NATIONAL INSTITUTE OF TECHNOLOGY ROURKELA

A SURVEY OF IMAGE DENOISING ALGORITHMS

BY

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A thesis submitted in partial fulfillment for the degree of

Bachelor of Technology

Under the guidance of

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NATIONAL INSTITUTE OF TECHNOLOGY CERTIFICATE

This is to certify that the work in the project entitled “A Survey of Image Denoising Algorithms” by Himanshu Singh is a record of their work carried out under my supervision and guidance in partial fulfillment of the requirements for the award of the degree of Bachelor of Technology in Computer Science and Engineering.

Prof. Ratnakar Dash

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Himanshu Singh

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ABSTRACT

Images play an important role in conveying important information but the images received after transmission are often corrupted and deviate from the original value.

When an Image is formed various factors such as lighting spectra, source, intensity and camera Characteristics (sensor response, lenses) affect the image. The major factor that reduces the quality of the image is Noise. It hides the important details of images and changes value of image pixels at key locations causing blurring and various other deformities. We have to remove noises from the images without loss of any image information. Noise removal is the preprocessing stage of image processing. There are many types of noises which corrupt the images. These noises are appeared on images in different ways: at the time of acquisition due to noisy sensors, due to faulty scanner or due to faulty digital camera, due to transmission channel errors, due to corrupted storage media.

The image needs image denoising before it can be used in applications to obtain accurate results. Various types of noises that create fault in image are discussed. Many image denoising algorithms exist none of them are universal and their performance largely depends upon the type of image and the type of noise. In this paper we will be discussing some of the image denoising algorithms and comparing them with each other. A quantitative measure of the image denoising algorithms is provided by the signal to noise ratio and the computation time of various algorithms working on a provided noisy image.

INTRODUCTION

Image denoising has become a critical step in processing of images and removing unwanted noisy data from the image. The image denoising algorithms have to remove the unwanted noisy elements and keep all the relevant features of the image. The image denoising algorithms have to tradeoff between the two parameters i.e. effective noise removal and preservation of image details.

Images play a very important role in many fields such as astronomy, medical imaging and images for forensic laboratories. Images used for these purposes have to be noise free to obtain accurate results from these images.

PROJECT OBJECTIVE:

The main objective of the project is to implement various denoising algorithms in matlab and give a comparative study of their efficiency. To be able to give a good comparative result a high quality image is selected and noise is added to the the image. Then various denoising algorithms are applied on the noisy image and the results are compared in terms of image to noise ratio efficiency by time consumed and by visual detection of the denoised images.

The image denoising model:

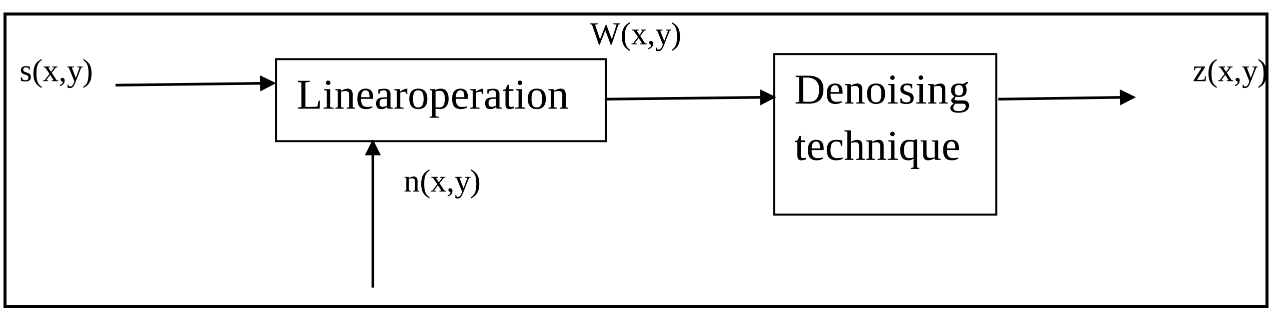

Figure 1.1

In case of denoising the characteristic of the system as well as the type of noise is known beforehand. The image s(x,y) is blurred by the linear operations causing the noise n(x,y) to add or multiply with the image. The noisy image then undergoes a denoising procedure and produces the denoised image z(x,y). How close the image z(x,y) is to the original image depends on the noise levels and the denoising algorithm use.

THEORY

The various types of images are:

Binary images:
Are the simplest types of images and they take discreet values either 0 or 1 hence called binary images. Black is denoted by 1 and white by 0. These images have application in computer vision and used when only outline of the image required.

Gray scale images:
They are also known as monochrome images as they do not represent any color only the level of brightness for one color. This type of image consists of only 8 bytes that is 256(0-255) levels of brightness 0 is for black and 255 is white in between are various levels of brightness.

Colored images:
Usually consist of 3 bands red green and blue each having 8 bytes of intensity. The various intensity levels in each band is able to convey the entire colored image it is a 24 bit colored image.

TYPES OF NOISES IN IMAGES

Noise in image is caused by fluctuations in the brightness or color information at the pixels. Noise is a process which distorts the acquired image and is not a part of the original image. Noise in images can occur in many ways. During image acquisition the optical signals get converted into electrical which then gets converted to digital signal. At each process of conversion noise gets added to the image. The image can also become noisy during transmission of the image in the form of digital signals. The types of noises are:

1. Gaussian noise
2. Salt and Pepper noise
3. Shot noise (Poisson noise)
4. Speckle noise

Gaussian Noise:

