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Iterative deconvolution approach for high resolution satellite imagery

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Abstract: High spatial resolution (better than 5 m) images of earth's surface acquired by a space-borne sensor are a valuable resource for various applications in the field of cartography, urban planning, disaster management and change detection. The images are acquired by specially designed imaging systems onboard a remote sensing satellite, having specific spatial, spectral and temporal resolution to suit the end application. For optical images acquired by push-broom Charge-Coupled Device (CCD) based sensors, systematic radiometric degradations in the form of blur and noise are typically observed. Recovery of original image from degraded observation or deconvolution of above images can be achieved through direct or iterative image restoration techniques. In this paper, iterative technique based on variational method and Total Variation (TV) operator for regularization is proposed for restoration of Cartosat-2A image, when system Point Spread Function (PSF) is known (non-blind) or unknown (blind). For non-blind iterative deconvolution, Stellar (star) image acquired by sensor is used as PSF estimate. To control noise amplification at various image textures, concept of adaptive tuning of regularization parameter based on local variance of image is introduced for non-blind and blind restoration. Theoretical background for variational method of iterative deconvolution, adaptive regularization approach and implementation methodology is discussed in the paper. The results of application using proposed technique over an image covering Cochin city in India along with qualitative analysis of the restored image are presented. Qualitative parameters like image fidelity, sharpness of image features and signal-to-noise ratio of restored images are studied. Sharpness and image fidelity is found to be higher for image restored with proposed technique as compared to direct, filtering based techniques. After adaptive tuning of regularization parameter, improvement in Signal-to-Noise Ratio (SNR) is observed in comparison to non-adaptive approach, thereby improving the radiometric quality of image.

Keywords: Point Spread Function (PSF), Deconvolution, Total variation, Restoration, Noise, Degradation

1. Introduction

High spatial resolution images of earth's surface are acquired by a space-borne sensor onboard a remote sensing satellite with specially designed imaging systems. In case of optical images, reflected energy from ground features is detected by telescope, CCD array and electronics assembly mounted on an agile, moving platform. To acquire multiple lines of imagery in the motion direction, push-broom scanning mechanism is typically used. The digitised image is further transmitted for ground-based processing.

Due to the limited resolution of imaging equipment and other imperfections such as movement during image acquisition, the observed image is not an exact replica of the original scene. Systematic blurring is caused due to optical aberrations, averaging effect of detectors and platform motion during imaging. Noise uncertainty is added during detector charge-up and radiometric quantization processes. To remove the systematic degradations observed in the images and improve its radiometric quality, image deconvolution is used as part of ground-based processing.

Deconvolution is a process which recovers the undegraded image from blurred and noisy observation. It improves the resolution of an observed image by mathematically removing the smearing effects of an imperfect instrument, using its known resolution function i.e. Point Spread Function (PSF) (Fessler, 2005; Banham and Katsaggelos, 1997). Besides post-processing of remote-sensing images, deconvolution techniques are applied for many other applications in field of data processing and in various domains of experimental science like signal restoration, tomography, magnetic resonance imaging etc.

Direct techniques of image restoration like Inverse filtering and Wiener filtering recover image in a single step with prior knowledge of PSF. Inverse or Pseudo-Inverse filtering is a simplest approach to restore the image, but causes poor deblurred image without proper noise suppression because of ill-posed nature of inverse operation (Katsaggelos, 1989; Lagendijk and Biemond, 1999). Wiener filtering is based on optimally recovering the image with knowledge of degradation function and power spectrum of original image and noise. This method suffers from possibility of ringing effect and introduction of "blue" noise (Lagendijk and Biemond, 1999). For overcoming some of the difficulties of excessive noise, iterative approaches are used. Iterative methods can be very efficient for spatially invariant as well as spatially variant blurs (Berisha and Nagy, 2013; Katsaggelos, 1989) and can incorporate different regularization approaches and boundary conditions. Richardson-Lucy is an iterative technique of image restoration (Berisha and Nagy, 2013; Lagendijk and Biemond, 1999), mostly used for astronomical and medical images.

