

# Remote Sensing Image Restoration Using Various Techniques: A Review

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**Abstract**—In the imaging process of the remote sensing, there was degradation phenomenon in the acquired images. In order to reduce the image blur caused by the degradation, the remote sensing images were restored to give prominence to the characteristic objects in the images. The images were restored. Image restoration is an important issue in high-level image processing. The purpose of image restoration is to estimate the original image from the degraded data. It is widely used in various fields of applications, such as medical imaging, astronomical imaging, remote sensing, microscopy imaging, photography deblurring, and forensic science, etc. Restoration is beneficial to interpreting and analyzing the remote sensing images. After restoration, the blur phenomenon of the images is reduced. The characters are highlighted, and the visual effect of the images is clearer. In this paper different image restoration techniques like Richardson-Lucy algorithm, Wiener filter, Neural Network, Blind Deconvolution.

**Keywords**—Image Restoration, Degradation model, Richardson-Lucy algorithm, Wiener filter, Neural Network, Blind Deconvolution.

## I. INTRODUCTION

For the space remote sensing camera, many factors will cause image degradation during the image acquisition process, such as aberration of the optical system, performance of CCD sensors, motion of the satellite platform and atmospheric turbulence [14]. 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. Therefore, restoring the degraded images is an urgent task in order to expand uses of the images. There are several classical image restoration methods, for example Wiener filtering, regularized filtering and Lucy-Richardson algorithm. These methods require the prior knowledge of the degradation phenomenon [16][19], which be denoted as the degradation function of the imaging system, i.e., the point spread function (PSF). As the operational environment of the remote sensing camera is special and the atmospheric condition during image acquisition is various, it is usually impossible to obtain accurate degradation function. The field of image restoration (sometimes referred to as image deblurring or image deconvolution) is concerned with the reconstruction or estimation of the uncorrupted image from a blurred and noisy one. Essentially, it tries to perform an operation on the image that is the inverse of the imperfections in the image formation system. The remote sensing images dealt with in this paper have high resolution. With the PSF as parameter, the images can be restored by the various techniques.

## II. RELATED WORK

The task of deblurring an image is image deconvolution; if

the blur kernel is not known, then the problem is said to be "blind". For a survey on the extensive literature in this area, see [Kundur and Hatzinakos 1996]. Existing blind deconvolution methods typically assume that the blur kernel has a simple parametric form, such as a Gaussian or low-frequency Fourier components. However, as illustrated by our examples, the blur kernels induced during camera shake do not have simple forms, and often contain very sharp edges. Similar low-frequency assumptions are typically made for the input image, e.g., applying a quadratic regularization. Such assumptions can prevent high frequencies (such as edges) from appearing in the reconstruction. Caron et al. [2002] assume a power-law distribution on the image frequencies; power-laws are a simple form of natural image statistics that do not preserve local structure. Some methods [Jalobeanu et al. 2002; Neelamani et al. 2004] combine power-laws with wavelet domain constraints but do not work for the complex blur kernels in our examples.

Deconvolution methods have been developed for astronomical images [Gull 1998; Richardson 1972; Tsumuraya et al. 1994; Zarowin 1994], which have statistics quite different from the natural scenes we address in this paper. Performing blind deconvolution in this domain is usually straightforward, as the blurry image of an isolated star reveals the point-spread-function.

Another approach is to assume that there are multiple images available of the same scene [Basile et al. 1996; Rav-Acha and Peleg 2005]. Hardware approaches include: optically stabilized lenses [Canon Inc. 2006], specially designed CMOS sensors [Liu and Gamal 2001], and hybrid imaging systems [Ben-Ezra and Nayar 2004]. Since we

would like our method to work with existing cameras and imagery and to work for as many situations as possible, we do not assume that any such hardware or extra imagery is available.

