Deblurring Images Using the Blind Deconvolution Algorithm

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Abstract

In image processing and applied mathematics, 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. 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 [12] is used in each iteration. 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

Keywords: point-spread function, Blind Deconvolution, deblurring, image restoration, Gaussian Filter.

I. Introduction

Photographic images, whether recorded by digital or analogue means, have imperfections which prevent them from conveying the "true" scene[1]. These degradations have a variety of causes but two types, blurring and noise, are especially common. The removal of blur, in the presence of noise, is generally an ill-posed deconvolution problem, the solution of which requires inversion of the blur operator followed by a smoothing step.

Although challenging, this type of problem is quite well understood if the extent of blur can be described in precise mathematical terms. However, there is a rapidly increasing interest in problems where the mathematical operation of blurring is known only approximately, for example in terms of a function which depends on unknown parameters that have to be computed from image data. This is a blind deconvolution problem [3] and is, of course, significantly more challenging than its more conventional, non-blind counterpart.

In this paper we suggest a new technique for blind deconvolution when the point-spread function, describing the manner in which blur degrades the true image, is available only up to unknown parameters. Our approach is of interest because it is closely linked to the physically meaningful notion of adjusting the parameters until the image is sharpest. In contrast to some earlier methods, ours does not require detailed information about the "true" image. Instead, we recognize that the sort of image that would be used to determine a point-spread function would usually be one that has relatively sharp boundaries, such as those in a photographic test pattern.

II. Blind Deconvolution

Blind deconvolution is an Image Restoration method that tries to obtain both the original object and

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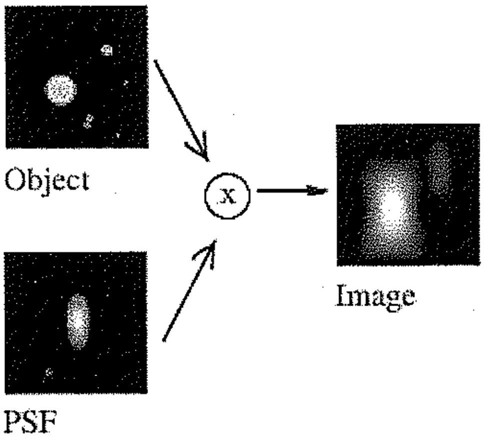
the Point Spread Function (PSF) simultaneously out of the degraded image. We can imagine that the image is formed in the microscope by *replacing* every original Sub Resolution light source by its correspondent Point Spread Function (PSF)[15]. This process is mathematically described by a Convolution equation of the form

$$g = f * h$$

Where the image g arises from the convolution of the real light sources f (the object) and the PSF h.



Restoring an image is, basically, solving the equation above, where we want to obtain the real object intensity distribution f given the acquired blurry image g: that is DeConvolution. Blind Deconvolution tries to solve that equation without knowing the PSF term h. Although some constraints can be applied, this is always risky, as it introduces a lot of indetermination in the solution of the equation, especially if we let h freely vary all over the space. How many solutions x, y can we find for an algebraically equation of the form $x \times y = 5$? We can make x as small as we want by increasing the value of y, and vice versa[13]. There is no determined solution, even if we put strong constraints. Something similar happens with solving the convolution equation: we can make the image f as *clean* as we wish (even totally washed out), just by making the PSF h stronger and stronger. But that does not imply that we are getting a good representation of real object. Blind deconvolution developed for astronomical images. As we may not know anything about the medium between the object and the telescope, we have limitations to know about the way the image is blurred. But in astronomy most of the objects are point-like, and this allows the application of strong constraints. Blind deconvolution is currently lacking of any scientific validation when applied to microscopy.

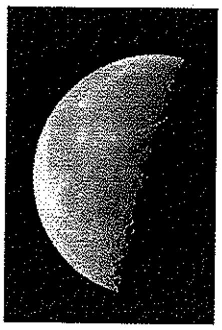
III. An Illustration of Blind Convolution Algorithm is given be low.

The deconvolution 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 algorithm restores the image and the PSF simultaneously, using an iterative process similar to the accelerated, damped Lucy-Richardson algorithm. The algorithm implements several adaptations to the original Lucy-Richardson maximum likelihood algorithm that address complex image restoration tasks. Using these adaptations, we can reduce the effect of noise on the restoration, account for non-uniform image quality (e.g., bad pixels) and we can handle camera read-out noise.

A. Step 1: Read Image

This step reads an intensity image. The algorithm can handle arrays of any dimension.

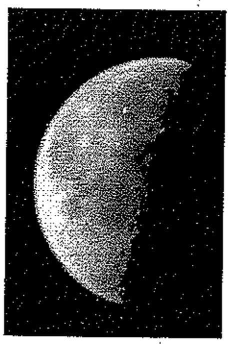
Original Image



B. Step 2: Simulate a Blur

Simulate a real-life image that could be blurred (e.g., due to camera motion or lack of focus). This step simulates the blur by convolving [8] a Gaussian filter [6] with the true image. The Gaussian filter then represents a point-spread function, PSF.

Blurred Image

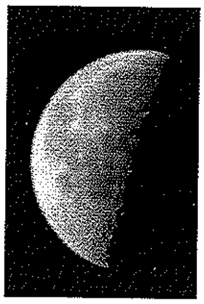


C. Step 3: Restore the Blurred Image Using PSFs of Various Sizes

To illustrate the importance of knowing the size of the true PSF, this step performs three restorations. Each time the PSF reconstruction starts from a uniform array—an array of ones.

