amplitudes are smaller than a certain statistical threshold value to zero while retaining the smoother detailed coefficients to reconstruct the ideal image without much loss in its detail. This process is sometimes called wavelet shrinkage since the detailed coefficients are shrunk towards zero. The schemes to shrink the wavelet coefficients, namely the "keep-or-kill" hard thresholding, and "shrink-or-kill" soft thresholding.

3.2.1 Hard Thresholding

In the hard thresholding, the input is kept if it is greater than the threshold λ, otherwise it is zero. The hard thresholding procedure removes the noise by thresholding only the wavelet coefficients of the detailed sub-band, while keeping the low-resolution coefficients unaltered.[8]

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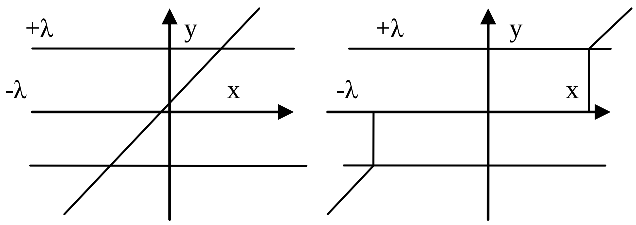

Fig: 3.2.1 Hard Thresholding

3.2.2 Soft Thresholding

In soft 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 the output is
|y| = |x – λ|.
Softthresholding is more popular than hard thresholding because it reduces the abrupt changes that occurs in hard thresholding and provides more visually pleasant recovered images [8]

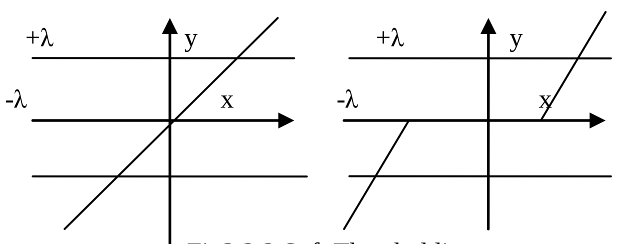

Fig3.2.2 Soft Thresholding

3.3 Proposed Algorithm

Step 1: Load a gray scale image orgimage(x, y).
Step 2: Input the variance of noise which we want to add in image
Step3: Add Gaussian noise to orgimage(x, y) and get g(x, y).
Step 4: Add salt-&-pepper noise to g(x, y) and get z(x,y).
Step 5: Input the type of threshold that whether it is soft threshold or hard threshold
Step 6: The Gaussian and salt-&-peppered noisy image is transformed into logarithmic form
Log Z(x, y) = log z(x, y) + log η(x, y)
Step7: Multilevel 2-D wavelet decomposition is performed on the logarithmic transformed image
Step 8: Now, Calculate σ noise variance of the corrupted image using sigmahat using MAD.
Step 9: For each level of decomposed structure calculate parameter J such that:

$$J = \sqrt{\log(S_i)}$$

Step a.: For each sub-band (except the low pass residual) compute the standard deviation $\boldsymbol{\sigma_x}$

Step 10: Input the threstype that whether it is soft threshold or hard threshold.
Step11: Threshold is calculated by the noisy coefficients using bayes shrinkage method.

$$\sigma_x = \sqrt{\max\left(\frac{\sum X(i,j)^2}{length(X)} - \sigma n^2, 0\right)}$$

$$Th2 = \begin{cases} \sigma_x = 0 & \max(abs(X)) \\ else & \sigma n^2/\sigma_x \end{cases}$$

Step12: After applying threshold to the decomposed image, denoised image is reconstructed as $I_R(x, y)$ using inverse wavelet transforms-IDWT.
IMG=waverec2 (img, S, filtype).

Step 13: Take exponent of the image obtained in above step and obtained the denoised image.
denoisedimg=exp(double(IMG));

Step 14: Now we get the denoised image.

IV. EXPERIMENTAL RESULTS

We used image in png format adding two noises such as Gaussian and salt-n-pepper noise in original image. De-noised all noisy images by median filter, wiener filter and proposed method.
To analyze the performance of the proposed denoising model, a set of standard gray scale images had been taken. The performance metrics Peak Signal to Noise Ratio (PSNR) is used. PSNR is a quality matrix between the originaland a denoised image. The higher the value of PSNR, the quality of the compressed or reconstructed image is the better.The experimental performance comparison is made in terms of PSNR.Table1 presents the performance of Proposed Method with soft threshold in terms of PSNR. Table2 presents the performance of Proposed Method with hard threshold in terms of PSNR and Coc.

Table 1 PSNR output for variance =0.02 for Soft Threshold

Algorithm	1.png	2.png	3.png
Wiener Filter	23.1332	21.1047	22.222
Median Filter	26.5781	27.1765	26.258
Proposed Technique	27.2136	28.9714	27.416

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Table 2 PSNR output for variance =0.02 for Hard Threshold			
Algorithm	**1.png**	**2.png**	**3.png**
Wiener Filter	23.1332	21.1047	22.2222
Median Filter	26.5781	27.1765	26.2581
Proposed Technique	27.3213	29.213	27.4958

Table 3 Coc output for variance =0.02 for Soft Threshold			
Algorithm	**1.png**	**2.png**	**3.png**
Wiener Filter	.9550	.9238	.9328
Median Filter	.9809	.9815	.9731
Proposed Technique	.9547	.9646	.9419

Table 4 Coc output for variance =0.02 for Hard Threshold			
Algorithm	**1.png**	**2.png**	**3.png**
Wiener Filter	.9550	.9238	.9328
Median Filter	.9809	.9815	.9731
Proposed Technique	.9514	.9655	.9464

V. CONCLUSION

Noises corrupt the image and often lead to incorrect coefficients of an image. Denoising is the concept of removing the noises by using the various types of filters and techniques. For this purpose, we proposed a new technique in which we used MDFB, median filter and discrete wavelet transform .By using this technique, we are able to remove two noises Salt-n-Pepper and Gaussian noise simultaneously from a single image and compare this proposed technique with median and wiener filter and perform the better result with PSNR value and Coc.

In future, we can combine more filters in this proposed technique to remove more noises simultaneously in an efficient way to get the better results and better visual quality.

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