In this paper, iterative approach based on research carried out by Chan and Wong (1998) and Wilson (2011) is explored, which are suitable for high-resolution remote sensing images acquired by Cartosat-2A. Cartosat-2A is a high resolution satellite in Cartosat series launched by Indian Space Research Organisation (ISRO) having imaging capabilities with spatial resolution of 0.8 m operating in panchromatic band. In the proposed approach, solution for iterative deconvolution is obtained by posing the problem in terms of a variational model. Focus of variational model is on minimization of energy function defined with two terms - fidelity i.e. closeness of the solution to observed data and regularization that enforces prior knowledge of solution in form of edge information. Minimization of energy function deals with ringing effect and proper noise suppression in restored images (Chan and Wong, 1998). Convergence criteria may be pre-defined to maintain the trade-off between sharpness and noise amplification. It may also be decided by user to stop the iterations when an acceptable result has been achieved.

This paper is organised as follows. In section 2, mathematical and theoretical concepts for iterative techniques are discussed. Section 3 presents experimental analysis of iterative non-blind method on Cartosat-2A imagery. In this section, the variation of energy function and image fidelity with increasing number of iteration is analyzed. Comparative evaluation of results recovered by iterative and direct methods is shown. In section 4, adaptive selection of regularization parameter to control noise amplification at various image textures are introduced. Comparison of Signal-to-Noise (SNR) is shown to indicate improvement in quality of restored images. Conclusions and future scope of work are presented in section 5.

2. Theoretical background

A blurred Image $g(x,y)$ is defined as the convolution of a true image $f(x,y)$with a two dimensional PSF$k(x, y)$. A model for degradation can be written as:

$$g(x,y) = k(x,y) * f = \int_{\Omega} k(x,y) f(x,y) \mathrm{d}x\mathrm{d}y = (Kf)(x,y) \quad (1)$$

Here, $f(x,y)$ is true image, $g(x,y)$ is blurred image, $k(x,y)$ is point spread function and Ω is set of all pixels within image. The convolution integral (Banham and Katsaggelos, 1997) is expressed with an operator K as shown in Equation (1). Noise arising due to various factors in image acquisition or transmission process, known to be additive, is not considered in Equation (1). In iterative methods, first an estimate of original image is made. It is convolved with the PSF to produce a new (second) estimate of the image. The first estimate is often set equal to the observed image. The two estimates are compared and an error criterion is established which is used to modify the last estimate and produce a new estimate. This process goes iteratively, until the mean difference between two estimates is less than a convergence parameter. Improved estimate is obtained by addition of certain constraints like regularization parameter (Kundur and Hatzinakos, 1996; Lagendijk and Biemond, 1991), due to which significant qualitative improvement can be obtained as the iteration proceeds. In this paper, an approach proposed by Chanand Wong (1998) for iterative restoration is considered. The solution for iterative non-blind deconvolution is obtained by posing the problem in terms of a variational model. In variational model, energy functional $E(f)$ is minimized to find out optimal image $f(x,y)$. Energy function $E(f)$ is defined with two terms called fidelity i.e. closeness of the solution $f(x,y)$ to the observed data $g(x,y)$, and another term called regularization which enforces prior knowledge of solution. Regularization deals with improving edge information with iterative estimates and is a way to avoid problems in restoration associated with ill-posed behaviour in inverse operation of K operator (Kundur and Hatzinakos, 1996). $E(f)$ can be written as per Equation (2) for the solution of non-blind technique.

$$E(f) = \underbrace{\int_{\Omega} |(kf)(x,y) - g(x,y)|^2 \mathrm{d}x\mathrm{d}y}_{\text{Fidelity}} + \underbrace{\alpha_1.(Rf)(x,y)}_{\text{Regularization}} \quad (2)$$

The parameter α_1 is called regularization parameter determines to what degree the image is regularized. It is useful to control the closeness of data to edge information as well as noise amplification during restoration (Lagendijk and Biemond, 1991, 1999).

