ISSN: 0976-9102(ONLINE)
DOI: 10.21917/ijivp.2012.0072

IMAGE RESTORATION: DESIGN OF NON-LINEAR FILTER (LR)

Shenbagarajan Anantharajan[1], A. Siva Ganesh[2], V. Rajesh Kumar[3] and C. Balasubramanian[4]
[1,3]Department of Computer Science and Engineering, P.S.R. Rengasamy College of Engineering for Women, India
E-mail: [1]asrme2008@gmail.com and [3]merajeshkumar2009@gmail.com
[2,4]Department of Computer Science and Engineering, P.S.R. Engineering College, India
E-mail: [2]sivaganesh@gmail.com and [4] rc.balasubramanian@gmail.com

Abstract
In this proposed method, various types of noise models are subjected to an image and apply the nonlinear filter to reconstruct the original image from degraded image. Image restoration is a technique to attempt of reconstructs the original image by using a degraded phenomenon. In this paper the Lucy-Richardson filter is reconstruct the degraded image which closely resembles the original image. This paper deals with the various noise models and nonlinear filter. Objective of this paper is to study the various noise models and restoration filters in depth at restoration area.

Keywords:
Noises, Non Linear Filter, Restoration, Convolution

1. RESTORATION PROCESS

The aim of image restoration is the removal of noise (sensor noise, motion blur, etc.) from images. The simplest possible approach for noise removal is various types of filters such as low-pass filters or median filters. More sophisticated methods assume a model of how the local image structures look like, a model which distinguishes them from the noise. By first analyzing the image data in terms of the local image structures, such as lines or edges, and then controlling the filtering based on local information from the analysis step, a better level of noise removal is usually obtained compared to the simpler approaches. The Fig.1 shows the example of damaged and restored image.

(a) Damaged Image (b) Restored Image

Fig.1. Example of Image Restoration

Restoration attempts to reconstruct or recover an image that has been degraded by using a priori knowledge of the degraded phenomenon. Thus, restoration techniques are oriented toward modeling the degradation and applying the inverse process in order to prevent the original image.

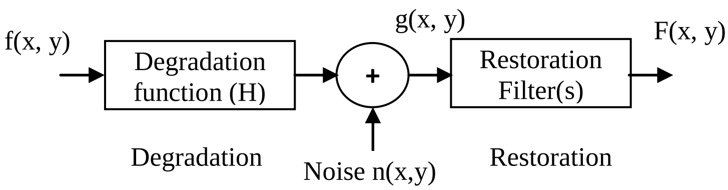

Fig.2. Model of the image degradation/restoration process

where,

g(x,y) is degraded image,

H is degradation function,

f(x,y) is given input image,

F(x,y) is restored image and

n(x,y) is additive noise.

2. NOISE MODELS

The ability to provide the behaviour and effects of noise is central to image restoration. There are two basic types of noise models. They are noise in the spatial domain and noise in the frequency domain, described by various Fourier properties of the noises. Some of the additive noises are,

- Gaussian Noise
- Salt & Pepper Noise
- Lognormal Noise
- Rayleigh Noise
- Exponential Noise
- Erlang Noise

3. RESTORATION FILTER

To restore degraded image using the nonlinear filter concept developed by Lucy-Richardson algorithm.

4. LUCY-RICHARDSON FILTER

It is a nonlinear filter. Lucy-Richardson (LR) algorithm arises from maximum likelihood function (Convolution Function) in which the image modeled with Poisson statistics. This approach often followed is to observe the output and stop the algorithm when a result acceptable in a given application has been obtained.

L-R nonlinear filter is obtained by the function is deconvlucy from Image Processing Toolbox, L-R's basic syntax is

O = deconvlucy(I, PSF, NUMIT, DAMPAR, WEIGHT)

where,

- "O" is the restored image,
- "I" is the degraded image,
- "PSF" is the Point Spread Function,
- "NUMIT" is the number of iterations,

- "DAMPAR" is the threshold deviation of the resulting image from input image (i), default value is 0(no damping),
- "WEIGHT" is an array size as i that assigns a weight to each pixel to reflect its quality.

Features of Lucy-Richardson filters are,

- Iterative in nature, inexpensive computational power.
- Compared to linear techniques, broad spectrum of applications.

