

Image Restoration using Spatial Domain Multi Pass Decomposition Algorithm for various noise attacks

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ABSTRACT

In this paper, we describe a sliding multipass technique for image restoration using a Wiener Filter and Wavelet Transform. The images with blurring and containing noise are first decomposed at different levels using an optimum wavelet family and subsequently the Wiener filter is applied to remove the noise and blurring effects from the distorted images. Wiener filter being a linear and spatially invariant filter does not produce non linear distortions. The limitation of Image Filters in terms of filtering passband is mitigated by multi pass decomposition using wavelet analysis. Finally the performance of the restoration algorithm is analyzed using standard parameters viz. Peak Signal to Noise Ratio(PSNR) and Mean Square Error(MSE). A substantial improvement in PSNR value is achieved and the same is depicted in results. The author believes that this novel approach would cater to the need of restoration of images affected by blurring and multi band noise.

Keywords: Image restoration, Wiener filter, Patch-based processing.

1. INTRODUCTION

During image acquisition, images are subject to a variety of degradations involved. These invariably include blurring from diffraction and noise from a variety of sources. Restoring such degraded images(digital images) is a fundamental problem in image processing that has been researched since the earliest days of digital images [6,2]. A wide variety of linear and nonlinear methods have been proposed. Many methods have focused exclusively on noise reduction, and others seek to address

multiple degradations jointly, such as blur and noise. A widely used method for image restoration, relevant to the current paper, is the classic Wiener filter [3]. The standard Wiener filter is a linear space-invariant between the desired signal and estimate, assuming stationary random signals and noise. It is important to note that there are many disparate variations of Wiener filters.

These include finite impulse response, infinite impulse response, transform-domain, and spatially adaptive methods [1,3]. Within each of these categories, a wide variety of statistical Models may be employed. Some statistical models are very simple, such as the popular constant noise-to signal power spectral density model, and others are far more complex. In the case of the empirical Wiener filter [1], no explicit statistical model is used at all. Rather, a pilot or prototype estimate is used in lieu of a parametric statistical model. While all of these methods may go by the name of 'Wiener filter', they can be quite different in their Character.

2. MATERIALS AND METHOD

2.1 Input Images :

In this proposed paper we are using all types of digital image for particular paper we have use MIT database image



Fig (a) fig (b)

Fig (a) & (b) is input test images

2.2 Image Decomposition Using Wavelets:
Below fig shows the decomposition of images using wavelets.

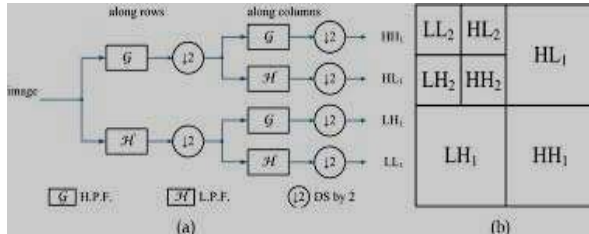


Fig (2) Decomposition of image using db 2 at leve-3

2.3 Image Restoration Using filter: Image Restoration is the process of reconstructing or recovering an image that has been degraded by some degradation phenomenon. Restoration techniques are primarily modelling of the degradation and applying the inverse process in order to recover the original image.

2.3.1 various noise attack

2.4 Performance calculation using PSNR :
The Mean Square Error (MSE) and the Peak Signal to Noise Ratio (PSNR) are the two error metrics used to compare image compression quality. The MSE represents the cumulative squared error between the compressed and the original image, whereas PSNR represents a measure of the peak error.

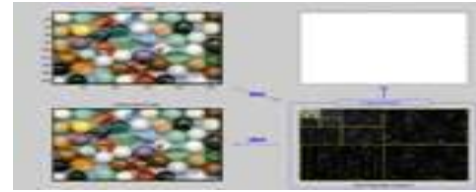
3. EXPERIMENTAL RESULTS

In this study we performed all the diagnosis process in MATLAB software.

3.1 Image Decomposition using DWT

Image decomposition process mat follow following step:

- 1.load image
- 2.select wavelet .
- 3.select level of decomposition .
- 4.show decomposed image.



Decomposed image

3.2 Restoration Using Filter :

Please use a 9-point Times New Roman font, or other as close as possible in appearance to Times New Roman in which these guidelines have been set. The goal is to have a 9-point text, as you see here. Please use sans-serif or non-proportional fonts only for special purposes, such as distinguishing source code text. Right margins should be justified, not ragged.



