



The Comparative Study of Image Deblurring Techniques

KEYWORDS

Image deblurring, restoration, Wiener filter, Regularized filter, Richardson-Lucy and Blind De-convolution.

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ABSTRACT

Deblurring the images to remove the noise from them can help scientists to gain a better insight into their data. Image restoration/deblurring methods can be considered as direct techniques when their results are produced in a simple one step fashion. Equivalently, indirect techniques can be considered as those in which restoration results are obtained after a number of iterations. A comparative study is performed for four different image deblurring techniques like Wiener filter, Regularized filter, Richardson-Lucy and Blind De-convolution on a set of standard images. These techniques have been evaluated on the basis of simulation results and performance measures.

I. Introduction

Image deblurring has become increasingly important in many scientific applications such as astronomy, satellite surveillance, medical imaging and others. A number of real world problems from astronomy to consumer imaging find applications for image deblurring /restoration is an easily visualized example of a larger class of inverse problems that arise in all kinds of scientific, medical, industrial and theoretical problems. It is an important issue in high level image processing which deals with recovering of an original and sharp image using a degradation and restoration model. During image acquisition process degradation occurs [11,12]. Image restoration is used to estimate the original image from the degraded data. In this age the use of imaging technology is a significant part of scientific research, recovering an approximation of an original image is the process of image de-blurring. To obtain true image it is essential by removing the effect of blur and noise on a corrupted image. Images both of a personal nature and of a scientific importance, they all carry information. However, any other form of data, the information within each picture can be affected by errors. These errors can come from various sources: while the image is taken, unfocused lens, illumination, or in the case of astronomical images, from atmospheric turbulence [5]. These errors are often responsible along with the noise for the blurred and unclear images.

Image restoration is an important issue in high level image processing which deals with recovering of an original and sharp image using a degradation and restoration model [1]. During image acquisition process degradation occurs. Image restoration is used to estimate the original image from the degraded data. The main motive of this research paper is to provide a comprehensive overview of most useful restoration models and comparison between them. The objective of image restoration is a process of reconstruction the primitive scene from degraded image. Image restoration is the process of reconstruction or recovering an image that has been corrupted by some degradation phenomenon. Degradation may occur due to motion blur, Gaussian blur, noise and camera mismatch [6]. Images are produced to record the useful information. Due to imperfections in the imaging and capturing process the recorded image invariably represents a degraded version of the original scene. The degradation results in image blur, affecting identification

and extraction of the useful information in the images. The degradation phenomenon of the acquired images causes serious economic loss and medical loss [12]. Therefore, restoring the degraded images is an important task in order to expand uses of the images. In general there are two types of restoration methods are used. One is non-blind restoration in which we need prior knowledge of transfer function and other one is blind restoration in which we do not need any prior knowledge of transfer function [7,14].

1.1 FUNDAMENTALS DEBLURRING

1.1.1 BLURRING

Blur is an unsharp image area caused by camera or subject movement, inaccurate focusing, or the use of an aperture that gives shallow depth of field [1]. 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. In digital image there are three common types of blur effects:

Average blur

The average blur is one of several tools one can use to remove noise and specks in an 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:

$$R = \sqrt{a^2 + b^2} \quad (1)$$

where a is the horizontal size blurring direction and b is vertical blurring size direction is the radius size of the circular average blurring.

Gaussian blur

Gaussian blur is that pixel weights aren't equal and they decrease from kernel center to edges according to a bell-shaped curve. The Gaussian blur effect is a filter that blends a specific number of pixels incrementally to a bell-shaped curve. The blurring is dense in the center and feathers at the edge. Apply Gaussian blur to an image when one want more control over the blur effect. Gaussian blur depends on the size and alpha.

Motion blur

The motion blur effect is a filter that makes the image appears to be moving by adding a blur in a specific direc-

tion. The motion can be controlled by angle or direction.

Atmospheric blur

It occurs due to random variations in the reflective index of the medium between the object and the imaging system and it occurs in the imaging of astronomical objects.

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. 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) [17]. 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 intensity distribution within the COC.

1.1.2 CONVOLUTION

The convolution is implemented in two ways; in spatial domain and in frequency domain. The process of applying of the blurring function to another function is called convolution, i.e. some area of the source image convolves into one pixel of the source image.

$$G(x, y) = H(x, y) * F(x, y) = \sum \sum H(i, j) F(x+i, y+j) \quad (2)$$

1.1.3 DEBLURRING MODEL

A blurred or degraded image can be approximately described by equation

$$g(x, y) = \text{PSF} * f(x, y) + n(x, y) \quad (3)$$

Where g is the blurred image, PSF distortion operator called point spread function, f is the original image and n is the additive noise introduced during image acquisition, that corrupts the image.

The task of restoration of a blurred image consists in finding the best approximation $f(x, y)$ to the source image. In the process of blurring the each pixel of a source image turns into a spot in case of de-focusing and into a line segment in case of a usual blurring due to movement [13]. Otherwise we can say that each pixel of a blurred image is assembled from pixels of some nearby area of a source image. All those overlap each other, which fact results in a blurred image. The principle according to which one pixel becomes spread is called the blurring function. The other synonyms are PSF, kernel and other. The size of this function is lower than the size of the image itself.

1.1.4 POINT SPREAD FUNCTION (PSF)

Point spread function (PSF) is the degree to which an optical system blurs a point of light. The PSF is the inverse Fourier transform of optical transfer function (OTF) [17]. In the frequency domain, the OTF describes the response of a linear, position-invariant system to an impulse.