5. ANALYSIS DESCRIPTION

This paper focuses the image restoration using nonlinear filter which implements Lucy-Richardson algorithm. Restoration attempts to reconstruct or recover an image that has been degraded by using a priori knowledge of the degraded phenomenon. Thus, restoration techniques are oriented toward modeling the degradation and applying the inverse process in order to prevent the original image[1] from blur effects and noises.

In this paper various noise models like gaussian noise, erlang noise, salt & pepper noise, lognormal noise & exponential noise[1] are subjected to an original image. Representing the pixel damages in original image using histogram technique, while comparing the damaged image of various noises subjected. Applying the nonlinear Lucy-Richardson filter to restore the image. The principle of image restoration using Lucy-Richardson algorithm is the blurred and noisy image is restored by the iterative, accelerated, damped Lucy-Richardson algorithm [5]. Analyzing the efficiency of filter used in this project for various noises applied to the original image.

Degraded image is taken as an input to non-linear Lucy-Richardson filter and applying the filter for restoring the degraded image by number of limited iterations, obtaining the restored image which resembles the original image.

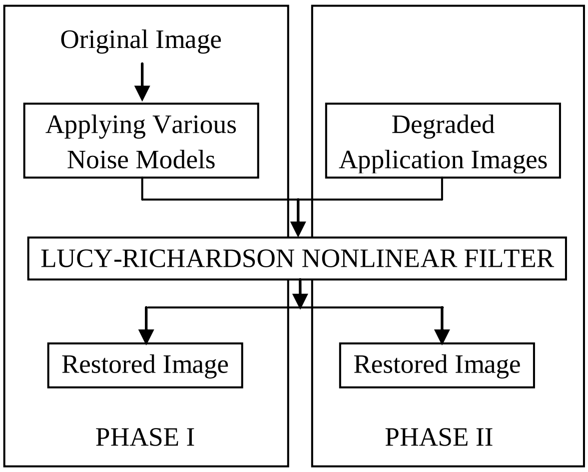

Fig.3. Functional Block Diagram

6. METHODOLOGY

* Input:
  Original Image
* Adding Noise:
  - GAUSSIAN NOISE
  - ERLANG NOISE
  - SALT & PEPPER NOISE
  - LOGNORMAL NOISE
  - EXPONENTIAL NOISE

  &Input: Original Image

  &Output: Degraded Image
* Filter:
  Input: Degraded Image
  Output: Reconstructed Image

7. OBSERVATIONS

In this system, consider an image which is non-degraded and apply the noise externally, i.e., knowing value of mean, variance and noise density of the noise applied to an image. Calculate the PSNR value between the input and noise added image for further purpose. Apply the number of iterations and calculate the PSNR value between noisy image and restored image till obtaining the highest PSNR value, because highest value provides the better quality image. As well as compared with the wiener and blind deconvolution filters obtain the PSNR values for analyzing the performance of my Lucy-Richardson Filter. The Table.1 has the list of grayscale images as input image.

Table.1. List of Grayscale Images (Non Degraded Images)

Sl. No.	Image name	Size(KB)	Dimension
1	Man.tif	21.9	88*127
2	Image(4).jpg	29.4	110*130
3	Time.bmp	126	208*208
4	Cameraman.jpg	56.9	256*256
5	Resim.jpg	29.4	424*530
6	Lena.jpg	30	512*512

Table.2 shows the PSNR value between input image and Gaussian noise applied image (mean = 0.05, variance = 0.07) number of iterations and PSNR value between restored and input image.

Table.2. LR Filter's Performance of Gaussian Noise on Grayscale Images

Sl. No.	Image	PSNR B/W I/N image	No. of iterations
1	Man.tif	12.49	3
2	Image(4).jpg	12.88	7
3	Time.jpg	12.29	1
4	Cameraman.jpg	12.53	5
5	Resim.jpg	12.52	8
6	Lena.jpg	12.34	1

Table.3 shows the PSNR value between input image and salt & pepper noise applied image (noise density = 0.05), number of iterations and PSNR value between restored and input image.

Table.3. LR Filter's Performance of Salt & Pepper Noise on Grayscale Images

Sl. No.	Image	PSNR B/W I/N image	No. of iterations	PSNR B/W I/R image
1	Man.tif	18.34	4	23.63
2	Image(4).jpg	17.56	6	22.10
3	Time.jpg	18.43	3	24.38
4	Cameraman.jpg	18.22	7	22.58
5	Resim.jpg	18.42	3	27.37
6	Lena.jpg	18.50	3	27.43

Table.4 shows the PSNR value between input image and speckle noise applied image (noise density = 0.08), number of iterations and PSNR value between restored and input image.

