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A Comparative Study and Analysis of Image Restoration Techniques Using Different Images Formats

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Abstract

Image Restoration is a field of Image Processing which deals with recovering an original and sharp image from a degraded image using a mathematical degradation and restoration model. This study focuses on restoration of degraded images which have been blurred by known or unknown degradation function. On the basis of knowledge of degradation function image restoration techniques can be divided into two categories: blind and non-blind techniques. Three different image formats viz..jpg(Joint Photographic Experts Group), .png(Portable Network Graphics) and .tif(Tag Index Format) are considered for analyzing the various image restoration techniques like Deconvolution using Lucy Richardson Algorithm (DLR), Deconvolution using Weiner Filter (DWF), Deconvolution using Regularized Filter (DRF) and Blind Image Deconvolution Algorithm (BID).The analysis is done on the basis of various performance metrics like PSNR(Peak Signal to Noise Ratio), MSE(Mean Square Error) , RMSE(Root Mean Square Error).

Keywords

Lucy Richardson Algorithm, Weiner Filter, Regularized Filter, Blind Image Deconvolution, Gaussian Blur, Point Spread Function, PSNR, MSE, RMSE.

1.Introduction

The main objective of Image Restoration is to recover the original image from a degraded image which is blurred by a degradation function, commonly by a Point Spread Function (PSF). Image Restoration Techniques are divided into two categories on the basis of knowledge about Point Spread Function (PSF):

1)Blind Image Restoration: This Technique allows the reconstruction of original images from degraded images even when we have very little or no knowledge about PSF. Blind Image Deconvolution (BID) is an algorithm of this type.

2)Non-Blind Restoration: This Technique helps in the reconstruction of original images from degraded images when we know that how image was degraded i.e. we have a knowledge about PSF. Deconvolution using Lucy Richardson Algorithm (DLR), Deconvolution using Weiner Filter (DWF), Deconvolution using Regularized Filter (DRF) are Non Blind Algorithms.

Degradation Model

In degradation model, the original image is blurred using degradation function and additive noise. The degraded image is described as follows:

$$g = h * f + n \quad (1)$$

In equation (1), g is the degraded image, h is the degradation function, f is an original image and n is the additive noise. The degradation Model is structured as follows:

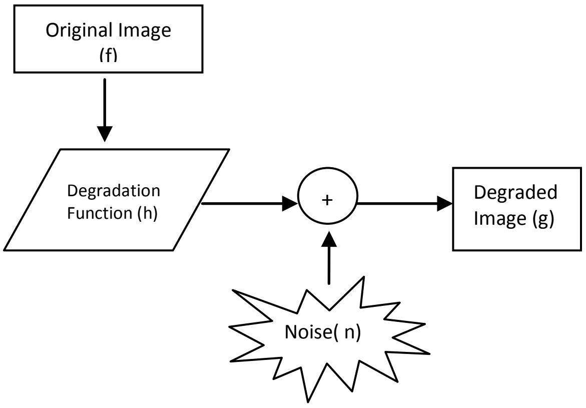


Fig. 1: Degradation Model

Restoration Model

In Restoration model, the degraded image is reconstructed using restoration filters. It performs the inverse process of degradation by removing additive noise and blur factor. We get an estimate of the original image as a result of restoration. The closer the estimated image is to the original image the more efficient is our restoration filter.

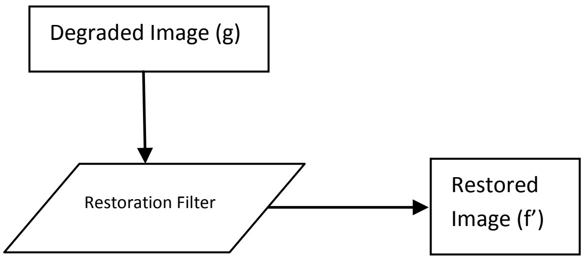


Fig. 2: Restoration Model

2. Methodology

This paper aims at studying , analyzing and comparing four different types of Image Restoration techniques viz. Deconvolution using Lucy Richardson Algorithm (DLR), Deconvolution using Weiner Filter(DWF), Deconvolution using Regularized Filter (DRF) and Blind Image Deconvolution Algorithm(BID). For making a comparison among all the above algorithms we will consider three image formats .jpg(Joint Photographic Experts Group), .png(Portable Network Graphics) and .tif(Tag Index File Format) . We will first degrade the original image using a Gaussian blur and then by using the above mentioned algorithms we will try to restore the original image from the degraded image.

