IMAGE RESTORATION TECHNIQUES

THESIS REPORT SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF

Bachelor of Technology
in
Electronics and Instrumentation Engineering

By

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Department of Electronics and Communication Engineering
National Institute of Technology
Rourkela
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CERTIFICATE

This is to certify that the thesis titled, *"Image Restoration Techniques"* submitted by Sri.Anandigari Bharath Kumar Reddy and Sri.Siba Prasad Tudu in partial fulfillment of the requirements for the award of Bachelor of Technology Degree in Electronics and Instrumentation Engineering at National Institute of Technology, Rourkela (Deemed University) is an authentic work carried out by them under my supervision and guidance.

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ABSTRACT

Image restoration is the process of restoring degraded images which cannot be taken again or the process of obtaining the image again is costlier. We can restore the images by prior knowledge of the noise or the disturbance that causes the degradation in the image. Image restoration is done in two domains: spatial domain and frequency domain. In spatial domain the filtering action for restoring the images is done by directly operating on the pixels of the digital image. In frequency domain the filtering action is done by mapping the spatial domain into the frequency domain by taking fourier transform of the image function. By mapping the image into frequency domain an image can provide an insight for filtering operations. After the filtering, the image is remapped into spatial domain by inverse fourier transform to obtain the restored image.

Different noise models were studied. Different filtering techniques in both spatial and frequency domains, were studied and improved algorithms were written and simulated using matlab. Restoration efficiency was checked by taking peak signal to noise ratio(psnr) and mean square error(mse) into considerations.

Chapter 1

INTRODUCTION

INTRODUCTION

Image restoration is the process of recovering an image that has been degraded by using a priori knowledge of the degradation phenomenon. Restoration techniques involves modeling of the degradation function and applying the inverse process to recover the original image. This process is processed in two domains: spatial domain and frequency domain.

1.1 A Model of image degradation and restoration process

The basic unit of a image is called a pixel or image element i.e. the image is divided into very small blocks called pixels. An image can be defined as a two dimensional function *I*

$$I = f(x,y) \tag{1.1}$$

where x and y are spatial coordinates. (x,y) represents a pixel. I is the intensity or grey level value which is the amplitude of f at any point (x,y). If the values of the coordinates (spatial coordinates) and the amplitude are finite and discrete, then it is called digital image. The degraded image $g(x,y)$ can be represented as

$$g(x,y) = h(x,y) * f(x,y) + \eta(x,y) \tag{1.2}$$

where $h(x,y)$ is the degradation function, $f(x,y)$ is the original image, the symbol * indicates convolution and $\eta(x,y)$ is the additive noise.

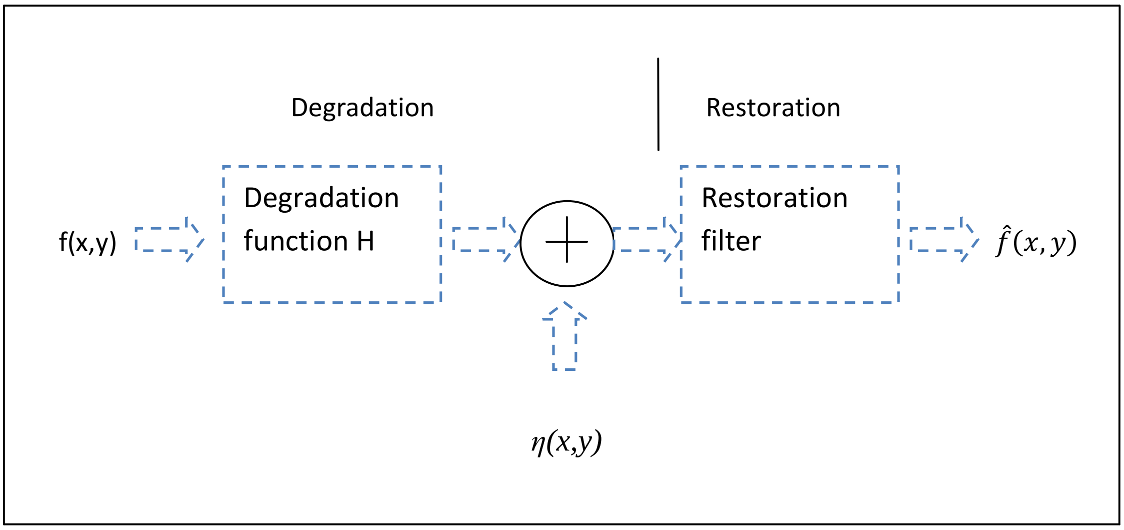

Fig 1.1: A Model of image degradation and restoration process

As we know, taking convolution of two functions in spatial domain is equivalent to the product of the Fourier transform of the two functions. So in the frequency domain we can represent equation 1.2 as

$$G(u,v) = F(u,v)H(u,v) + N(u,v) \tag{1.3}$$

Where the terms in capital letters are the Fourier transforms of the corresponding terms in equation(1.2).

1.2 Noise Models

In order to restore an image we need to know about the degradation functions. Different models for the noise are described in this section. The set of noise models are defined by specific probability density functions (PDFs). Some commonly found noise models and their corresponding PDFs are given below.

1.2.1 Gaussian Noise

Gaussian noise is the noise which can be defined by the probability density function of the normal distribution (also known as Gaussian distribution). The noise function acquires the values of the Gaussian distribution function.

The PDF is given by

$$p(z)=\frac{1}{\sqrt{2\pi}\sigma}\, e^{-(z-\mu)^2/2\sigma^2} \qquad (1.4)$$

Where 'z' is the Gaussian random variable representing noise.

