STATISTICAL ANALYSIS OF FREQUENCY DOMAIN FILTERS FOR IMAGE DENOISING

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Abstract – With the advent of the digital world, the use of digital images has become widespread. During the process of image acquisition, image contamination by noise becomes an inevitable part of the image, leading to a significant reduction in quality. Traditionally, filters remove noise from images. Technological advances in the arena of image processing have led to growth of more efficient techniques of image denoising. These techniques make use of wavelets and Curvelet transforms, which can be blended with known parts of noisy image to estimate the unknown parts of the image better. In this paper, we apply various image denoising techniques to a random image that is corrupted by either Gaussian noise, speckle noise or salt and pepper noise. The evaluation results in terms of Mean Squared Error, Peak Signal to Noise Ratio, Structural Similarity Index and Computation time will help to decide the best technique that is used for denoising an image distorted by noise.

***Keywords**: Image denoising techniques, Curvelet, discrete wavelet transform, filters*
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1. Introduction

Technology occupies an essential role in the 21st century. The data revolution has vastly increased the scope of digital devices in our lives. The use of digital images has massively increased due to its cost-effectiveness and easy portability. However, digital images have some disadvantages. It can get corrupted by noise, which is an unwanted signal during any stage, be it image acquisition, segmentation or representation. Research in the field of digital image processing has determined three significant forms of noise that can taint an image. The three major types of noise are Gaussian noise, speckle noise and salt and pepper noise.

The percentage of corrupted pixels quantifies noise. Corrupted pixels are moreover set to the maximum or have single bits. There are several algorithms to remove salt and pepper noise [1,2,3]. The adaptive filter [4] gave noticeable results in the statistical analysis of various denoising techniques in MR images. Image retrieval [5,6] turned out to be an appealing field of interest. The convolution techniques instigated in [7] use kernels for filtering. Liu [8] explored the denoising algorithm employing a Wiener filter. Burger [9] proclaimed the impact of total variation algorithm in the reconstruction of images. Salloum [10] endorsed adaptive wavelet for data compression.

This paper commends various techniques for effective noise removal from any image. The methods incorporate Mean filter [7], Median and Wiener filter [8], Bilateral filter, Fourier transform, Haar wavelet, Daubechies wavelet and Curvelet transform. The quality parameters of the denoised images obtained by various techniques are analyzed and arrive at the best denoising technique.

2. Proposed Method

In this paper, we propose to compare various image denoising techniques that remove noise from an image. The images that have been denoised using each method can be compared based on some parameters and find the best image denoising technique with the best performance parameters. The following diagram indicates the work that we propose to do.

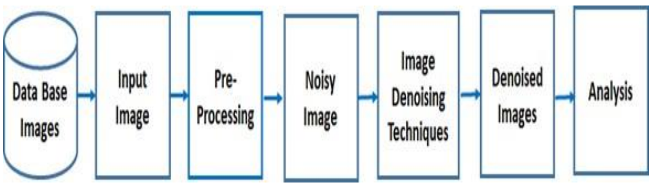

Fig. 1. Illustration diagram of the proposed system

Wang database has been used as it has a collection of 1000 random images from 10 different categories of images. Any image can be randomly selected from the database as an input for processing. The type of noise which must be tested can also be randomly chosen from Gaussian, speckle or salt and pepper noise. The input image is intentionally corrupted with the chosen noise to obtain a noisy image and test all the image denoising techniques for their performance and capability.

Image denoising makes use of spatial domain filtering or transform domain filtering. Filtering in spatial domain involves use of linear filters or non-linear filters that include mean filter, median filter, Wiener filter along with Bilateral filter. Filtering in transform domain have Fourier transform, Haar transform, Daubechies wavelet transform, and Curvelet transform.

The original input image is denoised using each of the image denoising techniques, and the quality of images can be compared using the parameters of the denoised image as peak signal-to-noise ratio, mean squared error and structural similarity index. The time taken to compute each denoised image is also available for comparison.

2.1 Types of Noise

Noise is unwanted data in an image. There are various ways for the introduction of noise. Some of them include the acquisition of the digital image, the film grain when scanning an image from a photograph.

Gaussian noise

It arises during the process of acquisition of digital images. It has a probability density function identical to normal Gaussian distribution, i.e., the values that can be taken by the noise are Gaussian-distributed.

Salt and pepper noise

It is also termed impulse noise or spike noise. An image will have dark pixels in vivid regions and vivid pixels in dark areas if it is corrupted with salt and pepper noise.