Deconvolution using Lucy Richardson Algorithm

DLR is a non blind technique of image restoration, used to restore a degraded image that has been blurred by a known PSF. It is an iterative procedure in which the pixels of the observed image are represented using the PSF and the latent image as follows:

$$d_i = \Sigma\, p_{ij}\, u_j \qquad (2)$$

In equation (2), d_i is the observed value at pixel position 'i', p_{ij} is the PSF ,the fraction of light coming from true location 'j' that is observed at position 'i' , u_j is the latent image pixel value at location 'j' .

The main objective is to compute the most likely 'u_j' in the presence of observed d_i and known PSF p_{ij} as follows:

$$u_j^{(t+1)} = u_j^{(t)} \sum_i \frac{d_i}{c_i} p_{ij} \qquad (3)$$

Where,

$$c_i = \sum_j p_{ij}\, u_j^{(t)} \qquad (4)$$

Deconvolution using Wiener Filter

Weiner Filtering is also a non blind technique for reconstructing the degraded image in the presence of known PSF. It removes the additive noise and inverts the blurring simultaneously. It not only performs the deconvolution by inverse filtering (highpass filtering) but also removes the noise with a compression operation (lowpass filtering).It compares with an estimation of the desired noiseless image. The input to a wiener filter is a degraded image corrupted by additive noise. The output image is computed by means of a filter using the following expression:

$$f' = g * (f + n) \qquad (5)$$

In equation (5), f is the original image , n is the noise, f' is the estimated image and g is the wiener filter's response.

Deconvolution using Regularized Filtering

Regularized filtering is used effectively when constraints like smoothness are applied on the recovered image and limited information is known about the additive noise. The blurred and noisy image is restored by a constrained least square restoration algorithm that uses a regularized filter. Regularized restoration provides similar results as the wiener filtering but it has a very different viewpoint. In regularized filtering less prior information is required to apply restoration. The regularization filter is often chosen to be a discrete Laplacian. This filter can be understood as an approximation of a Wiener filter.

Blind Image Deconvolution

As the name suggests, BID is a Blind technique of image restoration which restores the degraded image that is blurred by an unknown PSF. It is a deconvolution technique that permits recovery of the target image from a single or set of blurred images in the presence of a poorly determined or unknown PSF.

In this technique firstly, we have to make an estimate of the blurring operator i.e. PSF and then using that estimate we have to deblur the image. This method can be performed iteratively as well as non-iteratively. In iterative approach, each iteration improves the estimation of the PSF and by using that estimated PSF we can improve the resultant image repeatedly by bringing it closer to the original image. In non-iterative approach one application of the algorithm based on exterior information extracts the PSF and this extracted PSF is used to restore the original image from the degraded one.

3. Implementation

All the implementation work is done in MATLAB 7.9. First of all the original image is degraded using a degradation function. The degraded image is then deblurred using all of the above discussed image restoration techniques. A comparison is done on the basis of various performance metrics like PSNR (Peak Signal to Noise Ratio), MSE (Mean Square Error), RMSE (Root Mean Square Error). Screen shots are as follows:

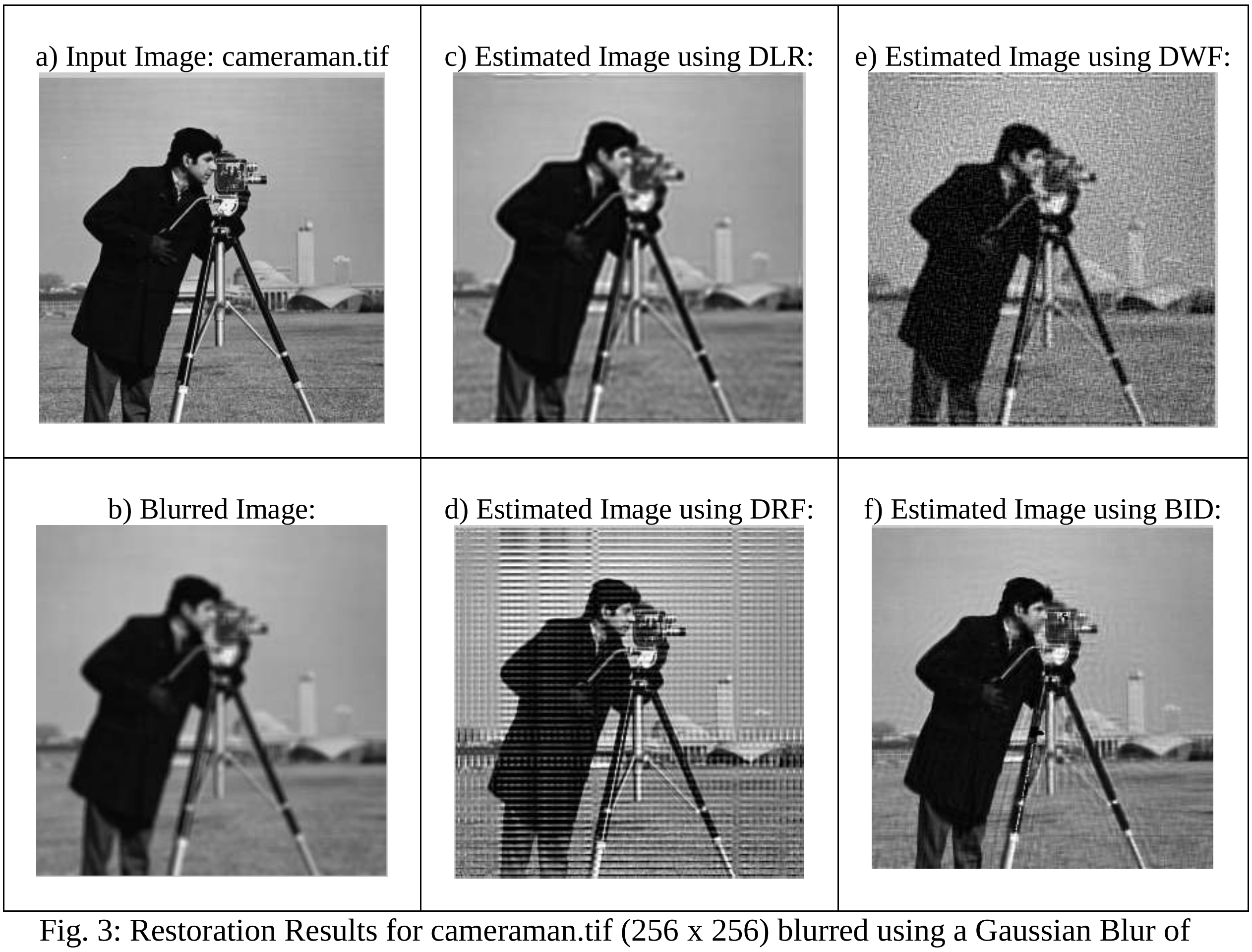


Fig. 3: Restoration Results for cameraman.tif (256 x 256) blurred using a Gaussian Blur of size=5 and standard deviation=5

Figure 3 illustrates the results of restoration of an image "cameraman.tif" of size 256 x 256 degraded by a Gaussian blur which is having size of 5 units and a standard deviation of value 5. Image (a) is the original image and image (b) is the blurred image. This blurred image is then tried with four different deconvolution algorithms for restoration producing resultant images (c), (d), (e) and (f) using DLR, DRF, DWF and BID respectively. From these images we can conclude about the quality of the resultant images.

