Implementation and Analysis of Image Restoration Techniques

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Abstract— **IMAGE restoration is an important issue in high-level image processing. Images are often degraded during the data acquisition process. The degradation may involve blurring, information loss due to sampling, quantization effects, and various sources of noise. The purpose of image restoration is to estimate the original image from the degraded data. It is widely used in various fields of applications, such as medical imaging, astronomical imaging, remote sensing, microscopy imaging, photography deblurring, and forensic science, etc. Often the benefits of improving image quality to the maximum possible extent for outweigh the cost and complexity of the restoration algorithms involved. In this paper we are comparing various image restoration techniques like Richardson-Lucy algorithm, Wiener filter, Neural Network approach, on the basis of PSNR (Peak Signal to Noise Ratio).**

Keywords— **Peak Signal to noise ratio, Image Restoration, Degradation model, Neural Network approach, Richardson-Lucy algorithm, Wiener Filter.**

I. Introduction

Images are produced to record or display useful information. Due to imperfections in the imaging and capturing process, however, the recorded image invariably represents a degraded version of the original scene [14]. The undoing of these imperfections is crucial to many of the subsequent image processing tasks. There exists a wide range of different degradations, which are to be taken into account, for instance noise, geometrical degradations (pincushion distortion), illumination and color imperfections (under / over-exposure, saturation), and blur [3]. Blurring is a form of bandwidth reduction of an ideal image owing to the imperfect image formation process [1]. It can be caused by relative motion between the camera and the original scene, or by an optical system that is out of focus. When aerial photographs are produced for remote sensing purposes, blurs are introduced by atmospheric turbulence, aberrations in the optical system, and relative motion between the camera and the ground [5]. Such blurring is not confined to optical images, for example electron micrographs are corrupted by spherical aberrations of the electron lenses, and CT scans suffer from X-ray scatter. In addition to these blurring effects, noise always corrupts any recorded image [10]. Noise may be introduced by the medium through which the image is created (random absorption or scatter effects), by the recording medium (sensor noise), by measurement errors due to the limited accuracy of the recording system, and by quantization of the data for digital storage [8].The field of image restoration (sometimes referred to as image deblurring or image deconvolution) is concerned with the reconstruction or estimation of the uncorrupted image from a blurred and noisy one. Essentially, it tries to perform an operation on the image that is the inverse of the imperfections in the image formation system [1]. In the use of image restoration methods, the characteristics of the degrading system and the noise are assumed to be known a priori. In practical situations, however one may not be able to obtain this information directly from the image formation process [3]. The goal of blur identification is to estimate the attributes of the imperfect imaging system from the observed degraded image itself prior to the restoration process.

A. Degradation Model

Capturing an image exactly as it appears in the real world is very difficult if not impossible. In case of photography or imaging systems these are caused by the graininess of the emulsion, motion-blur, and camera focus problems. The result of all these degradations is that the image is an approximation of the original. The above mentioned degradation process can adequately be described by a linear spatial model as shown in Figure 2.1. The original input is a two-dimensional (2D) image $f(x, y)$. This image is operated on by the system H and after the addition of $n(x, y)$. one can obtain the degraded image g(x,y). Digital image restoration may be viewed as a process in which we try to obtain an approximation to $f(x, y)$. given $g(x, y)$. and H and after applying Restoration filters we obtain restored image $f'(x, y)$ [11].

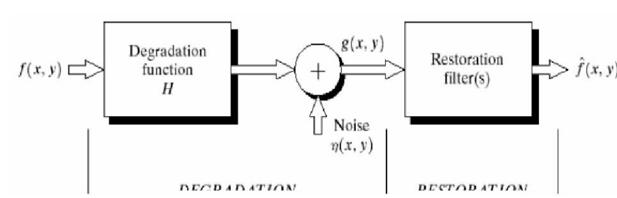


Fig 1: Degradation Model

B. Blurring

Blur is unsharp image area caused by camera or subject movement, inaccurate focusing, or the use of an aperture that gives shallow depth of field [7]. Blur effects are filters that make smooth transitions and decrease contrast by averaging the pixels next to hard edges of defined lines and areas where there are significant color transition [3].