Table.4. LR Filter's Performance of Speckle Noise on Grayscale Images

Sl. No.	Image	PSNR B/W I/N image	No. of iterations	PSNR B/W I/R image
1	Man.tif	16.86	1	23.00
2	Image(4).jpg	17.30	6	22.08
3	Time.jpg	16.84	2	24.29
4	Cameraman	16.64	8	22.33
5	Resim.jpg	18.98	12	24.05
6	Lena.jpg	16.89	2	26.91

Table.5 shows the PSNR value between the input image and Gaussian (mean = 0.05, variance = 0.07) and salt & pepper noise applied image (noise density = 0.05), number of iterations and PSNR value between restored and input image.

Table.5. LR Filter's Performance of Gaussian and Salt & Pepper Noise on Grayscale Images

Sl. No.	Image	PSNR B/W I/N image	No. of iterations	PSNR B/W I/R image
1	Man.tif	11.58	2	20.58
2	Image(4)	11.82	5	18.59
3	Time.jpg	11.53	1	20.78
4	Cameraman	11.62	4	19.04
5	Resim.jpg	11.54	5	17.65
6	Lena.jpg	11.56	5	21.60

Table.6 shows the PSNR value between input image and speckle (variance = 0.05) and salt & pepper noise applied image (noise density = 0.08), number of iterations and PSNR value between restored and input image.

Table.6. LR Filter's Performance of Speckle and Salt & Pepper Noise on Grayscale Images

Sl. No.	Image	PSNR B/W I/N image	No. of iterations	PSNR B/W I/R image
1	Man.tif	14.92	4	22.48
2	Image(4)	14.84	6	21.33
3	Time.jpg	14.94	2	23.81
4	Cameraman	14.70	8	21.67
5	Resim.jpg	15.64	6	22.58
6	Lena.jpg	15.03	4	25.71

Table.7 contains the list of color images which noise models are affected.

Table.7. List of Color Images

Sl. No.	Image	Size (KB)	Dimension
1	Lady.jpg	2.62	65*137
2	Flower.jpg	3.91	124*93
3	Man.jpg	21.6	491*312
4	Lena.jpg	67.5	512*512
5	Cat.jpg	259	600*900
6	Highest.jpg	1100	1597*1200

Table.8 shows the PSNR value between input image and Gaussian noise (mean = 0.05, variance = 0.07) on color image, number of iterations and PSNR value between restored and input image.

Table.8. LR Filter's Performance of Gaussian Noise on Color Images

Sl. No.	Image	PSNR B/W I/N image	No of iterations	PSNR B/W I/R image
1	Lady	13.484	6	18.257
2	Flower	14.081	12	17.366
3	Man	20.617	1	20.617
4	Lena	12.561	1	22.458
5	Cat	12.358	1	21.256
6	Highest	14.1917	1	24.137

Table.9 shows the PSNR value between input image and salt & pepper noise (noise density = 0.08) to color image, number of iterations and PSNR value between restored and input image.

Table.9. LR Filter's Performance of Salt & Pepper Noise on Color Images

Sl. No.	Image	PSNR B/W I/N image	No of iterations	PSNR B/W I/R image
1	Lady	17.304	8	19.678
2	Flower	16.951	16	19.470
3	Man	17.627	1	26.970
4	Lena	18.165	2	27.057
5	Cat	18.42	6	24.645
6	Highest	17.094	1	29.923

Table.10 shows the PSNR value between input image and speckle noise (variance = 0.07) of color image, number of iterations and PSNR value between restored and input image.

Table.10. LR Filter's Performance of Speckle Noise on Color Images

SI. No	Image	PSNR B/W I/N image	No of iterations	PSNR B/W I/R image
1	Lady	16.308	6	19.142
2	Flower	15.939	15	17.48
3	Man	19.670	1	26.686
4	Lena	16.913	2	26.004
5	Cat	16.592	6	24.15
6	Highest	14.825	1	22.721

Table.11 shows the PSNR value between input image and Gaussian noise (mean = 0.05, variance = 0.07) and Salt & pepper noise (noise density = 0.05) on color image, number of iterations and PSNR value between restored and input image.

