

Comparative Study of Various Image Restoration Techniques on the Basis of Image Quality Assessment Parameters

¹Raman Kumar, ²Anil Gupta

¹Dept. of CSE, DAV Institute of Engineering and Technology, Jalandhar, Punjab, India

²Dept. of IT, Model Institute of Engineering and Technology, Kot Balwal, Jammu, India

Abstract

One of the big challenges in digital photography is motion blur. To remove blur, we need: (i) To estimate how the image is blurred (i.e. the blur kernel or the point-spread function) and (ii) To restore a natural looking image through deconvolution. The blur kernel estimation is challenging because the algorithm needs to distinguish the correct image pair from incorrect ones that can also adequately explain the blurred image. The process of deconvolution is also difficult because the algorithm needs to restore high frequency image contents attenuated by blur. In this paper, we address a few aspects of these challenges. We introduce an insight that a blur kernel can be estimated by analyzing edges in a blurred photograph. We can recover the blur using the inverse radon transform. This method is computationally attractive and is well suited to images with many edges. Blurred edge profiles can also serve as additional cues for existing kernel estimation algorithms. We have introduced a method to integrate this information into a maximum-a-posteriori kernel estimation framework, and show its benefits. In this paper, we compared restored gaussian blurred images, by using four types of techniques of deblurring images such as Wiener filter, Inverse filter, Lucy Richardson deconvolution algorithm and our purposed algorithm on the basis of well-known image quality assessment parameters like mean squared error (MSE) and peak signal-to-noise ratio (PSNR).

Keywords

Bilateral Filter, Deblurring, Deconvolution, Gaussian Blur, Motion blur, Radon Transform.

I. Introduction

The restoration of image is very important process in the digital image processing. To restore the image by using the image processing techniques we have to easily understand this image without any artifacts errors [1]. In this case there are many studies undertaken in that scope and this some of these are discussed in this paper. The present is a novel algorithm to estimate direction and length of motion blur, using Radon transform concepts. This method was tested on a wide range of different types of standard images that were degraded with different gaussian noise values. The results showed that the method works highly satisfactory and supports lower MSE and higher PSNR values as compared with other algorithms [2]. For correct restoration of the degraded image it is useful to know the point-spread function (PSF) of the blurring system. We propose straightforward method to restore Gaussian blurred images given only the blurred image it, the method first identifies the PSF of the blur and then use it to restore the blurred image with bilateral filter [3].

II. 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. The Blur effects are filters that smooth transitions

and decrease contrast by averaging the pixels next to hard edges of defined lines and areas where there are significant color transition [2].

A. Blurring Types

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

1. Average Blur

The Average blur is one of several tools you can use to remove noise and specks in an image. Use it when noise is present over the entire image. This type of blurring can be distribution in horizontal and vertical direction and can be circular averaging by radius R which evaluated by the formula:

$$R = \sqrt{h^2 + v^2}$$

Where: h is the horizontal size blurring direction and v is vertical blurring size direction is the radius size of the circular average blurring [3].

2. Gaussian Blur

Gaussian Blur is that pixel weights aren't equal - they decrease from kernel centre to edges according to a bell-shaped curve. 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 centre and feathers at the edge. Apply gaussian blur to an image when you want more control over the Blur effect. Gaussian blur depends on the size and alpha [4].

3. 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 (0 to 360 degrees or -90 to +90) and/or by distance or intensity in pixels (0 to 999), based on the software used [5].

4. Degradation Model

In degradation model, the image is blurred using filters and additive noise. Image can be degraded using Gaussian Filter and Gaussian Noise. Gaussian Filter represents the PSF which is a blurring function. The degraded image can be described by the following equation (1), as shown in fig. 1.

$$g = H * f + n$$

In this equation, g is degraded/blurred image, H is space-invariant function i.e blurring function, f is an original image, and n is additive noise. The fig. 1, represents the structure of degradation model [11].