Speckle noise

It is inherently present in the image. Random values augmented by pixel values can model this noise. Consequently, it is labeled multiplicative noise. Speckle noise is significant obstacle in radar applications.

Fig. 2. Illustration of original image and image with types of noise

2.2 Filters

Image denoising is essential to ensure a minimum acceptable quality of an image. Denoising of images is distinct from enhancement. Image enhancement is an unbiased process, while image denoising is a skewed process. Many denoising algorithms are applied to generate the best estimate of an image using a noisy image.

2.2.1 Mean filter

It is a sliding-window filter in spatial frequency domain which replaces center value with mean of all pixel values in window function.

2.2.2 Median filter

It is a sliding-window filter in spatial frequency domain which replaces median value with mean of all pixel values in window function.

2.2.3 Wiener filter

It figures a statistical assessment of an anonymous signal using an associated signal as input besides filtering that known signal to generate the approximate as an output.

2.2.4 Bilateral filter

It smooths images while maintaining edges, using non-linear blend of adjacent pixel values. It performs both range and domain filtering and replaces a bright pixel with an average of nearby bright pixels(while ignoring dark pixels). It returns a dark pixel with an average of nearby dark pixels(while ignoring bright pixels).

2.2.5 Fourier transform filters

Fourier transform filters generally specify the frequency and not time, and hence they are not preferred. It can give the frequency components existing in a signal but cannot capture the time at which the frequency components occur.

2.2.5 Wavelet transform filters

A tiny wave-like fluctuation with an amplitude that commences at zero, boosts and declines back to zero is termed wavelet. It has its energy focused on time along with frequency. Wavelets have identifiable properties that make them incredibly beneficial for image processing. Wavelets can be merged with well-known sections of a noisy signal to extricate the information from unidentified servings through convolution.

All wavelet transforms generally involve the following three steps

•Forward Wavelet Transform is employed to obtain wavelet coefficients.

•Obtain clean coefficients from noisy ones through estimation using hard thresholding or soft thresholding.

•Inverse Wavelet Transform is used to attain denoised image from the clean coefficients.

2.2.5 Curvelet transform filters

Curvelets are pertinent basis for characterizing images which are smooth except for singularities beside smooth curves, where objects in the image have a least length scale and curves have bounded curvature. This holds for caricatures, geometrical drawings, and wording. The edges seem gradually straight as one whizzes in on such images. Curvelets take benefit by describing the better resolution curvelets to be more stretched than the lower resolution curvelets. Curvelets are preferred to wavelets because

•It is an optimally sparse portrayal of objects along with edges.
•It provides for optimal image reconstruction.

3. Evaluation Results

The noisy images are being denoised using a variety of image denoising techniques. Therefore, some parameters are required to judge the quality and acceptability of the denoised image. The parameters for evaluation are

- Mean Squared Error (MSE)
- Peak Signal-to-Noise Ratio (PSNR)
- Structural Similarity Index (SSI)
- Computation Time (CT)

Mean Squared Error

It represents the middling of squares of errors amid original image and noisy/denoised image. The error is quantity with which the values of original image vary from noisy/denoised image.

Given original m x n image I combined with its approximation K, mean squared error can be estimated using:

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - K(i,j)]^2 \quad (1)$$

Peak Signal-to-Noise Ratio

It is ratio stuck between extreme possible value (power) of signal and power of misleading noise that alters quality of its interpretation. It is articulated in decibels and calculated using the formula:

$$PSN(in\ dB) = 10\log_{10}\left(\frac{MAX^2}{MSE}\right) \quad (2)$$

where MAX stands for extreme possible pixel value of image. For 8-bit images, MAX = 2^8-1 = 255, and MSE is mean-squared error.

Structural Similarity Index

It measures the resemblance between two images. By taking the original image as a reference, the SSIM indicates the degree of similarity stuck between noisy/denoised image and the original image. The value of SSIM is always between 0 and +1. The value 1 is possible only with identical sets of data, (i.e. same images). A value of 0 signifies no structural resemblance. More the value of SSIM, clearer is the quality of the denoised image.

Computation Time

The computation time of each technique is calculated in MATLAB using the timer that is present in MATLAB. The command 'tic' begins the timer while command 'toc' closes the timer, and display the lapsed time (in seconds).

