A Comparative Study and Analysis of Image Deblurring Techniques
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Abstract: Vision is the foremost trusted source of information compared to other human perceptions and Image is the basic container of any pictorial information. High quality digital images have become pervasive in modern scientific and everyday life. However, there are always limits to the quality of these images. This paper focused on image restoration which is referred to image deblurring. Image restoration is concerned with the restoration of original image from the blurred and noisy one. Deconvolution algorithm can be used effectively for image restoration. On the basis of knowledge of degradation function, the image restoration techniques can be classified as non-blind if the point spread function (PSF) is known, and blind if PSF is unknown\cite{1}. The aim of this paper is to compare the Non-blind and Blind Deconvolution algorithms for image restoration. Popular performance metrics viz., peak signal-to-noise ratio (PSNR) and mean squared error (MSE) are used for an assessment. Through this comparative analysis the properties and limitations of these deblurring algorithms are explored. The algorithms can be simulated in MATLAB.

Key Words: PSF, Deconvolution, Blind deconvolution

1. INTRODUCTION

Photographic images, whether recorded by digital or analogue means, have imperfections which prevent them from conveying the true scene. These degradations have a variety of causes mainly of two types, blurring and noise. The removal of blur, in the presence of noise, is a challenging area and has always attracted the attention of photographic practitioners and research community. The goal of image restoration is to find uncorrupted images from noisy, blurred ones. Image restoration is widely used in fields of application such as remote sensing\cite{12}, enhancement of images in photo and video cameras, in astronomical imaging\cite{11}, microscopy imaging, in tomography\cite{13}, medical imaging, forensic science etc. Mostly a blurred image is given, for example blurred by a defocused photo camera, and the image as it would be without blurring is to be found. In the example above the degradation function or point spread function is known and therefore can be used to reconstruct the image. In other applications, like in some medical imaging problems, the point spread function or blur kernel is unknown and has to be reconstructed together with the image.

The degradation process is usually modeled as a convolution:

\[ g = f \ast h + n \]  

In Equation(1), ‘\( g \)’ is the blurred, noisy image i.e. the data available, ‘\( f \)’ is the original image, ‘\( h \)’ is the point spread function modeling the blurring and ‘\( n \)’ is Gaussian noise added to the blurred image. Image degradation model is described in the next section. The process of image restoration can be classified into two classes, dependent on whether information about the degradation process is provided. If this process is known, i.e. an estimation of the point spread function ‘\( h \)’ is known, then the restoration of original image ‘\( f \)’ from blurred image ‘\( g \)’, is known as non-blind deconvolution. If, on the other hand, very little or no information about the point spread function is provided; the method is regarded as blind deconvolution. The deconvolution of blurred, noisy image ‘\( g \)’ is a typical inverse problem\cite{2,3}. As often with inverse problems this problem is ill-posed which means that, the little change in the input variable, here corrupted image ‘\( g \)’, or both corrupted image ‘\( g \)’ and point spread function or degradation function ‘\( h \)’, generates a large change in the output or a completely different output, here original image ‘\( f \)’.

The overall approach comprises of taking a standard or non-blurred image, creating a known blurring function, and then filtering the image with this function so as to add blur into it. This image is further corrupted by different amount of additive Gaussian noise. The aim is to deblur this image by non-blind deconvolution deblurring algorithms viz., Wiener filtering, Regularized filtering, Richardson-Lucy algorithm and blind deconvolution algorithm. Further their performances are analysed and compared as well. Experimental evaluation is carried out in MATLAB environment on standard images in a variety of blur and noise conditions.
2. MODEL OF IMAGE RESTORATION PROCESS

The degradation process can be modeled as a degradation function that together with an additive noise term operates on an original input image ‘f’, to produce a degraded image ‘g’. The objective of restoration is to obtain an estimate ‘f^’ of an original image[4].

![Degradation model](image)

Figure 2.1 Degradation model

Figure(2.1) shows the degradation model. The blurring of an image is modeled as the convolution of an original image ‘f’ with point spread function as given in equation(1).

2.1 BLUR TYPES

2.1.1 Gaussian Blur
The Gaussian Blur effect is a filter that blends a specific number of pixels incrementally, following a bell-shaped curve. The blurring is dense in the center and feathers at the edge.

2.1.2 Motion Blur
The Motion Blur effect is a filter that makes the image appear to be moving by adding a blur in a specific direction. The motion can be controlled by angle or direction and/or by distance or intensity in pixels.

2.2 GAUSSIAN NOISE
The ability to simulate the behavior and effects of noise is central to image restoration. Gaussian noise is a white noise with constant mean and variance. The default values of mean and variance are 0 and 0.01 respectively.