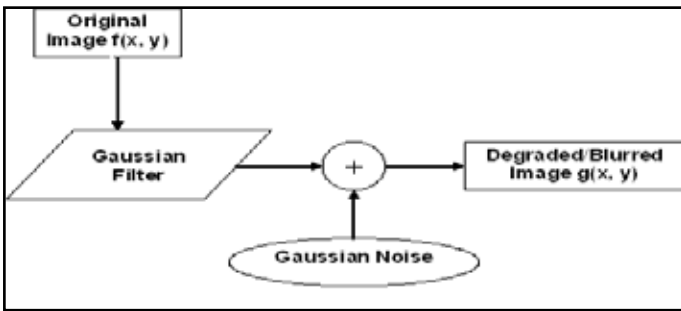


Fig. 1: Degradation Model

B. Classical Deconvolution Methods

The classical deconvolution algorithms perform deblurring operation on the already blurred and noise corrupted image g and produces an estimate $\hat{f}$ of the undegraded image f . The non-blind methods which are discussed here are namely, inverse, Wiener, Richardson-Lucy (R-L) algorithm, where it is assumed that the characteristics of the degrading system and the noise are known a priori. Another class which is based on real life fact that such information about degrading system at the time of image formation is rarely available is blind deconvolution, which is also described in this paper.

1. Direct Inverse Filtering

If a good model of the blurring function that corrupted an image is known or can be developed, then inverse filtering is the quickest and easiest way to restore the blurred image. Since blurring is equivalent to low pass filtering of an image, inverse filtering provides with high pass filtering action to reconstruct the blurred image without much effort. Fig. 2, depicts complete blurring and deblurring operation that the image undergoes in case of direct inverse filtering as shown in fig. 2.

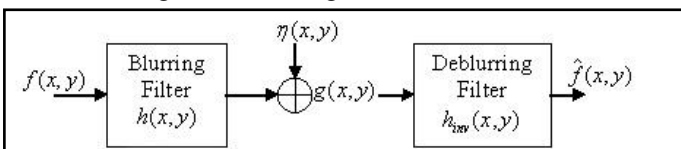


Fig. 2: A Block Diagram Representation of Direct Inverse Filter

Generally, we can write equation for every image degraded by a linear point spread function.

$$g(x, y) = f(x, y) * h(x, y) + n(x, y)$$

where $f(x, y)$ is the original image, $h(x, y)$ is the degrading function (Point Spread Function: PSF), $n(x, y)$ is additive noise, $g(x, y)$ is the observed image, and $*$ is the convolution sign. When the additive noise is unknown, it is assumed to be zero. This gives us direct filtering requiring only the blur PSF as a priori knowledge, and it allows for perfect restoration in the case that noise is absent. Unfortunately, since the inverse filter is a form of high pass filter, inverse filtering responds very badly to any noise that is present in the image because noise tends to be high frequency. Although there are some schemes to improve the performance of inverse filter viz., thresholding and iterative methods, they try to tackle the noise term for limiting the amplification of it, but there lies trade-off between deblurring and denoising. A thresholding scheme that handles the smaller or near zero values of inverse filter is pseudo-inverse filtering.

2. Wiener Filter Deblurring Method

Wiener filter is a method of restoring image in the presence of blur and noise [6]. The frequency-domain expression for the Wiener

filter is:

$$W(s) = H(s) / F^+(s)$$

$$H(s) = F_{x,s}(s) e^{as} / F_x(s)$$

Where: $F(s)$ is blurred image, $F^+(s)$ causal, $F_x(s)$ anti-causal.

3. Lucy-Richardson Algorithm Method

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 [7].

4. Blind Deconvolution Algorithm Method

Definition of the blind deblurring method can be expressed by:

$$g(x, y) = \text{PSF} * f(x, y) + \eta(x, y)$$

Where: $g(x, y)$ is the observed image, PSF is Point Spread Function (x, y) is the constructed image and $\eta(x, y)$ is the additive noise term.

III. Blur Kernel Estimation From EDGES

In this section, we introduce our image formation model and give a brief introduction to the Radon transform. Then, we build upon these concepts to estimate the blur kernel using the edges in the blurred image.