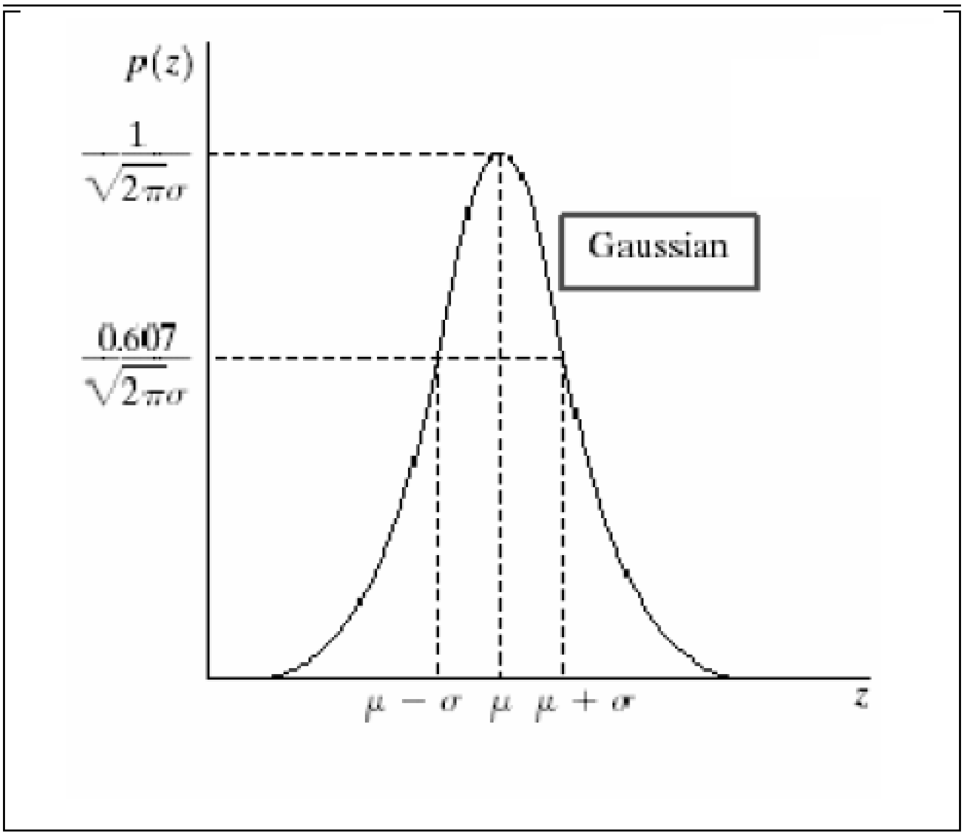

Fig 1.2: The probability density function for Gaussian distribution

Gaussian noise is additive in nature i.e. the Gaussian distributed noise values gets added to the intensity values of the image.

1.2.2 Rayleigh Noise

The PDF function of Rayleigh noise is given by

$$P(z)=\begin{cases} \frac{2}{b}(z-a)e^{-((z-a)^2)/b} & for\ z \geq a \\ 0 & for\ z \leq a \end{cases} \qquad (1.5)$$

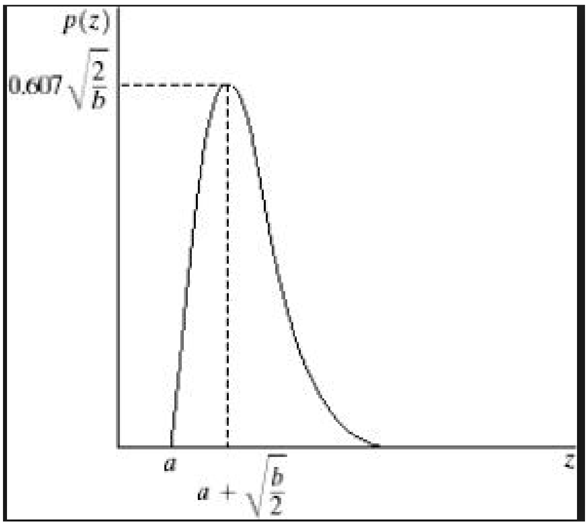

Fig 1.3: The probability density function for Gaussian Distribution

The mean is given by

$$\bar{z} = \frac{a+b}{2} \qquad (1.6)$$

And variance by

$$\sigma^2 = \frac{(b-a)^2}{12} \qquad (1.7)$$

1.2.3 Uniform Noise

It is another commonly found image noise i.e. uniform noise. Here the noise can take on values in an interval [*a,b*] with uniform probability. The PDF is given by

$$p(z) = \begin{cases} \frac{1}{b-a} & if\ a \le z \le b \\ 0 & otherwise \end{cases} \qquad (1.8)$$

