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COMPARATIVE ANALYSIS OF IMAGE RESTORATION OF REMOTE SENSING IMAGES USING LUCY RICHARDSON,WIENER AND BLIND DECONVOLUTION

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***Abstract*— Remote sensing works on the principle of the inverse problem. While the object or phenomenon of interest (the state) may not be directly measured, there exists some other variable that can be detected and measured (the observation), which may be related to the object of interest through the use of a data-derived computer model. The common analogy given to describe this is trying to determine the type of animal from its footprints. For example, while it is impossible to directly measure temperatures in the upper atmosphere, it is possible to measure the spectral emissions from a known chemical species (such as carbon dioxide) in that region. The frequency of the emission may then be related to the temperature in that region via various thermodynamic relations. The images captured by satellite using remote sensing technique will analyzed. To obtain the image data, satellite sends signals to the object and then captures the reflection of the object surface. This data must be treated correctly though to acquire the images of the surface. The area of interest in given image, called region of interest can be defined. After defining the region of interest apply the Lucy Richardson, Wiener and Blind Deconvolution to refine the region of interest in image to get the useful information from captured image.**

***Keywords*— PSF,Region of Interest, Lucy Richardson, Wiener Filtering and Blind Deconvolution.**

I. INTRODUCTION

Remote Sensing

Systematic aerial photography was developed for military surveillance and reconnaissance purposes beginning in World War I and reaching a climax during the Cold War with the use of modified combat aircraft such as the P-51, P-38, RB-66 and the F-4C, or specifically designed collection platforms such as the U2/TR-1, SR-71, A-5 and the OV-1 series both in overhead and stand-off collection. A more recent development is that of increasingly smaller sensor pods such as those used by law enforcement and the military, in both manned and unmanned platforms. The advantage of this approach is that this requires minimal modification to a given airframe.The development of artificial satellites allowed remote sensing to progress to a global scale as of the end of the Cold War.

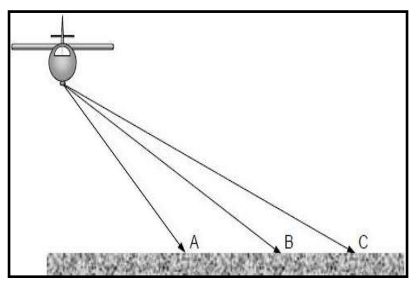

Fig:1.1-Remotesensing

Space probes to other planets have also provided the opportunity to conduct remote sensing studies in extraterrestrial environments, synthetic aperture radar aboard the Magellan spacecraft provided detailed topographic maps of Venus, while instruments aboard SOHO allowed studies to be performed on the Sun and the solar wind, just to name a few examples.

II Methodology

The main aim of this paper is to analyze the images captured by satellite using remote sensing technique. To obtain the image data, Satellite sends signals to the object and then captures the reflection of the object surface. This data must be treated correctly though to acquire the images of the surface we want to define. To obtain the final image there are some basic steps to follow to do it properly. First of all, mark the region of interest in the given image and after getting the region, apply Lucy Richardson, Wiener and Blind Deconvolution Algorithms.

Region of Interest

A region of interest (ROI) is a portion of an image that you want to filter or perform some other operation on. You define an ROI by creating a binary mask, which is a binary image that is the same size as the image you want to process with pixels that define the ROI set to 1 and all other pixels set to 0. You can define more than one ROI in an image. The regions can be geographic in nature, such as polygons that encompass contiguous pixels, or they can be defined by a range of intensities. In the latter case, the pixels are not necessarily contiguous.

ROI Filtering

Filtering a region of interest (ROI) is the process of applying a filter to a region in an image, where a binary mask defines the region. For example, you can apply an intensity adjustment filter to certain regions of an image. To filter an ROI in an image, you use the following parameters:

1.Input image to be filtered

2.Binary mask image that defines the ROI

3.Filter (either a 2-D filter or function)

Lucy–Richardson deconvolution

It is an iterative procedure for recovering a image that has been blurred by a known point spread function. Pixels in the observed image can be represented in terms of the point spread function and the latent image as

$$d_i = \sum_j Pij \text{ uj} \quad (1)$$

here Pij is the point spread function (the fraction of light coming from true location j that is observed at position i), uj is the pixel value at location j in the latent image, and di is the observed value at pixel location i. The statistics are performed under the assumption that uj are Poisson distributed, which is appropriate for photon noise in the data.