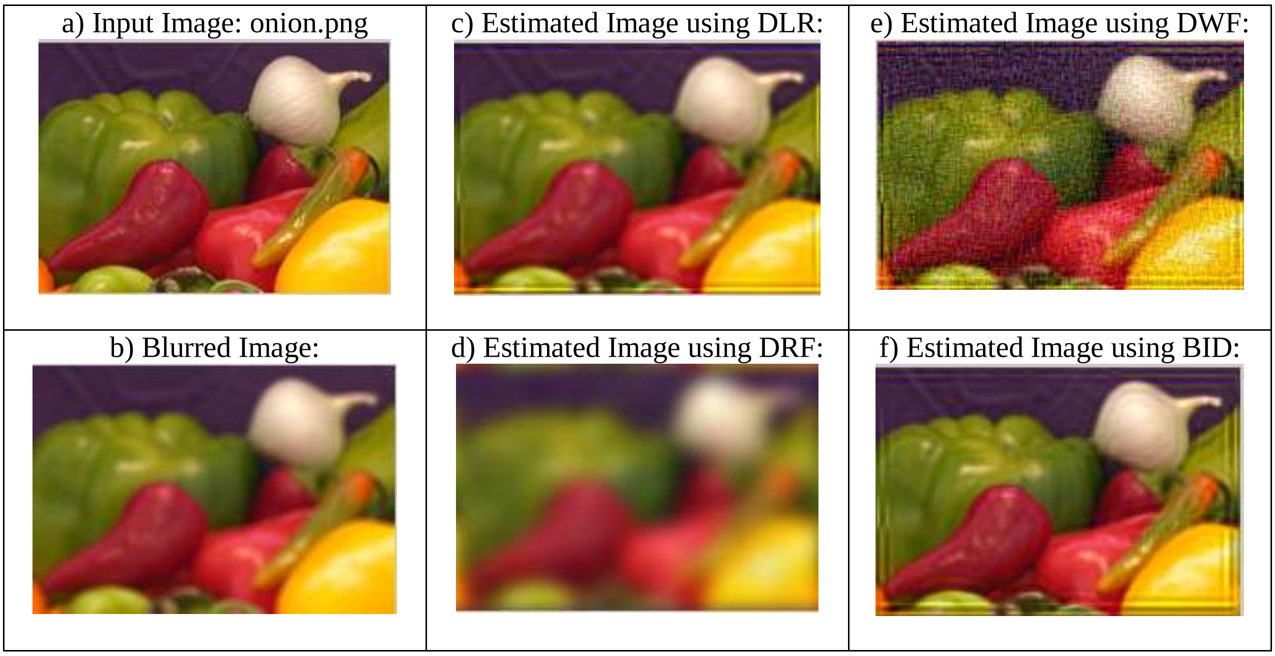
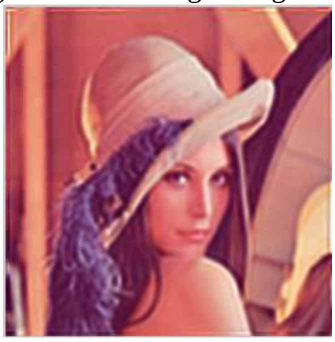


Fig. 4: Restoration Results for onion.png (198 x 135) blurred using a Gaussian Blur of size=5 and standard deviation=5

Figure 4 illustrates the results of restoration of an image "onion.png" of size 198 x 135 degraded by a Gaussian blur which is having size of 5 units and a standard deviation of value 5. Image (a) is the original image and image (b) is the blurred image. This blurred image is then tried with four different deconvolution algorithms for restoration producing resultant images (c), (d), (e) and (f) using DLR, DRF, DWF and BID respectively. From these images we can conclude about the quality of the resultant images.