3. IMAGE DEBLURRING METHODS

Deblurring operation should be performed on the degraded image to produce an estimate of the undegraded image.

3.1 NON-BLIND IMAGE DEBLURRING TECHNIQUES

3.1.1 Wiener Filter Deblurring Technique
In Weiner Filtering is a non-blind technique of image reconstruction in which an image is restored in the presence of known PSF. In this method, images and noise are considered as random variables, and the objective is to find an estimate ‘f^’ of the uncorrupted image ‘f’ such that the mean square error between them is minimized.

The Wiener filter isolates lines in a noisy image by finding an optimal trade-off between inverse filtering and noise smoothing. It removes the additive noise and inverts the blurring simultaneously so as to emphasize any lines which are hidden in the image. This filter operates in the frequency domain. The Wiener filter in Fourier domain can be expressed as follows:
\[ H_{\text{wiener}}(u, v) = \frac{H^*(u, v)}{H^*(u, v)H(u, v) + \frac{S_n(u, v)}{S_f(u, v)}} \] (2)

Where \( H(u, v) \) is degradation function, \( H^*(u, v) \) is the complex conjugate of \( H(u, v) \), \( S_f(u, v) \) and \( S_n(u, v) \) are the power spectrum of the ideal image and the noise, respectively. In the noiseless case \( S_n(u, v) = 0 \), thus the Wiener filter approximates the inverse filter. The ratio of \( S_n(u, v) \) and \( S_f(u, v) \) in Equation (2), is termed as noise-to-signal ratio (NSR). Wiener filter requires the power spectra of noise and image to be known. Wiener performs better than direct inverse method in presence of noise, but subject to a priori knowledge about blurring function.

### 3.1.2 Regularized Filter Deblurring Technique

Regularized filter is the non-blind deblurring method to deblur an image by using deconvolution function ‘deconvreg’ which is effective when the limited information is known about additive noise.

This is another approach for overcoming some of the difficulties of the inverse filter and wiener filter. The blurred and noisy image is restored by a constrained least square restoration algorithm[5],[6] that uses a regularized filter. In regularized filtering less prior information is required to apply restoration. The regularization filter is often chosen to be a discrete Laplacian. The constrained least square (CLS) algorithm is based on finding a direct solution using a criterion C, which ensures optimal smoothness of the deblurred image. This filter in frequency domain is given by the expression,

\[ H_{\text{cls}}(u, v) = \frac{H^*(u, v)}{H^*(u, v)H(u, v) + \alpha P(u, v)} \] (3)

Where \( \alpha \) is the parameter that must be adjusted so that the constraint \( C \) is satisfied. \( P(u, v) \) is Laplacian operator in the frequency domain. Choosing the value of the regularization parameter \( \alpha \) is a critical issue in regularized restoration, since it controls the trade-off between fidelity to the data and smoothness of the solution and therefore the quality of the restored image.

### 3.1.3 Richardson-Lucy Algorithm Technique

The Richardson-Lucy algorithm arises from a maximum-likelihood formulation in which the image is modeled with Poisson statistics. This iterative method was developed independently by Richardson and Lucy[8],[9]. This is an iterative procedure for recovering a latent image that has been blurred by a known point spread function. Pixels in the observed image can be represented in terms of the point spread function and the latent image as,

\[ d_i = \sum p_{ij} u_j \] (4)

where, \( d_i \) is the observed value at pixel position ‘i’, \( p_{ij} \) is the point spread function, the fraction of light coming from true location ‘j’ that is observed at position ‘i’, \( u_j \) is the latent image pixel value at location ‘j’.

The basic idea is to calculate the most likely \( u_j \) given the observed \( d_i \) and known \( p_{ij} \). This leads to an equation for \( u_j \) which can be solved iteratively according to,

\[ u_j^{(\epsilon+1)} = u_j^{(\epsilon)} \sum_i \frac{d_i}{c_i} p_{ij} \] (5)

Where,

\[ c_\epsilon = \sum_j p_{ij} u_j^{(\epsilon)} \] (6)

It has been shown empirically that if this iteration converges, it converges to the maximum likelihood solution for \( u_j \). Increasing the number of iterations not only slows down the computational process, but also
amplifies noise and introduces the ringing effect. Thus for the good quality of restored image, the optimal number of iterations are determined manually for every image as per the point spread function size.