The basic idea is to calculate the most likely uj given the observed di and known pij. This leads to an equation for uj which can be solved iteratively according to

$$u_j^{(t+1)} = u_j^{(t)} + \sum_i \frac{d_i}{c_i} Pij \quad (2)$$

where

$$c_i = u_j^{(t)} + \sum_j Pij \quad (3)$$

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

Weiner Filtering

Its purpose is to reduce the amount of noise present in a signal by comparison with an estimation of the desired noiseless signal. The discrete-time equivalent of Wiener's work was derived independently by Kolmogorov and published in 1941. Hence the theory is often called the Wiener-Kolmogorov filtering theory. The Wiener-Kolmogorov was the first statistically designed filter to be proposed and subsequently gave rise to many others including the famous Kalman filter. A Wiener filter is not an adaptive filter because the theory behind this filter assumes that the inputs are stationary.

The goal of the Wiener filter is to filter out noise that has corrupted a signal. It is based on a statistical approach Typical filters are designed for a desired frequency response. However, the design of the Wiener filter takes a different approach. One is assumed to have knowledge of the spectral properties of the original signal and the noise, and one seeks the linear time-invariant filter whose output would come as close to the original signal as possible. Wiener filters are characterized by the following:

1. Assumption: signal and (additive) noise are stationary linear stochastic processes with known spectral characteristics or known autocorrelation and cross-correlation
2. Requirement: the filter must be physically realizable/causal (this requirement can be dropped, resulting in a non-causal solution)
3. Performance criterion: minimum mean-square error (MMSE)

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). 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.

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. Nonetheless, the emphasis in blind equalization is on online estimation of the equalizer filter, which is the inverse of the channel impulse response, rather than the estimation of the channel impulse response itself. This is due to blind deconvolution common mode of usage in digital communications systems, as a mean to extract the continuously transmitted signal from the received signal, with the channel impulse response being of secondary intrinsic importance.The estimated equalizer is then convolved with the received signal to yield an estimation of the transmitted signal.

III Implementation

MATLAB-7.0 is for the implementation. First of all, mark the region of interest on the given input image. After getting the ROI, refine the ROI by using various techniques. After that comparison of LRA with the other algorithms.

Following are the screenshots of implementation

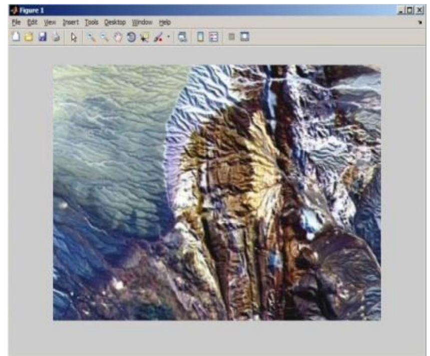

Figure :3.1-Input image

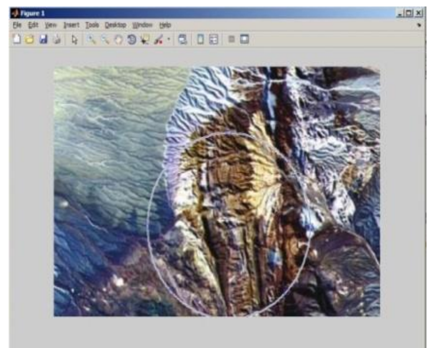

Figure:3.2 ROI-I

Above figure shows the initial marking for region of interest.

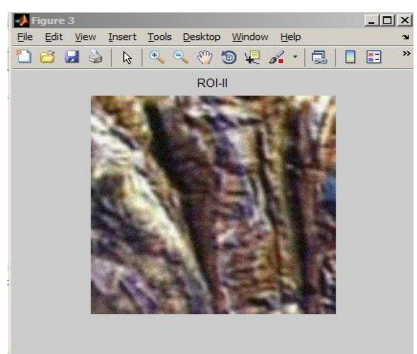

Figure:3.3 ROI-II

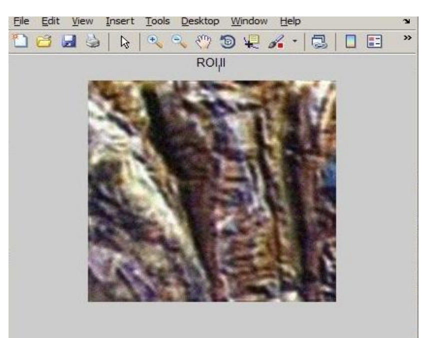

Figure:3.4- Output image of Lucy-Richardson Algorithm

Figure:3.4- Output image of Wiener Filtering

Figure:3.6- Output image of Blind Deconvolution

IV. Results And Analysis

Table I- Quality measurement for input image

PSNR	+14.93901 dB
MSE	2101.73934
RMSE	45.84473
UIQI	0.14376
SNR	-9.16793 dB
MAE	31.38706

As per the above table I, the value for PSNR is +14.93901 dB, value of MSE is 2101.73934, value of RMSE is 45.84473, value of Universal Image Quality Index is 0.14376, value of SNR is -9.16793 dB and the value of MAE is 31.38706.