Has normal Gaussian distribution. It is evenly distributed over the image signal. Gaussian distribution is given by

$$F(g) = \frac{1}{\sqrt{2\Pi\sigma^2}} e^{-(g-m)^2/2\sigma^2} \qquad \ldots 1$$

g- Grey level

m- Mean of function

Sigma- standard deviation of noise

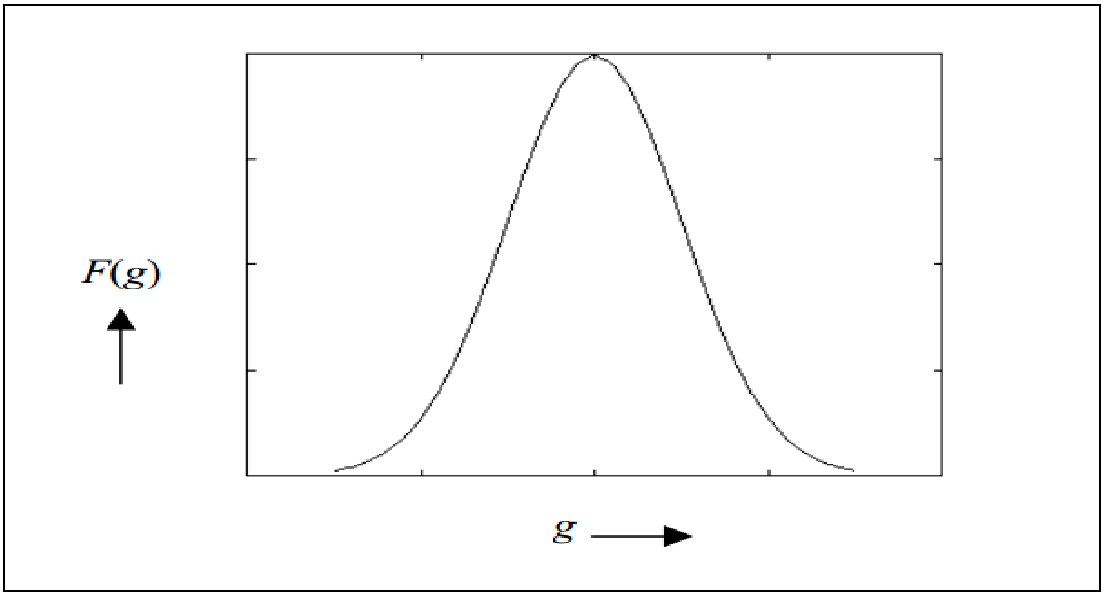

Figure 2.1 Bell Shaped Curve for Gaussian distribution

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Salt and Pepper Noise:

It is an impulse type noise comprising of intensity spikes. It has two possible values a and b the probability of each of the values is less than 0.1. The pixels corrupted with salt and pepper noise alternate between the minimum and maximum value it causes randomly occurring black and white pixels. The main causes of this type of noise are malfunctioning of pixel elements in camera, malfunctioning of analog to digital conversion in camera.

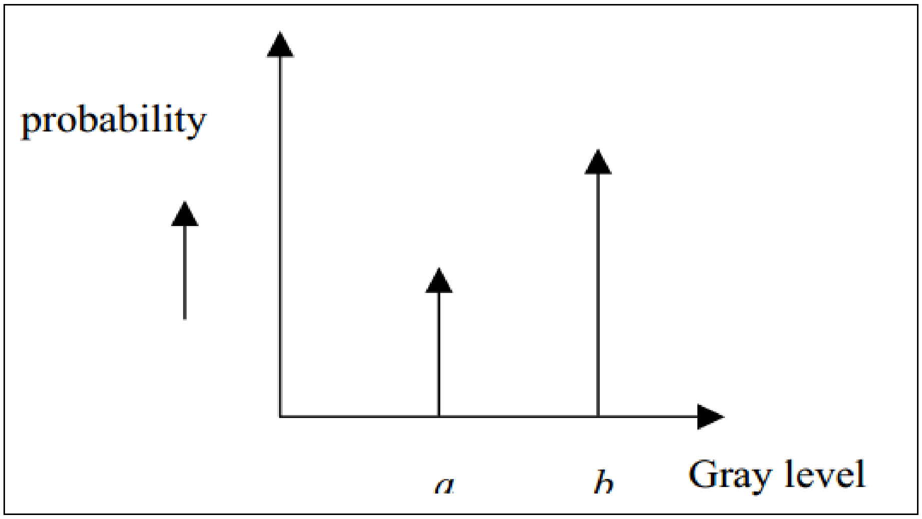

Figure 2.2 Salt and Pepper Noise

Speckle Noise:

It is a multiplicative noise occurring mostly in medical images in all coherent imaging systems like laser, acoustics ultrasound etc. It follows gamma distribution.

$$F(g) = \frac{g^{\alpha-1}}{(\alpha-1)!\alpha^{\alpha}} e^{\frac{-g}{a}} \qquad \ldots 2$$

a is the standard deviation and alpha and g are the grey levels

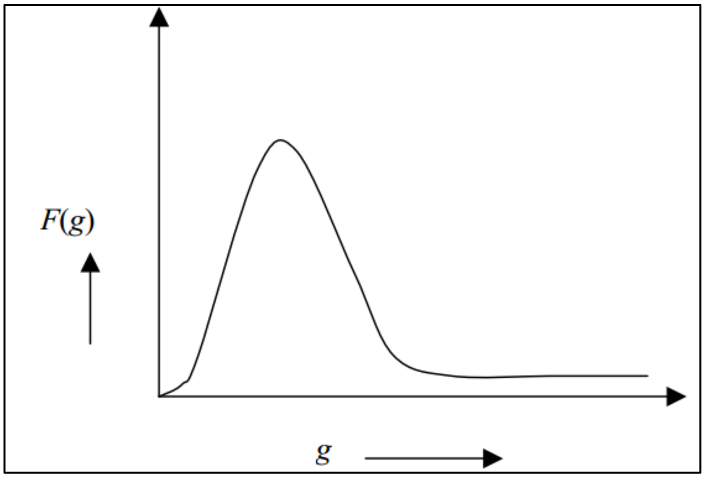

Figure 2.3 Gamma Distribution

Brownian Noise

Brownian noise comes under the category of fractal or 1/f noises. The mathematical model for 1/f noise is fractional Brownian motion. Fractal Brownian motion is a non-stationary stochastic process that follows a normal distribution. Brownian noise is a special case of 1/f noise

