BLIND DECONVOLUTION WITH CANNY EDGE DETECTION: AN EFFICIENT METHOD FOR DEBLURRING

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Abstract—This paper tries to understand the study of Restored Motion Blurred Images by using four types of deblurring methods: Regularized filter, Wiener filter, Lucy Richardson and Blind Image Deconvolution. There are some indirect restoration techniques like Regularized filtering, Weiner filtering, LR Filtering in which restoration results are obtained after number of iterations. The problem of such method is that they require knowledge of blur function that is point spread function (PSF), which is unfortunately unknown when dealing with image deblurring. In this paper Blind deconvolution for image restoration is discussed which restores blurred image when the blur kernel is unknown.

The fundamental task of image deblurring is to de-convolute the blurred/degraded image with the PSF that exactly describes the distortion. Firstly the original image is degraded using the Degradation Model. They can be performed by Gaussian filter which is the low-pass filter used to blur an image. There is an edge of the blurred image; the ringing effect can be detected using Canny Edge Detection method. The ringing effect is reduced by weighting function. Image restoration is concerned with the reconstruction of blur parameters of the uncorrupted image from a blurred and noisy one. Blind Deconvolution algorithm can be used effectively when no information about the blurring and noise is known. The aim of this paper to show the effective Blind Deconvolution algorithm which can effectively remove complex motion blurring from natural images without requiring any prior information of the motion-blur kernel.

Keywords— Blurred image, Blind Deconvolution, Motion blur, PSF, Lucy- Richardson Algorithm, Regularized Filter, Weiner Filter

I. INTRODUCTION

Blurring is a form of bandwidth reduction of the image due to imperfect image formation process. It can be caused by relative motion between camera and original images. Normally, an image can be degraded using low-pass filters and its noise. This low-pass filter is used to blur the image using certain functions. In digital image there are 3 common types of Blur effects: - i) Average Blur, ii) Gaussian Blur, iii) Motion Blur Out of these, motion blurring is one of the prime causes of poor image quality in digital imaging ([1] - [4]). When an image is captured by a digital camera, the image represents not just the scene at a single instant of time, but the scene over a period of time. If objects in a scene are moving fast or the camera is moving over the period of exposure time, the objects or the whole scene will look blurry along the direction of relative motion between the object/scene and the camera. Camera shake is one main cause of motion blurring ([5] and [6]), particularly when taking images using telephoto lens or using long shutter speed under low lighting condition. Previously, many researchers have been working on removing blurring from motion-blurred images. (e.g. [7] and [8]) The motion blur caused by camera shiver usually is modeled by a spatial invariant blurring process:

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

Where \( \ast \) is the convolution operator, \( g \) is the clear image to recover, \( f \) is the observed blurred image, \( h \) is the blur kernel (or point spread function) and \( n \) is the noise. How to recover the original image \( g \) from the observed image \( f \) is the so-called image deconvolution problem. In the past, there have been extensive research literatures on the nonblind deconvolution algorithm (e.g. [9] - [18]).

Based on the availability of, there are two categories of image deconvolution problems. First is nonblind, in which the blurring operator i.e. kernel \( p \) is given. And blind, in which the blurring operator kernel \( p \) is unknown. In general, blind deconvolution is a very challenging ill-conditioned and ill-posed inverse problem because it is not only sensitive to image noise but also under constrained with infinitely many solutions [19].

There are two broad classes of image restoration concept as Blind Image Deconvolution and Image Deconvolution. Blind Image Deconvolution is a more difficult image recovered where image recovery is performed with no prior knowledge of the degrading PSF. Image Deconvolution is a linear image restoration problem where the specifications of the original image are estimated using the observed or degraded image and a known PSF (Point Spread Function) ([21] & [22]). Point Spread Function (PSF) is the degree to which an optical system blurs (spreads) a point of light. 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).

The Blind Deconvolution Algorithm can be used effectively when no information about the distortion (blurring and noise) is known. The algorithm restores the image and the point-spread function (PSF) simultaneously. The accelerated, damped Richardson-Lucy algorithm is used in each iteration [20]. Additional optical system (e.g., camera) characteristics can be used as input parameters that could help to improve the quality of the image restoration. PSF constraints can be passed in through a user-specified function. The features of Deconvolution are higher resolution and better quality.