Table II.-Quality measurement for LRA

PSNR	+14.95358 dB
MSE	2094.70051
RMSE	45.76790
UIQI	0.16502
SNR	-9.15569 dB
MAE	31.32985

As per the above table II, the value for PSNR is +14.95358 dB, value of MSE is 2094.70051, value of RMSE is 45.76790, value of Universal Image Quality Index is 0.16502, value of SNR is -9.15569 dB and the value of MAE is 31.32985.

Table III-Quality measurement for Wiener

PSNR	+14.82631 dB
MSE	2156.99604
RMSE	46.44347
UIQI	0.17325
SNR	-9.29219 dB
MAE	32.36310

As per the above table III, the value for PSNR is +14.82631 dB, value of MSE is 2156.99604, value of RMSE is 46.44347, value of Universal Image Quality Index is 0.17325, value of SNR is -9.29219 dB and the value of MAE is 32.36310.

Table IV-Quality measurement for BDC

PSNR	+14.86019 dB
MSE	2140.23048
RMSE	46.26263
UIQI	0.23960
SNR	-9.28360 dB
MAE	32.07995

As per the above table IV, the value for PSNR is +14.86019 dB, value of MSE is 2140.23048, value of RMSE is 46.26263, value of Universal Image Quality Index is 0.23960, value of SNR is -9.28360 dB and the value of MAE is 32.07995.

V. CONCLUSION

Many solutions have been implemented to obtain the high resolution image by reducing the effect of noise. Our proposed method can improve the quality of the remote sensing image and enhance its resolution. It considers the different quality parameters i.e. Peak Signal to Noise Ratio, Signal to Noise Ratio, Mean squared error, Root Mean squared error, Mean absolute error and Universal Image Quality Index.

First of all, analysed the given input image and after that defined the region of interest. After that used different algorithms for refinement and obtained the refined images produced by each algorithm.

Table V-Quality measurement for different algorithms

	Input Image	LRA	Wiener	BDC
PSNR	14.93901	14.95358	14.82631	14.86019
MSE	2101.73934	2094.70051	2156.99604	2140.23048
RMSE	45.84473	45.7679	46.44347	46.26263
UiQi	0.14376	0.16502	0.17325	0.2396
SNR	-9.16793	-9.15569	-9.29219	-9.2836
MAE	31.38706	31.32985	32.3631	32.07995

PSNR value for LRA algorithm is very high as compared to other algorithms and it is low for wiener algorithm which is slightly less than the PSNR value of BDC algorithm. Input image's PSNR is slightly less than the LRA's PSNR value. Thus ,LRA algorithm has enhanced the value of PSNR as compared to other algorithms.

MSE value for LRA algorithm is very low as compared to other algorithms and it is highest for wiener algorithm which is slightly large then the MSE value of BDC algorithm. Input image's MSE is slightly large then the LRA's MSE value but less than others. Thus LRA algorithm has reduced the value of MSE as compared to other algorithms.

RMSE value for LRA algorithm is very low as compared to other algorithms and it is highest for wiener algorithm which is slightly large then the RMSE value of BDC algorithm. Input image's RMSE is slightly large then the LRA's RMSE value but less than others. Thus LRA algorithm has reduced the value of RMSE as compared to other algorithms.

UIQI value for LRA algorithm is very low as compared to other algorithms and it is highest for BDC algorithm which is slightly large then the UIQI value of wiener algorithm and Input image's UIQI is less than others. LRA algorithm has slightly enhanced the value of UIQI as compared to other algorithms.

SNR value for LRA algorithm is very low as compared to other algorithms and it is highest for wiener algorithm which is slightly large then the SNR value of BDC algorithm. Input image's SNR is slightly large then the LRA's SNR value but less than others. Thus, LRA algorithm has reduced the value of SNR as compared to other algorithms.

MAE value for LRA algorithm is very low as compared to other algorithms and it is highest for wiener algorithm which is slightly large then the MAE value of BDC algorithm. Input image's MAE is slightly large then the LRA's MAE value but less than others. Thus, LRA algorithm has reduced the value of SNR as compared to other algorithms.

As per the above discussion, we can conclude that LRA algorithm works in a better way to enhance the different quality parameters related to image.