C. Blurring Types

In digital image there are 3 common types of Blur effects:

- Average Blur
  The Average blur is one of several tools you can use to remove noise and specks in an image. We can use this tool when noise is present over the entire image [14]. This type of blurring can be distribution in horizontal and vertical direction and can be circular averaging by radius R which is evaluated by the formula: $R = \sqrt{g2 + f2}$ (1)

  Where: g is the horizontal size blurring direction and f is vertical blurring size direction and R is the radius size of the circular average blurring.

- Gaussian Blur
  The Gaussian Blur effect is a filter that blends a specific number of pixels incrementally, following a bell-shaped curve [8]. Blurring is dense in the center and feathers at the edge. Apply Gaussian Blur filter to an image when you want more control over the Blur effect [6].

- Motion Blur
  The Many types of motion blur can be distinguished all of which are due to relative motion between the recording device and the scene. This can be in the form of a translation, a rotation, a sudden change of scale, or some combinations of these. The Motion Blur effect is a filter that makes the image appear to be moving by adding blur in a specific direction [10]. The motion can be controlled by angle or direction (0 to 360 degrees or –90 to +90) and/or by distance or intensity in pixels (0 to 999), based on the software used [15].

- Out of Focus Blur
  When a camera images a 3-D scene onto a 2-D imaging plane, some parts of the scene are in focus while other parts are not [12]. If the aperture of the camera is circular, the image of any point source is a small disk, known as the circle of confusion (COC). The degree of defocus (diameter of the COC) depends on the focal length and the aperture number of the lens, and the distance between camera and object. An accurate model not only describes the diameter of the COC, but also the intensity distribution within the COC [16].

II. DEBLURRING TECHNIQUES

A. Lucy- Richardson Algorithm Technique

The Richardson–Lucy algorithm, also known as Richardson–Lucy deconvolution, is an iterative procedure for recovering a latent image that has been the blurred by a known PSF [16].

$$c_i = \sum_j p_{ij} . u_j \quad (2)$$

Where: p_{ij} is the point spread function (the fraction of light coming from true location j that is observed at position i), u_j is the pixel value at location j in the latent image, and c_i is the observed value at pixel location i. The statistics are performed under the assumption that u_j are Poisson distributed, which is appropriate for photon noise in the data. The basic idea is to calculate the most likely u_i given the observed c_i and known p_{ij}. This leads to an equation for u_i which can be solved iteratively according to:

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

Where

$$c_i = \sum_j u_j^{(t)} . \; p_{ij} \quad (4)$$

It has been shown empirically that if this iteration converges, it converges to the maximum likelihood solution for uj.

- Point Spread Function (PSF)
  Point Spread Function (PSF) is the degree to which an optical system blurs (spreads) a point of light [1]. The PSF is the inverse Fourier transform of Optical Transfer Function (OTF).in the frequency domain ,the OTF describes the response of a linear, position-invariant system to an impulse.OTF is the Fourier transfer of the point (PSF) [16].

B. Inverse Filter

Inverse filtering is one of the techniques used for image restoration to obtain a recovered image $f'(x, y)$ from the image data $g(x, y)$ so that $f^{'}(x, y) = f(x, y)$ in the ideal situation $n(x, y)$= 0,

$$h(x, y) * h'(x, y) = \delta(x, y) or H(w_x, w_y) H'(w_x, w_y) = 1. \quad (5)$$

C. Wiener Filter De-blurring Technique

Wiener filter's working principle is based on the least squares restoration problem [4]. It is a method of restoring image in the presence of blur and noise. The frequency-domain expression for the Wiener filter is:

W(s) = H(s)/F+(s), H(s) = Fx,s (s) eas /Fx(s) (6)

Where: F(s) is blurred image, F+(s) causal, Fx(s) ant causal[5].