Table.11. LR Filter's Performance of Gaussian and Salt & Pepper Noise on Color Images

Sl. No.	Image	PSNR B/W I/N image	No of iterations	PSNR B/W I/R image
1	Lady	12.115	8	17.523
2	Flower	12.317	12	16.324
3	Man	11.557	1	19.668
4	Lena	11.679	1	21.869
5	Cat	11.566	1	20.928
6	Highest	12.543	1	22.353

Table.12 shows the PSNR value between input image and speckle noise (variance = 0.08) and Salt &pepper noise (noise density = 0.05) on color image, number of iterations and PSNR value between restored and input image.

Table.12. LR Filter's Performance of Speckle and Salt & Pepper Noise on Color Images

Sl. No.	Image	PSNR B/W I/N image	No of iterations	PSNR B/W I/R image
1	Lady	14.098	6	18.394
2	Flower	13.528	11	16.419
3	Man	16.142	1	25.382
4	Lena	14.891	2	24.773
5	Cat	14.795	3	23.607
6	Highest	12.978	1	20.882

From the above results obtained by my project, observed the following facts for color and gray scale images. If the size of the image, good resolution of image, dimension of image increases, attack of noise models are get decreased in color images. When the size of the image increases, number of iterations gets decreases in color image. As well as number of iterations depends on the color and good resolution of image of the color image. In grayscale image, number of iterations directly proportional to the size and its properties. Attack of noise in grayscale image increases according to its size.

Figure 4 shows the first phase output of grayscale image affected by Gaussian noise and its restored image with highest PSNR value and number of iterations.

Fig.4. Grayscale Image Output of Unknown noise model

Figure 5 shows the first phase output of color image affected by Gaussian noise and its restored image with highest PSNR value and its number of iterations.

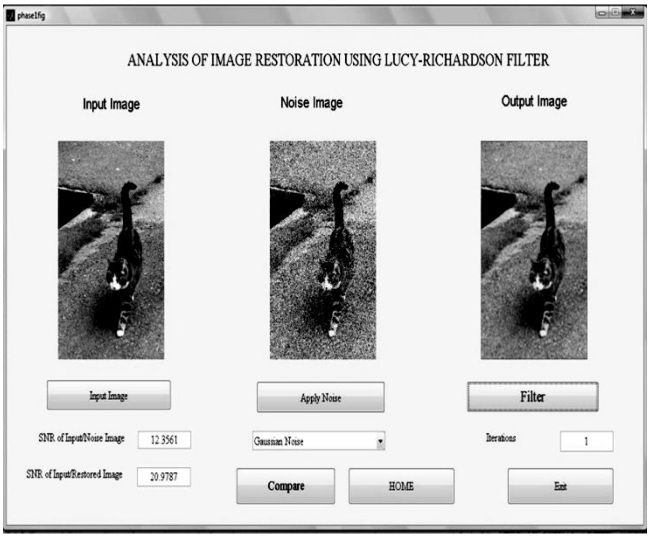

Fig.5. Color Image Output of Unknown noise model

8. REMOVAL OF UNKNOWN NOISE MODELS

In this system, consider an image which is degraded and contains the noise while taking pictures from cameras, i.e., unknown value of mean, variance and noise density of the noise applied to an image. Calculate the PSNR value between the input and noise added image for further purpose. Apply the number of iterations and calculate the PSNR value between noisy image and restored image till obtaining the highest PSNR value, because highest value provides the better quality image. As well compared with the wiener and blind deconvolution filters obtain the PSNR values for analyzing the performance of my Lucy-Richardson Filter.

Table.13 shows the PSNR value between input image as degraded grayscale image i.e., unknown noise values and number of iterations.

Table.13. LR Filter Performance on Grayscale Noise Image

Sl. No.	No of Iterations	PSNR Value
1	5	12.1874
2	10	12.8443
3	15	13.2801
4	20	13.6053
5	25	13.8634
6	30	14.0562
7	35	14.2095
8	40	14.3336
9	45	14.4344
10	50	14.5169