Variational procedure consists of iteratively updating a Partial Derivative Equation (PDE) that is consistent with gradient descent of $E(f)$. PDE for this model is shown in Equation (3). In PDE, the derivative is with respect to *'t'*, a linearization parameter, which helps to derive iterative scheme for variational model.

$$\frac{\partial f(x,y)}{\partial t} = -K^*((Kf)(x,y) - g(x,y)) + \alpha_1.(Rf)(x,y) \quad (3)$$

In Equation (3), K^* is the adjoint of K operator. The image is estimated in each iteration according to the rules of PDE until the mean change in the image $f(x,y)$ is within tolerance of convergence. For an iterative scheme, Laplacian regularization operator, is defined as $\nabla^2 f(x,y)$ i.e. second derivative of an image in both x and y direction using discrete five point manipulation in image (Banham and Katsaggelos, 1997; Gonzalez, 2008). Total variation is another method of regularization in which, the second derivative at a given pixel is approximated by interpolating across the corresponding half pixel derivatives (Chan and Wong,

1998) can be given as:

$$(Rf)(x,y) = \int_{\Omega} |\nabla f(x,y)| \mathrm{d}x\mathrm{d}y = \int_{\Omega} \nabla . \frac{\nabla f(x,y)}{|\nabla f(x,y)|} \quad (4)$$

Using the framework of variational model, blind recovery of image can also be carried out, in which, the PSF is unknown initially. For this type of blind recovery, the energy functional is comprised of a fidelity term, an image regularization term, and additionally PSF regularization term as follows:

$$E(f) = \underbrace{\int_{\Omega} |(kf)(x,y) - g(x,y)|^2 \mathrm{d}x\mathrm{d}y}_{\text{Image Fidelity}} + \underbrace{\alpha_1 . (Rf)(x,y) + \alpha_2 . (Rk)(x,y)}_{\text{Image and PSF regularization}} \quad (5)$$

Here, α_2 is a parameter to control degree of regularization of PSF. Chan and Wong (1998) describe alternating minimization method of solving iterative blind restoration problem. In this method, initial PSF is assumed to be a Dirac delta function (You and Kaveh, 1996). In the first step, the PDE of PSF is iterated, maintaining image as constant as per Equation (6).

$$\frac{\partial k(x,y)}{\partial t} = -f * (f(k) - k_0) + \alpha_2 . (Rk)(x,y) \quad (6)$$

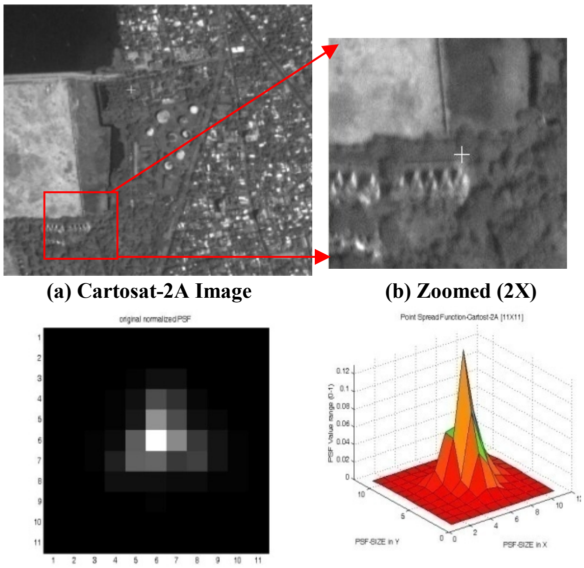
Here, k is estimated PSF at each iteration, k_0 is initial PSF. In the second step, the PDE of Image estimation same as Equation (3) used to recover image maintaining PSF as constant (k). This procedure is repeated until mean change in the image and PSF are within tolerances.

3. Application of non-blind iterative technique on Cartosat-2A imagery

Cartosat-2A satellite image of Cochin, India was considered for analysis of non-blind method as shown in Figure 1.

