Image Restoration Based On Deconvolution by Richardson Lucy Algorithm

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Abstract— **This article presents the performance analysis of different basic techniques used for the image restoration. Restoration is a process by which an image suffering from degradation can be recovered to its original form. Removing blur and noise from image is very difficult problem to solve. We have implemented the three different techniques of image restoration and tested our implementation for the blurred image in the standard environment. We have obtained the blurred image with the standard blurring functions and the noise. The degraded images have been restored by the use of Wiener deconvolution, Inverse deconvolution and Richardson–Lucy algorithm. Further we have compared the different results on the basis of PSNR and MSE values of the restored image. Finally the conclusion is formulated.**

Keywords— **Inverse filter, Wiener filter, Lucy- Richardson, MSE (mean square error), PSNR (peak signal to noise ratio).**

1. INTRODUCTION

The task of deblurring, a form of image restoration, is to obtain the original, sharp version of a blurred image.[1-3] There exist many applications for image restoration, including astronomical imaging, medical imaging, law enforcement, and digital media restoration. The problem has attracted strong research interest and will continue to do so, not only because it has many applications but also because it has a simple mathematical formulation yet it is a classical inverse problem for which good solutions are not easily obtained. The simple equation for expressing image blurring/degradation is as follows;

$$g = f * h + \eta \qquad \textbf{(1)}$$

Where f is the original image and g is the version that has been degraded through blurring (convolution $*$) by kernel h and the addition of random noise η. This degradation model represents a linear relationship between f and g; hence, the problem of recovering f from g is called linear image restoration. Often the blur kernel is assumed to be space-invariant [4-5]. If we lack prior knowledge of the blur kernel or point spread function h, we have the more difficult blind (linear) image restoration problem in which h also needs to be estimated. Also we have

$$G(u) = F(u)H(u) + N(u) \qquad (2)$$

The $\boldsymbol{G}, \boldsymbol{F}, \boldsymbol{H}, \boldsymbol{N}$ are the Fourier transform of g, f, h, η.

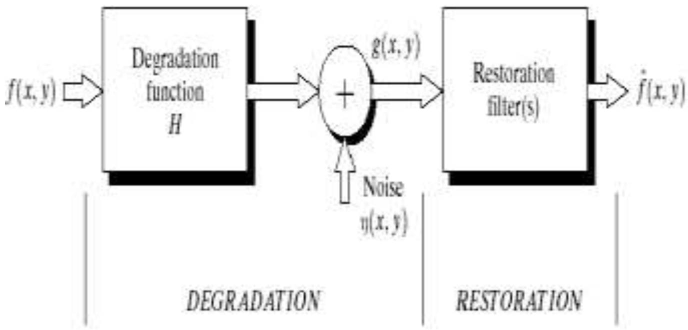

Fig. 1 Image Blurring model

Image deconvolution methods are used to estimate the latent image from the degraded image. They can be divided into two categories, non-blind and blind deconvolution [6-7]. In non-blind deconvolution, the PSF is known and f can be restored through an error.

Minimization process. The Weiner deconvolution and the Inverse deconvolution are the two commonly used methods, within this category.

Richardson–Lucy deconvolution is algorithm which is based on iteration process. Its performance in the presence of noise is found to be superior to that of other deconvolution algorithms[8-9].

3. INVERSE DECONVOLUTION METHOD FOR IMAGE DEBLURRING

Direct inverse Filtering is the simplest approach to restoration [9]. In this method, an estimate of the Fourier transform of the image $\hat{f}$ (u, v) is computed by dividing the Fourier transform of the degraded image by the Fourier transform of the degradation function

$$\hat{f}(u, v) = G(u, v) / H(u, v) \qquad (3)$$

This method works well when there is no additive noise in the degraded image. That is, when the degraded image is given by

$$g(x, y) = f(x, y)*h(x, y) \qquad (4)$$

But if noise gets added to the degraded image then the result of direct inverse Filtering is very poor. Equation 1.gives the expression for g(u, v). Substituting for G(u, v) in the above equation, we get

$$\hat{F}(u, v) = F((u, v) + N(u, v)H(u, v) \qquad (5)$$

The above equation shows that direct inverse Filtering fails when additive noise is present in the degraded image. Because noise is random and so we cannot find the noise spectrum $N(u, v)$.

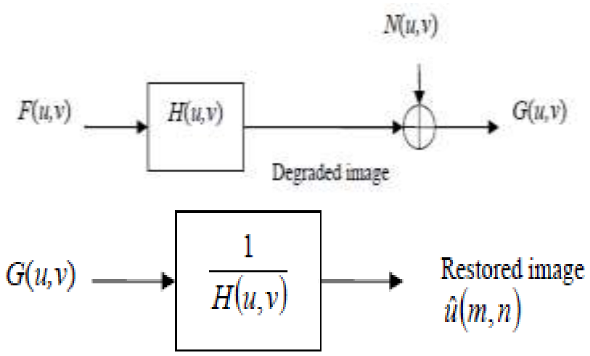

Fig. 2 Inverse Deconvolution

4. WEINER DECONVOLUTION METHOD FOR IMAGE DEBLURRING

Weiner deconvolution is named after Norbert Weiner, who first proposed the method in 1942 w Weiner filtering is one of the earliest and best known approaches to linear image restoration [9].