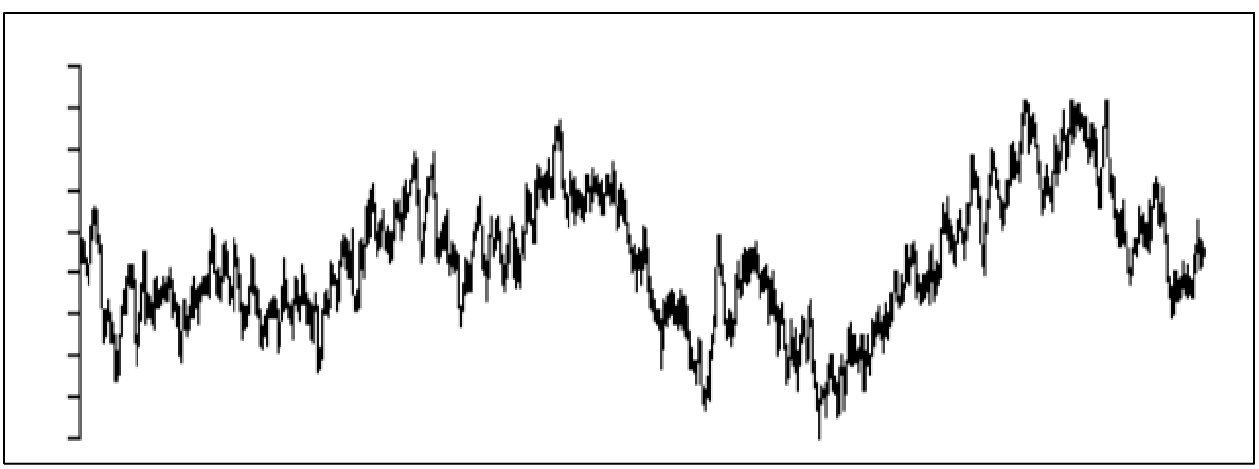

Figure 2.4 Brownian Noise Distribution

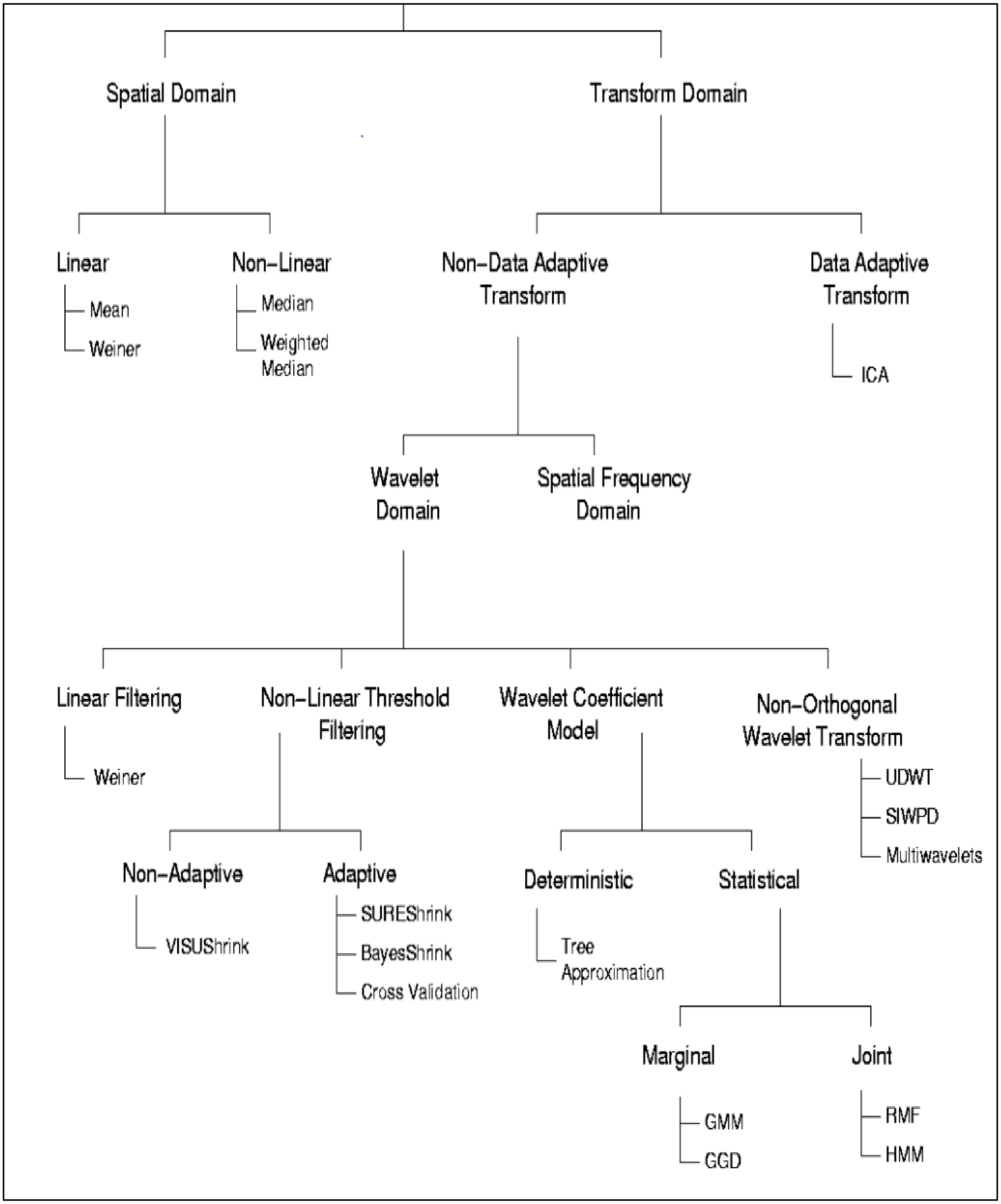

Figure 3.1 Categorization of Various Image Denoising methods

Classification of Denoising algorithms:

1. Spatial Filtering :

   It has two further classifications:

a. Non Linear Filters:

   Without explicitly determining the noise this algorithm is used. These filters assume that the noise lies in the high frequency region. Low pass filters are employed to separate image from noise. Spatial filters remove noise to a good extent but cause blurring of images which makes the edges in pictures not visible.

b. Linear Filters:

i. Mean Filter:

   A mean filter is the optimal linear filter for Gaussian noise in the sense of mean square error. They perform poorly in the presence of signal dependent noise. Linear filters too tend to blur sharp edges, lines and other valuable image details.

ii. Wiener Filter:

   It works well only if the underlying signal is smooth. The wiener filtering method requires details about the spectra of the noise and the original signal.

2. Transform Domain Filtering:

   It is further classified according to the choice of basis function. The basis function is of two type's data adaptive and non-adaptive.

a. Non data Adaptive Transform Domain Filtering:

i. Spatial Frequency Filtering:

   Spatial-frequency filtering uses low pass filters using Fast Fourier Transform (FFT). In frequency smoothing methods the removal of the noise is achieved by obtaining a frequency domain filter and a cut-off frequency when the noise components are DE correlated from the useful signal in the frequency domain. These methods take a lot of time and depend on the cut-off frequency and the filter function behavior. They may produce artificial frequencies in the processed image.

ii. Wavelet Domain:

- Linear Filters:

  Linear filters such as Wiener filter in the wavelet domain yield optimal results when the signal corruption is of the Gaussian type and the criteria are Mean Square Error (MSE). However, designing a filter based on this assumption frequently a result in a filtered image that is visually revolting than the original noisy signal, even though the filtering operation successfully reduces the MSE.

- Non Linear Threshold Filtering:
  It is the most sought after method based on wavelet domain.
  The procedure makes use of two properties:

1. Sparsity property of wavelet transform
2. Wavelet transformation maps white noise in signal domain to white noise in transform domain.
   The important fact that signal energy gets concentrated into few coefficients in the transform domain while noise energy does not, is used for the separation of signal from noise.

   Hard Thresholding: small coefficients are removed while others left unchanged. This method causes spurious blips called artifacts as it is not successful in removing large noise coefficients.

   Soft Thresholding:
   This method overcomes the demerits of hard thresholding. Coefficients above threshold are shrunk by the absolute of the threshold.

- Non Adaptive Thresholds:
  VISUShrink is non-adaptive universal threshold, which depends only on number of data points. It has asymptotic equivalence hence has the best performance in terms of MSE when the number of pixels reaches infinity. VISUShrink is known to yield overly smoothed images because its threshold choice can be unwarrantedly large due to its dependence on the number of pixels in the image.

- Adaptive Thresholds:
  SUREShrink uses a combination of the universal threshold and the SURE [Stein's Unbiased Risk Estimator] threshold and gives better output than VISUShrink. BayesShrink minimizes the Bayes' Risk Estimator function assuming Generalized Gaussian prior and thus yielding data adaptive threshold. BayesShrink outperforms SUREShrink most of the times. Cross Validation replaces wavelet coefficient with the weighted average of neighborhood coefficients to minimize generalized cross validation (GCV) function providing optimum threshold for every coefficient. The assumption that one can distinguish noise from the signal solely based on coefficient

magnitudes is violated when noise levels are higher than signal magnitudes. Under this high noise circumstance, the spatial configuration of neighboring wavelet coefficients can play an important role in noise-signal classifications. Signals tend to form meaningful features (e.g. straight lines, curves), while noisy coefficients often scatter randomly.

- Non Orthogonal Wavelet Transform:
  Undecimated Wavelet Transform (UDWT) has also been used for decomposing the signal to provide visually better solution. Since UDWT is shift invariant it avoids visual artifacts such as pseudo-Gibbs phenomenon. Though the improvement in results is much higher, use of UDWT adds a large overhead of computations thus making it less feasible. In normal hard/soft thresholding was extended to Shift Invariant Discrete Wavelet Transform. In Shift Invariant Wavelet Packet Decomposition (SIWPD) is exploited to obtain number of basis functions. Then using Minimum Description Length principle the Best Basis Function was found out which yielded smallest code length required for description of the given data. Then, thresholding was applied to denoise the data. In addition to UDWT, use of Multiwavelets is explored which further enhances the performance but further increases the computation complexity. The Multiwavelets are obtained by applying more than one mother function (scaling function) to given dataset. Multiwavelets possess properties such as short support, symmetry, and the most importantly higher order of vanishing moments. This combination of shift invariance & Multiwavelets is implemented in which give superior results for the Lena image in context of MSE.

- Wavelet Coefficient Model:
  This approach focuses on exploiting the multiresolution properties of Wavelet Transform. This technique identifies close correlation of signal at different resolutions by observing the signal across multiple resolutions. This method produces excellent output but is computationally much more complex and expensive.
  The modeling of the wavelet coefficients can either be deterministic or statistical.

o Deterministic:
  The Deterministic method of modeling involves creating tree structure of wavelet coefficients with every level in the tree representing each scale of transformation and nodes representing the wavelet coefficients. This approach is adopted in. The optimal tree approximation displays a hierarchical interpretation of wavelet decomposition. Wavelet coefficients of singularities have large wavelet coefficients that persist along the branches of tree.
  Thus if a wavelet coefficient has strong presence at particular node then in case of it being signal, its presence should be more pronounced at its parent nodes. If it is noisy coefficient, for instance spurious blip, then such consistent presence will be missing.