A. Background on the Radon Transforms

The 2D Radon transformation is the projection of the image intensity along a radial line oriented at a specific angle. Radon expresses the fact that reconstructing an image, using projections obtained by rotational scanning is feasible [8].

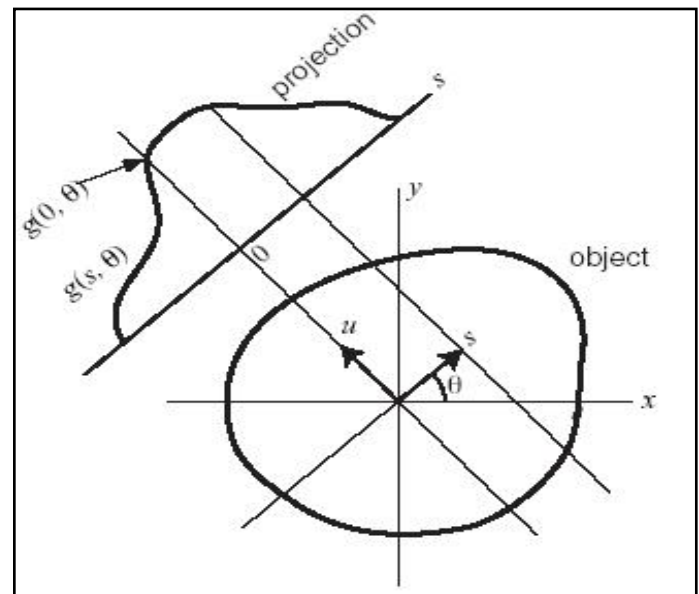


Fig. 3: The Radon Transform Computation

Suppose a 2-D function $f(x, y)$ (Fig. 3). Integrating along the line, whose normal vector is in θ direction, results in the $g(s, \theta)$ function which is the projection of the 2D function $f(x, y)$ on the axis s of θ direction. When s is zero, the g function has the value $g(0, \theta)$ which is obtained by the integration along the line passing the origin of (x, y) -coordinate. The points on the line whose normal vector is in θ direction and passes the origin of (x, y) -coordinate satisfy the equation:

$$\frac{y}{x} = \tan\left(\theta + \frac{\pi}{2}\right) = \frac{-\cos \theta}{\sin \theta} \Rightarrow$$

$$\Rightarrow x \cos \theta + y \sin \theta = 0$$

The integration along the line whose normal vector is in θ direction and that passes the origin of (x, y) -coordinate means the integration of $f(x, y)$ only at the points satisfying the previous equation. With the help of the Dirac "function" δ , which is zero for every argument except to 0 and its integral is one, $g(0, \theta)$ is expressed as:

$$g(0, \theta) = \iint f(x, y) \cdot \delta(x \cos \theta + y \sin \theta) dx dy$$

Similarly, the line with normal vector in θ direction and distance s from the origin is satisfying the following equation:

$$(x - s \cdot \cos \theta) \cdot \cos \theta + (y - s \cdot \sin \theta) \cdot \sin \theta = 0 \Rightarrow x \cos \theta + y \sin \theta - s = 0$$

So the general equation of the Radon transformation is acquired

$$g(s, \theta) = \iint f(x, y) \cdot \delta(x \cos \theta + y \sin \theta - s) dx dy$$

The inverse of Radon transform is calculated by the following equation [14] :

$$f(x, y) = \int_{-\pi/2}^{\pi/2} \rho \cdot R_{\theta}(s(x, y)) d\theta$$

where R_{θ} is the Radon transformation, ρ is a filter and

$$s(x, y) = x \cos \theta + y \sin \theta$$

B. Proposed Method

Proposed algorithm based on Radon Transform estimate a blur kernel by analyzing blurred edges [9]. Intuitively, edges along different orientations are affected differently by noise; therefore this research can consider different edge profiles as "signatures" of the blur kernel. This work formalize this intuition and show how to use blurred edges to recover the Radon transform of the blur kernel, that is, a set of projections of the blur kernel in different orientations.

