Comparative Analysis of Various Restoration Algorithm used for Blur Image for Gaussian Noise

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Abstract: Visual information transmitted in the form of digital images is becoming a major method of communication in the modern age, but the image obtained after transmission is often corrupted with noise. The received image needs processing before it can be used in applications. Image denoising involves the manipulation of the image data to produce a visually high quality image. This paper reviews the existing denoising algorithms, such as filtering approach, wavelet based approach, and multifractal approach, and performs their comparative study. Different noise models including additive and multiplicative types are used. They include Gaussian noise, salt and pepper noise, speckle noise and Brownian noise. Selection of the denoising algorithm is application dependent. Hence, it is necessary to have knowledge about the noise present in the image so as to select the appropriate denoising algorithm. The filtering approach has been proved to be the best when the image is corrupted with salt and pepper noise. The wavelet based approach finds applications in denoising images corrupted with Gaussian noise. In the case where the noise characteristics are complex, the multifractal approach can be used. A quantitative measure of comparison is provided by the signal to noise ratio of the image.

Keywords: Blur, Defocusing, Filter, Noise, PSF,PSNR,SSIM.

Introduction

A very large portion of digital image processing is devoted to image restoration. This includes research in algorithm development and routine goal oriented image processing. Image restoration is the removal or reduction of degradations that are incurred while the image is being obtained [1].

Degradation comes from blurring as well as noise due to electronic and photometric sources. Blurring is a form of bandwidth reduction of the image caused by the imperfect image formation process such as relative motion between the camera and the original scene or by an optical system that is out of focus [2]. When aerial photographs are produced for remote sensing purposes, blurs are introduced by atmospheric turbulence, aberrations in the optical system and relative motion between camera and ground. In addition to these blurring effects, the recorded image is corrupted by noises too. A noise is introduced in the transmission medium due to a noisy channel, errors during the measurement process and during quantization of the data for digital storage. Each element in the imaging chain such as lenses, film, digitizer, etc. Contribute to the degradation. Image denoising is often used in the field of photography or publishing where an image was somehow degraded but needs to be improved before it can be printed. For this type of application we need to know something about the degradation process in order to develop a model for it. When we have a model for the degradation process, the inverse process can be applied to the image to restore it back to the original form. This type of image restoration is often used in space exploration to help eliminate artifacts generated by mechanical jitter in a spacecraft or to compensate for distortion in the optical system of a telescope. Image denoising finds applications in fields such as astronomy where the resolution limitations are severe, in medical imaging where the physical requirements for high quality imaging are needed for analyzing images of unique events, and in forensic science where potentially useful photographic evidence is sometimes of extremely bad quality [2].

Let us now consider the representation of a digital image. A 2-dimensional digital image can be represented as a 2-dimensional array of data s(x,y), where (x,y) represent the pixel location. The pixel value corresponds to the brightness of the image at location (x,y). Some of the most frequently used image types are binary, gray-scale and color images [3].

In this paper, a study is made on the various denoising algorithms, their efficacy and elaboration that which technique will be used for what operation.

Sources of Blur

In case of imagedenoising methods, the characteristics of the degrading system and the noises are assumed to be known beforehand. The image s(x,y) is blurred by a linear operation and noise n(x,y) is added to form the degraded image w(x,y). This is convolved with the restoration procedure g(x,y) to produce the restored image z(x,y). The "Linear operation" shown in Figure 1.1 is the addition or multiplication of the noise n(x,y) to the signal s(x,y) [4].

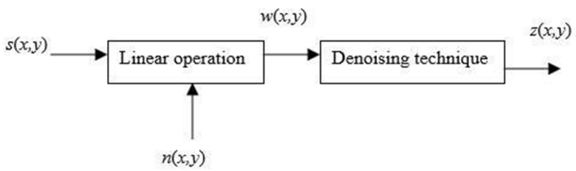


Figure 1.1 Degradation model

Three popular techniques are studied in this paper. Noise removal or noise reduction can be done on an image by filtering,by wavelet analysis, by multifractal analysis or by blind deconvolution method. Each technique has its advantages and disadvantages. Denoising by wavelets and multifractal analysis are some of the recent approaches. Wavelet techniques consider thresholding while multifractal analysis is based on improving the Holder regularity of the corrupted image. While blind deconvolution method is usefull when one have no information about the PSF.