II. PAPER ORGANIZATION

The paper organization is as follows III Image Deblurring Techniques, IV Deconvolution using Wiener Filter, V Deconvolution using Regularized Filter, VI Deconvolution using Lucy-Richardson Filter, VII Blind Image Deconvolution VIII Degradation model, IX Gaussian filter, X Overall Architecture and deblurring algorithm, XI Results for deblurred images, XII Performance measures and iteration wise results, XIII Conclusion.

III. IMAGE DRBLURRING TECHNIQUES

In image restoration the upgrading in value of the restored image over the recorded blurred one is calculated by the signal-to-noise ratio improvement and Mean square error decrement rate. When applying restoration filters to real images of which the true image is not obtainable, often only the visual judgement of the restored image can be relied upon. There are two types of deblurring techniques A. Non Blind image deblurring technique, B. Blind image deblurring technique

IV. DECONVOLUTION USING WIENER FILTER

This filter can be used efficiently when the frequency features of the image and additive noise are known, to at least certain degree. Wiener filters are very often applied in the frequency domain. An important advantage of this algorithm is that it eliminates the additive noise and reverses the blurring simultaneously. The Wiener filter is the optimal linear filter to improve MSE for images corrupted by additive noise and blurring. In mathematics, Wiener deconvolution is an application of the Wiener filter to the noise complications inherent in deconvolution. It attempts to reduce the impact of deconvolved noise at frequencies which have a poor signal-to-noise ratio. A drawback of the Wiener filters is that they are unable to rebuild frequency components which have been corrupted by noise, but can only suppress them. These filters are somewhat slow to apply, since they need to work in the frequency domain. It removes the additive noise and inverts the blurring simultaneously so as to emphasize any lines which are hidden in the image. The Wiener filter in Fourier domain can be expressed as follows:

\[
W(f_1,f_2) = \frac{H^*(f_1,f_2)S_{x_1}(f_1,f_2)}{|H(f_1,f_2)|^2S_{x_1}(f_1,f_2) + \sigma_n^2(f_1,f_2)}
\]

Where \(S_{x_1}(f_1,f_2)\) and \(S_{y_2}(f_1,f_2)\) are respectively the power spectra of the original image and the additive noise, and \(H(f_1,f_2)\) is the blurring filter. Here one can see that the Wiener filter has two separate parts, an inverse filtering part and a noise smoothing part. It not only performs the deconvolution by inverse filtering (high pass filtering) but also removes the noise with low pass filtering.

Regulated filter is the deblurring method to deblur an image by using deconvolution function deconverge which is effective when the limited information is known about 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 to Wiener filtering but is justified by a very different viewpoint. Also, less prior information is required to apply regularized restoration. Regularization trades off two desirable goals -- i) the closeness of the model fit and ii) the closeness of the model behavior to something that would be expected in the absence of specific knowledge of the model parameters or data.

VI. DECONVOLUTION USING LUCY-RICHARDSON FILTER

This procedure was introduced by W.H. Richardson (1972) and L.B. Lucy (1974). The Richardson–Lucy
algorithm, also identified as Lucy–Richardson deconvolution, is an iterative technique for improving a latent image that has been distorted by a known point spread function. The Lucy-Richardson procedure can be used successfully when the point-spread function PSF (blur kernel is known, but little or no information is offered for the noise. The blurred and noisy image is repaired by the iterative, accelerated, damped Lucy-Richardson algorithm. The additional optical system such as camera features can be used as input parameters to recover the quality of the image restoration. The algorithm needs a good estimate of the process by which the image is corrupted for accurate restoration. The degradation can be produced in many ways, such as subject movement, out-of-focus lenses, or atmospheric turbulence, and is defined by the point spread function (PSF) of the system. Non-point sources are effectively the sum of many individual point sources, and pixels in an observed image can be represented in terms of the point spread function and the latent image as

\[ \hat{I}_i = \sum_j \hat{P}_{ij} u_j \]

Where \( \hat{P}_{ij} \) 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 \( \hat{I}_i \) is the observed value at pixel location \( i \). The statistics \( u_j \) are performed under the assumption that are Poisson distributed, which is appropriate for photon noise in the data.

**VII. BLIND IMAGE DECONVOLUTION**

In image processing, blind deconvolution is a deconvolution technique that permits recovery of the target scene from a single or set of "blurred" images in the presence of a poorly determined or unknown point spread function (PSF). Regular linear and non-linear deconvolution techniques utilize a known PSF. For blind deconvolution, the PSF is estimated from the image or image set, allowing the deconvolution to be performed. Researchers have been studying blind deconvolution methods for several decades, and have approached the problem from different directions.