1.2 PERFORMANCE MEASURES

The simplest and most widely used full-reference quality metric is the mean squared error (MSE), computed by averaging the squared intensity differences of distorted and reference image pixels, along with the related quantity of peak signal-to-noise ratio (PSNR). These are appealing because they are simple to calculate, have clear physical meanings, and are mathematically convenient in the context of optimization. But they are not very well matched to perceived visual quality. MSE and PSNR lack a critical feature: the ability to assess image

similarity across distortion types. In the last three decades, a great deal of effort has gone into the development of quality assessment methods that take advantage of known characteristics of the human visual system.

II. PROPOSED METHODOLOGIES

2.1 WIENER FILTER METHOD

Wiener filter is a method of restoring image in the presence of blur and noise [2]. The frequency-domain expression for the Wiener filter is

$$F = (G / H) * (|H|^2 / (k + |H|^2)) \quad (4)$$

Where G is Fourier transform of original blurry image, H the Fourier transform of blur kernel and k the de-blurring parameter ($k \geq 0$). Setting the value of k is a tedious task. The value should depend on the amount of noise we expect in the image. If the $M \times N$ image has Gaussian white noise with variance σ^2 , then can be set $k = MN \sigma^2$. But in general, the variance of the noise is unknown so we will have to estimate it. Note that if the image has no noise (blur only), then we can set $k=0$.

2.2 REGULARISED FILTER

Regularized filtering is used in a better way when constraints like smoothness are applied on the recovered image and very less information is known about the additive noise. The blurred and noisy image is regained by a constrained least square restoration algorithm that uses a regularized filter [3]. Regularized restoration provides almost similar results as the wiener filtering but viewpoint of both the filtering techniques are different. In regularized filtering less previous information is required to apply restoration.

2.3 RICHARDSON-LUCY ALGORITHM

The Richardson-Lucy algorithm, also known as Richardson-Lucy de-convolution, is an iterative procedure for recovering a latent image that has been blurred by a known PSF [1]. Noise amplification is a common problem of maximum likelihood methods that attempt to fit data as closely as possible. After much iteration, the restored image can have a speckled appearance, especially for a smooth object observed at low signal-to-noise ratios. These speckles do not represent any real structure in the image, but are artifacts of fitting the noise in the image too closely. To control noise amplification, damping parameter threshold level is set for the deviation of the resulting image from the original image, below which damping occurs.

2.4 BLIND DECONVOLUTION

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 de-convolution algorithm can be used effectively when no information about the distortion (blurring and noise) is known [7, 8]. The blind de-convolution restores the image and the PSF simultaneously, using an iterative process similar to the accelerated, damped Lucy-Richardson algorithm. The blind de-convolution can reduce the effect of noise on the restoration, account for non-uniform image quality and handle camera read-out noise. Definition of the blind deblurring method can be given by

$$g(x, y) = \text{PSF} * f(x, y) + \eta(x, y) \quad (5)$$

Where $g(x, y)$ is the observed image, PSF is point spread function, $f(x, y)$ is the constructed image and $\eta(x, y)$ is the additive noise term.

III. SIMULATION RESULTS

Fig. 1 shows the set of original images used for the experiment. Fig. 2 shows the Gaussian blurred images obtained by convolution of PSF with the original image. Fig.3 shows the images which are restored using wiener filter and in the absence of noise, the Wiener filter reduces to the ideal inverse filter. It is a linear space-invariant filter that makes use of the power spectrum of both the image and the noise to prevent the noise amplification problem. Wiener filter is used when our aim is to reduce the mean square error value. Fig. 4 shows the images restored using the regularized filter this filter introduces the smoothing effect which can also be seen from the figures. Fig.5 shows the images restored using Richardson-Lucy Algorithm but after much iteration, the restored image can have a speckled appearance, especially for a smooth object observed at low signal-to-noise ratios. These speckles do not represent any real structure in the image, but are artifacts of fitting the noise in the image too closely. Fig.6. shows the images restored using the blind deconvolution which is best when no information is known about the PSF.



Fig. 1: Original images



Fig. 2: Blurred images with Additive Gaussian Noise



Fig. 3: Restored images by Wiener filter



Fig. 4: Restored images by Regularized filter



Fig. 5: Restored images by Richardson-Lucy



IV. CONCLUSIONS

Deblurring gaussian blur from images is a very difficult problem to resolve. On the basis of simulation results obtained and according to the values of MSE and PSNR we have reached to the conclusion that when PSF is not known blind deconvolution is the best method to restore an image. The best results are obtained with Wiener filter method with a very good value of PSNR. Wiener filter is optimally good to get low value mean square error out these four techniques.

Fig. 6: Restored images by Blind de-convolution

Table 1: Performance measures

Standard Images	Wiener		Regular		R-L		Blind de-convolution	
	MSE	PSNR	MSE	PSNR	MSE	PSNR	MSE	PSNR
LENA	.0043	71.8034	231.2890	24.4893	720.964	19.557	25.6526	34.0395
MAN	.0059	70.3962	368.9558	22.4611	732.004	19.485	50.8426	31.0685
BABOON	.0057	71.0593	537.7286	20.8252	876.981	18.709	168.0746	25.8758
CAMERA-MAN	.0109	67.7407	859.9329	18.7862	806.100	19.066	134.9561	26.8289
BARBARA	.0084	68.9128	574.7913	20.5357	800.631	19.096	149.7391	26.3775
BOATS	.0062	70.2344	398.9684	22.1214	727.859	19.510	35.1325	32.6737
COLUMBIA	.0056	71.1543	483.0563	21.2908	687.957	19.755	24.4175	34.2538
GOLDHILL	.0075	69.3911	564.08	19.098	733.531	19.476	32.7292	32.9814
COUPLE	.0055	70.0593	436.3022	21.7329	740.258	19.437	60.2880	30.3285

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