Table 1. Comparison of an optimal solution for Gaussian Noisy Image

	MSE	PSNR	SSI	CT
Noisy Image	624.92	20.173	0.36929	0
Linear Filter	6904.4	9.7396	0.10736	0.22866
Median Filter	1216.6	17.279	0.45462	0.26344
Wiener Filter	840.85	18.884	0.4665	0.41511
Bilateral Filter	340.45	22.810	0.48007	0.24118
Fourier Transform	624.78	20.174	0.36933	0.15731
Haar Transform	240.6	24.318	0.65024	0.23836
Daubechies wavelet Transform	246.57	24.211	0.68629	0.35277
Curvelet Transform	128.18	27.052	0.78773	0.26786

For image corrupted with Gaussian noise, among all the spatial filters that we have used Bilateral filter is best and efficient because it has a least MSE value of 340.45, highest PSNR value of 22.81 and highest SSI value of 0.48007.

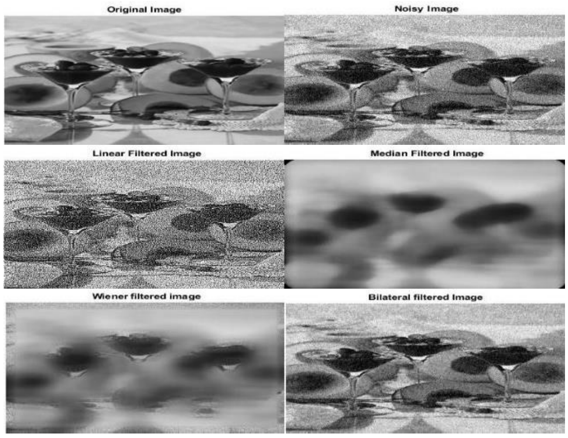

Fig. 3. Computational results with spatial domain filters for Gaussian Noisy image

When compared with all other transform filters, curvelet transform is best because it has the least MSE value of 128.18, highest PSNR value of 27.052 and highest SSI value of 0.78773.

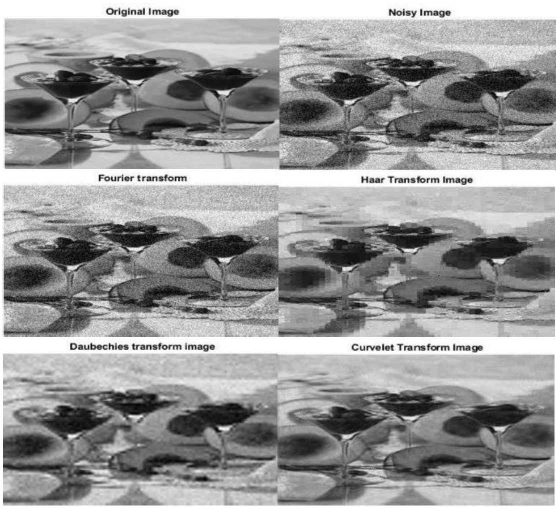

Fig. 4. Computational results with transform domain filters for

Gaussian Noisy image

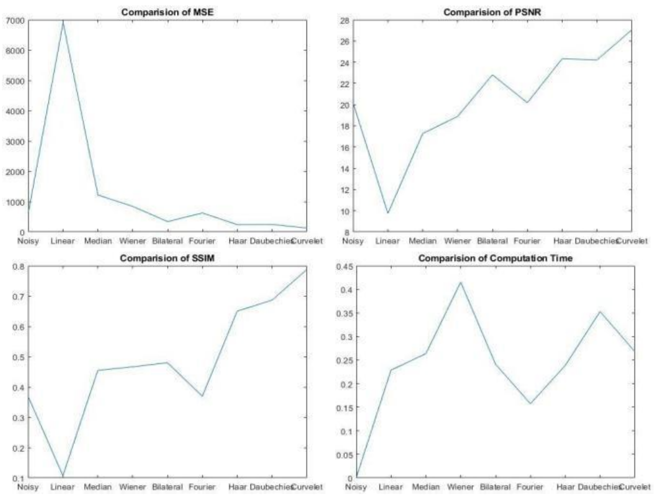

Fig. 5. Graph of evaluation parameters for removal of Gaussian noise using various filters

Table 2. Comparison of an optimal solution for Salt and Pepper Noisy Image

	MSE	PSNR	SSI	CT
Noisy Image	1247.3	17.171	0.5311	0
Linear Filter	2824.1	13.622	0.40994	1.1773
Median Filter	2719.3	13.786	0.32027	1.3707
Wiener Filter	1804.7	15.567	0.31499	2.0568
Bilateral Filter	1252.2	17.154	0.50507	1.1745
Fourier Transform	1243.9	17.183	0.53131	0.40214
Haar Transform	1196.6	17.351	0.49437	0.68565
Daubechies wavelet Transform	670.25	19.868	0.59369	0.84875
Curvelet Transform	1001.3	18.125	0.53493	0.79413

For image distorted with salt and pepper noise, among all the spatial filters that we have used Bilateral filter is best and efficient because it has a least MSE value of 1252.2, highest PSNR value of 17.154 and highest SSIM value of 0.50507.