Blind deconvolution can be performed iteratively, whereby each iteration improves the estimation of the PSF. Use the deconvblind function to deblur an image using the blind deconvolution algorithm. The algorithm maximizes the likelihood that the resulting image, when convolved with the resulting PSF, is an instance of the blurred image, assuming Poisson noise statistics. The blind deconvolution algorithm can be used effectively when no information about the distortion (blurring and noise) is known. The deconvblind function restores the image and the PSF simultaneously, using an iterative process similar to the accelerated, damped Lucy-Richardson algorithm. The deconvblind function just like the deconvlucy function, implements several adaptations to the original Lucy-Richardson maximum likelihood algorithm that address complex image restoration tasks. Using these adaptations, you can reduce the effect of noise on the restoration, account for nonuniform image quality (e.g., bad pixels), handle camera read-out noise.

**VIII. DEGRADATION MODEL**

In degradation model for blurring image, the image is blurred using filters and an additive noise. The image can be degraded done by using Gaussian Filter and Gaussian Noise. Gaussian Filter represents the Point Spread Function which is a blurring function. The degraded image can be express by the equation \( f = g \ast h + n \); Where \( \ast \) is the convolution operator, \( g \) is the clear image to recover, \( f \) is the observed blurred image, \( h \) is the blur kernel (or point spread function) and \( n \) is the noise. The below Fig.1 represents the formation of degradation model. Image deblurring can be performed by the technique, Gaussian Blur. They are the convolution of the image with 2-D Gaussian function. ([7] and [19])

![Image of degradation model](image_url)

**Fig.5: Degradation Model for Blurring Image**
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IX. GAUSSIAN FILTER

Gaussian filter is useful for blur an image by Gaussian function. It requires two specifications such as mean and variance. They are weighted blurring. Gaussian function is of the following form where $\sigma$ is variance and $x$ and $y$ are the distance from the origin in the x axis and y axis respectively. [26]

X. OVERALL ARCHITECTURE AND DEBLURRING ALGORITHM

The below Fig. 2 shows the overall architecture of Image restoration paper. The original image is degraded or blurred using degradation model to produce the blurred image. The blurred image should be an input to the deblurring algorithm. Various algorithms are available for deblurring. In this paper, we are going to use blind deconvolution algorithm. The result of this algorithm produces the deblurring image which can be compared with our original image. This algorithm can be achieved based on MLE (Maximum Likelihood Estimation). [24]

Deblurring Algorithm

1) Read an original input image $f(x, y)$.
2) Degrade the original image with Gaussian Blur function to get a blurred image $g(x, y)$.
3) Restored blurred image PSFs of various sizes. This performs three restorations viz-
   i) Deblurring with undersized PSF
   ii) Deblurring with oversized PSF
   iii) Deblurring with initial PSF
4) Analyzing the restored PSF.
3) Now restore the degraded image with deconvblind function to get a restored image having ringing effects at its edges.
4) To remove the ringing effect at edges, Canny edge detection technique is used
5) Apply edge taper function to remove ringing effects
6) Finally, we get a restored image

XI. RESULTS FOR DEBLURRED IMAGES

The proposed approach is experimented using a test image “cameraman.tif” of size 256 x 256. The below images represent the result of degradation model using Gaussian blur.
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:

**Table.1: Comparative analysis of MSE values for the four mentioned (LRA, WF, RF, and BID) techniques for deblurring.**

<table>
<thead>
<tr>
<th>Sr. No</th>
<th>Image Size</th>
<th>Mean Square Error (MSE)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>RF</td>
<td>WF</td>
</tr>
<tr>
<td>01</td>
<td>Cameraman.tif (512 x 512)</td>
<td>1112.71</td>
</tr>
<tr>
<td>02</td>
<td>Cameraman.tif (256 x 256)</td>
<td>1112.71</td>
</tr>
<tr>
<td>03</td>
<td>Lena.png (256 x 256)</td>
<td>550.47</td>
</tr>
<tr>
<td>04</td>
<td>Onion.png (198 x 135)</td>
<td>434.98</td>
</tr>
</tbody>
</table>