Methods for Restoration of Image

Image restoration in the presence of noise only

Spatial filters are useful for removing noise. Image restoration spatial filters are of two types- mean filter and order-statistic filter. The difference is that, mean filter is based on the concept of convolution, whereas order- statistics filter doesnot use convolution, but only orders the pixels of the neighborhood and selects a pixel value based on its order.

Mean filters

A mean filter [5] acts on an image by smoothing it; that is, it reduces the intensity variation between adjacent pixels. The mean filter is nothing but a simple sliding window spatial filter that replaces the center value in the window with the average of all the neighboring pixel values including itself. By doing this, it replaces pixels that are unrepresentative of their surroundings. It is implemented with a convolution mask, which provides a result that is a weighted sum of the values of a pixel and its neighbors. It is also called a linear filter. The mask or kernel is a square. Often a 3×3 square kernel is used. If the coefficients of the mask sum up to one, then the average brightness of the image is not changed. If the coefficients sum to zero, the average brightness is lost, and it returns a dark image. The mean filter is used in applications where the noise in certain regions of the image needs to be removed. In other words, the mean filter is useful when only a part of the image needs to be processed.

Order statistics filter

Order statistics (also known as rank, rank order, or order) filters are a general form of filters that are not based on the convolution. Here, instead of using convolution, the pixels that come under the mask are simply ordered. Then depending upon the filter requirement, based on a predetermined value of n, the nth value of the list is chosen as this value replaces the central pixel.

Median Filter

A median filter belongs to the class of nonlinear filters unlike the mean filter. The median filter also follows the moving window principle similar to the mean filter. Median filtering is done by, first sorting all the pixel values from the surrounding neighborhood into numerical order and then replacing the pixel being considered with the middle pixel value.

The median is more robust compared to the mean. Thus, a single very unrepresentative pixel in a neighborhood will not affect the median value significantly. Since the median value must actually be the value of one of the pixels in the neighborhood, the median filter does not create new unrealistic pixel values when the filter straddles an edge. For this reason the median filter is much better at preserving sharp edges than the mean filter. These advantages aid median filters in denoising uniform noise as well from an image.

Maximum Filter

This filter selects the largest value in the sorted list. The largest value is the last element of the list. This filter is used for removing pepper type noise. Minimum and maximum filters, also known as erosion and dilation filters, respectively, are morphological filters that work by considering a neighborhood around each pixel. From the list of neighbor pixels, the minimum or maximum value is found and stored as the corresponding resulting value. Finally, each pixel in the image is replaced by the resulting value generated for its associated neighborhood.

Minimum Filter

This filter selects the smallest value, which is the first element of the sorted list. It is very effective in eliminating salt type noise. An important application of minimum filtering to astrophotographical images was devised by Mike Cook. Many wide field deep sky images have so many, so small, and so bright stars, that nonstellar objects as diffuse nebulae and Milky Way condensations, can be greatly obscured by them. A modulated minimum filter (Amount parameter less than 1) can be applied in these cases to decrease the visual impact of stars, giving nonstellar objects their deserved importance in the scene.

Midpoint filter

This filter selects the midpoint. The mid-point is (f1+fN/2). This nothing but the average of the minimum and the maximum values. This filter is effective in removing Gaussian Noise and Uniform Noise. In the midpoint method, the color value of each pixel is replaced with the average of maximum and minimum (i.e. the midpoint) of color values of the pixels in a surrounding region. A larger region (filter size) yields a stronger effect.

LMS Adaptive Filter

An adaptive filter does a better job of denoising images compared to the averaging filter. The fundamental difference between the mean filter and the adaptive filter lies in the fact that the weight matrix varies after each iteration in the adaptive filter while it remains constant throughout the iterations in the mean filter. Adaptive filters are capable of denoising non-stationary images, that is, images that have abrupt changes in intensity. Such filters are known for their ability in automatically tracking an unknown circumstance or when a signal is variable with little a priori knowledge about the signal to be processed [11].In general, an adaptive filter iteratively adjusts its parameters during scanning the image to match the image generating mechanism. This mechanism is more significant in practical images, which tend to be non-stationary. Compared to other adaptive filters, the Least Mean Square (LMS) adaptive filter is known for its simplicity in computation and implementation. The basic model is a linear combination of a stationary low-pass image and a non-stationary high-pass component through a weighting function [11, 12]. Thus, the function provides a compromise between resolution of genuine features and suppression of noise.