Recent work in computer vision has shown the usefulness of heavy-tailed natural image priors in a variety of applications, including denoising [Roth and Black 2005], superresolution [Tappen et al.2003], intrinsic images [Weiss 2001], video matting [Apostoloff and Fitzgibbon 2005], inpainting [Levin et al. 2003], and separating reflections [Levin and Weiss 2004]. Each of these methods is effectively “non-blind”, in that the image formation process (e.g., the blur kernel in superresolution) is assumed to be known in advance. Miskin and MacKay [2000] perform blind deconvolution on line art images using a prior on raw pixel intensities. Results are shown for small amounts of synthesized image blur. We apply a similar variational scheme for natural images using image gradients in place of intensities and augment the algorithm to achieve results for photographic images with significant blur.

### III. IMAGE DEGRADATION THEORY

#### A. Image degradation model

As Fig 1 shows, image degradation process can be modeled as a degradation function together with an additive noise, operates on an input image  $f(x,y)$  to produce a degraded image  $g(x,y)$  [4]. As a result of the degradation process and noise interfusion, the original image become degraded image, representing image blur in different degrees. If the degradation function  $h(x, y)$  is linear and spatially invariant, the degradation process in the spatial domain is expressed as convolution of the  $f(x,y)$  and  $h(x, y)$ , given by

$$g(x,y)=f(x,y) * h(x,y)+n(x,y) \quad (1)$$

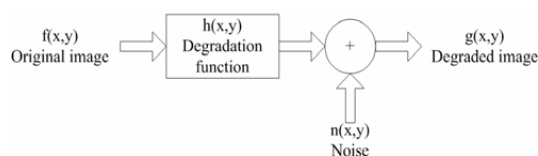


Figure1. Image degradation model

According to the convolution theorem, convolution of two spatial functions is denoted by the product of their Fourier transforms in the frequency domain. Thus, the degradation process in frequency domain can be written as

$$G(u,v)=F(u,v)H(u,v)+N(u,v) \quad (2)$$

#### B. Image restoration theory

The objective of image restoration is to reduce the image blur during the imaging process. If we know the prior knowledge of the degradation function and the noises, the inverse process against degradation can be applied for restoration, including denoising and deconvolution. In frequency domain, the restoration process is given by the expression

$$F(u,v)=\frac{G(u,v)-N(u,v)}{H(u,v)} \quad (3)$$

Because restoration will enlarge the noises, denoising is done before restoration to remove the noises. Denoising can be performed both in the spatial domain and in the frequency domain. The usual method is to select an appropriate filter according to the characters of the noises to filter out the noises. Spatial convolution is defined as multiplication in the frequency domain, and its inverse operation is division.

Therefore, deconvolution is carried out in the frequency domain as a rule. At last, the inverse Fourier transform is done to  $F(u,v)$  to complete the restoration.

#### C. 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 [7]. Blur effects are filters that make smooth transitions and decrease contrast by averaging the pixels next to hard edges of defined lines and areas where there are significant color transition [15].

#### D. Blurring Types

In digital image there are 3 common types of Blur effects:

- Average Blur

The Average blur is one of several tools you can use to remove noise and specks in an image. We can use this tool when noise is present over the entire image [12]. This type of blurring can be distribution in horizontal and vertical direction and can be circular averaging by radius R which is evaluated by the formula:

$$R=\sqrt{g^2 + f^2} \quad (4)$$

Where: g is the horizontal size blurring direction and f is vertical blurring size direction and R is the radius size of

the circular average blurring.

- Gaussian Blur

The Gaussian Blur effect is a filter that blends a specific number of pixels incrementally, following a bell-shaped curve [10]. Blurring is dense in the center and feathers at the edge. Apply Gaussian Blur filter to an image when you want more control over the Blur effect [1].

- Motion Blur

The Many types of motion blur can be distinguished all of which are due to relative motion between the recording device and the scene. This can be in the form of a translation, a rotation, a sudden change of scale, or some combinations of these. The Motion Blur effect is a filter that makes the image appear to be moving by adding blur in a specific direction [2]. 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 [9].

- 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 [5]. 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). 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 the intensity distribution within the COC [7].