Weiner Filtering is more robust in the presence of additive noise. Weiner filtering incorporates both degradation function and statistical characteristics of noise into the restoration process. The objective of this technique is to find an estimate $\hat{f}$ of the original image f such that the mean square error between them is minimized. This error measure is given by

$$e^2 = E\{(f - \hat{f})^2\} \qquad (6)$$

Where E{.} is the expected value of the argument. The method is founded on considering image and noise as random processes and objective is to find an estimate $\hat{f}$ of the uncorrupted image f such that the mean square error between them is minimized. If the noise is zero, then the noise power spectrum vanishes and the wiener filter reduces to the inverse filter.

5. RICHARDSON–LUCY DECONVOLUTION ALGORITHM

The non blind de-convolution is the category of de-convolution method in which the PSF is known. The Richardson–Lucy deconvolution algorithm has become popular in the fields of astronomy and medical imaging. Initially it was derived from Bayes theorem in the early 1970's by Richardson and Lucy. In the early 1980's it was redeliver by Shepp and Vardi as an algorithm to solve positron emission tomography imaging problems, in which Poisoning statistics are dominant. Their method used a maximum-likelihood solution, which was found by use of the expectation maximization algorithm of Dempster et al

The reason for the popularity of the Richardson–Lucy algorithm is its implementation of maximum likelihood and its apparent ability to produce reconstructed images of good quality in the presence of high noise levels. We therefore assumed that a non blind form of this algorithm would have the same characteristics [2-6].

Non linear iterative technique is better than the linear technique. Non linear behaviors is not always predictable and required computational resource's-R algorithm which is arise from the maximum like hood formulation

$$\hat{f}_{k+1}(x,y) = \hat{f}_k(x,y)[h(-x,-y) * g(x,y)/h(x,y) * \hat{f}_k(x,y)] \quad (7)$$

Where * is the convolution operation. $\hat{F}$= is the estimate of the un degraded image. We have used the R-L algorithm iteratively staring from the blurred image. The image restored after each iteration moves closer to the original image thus reducing MSE with number of iterations. The program execution is terminated when MSE obtained becomes constant in consecutive iterations

7. PERFORMANCE PARAMETERS

Image restoration research aims to restored image to from a blurred and noisy image A widely used measure of reconstructed image fidelity for an N * *M* size image is the mean square error (MSE) and is given by –

$$MSE = \frac{1}{M.N}\sum_{i=0}^{N-1}\sum_{j=0}^{M-1}|f(i,j) - \hat{f}(i,j)|^2 \quad (8)$$

$$PSNR = 10\log_{10}\left(\frac{255^2}{MSE}\right) \quad (9)$$

6. RESULTS AND ANALYSIS

We have evaluated the results for different images .The results are shown for the two images for the different variance and image sizes.

Table 1 Results for the Cameraman image

Image size		256x256				512x512			
Noise variance		0.05		0.007		0.05		0.007	
		MSE	PSNR	MSE	PSNR	MSE	PSNR	MSE	PSNR
Inverse filter		0.0262	15.8123	0.0068	21.7024	0.0042	22.7645	0.0083	20.7954
Wiener filter		0.0138	18.5958	0.0061	22.1819	0.0020	27.0082	0.0028	25.5632
Richard-son lucy	Iteration 1	0.0680	11.6762	0.0654	11.8434	0.0210	16.7799	0.0440	13.5639
	Iteration 10	0.0268	15.7245	0.0245	16.1020	0.0019	27.1238	0.0064	21.9615
	Iteration 20	0.0112	19.5254	0.0071	21.5087	0.0011	29.6501	0.0022	26.6454
	Iteration 30	0.0070	21.5233	0.0035	24.6023	8.9311e-004	30.4910	0.0018	27.4981

Table 2 Results for the peppers image

Image size		256x256				512x512			
Noise variance		0.05		0.007		0.05		0.007	
		MSE	PSNR	MSE	PSNR	MSE	PSNR	MSE	PSNR
Inverse filter		0.0200	16.9817	0.0045	23.4626	0.0202	16.9483	0.0042	22.7645
Winer filter		0.0052	22.8473	0.0061	22.1819	0.0057	22.4348	0.0020	27.0082
Richard-son lucy	Iteration 1	0.0402	13.9617	0.0307	15.1323	0.0270	15.6885	0.0210	16.7799
	Iteration 10	0.0046	23.3504	0.0021	26.8659	0.0033	24.8779	0.0019	27.1238
	Iteration 20	0.0032	24.9371	0.0012	29.3916	0.0024	26.1250	0.0011	29.6501
	Iteration 30	0.0028	25.5736	9.0215e-004,	30.4472	0.0025	25.9579	8.9311e-004	30.4910