The image is of size 1024×1024 pixels with spatial resolution of 0.8m. Systematic blurring due to optics, detector averaging and platform motion is captured in the impulse response of the sensor, given by its PSF. Stars are natural point sources, therefore, stellar image acquired by the sensor (Figure 1 (*c*)) is considered as PSF for restoration.

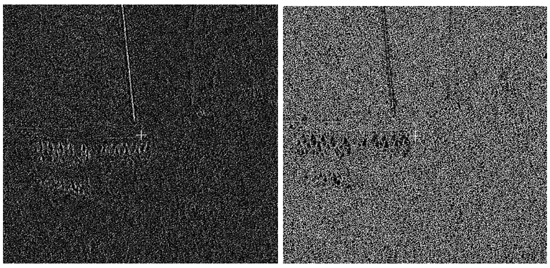
Non blind iterative method for restoration as described by Equation (3) is implemented in C++ for image recovery. A number of parameters such as *'d_t'* (used for linear approximation), α_1 (type of regularization operator), number of iterations and criterion for convergence were tuned for generating recovered result. Parameter *'d_t'*, related to linear approximation of partial derivative, was fixed to 0.1 for iterating the PDE. Two types of regularization, Laplacian and Total Variation were implemented. Edge information in the original image is enhanced through regularization operator as shown if fig. 2.



(a) Cartosat-2A Image **(b) Zoomed (2X)**

(c) PSF (11x11) **(d) PSF-Plot (11X11)**

Figure 1: Image data and known Point Spread Function (PSF)



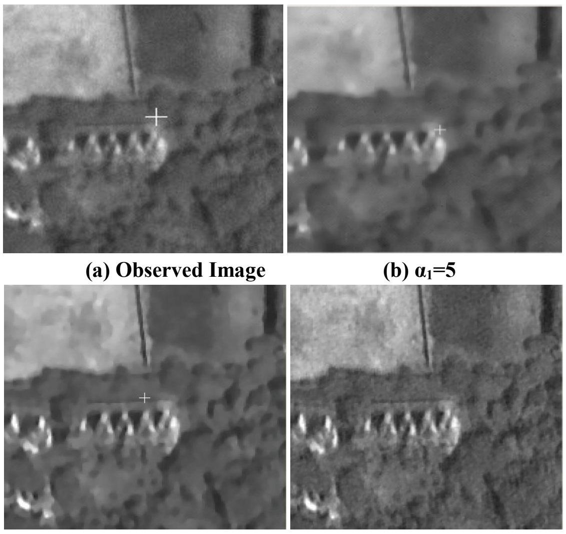
(a) Laplacian **(b) Total Variation**

Figure 2: Comparison of Laplacian and total variation regularization

It is observed that total variation preserved more edges and therefore considered as suitable operator for further analysis. Different values of regularization parameter (α_1) were used for different number of iterations.

Figure 3(b), (c) and (d) shows results of restored images with regularization parameter α1 set to 5, 1 and 0.0001 respectively using 100 iterations. It is observed that large value of α1 (i.e. >=1) results in a smoother image and is necessary if the noise is high. On the other hand, a small value of α1showsmoreimage details but noise increases as value decreases further (Berisha and Nagy, 2013; Thompson et al., 1991).

A single value of α_1(0.001) was chosen to study the variation in energy functional i.e. Equation (2) and image fidelity at different iterations. Figure 4 shows plot of energy functional i.e. Equation (2) at various iterations using total variation regularization operator. It is seen that at first iteration, value of total energy is high. During initial iterations, value is reduced and further the value is stabilised.