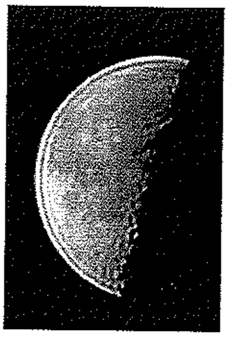
The first restoration uses an undersized array say A1, for an initial guess of the PSF. The size of the undersized array is 4 pixels shorter in each dimension than the true PSF.

Deblurring with Undersized PSF



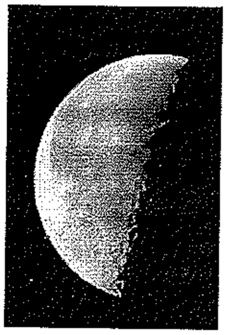
The second restoration uses an array of ones say A2, oversized for an initial PSF that is 4 pixels longer in each dimension than the true PSF.

Deblurring with Oversized PSF



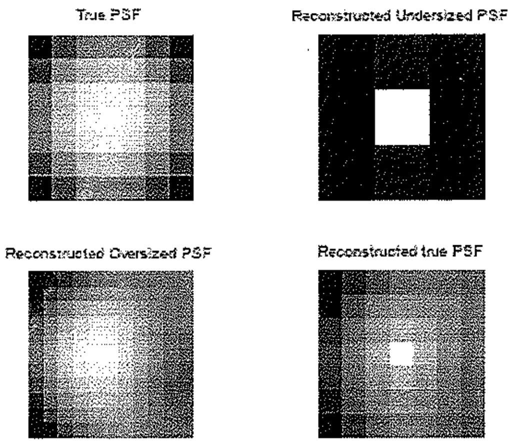
The third restoration uses an array of ones say A3, for an initial PSF that is exactly of the same size as the true PSF.

Deblurring with INITPSF



D. Step 4: Analyzing the Restored PSF

All three restorations also produce a PSF. The following pictures show how the analysis of the reconstructed PSF might help in guessing the right size for the initial PSF. In the true PSF, a Gaussian filter, the maximum values are at the center (white) and diminish at the borders (black).

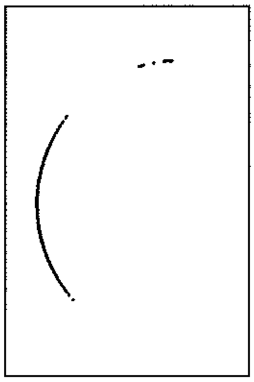


The PSF reconstructed in the first restoration obviously does not fit into the constrained size. It has a strong signal variation at the borders. The corresponding image does not show any improved clarity vs. the blurred image, Blurred. The PSF reconstructed in the second restoration becomes very smooth at the edges. This implies that the restoration can handle a PSF of a smaller size. The corresponding image shows some deblurring but it is strongly corrupted by the ringing. Finally, the PSF reconstructed in the third restoration is somewhat intermediate between A1 and A2. The array resembles the true PSF very well. The corresponding image shows significant improvement; however it is still corrupted by the ringing.

E. Step 5: Improving the Restoration

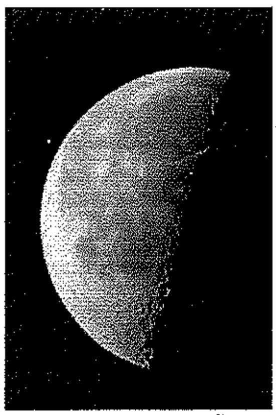
The ringing in the restored image occurs along the areas of sharp intensity contrast in the image and along the image borders. This step shows how to reduce the ringing effect by specifying a weighting function. The algorithm weights each pixel according to the weight array while restoring the image and the PSF. In our example, we start by finding the "sharp" pixels using the edge function. By trial and error, we determine that a desirable threshold level is 0.3.

Weight array



The image is restored by calling deconvolution with the weight array and an increased number of iterations (30). Almost all the ringing is suppressed.

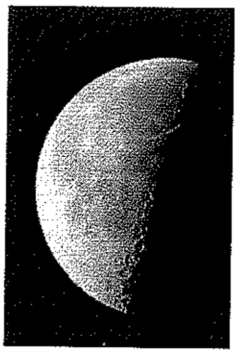
Deblurred Image



F. Step 6: Using Additional Constraints on the PSF Restoration

This step shows how we can specify additional constraints on the PSF. Here we modify the PSF by cropping it by A1 and A2 number of pixels in each dimension, and then padding the array back to its original size with zeros. This operation does not change the values in the center of the PSF, but effectively reduces the PSF size by 2*A1 and 2*A2 pixels. The size of the initial PSF, oversized PSF, is 4 pixels larger than the true PSF. Setting A1 and A2 as parameters effectively makes the valuable space in oversized PSF, the same size as the true PSF. Therefore, the outcome is similar to the result of deconvolution with the right sized PSF.

Deblurred Image



CONCLUSION

This paper presented a method for deblurring images. The method will be able to recover images [2] which have suffered a wide range of degradations. The restoration quality using blind convolution algorithm method was visually and quantitatively better than those of the other algorithms [14] such as wiener Filter algorithms and Regularization algorithm. The advantage of our proposed Blind Deconvoultion algorithm is used to deblur the degraded image without prior knowledge of PSF and additive noise.

It focused on the problem of estimating the point-spread function, rather than the obviously related one of image [7] restoration, since there are a great many approaches to solving the degradation problem[5]. Moreover, there is usually intrinsic interest in the point-spread function, not the least because knowing the nature of that function is an important step in determining the blurring mechanism, so as to improve performance of the imaging device.

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