# IMAGE RESTORATION USING LUCY-RICHARDSON ALGORITHM

P.Manga Rao[1],M.Ashok[2] ,G.Mahesh[3],M.Gnanesh Goud[4]

*Electronics and Communication Engineering Dept[1, 2,3,4] TKR College of Engineering and Technology, Affiliated to JNTUH Hyderabad, Telangana, India.*

***Abstract:*** *Image restoration is the process of recovering the original image from the degraded image. Aspire of the project is to restore the blurred/degraded images using Lucy-Richardson algorithm. The fundamental task of Image deblurring is to de-convolute the degraded image with the PSF that exactly describe the distortion. Firstly, the original image is degraded using the Degradation Model. Lucy-Richardson algorithm is applied to the blurred image. It is possible to renovate the original image with having specific knowledge of degradation filter, additive noise and PSF.*

***Key Words:*** *Image, PSF, Gaussian noise, Regular filter.*

## I.INTRODUCTION

The **deconvlucy** function is used to deblur an image using the accelerated,damped, Lucy-Richardson algorithm. The algorithm maximizes the likelihood that the resulting image, when convolved with the PSF[1], is an instance of the blurred image, assuming Poisson noise statistics. This function can be effective when you know the PSF but know little about the additive noise in the image.

**Understanding Deblurring**: This section provides some background on deblurring techniques[2]. The section includes these topics:

- Causes of Blurring
- Deblurring Model

**Causes of Blurring:** The blurring, or degradation, of an image can be caused by many factors:

(i) Movement during the image capture process, by the camera or, when long exposure times are used, by the subject.

(ii) Out-of-focus optics, use of a wide-angle lens, atmospheric turbulence, or a short exposure time, which reduces the number of photons capture.

(iii) Scattered light distortion in confocal microscopy

**Deblurring Model:** A blurred[2] or degraded image can be approximately described by the equation: $g=Hf + n$, where g-The blurred image, H-The distortion operator, also called the point spread function(PSF), f-The original true image, n-Additive noise

## II.POINT SPREAD FUNCTION (PSF)

The distortion operator, also called the point spread function(PSF)[1]. In the spatial domain, the PSF describes the degree to which an optical system blurs (spreads) a point of light. The PSF is the inverse Fourier transform of the optical transfer function (OTF)[2]. In the frequency domain, the OTF describes the response of a linear, position-invariant system to an impulse. The OTF is the Fourier transform of the point spread function (PSF). The distortion operator, when convolved with the image, creates the distortion. Distortion caused by a point spread function is just one type of distortion. Based on this model, the fundamental task of deblurring is to deconvolve the blurred image with the PSF that exactly describes the distortion. Deconvolution is the process of reversing the effect of convolution. The quality of the deblurred image is mainly determined by knowledge of the PSF.

The **fspecial** function to create a PSF that simulates a motion blur, specifying the length of the blur in pixels, (LEN=31), and the angle of the blur in degrees (THETA=11). Once the PSF is created, the example uses the **imfilter** function to convolve the PSF with the original image, to create the blurred image, Blurred. (To see how deblurring is the reverse of this process, using the same images, see “Deblurring with the Wiener Filter”[3].

**Deblurring functions:**

**deconvwnr** :Implements deblurring using the Wiener filter. **deconvreg :**Implements deblurring using a regularized filter **deconvlucy:**Implements deblurring using the Lucy-Richardson algorithm **deconvblind:**Implements deblurring using the blind deconvolution algorithm.

## III.WIENER FILTER

The most important technique for removal of blur in images due to linear motion or unfocussed optics is the Wiener filter[3]. From a signal processing standpoint, blurring due to linear motion in a photograph is the result of poor sampling. Each pixel in a digital representation of the photograph should represent the intensity of a single stationary point in front of the camera. Unfortunately, if the shutter speed is too slow and the camera is in motion, a given pixel will be an amalgram of intensities from points along the line of the camera's motion. This is a two-dimensional analogy to ***G(u,v)=F(u,v)H(u,v)*** where F is the fourier transform of an "ideal" version of a given image, and H is the blurring function.

## IV.DEBLURRING WITH THE LUCY-RICHARDSON ALGORITHM

The deconvlucy function implements several adaptations to the original Lucy-Richardson maximum likelihood algorithm[4] that address complex image restoration tasks. Using these adaptations, you can

• Reduce the effect of noise amplification on image restoration

• Account for non uniform image quality (e.g., bad pixels, flat-field variation)

• Handle camera read-out and background noise

• Improve the restored image resolution by sub sampling

The following sections provide more information about each of these adaptations.

