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

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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 to reconstruct 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.

![Example of Image Restoration](image1.png)

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.

![Model of the image degradation/restoration process](image2.png)

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

\[
O = \text{deconvlucy}(I, \text{PSF}, \text{NUMIT}, \text{DAMPAR}, \text{WEIGHT})
\]

where,

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

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.jpg   | 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.

| Sl. No. | Image name | Size(KB) | Dimension |
|--------|------------|----------|-----------|
| 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 shows the 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

| Sl. 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.

514
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    |

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       | Castlnoisy  | 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     |
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.

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

| Sl. No. | Image           | No of Iterations | PSNR Value of LR Filter | PSNR Value of Wiener Filter | PSNR Value of 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.

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.
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.

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