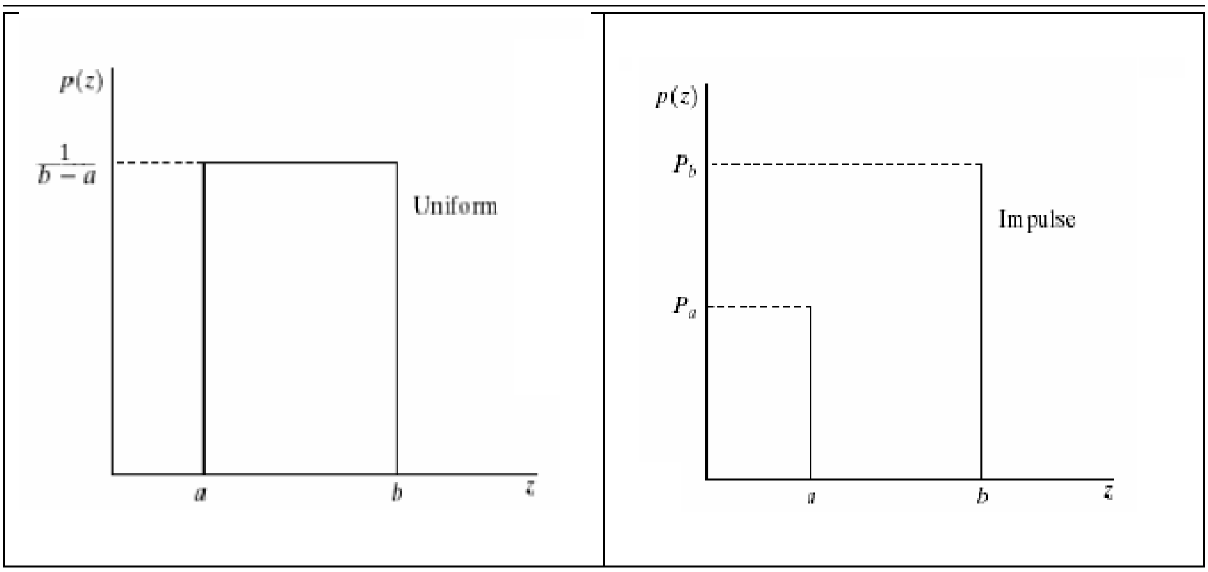

Fig 1.4: (a) Probability density functions for Uniform Noise. **(b)** Probability density function for salt and pepper noise

1.2.4 Impulse (salt-and-pepper) Noise

The PDF of impulse noise is given by

$$p(z)=\begin{cases} Pa & for\ z = a \\ Pb & for\ z = b \\ 0 & otherwise \end{cases} \qquad (1.9)$$

If *b>a* , intensity *b* will appear as a light dot in the image. And the vice-versa, level *a* will appear like a dark dot.

If P_a or P_b is zero, the impulse noise is called unipolar.

1.2.5 Exponential Noise

The PDF of exponential noise is given by

$$p(z)=\begin{cases} ae^{-az} & for\ z \geq 0 \\ 0 & for\ z < 0 \end{cases} \qquad (1.10)$$

Where *a>0.*

Mean, $\bar{z} = \frac{1}{a}$ (1.11)

Variance, $\sigma^2 = \frac{1}{a^2}$ (1.12)

1.3 Denoising Techniques

The noise removal is done by filtering of the degraded image. Basically the filtering is done in two different methods viz.

1. Filtering in spatial domain
2. Filtering in frequency domain

1.3.1 Spatial Domain Filtering

The most widely used filtering techniques in Image Processing are the Spatial Domain filtering techniques. Spatial Domain is referred as the grid of pixels that represent an image. The relative positions and the values of a local neighborhood of pixels are the factors that are used in Spatial Domain filtering technique

The main idea behind Spatial Domain Filtering is to convolve a mask with the image. The convolution integral of two functions $f(x)$ and $g(x)$ is defined as:

$$f(x) * g(x) = \int_{-\infty}^{\infty} f(u)g(x-u)du \qquad (1.13)$$

1.3.2 Frequency Domain Filtering

The frequency domain is an alternate way to represent an image. It deals with the frequency of the gray levels of the pixels in the image i.e. the variation in the gray level. Considering the frequency components of an image can provide an insight and rationale for certain filtering and processing operations.

In frequency domain filtering the image is mapped from spatial domain to frequency domain by taking Fourier transform of the image. After mapping filtering operation is done on the image (like low pass and high pass filtering etc). After doing the filtering operation the image is remapped to spatial domain by inverse Fourier transform to obtain the restored image.

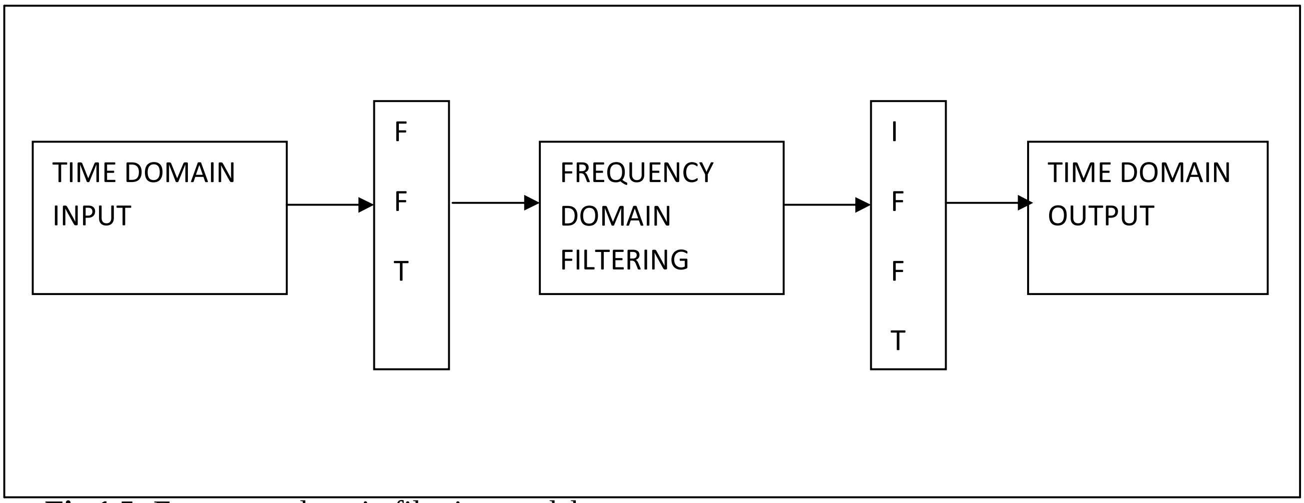

Fig 1.5: Frequency domain filtering model.

Chapter 2

Filtering in Spatial Domain

INRODUCTION

In spatial domain filtering the filtering action is done directly on the pixel itself to discard the noise. This method is applied if the degradation function is noise i.e.

$$g(x,y) = f(x,y) + \eta(x,y) \qquad (2.1)$$

This technique is very widely used in Image Processing. In Spatial Domain the filtering operation is done by convolving the image pixels with the pixels of the mask. A mask is a small sub image, often of size 3 × 3 pixels. The mask size is varied according to the requirement.