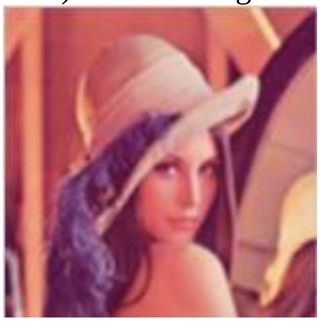
a) Input Image: leena.jpg

c) Estimated Image using DLR

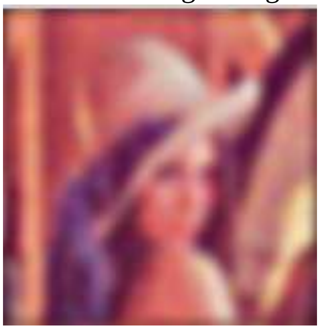


e) Estimated Image using DWF

b) Blurred Image:



d) Estimated Image using DRF



f) Estimated Image using BID

Fig. 5: Restoration Results for leena.jpg (256 x 256) blurred using a Gaussian Blur of size=5 and standard deviation=5

Figure 5 shows the results of restoration of an image "leena.jpg " of size 256 x 256 degraded by a Gaussian blur which is having size of 5 units and a standard deviation of value 5. Image (a) is the original image and image (b) is the blurred image. This blurred image is then tried with four different deconvolution algorithms for restoration producing resultant images (c), (d), (e) and (f) using DLR, DRF, DWF and BID respectively. From these images we can conclude about the quality of the resultant images.

4. Conclusion

This work makes a comparison between various image restoration techniques considering three different image formats viz. .jpg, .png and .tif . Following are tabular results obtained after the comparison:

cameraman.tif				
	DLR	**DRF**	**DWF**	**BID**
PSNR	24.98	17.70	22.52	26.76
MSE	207.98	1112.71	366.66	138.29
RMSE	10.31	33.36	19.15	11.76

Table 1: Estimation results of cameraman.tif

Table-1 shows the results of estimation of cameraman.tif image. BID algorithm produces the largest value of PSNR among all the four restoration techniques.BID has a PSNR value of 26.76, DLR has second place with a value of 24.98 while DWF has 22.52 as PSNR value, DRF has the lowest PSNR value of 17.70. Considering the MSE values BID is again proved to be better among all four techniques as it has least MSE of 138.29 while DRF has highest MSE of 1112.71. Similarly BID has a least RMSE value of 11.76 and DRF has highest RMSE of 33.36.

onion.png				
	DLR	**DRF**	**DWF**	**BID**
PSNR	23.38	21.75	21.81	26.09
MSE	298.70	434.98	428.67	159.82
RMSE	17.28	20.86	20.70	12.64

Table 2: Estimation results of onion.png

Table-2 shows the restoration results of onion.png image for all the above mentioned restoration techniques. For .png images also, BID is proved to be best as it has highest PSNR value of 26.09, least MSE value of 159.82 and least RMSE value of 12.64. While DLR has PSNR value of 23.38,MSE value of 298.70 and RMSE value of 17.28. DRF and DWF has approximately close values of PSNR 21.75 and 21.81 respectively, MSE values of 434.98 and 428.67 respectively, RMSE values of 20.86 and 20.70 respectively.

leena.jpg				
	DLR	**DRF**	**DWF**	**BID**
PSNR	27.86	20.72	21.80	28.26
MSE	106.34	550.47	429.85	97.04
RMSE	10.31	23.46	20.73	9.85

Table 3: Estimation results of leena.jpg

Table-3 describes the restoration results of leena.jpg image using all the four restoration techniques. For this type of image formats also BID has highest PSNR value of 28.26, followed by DLR with a PSNR value of 27.86 , DWF with 21.80 and then by DRF with 22.51. Considering MSE values, BID has lowest value of 146.52 and DWF has highest value of 434.82 and considering RMSE values, BID again has a minimum value of 12.10 and DWF has largest value of 20.85.

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