- Statistical Modeling of Wavelet Coefficients:

  This approach focuses on some more interesting and appealing properties of the Wavelet Transform such as multiscale correlation between the wavelet coefficients, local correlation between neighborhood coefficients etc. This approach has an inherent goal of perfecting the exact modeling of image data with use of Wavelet Transform. The following two techniques exploit the statistical properties of the wavelet coefficients based on a probabilistic model.

- Marginal Probabilistic Model:

  A number of researchers have developed homogeneous local probability models for images in the wavelet domain. Specifically, the marginal distributions of wavelet coefficients are highly kurtotic, and usually have a marked peak at zero and heavy tails. The Gaussian mixture model (GMM) and the generalized Gaussian distribution (GGD) are commonly used to model the wavelet coefficients distribution. Although GGD is more accurate, GMM is simpler to use. In [30], authors proposed a methodology in which the wavelet coefficients are assumed to be conditionally independent zero-mean Gaussian random variables, with variances modeled as identically distributed, highly correlated random variables. An approximate Maximum A Posteriori

  (MAP) Probability rule is used to estimate marginal prior distribution of wavelet coefficient variances. All these methods mentioned above require a noise estimate, which may be difficult to obtain in practical applications.

1. Non Data Adaptive Transform:

   Recently a new method called Independent

   Component Analysis (ICA) has gained wide spread attention. The ICA method was successfully implemented in denoising Non-Gaussian data. One exceptional merit of using ICA is it’s assumption of signal to be Non-Gaussian which helps to denoise images with Non-Gaussian as well as Gaussian distribution. Drawbacks of ICA based methods as compared to wavelet based methods are the computational cost because it uses a sliding window and it requires sample of noise free data or at least two image frames of the same scene. In some applications, it might be difficult to obtain the noise free training data.

Mean Filter:

It is a simple sliding window spatial filter. It replaces the center value of the window with average of all the pixels in the window. Convolution mask provides weighted sum of values of pixels and its neighbors. The convolution mask is square and works on the shift multiply sum principle as depicted:

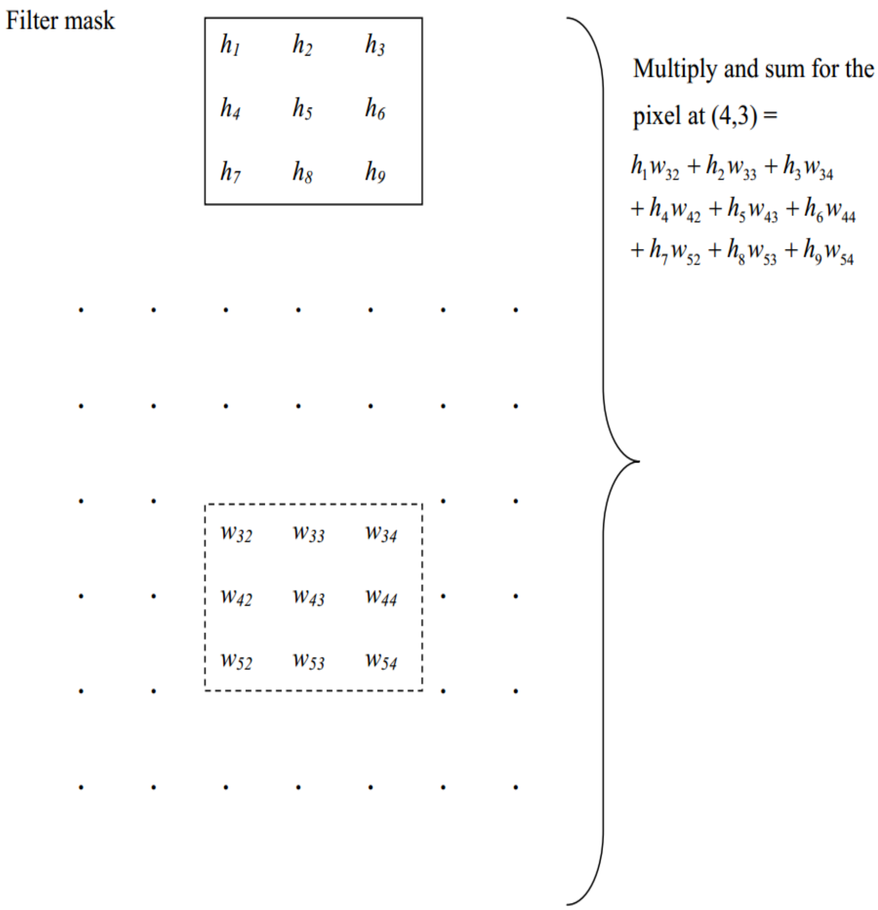

Figure 4.1 Multiply Sum Method

This convulsion mean filtering is effective when the noise in impulsive. The mean filter acts like a low pass filter and does not allow the high noise frequencies to pass through.