To convolve a mask with an image:

1. Move the mask to every image location.
    - move the mask in both the horizontal and vertical directions of the image pixel.
    - every pixel is needed to be included
    - at the edges the mask components will fall outside the image boundry. So we have pad all the sides of the image with 0 to accommodate all the mask elements.

2. With each move of the mask, the values of the multiplication of the underlying pixels of the image with the underlying pixels of the mask of the filter is summed.

3. The center pixel value at that position is replaced with the summed value at that position.

Spatial Noise Filters

The different classes of filtering techniques in spatial domain filtering.

- Mean Filters
- Order-Statistics Filters
- Adaptive Filters

2.1 Mean Filters

2.1.1 Arithmetic Mean Filter

In this type of mean filter the middle pixel value of the mask is replaced with the arithmetic mean of all the pixel values within the filter window. A mean filter simply smoothes local variations in an image. Noise is reduced and as a result the image smoothens, but edges within the image get blurred.

If S_{xy} represent a rectangular subimage window of size $m \times n$, centered at point (x,y) , then the value of restored image (let it be $\hat{f}(x,y)$) at point (x,y) is defined as

$$\hat{f}(x,y) = \frac{1}{mn}\sum_{(s,t)\in Sxy} g\,(s,t) \tag{2.2}$$

Where $g(x,y)$ is the corrupted image.

2.1.2 Geometric Mean Filter

The working of a geometric mean filter is same as the arithmetic mean filter; the only difference is that instead of taking the arithmetic mean the geometric mean is taken.

The restored image is given by the expression

$$\hat{f}(x,y) = \left[\prod_{(s,t)\in Sxy} g(s,t)\right]^{1/mn} \tag{2.3}$$

Value of each restored pixel is the product of pixels in the mask, raised to a power 1/mn.

2.1.3 Harmonic Mean Filter

In the harmonic mean method, the gray value of each pixel is replaced with the harmonic mean of gray values of the pixels in a surrounding region.

The harmonic mean is defined as:

$$H = \frac{n}{\frac{1}{x1}+\frac{1}{x2}+\cdots+\frac{1}{xn}}$$

The restored image is given by the function:

$$\hat{f}(x,y) = \frac{mn}{\sum_{(s,t)\in Sxy}\frac{1}{g(s,t)}} \qquad (2.4)$$

2.1.4 Contraharmonic Mean Filter

The restored image is given by the equation

$$\hat{f}(x,y) = \frac{\sum_{(s,t)\in Sxy} g\,(s,t)^{Q-1}}{\sum_{(s,t)\in Sxy} g\,(s,t)^{Q}} \qquad (2.5)$$

Where Q is the order of the system.

If Q=0, it behaves as arithmetic mean filter

If Q=1, it behaves as harmonic mean filter.

2.2 Order-Statistic Filters

2.2.1 Median Filter

Order-statistics filters are based on ordering the pixels contained in the mask. Median filter comes under this class of filters. Median filter replaces the value of a pixel with the median value of the gray levels within the filter window or mask. Median filters are very effective for impulse noise.

$$\hat{f}(x,y) = median_{(s,t)\varepsilon\, Sxy}\,\{g(s,t)\} \qquad (2.6)$$

2.2.2 Max and Min Filters

The maximum filter is defined as the maximum of all pixels within a local region of an image. So it replaces the center pixel value with the maximum value of pixel in the subimage window. Similarly the minimum filter is defined as the minimum of all pixels within a local region of an image and the center pixel value is replaced with the minimum value of pixel in the subimage window.

$$\hat{f}(x,y) = max_{(s,t)\varepsilon\, Sxy}\,\{g(s,t)\} \qquad \textit{for max filter} \qquad (2.7)$$

$$\hat{f}(x, y) = min_{(s,t)\varepsilon\, Sxy} \{g(s,t)\} \qquad \textit{for min filter} \qquad (2.8)$$

2.2.3 Midpoint Filter

This filter computes the midpoint between the maximum and minimum values in the area encompassed by the filter.

$$\hat{f}(x, y) = ½[max_{(s,t)\varepsilon\, Sxy} \{g(s,t)\} + min_{(s,t)\varepsilon\, Sxy} \{g(s,t)\}] \qquad (2.9)$$

2.2.4 Alpha-trimmed mean filter

In Alpha-trimmed filter the d/2 lowest and d/2 highest intensity values of $g(s,t)$ in the neighborhood S_{xy} are deleted and the remaining $mn\text{-}d$ pixels are averaged. The center pixel value is replaced with this averaged value.

The estimation function for the restored image is given by

$$\hat{f}(x,y) = \frac{1}{mn-d} \sum_{(s,t)\in Sxy} gr(s,t) \tag{2.10}$$

2.3 Adaptive Filters

The behavior of the Adaptive filters changes with the statistical characteristics of the image inside the filter window. Therefore the performance of Adaptive filters is much better in comparison with the non-adaptive filters. But the improved performance is at the cost of added filter complexity.

Mean and variance are two important statistical measures on which the adaptive filtering is depends upon. For example if the local variance is high compared to the overall image variance, the filter should return a value close to the present value. Because high variance is usually associated with edges and edges should be preserved.

CHAPTER 3

FREQUENCY DOMAIN FILTERING

INTRODUCTION

Image smoothing and image sharpening can be achieved by frequency domain filtering. Smoothing is done by high frequency attenuation i.e. by low pass filtering. Sharpening is done by high pass filtering which attenuates the low frequency components without disturbing the high frequency components.