(a) Observed Image (b) α_1=5

(c) α_1= 1 (d) α_1=0.0001

Figure 3: Restored images with different values of α_1 and 100 iterations

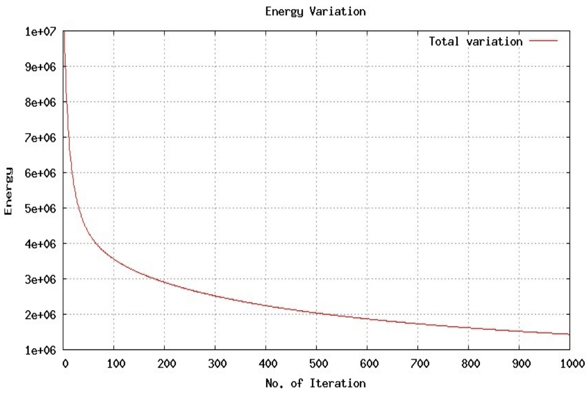


Figure 4: Plot of energy functional with respect to number of iterations using total variation regularization

In energy function two terms included are image fidelity and regularization. At the first iteration, there is high error component in image fidelity due to approximate first guess, which is set equal to the observed image. Image fidelity is defined as sum of squares of pixel-wise error between observed image and recovered image convolved with PSF. If the recovered image is close to actual object, after convolution, the image fidelity with respect to observed image tends to zero. Therefore image fidelity can be considered to be a good quantitative measure of quality of recovered image.

Figure 5 shows a plot of image fidelity with and without regularization operator. It can be seen that though at first iteration, image fidelity is equal, for recovery without regularization; it diverges to a very high value, signifying that image is unrecoverable without regularization. For recovery with regularization using total variation operator, about 25% reduction in error due to fidelity is observed in the first 100 iterations. Correspondingly, a large reduction in total energy functional is observed (see Figure 4) due to application of regularization constraint at each iteration.

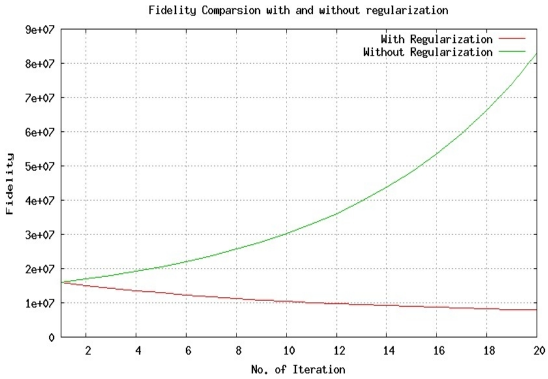
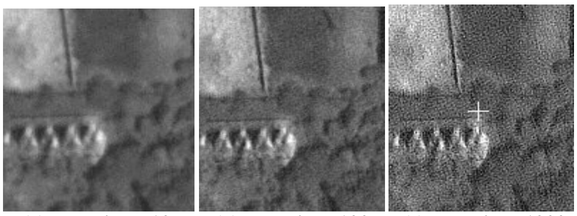


Figure 5: Comparison of Image Fidelity with and without Regularization

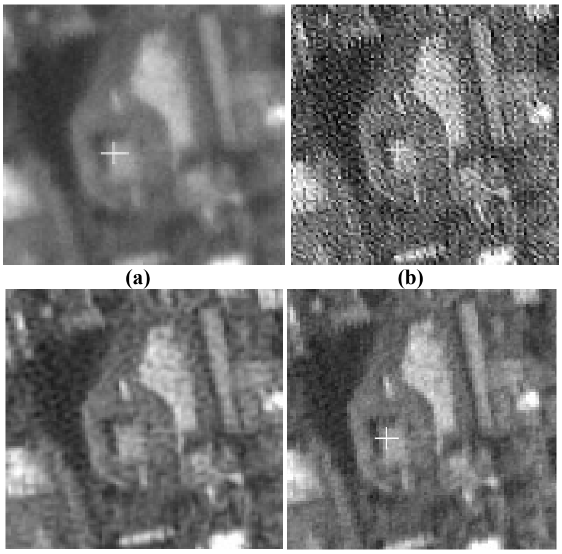


(a) Iteration =10 (b) Iteration=100 (c) Iteration=1000

Figure 6: Recovered images for different iterations with constant α_1

Results of recovered image for 10, 100 and 1000 iterations are shown in Figure 6. It can be seen that at 1000 iterations, recovered image is sharper at edges and value of energy functional is minimum. However, some effect of noise is seen in homogeneous regions which is undesirable.