The LMS adaptive filter incorporating a local mean estimator works on the following concept. A window, W, of size m×n is scanned over the image. The mean of this window, μ, is subtracted from the elements in the window to get the residual matrix W^r.

$$^{r} = -\mu$$

A weighted sum □, is computed in a way similar to the mean filter using

$$z = \sum_{(,)\in W} h(,)W^{r}$$

Where h(i, j) represents elements of the weight matrix shown in Figure . A sum of the weighted sum$z$ and the mean μ of the window replaces the center element of the window. Thus, the resultant modified pixel value is given as

$$z = z + \mu$$

For the next iteration, the window is shifted over one pixel in row major order and the weight matrix is modified. The deviation e is computed by taking the difference between the center value of the residual matrix and the weighted sum as Equation .

$$= W^{r} - z$$

The largest eigenvalue λ of the original window is calculated from the autocorrelation matrix of the window considered. The use of the largest eigenvalue in computing the modified weight matrix for the next iteration reduces the minimum mean squared error [12]. A value η is selected such that it lies in the range (0, 1/ λ). In other words,

$$0 < \eta < 1/\lambda.$$

The new weight matrix hK+1 is

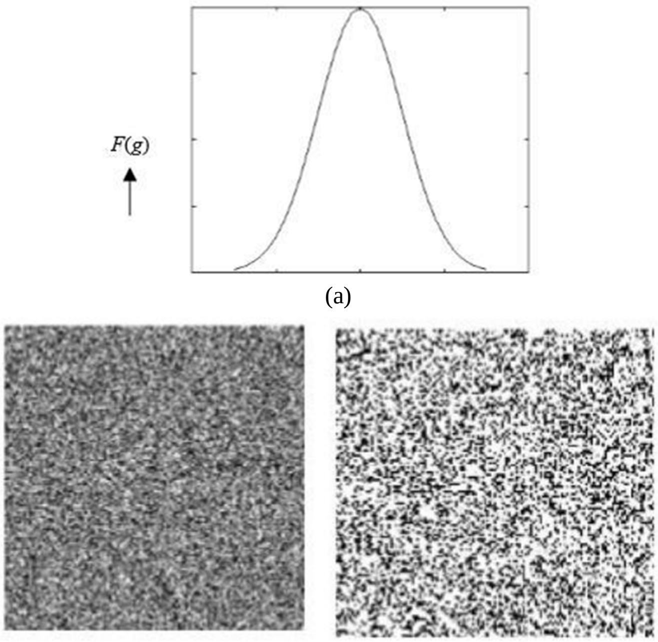
$h_{+1} = \ h \ + \eta \times \ \times W^{r}$

Where hk is the weight matrix from the previous iteration. The weight matrix obtained this way is used in the next iteration. The process continues until the window covers the entire image.

Figure 1.2.1(a): Input to LMS adaptive filter corrupted with salt and pepper noise

Gaussian Noise

Gaussian noise is evenly distributed over the signal. This means that each pixel in the noisy image is the sum of the true pixel value and a random Gaussian distributed noise value. As the name indicates, this type of noise has a Gaussian distribution, which has a bell shaped probability distribution function given by,[4]



(a)

(b) (c)

Figure 2.1 (a) Gaussian distribution(b) Gaussian Noise (mean=0; Varience= 0.05) (c) Gausian Noise (Mean = 0; Varience = 1.5)

Salt and Pepper Noise

Salt and pepper noise is an impulse type of noise, which is also referred to as intensity spikes. This is caused generally due to errors in data transmission. It has only two possible values, a and b. The probability of each is typically less than 0.1. The corrupted pixels are set alternatively to the minimum or to the maximum value, giving the image a “salt and pepper” like appearance. Unaffected pixels remain unchanged. For an 8-bit image, the typical value for pepper noise is 0 and for salt noise 255. The salt and pepper noise is generally caused by malfunctioning of pixel elements in the camera sensors, faulty memory locations, or timing errors in the digitization process. The probability density function for this type of noise is shown in Figure 3.1 (a). Salt and pepper noise with a variance of 0.05 is shown in Figure 3.1 (b)[3]