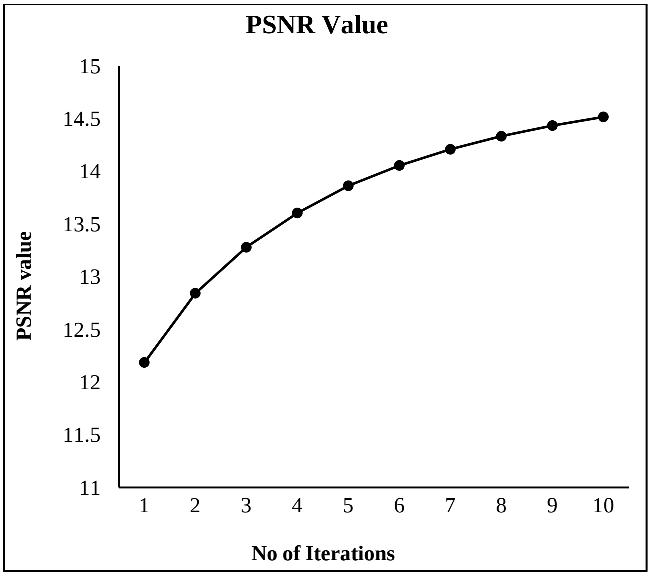

Fig.6. Graph of LR Filter Performance on Grayscale Noise Image

The graph provides the result of Lucy-Richardson filter's performance on grayscale image as the PSNR value is directly proportional to the number of iterations.

Table.14 shows the Comparison of the PSNR values with Lucy-Richardson filter, wiener filter and blind deconvolution for grayscale image.

Table.14. Comparison of the PSNR Values with Lucy-Richardson Filter, Wiener Filter and Blind Deconvolution for Grayscale Image

Sl. No.	Image	No of Iterations	LR Filter	Wiener Filter	Blind Deconvolution
1	Castlenoisy	22	20.29	19.57	20.29
2	Barbara	27	19.82	19.45	19.82
3	Speckleroad	7	24.02	20.10	23.99

Table.15 shows the PSNR value between input image as degraded color image i.e., unknown noise values and number of iterations.

Table.15. LR Filter Performance on Color Image with Unknown Noise Value

Sl. No.	No of iterations	PSNR value
1	1	20.8755
2	5	21.0336
3	6	21.0209
4	7	20.9946
5	8	20.9599
6	9	20.9221
7	10	20.8832
8	11	20.843

9	12	20.7993
10	13	20.7527
11	14	20.7006
12	15	20.6437
13	20	20.3105

The graph shows the Lucy-Richardson filter performance on color image as the value of PSNR increases to certain iteration and it decreases the number of iterations gets increased.

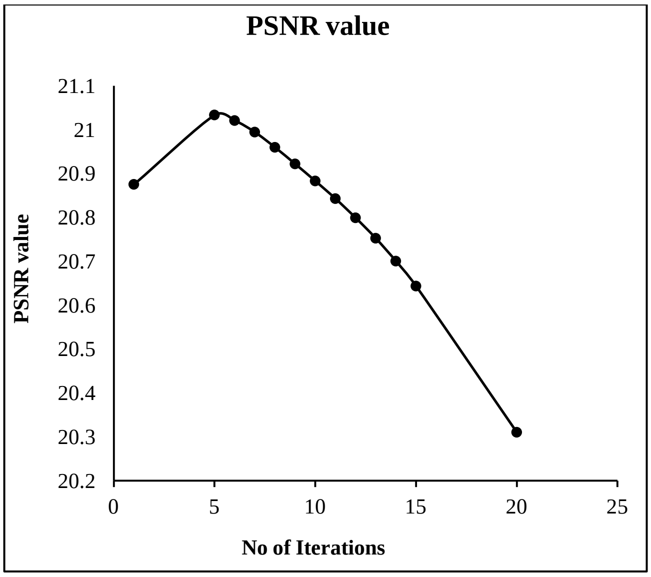

Fig.7. Graph of LR Filter Performance on Color Degraded Image

Table.16 shows the comparison of PSNR values with Lucy-Richardson filter, wiener filter and blind deconvolution for color image.

Table.16. Comparing the PSNR Values of Lucy-Richardson Filter, Wiener Filter and Blind Deconvolution for Color Image

Sl. No.	Image	No of Iterations	LR Filter	Wiener Filter	Blind Deconvolution
1	Moiré-patt	1	23.99	16.54	23.99
2	Grain-alias	1	26.18	16.02	26.18
3	Nose-taj	5	21.03	18.45	21.0
4	Noisy-Cannon	12	20.78	19.35	20.78

From the above results, Lucy Richardson filter provides the best result on color images than grayscale images. In grayscale image, number of iteration gets increased with the PSNR value, this results takes much more time reconstruct the image as much as close as clear image.