D. Neural Network Approach

Neural networks is a form of multiprocessor computer system, with simple processing elements, a high degree of interconnection, adaptive interaction between elements, When an element of the neural network fails, it can continue without any problem by their parallel nature [13].

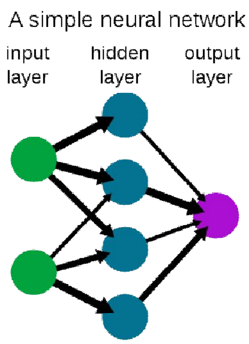


Fig 2: Artificial Neural Network

ANN provides a robust tool for approximating a target function given a set input output example and for the reconstruction function from a class a images. Algorithm such as the Back propagation and the Perceptron use gradient-decent techniques to tune the network parameters to best-fit a training set of input-output examples. Here we are using Back propagation neural network approach for image restoration. This approach is capable of learning complex non-linear functions is expected to produce better structure especially in high frequency regions of the image. We used a two-layer Back propagation network with full connectivity.

III. MOTION ORIENTED ESTIMATION

If we calculate the Fourier spectrum of the motion blurred images, we can extract good information about the motion vector. In figure 3 we show the Fourier spectrum of an image and the Fourier spectrum of the same image blurred with linear motion. The Fourier spectrum of the motion blurred image has parallel lines orthogonal (with right angle) with the motion orientation. So the task of calculating motion orientation is reduced to the task of calculating the orientation of these parallel lines. Radon transform [9] is known to be an efficient method for calculating the orientation of lines in images. We applied it to find the parallel line orientation. The result is shown in figure 4.

To determine motion orientation, we should search for the bright points in figure 4. To determine motion orientation, we should search for the bright points in figure 4. As we can see in figure 3-d, the image is blurred with motion orientation of 45±, and we can see one bright point exactly at that angle. For better distinguishing of these bright points, we find the maximum response of Radon transform in every angle from 0 to 179 in figure 5. The motion orientation is the angle in which the diagram in figure 4 takes its maximum value. To obtain a more accurate result, this diagram can be smoothed with a low pass filter with window size of 3.

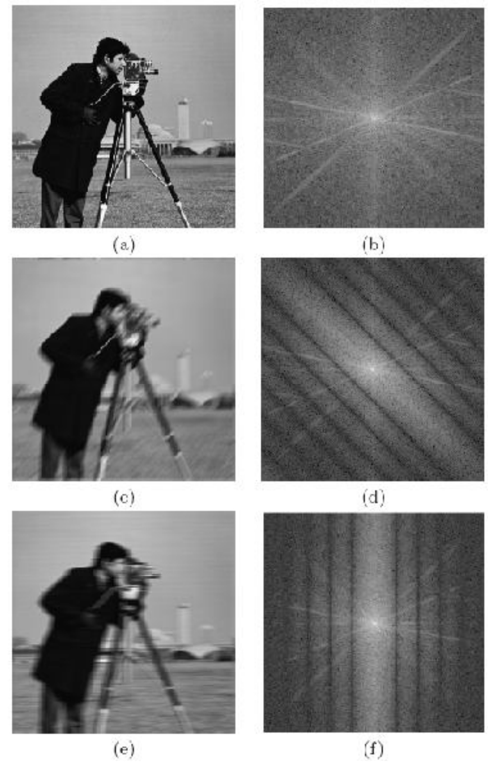


Fig 3: (a), (b) The original image and its Fourier spec- trum. (c) The blurred image with motion orientation 45± and motion length 10 pixels. (d) Fourier spectrum of image (c). (e) Image blurred with motion length of 10± pixels and 0± orientation. (f) The Fourier spectrum of image (e).