To recover the blur kernel, explicitly invert the Radon transform of the blur kernel. This method is advantageous because (i) we do not deconvolve the blurred image to refine the estimated kernel and that (ii) This work performs a bulk of the computation at the size of the kernel, which is often considerably smaller than the image. The simplicity of this Modified algorithm comes at a price of restricted set of applicable images. This proposed algorithm is well-suited for scenes with numerous edges such as man-made environments.

Even if a blurred image does not contain many edges in different orientations, however, this approach can still exploit kernel projections. As a second contribution, this work introduces a proposed Radon transform algorithm [fig. 4] that integrates Radon transform constraints in a maximum-a-posteriori kernel estimation framework to improve the kernel estimation performance. This alternative method is computationally more expensive, but it is more stable for specific images (such as .tiff) [10].

C. Experimental Results:

In this section we make a comparison between existing deblurring algorithms and our purposed algorithm implementing these methods in Matlab (8.0.2). Following parameters considered for comparison.

Two of the error metrics used to compare the various image deblurring techniques is the Mean Square Error (MSE) and the Peak Signal to Noise Ratio (PSNR). The MSE is the cumulative squared error between the compressed and the original image, whereas PSNR is a measure of the peak error. The mathematical formulae for the two are MSE value is:

$$\frac{1}{MN} \sum_{y=1}^M \sum_{x=1}^N [I(x, y) - I'(x, y)]^2$$

$$\text{PSNR} = 20 * \log_{10} (255 / \sqrt{\text{MSE}})$$

where $I(x, y)$ is the original image, $I'(x, y)$ is the approximated version (which is actually the decompressed image) and M, N are the dimensions of the images. A lower value for MSE means lesser error, and as seen from the inverse relation between the MSE and PSNR, this translates to a high value of PSNR. Logically, a higher value of PSNR is good because it means that the ratio of Signal to Noise is higher. Here, the 'signal' is the original image, and the 'noise' is the error in reconstruction. So, if you find a compression scheme having a lower MSE (and a high PSNR), you can recognise that it is a better one. The proposed algorithms to support various experimental results are as follows:

Proposed Algorithm

Step 1 Load the Input image I.

Step 2 Add the Blur and Gaussian Noise to the Input Image.

Step 3 Find the Radon transform of the blur kernel.

Step 4 Take the inverse radon transform of the blur kernel to recover kernel

Step 5 Deblur the image using the Standard Equation of the Deblurring.

Step 6 Filter the Deblurred Image using the bilateral filter to remove ringing and noise.

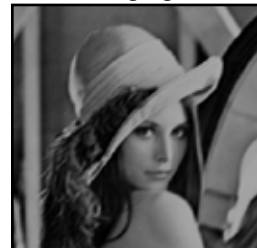


Fig. 4: Original Image

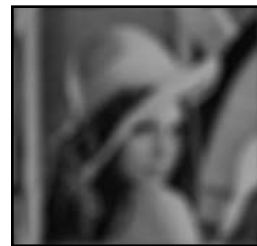


Fig. 5: Blurred and Noisy Image



Fig. 6: Deblurred Using Inverse Filter



Fig. 7: Deblurred Using Wiener Filter



Fig. 8: Deblurred using Lucy Richardson's Filter



Fig. 9: Deblurred using Purposed Method

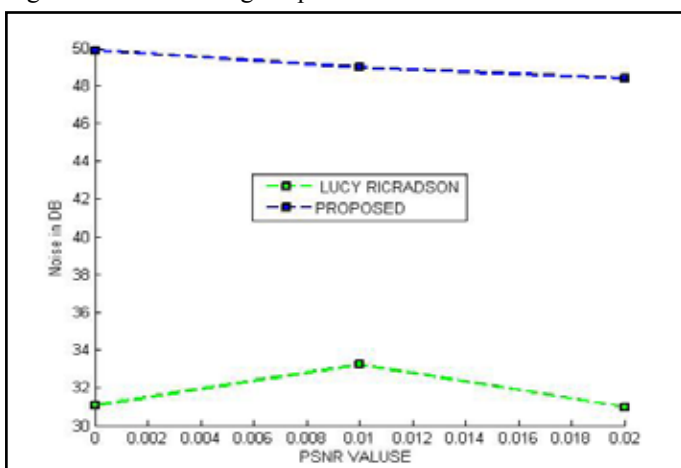


Fig. 4: Plot of PSNR vs Noise Levels for Different Image Formats

Different operations have been applied on the standard test images of Lena and then these images are assessed for image quality. Following operations are applied on the original standard test image:

- Change in Contrast
- Add Blur
- Addition of Gaussian Noise

After applying these operations on standard test images. MSE, PSNR, RMSE are calculated and the results are compared.[Table 1]

IV. Conclusion

This Paper investigated new ideas to address a long-standing problem in photography: Noise removal. Noise removal is challenging because many noise image pairs can explain the noisy photograph and we need to pick the correct pair from them. The challenge is aggravated since the blur can be spatially variant depending on the relative motion between the camera and the scene.

The Proposed Radon MAP algorithm is used for removing noise from photographs. This approach showed that (i) it is possible to estimate blur kernel projections by analyzing blurred edge profiles and that (ii) it can reconstruct a blur kernel from these projections using the inverse Radon transform. This method is conceptually simple and computationally attractive, but is applicable only to images with many edges in different orientations.

This work showed that it is possible to recover a blur kernel by analyzing blurred edge profiles. One of the assumptions is that an image consists of isolated step edges oriented in different directions, and this assumption limits the algorithm's applicability. In fact, even piecewise smooth logos sometimes have thin bands at boundaries, making this algorithm inappropriate.

There are two ways to incorporate blurred line profiles. The first method models a line profile as a box filter of unknown width. If the blur kernel is known, it is possible to estimate the line widths; if the line widths are known, it can be possible estimate the blur kernel from the blurred line profiles using a proposed approach. Therefore, iteratively estimate the line width and the blur kernel from blurred line profiles, assuming that one of the two is known in each iteration. It attempts to recover both the blur kernel and the deblurred line profiles from blurry line profiles.

The limitations of this proposed approach is that it works best for specific type of images rather than all types of images.

As a future work one can extend the limitations as we are suffering, here one of the important factors is the choice of image slices for different dimensional images. That can be done in future as a same number of slices for all dimensional images.

V. Future Work

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Mr. Raman Kumar is working as an Assistant Professor with the Department of Computer Science and Engineering, D A V Institute of Engineering and Technology, Jalandhar, Punjab, India. Before joining D A V Institute of Engineering and Technology, Jalandhar, he did his Bachelor of Technology with honours in Computer Science and Engineering from Guru Nanak Dev University; Amritsar (A 5 Star NAAC University). He did his Master of Technology with honours in Computer Science and Engineering from Guru Nanak Dev University; Amritsar (A 5 Star NAAC University). His major areas of research are Digital Image Processing, Cryptography, Security Engineering and Information security. He has various publications in National as well as International Conferences and Journals on his research areas.



Mr. Anil Gupta is working as a Lecturer with the Department of Information Technology, Model Institute of Engineering and Technology, Kot Balwal, Jammu, India.

Table 1: Table Analysis of Lena Image on the Basis of MSE , RMSE and PSNR values

Noise Mean 0.0001			
Filtering Method	MSE	RMSE	PSNR
Inverse	+50.91365	+7.13538	+31.09646
Wiener	+50.91304	+7.13534	+31.09651
Lucy Ricardson	+51.13259	+7.15071	+31.07782
Purposed	+0.95998	+0.97980	+48.34194
Noise Mean 0.0003			
Inverse	+114.10806	+10.68214	+27.59164
Wiener	+114.10899	+10.68218	+27.59160
Lucy Ricardson	+113.72083	+10.66400	+27.60640
Purposed	+0.83252	+0.91243	+48.96084
Noise Mean 0.0005			
Inverse	+27.63832	+5.25722	+33.74968
Wiener	+27.90316	+5.28234	+33.70826
Lucy Ricardson	+26.20588	+5.11917	+33.98081
Proposed	+0.95393	+0.97672	+48.36923