In color images Lucy-Richardson filter produces best result i.e., highest PSNR value in limited number of iterations and takes minimum time to restore the color image. The obtained Lucy Richardson filter results compared with Wiener filter and Blind deconvolution, for color images LR provides better result than wiener and close to the blind deconvolution technique for the same number of iterations. Similarly, for grayscale image also. Lucy- Richardson filter provides best result than wiener and blind deconvolution method.

Figure 8 shows the output of grayscale degraded image unknown noise value and the restored image with the highest PSNR value and number of iterations.

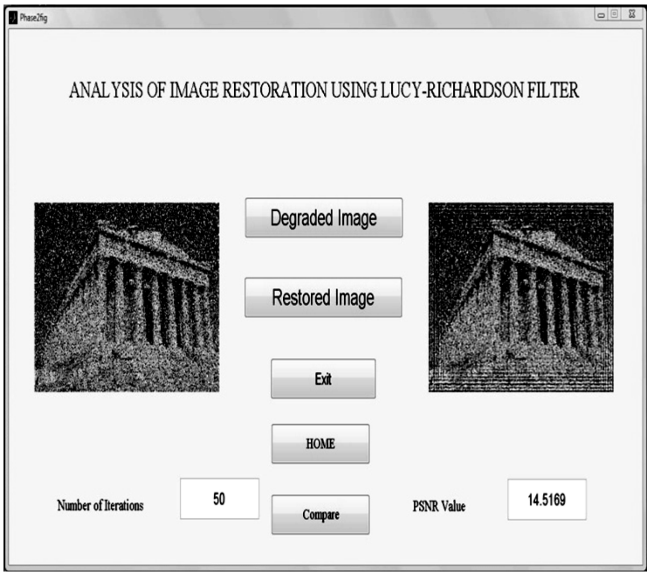

Fig.8. Grayscale image output of Known noise model

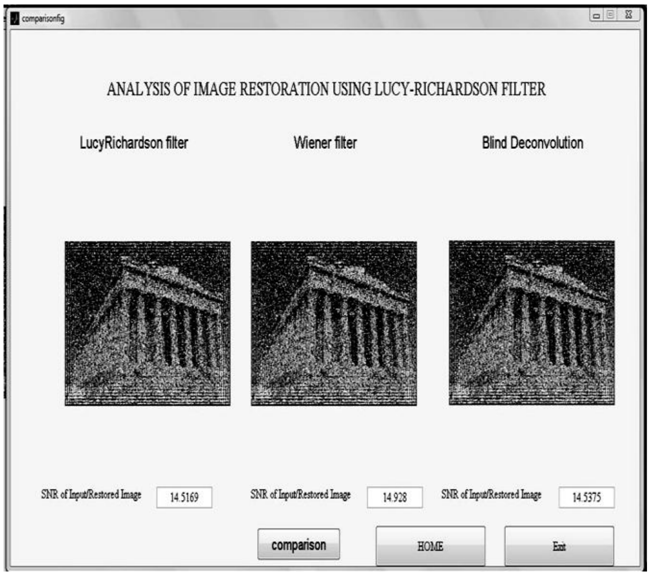

Fig.9. Comparison of Lucy-Richardson, Wiener and Blind Deconvolution restored gray scale image of Known noise model

Figure 9 shows the output of grayscale degraded image (unknown noise value) and the restored image by Lucy-Richardson filter, Wiener filter and Blind deconvolution with the highest PSNR value.

Figure 10 shows the output of grayscale degraded image unknown noise value and the restored image with the highest PSNR value and number of iterations.