A comparison of images recovered with iterative and direct methods is shown in Figure 7. Direct methods are implemented with known PSF and restoration filter applied in frequency domain. For Psuedo-inverse filtering i.e. Figure 7(*b*), value of constant is added to degradation function to avoid absurd results at high frequencies. Wiener filtering is implemented by assuming an exponentially increasing model of noise-to-signal ratio (NSR) with respect to spatial frequency. Fidelity error was computed for image recovered with direct approaches and iterative approach as described by Equation (2). For Wiener filtering, NSR was set to vary between minimum value (0.01 to 0.001) and maximum value of 1.0. Table 1 shows error due to fidelity (f') in recovered images. The corresponding total fidelity term is given by $f'x10^6$. It can be seen from Table 1, that good recovery (i.e. low value of fidelity error) can be achieved by using iterative methods as compared to direct methods.



(a) (b) (c) (d)

Figure 7: Comparison of direct and iterative methods (a) Original image; (b) Pseudo-inverse; (c) Wiener filtering (NSR_{min}=0.001); and (d) Non-blind iterative approach (100 Iterations)

Table 1: Comparison of fidelity error by various restoration approaches

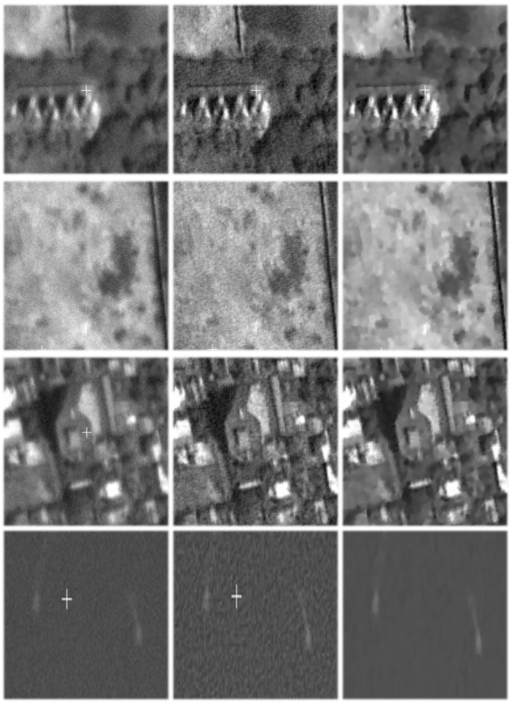
Method	Pseudo Inverse	Wiener (NSR_{min} =0.001)	Wiener (NSR_{min} =0.01)	Non-blind i=10	Non-blind i=100	Non-blind i=1000
f’	426	37	19.99	7.28	3.56	1.43

Effect of improved fidelity by iterative approach is seen as consistent improvement in image sharpness at various image textures with considerably low artefacts such as ringing, as compared to direct methods. Terms fidelity and regularization provide competing effects for energy function. So, minimization of $E(f)$ can be convergent to an optimal $f(x,y)$ for certain values of α_l. If $\alpha_l$parameter is not chosen properly with respect to image content, then it generates noise in homogeneous regions. In the next section, an approach for adaptive selection of regularization parameter α_l based on image variance is proposed to handle improper noise amplification in recovered image.

4. Adaptive tuning of image regularization parameter

Noise amplification, mostly seen in homogeneous areas of the image, is undesirable. To maintain smoothness and sharpness in different regions, varying model of α_l based on local variance of the image pixel to be restored is used. Two values of $\alpha_l$are selected in this regularization that gives sharpness (i.e. α_{sharp}) is set to 0.001 and regularization for smoothing (i.e. α_{smooth}) is set to 0.5. For deciding upon the value of regularization to be used, a variance image is generated for recovered image. At each pixel, local variance value is examined. If it is greater than a threshold (typically set as value of variance at edge-regions) then α_{sharp} is used for recovery. If the value is less than threshold, as seen in homogenous regions of the image, value corresponding to α_{smooth} is chosen. The variance threshold was set to be equal to the mean value of variance of the recovered image with corresponding iteration (in this case it was found to be ~100).