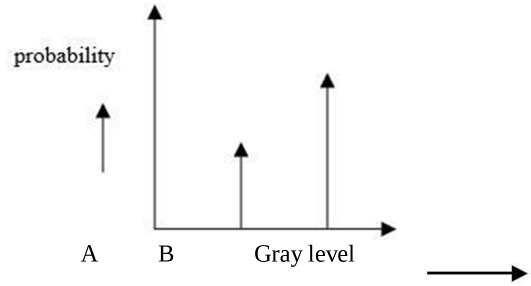


Figure 3.1 (a): PDF for salt and pepper noise

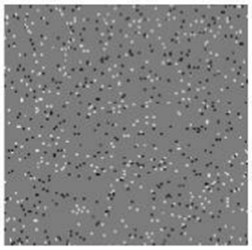


Figure 3.1 (b): Salt and pepper noise

Image Degradation Model

No image is perfect. An image is corrupted by so many degradation which start from the stage of image acquisition itself. Images are degraded by noise, blur and distortion or artifacts. This process of image degradation happens in all the stages- image acquisition, image processing, image storage, and transmission. Noise is a disturbance which causes fluctuations in the pixel values. Similarly, the image capturing system itself doesn't capture a point as point. Instead, it produces a blur. Thus the image formation itself introduces problems.

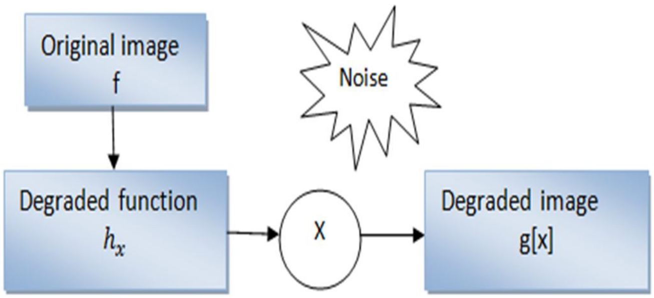


Figure 4.1: Degradation Model

Because both f and hx are unknown, the blur estimationis highly ill-posed, and thus prior knowledge about the latentimage content f is required. Although the distribution of $f$is difficult to describe, we assume that its gradient field can be locally modeled as white Gaussian. Specifically, in a small analysis window η of size $N \times N$ we have:

Δ [] = ($\Delta\otimes$

)[]~N(0, x), o al□ ∈ η

Where, ∇ denotes a derivative operator in a particular direction(horizontal or vertical).x Represents local variance in the window η around **x**. We assume that blur kernel hx is constant inside η.

Categories of Image degradations

To remove image degradations, it is necessary to understand them. Degradations are of three types and are shown in figure 1.9 [17, 18, 19, 20]. This is not an exclusive classification as there is an overlap of classes. Nevertheless, classification always helps to understand the phenomena better.

Noise modeling

Noise is a disturbance which causes fluctuations in the pixel values. Hence the pixel values show random variation and this cannot be avoided. Hence suitable strategies should be designed to model and manage noise. Noise can be viewed in multiple ways some of the frequent noises that are encountered in image processing are categorized based on the criteria of distributions, correlation, nature, and source.

Noise categories based on distribution

Since noise is a fluctuation of pixel values, it is categorized as a random variable. A random variable probability distribution is an equation that links the value of the statistical result with its probability of occurrence. Noise categorization based on probability distributions is very popular. On the basis of its distribution, it can be classified as follow:

Gaussian Noise

Gaussian noise is evenly distributed over the signal. This means that each pixel in the noisy image is the sum of the true pixel value and a random Gaussian distributed noise value. As the name indicates, this type of noise has a Gaussian distribution, which has a bell shaped probability distribution function given by [21],

$$\frac{1}{\sqrt{2\pi\sigma^2}} e^{-(g-m)^2/2\sigma^2}$$

Where g represents the gray level, m is the mean or average of the function and σ is the standard deviation of the noise. Graphically, it is represented as shown in Figure 1.10 (a). When introduced into an image, Gaussian noise with zero mean and variance as 0.05 would look as in Figure 1.10 (b). Figure 1.11(c) illustrates the Gaussian noise with mean (variance) as 1.5 over a base image with a constant pixel value of 100.

Literature Review

Sumali and Mitsukura[1], In their paper used Blind deconvolution technique for restoring the image. They found that Gaussian Filter gives efficient implementation that allows it to create a very blurry blur image in a relatively short time. Improvement in Canny method is shown to detect strong and weak edges of an image and it shows better quantity edges than traditional canny edge detection method. The advantage of using this Blind Deconvolution algorithm is to deblur the degraded image without prior knowledge of PSF and additive noise. But in other algorithms, we should have the knowledge over the blurring parameters.