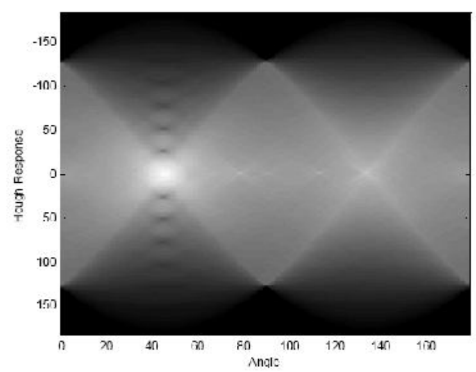


Fig 4: The Radon transform of image (d) in fig 2.

IV. MOTION BLUR LENGTH ESTIMATION

Our algorithm introduces a new approach for motion length estimation. In previous methods, such as [1] motion length estimation is proposed only for noise free images. In addition, this method cannot handle the motion length with more than 35 pixels. In [3][2] still the problem of robustness in dealing with noise exists. Motion length estimation should take the advantage of the fact that, when motion length increases, the parallel dark lines in Fourier spectrum of the blur image get closer to each other.

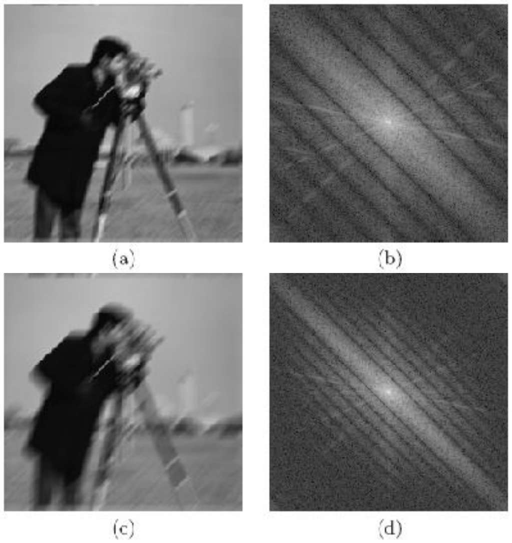


Fig 5: (a) Blurred image with motion length 10 pixels and orientation of 45± degrees. (b) Frequency response of a. (c) Blurred image with motion length of 20 pixels and 45± degrees. (d) Frequency response of c.

As figure 5 shows, for estimating the motion length, we should measure the distance between parallel dark lines from each other, then with an equation we map this distance to the motion length.Let us show the distance between these lines by d. In [2] and [3], d is calculated by simply drawing the line

$$y = mx \tag{7}$$

where: m = tan(µ) and µ is the orientation of the motion vector. [1] Uses Ceptrual analysis of the image to find the motion length. If we carefully look at figure 3 again, we can see that there are many dark points above and below the brightest point seen at angle about 45±, which shows the motion orientation.

For better illustration we show the Radon transform response in motion orientation (i.e. 45±) and we call it collapsed Radon transform in the orientation angle. For better reliability, again we can apply another low pass filter with window size as 3, we calculate the distance between two neighbor maximums (or minimums) to ¯nd the pitch of the function. This can be done also by calculating the distance between lots of neighbor maximums (or minimums) and then averaging between all results. We call the pitch result as d [1].

The next step is just to find an equation to relate d with the motion length. In our experiments we used 5 standard images. We blurred them with different motion lengths and orientations, and then we calculated the parameter d from them. In experiment we know the motion length so we have lots of points (d; L), in which L shows the original motion length [14] and here we are using image Lena for experimental result.

$$L = -1.44d3 + 5.37d2 - 8.34d + 13.5 \tag{8}$$

V. Simulation Result

In this section, experimental results are presented which explored the characteristics of the various restoration techniques used and tested. The comparative analysis has been presented on the basis of different percentage of noise for the standard LENA image which is shown in the Table (1). The result has been taken by comparing the performance Neural Network, Lucy, Inverse & Wiener filtering approach on the basis of PSNR where we are taking different values of SNR and constant values of angle and length.