### III. DEBLURRING TECHNIQUES

#### A. Lucy-Richardson Algorithm Technique

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 [15].

$$C_i = \sum_j p_{ij} \cdot u_j \quad (5)$$

Where:  $p_{ij}$  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  $C_i$  is the observed value at pixel location  $i$ . The statistics are performed under the assumption that  $u_i$  are Poisson distributed, which is appropriate for photon noise in the data. The basic idea is to

calculate the most likely  $u_i$  given the observed  $C_i$  and known  $p_{ij}$ . This leads to an equation for  $u_i$  which can be solved iteratively according to:

$$u_j^{t+1} = u_j^t \sum_i \frac{C_i}{c_i} p_{ij} \quad (6)$$

Where

$$C_i = \sum_j u_j^{(t)} \cdot p_{ij} \quad (7)$$

It has been shown empirically that if this iteration converges, it converges to the maximum likelihood solution for  $u_j$ .

- Point Spread Function (PSF)

Point Spread Function (PSF) is the degree to which an optical system blurs (spreads) a point of light [11]. 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) [6].

#### B. Inverse Filter

Inverse filtering is one of the techniques used for image restoration to obtain a recovered image  $f'(x,y)$  from the  $g(x,y)$  image data so that  $f'(x,y) = f(x,y)$  in the ideal situation  $n(x,y) = 0$ .

$$h(x,y) * h'(x,y) = \delta(x,y) \text{ or } H(w_x, w_y) H'(w_x, w_y) = 1 \quad (8)$$

#### C. Wiener Filter De-blurring Technique

The data amount of remote sensing images is huge. Therefore, the Wiener filtering is selected for image restoration after getting the PSF of the image system. Wiener filtering has good performance. It doesn't have iterative process, and saves time than other methods. Wiener filtering seeks an approximate estimation which has the minimum mean square error with the original image. The solution of Wiener filtering in the frequency-domain can be simplified to (7), where  $H(u,v)$  is the two-dimensional Fourier transform of the Gaussian fitted PSF.  $K$  is the regularized constant in the restoration process.

#### D. Neural Network Approach

Neural networks is a form of multiprocessor computer system, with simple processing elements, a high degree of interconnection, adaptive interaction between elements,

When an element of the neural network fails, it can continue without any problem by their parallel nature [13].

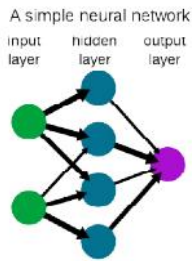


Fig 2: Artificial Neural Network

ANN provides a robust tool for approximating a target function given a set input output example and for the reconstruction function from a class a images. Algorithm such as the Back propagation and the Perceptron use gradient- decent techniques to tune the network parameters to best-fit a training set of input-output examples. Here we are using Back propagation neural network approach for image restoration. This approach is capable of learning complex non-linear functions is expected to produce better structure especially in high frequency regions of the image. We used a two-layer Back propagation network with full connectivity.

D. Modified Wiener filter

Following the least-squares procedure, a modified Wiener filter has been developed with the possibility of having an extra constraint and so improving its performance.

As a first approach, the additional constraint is set to be  $\|Tb - Hf\|^2 = \|e\|^2$ , where Tb is a brightness temperature model extracted adequately from a land/sea mask and e is a tolerance error. Hence, two Lagrange multipliers,  $\lambda_1$  and  $\lambda_2$ , will be used to include the two constraints so that:

$$J(f) = \|Qf\|^2 + \lambda_1 (\|g - Hf\|^2 - \|n\|^2) + \lambda_2 (\|Tb - Hf\|^2 - \|e\|^2) \tag{9}$$

Differentiating with respect to f, setting the result to zero and solving it for f gives us the following expression in the spatial domain:

$$f = (Q^T Q + \lambda_1 H^T H + \lambda_2 H^T H)^{-1} \cdot H^T (\lambda_1 g + \lambda_2 Tb) \tag{10}$$

At this point, the Wiener concept is used to set the value of Q. Making use of the diagonalization procedure, we get the following expression in the frequency domain:

$$\tag{11}$$

$$K(u,v) = \left[ \frac{H^*(u,v)(G(u,v) + \beta \cdot Tb)}{(1 + \beta)|H(u,v)|^2 + \frac{\sigma_n(u,v)}{\sigma_f(u,v)}} \right] \tag{11}$$

where  $\gamma \cong 1/\lambda_1$  and  $\beta \cong \lambda_2/\lambda_1$  for ease of notation and Tb is the Fourier transform of Tb. Note that if we don't add the second constraint,  $\lambda_2 = 0$ , this new filter reduces to the Wiener filter.