3.2 BLIND DECONVOLUTION METHOD

Blind image Deconvolution method involves image restoration from degraded observation with either unknown or partially known information on the type and extent of the blur. The attribute ‘blind’ applied to the super resolution problem denotes the lack of information on the function representing the blur in the system. This technique is suitable for high resolution image deblurring. For blind deconvolution, the PSF is estimated from the image or image set, allowing the deconvolution to be performed. In Blind deconvolution method an image ‘f’ is identified directly from the convolved signal ‘g’ using partial or no information about the blurring process and true image. Thus, BID is the process of estimating both the true image and the blur from the degraded image characteristics using partial information about the imaging system.

Blind deconvolution can be performed iteratively, whereby each of the iteration improves the estimation of the PSF and the scene, or non-iteratively, where one application of the algorithm, based on exterior information, extracts the PSF.

The iterative blind deconvolution (IBD) algorithm iteratively estimates the original image as well as the PSF. IBD makes use of spatial domain as well as frequency domain constraints. In spatial domain, positivity constraint is used on both the image as well as PSF. Positivity is used in spatial domain because image pixel intensity values are always positive. Similarly, PSF values are observed to be always positive. The Fourier domain constraint may be described as constraining the product of the Fourier spectra of f(x, y) and h(x, y) to be equal to the Fourier spectra of g(x, y), as followed in equation

\[ G(u, v) = F(u, v) H(u, v) \]  

4. PERFORMANCE EVALUATION

According to degradation model, an original image is degraded using degradation function. The original image “plant.tif” is shown in Fig.(4.1).

An image in Fig.(4.2) is degraded by Gaussian blur and a Gaussian noise. The degraded image is then deblurred using above mentioned non-blind techniques and blind deconvolution method of image deblurring

If degraded image is deblurred by Wiener filtering technique, it gives the image result shown in Fig.(4.3) and the image result by Regularized filtering method shown in Fig.(4.4), in both the results the amount of noise is noticeable. Fig.(4.5) shows the image estimated from R-L method. Comparatively good image result is obtained by Blind deconvolution method, shown in the Fig.(4.6)
TABLE 4.1 ESTIMATION RESULTS FOR BLACK AND WHITE IMAGE “PLANT.TIF” OF SIZE 256X256.

<table>
<thead>
<tr>
<th>plant.tif</th>
<th>Wiener filtering</th>
<th>Regularized Filtering</th>
<th>R-L Method</th>
<th>BD Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>PSNR</td>
<td>22.211</td>
<td>24.343</td>
<td>25.779</td>
<td>29.384</td>
</tr>
<tr>
<td>MSE</td>
<td>390.8</td>
<td>239.2</td>
<td>171.87</td>
<td>74.94</td>
</tr>
<tr>
<td>RMSE</td>
<td>19.769</td>
<td>15.466</td>
<td>13.11</td>
<td>8.6568</td>
</tr>
</tbody>
</table>

Following figures illustrates the results of restoration of an image “kid.jpg of size 256 x 256. Fig.(4.7) shows original image which is degraded by a Gaussian blur and Gaussian noise is added to it. Degraded image is shown in fig.(4.8).

The blurred image is then tried with different non-blind deblurring methods, producing resultant images in Fig.(4.9), Fig.(4.10), and Fig.(4.11) Wiener filtering, Regularized filtering and R-L method respectively.

The result obtained by Blind deconvolution method in Fig.(4.12) shows good image quality as compared to other methods.
TABLE 4.2 ESTIMATION RESULTS FOR COLOR IMAGE “KID.JPG” OF SIZE 256X256

<table>
<thead>
<tr>
<th></th>
<th>Wiener filtering</th>
<th>Regularized Filtering</th>
<th>R-L Method</th>
<th>BD Method</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>PSNR</strong></td>
<td>17.594</td>
<td>18.6</td>
<td>26.257</td>
<td>32.583</td>
</tr>
<tr>
<td><strong>MSE</strong></td>
<td>1131.6</td>
<td>897.54</td>
<td>153.95</td>
<td>34.498</td>
</tr>
<tr>
<td><strong>RMSE</strong></td>
<td>33.639</td>
<td>29.959</td>
<td>12.408</td>
<td>5.338</td>
</tr>
</tbody>
</table>

Images used in above results are blurred by Gaussian blur. The Gaussian noise is added to the blurred image.

5. CONCLUSION
In this paper the performance of the basic deblurring techniques are studied and compared for synthetically blurred images. The Wiener and Regularized filtering method shows comparable results, which comprise a lot of low frequency ringing. The Richardson-Lucy algorithm restores the blurred and noisy image better than the former two methods and outperforms. In the Blind deconvolution method, the majority of the blur is successfully removed, producing better result than non-blind techniques. Thus, in the blind deconvolution, it is possible to restore blurred image based upon correct PSF estimation.

REFERENCES