3.1 Low pass filters

3.1.1 Ideal Low Pass Filter

A 2-D low pass filter that passes without attenuation all frequencies within a circle of radius D_o from the origin of the frequency spectrum rectangle. It cuts off all frequencies outside the circle. An ideal low pass filter can be represented by

$$H(u,v)=\begin{cases} 1 \;\; if \;\; D(u,v) \;\leq\; Do \\ 0 \;\; if \;\; D(u,v) \;\geq\; Do \end{cases} \tag{3.1}$$

Where $D(u,v)= [(u\text{-}P/2)^2 + (v\text{-}Q/2)^2]^{1/2}$ is the distance between a point (u,v) and the center of the frequency spectrum rectangle.

3.1.2 Gaussian Low Pass Filter

Gaussian low pass filters have the form

$$H(u,v) = exp\{-D^2(u,v)/D^2{}_o\} \qquad (3.2)$$

where $D(u,v)= [(u\text{-}P/2)^2 + (v\text{-}Q/2)^2]^{1/2}$

3.1.3 Butterworth Low Pass Filters

Butterworth low pass filter (BLPF) of order n having cutoff frequency at a distance D_o from origin has the transfer function

$$H (u,v) = 1/1+[D(u,v)/D_o]^{2n} \qquad (3.3)$$

For higher orders, the butterworth filter approaches to ideal low pass filter.

For lower orders, the butterworth filter approaches to Gaussian low pass filter.

3.2 High pass filters

3.2.1 Ideal High Pass Filter

A 2-D high pass filter is defined as

$$H(u,v) = \begin{cases} 0 & if \;\; D(u,v) \leq Do \\ 1 & if \;\; D(u,v) \geq Do \end{cases} \qquad (3.4)$$

It is the opposite of the ideal high pass filter.

$$H_{IHP}(u,v) = 1 - H_{ILP}(u,v) \qquad (3.5)$$

3.2.2 Gaussian High Pass Filter

The transfer function of the Gaussian high pass filter (GHPF) with cutoff frequency, locus at a distance D_o from the center of the frequency rectangle is given by

$$H(u,v) = 1 - exp[-D^2(u,v)/D_o^2] \qquad (3.6)$$

where $D(u,v) = [(u-P/2)^2 + (v-Q/2)^2]^{1/2}$

It is the opposite of Gaussian low pass filter.

$$H_{GHP}(u,v) = 1 - H_{GLP}(u,v) \qquad (3.7)$$

3.2.3 Butterworth High Pass Filters

A 2-D Butterworth high pass filter of order n and cutoff frequency D_o is defined as

$$H(u,v) = 1/1+[D_o/D(u,v)]^{2n} \qquad (3.8)$$

BHPFs give smoother images than IHPFs.

3.3 Wiener Filtering

Wiener filtering incorporates both the degradation function and statistical characteristics of noise into the restoration process. This method is found on considering images and noise as random variables, and the objective is to find an estimate f^ of the uncorrupted image f such that the mean square error between then is minimized.

The error measure is given by

$$e^2 = E\{\left(f - \hat{f}\right)^2\} \qquad (3.10)$$

In the frequency domain $\hat{f}$ is given by

$$\hat{F}\ (u,v) = [H^*(u,v)S_f(u,v)/\{S_f(u,v)|H(u,v)|^2 + S_n\,(u,v)\}]G(u,v) \qquad (3.11)$$

Chapter 4

Simulation and Results

4.1 Spatial Domain Filters

4.1.1 Mean Filters

4.1.1.1 Arithmetic Mean filter

Fig 4.1: (a) Image corrupted with Gaussian noise (b) Arithmetic mean filtered image

Noise %	PSNR (dB)	MSE
2%	64.2788	0.0243
10%	58.5324	0.0912
50%	52.9658	0.3285
80%	51.7971	0.4299

Table 4.1 List of PSNR and MSE values for different noise percentage.

4.1.1.2 Geometric Mean Filter

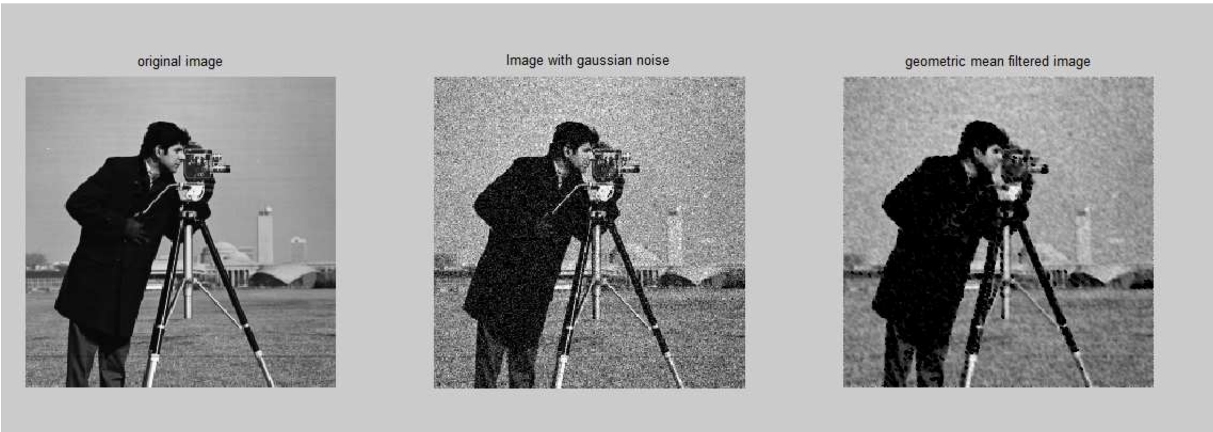

fig 4.2: (a)Original image (b)Image with gaussian noise (c)Geometric mean filtered image.

Noise %	PSNR (dB)	MSE
2%	64.2788	0.0243
10%	58.5324	0.0912
50%	52.9658	0.3285
80%	51.7971	0.4299

Table 4.2 List of PSNR and MSE values for different noise percentage.