### REDUCING THE EFFECT OF NOISE AMPLIFICATION:

Noise amplification is a common problem of maximum likelihood methods that attempt to fit data as closely as possible. After many iterations, the restored image can have a speckled appearance, especially for a smooth object observed at low signal-to-noise ratios. These speckles do not represent any real structure in the image, but are artifacts of fitting the noise in the image too closely.

To control noise amplification, the deconvlucy function uses a damping parameter[4], DAMPAR.This parameter specifies the threshold level for the deviation of the resulting image from the original image, below which damping occurs. For pixels that deviate in the vicinity of their original values, iterations are suppressed.

Damping is also used to reduce ringing, the appearance of high-frequency structures in a restored image. Ringing is not necessarily the result of noise amplification.

### ACCOUNTING FOR NONUNIFORM IMAGE QUALITY:

Another complication of real-life image restoration is that the data might include bad pixels, or that the quality of the receiving pixels might vary with time and position. By specifying the WEIGHT array[5] parameter with the deconvlucy function, you can specify that certain pixels in the image be ignored. To ignore a pixel, assign a weight of zero to the element in the WEIGHT array that corresponds to the pixel in the image.

The algorithm converges on predicted values for the bad pixels based on the information from neighborhood pixels. The variation in the detector response from pixel to pixel (the so-called flat-field correction) can also be accommodated by the WEIGHT array[5]. Instead of assigning a weight of 1.0 to the good pixels, you can specify fractional values and weight the pixels according to the amount of the flat-field correction.

### HANDLING CAMERA READ-OUT NOISE:

Noise in charge coupled device (CCD) detectors has two primary components:

• Photon counting noise with a Poisson distribution

• Read-out noise with a Gaussian distribution

The Lucy-Richardson iterations intrinsically account for the first type of noise. You must account for the second type of noise; otherwise, it can cause pixels with low levels of incident photons to have negative values.

The deconvlucy function uses the READOUT input parameter to handle camera read-out noise. The value of this parameter is typically the sum of the read-out noise variance and the background noise (e.g., number of counts from the background radiation). The value of the READOUT parameter specifies an offset that ensures that all values are positive.

### HANDLING UNDERSAMPLED IMAGES:

The restoration of undersampled data can be improved significantly if it is done on a finer grid. The deconvlucy function uses the SUBSMPL parameter to specify the subsampling rate, if the PSF is known to have a higher resolution.

## V.PROCEDURE

Step 1: Read Image

Step 2: Simulate a Blur

Step 3: Restore the Blurred Image Using PSFs of Various Sizes

Step 4: Analyzing the Restored PSF

Step 5: Use deconvlucy to restore the blurred and noisy image, specifying the PSF used to create the blur, and limiting the number of iterations to 5 (the default is 10).

Step 6: Improving the Restoration

## VI.RESULTS


Figure-1: Captured Image

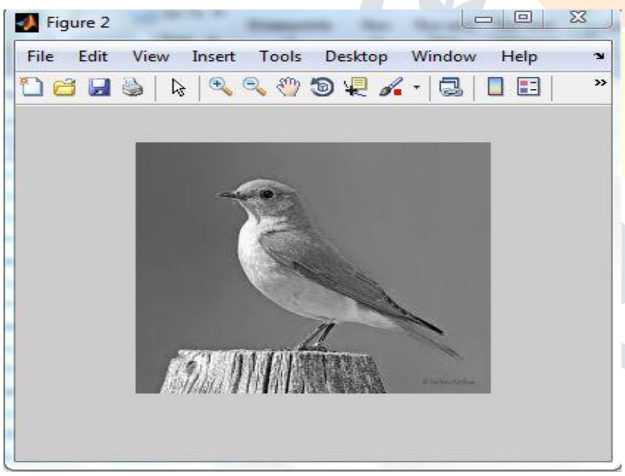


Figure-2: Gray scaled Image (256*256)