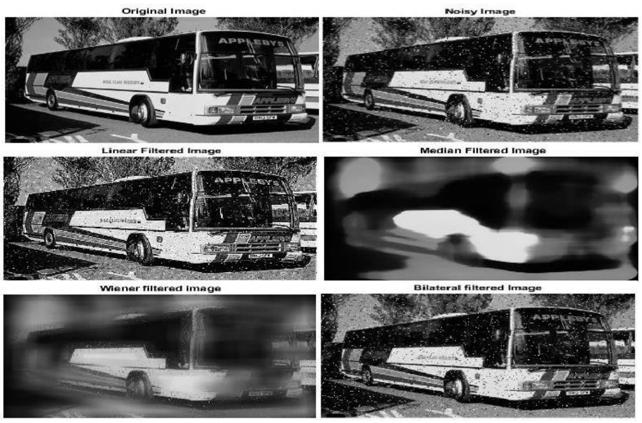

Fig. 6. Computational results with spatial domain filters for Salt and pepper noisy image

When compared with all other transform filters, the Daubechies wavelet transform is best because it has the least MSE value of 670.25, highest PSNR value of 19.868 and highest SSI value of 0.59369.

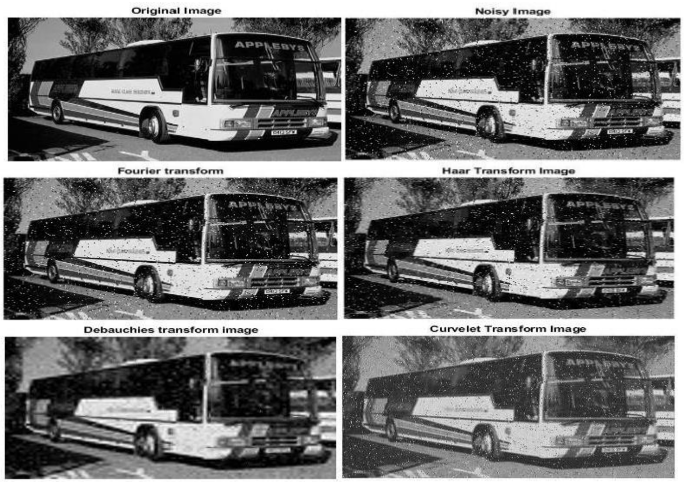

Fig. 7. Computational results with transform domain filters for Salt and pepper noisy image

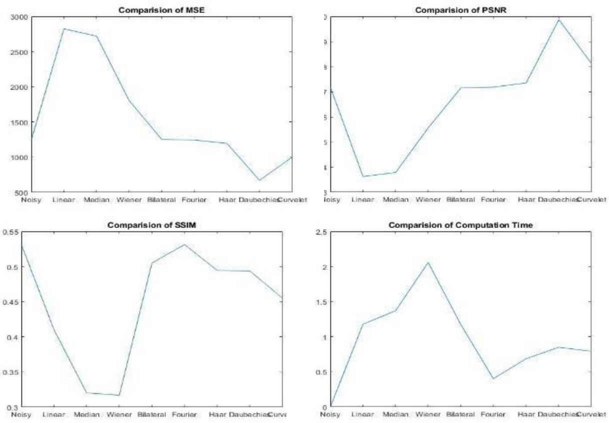

Fig. 8. Graph of evaluation parameters for removal of Salt and pepper noise using various filters

Table 2. Comparison of an optimal solution for Speckle Noisy Image

	MSE	PSNR	SSI	CT
Noisy Image	912.36	18.529	0.47336	0
Linear Filter	8516.6	8.8281	0.16013	0.54458
Median Filter	1414.2	16.626	0.23841	0.46556
Wiener Filter	933.1	18.432	0.3176	0.76087
Bilateral Filter	671.79	19.858	0.53618	0.48738
Fourier Transform	911.9	18.531	0.47333	0.35465
Haar Transform	617.11	20.227	0.45127	0.44084
Daubechies wavelet Transform	344.98	22.753	0.54309	0.56682
Curvelet Transform	285.2	23.579	0.63202	0.92741

For image corrupted with Speckle noise, among all the spatial filters that we have used Bilateral filter is best and efficient because it has a least MSE value of 671.79, highest PSNR value of 19.858 and highest SSI value of 0.53618.