4.1.1.3 Harmonic Mean Filter

fig 4.3: (a)Original image (b)Image with salt and pepper noise (c)Harmonic mean filtered image

Noise %	PSNR (dB)	MSE
2%	64.2788	0.0243
10%	58.5324	0.0912
50%	52.9658	0.3285
80%	51.7971	0.4299

Table 4.3 List of PSNR and MSE values for different noise percentage.

4.1.2 Order Statistic Filters

4.1.2.1 Median Filter

fig 4.4: (a) Image with salt and pepper noise (b)Image after median filtering.

Noise %	PSNR (dB)	MSE
2%	62.3216	0.0381
10%	57.3508	0.1197
50%	52.6694	0.3517
80%	51.6770	0.4420

Table 4.4 List of PSNR and MSE values for different noise percentage.

4.1.2.2 Max Filter

fig 4.5: (a)Original image (b)Image with salt and pepper noise (c)Max filtered image

Noise %	PSNR (dB)	MSE
2%	62.3216	0.0381
10%	57.3508	0.1197
50%	52.6694	0.3517
80%	51.6770	0.4420

Table 4.5 List of PSNR and MSE values for different noise percentage.

4.1.2.3 Min Filter

fig 4.6: (a)Original image (b)Image with salt and pepper noise (c)Min filtered image

Noise %	PSNR (dB)	MSE
2%	62.3216	0.0381
10%	57.3508	0.1197
50%	52.6694	0.3517
80%	51.6770	0.4420

Table 4.6 List of PSNR and MSE values for different noise percentage.

4.1.2.4 Midpoint Filter

fig 4.7: (a)Original image (b)Image with salt and pepper noise (c)Mid point filtered image

Noise %	PSNR (dB)	MSE
2%	62.3216	0.0381
10%	57.3508	0.1197
50%	52.6694	0.3517
80%	51.6770	0.4420

Table 4.7 List of PSNR and MSE values for different noise percentage.

4.1.2.5 Alpha-trimmed mean Filter

fig 4.8: (a)Original image (b)Image with salt and pepper noise (c)Alpha-trimmed filtered image

Noise %	PSNR (dB)	MSE
2%	53.7408	0.2748
10%	53.5394	0.2878
50%	52.2348	0.3887
80%	51.5332	0.4568

Table 4.8 List of PSNR and MSE values for different noise percentage.

4.1.3 Adaptive filter

4.1.3.1 Local noise reduction filter

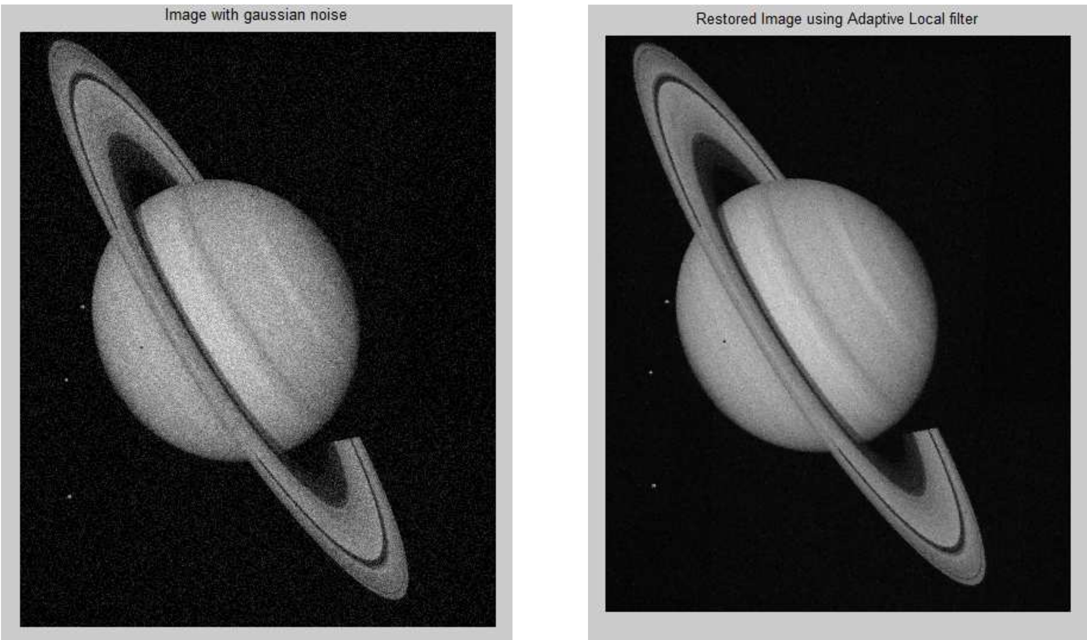

fig 4.9 (a) Image with Gaussian noise (b)Restored Image using Adaptive Local filter