Nakamura, Hanada[2], This paper proposed a novel image restoration method based on blind image deconvolution with PCA by boosting the high- frequency components. The proposed method improves the performance of image restoration by introducing an iterating PCA restoration algorithm. The method for generating an ensemble can extract the high-frequency components. Furthermore, iterative PCA restoration algorithm can boost it effective. Our future works are the optimization of the iteration number to boost high-frequency components and ensuring the robustness against noise.

Eliahu cohen, Heiman,hader[3], In this paper , the results of ising algorithm are presented. They are used 6 images out of Matlab library. Salt & Pepper noise was inserted artificially. It can be seen how the Ising -based model improves the quality of the pictures and removes the noise. Moreover, a comparison is drawn between given model, the 3x3 and 5x5 median filters (according to which the value of each pixel is determined as the median of 3 / 5 long sequences of horizontal and vertical neighbors, including its own value).

Proposed 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.

Table 1. Summary of Literature Survey

	Method used	Noise Type	Parameter	Published Year
Blind Image Restoration Method by PCA-Based Subspace Generation	Blind Lucy Richardson	Gaussian Noise	PSNR = 33.03 dB, SSIM = 0.960	IEEE 2015
Iterative PCA Approach for Blind Restoration of Single Blurred Image	Blind deconvolution	Gaussian Noise	PSNR = 34.53 dB, SSIM = 0.866	IEEE 2013
Image Restoration via Ising Theory and Automation Noise Estimation	Ising Based Model	Salt &Pepper Noise	PSNR = 15.08 dB, SSIM= 0,45	IEEE 2013

Weiner Filtering Approach for Image Restoration

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:

Algorithm to Implement the Weiner Filtering

1 Read image
2 Simulate a motion blur
3 Restore the Blurred image
4 Simulate blur and noise
5 Restore the blurred and noisy image: first attempt
6 Restore the blurred and noisy image: Second attempt
7 Simulate blur and 8 bit quantization Noise
8 Restored the blurred, quantized image:

first attempt Restored the blurred, quantized image: second attempt

Regularized Filter(or Constrained Least Mean

Square Algorithm) Least mean squares (LMS)
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.[10]

Algorithm to Implement the Regularized filter method
1. Read image
2. Simulate a blur and noise
3. Restore the blurred and noisy image
4. Reduce noise amplification and ringing
5. Use the Lagrange multiplier
6. Use a different constraint.

Image Restoration 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:[13]

Algorithm to Implement the Lucy Richardson Algorithm
1. Read an image into the MATLAB workspace.
2. Create the PSF
3. Create a simulated blur in the image and add noise.
4. Iterate to explore the restoration
5. Control noise amplification by damping
6. Create the sample image
7. Simulate a blur
8. Provide the weight array
9. Provide a finer sampled PSF

Image Restoration using Blind deconvolution Algorithm
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.[16]

Algorithm to Implement the Blind deconvolution method:
1. Read the image into the MATLAB workspace
2. Create the PSF
3. Create a simulated blur in the image
4. Deblur the image, making an initial guess at the size of the PSF
5. Eliminate high contrast areas from the processing (this can reduce contrast related ringing in the result).
6. Specifying a better PSF
7. Use additional constraints on the PSF Restoration.

Expected Result

- In this paper it is proposed to compare the different Restoration methodology for Blur image caused by degradation model. It is expected to differentiate the utility of a specific methodology for a specific noise. Specially, we are taking here two kind of noise Gaussian Noise and Salt and pepper Noise, so it will be an efficient way to represent that for a specific task which method will be appropriate to implement.

- This paper will estimate the performance analysis using various parameters using MSE (Mean Square Error), PSNR (Peak signal to noise ratio), SSIM (Structural Similarity Index Measurement) & Entropy of Original and Restored Image, hence it will differentiate all methodology efficiently.

Conclusion

- This Presentation depicts the idea to perform the Comparative analysis of different Restoration Method. In this presentation all the basics related to different methodology has been discussed in brief. The objectives of the thesis is defined and different flow chart shows the Proposed way to implement those algorithm. At last performance evolution parameter is also discussed which is essential part of the analysis.
- It is expected that we will differentiate very effectively that which method is more efficient to remove which type of noise.

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