Comparatively, Neural Network gives the best result in terms of PSNR criterion for the full range of the impulsive noise rate. The above conclusion is on the basis of image of LENA, the result of which is shown in figure 6.

TABLE 1: COMPARISON OF PSNR VALUES

SNR	Angle	Length	Image Restoration Techniques			
			Lucy	Inverse	Wiener	NN
10	45	6	11.8423	12.8899	14.5264	30.1135
30	45	6	11.8441	12.8512	14.5329	30.0731
50	45	6	11.8449	12.9172	14.5339	30.1349
70	45	6	11.844	12.8419	14.5343	30.0934
90	45	6	11.8435	12.8899	14.5346	30.1135

VI. Experimental Result

(a)


restoration_start
IMAGE RESTORATION
LOAD
< ADD NOISE >
BLUR
Blur parameters
Enter blur angle
45
Enter blur length
6
Enter SNR
20
LUCY Richardson
Inverse Filter
WIENER FILTER
NN Restoration
Compare Restoration Methods
Guided by :- K Nagwanshi, Developed By:- Charu Khare

(b)


restoration_start
IMAGE RESTORATION
LOAD
< ADD NOISE >
BLUR
Blur parameters
Enter blur angle
45
Enter blur length
6
Enter SNR
20
LUCY Richardson
Inverse Filter
WIENER FILTER
NN Restoration
Compare Restoration Methods
Guided by :- K Nagwanshi, Developed By:- Charu Khare

(c)


restoration_start
IMAGE RESTORATION
LOAD
< ADD NOISE >
BLUR
Please wait...
LUCY Richardson
Inverse Filter
WIENER FILTER
NN Restoration
Compare Restoration Methods
Guided by :- K Nagwanshi, Developed By:- Charu Khare

(d)

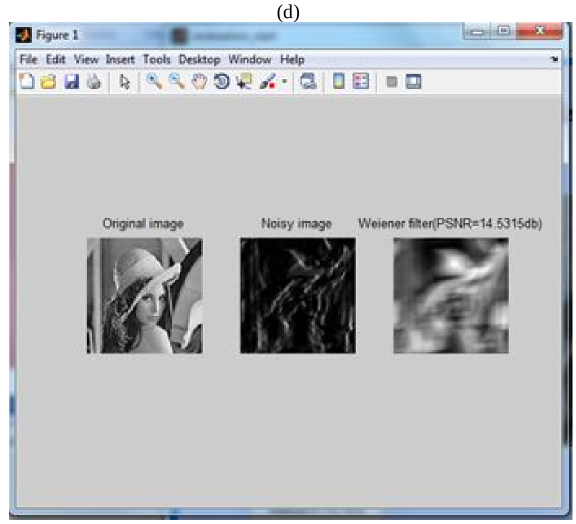


Figure 1
File Edit View Insert Tools Desktop Window Help
Original image
Noisy image
Weiener filter(PSNR=14.5315db)

(e)

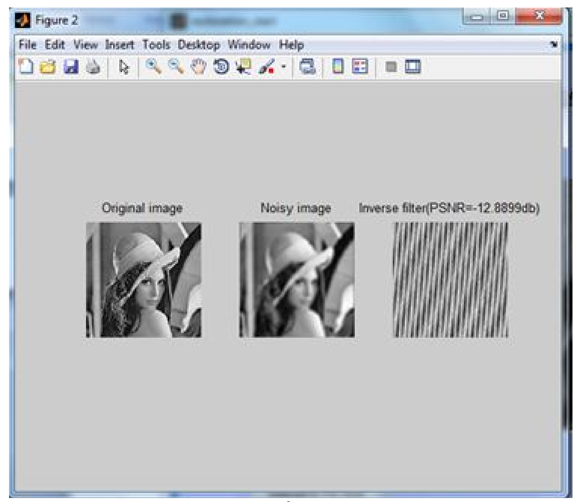


Figure 2
File Edit View Insert Tools Desktop Window Help
Original image
Noisy image
Inverse filter(PSNR=-12.8899db)