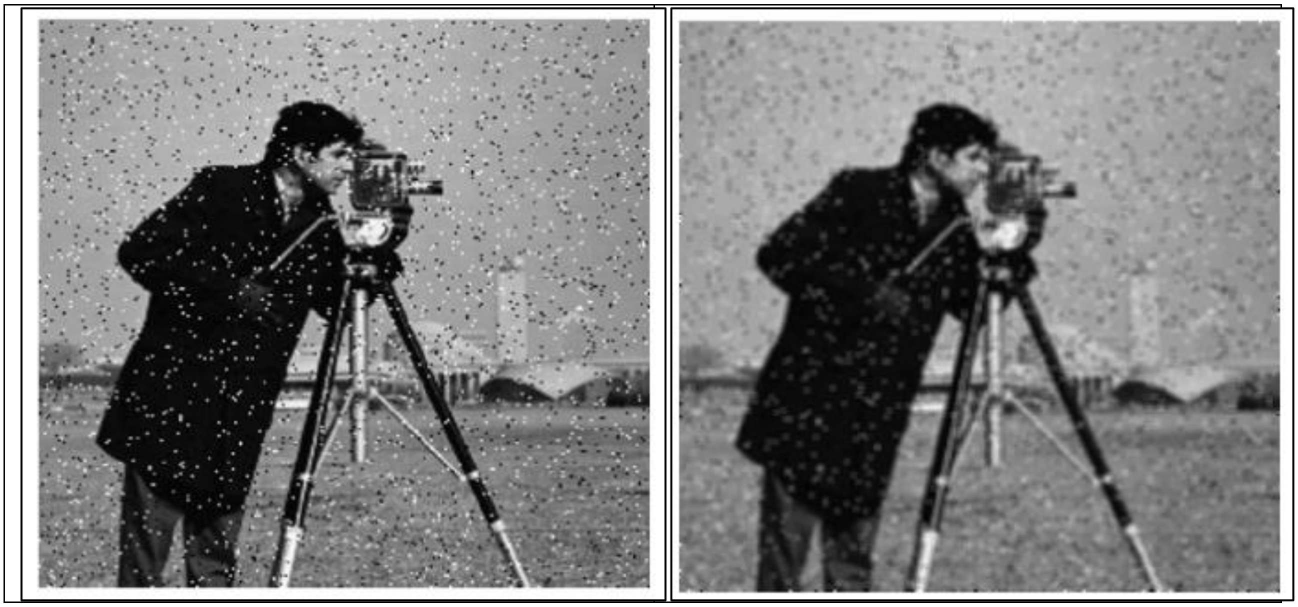

Figure 4.2

Input Image with salt and Pepper Noise Output Image

LMS Adaptive Filter:

The weighted sum is obtained by: The main difference between mean filter and an adaptive filter is that in an adaptive filter, the weighted matrix changes after each iteration. It is useful for images with variable noise and can be applied to unknown image type without the knowledge of the type of noise present in it. It is a combination of non-changing low pass filter and a changing high pass filter. It works in the following manner:

Window of size a*b is chosen over image, u is the mean of the window, it is deduct from each element of the window and the resultant matrix is Wr.

$$Wr = W - u \qquad \ldots 3$$

$$z = \sum_{(i,j)\in W} h(i,j) W^{r} \qquad \ldots 4$$

H(I,j) element of the weighted matrix.The sum of z and mean of window change with the center value of window. The pixel value now is:

$$z = \tilde{z} + \mu \qquad \ldots 5$$

In the next step the window is changed one pixel in row major order and the weight matrix is modified as follows:

$$e = W^r - \tilde{z} \qquad \ldots 6$$

E is the deviation. Largest eigenvalue of the original window is calculated.

$$0 < \eta < 1/\lambda. \qquad \ldots 7$$

The new weighted matrix is:

$$h_{k+1} = h_k + \eta \times e \times W^r \qquad \ldots 8$$

This is used in the next iteration. The process continues till the entire image is covered.

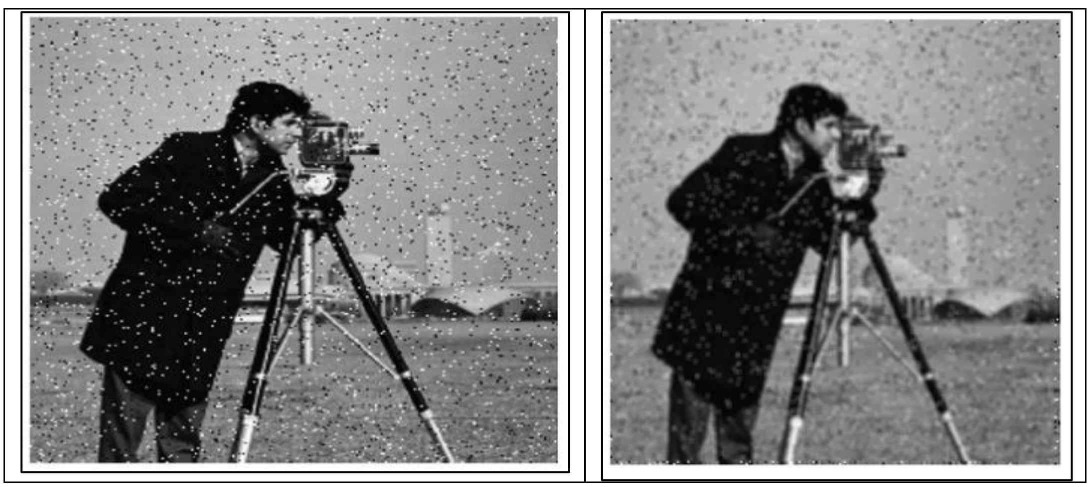

Figure 4.3Image with Salt and Pepper Noise Output Image

Median Filter:

It is a nonlinear filter. Has the same sliding window concept but the center pixel value is exchanged with the median of the neighboring pixels. All pixels are sorted numerically and then the center value is exchanged with the median of the window. Median filter is very resistant towards pixrl value with unusual values not matching the pixel values in the image.

Figure 4.4

Input Image Output Image

VISU Shrink:

It is a general purpose hard thresholding method; the threshold value is proportional to the standard deviation of the noise. The threshold value is given by:

$$t = \sigma\sqrt{2\log n} \quad \ldots 9$$

Sigma square is the variance of noise and n is the number of samples. The noise variance is estimated by:

$$\hat{\sigma} = \frac{median\left(\left\{|\, g_{j-1,k}\,| : k = 0,1,...,2^{j-1}-1\right\}\right)}{0.6745} \quad ...10$$

G (j-1, k) is the detail coefficients in wavelet transform.