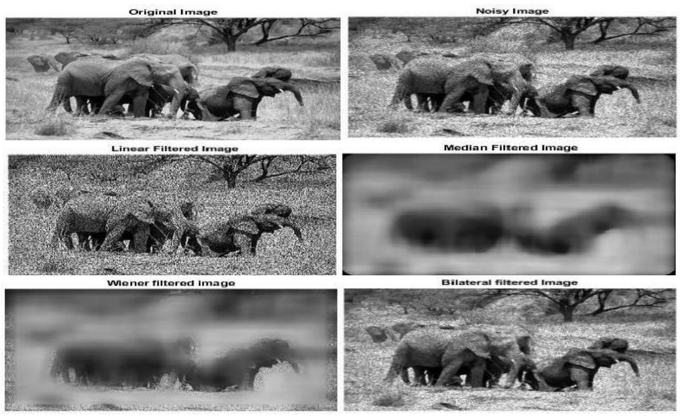

Fig. 9. Computational results with spatial domain filters for Speckle noisy image

When compared with all other transform filters, curvelet transform is best because it has the least MSE value of 285.2, highest PSNR value of 23.579 and highest SSI value of 0.63202.

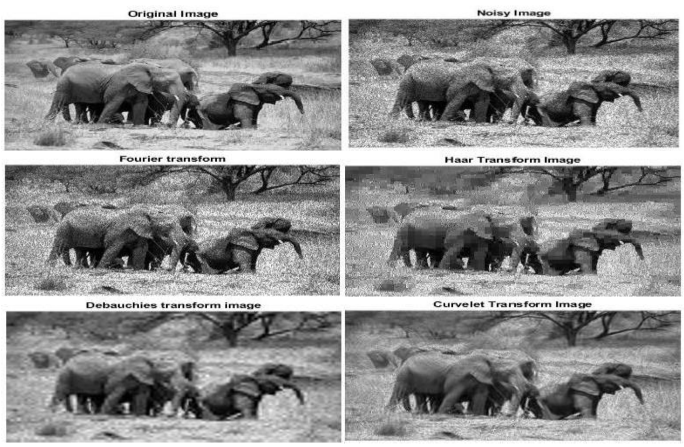

Fig. 10. Computational results with spatial domain filters for Speckle noisy image

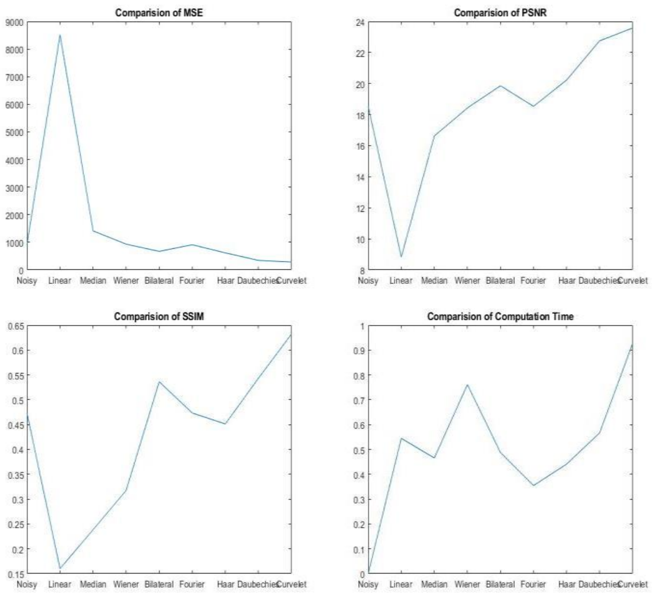

Fig. 11. Graph of evaluation parameters for removal of Speckle noise using various filters

4. Conclusion

A random image from Wang database is distorted through either Gaussian noise or Salt and Pepper noise or Speckle noise. Then spatial and transform domain filters have been used for denoising the image. The quality parameters for evaluation unveiled the most optimum denoising technique. It is evident that in the case of Gaussian noise and speckle noise, Curvelet transform outperforms all other image denoising techniques, and Salt and pepper noise is most effectively removed by Debauchies wavelet transform. In the future, Deep Learning may generate a deep neural network that has better image denoising capability concerning any noise.

Acknowledgements

The author thanks the evaluators for their valued assessment and recommendation of this manuscript.

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