**Table.2: Comparative analysis of PSNR for the four mentioned (LRA, WF, RF, and BID) techniques for deblurring.**

<table>
<thead>
<tr>
<th>Sr. No</th>
<th>Image Size</th>
<th>Peak Signal To Noise Ratio (PSNR)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>RF</td>
<td>WF</td>
</tr>
<tr>
<td>01</td>
<td>Cameraman.tif (512 x 512)</td>
<td>17.70</td>
</tr>
<tr>
<td>02</td>
<td>Cameraman.tif (256 x 256)</td>
<td>17.70</td>
</tr>
<tr>
<td>03</td>
<td>Lena.png (256 x 256)</td>
<td>20.72</td>
</tr>
<tr>
<td>04</td>
<td>Onion.png (198 x 135)</td>
<td>21.75</td>
</tr>
</tbody>
</table>

We can compare these results with other reference papers; we can conclude this method is very efficient for restoring the motion blur. ([03], [04], [23] - [26])

**XII. PERFORMANCE MEASURES**

**MSE:**

The mean squared error abbreviated as MSE is an estimator that measures the average of the squares of the “errors”, that is, the difference between the
estimator and what is estimated. Mean Square Error can be estimated in one of many ways to quantify the difference between values implied by an estimate and the true quality being certified.

\[
MSE = \frac{1}{m \cdot n} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [I(i,j) - K(i,j)]^2
\]

Where, m\times n monochrome images I and its noisy approximation K.

**PSNR:**

Peak signal-to-noise ratio abbreviated as PSNR, is a technical term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. PSNR is usually expressed as decibel scale. The PSNR is commonly used as a measure of quality reconstruction of image. High value of PSNR indicates the high quality of image.

\[
PSNR = 10. \log_{10} \left( \frac{\text{MAX}^2}{MSE} \right)
\]

\[
= 20. \log_{10} \left( \frac{\text{MAX}}{\text{MSE}} \right)
\]

Here, MAXI is the extreme possible pixel value of the image. When the pixels are denoted using 8 bits per sample, this is 255.

**XIII. ITERATION WISE RESULTS**

In this paper we have also derived the iterative results in the form of deblurred image, PSNR and MSE values for Blind deconvolution algorithm. When we set the iterations to 30 for our experiment then we have received the output image along with the PSNR value as 27.31 and MSE value as 120.85. Further as we increase the iteration we will get clearer image. When we increase the number of iterations to 80, MSE value which decrement to 83.66 and PSNR value is 28.91. Further increase in iteration will give high MSE and low PSNR values. Hence we select 80 iterations.

<table>
<thead>
<tr>
<th>Sr. No.</th>
<th>Iterations</th>
<th>MSE</th>
<th>PSNR</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>30</td>
<td>120.85</td>
<td>27.31</td>
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<tr>
<td>2</td>
<td>40</td>
<td>103.46</td>
<td>27.98</td>
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<tr>
<td>3</td>
<td>50</td>
<td>92.91</td>
<td>28.45</td>
</tr>
<tr>
<td>4</td>
<td>60</td>
<td>86.88</td>
<td>28.74</td>
</tr>
<tr>
<td>5</td>
<td>70</td>
<td>83.94</td>
<td>28.89</td>
</tr>
<tr>
<td>6</td>
<td>80</td>
<td>83.66</td>
<td>28.91</td>
</tr>
<tr>
<td>7</td>
<td>90</td>
<td>85.31</td>
<td>28.82</td>
</tr>
<tr>
<td>8</td>
<td>100</td>
<td>88.38</td>
<td>28.47</td>
</tr>
</tbody>
</table>

**CONCLUSION**

Four approaches of Image Restoration are studied in this paper. It can be concluded that Weiner Filter, Lucy Richardson, Regularize are Non- Blind deconvolution Image Restoration techniques since they require prior knowledge regarding PSF and additive noise. A new algorithm has been presented to remove camera shake from a single image. Gaussian Filter has an efficient implementation that allows it to create a very blurry image in a relatively short time. Again the Canny Edge detection has better performance results than the other methods like Sobel, Roberts etc. The ringing effect is reduced by using edgetaper function. The advantage of our proposed Blind Deconvolution algorithm is used to deblur the degraded image without prior knowledge of PSF and additive noise. The above experimental results that are MSE, PSNR values indicate that this method is very efficient for deblurring the motion blur.

The future work of this paper is to increase the speed of the deblurring process that is reducing the number of iteration using for deblurring the image for achieving better quality image and we would like to extend our proposed algorithm to remove non-uniform motion blurring from images.

**REFERENCES**


Blind Deconvolution With Canny Edge Detection: An Efficient Method For Deblurring

[27] www.wikipedia.org/wiki/Gaussian_filter

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