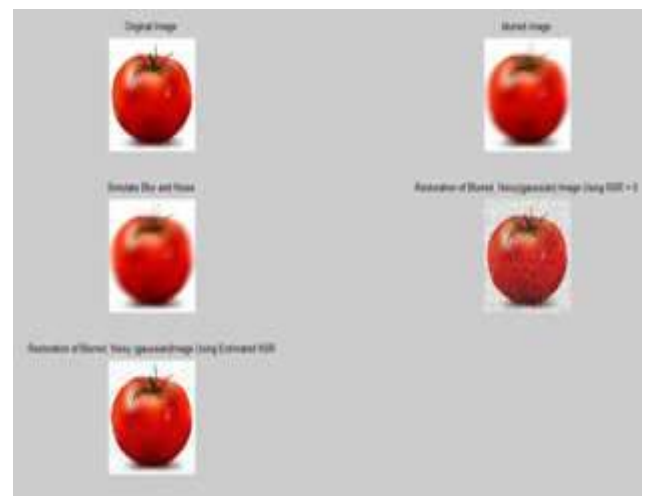
Fig 3. Proposed model for filter

3.3 PSNR Calculation

Large value of PSNR represent highly accurately recovery of image is performed with the help of non linear filter (using Spatial Domain Multi Pass Decomposition Algorithm)

4. Results

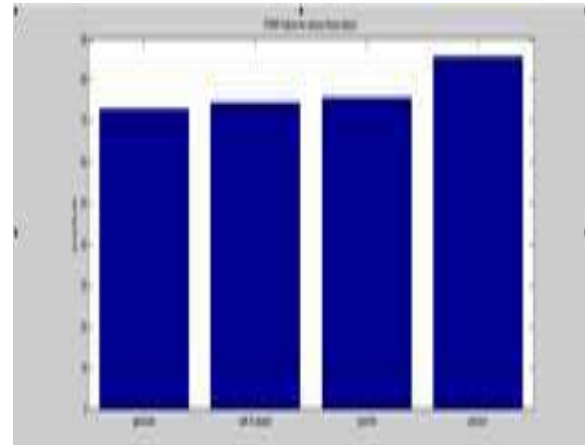
4.1 Restored image after Gaussian noise attack



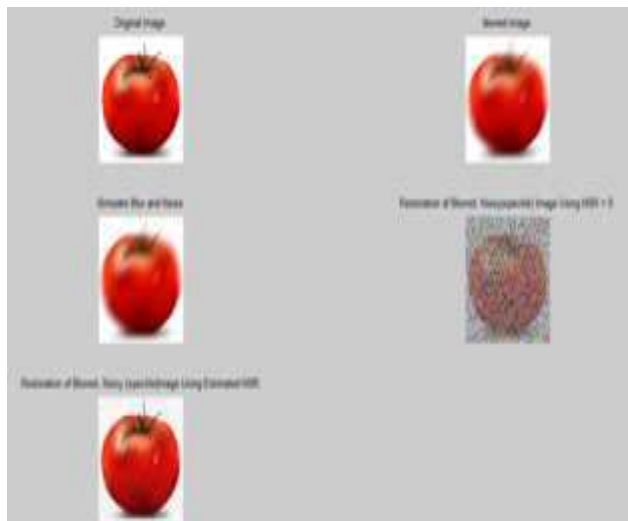
4.2 Restored image after black and pepper noise attack



4.5 Bar graph of PSNR Value for various noise attack.



4.3 Restored image after speckle noise attack

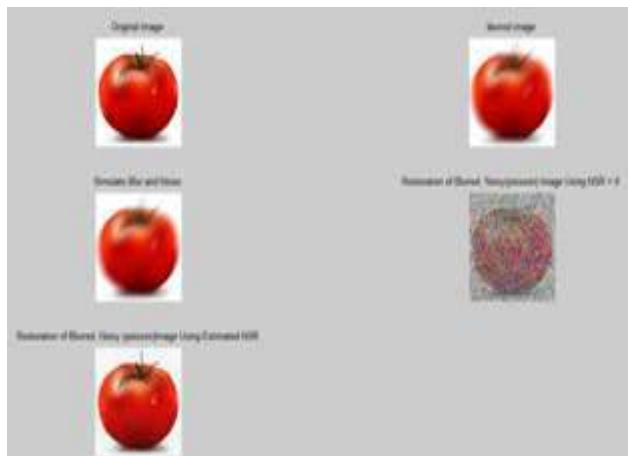


5. Comparison Table:

Table.1 : comparison table for all applied noise with various values of theta in proposed filter

Noise	PSNR WITH (Theta=11)	PSNR WITH (Theta=21)	PSNR WITH (Theta=41)
Gaussians	72.98813	71.63927	70.67281
Black & pepper	74.49745	70.27924	68.76979
Speckle	75.69486	74.95381	74.33591
Poisson	85.73983	85.23368	84.94004

4.4 Restored image after Poisson noise attack



6. Conclusion

The main contribution of this filter is to the problem is obtaining denoised and deblurred values using linear filter response which does not introduce non linear distortions which non linear filters may inflict. Removal of distortions from a ultrawideband frequency range is achieved by decomposing the images in different levels using optimum level and family of selected wavelet.

Large value of PSNR represent highly accurately recovery of image is performed with the

help of non linear filter (using Spatial Domain Multi Pass Decomposition Algorithm)

According to comparison table we absorbed that Poisson noise well give largest PSNR value for loaded input image.

7. References

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