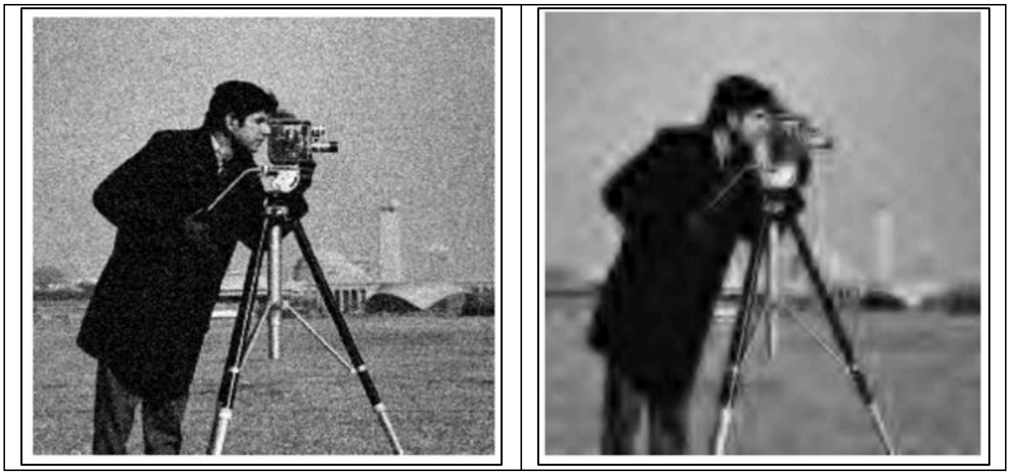

Figure 4.5

Image Corrupted with Gaussian Noise variance 0.005   Output Image

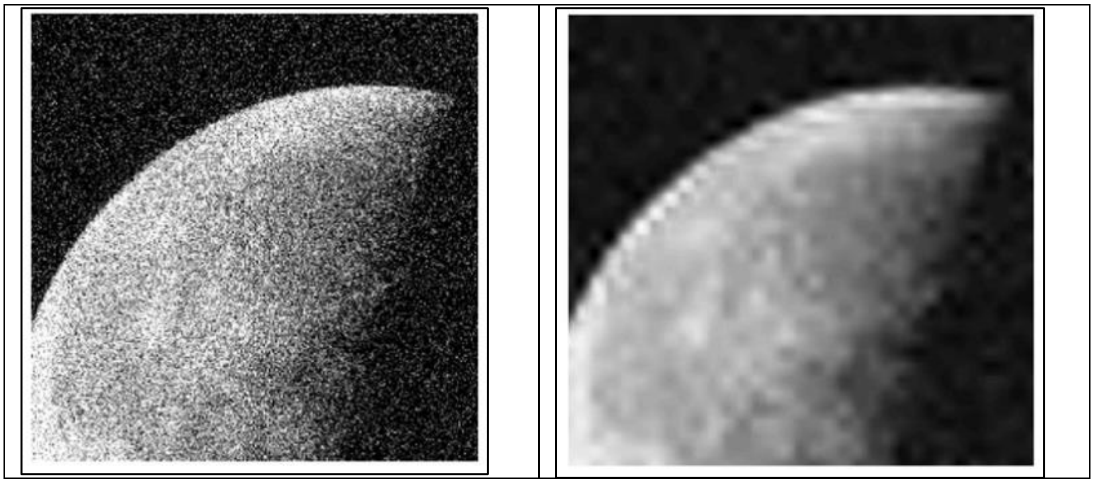

Figure 4.6 Image with Gaussian Noise variance, 0.05   Output Image

SURE Shrink:

Threshold is chosen by StiensUnbaised Risk Estimator function. It is combination of universal threshold ad SURE threshold. A threshold value tj is obtained for every resolution level j in wavelet transform. It minimizes MSE.

$$\text{MSE} = \frac{1}{n^2} \sum_{x,y=1}^{n} (z(x,y) - s(x,y))^2 \,, \qquad \ldots 11$$

Z(x,y) estimate of signal s(x,y) original value without noise, n is the number of samples of signal. These method thresholds empirical wavelet coefficients. The threshold is defined as:

$$t = \min(t, \sigma\sqrt{2\log n}) \qquad \ldots 12$$

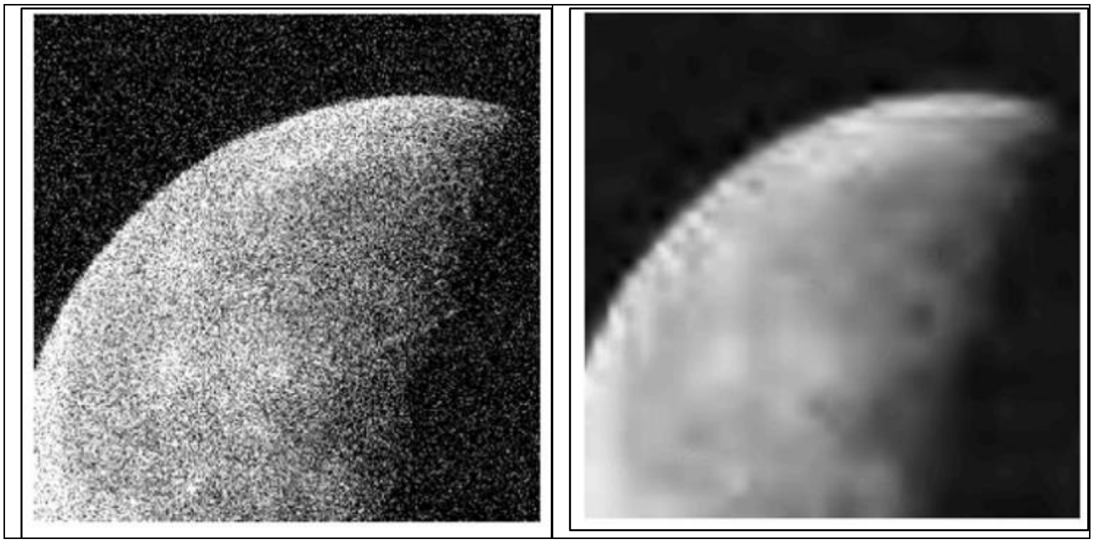

Figure 4.7

Image with Gaussian Noise Output Image

Bayes Shrink:

It is a soft thresholdig method. The thresholdig is doe at each resolution bad I the wavelet domain. The threshold is defined as:

$$t_B = \sigma^2 / \sigma_s . \quad \ldots 13$$

σ^2 Is the noise variance σ_s^2 is the variance without noise.