Figure-3: Original Image

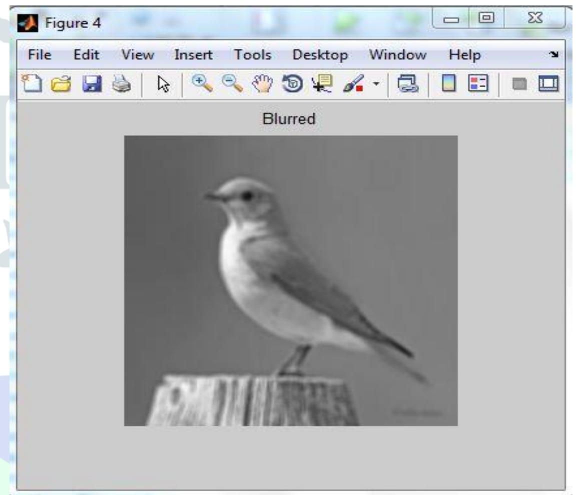


Figure-4: Blurred image

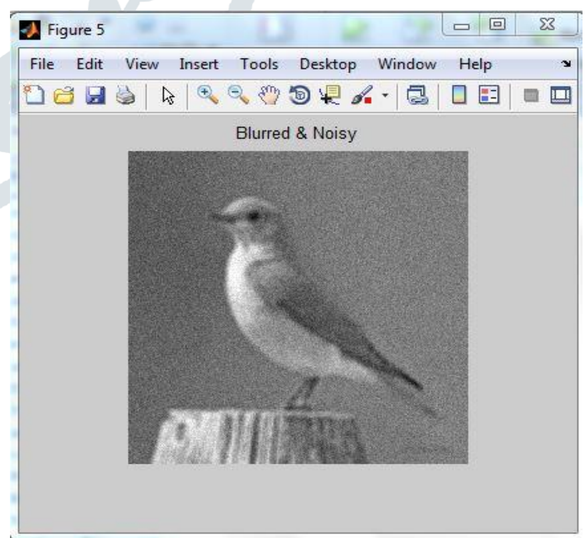


Figure-5: Blurred and Noisy image

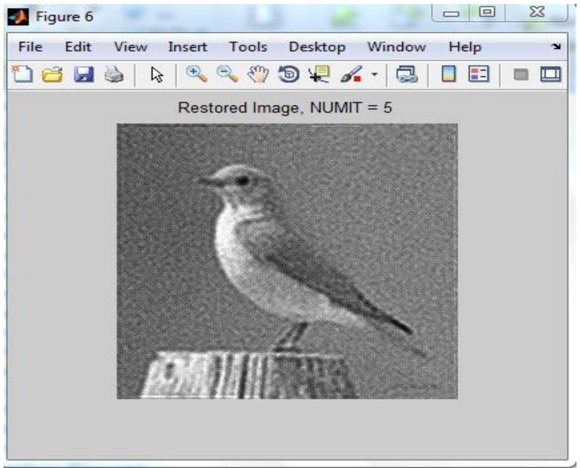


Figure-6:Restored image

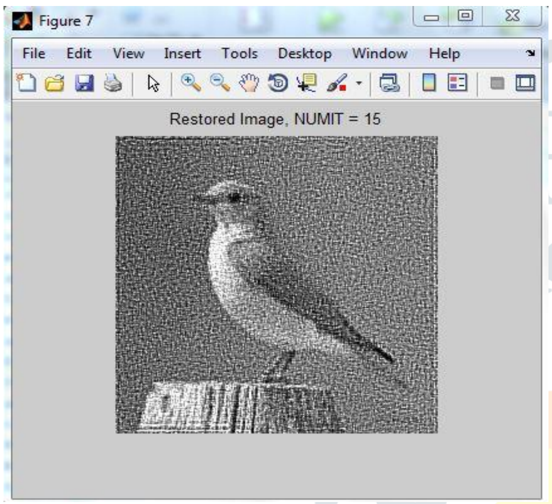


Figure-7: Restored image

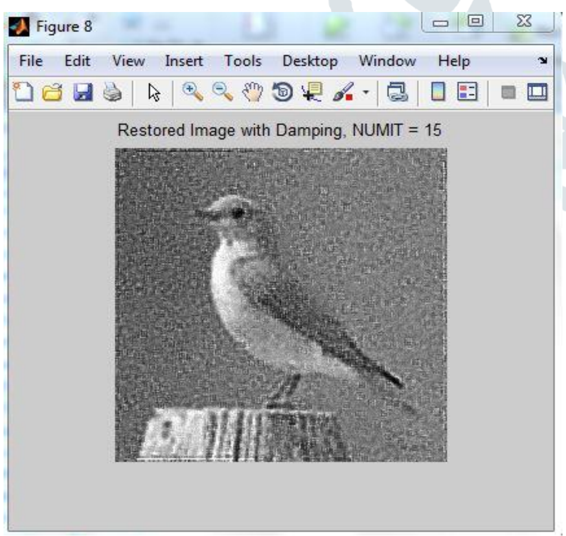


Figure-8: Restored image with Damping

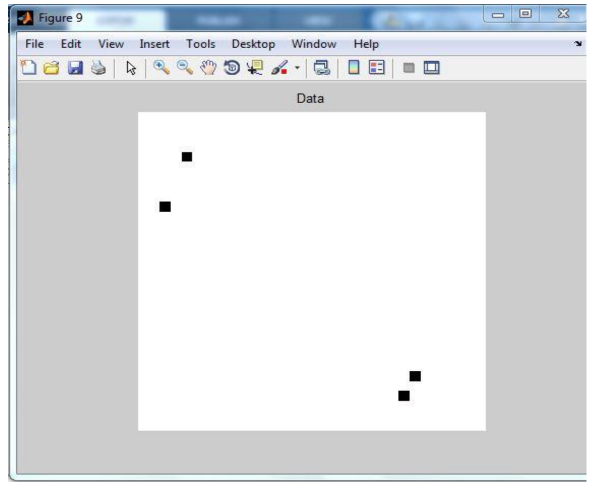


Figure-9: Data

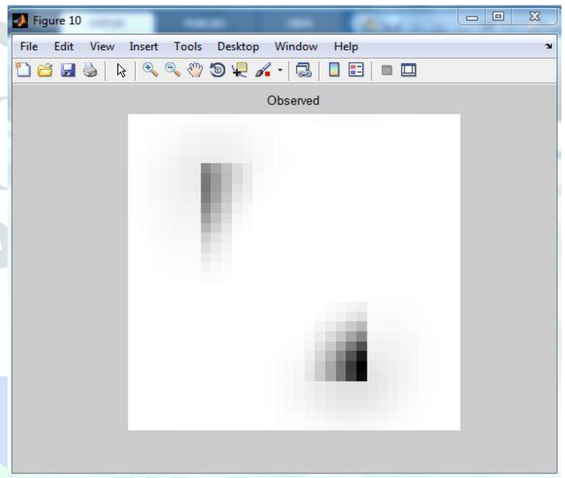


Figure-10: Observed

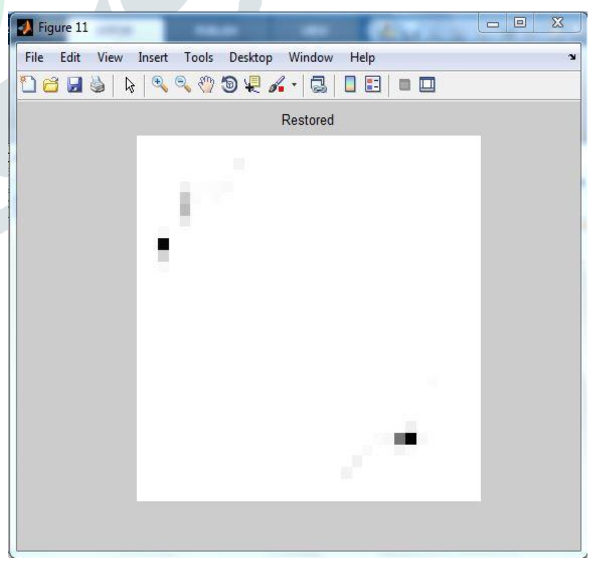


Figure-11: Restored

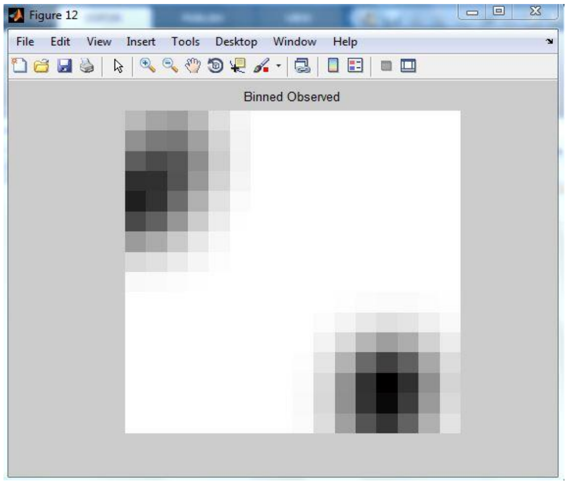


Figure-12: Binned Observed

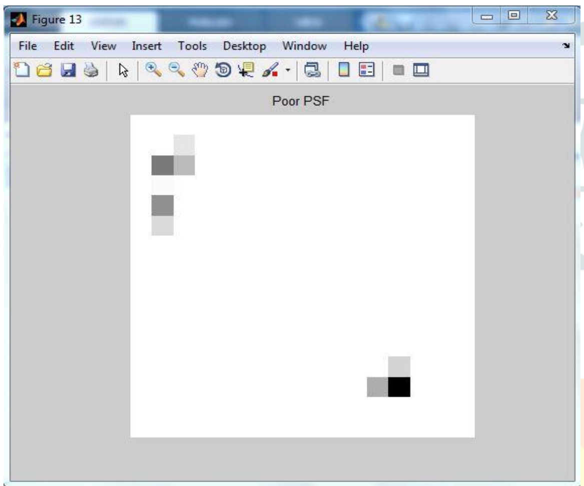


Figure-13: Poor PSF

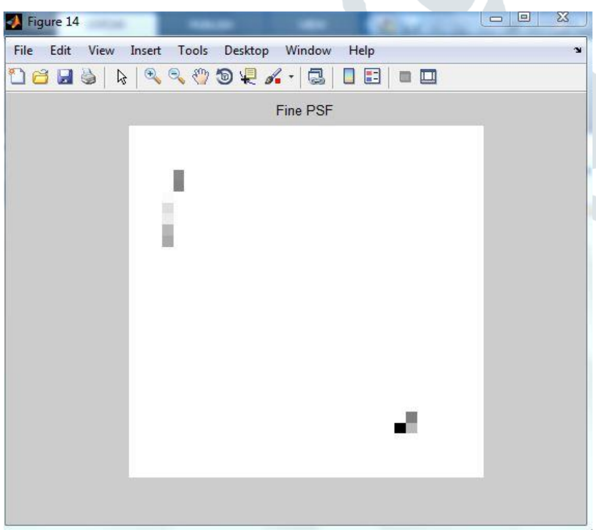


Figure-14: Fine PSF

## VII. CONCLUSION

The deconvlucy function, by default, performs multiple iterations of the deblurring process. You can stop the processing after a certain number of iterations to check the result, and then restart the iterations from the point where processing stopped. To do this, pass in the input image as a cell array,for example,{Blurred