E. BLIND DECONVOLUTION

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).

Blind deconvolution can be performed iteratively, whereby each 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. Iterative methods include maximum a posteriori estimation and expectation-maximization algorithms. A good estimate of the PSF is helpful for quicker convergence but not necessary.

F. Edge-Preserving Regularization

The restoration image can be solved with the methods of deterministic regularization and maximum a posteriori estimation (MAP), and the result regularized solution of equation is:

$$\hat{f} = \text{argmin}[L(g,f) + \lambda U(f)] \tag{12}$$

In the equation, L(g,f) is the data consistency constraint, U(f) is the regularization term,  $\lambda$  is the regularization parameter.

For the data consistency constraints L(g,f), if the hypothetical model is random, distributed independent and zero averaged Gaussian type, the resulting L(g,f) is the standard based of the proposed method, the "lena" image is used. Firstly, the original clear image is blurred and added some noise, and then our method is used to perform the restoration of degradation image, lastly, the restoration image is compared with the original clear image to shown the effectiveness. The PSF is estimated from the image or image set, allowing the deconvolution to be performed

### G. Discrete formulation

A discrete convolution formulation can be derived from Eq.

$$g = h \otimes f + n \quad (13)$$

where  $g$  is a column vector containing the real observations,  $f$  is a column vector containing the unknown TB at the desired resolution,  $n$  is a column vector that includes all that might be considered noise,  $h$  is the matrix representation of the antenna response function, and  $\otimes$  indicates convolution.

Assuming that  $f$  and  $h$  are two dimensional periodic functions of periods  $M$  and  $N$  adequately padded with zeros to avoid overlap between different periods, and using the lexicographic notation as above:

$$g = H \cdot f + n \quad (14)$$

where  $f$ ,  $g$ , and  $n$  are of dimension  $(MN) \times 1$  and  $H$  is of dimension  $MN \times MN$ . This matrix consists on  $M^2$  partitions, each partition being size  $N \times N$  and ordered according to:

$$H = \begin{bmatrix} H_0 & H_{M-1} & H_{M-2} & \dots & H_1 \\ H_1 & H_0 & H_{M-1} & \dots & H_2 \\ H_2 & H_1 & H_0 & \dots & H_3 \\ \vdots & & & & \\ H_{M-1} & H_{M-2} & H_{M-3} & \dots & H_0 \end{bmatrix} \quad (15)$$

Each partition  $H_j$  is constructed from the  $j$ th row of the extended function  $h$  by a circular shifting it to the right [6].

A direct solution of (2) is not computationally feasible as, just for images of a practical size, it will require an inversion of a too high number of simultaneous linear equations. Fortunately, as the matrix  $H$  is block-circulant, it can be diagonalized and therefore the problem can be considerably reduced by working in frequency domain [2]. The Fourier space equivalent of (2) can be written as:

$$G = H \cdot F + N \quad (16)$$

where  $G$ ,  $H$ ,  $F$  and  $N$  are the Fourier transforms of  $g$ ,  $h$ ,  $f$  and  $n$  respectively. Using frequency-domain based deconvolution methods the computation time is no longer a limitation since nowadays there are very powerful tools to perform Fast Fourier Transforms.

### IV. CONCLUSION

For image blur caused by the degradation in the imaging process of the remote sensing images. An effective image restoration techniques has been presented in this paper. The details of the restored image become clearer. The image restoration is benefit to image interpretation and analysis.

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