4.2 Frequency Domain Filters

4.2.1 Ideal Low Pass Filter

fig 4.10: (a)Original image (b)Filtered Image

4.2.2 Gaussian Low Pass Filter

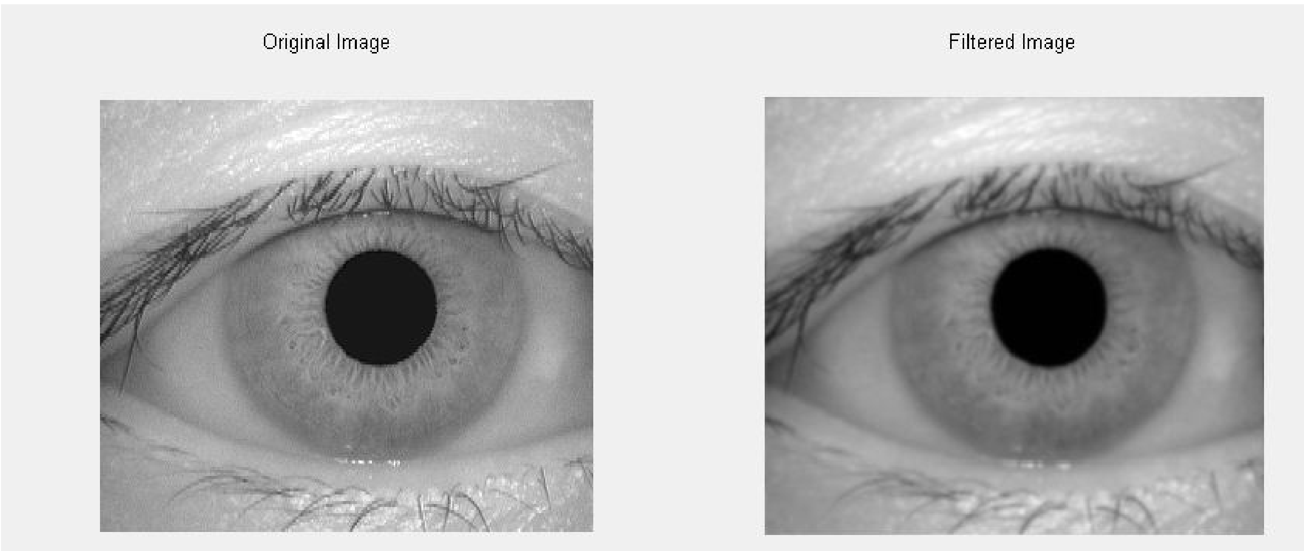

fig 4.11: (a)Original image (b)Filtered Image

4.2.3 Butterworth Low Pass Filters

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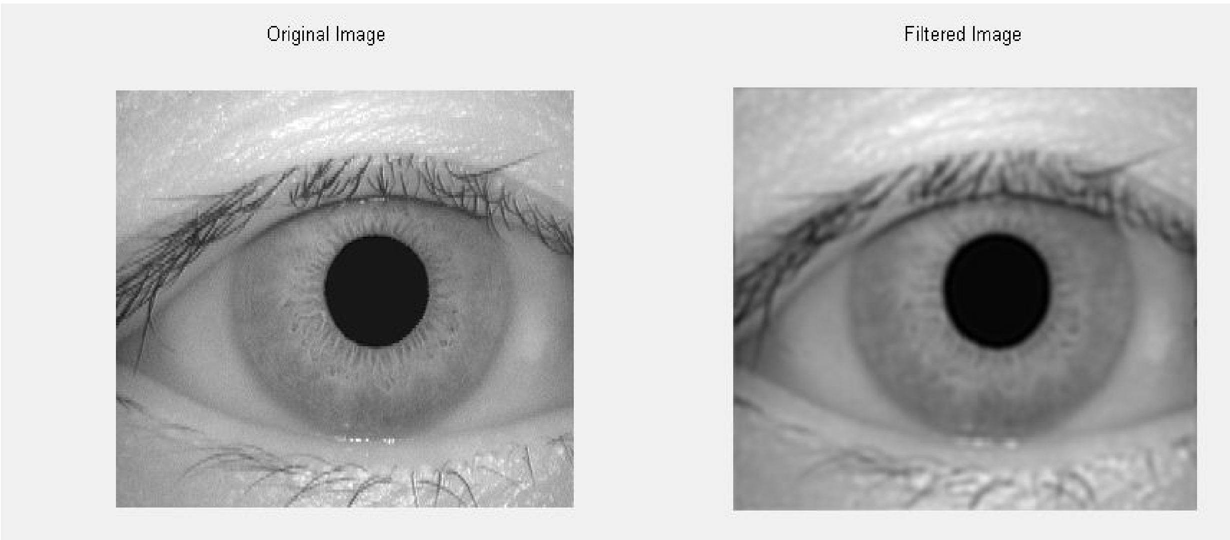