Noisy}. The deconvlucy function returns the output image as a cell array that you can then pass as an input argument to Deconvlucy to restart the deconvolution. The deconvlucy function supports several other optional arguments you can use to achieve the best possible result, such as specifying a damping parameter to handle additive noise in the blurred image. To see the impact of these optional arguments, view the Image Processing Toolbox deblurring demos.

## VIII.REFERENCES

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## IX. ABOUT AUTHORS

**P.Manga Rao,** received his B.Tech degree in Electronics and Communication Engineering from Jawaharlal Nehru technological University in 2010,and he completed his M.Tech(ECE) from Jawaharlal Nehru technological University in 2015. Currently he is working as Assistant professor in TKR College of engineering and technology, Hyderabad.His current research interests include Image and Video Processing, Speech Processing.

**M.Ashok,** received his B.Tech degree in Electronics and Communication Engineering from Jawaharlal Nehru technological University in 2011,and he completed his M.Tech(ECE) from Jawaharlal Nehru technological University in 2014. Currently he is working as Assistant professor in TKR College of engineering and technology, Hyderabad.His current research interests include Image and Video Processing, Speech Processing.

**G.Mahesh,**received his B.Tech degree in Electronics and Communication Engineering from Jawaharlal Nehru technological University in 2012, and he did his M.Tech in VLSISD from Jawaharlal Nehru technological University in 2014, currently he is working as Assistant professor in TKR College of engineering and technology, Hyderabad.

His current research interests include Image and Video Processing, VLSI System Designs.

**M.Gnanesh Goud,** received his B.Tech degree in Electronics and Communication Engineering from Jawaharlal Nehru technological University in 2012,and he completed his M.Tech(SSP) from Jawaharlal Nehru technological University in 2014. currently he is working as Assistant professor in TKR College of engineering and technology, Hyderabad.His current research interests include Image and Video Processing, Speech Processing.