References

[1] NASA (1986), Report of the EOS data panel, Earth Observing System, Data and Information System, Data Panel Report, Vol. IIa., NASA Technical Memorandum 87777, June 1986, 62 pp. Available at http://hdl.handle.net/2060/19860021622.

[2] P. S. NAIDU AND V. V. KRISHNA REDDY, "Fraunhoffer Diffraction Analysis of Satellite Cloud Imagery", IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING, VOL. GE-25, NO. 4, 1987.

[3] Hiroshi Hanaizumi, Hosei University, College of Engineering Department of Industrial and System Engineering, Sadao Fujimura, University of Tokyo,, Japan, "An Automated Method For Registration Of Satellite Remote Sensing Images".-1993.

[4] CR. Nagaraja Rao' and Jianhua Chen2 ': NOAA/MESDIS Office of Research and Applications(E/RA14), NOAA Science Centr-Washington,"Calibration And Characterization Of The Post-Launch Performance Of The Visible, And Near-Infrared Channels Of The Advanced Very High Resolution, Radiometer(Avhrr) On Board The Noaa-7, -9, And -11 Spacecraft", 1995.

[5] Vito Pascazio 1, Gilda Schirinzi 2,1Ism.uto di Teoria e Tecnica delle On& Elettromagnetiche, Istituto Universitario Navale Via A. Acton 38, 80133 Napoli, Italy,"Reduction of Multiplicative Noise in SAR Imaging by Wiener Filtering",IEEE-1996

[6] Kundur, D.; Hatzinakos, D.; Leung, H. Dept. of Electr. & Comput. Eng., Toronto Univ., Ont," A novel approach to robust blind classification of remote sensing imagery", IEEE-1997

[7] Neon A. Armand, Vsevolod V. Efremenko Institute of Radio Engineering and Electronics of Russian Academy of Sciences, RUSSIA, Luca Pantani, Ivan Pippi C.N.R.- I.R.O.E. "Nello Carrara", ITALY, "ENVIRONMENTAL MONITORING IN ITALY USING THE OPTICAL SENSORS OF THE PRIRODA MODULE", IEEE-1997

[8] FmyX Hardin, Ryan R. Jensen, David G. Long and Quinn P. Remund, Miemwave ~ Earth Remote Sensing tzttrerrdorqr, CB. Brigham Young University, Provo, Testing of cloud reoval Algorithms for SSM/I"IEEE-1999.

[9] Scott A. Starks, University of Texas at El Paso, El Paso, Texas, USA "Interval and Fuzzy Methods in Remote Sensing and Satellite Image Processing", IEEE-2001.

[10] Oleg V. Goriachkin and Daniel D. Klovsky, Remote sensing technology laboratory of Volga State Academy of Telecommunications and Informatics,Russia,"Techniques of blind SAR processing: theory and practical applications",2002.

[11] Filip ˇSroubek and Jan Flusser, Senior Member, IEEE,"Multichannel Blind Iterative Image Restoration",IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL. 12, NO. 9, SEPTEMBER 2003.

[12] W. Souid2ne1p2, K. Abed-Meraim', A. Beghdadi', ILaboratoire de Traitement et de Transport de I'Information (L2TI) Institut Galilie, Universitk Paris 13,99 avenue J.B. Clhent, Villetaneuse 93430 'Signal and Image Processing Department, Telecom Paris, 46, rue Barrault, 75013, Paris,"Blind Multichannel Image Deconvolution with Regularization".

[13] Alexmder M. Bron.rtebi, Micliael Zibiclevsky. Yehnshuri Z Zeevi,Michael M. Brorisieiri Departmcnt of Computer Science Tcchnion - Israel Institute of Technology-Israel,"FAST RELATIVE NEWTON ALGORITHM FOR BLIND DECONVOLUTION OF IMAGES",2004 International Conference on Image Processing (ICIP)-2004.

[14] Sun Tao, Electronic Information School, Yang Zhigao Lin Liyu Qin Qianqing National Laboratory for Information Engineering in Surveying, Mapping and Remote Sensing Wuhan University Wuhan, China, "Single-Frame Remote Sensing Image Superresolution Reconstruction with Sub-blocks Noniterative Scheme", China National "973" Foundation.No. 2004.

[15] Lihong Yang, Graduate School,Jianyue Ren, Space Optics Research Lab Changchun Institute of Optics, Fine Mechanics and Physics, Chinese Academy of Sciences, Changchun, China,"Remote Sensing Image Restoration using Estimated Point Spread Function",2010 International Conference on Information, Networking and Automation (ICINA).