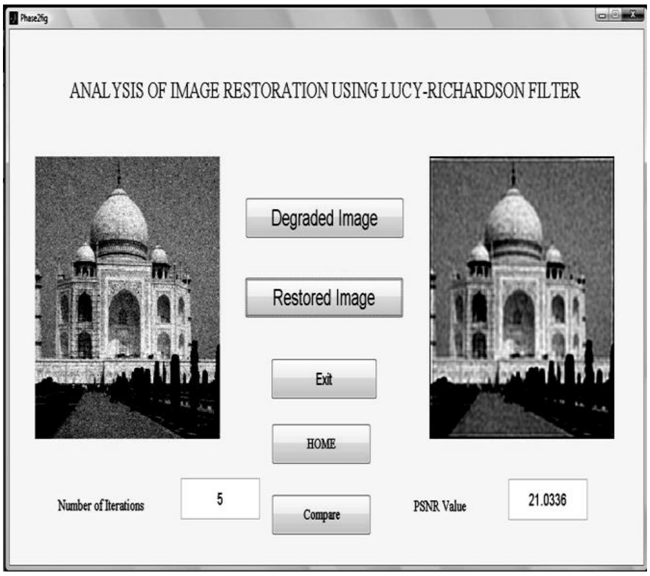

Fig.10. Color image output of known noise model

Figure 11 shows the output of color degraded image (unknown noise value) and the restored image by Lucy-Richardson filter, Wiener filter and Blind deconvolution with the highest PSNR value.

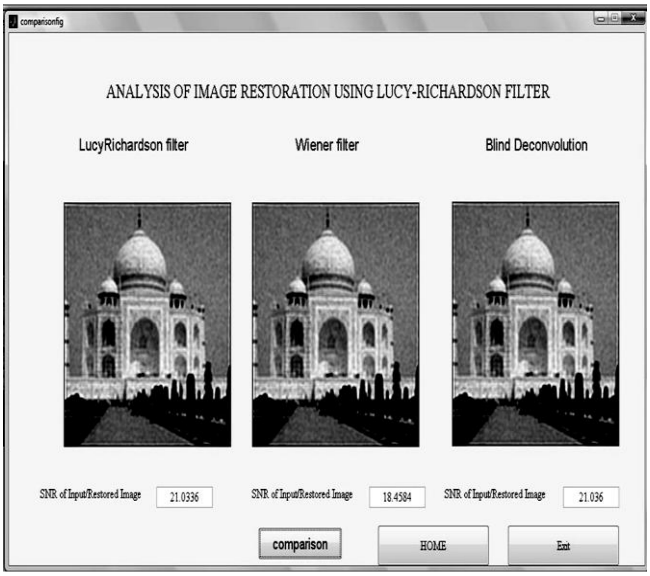

Fig.11. Comparison of Lucy-Richardson, Wiener and Blind Deconvolution restored color image of known noise model

9. CONCLUSION

In this paper, Lucy-Richardson filter performances are analyzed by comparing the PSNR values and number of iterations with the noise models (mean, density and variance known). Lucy-Richardson filter applied to both the color and grayscale images as well as compared the results with the filters like wiener filter and blind deconvolution filter in first phase. Number of iterations in my filter varies on the size of the image and its resolutions. Similarly, my filter applied to the degraded images which noise values are unknown. By end of the result, Lucy-Richardson filter provides best result than other two filters for grayscale image. For color images, Lucy-Richardson provides the results better than wiener filter and as much as close to the blind deconvolution technique for same number of iterations considered for all the filters. Thus, all the observations are noted and its results are analyzed. From the results, I concluded my filter is better than the wiener and blind deconvolution filter.

REFERENCES

[1] Rafael C. Gonzalez, Richard E. Woods and Steven L. Eddins, “*Digital Image Processing Using MATLAB*”, Pearson Prentice Hall, 2003.
[2] Rafael C. Gonzalez and Richard E. Woods, “*Digital Image Processing*”, Prentice Hall, 2008.
[3] A.K. Jain, “*Fundamentals of Digital Image Processing*”, Prentice Hall, 1989.
[4] Pitas I and A.N. Venetsanopoulos, “Nonlinear Mean Filters in Image Processing”, *IEEE Transactions on Acoustics, Speech and Signal Processing*, Vol. 34, No.3, pp. 573-584, 1986.
[5] http://en.wikipedia.org/wiki/Linear_filter
[6] http://en.wikipedia.org/wiki/Nonlinear_filter
[7] http://www-rohan.sdsu.edu/doc/matlab/toolbox/images/deblurr8.html
[8] http://www.mathworks.com/applications/imageprocessing/demos.html?file=/products/demos/shipping/images/ipexlucy.html
[9] http://www.owlnet.rice.edu/~elec539/Projects99/BACH/proj2/intro.html
[10] http://en.wikipedia.org/wiki/noise models
[11] http://en.wikipedia.org/wiki/signal-to-noise ratio
[12] MATLAB help
[13] www.google.com(For all degraded and noise free images)