fig 4.12: (a)Original image (b)Filtered Image

4.2.4 Ideal High Pass Filter

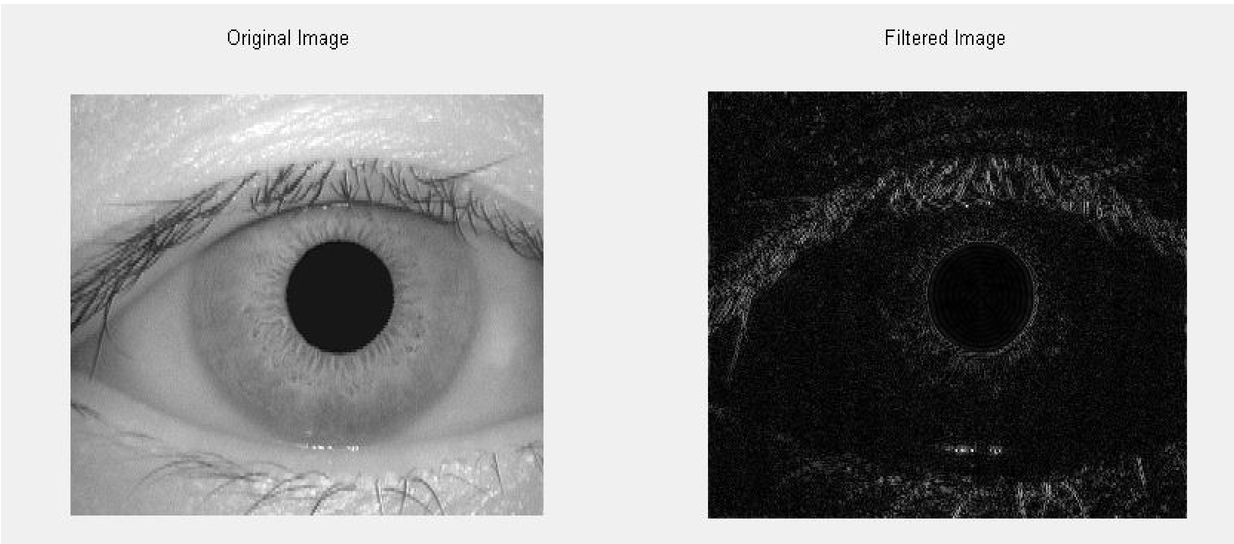

fig 4.13: (a)Original image (b)Filtered Image

4.2.5 Gaussian High Pass Filter

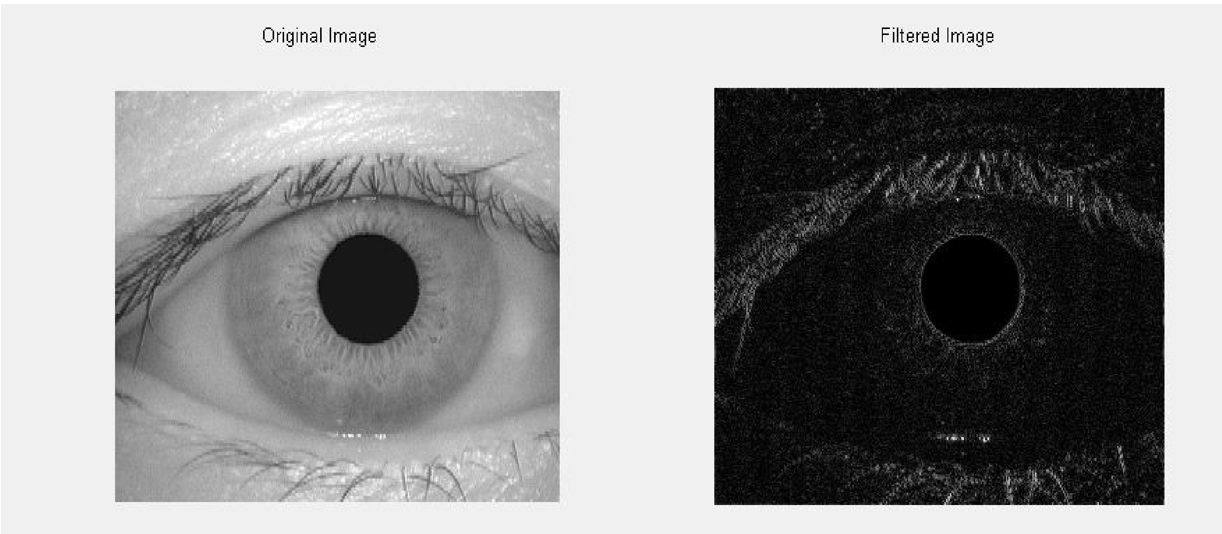

fig 4.14: (a)Original image (b)Filtered Image

4.2.6 Butterworth High Pass Filters

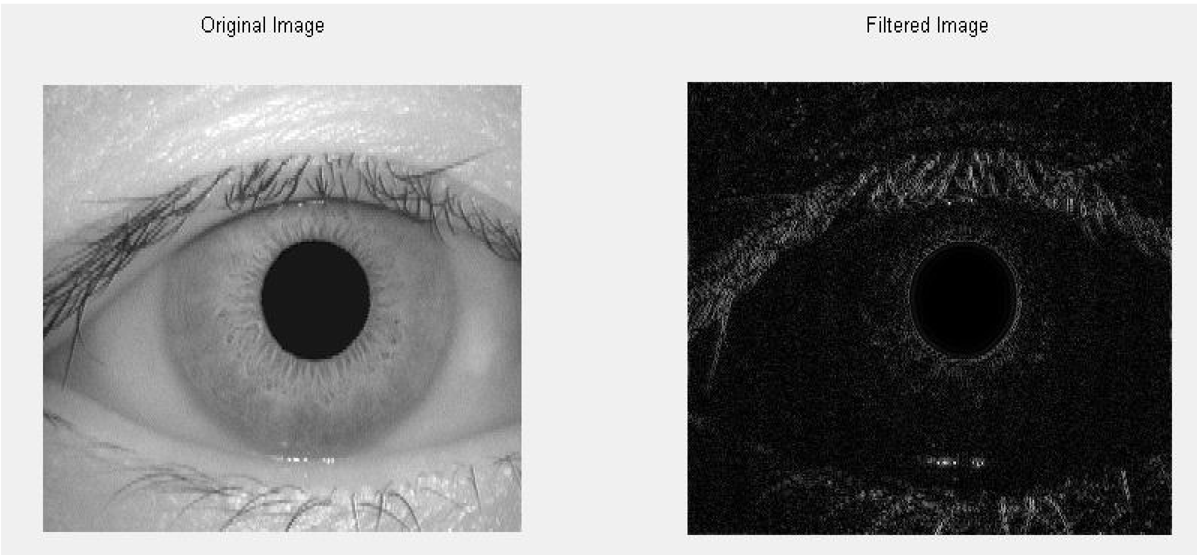

fig 4.15: (a)Original image (b)Filtered Image

4.2.7 Wiener Filtering

fig 4.16: Wiener filtering

CONCLUSIONS AND FUTURE WORK

Among mean filters, geometric mean filter smoothens images and loses less image detail. Harmonic filter works best with salt noise only. Contraharmonic mean filter can be used to filter both salt and pepper noise combined. Median filters are effective in presence of unipolar and bipolar impulse noise. Max filter is useful for finding brightest points and thus reduces pepper noise. Min filter is useful for finding darkest points and thus reduces salt noise. Midpoint filters work best for randomly distributed noise like gaussian noise or uniform noise. Alpha-trimmed mean filter is useful in situations involving multiple noise, such as combination of salt and pepper noise and Gaussian noise. Low pass filters are used in image smoothening. High pass filters are used in image sharpening. Adaptive local filters help in reducing local variances in an image. Frequency domain filters such as high pass filters help in preserving the image details such as edges.

The work done is only on gray scale images. It can be extended to coloured images. Image restoration mainly required prior knowledge of the degradation function. Techniques can be developed to estimate these degradation functions more accurately.

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