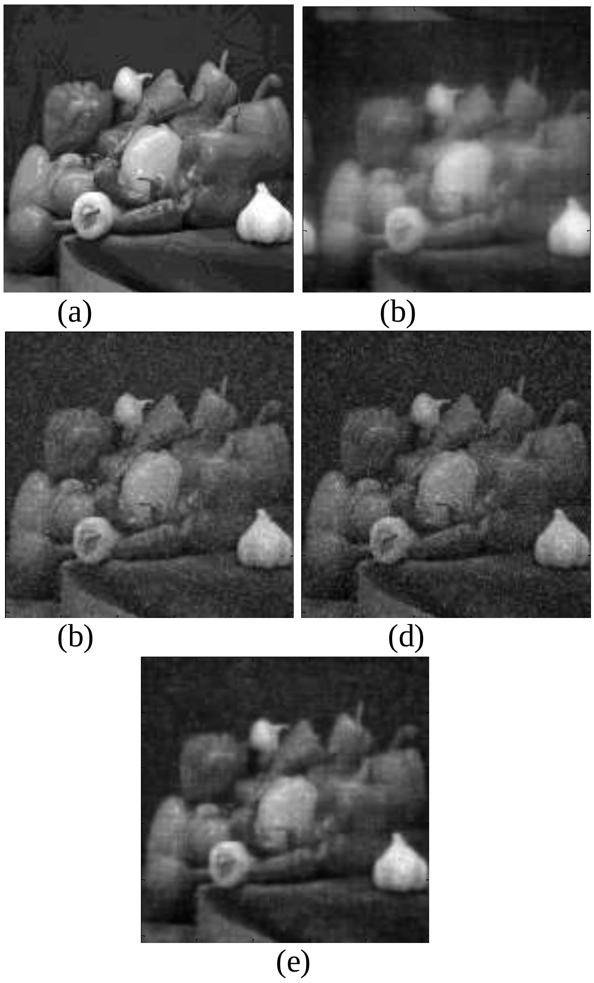

Fig.3 Results of pepper.png (a) original image (b) blurred image (c) Restored by Inverse filter (d) Restored by Wiener filter (e)Restored by R-L at iteration 30.

From Fig.(3) (c) & (d), and Fig.4 (c) & (d), the above results we found that the inverse filter works better than the Weiner filter, under noise conditions. When the variance of noise increases the performance of inverse filtering not provides the sufficient PSNR. The Weiner filtering gives the good PSNR regardless of the noise variance

Form Fig.3 (e) and 4 (e), the results obtained by the Richardson Lucy method, we have found that the PSNR increases with the number of iterations and also the quality of the image enhances.(See Table 1 and 2).

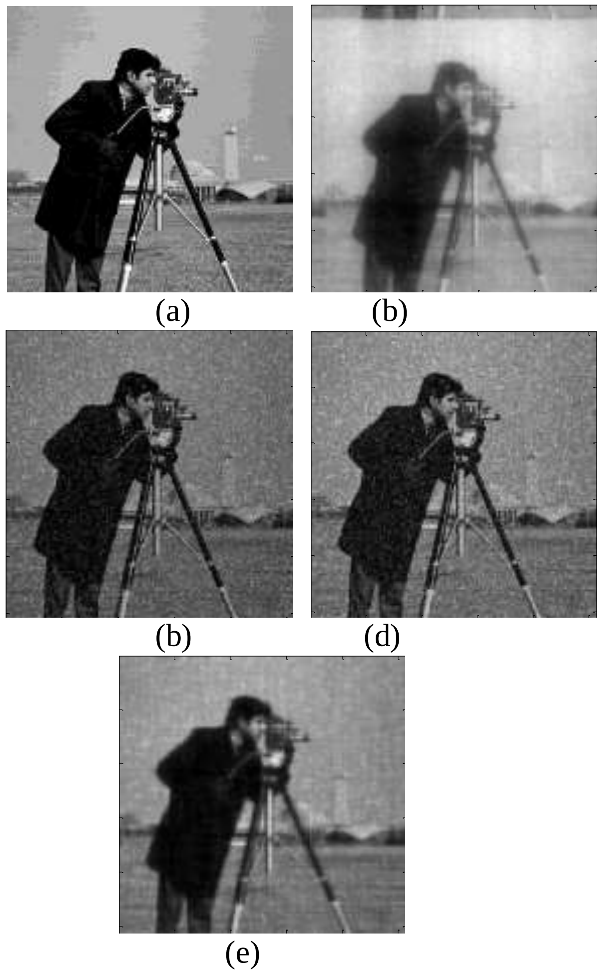

Fig.4 Results of cameraman.tif (a) original image (b) blurred image (c) Restored by Inverse filter (d) Restored by Wiener filter (e)Restored by R-L at iteration 30.

8. CONCLUSION

We have seen the requirement and significance of image de-blurring. We have seen the mathematical formulation for the blurred image. we already have the knowledge of point spread function .

Weiner filtering provides the better results than the inverse filtering almost in every condition except when the noise having very less variance.

The Richardson Lucy provides good estimate for the blurring function and gives better PSNR within the limited iterations. Yet if we use this method with the known point spreading function then it is a time taking method, still it can provides the PSNR even better than Weiner deconvolution.

With the help of the basic method of deconvolution, we may try to form some deconvolution method which can provide better

PSNR within the very less iterations for the blind deconvolution.

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