(f)

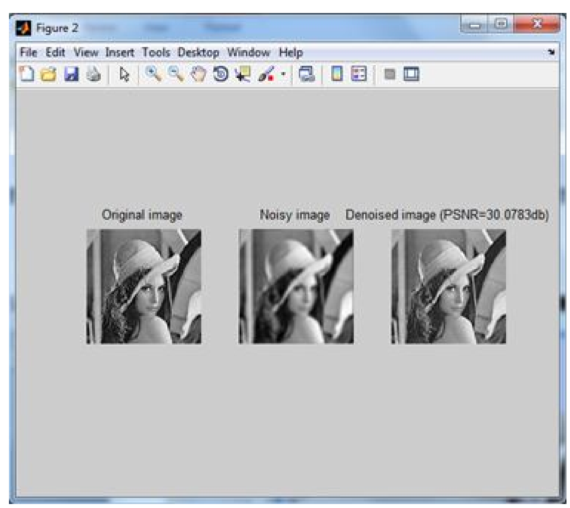
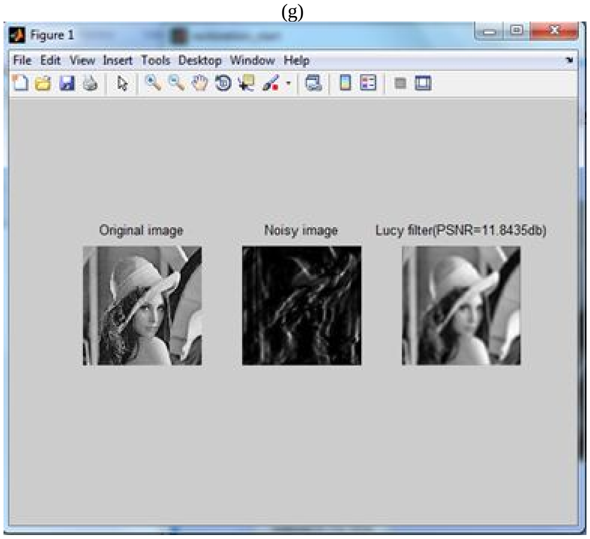
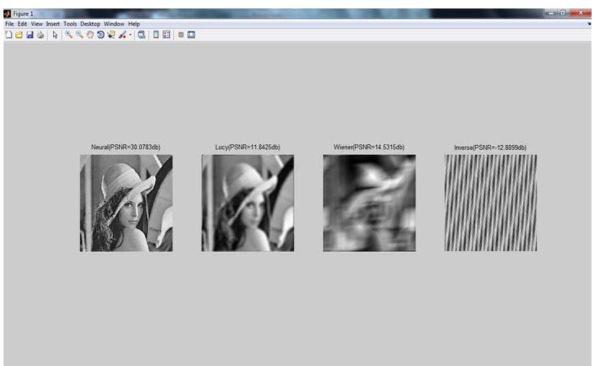


Figure 2
File Edit View Insert Tools Desktop Window Help
Original image
Noisy image
Denoised image (PSNR=30.0783db)

(g)



(h)



(i)

Fig 6: (a) Loading a Image without noise (b) Adding Noise Parameters (c) Image with added Noise (d) Wait for Processing (e) Deblurring using Wiener Filter (f) Deblurring using Inverse Filter(g) Deblurring using Neural Network (h) Deblurring using Lucy Richardson (i) Comparison of Restored Image.

VII. CONCLUSION

In this paper, we showed that better restoration based on neural network with PSNR = 30.1135. as compare to Lucy Richardson , Inverse filter and Wiener filter.

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