First column of Figure 8 shows different feature types i.e. edge, ground, urban and water images of Cartosat-2A of size 256x256. In the second and third column, images recovered by non-blind, non-adaptive approach (section 3) and non-blind adaptive approach as explained in this section are shown. For both approaches 100 iterations were carried out. Figure 8 indicates qualitative improvement in adaptive method with respect to non-adaptive method as it is able to control noise and maintain sharpness. A metric SNRis good measure of quality of recovered images (Barisha and Nagy, 2013; Lagendijk and Biemond, 1999).



(a) Observed Images (b) Non-adaptive (c) Adaptive

Figure 8: Comparison of non-adaptive and adaptive recovered images with observed image.

Table 2 shows comparison of improvement in restored images with proposed adaptive technique in different types of images. The SNR is calculated as per Equation (7) where f(x, y) denotes the pixels of given image of size $m \times n$ pixels.

$$SNR = 20\, log_{10} \frac{max\big(f(x,y)\big) - min\big(f(x,y)\big)}{\sqrt{\sum_{x=0}^{m-1}\sum_{y=0}^{n-1}\big[f(x,y) - \bar{f}(x,y)\big]^2}} \quad (7)$$

For edge, urban and ground areas, improvement in SNR by adaptive method is observed with respect to original as well as image restored with non-adaptive approach. For water, SNR improvement is seen when compared to non-adaptive restored image. The proposed approach of adaptive tuning of regularization parameter is applied to blind type of recovery explained in section II by Equation (5) and (6). Figure 9 shows images recovered with blind adaptive approach. In this method 50 implicit iterations were carried out for image recovery with total variation as regularization operator. For PSF recovery, three explicit iterations were carried out.

Table 2: Signal-to-noise ratio (SNR) values in (dB) for iterative recovered images (original image, non adaptive and adaptive)

Area	Original SNR (in dB)	Non-Adaptive SNR (in dB)	Adaptive SNR (in dB)
Edge	16.51	18.47	18.54
Ground	17.53	20.4	20.9
Urban	22.75	25.48	25.73
Water	25.28	22.6	24.5

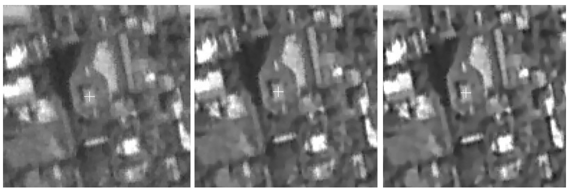


Figure 9: Blind deconvolution adaptive: With explicit iteration 1, 2 and 3

The recovered image with explicit iteration 2 and 50 implicit iterations is comparable to non-blind adaptive result as shown in Figure 8 (row 3, column 3). This approach can be used for image restoration when estimate of sensor PSF is not available. Comparison of time taken for blind and non-blind restoration is given in Table-3.

Table 3: System configuration and time taken for iterative image restoration

System Configuration	8 GB RAM, Intel Xeon Dual Core Processor 3.40 GHz, Linux 5(32 bit)	
Image Size	1024x1024 pixels	
No. of Iterations	Time taken (in seconds)	
	Non-blind Iterative	Blind Iterative
5	3	5
20	14	17
30	28	32
50	71	78
100	170	188

5. Conclusion and future work

In this paper, iterative techniques for deconvolution of high resolution images acquired by Cartosat-2A are explored. Using iterative non-blind restoration model, the recovered image was obtained by using sensor PSF and total variation regularization operator. Fidelity error for images recovered by iterative technique was found to be low, when compared with conventional direct methods such as Inverse and Wiener filtering, indicating better recovery. To control noise amplification, adaptive technique for tuning of regularization parameter based on local variance is proposed. Adaptive tuning was applied to non-blind as well as blind restoration, in which PSF is unknown initially. Qualitative and quantitative results of recovered images using adaptive technique are presented which indicate improved recovery by increased signal-to-noise ratio. Tuning of regularization techniques combined with pre-conditioning of images for further improvement of fidelity and faster processing approach is proposed as future work.

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