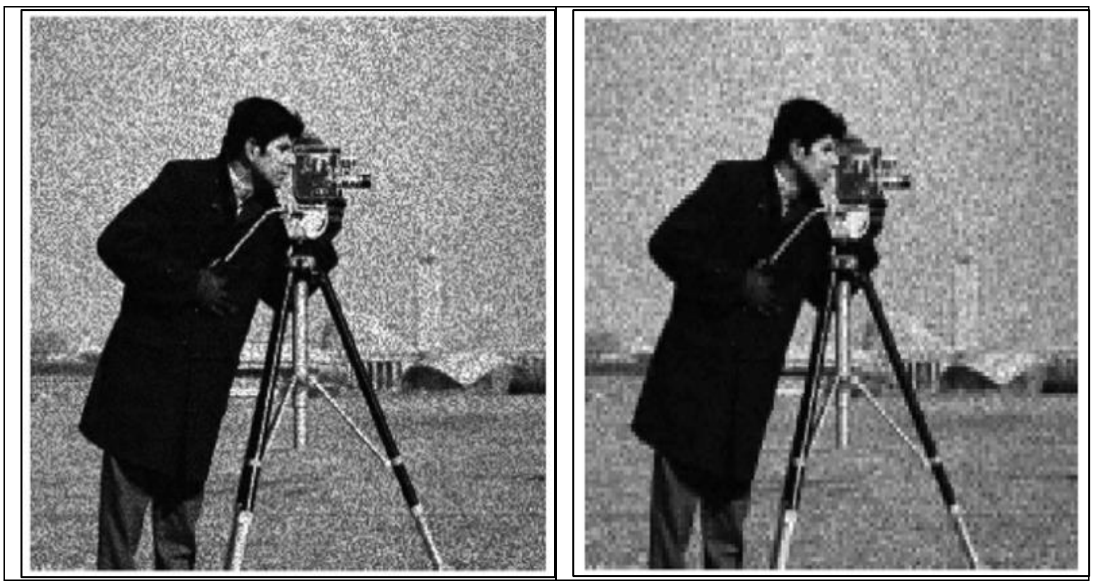

Figure 4.8 Image with Speckle Noise Output Image

RESULTS

It is imperative to critically analyze denoising techniques as they are application dependent. There is no concrete method to analyze the denoising techniques. Therefore a test scenario is created wherein a test image is used with all the pixel values 100 is created and noise is added to it. Denoising is carried out and the result is obtained in the form of SNR. Signal to Noise Ratio (SNR) for each of these outputs is computed. The SNR is defined as

$$\text{SNR} = 20\log_{10}\left(\frac{a_{\max} - a_{\min}}{s_n}\right)$$

…14

The variable Amax refers to the pixel value with maximum intensity while Amin refers to the pixel value with minimum intensity in the image of interest. Variable sn is the standard deviation of the noise defined as

$$s_n = \sqrt{\frac{1}{\Lambda - 1}\sum_{(m,n)\in R}(a[m,n] - m_a)^2}\ ,$$

…15

Where ma is the sample mean of the pixel brightness in the region R which is the entire image in all the experiments done in this thesis. The parameter Λ refers to the number of pixels in the region R and a[m,n] is the pixel value. Sample mean is computed as

$$m_a = \frac{1}{\Lambda}\sum_{(m,n)\in R} a[m,n]\,.$$

…16

Tables show the SNR of the input and output images for the filtering approach and wavelet transform approach, respectively.

Table for Filtering Approach

Method	**SNR input image**	**SNR of output image**	**Noise Type and variance**
Mean Filter	18.88	27.43	Salt and pepper,0.05
Mean Filter	13.39	21	Gaussiam, 0.05
Median Filter	18.88	47.97	Salt and pepper, 0.05
Median Filter	13.39	22.79	Gaussian 0.05
LMS adaptive filter	18.88	28.01	Salt and pepper 0.05
LMS adaptive filter	13.39	22.40	Gaussian, 0.05

Table 1.1

Table for Wavelet Transform Approach

Visu Shrink	**13.39**	**31.17**	**Gaussian 0.05**
Visu Shrink	18.88	19.01	Salt and Pepper 0.05
SURE Shrink	13.39	36.46	Gaussian, 0.05
SURE Shrink	18.88	40.67	Salt and Pepper, 0.05
Bayes Shrink	13.39	30.98	Gaussian 0.05
Bayes Shrink	18.88	18.92	Salt and pepper, 0.05

Table 1.2

CONCLUSION

The mathematical results and the output image help us in deriving the following conclusions.

For images corrupted with Gaussian noise wavelet shrinkage denoising is optimal. SURE shrink has the best SNR compared to Bayes Shrink and VISU Shrink. Bayes Shrink gives high quality image but it is not effective for noise with variance higher than 0.05.

For images corrupted with salt and pepper, noise median filter is the most optimal compared to Mean and LMS adaptive filter. Median filter produces the maximum SNR. The output obtained from LMS adaptive filter is better than mean filter but the time complexity is much greater than Bayes and VISU shrink.

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